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Inference on Causal Risk Differences: Testing Statistical Hypotheses

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Abstract

The use of unconditional tests for comparing hypotheses on the 2×2 binomial trial is still not widespread in the applications, despite these preserve the significance level and usually are more powerful than conditional exact tests for moderate to small samples. Previously, this was due to the bigger computational demand of this approach with respect to the conditional approach. Today, softwares can easily compute the p-values of both conditional and unconditional tests. In this thesis the Suissa and Shuster (1985)'s unconditional test is reviewed and a new R algorithm aimed to derive exact unconditional p-values is proposed. We use both the classical Lehmann (1959)'s procedure and the Berger and Boos (1994)'s procedure, which calculates the p-values by maximizing the null power function on a confidence interval for the nuisance parameter. Optimal values for the confidence level are derived for different degrees of imbalance of the sample sizes. Furthermore, we propose the use of the unconditional approach for testing statistical hypotheses within the framework of the Rubin Causal Model.

Introduction

Science unavoidably deals with cause, since the main purpose of most scientific works is to disclose causal relations. Physicians aim to discover if our way of life can cause cancer and why; psychologists explore the relation between our gene pool and our patterns of behaviour (e.g. those related to criminality); economists study whether human capital is positively correlated with our chances to succeed. In this highly demanding *society of knowledge*, the *mission* of statistics is to develop adequate and robust methodological tools. Standard statistical methods do not allow a researcher to draw inference on the causal nature of an observed relation. If we expect that the association between two variables is not only due to chance, we'll consider and check the correlation between those two variables. Nevertheless, other variables could affect the relation we're interested in. Such variables are classically referred to as *counfounders* by the epidemiology literature, and the type of relation they create is typically known as *spurious.*

Nowadays, many statistical tools in order to study these relations in a multivariate framework are currently used by applied researchers. These range from those relatively simple and widespread such as multiple regression (see for instance Angrist and Pischke (2008) for a modern approach), to those highly complex and recently developed like structural equation modeling (e.g. Loehlin (2004)) multilevel mixture models (e.g. Vermunt (2007)) and multilevel latent class models (e.g. Vermunt (2003); Vermunt and Magidson (2005)). For instance, the latent class approach is currently used for analyzing and segmenting markets (e.g. Wedel and Kamakura (2000)). Overall, these methods allow a researcher to evaluate the effect of one or more variables on one ore more outcomes, hence allowing them to make well-grounded assertions on the importance of the relation they're studying. However, multivariate methods, also those highly sophisticated and provided with good estimation tools, do not permit *per se* to get information on the *nature* of the relations among variables and do not allow *per se* to identify confounding. In order to leap over the hedge and consider the *causal* nature of the relation we're studying, at first we do not need to develop new statistical tools, but we have to *change our way of looking at world*. Indeed, this is the first step towards *causal inference* and to the *Rubin's causal model*.

Causal inference not only aims to analyze data, but also to disclose the mechanisms that have generated data. Hence, the dynamics of change can be retrospectively examined and prospectively foreseen. It can be rightly asserted that the origin of modern statistics are inextricably related to the problem of causality. Indeed, most of the modern statistical approaches to causal inference (see Holland (1986) for an introduction) originate from the seminal analyses of randomized controlled trials proposed by Fisher (1925) and Neyman (1923). During the 1970s, Donald Rubin developed the framework for the well-known approach to the analysis of causal effects (Rubin, 1973a,b, 1974, 1977, 1978). The "core" of the Rubin's proposal refers to the philosophical theory of *counterfactuals* put forth by contemporary philosophers such as David Lewis (e.g. Lewis (1973)). Basically, this approach suggests to consider causal relations in terms of comparison between *potential outcomes*. These are pairs of possible outcomes, defined on the same unit, which refer to two possible and alternative "states of the world" (we'll precisely justify and develop this statement in Chapter 2). Note that the Rubin's approach to causality is not certainly the *only* modern approach to causality. For instance, influential statisticians such as Philip Dawid, have recently proposed a different statistical framework to causality (e.g. Dawid (2000)), which essentially refers to the philosophical works of Wesley Salmon (e.g. Salmon (1984)).

Rubin's model of causality is also known as *Program Evaluation Approach*, since its main purpose is to draw inference from the outcomes generated by exposure of a set of units to a program or treatment. Truly, a program can be made of more than a single treatment. Nevertheless, in the present work we'll only consider the case in which units are only exposed to a single treatment. In this case, the members of the population who take part in the program will be denoted as *participants* (or exposed, treated), whereas those who do not take part in the program will be referred to as *non-participants* (or non-exposed, non-treated). Causal inference aims to ascertain whether participation to a certain program does have or does not have a *causal effect* on a certain outcome.

The statistical literature has been so far mostly interested in the problem of *estimation* in causal inference (see Wooldridge (2007) for a recent review) whereas less attention has been given to the problem of *testing statistical hypotheses*. As far as estimation is concerned, literature has classically focused on estimation under the fundamental hypothesis of *unconfoundedness*, which will be discussed in Chapter 2 and 3. More recently also another hypothesis, known as *selection on unobservables*, has been deeply considered and methods for estimation under this hypothesis have been proposed. Such a rich literature focusing on estimation contrasts with the small number of works that have considered the problem of testing statistical hypotheses from a causal point of view. Most of these works are due to Rubin and coworkers (see Imbens and Rubin (2011) for a review) and pertain to two basic methodologies to the problem of testing statistical hypotheses in randomized experiments: the classic Fisherean approach and the Neyman's repeated sampling approach.

In the present thesis we'll consider in depth the problem of testing statistical hypotheses in a causal framework. In Chapter 1 we'll introduce causal inference from a philosophical point of view. A historical background shall be given, going back from Plato's and Aristotle's original speculation to the Kantian conception of cause. Subsequently, four among the modern most influential perspectives on causality will be reviewed: the Mechanistic theories (Wesley Salmon and Phil Dowe); the Probabilistic theories (Hans Reichenbach; Patrick Suppes); the Counterfactual theories (David Lewis) and the Agent-oriented theories (Huw Price; Peter Menzies). After this historical background, we'll put forward an operational definition of causality proposed in Bollen (1989) and we'll discuss the famous Hill's criteria for causality, which have been published in 1965 in a very influential paper on the *Proceedings of the Royal Society of Medicine*. An analytical review on causality from a statistical perspective cannot get along without considering these criteria, that have found large agreement among epidemiologists.

In Chapter 2 we'll introduce causal effects within the Potential Outcomes Framework and basic definitions will be given. We'll consider the assignment mechanism and define different types of studies (classical randomized studies, completely randomized studies, observational studies). Afterwards, basic assumptions to draw causal inference will be introduced and discussed. We'll define average causal effects and how to measure them. In particular, we'll introduce the concepts of *risk difference*, *risk ratio* and *odds ratio*. In the following chapters, only risk difference will be considered and methods aimed to test hypotheses for risk difference will be reviewed. We'll apply these concepts in the case of randomized experiments and we'll introduce both the Fisher's and the Neyman's approaches to testing statistical hypotheses. Last, a brief note on the James Heckman's *Structural Approach* to causal inference will be given.

In Chapter 3 we'll first consider how to estimate causal effects under unconfoundedness. We'll introduce regression methods, methods based on the propensity score, matching methods, methods that combine regression with propensity score weighting, methods that combine matching and regression. We'll briefly discuss how to assess the unconfoundedness assumption, and it will be shown that only indirect methods can be used. Furthermore, we'll consider estimation methods when the fundamental hypothesis of unconfoundedness is not expected to hold (*selection on unobservables*). We shall go over bound methods, sensitivity analysis, the methods based on instrumental variables, regression discontinuity designs and difference-in-differences methods. Last, we'll briefly mention at James Heckman's work on observational studies and on choice modeling.

The first three chapters of the present work have to be considered as a general framework, in the light of which examining the problem of testing statistical hypotheses. As it has been mentioned, we'll narrow our attention on risk difference and on the exact analysis of 2×2 binomial trials. A brief review on optimal and suboptimal testing of statistical hypotheses will be given. Subsequently, the main methods developed to test statistical hypotheses on the 2×2 binomial trial will be reviewed. Differently from the most recent reviews on this issue (e.g. Lydersen *et al.* (2009)), which mainly classify tests from a design of experiment point of view, we'll also focus on the theoretical properties of testing, with particular emphasis on concepts such as those of *admissible test* and *valid p-value*. Moreover, we'll compare the various tests that have been proposed in the literature in terms of degree of conservatorism and power. Last, we'll introduce the issue of unbiased estimation of risk differences in the Potential Outcomes Framework and its connection with the problem of testing statistical hypotheses.

In Chapter 5 we'll present an unconditional approach to testing statistical hypotheses on a $2{\times}2$ binomial trial, originally proposed by Suissa and Shuster (1985). This is a test which considers standardized risk differences as a test statistic. We'll shed into light the advantages that can be obtained using an unconditional rather than a conditional (e.g. Fisher's exact test) approach to this problem. Nevertheless, as it shall be clear, the original Suissa and Shuster (1985)'s paper presents with some limitations and shortcomings, also due to the limited computational capacity in the 1980s.

In Chapter 6 we'll re-consider the Suissa & Shuster' s test, developing a new R algorithm aimed to derive the p-values of the test using the classic *maximization procedure* described in Lehmann (1959). One of the limitations of the Suissa and Shuster (1985)'s paper is that the p-values are only tabulated in the case of balanced sample sizes. We'll describe a new algorithm that can derive the p-values in a more direct way than the Fortran original algorithm, for both the balanced and the imbalanced case. We'll comment the results we've obtained by means of this algorithm, in the *unpooled* and the *pooled* cases, comparing both the degree of conservatorism and the p-values of the tests. Furthermore, we'll introduce the fundamental paper by Berger and Boos (1994) in which an alternative maximization procedure with respect to the original Lehmann (1959)'s procedure is put forward. By means of this new procedure, p-values are derived by maximizing the null power function not on the entire nuisance parameter space, but on a confidence set for the nuisance parameter. We'll highlight on the advantages of this approach and we'll show that the p-values thus obtained are *valid*. However, at the actual "state of the art", it is not clear how to *optimally* compute this confidence set. In particular, the two following questions can be posed: i) Which is the best method in order to construct the confidence set? ii) Which are the optimal values for the confidence level to be set? In this thesis, we'll not discuss the first question (which will be left for further research), and we'll only calculate asymptotic confidence sets (which are also adopted by Berger and Boos (1994)). We'll examine the second question, and we'll discuss which confidence levels have to be considered as optimal for deriving the p-values of the Suissa & Shuster's test. Monte Carlo simulations will be used in order to calculate the confidence intervals using different confidence levels. Last, we'll critically discuss our results, comparing both the degree of conservatorism and the power achieved using different versions of the Berger & Boos' modification for the Suissa & Shuster's test.

Clearly, the Conclusions that will be drawn from the present work will not certainly be conclusive. Further research will be sketched out with respect both to the theoretical properties of these tests and to further simulation work that will be performed. Furthermore, we'll propose to use the unconditional approach for testing statistical hypotheses on the 2×2 binomial trial also in the Potential Outcomes Framework. In particular, also in this case we'll focus on risk differences.

Actually, the present thesis has started from a concrete problem: that of testing statistical hypotheses on 2×2 binomial trials in the context of voxel-based lesion-symptom mapping (VLSM). We'll mention at this problem in the Conclusion and we shall point out some tracks for further studies applied to the neuroscience field.

Chapter 1

An Introduction to Causation and Causal Inference

1.1 Overview

One of the contemporary statisticians' main concerns is related to the causal interpretation of the results of experimental trials and observational studies. The issue of causality can be considered as a *philosophical keystone* in the history of human thinking, dating back to the pre-socratic wisdom, to Plato's and Aristotle's seminal speculations, and carried on also in contemporary philosophy. Fundamentally, we could assert that *drawing causal inference is the essence of applied sciences*. Since the history of mankind, human beings have always tried to draw inferences from the observation of nature: How long does corn take to grow? Why does the sun rise at different times? Is there any relationship between the phases of the moon and tides? Even if nowadays the previous questions have been answered, many others –such as the causes of cancer, the origin of the species, the destiny of stars and the anatomical foundation of human language– remain unresolved. The basic problem for applied researchers is that a general definition of causality does not exist which is routinely accepted. Modern philosophers, such as Bertrand Russell, have also proposed to definitely abandon the idea of causality. Moreover, as we shall see, hypotheses which are not directly testable are usually needed for causal inference in fields such as epidemiology or psychometrics. This might appear as an unconquerable obstacle to draw causal inference from our data. In this chapter, after briefly discussing the issue of the nature of causality from a historical perspective, we will examine which practical problems have to be faced in the search for causality from an applied point of view. The "philosophy" underlying this chapter is the following:

> One admits that causal thinking belongs completely on the theoretical level and that causal laws can never be demonstrated empirically. But this does not mean that it is not helpful to *think* causally and to develop causal models that have implications that are indirectly testable. In working with these models it will be necessary to make use of a whole series of untestable simplifying assumptions, so that even when a given model yields correct empirical predictions, this does not mean that its correctness can be demonstrated. [Blalock (1964), p. 6]

The first and basic question is: *Why do we really need causal inference*? Consider the following examples:

1. Is tobacco smoking a cause of lung cancer?
2. To what extent is Alzheimer's disease caused by environmental or genetic factors?
3. Is passive smoking a cause of cardiovascular diseases?
4. Does long-term use of hormone replacement therapy (HRT) cause breast cancer?
5. Can obesity be prevented by physical activity?

All the previous questions have long been debated in epidemiology and represent relevant topics in health policies and health services programming. These are some important reasons for which we need causal inference, i.e. not only for theoretical or philosophical purposes, but also for answering practical questions. The main problem we have to face, in the attempt to answer the previous questions, is that the observation of a correlation between two variables does not indicate *per se* the presence of an underlying causal relation. For instance, many people believe that the presence of immigrants is one of the causes of crime in urban areas. However, less people know that if the relation between these two variables were balanced with respect to other variables, such as years of school attended or occupational status, the relationship would probably disappear. So, the first lesson to be learned in the analysis of causality is that the relation among variables should always be checked in a multi-variate and not a bi-variate framework.

In the present chapter, a philosophical background on cause and causation will be briefly given (§1.2). The main reference for this section will be the book of Menno Hulswit on cause and causation from a Peircean perspective (Hulswit (2002)). Nevertheless, it would take too long to analyze the contributes of all the philosophers that have argued about concepts such as those of cause and causation. In the present work the attention will be especially focused on the diatribe between rationalist thinkers and empiricist thinkers. A brief overview about modern theories on cause and causation, as summed up by Williamson (2005), will also be given. In paragraph 1.3 the philosophical speculation will be put aside, and some practical problems with respect to the analysis of the relation among variables shall be faced; the main reference for this paragraph will be the seminal book of Kenneth Bollen on structural equation modeling (Bollen, 1989). Last, in paragraph 1.4, a different perspective on the same problems faced in paragraph 1.3 will be discussed: this is the Austin Bradford Hill's proposal of nine criteria to establish causality from an epidemiologic point of view (the main reference for this section will be Rothman *et al.* (2008)). These criteria are presented here also as a preamble to the second chapter on the Rubin Causal Model. Even if these criteria have rightly been criticized by many authors, they continue to be a useful framework for formalizing the main questions a researcher must make when dealing with the problem of identifying causal relations.

1.2 Historical Background

A first clear definition of *cause* can be found in *Plato*'s [424 B.C. - 348 B.C.] *Timaeus*: "everything that becomes or changes must do so owing to some cause; for nothing can come to be without a cause" (Timaeus 28a). After this seminal outlining, a good starting point for analyzing the development of the concept of cause from a historical perspective is given by the *Aristotle*'s [384 B.C. - 322 B.C.] speculation (consider in particular his *Posterior Analytics*, *Physics* and *Metaphysics*). The Greek philosopher built a metaphysical system in which the concept of cause was developed as an answer to the basic question: *What is this?*. A cause, i.e. something without which the things would not be (*aitia*), can be thought according to four different meanings: i) *material cause*, indicating the material nature of an entity; ii) *formal cause*, indicating the idea or abstract concept underlying a thing; iii) *efficient cause*, expressing the effect of antecedent events; iv) *final cause*, indicating the reason or the purpose of a thing.

> Thus, given a marble statue, the question "What is this?" could correctly be answered in one of the following ways: "This is marble", "This is what was made by Phydias", "This is something to be put in the temple of Apollo" and "This is Apollo". These answers are the answers to four different questions, respectively: "What is this made of?", "Who is this made by?", "What is this made for?" and "What is it that makes this what it is and not something else?". The answers have come to be known as, again respectively, the material cause, the efficient cause, the final cause and the formal cause. Though a complete answer to the original question would encompass those four different answers, and therefore the four different causes, Aristotle argued that the most important and decisive cause was the formal cause (Physics II, 194b23-195a3). Only the *efficient aitia* has features we now associate to the idea of causation. Aristotle conceived efficient causes as "things responsible" in the sense that an efficient cause is a thing that by its activity brings about an effect in another thing. Thus, the efficient cause was defined by reference to some substance performing a change: it is the "primary source of the change" (*Metaphysics* V.4, 1014b18-20). [Hulswit (2002), p. 17]

In Aristotle's view, causes are something that can be completely known from human beings, and causes are *necessarily* the antecedents of their effects. Whether Aristotle really proposed the concept of cause in terms of necessity it is still an open issue, but this *linkage* between the two concepts became the *bone of contention* among later philosophers. For instance, the concept of necessity was routinely accepted by the Stoic theorists:

> Thus, one of the main innovations of the Stoics was that the idea of cause is linked both to an exceptionless regularity and to necessity. The Stoics strictly held the view that each event has a cause. They rejected the idea that there could be any uncaused events, because that would undermine their basic belief in the coherence of the universe (e.g. Cicero, *De Fato*, 43). They held, moreover, that each particular event *necessitates* its effect. According to Alexander, for example, it is *necessary* that the same effect will recur in the same circumstances, and it is not *possible* that it be otherwise. [Hulswit (2002), p. 18]

In the Middle Ages, Aristotle's view of necessity was tried to be reconciled with the Christian belief of Creation. In fact, Aristotle's proposal of efficient cause was revised, distinguishing a *causa prima* from a *causa secunda*:

> The first type of efficient cause is the originative source of being. The second type of efficient cause is to be found only in created things, and refers to the origin of beginning of motion or change. The First Cause works in all secondary causes, which may be considered as instrumental causes subservient to the first. This conception of the primary efficient cause involves *a radical switch in respect of the Aristotelian notion of efficient causality*. Whereas in Aristotle, efficient causation was the origin of a change or a motion by means of the transmission of form, in medieval philosophy, primary efficient causality concerns the creation of both matter and form. [Hulswit (2002), p. 19]

The most influential among the Middle Ages' philosophers was Thomas Aquinas [1225-1274], who further differentiated an *internal* from an *external* final cause.

> Whereas all natural things have internal final causes themselves, created by God, the ultimate external goal is God himself. For, while the primary goal of created things is self-realization, this striving towards self-realization coincides with the striving toward the ultimate goal, which is God. In the formation of the world, but also in all created causality, final causality comes first and works in and through the efficient causes. The efficient causes are subordinate to the final causes inasmuch as they are *means* to ends. [Hulswit (2002), p. 20]

The Aristotelian conception of necessity was maintained and, at the same time, a distinction between *tight* causes and *loose* causes was proposed. The effect of a tight cause necessarily follows from the cause itself, whereas the effect of a loose cause requires other conditions to be fulfilled.

Some decades later, also *William of Ockham* [1288-1348] revised Aristotle's view of causation, proposing that cause is not a necessity by itself, since God can always intervene in the human history, changing the flow of events. It is important to note that both Thomas Aquinas and William of Ockham did not reject the metaphysical conception of cause put forth by Aristotle, but tried to bring together those original ideas with their Christian beliefs.

Such Christian Middle-Ages theologists' speculations were abandoned in the seventeenth century by modern philosophers who, instead of combining metaphysics with theology, tried to reconcile metaphysics with the new natural sciences.

> In the seventeenth century a movement of thought arose that has come to be known as modern science. This evolution involved a radical change in the development of the concept of cause. Explanations by formal causation and final causation were rejected; the only valid explanations were explanations by efficient causation. Moreover, the concept of efficient causation itself had radically changed. More specifically, in the seventeenth century the idea took root that (a) all causation refers exclusively to locomotion, (b) that causation entails determinism, and (c) that efficient causes were just the inactive nodes in the chain of events, rather than the active origination of a change. These changes have had a lasting influence on the evolution of our concept of cause, and indeed our entire Western outlook. [Hulswit (2002), p. 21]

The debate among modern thinkers regarded the idea and the nature of *determinism*. From one side, rationalist philosophers such as *René Descartes* [1596-1650], *Thomas Hobbes* [1588-1679], *Baruch Spinoza* [1632-1677] and *Gottfried Wilhem Leibniz* [1646-1716] held that the relationship between cause and effect is of a logical type. On the other side, *David Hume* [1711-1776] held an empiricist approach to causation, claiming that causal necessity is not logical but partly due to our observation of the constant conjunction of certain objects, and partly due to the feeling of their necessary connection. Note that, as remarkably observed by Hulswit, Hume's radical empiricism was not supported by other empiricist philosophers:

> Hume's view was far from being shared by all empiricist philosophers. Indeed, by suggesting that his fellow empiricists held the belief that necessity is synonymous with power, he seriously misrepresented their views. For, both Locke and Newton explicitly denied that the idea of causation or power involved the idea of necessary connection according to law. According to Newton, these two notions are even mutually exclusive because complete uniformity or necessary connection would entail a denial of causal efficacy. For Locke, as for Newton, causality is related to the Aristotelian belief that causes are substantial powers that are put to work. Therefore, Hume's famous criticism only concerns the rationalist scientific conception of cause, which, from an historical perspective, is merely a derivative sense of "cause". [Hulswit (2002), p. 37]

Let's briefly consider this debate more in detail. Rationalist authors proposed –in similar ways– the concept for which all things are causally determined, and determinism is entailed in the idea of God's omnipotence and omniscience. *René Descartes* was the most important among rationalist thinkers. First of all, Aristotle's original idea of efficient cause was substituted in Descartes' view by the idea of *types*, i.e. not particular but general deterministic laws. Second, these laws would ultimately belong to God's action. In this way, far from mistrusting the principle of causation, Descartes abandoned the Aristotelian-Scholastic doctrine, supporting instead a concept of cause delineated by the principles of mechanics.

> The rejection of the fourfold causality of Aristotle and the Scholastics by Descartes (and Galilei and Bacon) had a profound influence on subsequent thinkers. Whereas he endorsed matter, and in this particular sense may be said to have subscribed to material causality, he rejected the idea of substantial forms or formal causality. And though he did not deny the existence of final causes –which he identified in God's intentions– he denied the usefulness of such a search. In order to explain nature, we need only examine the efficient causes of things. Thus, in effect, there was only one type of cause for Descartes: the efficient cause. [Hulswit (2002), p. 20]

Furthermore, the father of rationalism distinguished between *general* and *particular* causes:

> Descartes attributed to God the status of a general cause, which insures the constancy of quantity of motion in the universe. Interestingly, the *particular causes* are not the motions of the individual parts of matter, but the *general* principles or laws of nature. In the beginning, God created matter and motion, and he conserves exactly the same quantity of motion for all time. God is the efficient cause of any change of motion in otherwise inert matter. And He does so according to the laws of nature, which became secondary causes. Thus, Descartes attributed some efficient causality to the laws of motion, which determine all particular effects. By doing so they provide causal, mechanical explanations. The only "active initiator of change" that remained was the cause of all causes: God. [Hulswit (2002), p. 20]

Also *Thomas Hobbes* revised Aristotle's original speculation about cause, rejecting the concepts of both formal and final causes while maintaining the distinction between efficient and material cause. The original conception of *necessity* was revised as well, and God was postulated as the causal origin of finite things. In such a view:

> The material and efficient causes are both part of the *entire cause*. *Necessity* or necessary connection is not associated with the efficient cause as such, but with the entire cause, which entails both the agent and the patient. Entire causes are complex conditions (of both agent and patients) that are necessary and sufficient for the occurrence of the effect. [Hulswit (2002), p. 24]

A very similar definition of cause as necessary and sufficient condition for the appearance of something was given also by *Galileo Galilei* [1564-1642]. A metaphysical conception of cause, similar to that of Descartes, but one that also took into consideration the Galilei's and Hobbes' perspectives was proposed by *Baruch Spinoza*, who put forth the concepts of *free* and *necessary* causes.

> Whereas free causes act from the necessity of their own nature (and therefore the initiators of a change) necessary causes are necessitated by other causes (and are therefore just inactive nodes in a chain). [...] God is the only *free cause*, by which is meant that, though He simply had to create what He did, He was not forced to do this by some external cause. He alone exists and acts from the necessity of his own nature. [Hulswit (2002), p. 24]

Note that Spinoza, agreeing with Descartes, strongly supported the idea for which causes are related to effects by logical necessity. A cause is the logical antecedent of any effect, and at the same time an effect is a logical subsequence of any cause.

An account of causation similar and integrated with both the views of Galilei and Spinoza was given by the philosopher *Gottfried Wilhem Leibniz* (1646-1716). He suggested the concept of *monad*, as constituent of all material bodies. This notion significantly differs from Descartes' proposal of *substance* as the ultimate constituent of things:

> The material bodies have monads as their constituents. The characteristic features of matter –extension, solidity, inertia, *etcetera*– are derived from the relations between the constituent monads. Thus matter is just a derivative entity, constituted of the *relations* between the primary existents. [Hulswit (2002), p. 25]

As a consequence, a new and different theory of causality was developed by Leibniz, who, from one side rejected the idea for which the monads would have causal relations to each other, and from the other side supported the view for which monads are inserted into a causal chain. The starting point of this chain is postulated to be God himself, who –as a good clockmaker who constructs a number of clocks that keep perfect time– would have pre-established the harmony of the universe at the beginning of things:

> Thus, all individual created substances are different expressions of the same "universal cause". However, though God caused their existence, their successive states are (normally) produced by their own natures. Every state of every monad is completely determined by its nature or *substantial form*, which is an internal, active causal principle. [...] Leibniz's doctrines of final causality and of spontaneity of simple substances fully agree with his brand of determinism: each monad behaves in accordance with its original purpose, that is to say, with its nature or substantial form, which it received through God's creation. Leibniz's determinism –which is based on his principle of sufficient reason– entails that the necessity involved in the relation between cause and effect is as strong as *logical necessity*. A complete knowledge of the causes would yield the premises from which by reasoning alone the effects could be concluded. [Hulswit (2002), pp. 26-27]

In this way, causal determinism is conceived by Leibniz in a rationalist framework. Nevertheless, the analogy between cause and change to locomotion proposed by other rationalist philosophers –such as Descartes, Hobbes and Spinoza– was rejected by Leibniz.

Modern metaphysical approaches to the concept of causality were criticized by the English philosopher *John Locke* [1632-1704], who abandoned the rationalist approach of Descartes, proposing instead the concept of *cause as power*. This notion may bring to mind the seminal Aristotelian formulation of efficient cause, since power is conceived as an abstract agent and as the source of change.

> Thus, a cause is a particular substance putting its power to work. Apparently, Locke conceived causes and effects as *particulars*. In his entire discussion of power there is no reference to either uniformity or necessary connection. "Power" and "necessary connection" are kept separate in Locke's thought, for although we do perceive powerful or changing objects and thus have the idea of power and cause, we do not perceive any necessary connections between ideas. By linking causation to power, but not to necessity, Locke clearly upheld what is nowadays called a singularist approach to causation. This view conflicts with the modern received view of causation (ever since Hume), according to which causation involves uniformity or necessary connection according to law. [Hulswit (2002), p. 27]

In analogy, according to *Isaac Newton* [1643-1727], causes are to be conceived as forces, the action of which makes the things move and behave differently than they would have done without them. This idea was formalized by Newton in three laws of motion, that are still the fundamental laws of classical physics and were implicitly stated in causal terms. Moreover:

> Newton may be said to radically reject the principle of universal causation, and to defend a *fundamental distinction between causation and law-like behavior*. For, there are two classes of events in Newton's universe: (a) those that happen according to law, and (b) those that are the effects of causes. Causation and law-like behavior (or necessary connection according to law) are mutually exclusive notions. [Hulswit (2002), p. 27]

In the eighteenth century, the rationalist approach originally proposed by Descartes was also challenged by a new theory of causation, centered on the concept of "constant conjunction", put forward by the empiricist philosopher *David Hume*.

> In this, only the content of experience can be known. Hume proposed an epistemological atomism in which the experienced world is a series of instantaneous, atomistic time slices, logically independent one another. Thus, even the experience of an object persisting in time is a construction of the mind, based on a series of time slices. This construction does not warrant the inference that the object will persist into the future. In fact, no inference about the future can be regarded as justified under radical empiricism. [...] Hume defined causation, therefore, as a construction of human mind, and how the characteristics of that construction arise. He said nothing about causation outside of experience, although he seemed to accept that there is such a thing and used causal terms in his own arguments. [White (1990), p. 4]

Hume's account of causality might be defined as both empiricist (from an epistemologic point of view) and constructivist (from a psychological perspective). Three basic factors are asserted to identify a causal relation: (i) contiguity in space and time of cause and effect; (ii) priority in time of cause to effect; (iii) connection (either explicitly identifiable or not) between cause and effect. Such a synthesis between empiricism and constructivism clearly distinguishes Hume's thinking from previous rational speculation. In the Scottish philosopher's view, no *logical necessity* has to be postulated, as remarkably noted by Hulswit:

> The problem is that given the concept of causal necessity, there seems to be no way of rationally justifying it. To Hume such justification could be given only if causal necessity could be shown to be as stringent as *logical necessity*. But this is impossible. Hence, the necessity that we read into causal relationship is illusory; the illusion is born from our expectations, which are due to habit. [...] The idea of necessity cannot be derived from our experience of individual cases of causation. For, in a single instance of causation, we can never discover any necessary connection or power. Instead, the idea of necessity arises from our experience of a great similar instances. The constant conjunction produces an *association* of ideas – so if we see a flame, by sheer habit an idea of heat will come to mind. Thus, there are two roots of our idea of necessity: *constant conjunction* of the objects, and the feeling of a necessary connection in the mind. The habitual transition from impression to idea *feels* like a necessitation, as if the mind were compelled to go from one to another. The necessary connection is not discovered in the world but is projected onto the world by our minds. [Hulswit (2002), p. 30]

In the nineteenth century, based upon Hume's concept of "constant conjunction", the philosopher *John Stuart Mill* (1806-1873) put forth some operational rules to ascertain the presence of causality (Mill (1967)):

1. *The Method of Agreement*: "If two or more instances of the phenomenon under investigation have only one circumstance in common, the circumstance in which alone all the instances agree, is the cause (or effect) of the given phenomenon". (p. 255)

2. *The Method of Difference*: "If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance in common save one, that occurring only in the former, the circumstance in which alone the two instances differ, is the effect, or cause, or a necessity part of the cause of the phenomenon". (p. 256)

3. *The Joint Method of Agreement and Difference*: "If two or more instances in which the phenomenon occurs have only one circumstance in common, while two or more instances in which it does not occur have nothing in common save the absence of that circumstance; the circumstance in which alone the two sets of instances differ, is the effect, or cause, or a necessary part of the cause, of the phenomenon". (p. 259)

However, Mill's concept of cause fundamentally differs from that of Hume, as Mill reintroduced the idea of necessity: an event A can be said to be the cause of B (the effect) if the two are unconditionally conjoined.

The concept of "constant conjunction" was criticized by *Immanuel Kant* (1724-1804), who proposed a distinction between regularities that are merely accidental and regularities that are nomic or necessary.

> Making this distinction would show constant conjunction to be inadequate as a statement of the causal relation and would restore necessity to the proper description of causation. If I look at a wall, there is an order in my perceptions of the wall that corresponds to the movements of my eyes. However, I could choose to move my eyes in any way, thus producing any order of perceptions of the wall. By contrast, when I observe a boat moving downstream, the order of perceptions of positions of the boat is fixed. This exemplifies "following according to a rule", and when this occurs some causal relation is involved. So for Kant a causal relation is a relation of necessary succession in time. [...] Where Kant disagreed with Hume was in arguing that necessity is not just a construction of the mind, but is ascertained by looking at which orders of representations of events are objectively determined. [White (1990), p. 5]

The main feature of Kant's philosophy can be identified in the attempt to reconcile empiric-based scientific knowledge with the principles of rationalism put forth by Descartes and other modern philosophers.

> Kant, much impressed by the obvious success and constant advance of scientific knowledge, Newtonian physics in particular, could not accept Hume's conclusion that neither causation nor induction can be rationally justified, and that, consequently, we cannot rationally justify scientific knowledge. His basic epistemological strategy was to ground the principle of causality in the structure of reason. Given the epistemologically disastrous consequences of Hume's critique, Kant attempted to justify causality by declaring it in an *a priori* conception. [Hulswit (2002), p. 31]

This *a priori* conception is formalized by postulating a set of twelve categories (among which there is also a principle of causality) that are supposed to shape the human mind.

> The principle of causality is an *a priori* conception, grounded in the structure of reason. It involves that (a) every event has a cause; (b) the cause of every event is a prior event; (c) the effect follows from the cause necessarily, and (d) in accordance with an absolutely universal rule; (e) this is known to us not from experience but a priori. [Hulswit (2002), p. 31]

Today, the debate between regularity and necessity theories of causation is still not conclusive. Contemporary perspectives on causation can be summed up by four main approaches:

1. Mechanistic theories (*Wesley Salmon*; *Phil Dowe*);
2. Probabilistic theories (*Hans Reichenbach*; *Patrick Suppes*);
3. Counterfactual theories (*David Lewis*);
4. Agent-oriented theories (*Huw Price*; *Peter Menzies*);

The aim of the *mechanistic account* of causality is to understand the physical processes linking cause and effect. As asserted by Williamson (2005):

> The mechanistic account is clearly a physical interpretation of causality, since it identifies causal relationships with physical processes. Such a notion of cause relates single cases, since only they are linked by physical processes, although causal regularities or laws may be induced from single-case causal connections. Causal mechanisms are understood objectively: if two agents disagree as to causal connection, then at least one is wrong. [Williamson (2005), p. 111]

This approach is well applicable to explanations in fields of sciences such as physics, whereas it does not seem appropriate in the fields of social sciences such as economics.

> One could maintain that the economists' concept of causality is the same as that of physics and is reducible to physical processes but one would be forced to accept that the epistemology of such a concept is totally unrelated to metaphysics. This is undesirable: if the grounds of knowledge of a causal connection have little to do with the nature of the causal connection as it is analyzed then one can argue that it cannot be the causal connection that we have knowledge of, but something else. On the other hand one could keep the physical account and accept that the economists' causality differs from the physicists' causality. But this position faces the further questions of what economists' causality is, and why we think that cause is a single concept when in fact it is not. These problems clearly motivate a more unified account of causality. [Williamson (2005), p. 111-112]

In this mechanistic framework, Salmon (1984) proposed the concepts of *causal processes*, *causal propagation* and *causal production*. From this philosopher's point of view, the basic units to be considered for causal inference are not events but processes. Causal propagation is the dynamic influence that one event can have on another, whereas causal production is given by the interaction between two causal processes.

> What is crucial in identifying causal processes is the ability to carry a mark. Consider a pulse of light traveling from a spotlight to the wall of a planetarium. This is a causal process because it can carry a mark: For example, if you interpose a red filter between the spotlight and the wall, the light will be read all the way from the filter to the wall. Now imagine that the spotlight is rotated so that the light moves around the wall. The motion of the light around the wall is not a causal process because it cannot carry a mark: If you put a red filter on the wall, the light will be red when it hits the filter, but will cease to be red as soon as it moves away from the filter. The mark will not be transmitted. [...] Salmon (1984) explained the persistence of a physical object by arguing that if a process can transmit a mark then it can transmit its own structure. [White (1990), p. 10]

Hume's original concept of "constant conjunction" was revised –from a regularist point of view– also by *Patrick Suppes* who proposed a *probabilistic framework* for causality.

> Suppes argued that constant conjunction is too restrictive in that it does not capture the probabilistic nature of many statements about causation in everyday life. Suppes defined events as subsets of fixed probability space, instantaneous, and with their time of occurrence included in the formal characterization of the probability space. He then proposed that "one event is the cause of another if the appearance of the first event is followed with a high probability by the appearance of the second, and there is no third event that we can use to factor out the probability relationship between the first and the second events" (p. 10). This is still a regularity theory, but constant conjunction has been replaced by probable conjunction. [White (1990), p. 6]

The aim of the probabilistic approaches to causality are more ambitious than those of the mechanistic approach. Williamson has tried to explain causal connections among variables in different fields of knowledge (ranging from natural sciences to social sciences):

> There is no firm consensus among proponents of probabilistic causality as to what probabilistic relationships among variables constitute causal relationships, but typically they appeal to the intuitions behind the Principle of Common Cause: if two variables are probabilistically dependent then one causes the other or they are effects of common causes which screen off the dependence. Indeed, Hans Reichenbach applied the Principle of Common Cause to an analysis of causality, as a step on the way to a probabilistic analysis of the direction of time. Similarly Patrick Suppes argued that causal relations induce probabilistic dependences and that screening off can be used to differentiate between variables that are common effects and variables that are cause and effect. [Williamson (2005), p. 112]

Such approaches have long been criticized, as the probabilistic conditions that have been proposed as principles of causality appear not to be general. Even if these conditions may hold in many problems, noteworthy counterexamples have been put forward, showing that the probabilistic analysis of causality is not conclusive.

The concept of *counterfactual conditional*, which is now very popular among statisticians, derives from modern theories in the regularist perspective.

> Regularity theorists are therefore not necessarily radical empiricists. The problem for regularity theorists is to distinguish between universal and nomological generalizations without resorting to some kind of necessity. The difference between these can be illustrated by the use of *counterfactual conditionals*, which are statements about what would happen if something were the case that in fact is not the case. For example, for the universal generalization “All of my friends know French”, a counterfactual conditional could be “If Confucious were a friend of mine, then he would speak French.” For a purported nomological generalization “All planets move in ellipses”, a counterfactual conditional could be “If the moon were a planet, it would move in an ellipse”. [...] There are other types of regularity theory. Although many philosophers have attempted to distinguish between causes and conditions, some have analyzed the causal relation in terms of conditionals. [White (1990), p. 5]

This approach was originally proposed by the philosopher David Lewis, who suggested that evidence for a causal inference is given if the two following conditions hold: i) if a cause C occurs, then the effect E has either to occur or its probability to occur would be significantly increased; ii) if cause C were not to occur, then the effect E either would not occur or its probability to occur would be significantly lowered. In Lewis’ view, the theory of causation is expressed in terms of subjunctive conditionals that state the semantics of two possible alternative worlds. Note that it does not matter whether the conditions expressed by such alternative worlds might be verified in reality, as the subjective conditionals express only hypothetical states of the world.

> Lewis’ counterfactual theory was developed to account for causal relationships between single-case events (which can be thought of a single-case variables which take the values “occurs” or “does not occur”), and the causal relation is intended to be mind-independent and objective. Many of the difficulties with this view stem from Lewis’ reliance on possible worlds. Possible worlds are not just indispensable *façon de parler* for Lewis, they are assumed to exist in just the way our world exists. But we have no physical contact with these other worlds, which makes it hard to see how their goings-on can be object of our causal claims and hard to see how we discover causal relationships. Moreover it is doubtful whether there is an objective way to determine which worlds are closest to our own if we follow Lewis’ suggestion of measuring closeness by similarity – two worlds are similar in some respects and different in others and choice of weighting of these respects is a subjective matter. Causal relations, on the other hand, do not seem to be subjective. [Williamson (2005), p. 116]

One of the most influential conditional theories of causation was developed by the Australian philosopher *John Leslie Mackie*, who put forward the concept of *causal field*.

> This is a defined region within which an effect sometimes occurs and sometimes does not. Defining a causal field is a way of directing or limiting causal analysis: Once a causal field is defined, then causal analysis consists in a search for some difference between times on which the effect occurred and times on which did not. For example, in asking “What caused this man’s skin cancer?” one may be setting up a causal field that consists of the man’s past history, and seek to answer the question by looking for a difference between the time when the skin cancer developed and the times when it did not. This has the important consequence that what one identifies as the cause may depend on how one

> defines the causal field. In the preceding example, one may decide that the man's cancer was caused by exposure to radiation. However, suppose one had asked "why did this man developed skin cancer, when other men who were exposed to radiation did not?" Now a different causal field has been defined and exposure to radiation cannot be identified as the cause because it does not differentiate the afflicted man from others in the causal field who were not afflicted. [White (1990), p. 6]

Furthermore, Mackie proposed the so-called *INUS* (Insufficient but Necessary; Unnecessary but Sufficient) condition for the definition of a cause. Let's further consider the example of skin cancer. A researcher suggests that sunlamp treatments and not sunbathing are a risk factor for skin cancer. In Mackie's INUS framework, the scenario in which sunlamp treatments are a cause of skin cancer might be described as an Unnecessary but Sufficient condition. Unnecessary, as skin cancers may notoriously occur also in people who do not take sunlamp treatments; Sufficient, as sunlamp treatment has been clearly reported as a risk factor for skin cancer by the medical literature. In the same scenario, the sunlamp is also an Insufficient but Necessary part of the causal statement. Insufficient, as no deterministic relationship exists between sunlamp treatments and skin cancer; Necessary, as sunlamp treatments and sunbathing are supposed to differ with respect to the effect of ultra-violet rays on skin cells.

A critique to the regularity theories of causation has come from the work of *Mario Bunge*. In this author's opinion, Hume's original claim of constant conjunction cannot definitively account for the concept of causality, since absence of coincidence cannot preclude the occurrence of an effect.

> The problem, then, was to find a formula that distinguishes between such invariable coincidences and causal connections and that excludes the former. To achieve this, Bunge (1963) regarded it as necessary to bring in some notion of "the active and productive nature that causal agents are usually supposed to possess" (p. 42). So the statement of the causal principle that Bunge regarded as adequate is "If C happens, then (and only then) E is always produced by it" (p. 47). Bunge did not regard causation and production as identical, but maintained that causation is a special case of production. He also argued that contiguity is not an essential part of causation. [White (1990), p. 6]

Last, a proposal on cause and causality commonly known as *agent-oriented* theory has been put forth by *Huw Price* and *Peter Menzies*. These authors tried to analyze the concept of causation from a subjective point of view, suggesting a prospect in which causes are considered in terms of the goals that active agents may achieve. In this view, a cause C has not only to be logically, but also semantically and pragmatically related to an effect E, as C is a cause of E if and only if it permits the agent to make decisions and realize his objectives.

> Here the strategy of bringing about C is deemed effective if a rational decision theory would prescribe it as a way of bringing about E. Menzies and Price argue that the strategy would be prescribed if and only if it raises the "agent probability" of the occurrence of E. Menzies and Price do not agree as to the interpretation of these probabilities: Menzies maintains

> that they are chances, while Price seems to have a Bayesian conception. Consequently it is not entirely clear whether they view causality as a physical or mental notion. [Williamson (2005), p. 116-117]

1.3 An Operational Definition of Causality

As it may appear from the previous paragraph, the concept of causality cannot be easily defined and, least of all, applied. Instead of approaching this problem from a philosophical point of view, in the following paragraphs we will try to move towards an *operational* criterion of cause.

Consider now the fourth question posed at the beginning of this chapter: Is HRT a cause of breast cancer? How can we check for the presence of such a causal relationship? For instance, let's consider two groups of women, matched by age and other risk factors, one given and the other not given HRT. After one year and subsequently after yearly follow-ups, we can examine whether the women in the two groups have or do not have breast cancer. In other words, the use of HRT is manipulated by the researcher in order to evaluate the causal effect on developing / not developing breast cancer. If a significant difference is found in the two groups, HRT can be seriously proposed as a cause (and a risk factor) of breast cancer. Following this view, we may think that *human manipulation* is a reasonable way to infer the presence of a causal relationships between two variables. This is true in some ways, but is not exhaustive. Variables such as gender, beliefs, political ideals...that by definition cannot be directly manipulated, can have causal effects as well. As proposed in Bollen (1989), an alternative starting point for the notion of causality might be the following:

> **...if two variables x_1 and y_1 are considered and each change in y_1 is accompanied by a change in x_1 –net of the influence of other variables– and each change of x_1 precedes a change in y_1, then x_1 can be assumed as a cause of y_1.**

The previous definition of causality is characterized by the presence of three components: *isolation*, *association* and *the direction of influence*.

> Isolation, association and direction of influence are three requirements for a cause. Human manipulation, such as occurs in an experiment, can be a tremendous aid toward creating isolation and establishing the direction of influence, but manipulation is neither necessary nor sufficient condition of causality. [Bollen (1989), p. 41]

A first major problem is that isolation does not currently hold in applied problems. Think, for instance, of a study which compares political beliefs on opinions about nuclear power. The relationship between these two variables cannot be isolated, since other variables such as sex, religious faith, years of school attended, can play a relevant role.

> Various experimental, quasi-experimental, and observational research designs attempt to approximate isolation through some form of control or randomization process. Regardless of the technique, the assumption of isolation remains a weak link in inferring cause and effect. [Bollen (1989), p. 41]

Let's consider again the question about HRT posed above: we were interested in ascertaining whether HRT (x_1) can be a cause of breast cancer (y_1). Building a statistical model might be a useful way to look at our problem.

> One way of dealing with the problem is to make use of theoretical models of reality. In developing these models the scientist temporarily forgets about the real world. Instead, he may think in terms of discrete "somethings", or systems, made up of other kinds of somethings (subsystems, elements) which have fixed properties and which act, or can be made to act, in predictable ways. [Blalock (1964), p. 7]

Imagine first that we are living in a world where determinants of breast cancer are totally unknown. This state of knowledge might be described by the following equation:

$$y_1 = \zeta_1 \tag{1.1}$$

where ζ_1 is a disturbance and not observable variable. ζ_1 provides for a latent factor, which by hypothesis is totally unknown but that can be thought to be related with y_1 in a deterministic way, i.e. every time ζ_1 holds, y_1 follows. This statement exemplifies David Hume's assumption of a "constant conjunction", for which every time a cause occurs, an effect should follow. Let's imagine ourselves in a better world, where scientists are not totally unaware of the determinants of breast cancer, but clear ideas with respect to risk factors –as x_1– can be put forth. Such information might be expressed by a more complex model:

$$y_1 = \gamma_{11}x_1 + \zeta_1 \tag{1.2}$$

This equation illustrates a *probabilistic* model of the relationship between the variables x_1 and y_1. In Equation 1.1, ζ_1 stands for a totally unknown random variable, with respect to which only an observable value is supposed to be known. For instance, if a value of $\zeta_i \geq 5$ were observed in a hypothetical experimental trial, then breast cancer would be found in patient y_i. In equation 1.2, the value of x_1 –weighted for an unknown but estimable coefficient γ_{11}– is supposed to be known. As in 1.1, ζ_1 is an unknown random variable, though distributional assumptions can be put forward (for instance, ζ_1 is normally distribute and $\mathbb{E}(\zeta_1) = 0$, as in linear regression models). The relationship expressed in Equation 1.2 is only true *on average*, and not in the sense of a deterministic function. Keeping such a model in mind, we might ask: *Does isolation between x_1 and y_1 hold?*

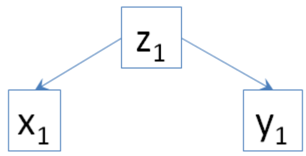

Figure 1.1: Example of a spurious relation between the variables x_1 and y_1

> For isolation to hold, no variable besides x_1 can be a cause of y_1. If the direction of influence from x_1 to y_1 is correct, the only way to change y_1 is by changing x_1. This follows since y_1 could be changed without going through x_1, then equation 1.2 cannot be valid and y_1 is not isolated. The association is straightforward to assess, since for each unit of shift in x_1, an exact γ_{11} shift in y_1 must occur. [Bollen (1989), p. 42]

In Equation 1.2, for isolation to hold, the regressor variable x_1 must be isolated from the unknown variable ζ_1, but so far as ζ_1 is unknown, we cannot check for this property. We can only *assume* that isolation holds, and this is a key-difference between a real state of the world and our knowledge of it, as expressed by a statistical model and its assumptions. Thus, our original condition of isolation for causality can be converted to a milder condition of *pseudo-isolation*:

> To establish x_1 as a cause of y_1, x_1 must be isolated from ζ_1. Since ζ_1 is an unobserved disturbance term, we cannot control it in any direct sense. Rather, we make assumptions about its behaviour to create a *pseudo-isolation* condition. The most common assumption is that ζ_1 is uncorrelated with x_1. This is a standard assumption in regression analysis, and it enables us to assess the influence of x_1 on y_1 "isolated"' from ζ_1. But the isolation is not perfect since for any observation, the y_1 to x_1 relation is disrupted by the disturbance. This is true whether the data come from an experiment where x_1 is a treatment applied with randomization to a subset of the observations or if the data are nonexperimental sources. [Bollen (1989), p. 43]

If we consider now a state of the world in which information with respect to q variables affecting the appearance of breast cancer might be obtained, the model expressed in Equation 1.2 would change to:

$$y_1 = \gamma_{11}x_1 + \gamma_{12}x_2 + \ldots + \gamma_{1q}x_q + \zeta_1$$

and the condition of pseudo-isolation would be given by $Cov(\mathbf{x}, \zeta_1) = \mathbf{0}$.

Violations to the condition of pseudo-isolation can be given by the presence of: i) a spurious relation (see Figure 1.1); ii) an indirect relation (see Figure 1.2); iii) a conditional relation (see Figure 1.3); iv) a reciprocal relation; v) the expression of a wrong functional form for the relation between two variables. In the first three cases, a variable z_1, that is a part of the unknown variable ζ_1, leads to a correlation between x_1 and ζ_1.

A *spurious relation* holds when the presence of covariation between two variables (x_1 and y_1) is not due to an underlying causal relation, but to the presence of a third variable (z_1) acting on both x_1 and y_1.

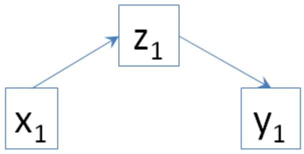

Figure 1.2: Example of an indirect relation between the variables x_1 and y_1

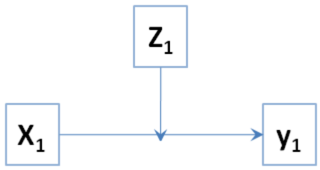

Figure 1.3: Example of a conditional relation between the variables x_1 and y_1

> The possibility of such spurious relations is the reason that the phrase "correlation is not causation" is appropriate. As an example, suppose that y_2 is the quality of a person's vision and y_1 is the proportion of gray scalp hairs. The variables correlate not because gray hair causes poor vision but because both are causally depended on age (x_1). On the other hand, we cannot automatically assume that all associations are spurious. This too should be demonstrated. For example, representatives of the tobacco industry sometimes argue that the correlation between smoking and cancer is spurious. One suggestion is that some people have a genetic predisposition to smoke and to get lung cancer. If such a factor is found, a stronger case for spuriousness could be made, but without it most remain skeptical of such a claim. [Bollen (1989), p. 50]

An *indirect relation* is characterized by the action of an intervening variable z_1 mediating the connection between two variables x_1 and y_1, supposed as causally related.

> Intervening variables are one type of omitted variables that can lead to violations of the pseudo-isolation condition. Left-out common causes of the explanatory and dependent variables often pose a more serious threat. [Bollen (1989), p. 48]

For instance, x_1 might be the ethnicity, y_1 the performance on an intelligence test, and z_1 the years of school attended. The relation between ethnicity and intelligence is not pure, but strongly mediated by the number of years of school attended. In this way, if subgroups of blacks and whites –balanced according to educational levels– are considered, the relation with intelligence disappears. Differing from the case of a spurious relation, the presence of an indirect relation does not indicate *per se* the absence of a causal relation, but the occurrence of a mediating mechanism activated by an intervening variable.

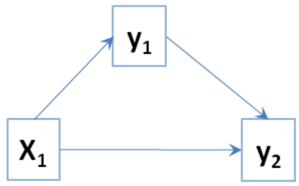

Figure 1.4: Example of a suppressor relationship

An interesting case linked to the presence of indirect effects is the detection of a *suppression relation* among variables. This is the case in which there is the presence of both a direct and an indirect effect of opposite signs but with similar magnitudes. Consider the following example: a researcher is interested in evaluating the relationship between the presence of strong soccer technical abilities (x_1) and the number of goals scored (y_2) by a group of soccer players. The presence of high scores on a technical-ability scale predicts a high number of goals scored. The following full-model is put forward:

$$y_2 = \gamma_{11}x_1 + \zeta_1$$

However, contrary to this prediction, only a mild value of the coefficient $\gamma_{11} = .202$ is found. In a second phase, a third variable (weight of the soccer players in kilograms, y_1) is introduced in the analysis. The model that is put forth is expressed by the following equations and represented in Figure 1.4:

$$\begin{aligned} y_1 &= \gamma_{11}x_1 + \zeta_1 \\ y_2 &= \beta_{21}y_1 + \gamma_{21}x_1 + \zeta_2 \end{aligned} \tag{1.3}$$

In this model, the coefficient γ_{21} is estimated at .648, indicating a strong relationship between technical abilities and the number of goals scored, whereas the coefficients γ_{11} and β_{21} are respectively estimated as $-.404$ and $-.712$, indicating the presence of negative relationships from one side between technical abilities and weight, and from the other side between weight and number of goals scored. This example indicates that omitting an intervening variable such as y_1 from the model can lead to underestimating the real impact of the contribution of the variable x_1 on the values of y_2.

Many researchers suggest that a bivariate association between a cause and an effect is a *necessary* condition to establish causality. The occurrence of suppressor relations casts doubt on this claim: no bivariate association can occur although a causal relation links two variables. The old saying that correlation does not prove causation should be complemented by the saying that *a lack of correlation does not disprove causation.* It is only when we isolate the cause from all other influences that correlation is a necessary condition of causation. Thus, without isolation or without at least pseudo-isolation, correlation is neither a necessary nor a sufficient condition for causality. Left-out intervening variables or

> left-out common causes are two ways in which the pseudo-isolation conditions can be violated. A third is when the omitted variable has an ambiguous relation to the explanatory variables. [Bollen (1989), p. 52]

A *conditional relation* is illustrated by the presence of a variable z_1 acting on the strength of the link connecting two other variables (x_1 and y_1). For instance, strength of sound (expressed in decibels) perceived by a listener (y_1) from the voice of a speaker (x_1) during a conference, is a phenomenon conditioned by the microphone adjustment (z_1). In the case of a conditional relation, the occurrence of a link between two variables x_1 and y_1 is not suppressed but regulated by the presence of a third variable z_1.

A *reciprocal relation* would occur in the case an independent variable (x_1) were found to be affected by a dependent variable (y_1). For instance, a researcher is interested in studying the influence of a psychological trait such as anxiety on the development of cardio-vascular diseases. The psychological literature strongly supports this hypothesis, but the researcher also aims to investigate whether a reciprocal relation holds or not. If this were the case, the presence and the severity of cardio-vascular diseases would be supposed to increase the levels of anxiety.

> In this and other cases where the endogenous variables affect an "exogenous" one, the assumption that the disturbance is uncorrelated with x_1 is no longer defensible. The solution is to turn the former "exogenous" variable into an endogenous one so that it has separate equation. We have estimators besides OLS to deal with such nonrecursive systems, provided it is an identified model for which the disturbances are uncorrelated with the true exogenous variables. [Bollen (1989), p. 55]

Furthermore, a common situation in which the condition of pseudo-isolation is violated is given by the expression of a wrong functional form for the relation between two variables. For instance, it may happen that the presence of a linear relation between x_1 and y_1 is supposed to hold, though, in fact, a quadratic or polynomial relation would be more plausible. In some cases, a transformation of the variables from one measurement scale to another might be useful to specify the functional form more clearly.

Last, Bollen (1989) suggests other situations in which pseudo-isolation might be violated:

> For instance, the usual assumptions of a disturbance being uncorrelated with the explanatory variables may be violated if a lagged endogenous variable appears as an explanatory variable and the disturbances of that equation are autocorrelated. [...] A nonrandom subsample of the relevant population is another way to violate pseudo-isolation. Special procedures that take these problems into account are available, but if these difficulties are ignored, faulty causal inferences are likely. In sum, many factors threaten the pseudo-isolation conditions necessary to establish a causal link between two variables. Omitted variables can inflate or deflate relations. Measurement errors, nonrandom sample selection, correlated disturbances, and other less obvious problems also can undermine pseudo-isolation. Though some research designs can lessen these potential problems, it is not possible to have certainty that two variables are totally isolated from other influences. Thus we should recognize the tentativeness of any claims for a causal relation while striving to eliminate as many threats to pseudo-isolation as possible. [Bollen (1989), p. 55]

Let's now consider the second condition that was put forth to establish causal relationships: the presence of an *association* between variables. Suppose that either violations to the condition of pseudo-isolation are not detected or pseudo-isolation holds. As we have seen, a necessary and sufficient condition for a causal relation between two variables x_1 and y_1 to hold is the presence of an association between them, without the influence of other variables. Nevertheless, as is commonly known, the presence of an association among variables does not imply *per se* the presence of a causal relation. Such a relation might be generated by *chance* (sample error always affects inference), by the presence of a *selection bias* (i.e. two sub-populations are not strictly comparable and are unbalanced with respect to one or more covariates) or *observable bias* (i.e. non-comparable information is used for contrasting two groups). Last, as we have seen, the relation among variables may be affected by the presence of one or more confounding variables.

As was asserted before, the problem of studying the relationship among variables is generally approached by constructing statistical models and estimating parameters that express the strength of the relationships. In fact, these estimates depend on the sampling error and it follows that only probabilistic warranties can be empirically obtained.

> More problematic is when the standard errors or test statistics that are the basis of the tests of statistical significance are incorrect. One such case is if the disturbances, ζ_1, from the preceding y_1 equation are heteroscedastic or autocorrelated. Then OLS still provides a consistent estimator of γ_{11}, but the usual standard errors and test statistics for the coefficient estimator are not dependable. Thus we could make faulty inferences about the association of x_1 to y_1 because we have the wrong standard error for $\hat{\gamma}_{11}$ Alternative estimators for regression equations that take into account heteroscedasticity or autocorrelation and provide suitable standard errors and test statistics are well-known. However, tests or corrections for heteroscedasticity or autocorrelated disturbances have received insufficient attention for models with latent variables. So for these models faulty inferences about association are possible. [Bollen (1989), p. 58]

A second problem that ought to be considered in measuring association is that of *multicollinearity*, for which a linear dependence exists between an explanatory variable and the other explanatory variables in an equation. The problem to be faced with multicollinearity is that it normally determines higher standard errors on parameter estimation. This happens because multicollinearity makes it more difficult to detect the unique contribution of each independent variable on the dependent variable.

Third, as is commonly known, the detection of an association requires that it is replicated by other researchers to be scientifically accepted. This should not be considered as an absolute rule because: i) the conditions that have to be met for the association to appear might be reproduced with difficulty; ii) spurious as well causal relations may be replicated.

Consider now the last condition that was hypothesized: the evaluation of the *direction of causation*. As we have seen in the historical review, Hume's

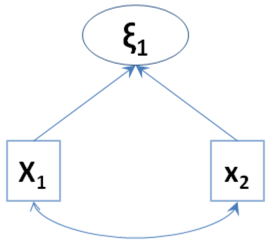

Figure 1.5: Example of a formative relationship between a latent factor ξ_1 and two observable variables x_1 and x_2

influential concept of "constant conjunction" required a cause C to be an antecedent of the effect E. This may be considered as a natural and intuitive condition, though in some experimental designs it cannot be very easy to temporally discriminate a cause from an effect. From one side, in a field such as physics, it might be the case that the contact between two molecules or two atomic particles A and B cannot be detected at a temporal resolution precisely enough to establish if either A has moved toward B or B has moved toward A. From the other side, the effect of some variables on other variables may be too long to be clearly identified. Consider, for instance, the effect of the natural environment on the appearance of biological mutations or, at an individual level, the effect of a mother's life-style during pregnancy on adult-age diseases.

The analysis of temporal priority among variables is particularly interesting when analyzing models containing *both latent and observable variables*. Consider, for instance, a latent variable ξ_1 and two observable variables x_1 and x_2. In some situations, it is not trivial to determine the direction of the relation connecting the latent factor with the observable variables (see Bollen (2002)). This relation may be conceived as either "formative" (see Figure 1.5) or "reflective" (see Figure 1.6). An example of a formative relation can be given considering a latent factor ξ_1 such as the socio-economic status of a person. In fact, this variable is determined considering indicators such as the income, the number of houses owned etc. An example of a reflective relation may be that of self-esteem as a latent factor affecting teenagers' performance on school tests. In other cases, it is really not easy to determine the direction of the relation:

> It is theoretically possible that simultaneous reciprocal causation may exist between an indicator and a latent variable. This could occur where each may be reasonably thought of as a cause of the other and when the observation period exceeds the causal lag. For example, the latent variable of "financial health" of a company measured by stock prices may have such a relation. Greater financial health can cause higher stock prices and higher stock prices can increase financial health. Or, consider academic grade expectations as a

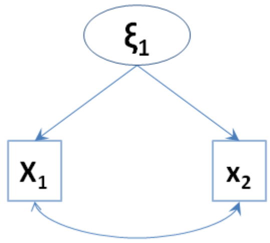

Figure 1.6: Example of a reflective relationship between a latent factor ξ_1 and two observable variables x_1 and x_2

> latent variable and measured grade as the indicator. High grade expectations may influence measured grades and grades can influence expectations. I know no empirical work that has tested possibilities like these, but it is clear that the estimation of such models could be difficult. [Bollen (1989), p. 66]

In some cases, experimental design can radically help a researcher to shed light on the direction of causality. For instance, in a randomized clinical trial a binary treatment x_1 is randomly assigned to participants and a response variable y_1 is observed. If such a response variable systematically changes following variations of the treatment variable x_1 –net of the influence of other variables– clear evidence on the direction of the causal relation is found. The major problem is that in many situations, especially in social and psychological sciences, a randomized design cannot be used for both economic and ethical reasons. However, as well underlined by Rothman and Greenland (2005):

> The nonexperimental nature of a science does not preclude impressive scientific discoveries: the myriad examples include plate tectonics, the evolution of species, planets orbiting other stars, and the effect of cigarette smoking on human health. Even when they are possible, experiments (including randomized trials) do not provide anything approaching proof, and in fact can be controversial, contradictory, or irreproducible. The cold-fusion debacle demonstrates well that neither physical nor experimental science is immune to such problems. [Rothman and Greenland (2005), p. 147]

1.4 Hill's Criteria

In the second paragraph of this chapter, the controversy between rationalists and empiricists about the nature of causality is briefly reviewed. In fact, Kant's attempt to reconcile this controversy has been strongly criticized by modern and contemporary philosophers. It would take too long to consider this controversy more in detail, since it is far from being solved yet. In the next chapter, a statistical model of causality, developed by many authors such as *Donald Rubin* will be summed up. This model, as we shall see, has to be studied in the framework of the counterfactual theories of causality, as originally proposed by Lewis. These theories ought to be thought as contemporary regularist theories, in the sense that they aim to establish a causal framework for empirical research, that typically make use of inductive methodologies. This approach has been strictly criticized by philosophers such as *Karl Popper*, who developed a deductive-falsificationist framework of causality. Nevertheless, as remarkably noted by Rothman and Greenland (2005) from an epidemiological perspective:

> Despite philosophical criticism of inductive inference, inductively oriented causal criteria have commonly been used to make such inferences. If a set of sufficient causal criteria could be used to distinguish causal from noncausal relations in epidemiologic studies, the job of the scientist would be eased considerably. With such criteria, all the concerns about the logic or lack thereof in causal inference could be forgotten: it would only be necessary to consult the checklist of criteria to see if a relation were causal. We know from philosophy that a set of sufficient criteria does not exist. Nevertheless, lists of causal criteria have become popular, possibly because they seem to provide a road map through complicated territory. [Rothman and Greenland (2005), p. 147-148]

As we have seen, philosophers such as *John Stuart Mill* tried to develop causal criteria for empirical research, based on the Humean conception of "constant conjunction". From a statistical perspective, these criteria have been differently developed by both social researchers (e.g. sociologists, econometricians, psychometricians) and epidemiologists. The discussion about the possible relations among variables –that was summed up in the previous paragraph– has been developed by social researchers such as *Hubert Blalock*, *Kenneth Bollen* and other authors, especially in the field of *structural equation modeling*.

From an epidemiologic perspective, a set of criteria for causal inference were proposed in an influential paper by *Austin Bradford Hill* in 1965. The criteria are: i) strength; ii) consistency; iii) specificity; iv) temporality; v) biological gradient; vi) plausibility; vii) coherence; viii) experimental evidence; ix) analogy. In the following these topics will be briefly reviewed, as they pose a useful framework for causal inference, also from a counterfactual point of view. Think of an association between two variables; the basic question Hill tried to answer is: *What aspects of the association should we especially consider before deciding that the most likely interpretation of it is causation*?

First, Hill proposed to consider the *strength* of an association: normally, strong associations are supposed to be causally interpreted more likely than weak associations. This is because if a third factor existed, one which would better explain the relation between the two variables, the effect of that factor is supposed to be even stronger than the observed association. It is difficult that a well-trained researcher would have forgotten to consider such a factor in his analysis. Thus, if a strong association is observed –without the influence of other variables– we can reasonably think that the underlying relation is a causal type. Examples cited by Hill are those of the associations between scrotal cancer and chimney sweepers, lung cancer and heavy cigarette smokers. However, as underlined by Rothman and Greenland (2005):

> To some extent this is a reasonable argument but, as Hill himself acknowledged, the fact that an association is weak does not rule out a causal connection. A commonly cited counterexample is the relation between cigarette smoking and cardiovascular disease: one explanation for this relation being weak is that cardiovascular disease is common, making any ratio measure of the effect comparatively small compared with ratio measures for diseases that are less common. Nevertheless, cigarette smoking is not seriously doubt as a cause of cardiovascular disease. Another example would be passive smoking and lung cancer, a weak association that few consider to be noncausal. Counterexamples of strong but noncausal associations are also not hard to find; any study with strong confounding illustrates the phenomenon. For example, consider the strong but noncausal relation between Down syndrome and birth rank, which is confounded by the relation between Down syndrome and maternal age. Of course, once the confounding factor is identified, the association is diminished by adjustment for the factor. These examples remind us that a strong association is neither necessary not sufficient for causality, nor is weakness necessary or sufficient for absence of causality. [Rothman and Greenland (2005), p. 147-148]

Second, the *consistency* of the observation is put forth as a useful criterion for causal inference. Hill's concept of consistency can be thought in the sense of repetition, i.e. the fact that an association is observed by different persons, in different places, circumstances and time. This can be considered as a *strong requirement* in every science, and it would be demanded by most philosophers of science as well. More precisely, consistency in epidemiology regards the possibility of observing an association in different populations under different circumstances. Indeed, meta-analytic studies aim to rule out the hypothesis that an association is due to some factor that varies across studies.

> Lack of consistency, however, does not rule out a causal association, because some effects are produced by their causes only under some circumstances. [...] These conditions will not always be met. Thus, transfusions can cause HIV infection but they do not always do so: the virus must also be present. Tampon use can cause toxic shock syndrome, but only rarely when certain other, perhaps unknown, conditions are met. Consistency is apparent only after all the relevant details of a causal mechanism are understood, which is to say very seldom. Furthermore, even studies of exactly the same phenomena can be expected to yield different results because they differ in their methods and random errors. [Rothman and Greenland (2005), p. 148]

Third, Hill proposes to consider the *specificity* of an association. This argument refers to the fact that a cause has to be linked to single and not multiple effects. However, as observed by Hill himself, it is not so fundamental that this criterion is met. For instance, smoking is a risk factor for many diseases, and not only for lung cancer. However, lack of specificity does not anyway rule out or diminish the importance of the causal relation between smoking and lung cancer.

Fourth, a criterion of *temporality* should be considered for causal inference. This criterion refers to the fact that, as stated by Hume's concept of "constant conjunction", a cause *must* precede an effect. There is a long debate in the philosophy of science with respect to the need of temporality as a necessary condition to identify causality. Some authors have criticized this concept, and causal theories on *synchronized causality* have also been put forward. As we have seen in the previous paragraph, it may be very difficult to identify the temporal lag separating a cause by its effect, and this is a serious problem for applied sciences such as epidemiology, as noted by Hill himself:

> Which is the cart and which is the horse? This is a question which might be particularly relevant with diseases of slow development. Does a particular diet lead to disease or do the early stage of the disease lead to those peculiar dietetic habits? Does particular occupation or occupational environment promote infection by the tubercle bacillus or are the men and women who select that kind of work more liable to contract tuberculosis whatever the environment – or, indeed, have they already contracted it? This temporal problem might not arise often but it certainly needs to be remembered, particularly with selective factors at work in industry. [Hill (1965), p. 297-298]

Hill's fifth criterion is the so-called *biological gradient* or *dose response curve*. This refers to the presence of a unidirectional dose-response curve. This is often the case in many applications; think for instance at the relation between smoking and cancer exposure: normally the death rate from lung cancer rises linearly with the number of cigarettes smoked daily. Other examples could be given by the relation between alcohol consumption and mortality, or by the relation between a dust environment in industry and respiratory diseases. In Hill's opinion, observing a clear-cut dose-response curve (for instance, exponential or linear) helps the researcher to establish the causal nature of a relationship. However, this criterion may be shaky, as observed by Rothman and Greenland (2005):

> Associations that do show a monotonic trend in disease frequency with increasing level of exposure are not necessary causal: confounding can result in a monotonic relation between a noncausal risk factor and disease if the confounding factor itself demonstrates a biological gradient in its relation with disease. The noncausal relation between birth rank and Down syndrome shows a biological gradient that merely reflects the progressive relation between maternal age and Down syndrome occurrence. These examples imply that the existence of a monotonic association is neither necessary nor sufficient for a causal relation. A nonmonotonic relation only refutes those causal hypotheses specific enough to predict a monotonic dose-response curve. [Rothman and Greenland (2005), p. 149]

The sixth criterion is that of *plausibility* of an association. Hill's concept of plausibility refers to the *biological* plausibility of a particular hypothesis, and it certainly depends on the biological knowledge of the day. In other words, the concept of plausibility in applied sciences is synonymous with theory-driven causal inference. In this way, from a statistical perspective, a Bayesian approach to causality ought to be thought as a gold-standard to draw plausible inferences according to Hill's criterion. As observed by Rothman and Greenland (2005):

> The Bayesian approach to inference attempts to deal with this problem by requiring that one quantify, on a probability (0 to 1) scale, the certainty that one has in prior beliefs, as

> well as in new hypotheses. This quantification displays the dogmatism or openmindedness of the analyst in a public fashion, with certainty values near 1 or 0 betraying a strong commitment of the analyst for or against a hypothesis. It can also provides a means of testing those quantified beliefs against new evidence. Nevertheless, the Bayesian approach cannot transform plausibility into an objective causal criterion. [Rothman and Greenland (2005), p. 149]

Seventh, a criterion of *coherence* with the generally known facts of the natural history and biology of the disease is proposed. As the criteria of the biological gradient and of plausibility, also the criterion of coherence may appear as a typical criterion of epidemiology. Nevertheless, it would not be difficult to generalize such a concept to other sciences, included social and economic sciences. As the previous concepts, it is also not easy to make this criterion usable and functional:

> Hill emphasized that the absence of coherent information, as distinguished, apparently, from the presence of conflicting information, should not be taken as evidence against an association being considered causal. On the other hand, presence of conflicting information may indeed refute a hypothesis, but one must always remember that the conflicting information may be mistaken or misinterpreted. [Rothman and Greenland (2005), p. 149]

The eighth criterion is that of *experimental evidence*. With this, Hill meant that sometimes it is possible that an association between an environmental exposure and a consequent disease is observed by chance. Subsequently, preventive programs may be developed by policy makers or health authorities, so that such an association is no longer observed. The results of this preventive strategy are to be considered as an implicit confirmation that the association which had been observed was of a causal nature. However, from a logical point of view, experimental evidence is far from being considered as a criterion for causality, but rather as a test of causal hypotheses.

The last criterion is that of *analogy*, for which the presence of a causal relation between the variables C and D may be hypothesized by analogy with the observation of another causal link between two other variables A and B. After a causal association between two variables A and B is observed, one may think that the more other possible associations can be put forward, the more such a causal relation between A and B has to be considered strong and relevant. This could be an interesting concept and, in some sense, also an appealing and challenging proposal. The problem is that, as observed by Rothman and Greenland (2005), this proposal cannot be accepted as a criterion for the evaluation of causality, as absence of such analogies only reflects lack of imagination or experience, not falsity of the hypothesis.

In conclusion, even if not conclusive, Hill's criteria are still today a good starting point for dealing with the problems of causal inference, also in social sciences. Though most of these criteria have been criticized, the questions that have been raised by Hill's paper are still relevant and noteworthy. In the next chapter, these general and philosophical problems on the nature of causality will not be further discussed, but will remain as a background for all the thesis. The so-called *Rubin Causal Model* will be introduced and briefly compared with James Heckman's *Structural Approach* to causality. These approaches (the former of statistical origin and the latter developed in the econometric perspective) can be considered as part of David Lewis' *counterfactual* approach to causality. In the third chapter, Rubin's proposal to the analysis of causality in observational studies will be reviewed.

Chapter 2

Causal Effects in the Potential Outcomes Framework

2.1 Overview

When we unofficially think about causal inference, we usually evaluate the effect of a certain action when is taken with the only hypothetical effect of not taking the same action. For instance, imagine Karl is an unemployed plumber, who is proposed to attend a course in order to improve his expertise. Karl mentally compares his possibilities to find a new job either attending or not attending the course; if these possibilities significantly change, he would assume a causal effect of attending the course. Imagine now you are the goalkeeper of the leading football team in the league. You're playing a very important match: if you don't lose, you'll win the championship. There are five minutes to go before the end of the game and the score is 2-2. The opposing striker is dribbling with the ball and is entering your area: what are you going to do? You rapidly think about two options: either you stay in your goal and wait for the shot or you decide not to wait anymore. In the latter case, you would quickly run to the ball, going down to the ground and sliding with your arms stretched out for the ball – also risking that the referee awards a penalty kick. You compare the effect of your actions, both waiting and not waiting in your goal and then you make your decision.

These examples show that, as human beings, we have an innate sense of causal concepts.

> Nevertheless, statistical theory has been relatively silent on questions of causality. Many textbooks avoid any mention of the term other than in settings of randomized experiments. Some mention it mainly to stress that correlation or association is not the same as causation, and some even caution their readers to avoid causal language in statistics. Nevertheless, for many users of statistical methods, causal statements are precisely the goal of their analysis. [Imbens and Rubin (2011), Ch. 1 pp. 1-2]

Suppose now you are a researcher, investigating the effects of alcohol consumption on school drop-out in a population of teenagers. Obviously, you cannot extract a sample from the population and randomize participants in alcohol/non alcohol abusers. In this case, you can do nothing but observe a group of teenagers, measure the variables of interest and try to draw inference from your data. However, alcohol consumption is not the only predictor of school dropout; for instance other key-variables might be sex, the socio-economic status and parents' degree. A causal link between abuse and dropout cannot be deduced without controlling for these variables, that may act as confounders. In the present context, a confounder can be defined in terms of a variable Z which interferes with the relationship between two other variables X and Y, and it is correlated with both of them. A confounder can obfuscates the relationship of interest by spuriously creating another one. In epidemiology, confounding is classically defined both as a *lack of comparability* and in terms of *bias*. Lack of comparability means that, if we consider two groups of subjects, exposed and unexposed to a certain treatment, had the exposed actually been unexposed, their outcome would have been different from that in the actual unexposed group. Moreover, confounding reflects to bias in the estimation of the effect of exposure on disease, due to inherent differences in risk between exposed and unexposed groups. Necessary conditions to be a confounder in epidemiology are: i) to be a risk factor; ii) to be correlated, positively or negatively, with exposure in the study population; iii) not be an intermediate step in the causal pathway between the exposure and the disease; iv) not to be affected by the exposure.

As we shall see, causal inference is not an easy matter in observational studies, due to the presence of confounding. Note further that, besides epidemiology, a fundamental field of application of theories on causal inference comes from the study of the effect of policies, as remarkably underlined by Angrist and Pischke (2008) in this example:

> A causal relationship is useful for making predictions about the consequences of changing circumstances or policies; it tells us what would happen in alternative (or "counterfactual") worlds. For example, as part of a research agenda investigating human productive capacity –what labor economists call human capital– we have both investigated the causal effect of schooling on wages. [...] The causal effect of schooling on wages is the increment to wages an individual would receive if he or she got more schooling. A range of studies suggest the causal effect of a college degree is about 40 percent higher wages on average, quite a playoff. The causal effect of schooling on wages is useful for predicting the earning consequences of, say, changing the costs of attending college, or strengthening compulsory attendance laws. This relation is also of theoretical interest since it can be derived from an economic model. [Angrist and Pischke (2008), p. 4]

In the following paragraphs we'll develop a theory aimed to formalize basic intuitions concerning cause and effect. We'll refer to this theory both as *Program Evaluation Approach* and as *Rubin Causal Model* (since this approach has been developed by Donald Rubin since the 1970s). First of all, some mathematical notation and definitions will be introduced:

- A *unit* is the person, place or thing upon which a treatment will operate, at a particular time. Recall that:

  > A unit can be a physical object, a firm, an individual person, or a collection of objects or persons, such as a classroom or a market, at a particular point in time. The same object or person at different times is, for our purposes, a different unit. From this perspective, a causal statement presumes that, although a unit was subject to, or exposed to, a particular action or treatment, at the same point in time an alternative action or treatment could have been taken. For instance, when deciding to take an aspirin to relieve your headache, you could also have chosen not to take the aspirin, or you could have chosen to take an alternative medicine. In this framework, articulating with precision the nature of the action could require a certain amount of imagination. For example, if we define race solely in terms of skin color, the action might be a pill that alters skin color. Such a pill may not currently exist (but then, neither did surgical procedures for heart transplants two hundred years ago), but we can still contemplate such an action. [Imbens and Rubin (2011), Ch. 1, p.2]

- A *treatment* is an intervention, the effects of which the researcher wishes to assess relative to no intervention. A dichotomous treatment will be stated by the variable A (1: treated, 0: untreated);

- A *target population* is a well-defined set of units to whom the treatment is directed to;

- A *dichotomous outcome* indicates an observable characteristic of the units of the population and will be stated by the variable Y (1/0, e.g. death/alive);

- The *assignment mechanism* is the process by means of which treatment is either assigned or not to participants (the basic condition for which at least one unit has to receive treatment and at least one unit has to be assigned to the control group is said *replication*);

- The *potential outcomes* or *counterfactual outcomes* can be defined as the values of a unit's measurement of interest after either application of treatment or no application of treatment. In the present chapter we will identify the potential outcomes as $Y(1)$ (the outcome had all the subjects been treated) and as $Y(0)$ (the outcome had all the subjects remained untreated). Both $Y(1)$ and $Y(0)$ are potentially observable, but only one of them is actually observed for each subject. Hence, we will indicate the factual outcome of the treated units with $Y(1)|A = 1$, and with $Y(0)|A = 0$ the factual outcome for the controls. Moreover, we will identify the counterfactual outcome of the treated units had they remained untreated with $Y(0)|A = 1$ and with $Y(1)|A = 0$ we will state the counterfactual outcome of the untreated units had they been treated;

- Following the definition of potential outcomes, a *causal effect* can be identified as the comparison between the potential outcomes under treatment and no treatment for each unit.

> There are two important aspects of this definition of a causal effect. First, the definition of a causal effect depends on the potential outcomes, but it does *not* depend on which outcome is actually observed. Specifically, whether you take an aspirin (and are therefore unable to observe the state of your headache with no aspirin), or do not take an aspirin (and are thus unable to observe the outcome with an aspirin) does not affect the definition of the causal effect. Second, the causal effect is the comparison of the outcomes at the same moment in time, whereas the time of the application of the treatment must precede that of the outcome. In particular, the causal effect is *not* defined in terms of comparisons of outcomes at different times, as in a before-and-after comparison of your headache before and after deciding to take or not take the aspirin. "The fundamental problem in facing interference for causal effects" (Rubin (1978)) is therefore the problem that, at most, only one of the potential outcomes can be revealed. [Imbens and Rubin (2011), Ch. 1, p.5]

Note that, as underlined by Hernán and Robins (2010), there is a slight semantic difference between the terms *potential* outcomes and *counterfactual* outcomes:

> Some authors prefer the terms "potential outcomes" to emphasize that, depending on the treatment that is received, either of these two outcomes can be potentially observed. Other authors prefer the term "counterfactual outcomes" to emphasize that these outcomes represent situations that may not actually occur (that is, counter to the fact situations). [Hernán and Robins (2010), p.4]

The fundamental objective of causal inference is to establish whether a certain treatment has / does not have an effect on each unit receiving this treatment (e.g. a pharmacological trail or an educational program). Since each unit can be either exposed or not exposed to the treatment, but cannot be both exposed and not exposed to the same treatment, it is not possible to draw causal inference at an *individual* level. This principle has been labeled by Holland (1986) as the "fundamental problem" of causal inference. This problem can be handled either considering different participants exposed to different levels of treatment or comparing the same units at different times.

> For estimation of causal effects, we will need to make different comparisons than the comparisons made for their definitions. For estimation and inference, we need to compare *observed* outcomes, that is, observed realizations of potential outcomes, and because there is only one realized potential outcome per unit, we will need to consider multiple units. For example, a before-and-after comparison of the same physical object involves distinct units in our set up, and also the comparison of two different physical units at the same time involves distinct units. Such comparisons are critical for *estimating* causal effects, but they do not *define* effects in our approach. [...] There is sometimes a tendency to view the same physical object at different times as the same unit. We view this as a fundamental mistake. "You at different times" are not the same unit in our approach to causality. Time matters for many reasons. For example, you may become more or less sensitive to aspirin, evenings may differ from mornings, or the initial intensity of your headache may affect

> the result. It is often reasonable to assume that time makes little difference for inanimate objects –we may feel confident, based on past experience, that turning on a faucet will cause water to flow from that tap– but this assumption is typically less reasonable for human subjects, and it is never correct to confuses assumptions (e.g. about similarities between different units), with definitions (e.g., of a unit). [Imbens and Rubin (2011), Ch.1, pp. 6-7]

2.2 Defining Causal Effects

Consider now: a drug trial or a training program, N participants indexed by $i = 1, ..., N$ who can enroll this program, a dichotomous variable A indicating whether an individual is exposed or not exposed to the program, a $K-$dimensional vector of pre-treatment covariates ($\mathbf{X}$) and two potential outcomes ($Y_i(0)$ and $Y_i(1)$). Remember that:

> The first, $Y_i(0)$, denotes the outcome that would be realized by individual i if he or she did not participate in the program. Similarly, $Y_i(1)$ denotes the outcome that would be realized by individual i if he or she did participate in the program. Individual i can either participate or not participate in the program, but not both, and thus only one of these potential outcomes can be realized. Prior to assignment being determined, both are potentially observable, hence the label potential outcomes. If individual i participates in the program $Y_i(1)$ will be realized and $Y_i(0)$ will *ex post* be a counterfactual outcome. If, on the other hand individual i does not participate in the program, $Y_i(0)$ will be realized and $Y_i(1)$ will be the *ex post* counterfactual. [Imbens and Wooldridge (2009), p. 4]

The Program Evaluation Approach only considers *ex-post* potential outcomes, whereas *ex-ante* potential outcomes are a hallmark of the Structural Approach to causal inference (see § 2.9). The potential outcomes are linked to the assignment mechanism by the following equation:

$$Y_i = Y_i(A_i) = Y_i(0)(1 - A_i) + Y_i(1)A_i \tag{2.1}$$

The selection mechanism A can be totally independent of subjective choices (i.e. in randomized studies) or it can provide for individual preferences (i.e. in observational studies) but in the Program Evaluation Approach preferences are not formalized by an explicit decision rule (see §2.9 for a different theoretical framework). Remember also that only one of the two potential outcomes is actually observed:

> The potential outcomes are tied to the specific manipulation that would have made one of them the realized outcome. The more precise the specification of the manipulation, the more well defined potential outcomes are. This distinction between the pair of potential outcomes $(Y_i(0), Y_i(1))$ and the realized outcome Y_i is the hallmark of modern statistical and econometric analyses of treatment effects. [Imbens and Wooldridge (2009), p. 5]

Before analyzing in detail the Rubin Causal Model, it is noteworthy to highlight the main reasons motivating a causal approach to inference. First, many questions starting research projects in different fields of knowledge (e.g. economics, psychology, medicine) are *per se* causal and need causal inference.

Second, a "frequentist" approach, aimed to estimate the likelihood of past and future events is not completely satisfactory for causal analysis, since this approach is only meaningful as long as the experimental conditions are invariant. Third, causal inference aims to identify mechanisms generating data, so that dynamics of events under changing conditions can be inferred. Fourth, the dynamics of change cannot be identified by probability laws, as these do not dictate how one property of a distribution ought to change when another property is modified (Imbens and Rubin, 2011).

The Rubin Causal Model is one of the main approaches to causal inference, which has the following advantages. First, this framework allows a researcher to define a causal effect before specifying an assignment mechanism, without explicitly stating any distributional assumption. This is a fundamental improvement with respect to a causal interpretation of the parameters of a regression function:

> The most common definition of the causal effect at the unit level is as the difference $Y_i(1) - Y_i(0)$, but we may wish to look at the ratios or other functions. Such definitions do not require us to take a stand on whether the effect is constant or varies across the population. Further, defining individual-specific treatment effects using potential outcomes does not require us to assume endogeneity or exogeneity of the assignment mechanism. By contrast, the causal effects are more difficult to define in terms of the realized outcomes. Often, researchers write down a regression function $Y_i = \alpha + \tau \dot{A}_i + \epsilon_i$. This regression function is then interpreted as a structural equation, with τ as the causal effect. Left unclear is whether the causal effect is constant or not, and what the properties of the unobserved component, ϵ_i are. The potential outcome approach separates these issues, and allows a researcher to first define the causal effect of interest without considering the probabilistic properties of the outcome or assignment. [Imbens and Wooldridge (2009), p. 5]

Second, the Program Evaluation Approach compels a researcher to consider and compare different scenarios. This is a basic feature of the Lewis' perspective on causality. By comparing different scenarios we are induced to consider the consequences of an action, both when it is taken and when it is not taken. By the way, this principle has been outstandingly represented by the Peter Howitt's movie *Sliding doors*, in which the plot splits into two parallel universes, according to the two paths Helen's (the leading actress) life can take depending on whether she catches a London Underground train or not. This is what should be made for evaluating causal relations from the Rubin's perspective. Third, in this approach the definition of the counterfactuals is separated from the assignment mechanism and no model is directly specified for the realized outcome. Fourth, this framework formulates the probabilistic assumptions in terms of conditional independence assumptions of *potentially observable* variables rather than in terms of *unobserved* components. This is another basic difference with the (structural) regression models:

> In this approach, many of the critical assumptions will be formulated as (conditional) independence assumptions involving the potential outcomes. Assessing their validity requires the researcher to consider the dependence structure if all potential outcomes were

> observed. By contrast, models in terms of realized outcomes often formulate the critical assumption in terms of errors in regression functions. To be specific, consider again the regression function $Y_i = \alpha + \tau \dot{A}_i + \epsilon_i$. Typically (conditional independence) assumptions are made on the relationship between ϵ_i and A_i. Such assumptions implicitly bundle a number of assumptions, including functional-form assumptions and substantive exogeneity assumptions. This bundling makes the plausibility of these assumptions more difficult to assess. [Imbens and Wooldridge (2009), p. 7]

Fifth, this framework clarifies where the uncertainty in the estimators comes from. Even if the entire population were observed, causal effects would remain uncertain, since only one of the potential outcomes can be observed for each unit.

2.3 The Assignment Mechanism

The assignment mechanism determines which potential outcome is observed for each unit. Formally, the assignment mechanism is a probabilistic or a deterministic rule for selecting some units to remain untreated and other units to receive treatment. Furthermore, the assignment mechanism defines the type of a study (e.g. completely randomized study, observational study...) as well as the acts of nature that lead to the observed data (Imbens and Rubin (2008)). In a population P of N units, each unit is characterized by a K-dimensional vector of characteristics, denoted by X_i for each unit i, with $\mathbf{X}$ denoting the $N \times K$ matrix of observed covariates. The potential outcomes $(\mathbf{Y}(1), \mathbf{Y}(0))$ and the assignment $\mathbf{A}, A_i \in \{0, 1\}$ jointly determine the values of the observed and missing outcomes:

$$Y_i^{obs} \equiv Y_i(A_i) = A_i \cdot Y_i(a_i = 1) + (1 - A_i) \cdot Y_i(a_i = 0)$$
$$Y_i^{mis} \equiv Y_i(1 - A_i) = (1 - A_i) \cdot Y_i(a_i = 1) + A_i \cdot Y_i(a_i = 0)$$

Formally, the assignment mechanism can be defined as a row-exchangeable function taking values on $\{0, 1\}^N$ to values in $[0, 1]$ defined as:

$$Pr(\mathbf{A}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1))$$

and satisfying:

$$\sum_{\mathbf{A}} Pr(\mathbf{A}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = 1 \qquad \text{for all} \quad \mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)$$

As Imbens and Rubin (2011) observe [1]:

[1] $\mathbf{W}$ is the assignment mechanism

This probability $Pr(\mathbf{W}|\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1))$ is *not* the probability of a unit of receiving the treatment. Instead it reflects a measure across the full population of N units, for instance the probability that a given assignment vector $\mathbf{W}$ – first two units treated, third a control, fourth treated, *etc.* – will occur. The definition requires that the probabilities across the full set of 2^N possible assignment vectors $\mathbf{W}$ sum to one. Note also that some assignment vectors may have zero probability. For example, if we were to design a study to evaluate a new drug, it is likely that we would want to rule out the possibility that all subjects received the control treatment, thereby assigning zero probability to the vector of assignments $\mathbf{W}$ with $W_i = 0$ for all $\mathbf{i}$, or perhaps even assigning zero probability to all vectors of assignments other than those with $\sum_{i=1}^{N} W_i = \frac{N}{2}$, for even N.

The assignment probability for unit i is:

$$p_i(\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1)) = \sum_{\mathbf{A}|A_i=1} Pr(\mathbf{A}|\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1))$$

The N functions $p_i(\cdot)$ can be written in terms of a common function $Pr(\cdot)$ that depends on the covariates and the potential outcomes for unit i:

$$p_i(\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1)) = Pr(A_i = 1|X_i, Y_i(0), Y_i(1)) \qquad \text{for all} \quad i = 1, 2, ..., N$$

The following definitions are essential (see Imbens and Rubin (2011), Ch. 3, pp. 8-):

Definition 1. *An assignment mechanism $Pr(\mathbf{A}|\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1))$ is said to be individualistic if, for some function $q(\cdot)$,*

$$p_i(\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1)) = q(X_i, Y_i(0), Y_i(1))$$

and

$$Pr(\mathbf{A}|\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1)) = c \cdot \prod_{i=1}^{N} q(X_i, Y_i(0), Y_i(1))^{A_i} \cdot \\ \cdot (1 - q(X_i, Y_i(0), Y_i(1)))^{1-A_i}$$

for $(\mathbf{A},\mathbf{X},\mathbf{Y}(0),\mathbf{Y}(1)) \in \mathbb{A}$ for some set $\mathbb{A}$, and zero elsewhere (c is the constant that ensures that the probabilities sum up to unit).

Definition 2. *If the assignment mechanism is individualistic, the propensity score $e(x)$ at x is the average unit probability for units with $X_i = x$:*

$$e(x) = \frac{1}{N_x} \sum_{i:X_i=x} q(X_i, Y_i(0), Y_i(1))$$

where $N_x = \#\{i = 1, .., N | X_i = x\}$ is the number of units with $X_i = x$. For values of x with $N_x = 0$, the propensity score is defined to be zero.

Definition 3. *An assignment mechanism* $Pr(\mathbf{A}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1))$*is said to be probabilistic if, for all* i *and all* $\mathbf{X}$*,* $\mathbf{Y}(0)$ *and* $\mathbf{Y}(1)$*, is strictly included between zero and one:*

$$0 < Pr(A_i = 1|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) < 1$$

Definition 4. *An assignment mechanism is said to be ignorable if it does not depend on the missing outcomes:*

$$Pr(A_i = 1|X_i, Y_i(0), Y_i(1)) = Pr(A_i = 1|X_i, Y_i^{obs})$$

Definition 5. *An assignment mechanism is said to be unconfounded if it does not depend on the potential outcomes:*

$$Pr(A_i = 1|X_i, Y_i(0), Y_i(1)) = Pr(A_i = 1|X_i)$$

Under individualistic assignment and unconfoundedness, the assignment mechanism can be written as:

$$Pr(\mathbf{A}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = c \cdot \prod_{i=1}^{N} q(X_i)^{A_i} \cdot (1 - q(X_i))^{1-A_i}$$

Under unconfoundedness (a condition that can also be labeled as *selection on observables* or *conditional independence*), the propensity score is not just the average assignment probability for units with covariate value $X_i = x$, but it can also be interpreted as the unit-level assignment probability for those units: $Pr_i(A_i = 1|X_i)$. The unconfoundedness assumption may be labeled in different ways in the literature, for instance as *selection on observables*, *exogeneity* and *conditional independence*.

Definition 6. *An assignment mechanism is called strongly ignorable if it is probabilistic and unconfounded.*

Note that an uncounfounded assignment is a particular case of an ignorable assignment, so that an unconfounded assignment is always ignorable while an ignorable assignment may be confounded. At the same time, a strongly ignorable assignment is a particular case of an unconfounded assignment. If the assignment mechanism is strongly ignorable, it can be represented as a regular assignment mechanism, which is proportional to the product of propensity scores:

$$Pr(\mathbf{A}|X, Y(1), Y(0)) \propto \prod_{i} Pr(A_i = 1|X_i)$$

We can now introduce other fundamental definitions that link the assignment mechanism to the type of a study:

Definition 7. *A randomized study is an experiment such that the assignment mechanism is probabilistic and a known function of its argument.*

Definition 8. *A classical randomized study is a randomized experiment with an assignment mechanism that is individualistic and unconfounded.*

Definition 9. *A completely randomized experiment is a classical randomized experiment in which the number of treated units, N_t is fixed a priori. In such a design N_t units are randomly selected to receive the active treatment from a population of N units, with the remaining $N_c = N - N_t$ assigned to the control group. In this case, each unit has unit assignment probability $q = N_t/N$ and assignment mechanism equals:*

$$Pr(\mathbf{A}|\mathbf{X}, \mathbf{Y}(0), \mathbf{Y}(1)) = \begin{cases} 1/\binom{N}{N_t} & if \sum_{i=1}^{N} A_i = N_t \\ 0 & otherwise \end{cases}$$

Definition 10. *An observational study is a non-randomized experiment such that the assignment mechanism is not a known function of its arguments.*

A special case of an observational study is given by a *regular assignment mechanism*:

Definition 11. *An assignment mechanism is said to be regular if it is probabilistic, individualistic and unconfounded.*

Note that a randomized study may be confounded (e.g. sequential randomized experiment) and, in general, observational studies have possibly confounded, nonignorable assignment mechanisms. Hence, it would be more pertinent to refer to this mechanism as *selection* mechanism and not assignment mechanism. Imbens and Rubin (2008) observe:

> The assignment mechanism describes why some study units will be (or were) exposed to the active treatment and why other study units will be (or were) exposed to the control treatment, and the reasons are formalized by the mathematical statement of the assignment mechanism. When the study is a true experiment, the assignment mechanism may involve the consideration of background (i.e., pre-treatment) variables for the purpose of creating strata of similar units to be randomized into treatment and control, thereby improving the balance of treatment and control groups with respect to these background variables (i.e., covariates). A true experiment automatically cannot use any outcome (post-treatment) variables to influence design because they are not yet observed. If the observed data were not generated by a true experiment, but rather by nonrandomized observational data, there still should be an explicit design phase. That is, in an observational study, the same guidelines as in an experiment should be followed [Imbens and Rubin (2008)].

In observational studies (discussed in the next chapter), a fundamental step to draw causal inference consists in identifying subset of units in order to approximate the structure of a true randomized experiment as closely as possible. Following Imbens and Rubin (2008):

> An observational study should be designed as if its data arose from a "broken" randomized experiment, where the unknown propensity scores must be reconstructed on the basis of the covariates X prior to ever observing any potential outcomes. In such settings, it is often quite advantageous to use estimated propensity scores [...]. When estimated propensity scores for some units are so low that they have essentially no chance of being treated, then those units should be discarded from further consideration when estimating the treatment effect in the treated [...]. The result of the design phase should be treatment and control groups with very similar distributions of observed Xs, either because of matching or subclassification. If a data set does not permit similar X distributions to be constructed in treatment and control groups, it cannot be used to support causal inferences without extraneous assumptions justifying extrapolations [Imbens and Rubin (2008)].

Imbens and Wooldridge (2009) add:

> Nevertheless, experimental evaluations remain relatively rare in economics. More common is the case where economists analyze data from observational studies. Observational data generally create challenges in estimating causal effects, but in one important special case, variously referred to as unconfoundedness, exogeneity, ignorability, or selection on observables, questions regarding identification and estimation of the policy effects are fairly well understood. All these labels refer to some form of the assumption that adjusting treatment and control groups for differences in observed covariates, or pretreatment variables, remove all biases in comparisons between treated and control units. This case is of great practical relevance, with many studies relying on some form of this assumption. [Imbens and Wooldridge (2009), (p.2)].

Note that there exists a third class of assignment mechanisms, in which some dependence of the assignment mechanism from the potential outcomes is supposed to hold. There is not a unique method to deal with this problem, but many techniques has been suggested, such as the use of instrumental variables, the regression discontinuity design and the difference-in-differences methods (see Chapter 3).

Let's now sum up two important issues discussed in this section. First, since a causal effect defined at an individual level cannot be definitely estimated, we turned our attention to a group level. Second, the mechanisms of assignment of individuals to treatments have been formalized, and these definitions have been linked to the type of a study (a classical randomized study, a completely randomized experiment and an observational study). Two other points now deserve to be underlined, and will be analyzed in the next section:

> First, there exists the possibility that units interfere with one another, such that one unit's potential outcome, when exposed to a specific treatment level, may also depend on the treatment received by another unit. Second, because in multi-unit settings, we must have available more than one copy of each treatment, we may face circumstances in which a unit receiving the same nominal level of one treatment could in fact receive different versions of that treatment. These are serious complications, serious in the sense that unless we restrict them, by assumption, and through careful study design and measurement to make these assumptions more realistic, there are only limited causal inferences that can be drawn. [Imbens and Rubin (2011), Ch.2, p.11]

2.4 Assumptions

Even if not explicitly mentioned, there are two implicit assumptions underlying all the previous definitions: *i*) *no interference between units* (Cox (1958));

ii) *consistency* (Robins *et al.* (2000)). The first assumption is part of the more general *stable-unit-treatment-value* assumption (SUTVA, Rubin (1980), Rubin (1986)) for which *ia*) there should be only one form of the treatment and one form of control *for each unit* and *ib*) a subject's counterfactual outcome under treatment $A = a$ should be independent from other subjects' treatment value. As stated in Morgan and Winship (2007), this assumption is also alluded to as *no-macro-effect* or *partial equilibrium assumption* in the econometric literature (Heckman (2000), Heckman (2005)). This hypothesis is commonly satisfied in most randomized experiments, but is not easily met in observational studies (e.g. educational or social programs).

> Note, however, that these assumptions, and other restrictions discussed later, are not directly informed by observations on similar treatments – fundamentally they are assumptions. That is, they rely on previous knowledge of the subject matter for their justification. Causal inference is impossible without such assumptions, and thus it is critical to be explicit about their content and their justifications. [Imbens and Rubin (2011), p. 9]

The first point (*ia*) of the SUTVA assumption has been remarkably commented by Imbens and Rubin (2011):

> The requirement is that the label of the aspirin tablet, or the nature of the administration of the treatment, does not contain any information regarding the potential outcome for any unit. This assumption does *not* require that all forms of each level of the treatment are identical across units, but only that unit i exposed to treatment level w specifies a well-defined potential outcome, $Y_i(w)$, for all i and $w \in \{0,1\}$. Strategies to make SUTVA more plausible include re-defining the treatment to comprise a larger set of treatments, or coarsening the outcome to make SUTVA more plausible. For an example of the latter, SUTVA may be more plausible if the outcome is defined as dead or alive rather than for a finer measurement of health status. [Imbens and Rubin (2011), Ch. 1, p. 11]

Let's now give a simple example in which the assumption (*ib*) does not hold. Imagine you are a neurologist, and you aim to verify the effect of *memantine* (a novel drug in the class of the Alzheimer's disease medications) on memory loss.
You select a sample of 100 units, who satisfy the inclusion criteria for a randomized pilot study. Consider now three subjects, u_1, u_2, u_3, whose potential outcomes under treatment/no treatment are reported in Table 2.1. The outcome variable is the score at the Mini-Mental State Examination (MMSE), a brief 30-point questionnaire that is used to screen for cognitive impairment. Consider, for instance, the 2^{nd} and the 5^{th} line for the subject u_1: note that counterfactuals under treatment are not independent from other subjects' assignments (when at least another subject is assigned to treatment $Y(1)$ increases and $Y(0)$ decreases), so that the underlying causal effects are a function of the treatment assignment pattern and SUTVA does not hold.

Think now you are a social *policy maker* and you are asked to increase the financial support to a program of private imprisonment in your county. Your office is planning a research project aimed to compare the percentage

Assignment			Outcome					
u_1	u_2	u_3	$Y_1(1)$	$Y_1(0)$	$Y_2(1)$	$Y_2(0)$	$Y_3(1)$	$Y_3(0)$
0	0	0	25	20	30	18	21	16
1	0	0	25	20	30	18	21	16
0	0	0	25	20	30	18	21	16
0	0	1	25	20	30	18	21	16
1	1	0	30	13	24	16	27	29
0	1	1	30	13	24	16	27	29
1	0	1	30	13	24	16	27	29
1	1	1	30	13	24	16	27	29

Table 2.1: An Example. Assignment mechanism and potential outcomes for three units u_1, u_2, u_3 in a Memantine Randomized Experiment. Outcomes indicate the score on the Mini-Mental State Examination (0-30, cutoff=18).

of suicides in public/private prisons. Does SUTVA hold in a similar context? Consider that private prisons detain far less inmates than public prisons and it is widely known that overcrowding is a risk factor for prison suicide. For SUTVA to hold, the number of suicides in private prisons cannot be a function of the number of inmates. Nevertheless, it may be the case that also in a non-natural assignment pattern, such that the populations of public/private prisons were balanced, the potential outcomes referred to suicides would be different. Interference between units causes no well-defined counterfactual outcomes $Y_i(a)$, since an individual outcome depends on other individuals' treatment values (a typical example in medicine is given by studies dealing with contagious diseases). There are also examples form economics and social sciences:

> There exist settings, however, in which the non-interference part of SUTVA can be quite suspect. In large scale job training programs, for example, the outcomes for one individual may well be affected by the number of people trained when the number is sufficiently large to create increased competition for certain jobs. In an extreme example, the effect on your future earnings of going to a graduate program in statistics would surely be different if everybody your age also went to the same program. [Imbens and Rubin (2011), Ch. 1, pp. 9-10]

In mathematical terms, SUTVA holds whether:

$$y_i(1) = y_i(1)|\mathbf{A} \qquad y_i(0) = y_i(0)|\mathbf{A} \qquad \text{for all i}$$

and

$$(Y_i(0), Y_i(1), A = a_i) \coprod (Y_j(0), Y_j(1), A = a_j) \qquad \text{for all i} \neq \text{j}$$

Morgan and Winship (2007) noticeably remark:

> Sometimes it is argued that SUTVA is so restrictive that we need an alternative conception of causality for the social sciences. We agree that SUTVA is very sobering. However, our position is that SUTVA reveals the limitations of observational data and perils of immodest causal modeling rather than the limitations of the counterfactual model itself. Rather than considering SUTVA as only restrictive, researchers should always reflect on the plausibility of SUTVA in each application and use such reflection to motivate a clear discussion of the meaning and scope of a causal effect estimate [Morgan and Winship (2007), p.38]

Note that there are also cases in which SUTVA *per se* does not hold and alternative assumption might be put forth as more appropriated, and should be kept into account to model the assignment mechanism:

> For example, in some early AIDS drug trial settings, many patients took some of their assigned drug and shared the remainder with other patients in hopes of avoiding placebos. Given this knowledge, it is clearly no longer appropriate to assert the no-interference element of SUTVA – that treatments assigned to one unit do not affect the outcomes for others. We can, however, use this specific information to model instead how treatments are received across patients in the study, making alternative –and in this case more appropriate– assumptions that allows some inference. [Imbens and Rubin (2011), Ch.3, p.12]

Another implicit assumption is that the treatment must be dichotomous, and this assumption is included in SUTVA; in case of multiple versions of treatment, the contrast of interest needs to be specified (Hernán and Robins (2010)). Last, a fundamental assumption is given by consistency, that can be defined as the condition according to which, for each subject, the potential outcome under exposure is precisely the observed outcome, i.e. the exposure is defined unambiguously. Cole and Frangakis (2009) remark:

> Consistency is guaranteed by design in experiments, because application of the exposure to any individual is under the control of the investigator. Consistency is plausible in observational studies of medical treatments, because one can imagine how to manipulate hypothetically an individual's treatment status. However, consistency is problematic in observational studies with exposures for which manipulation is difficult to conceive [Cole and Frangakis (2009), p.3].

Consistency can be formally stated by the formula:

$$\text{if} \quad A_i = a \quad \text{then} \quad Y_i(a) = Y_i$$

Note that, in applications, consistency is usually assumed and not discussed or verified by most authors.

2.5 Average Causal Effects

The fundamental problem of causal inference is that, at an individual level, a causal effect is defined comparing two counterfactual outcomes $Y(1)$ and $Y(0)$, but *only one* of these potential outcomes is factually observed. It follows that, normally, causal effects cannot be identified at an individual level for a problem of *missing values*. Consequently, we can turn our attention to *average causal effects* in the population. There are different measures that can be considered. First, the so called *average treatment effect* (ATE), that can be obtained by comparing the outcomes of two different group of participants, treated and not treated:

$$ATE = \mathbb{E}[(Y(1)|A = 1) - (Y(0)|A = 0)] \tag{2.2}$$

Second, the *average treatment effect on treated* (ATT), that compares the outcome of the treated if treated (factual) and whether they had not been treated (counterfactual):

$$ATT = \mathbb{E}[(Y(1)|A = 1) - (Y(0)|A = 1)] \tag{2.3}$$

In the counterfactual approach to causal inference ATT is considered as a more appropriate measure for a causal effect, since it compares the potential outcomes of the same subjects. ATE does not coincide with ATT, for the presence of the so-called *selection bias*, that is defined as the outcomes difference that would be observed between treated and untreated units if the treatment was not implemented. Indeed, ATE can be rewritten as:

$$\begin{aligned} ATE &= \mathbb{E}[(Y(1)|A = 1) - (Y(0)|A = 0)] \\ &= \underbrace{\mathbb{E}[(Y(1)|A = 1)] - E[(Y(0)|A = 1)]}_{ATT} + \\ &+ \underbrace{\mathbb{E}[(Y(0)|A = 1)] - E[(Y(0)|A = 0)]}_{\text{selection bias}} \end{aligned} \tag{2.4}$$

ATE is given by the sum of ATT and the selection bias, that captures pre-existing differences between the two groups that cannot be attributed to the program. As we can see, the selection bias comprises a term which is observable, and a term which is not observable (counterfactual) and it cannot be definitely measured. This is the reason for which ATE cannot commonly be given a causal interpretation.

Consider now that, in many applied problems, researchers can gain information on unit-specific background attributes of subjects (pre-treatment covariates):

> The final and most important role for covariates in our context, however, concerns their effect on assignment mechanism. Young unemployed individuals may be more interested in training programs aimed at acquiring new skills, or high risk groups may be more likely to take flu shots. As a result, those taking the active treatment may differ in the distribution of their background characteristics from those taking the control treatment. At the same time, these characteristics may be associated with the potential outcomes. As a result, assumptions about the assignment mechanism and its possible freedom from dependence on potential outcomes are often more plausible within subpopulations that are homogeneous with respect to some covariates, i.e., conditionally given the covariates, than unconditionally. [Imbens and Rubin (2011), Ch.3, p. 15].

If we now consider the vector of covariates $\mathbf{X}$, we can define two other measure effects that have been proposed in the literature, that are the *conditional average treatment effect* (CATE):

$$CATE = \mathbb{E}[(Y(1)|A = 1, X = x) - (Y(0)|A = 0, X = x)] \tag{2.5}$$

and the *conditional average treatment effect on treated* (CATT):

$$CATT = \mathbb{E}[(Y(1)|A = 1, X = x) - (Y(0)|A = 1, X = x)] \tag{2.6}$$

Alternatively, also *quantile treatment effects* can be used:

$$\tau_q = F^{-1}_{Y(1)}(q) - F^{-1}_{Y(0)}(q) \tag{2.7}$$

where 2.7 indicates the difference between the quantiles of the two potential outcomes distributions. The quantile of the unit level effect is defined as:

$$\tilde{\tau}_q = F^{-1}_{Y(1)-Y(0)}(q)$$

> In general the quantile of the difference, $\tilde{\tau}_q$ differs from the difference in quantiles, τ_q, unless there is perfect rank correlation between the potential outcomes $Y_i(0)$ and $Y_i(1)$ (the leading case of this is the constant additive treatment effect). The quantiles of the treatment effect, $\tilde{\tau}_q$, have received much less attention than the quantile treatment effect, τ_q. The main reason is that the $\tilde{\tau}_q$ are generally not identified without assumptions on the rank correlation between the potential outcomes, even with data from randomized experiment. Note that this issue does not arise if we look at average effects because the mean of the difference is equal to the difference of the means: $\mathbb{E}[Y_i(1) - Y_i(0)] = \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)]$. [Imbens and Wooldridge (2009), p.13]

The conditional difference between quantiles can be defined as well:

$$\tau_q(x) = F^{-1}_{Y(1)|X}(q|x) - F^{-1}_{Y(0)|X}(q|x)$$

Some authors have also proposed to consider the difference between *medians*, although the median, in general, is not a linear operator:

$$Med[Y(1) - Y(0)] \neq Med[Y(1)] - Med[Y(0)]$$

Also the variance parameter, as is commonly known, is not linear:

$$Var[Y(1) - Y(0)] = Var[Y(1)] + Var[Y(0)] - 2Cov[Y(1), Y(0)]$$

Last, causal effects can be defined within subpopulations of interest according to the realized outcome:

> One may be interested in the average effect of a job training program on earnings, averaged only over those individuals who would have been employed (with positive earnings) irrespective of the level of the treatment:
>
> $$\tau_{pos} = \frac{1}{N_{pos}} \sum_{i:Y_i(0)>0, Y_i(1)>0} (Y_i(1) - Y_i(0))$$
>
> where $N_{pos} = \sum_{i=1} N \mathbb{1}_{Y_i(0)>0, Y_i(1)>0}$. Because the conditioning variable (being employed irrespective to the treatment level) is a function of potential outcomes, the conditioning is (partly) on potential outcomes. [Imbens and Rubin (2011), p.17].

2.6 Measuring Causal Effects

In the previous section, only measures based on risk differences have been introduced. Nevertheless, also other measures –alternative to risk differences– are used in applied research projects. Imagine, for instance, a researcher is testing a new drug for asthma which can cause skin macules as side effects. Let P be a population of 1 million individuals in which 50 persons would develop the outcome if treated and 5 persons would develop the outcome even if untreated. Three different effect measures can be defined:

$$\text{Risk Difference} \quad Pr[Y(1)=1]-Pr[Y(0)=1]$$

$$\text{Risk Ratio} \quad \frac{Pr[Y(1)=1]}{Pr[Y(0)=1]}$$

$$\text{Odds Ratio} \quad \frac{Pr[Y(1)=1]/Pr[Y(1)=0]}{Pr[Y(0)=1]/Pr[Y(0)=0]}$$

In the example above, risk difference is .000045, risk ratio is 10 and odds ratio would be 10.0526. The basic difference between risk difference and the ratios is that the former keeps into account the magnitude of an effect with respect to the dimension of the population that has been examined. As noted in Hernán and Robins (2010):

> The causal risk ratio (multiplicative scale) is used to compute how many times treatment, relative to no treatment, increases the disease risk. The causal risk difference (additive scale) is used to compute the absolute number of cases of the disease attributable to the treatment. The use of either the multiplicative or additive scale will depend on the goal of the inference. [Hernán and Robins (2010), p.7]

2.7 Randomized Experiments

In the present chapter, the Rubin Causal Model has been introduced and the language of counterfactuals has been summed up. It has been mentioned that, normally, causal inference cannot be obtained at an individual level. Hence, we turned our attention to aggregate measures based on the evaluation of risk differences, such as ATE, ATT, CATE and CATT. Subsequently, other effect measures such as risk ratio and odds ratio have been introduced. In the present paragraph, we analyze randomized experiments, that have to be considered as a sort of *gold standard* from the Program Evaluation perspective. This is because randomization guarantees that missing values occurred by chance and, consequently, effect measures can be estimated despite the missing data. Classically, randomized experiments are used in chemistry, medicine, engineering, though they have also been conceived in the social contexts, as exemplified by the famous Perry preschool project:

> A case in point is the Perry preschool project, a 1962 randomized experiment designed to assess the effects of an early intervention program involving 123 black preschoolers in Ypsilanti, Michigan. The Perry treatment group was randomly assigned to an intensive intervention that included preschool education and home visits. It's hard to exaggerate the impact of the small but well-designed Perry experiment, which generated follow-up data through 1993 on the participants at age 27. [...] Most important, the Perry school project provided the intellectual basis for the massive Head Start preschool program, begun in 1964, which ultimately served (and continues to serve) millions of American children. [Angrist and Pischke (2008), p. 12]

Let's now briefly consider the following example: imagine you want to test the effect of a new anti-cholesterol drug; you select a sample from a target population and you randomly assign participants to receive either the new drug or a placebo. Afterwards, you compare the outcomes in the two groups of participants in order to establish whether the mean values of cholesterol significantly differ between the two groups. Suppose that our experiment is an *ideal randomized experiment*, for which: i) there is no any loss of participants at the follow-ups; ii) there is full compliance of patients and full observance to the assigned treatment over the duration of the study; iii) the assignment is double-blind. If such conditions are met, an important property, known as *exchangeability* or *exogenity*, holds. For, the expected improvement in the cholesterol values in the group of treated would have been the same as the expected improvement in the group of controls had subjects in the control group received the treatment given to those in the active treatment group. If we consider a dichotomized outcome ($Y = 1$: improved / $Y = 0$: not improved), the following equations hold under exchangeability:

$$Pr[Y(1) = 1|A = 1] = Pr[Y(1) = 1|A = 0]$$
$$Pr[Y(0) = 1|A = 1] = Pr[Y(0) = 1|A = 0]$$
$$Pr[Y(1) = 0|A = 1] = Pr[Y(1) = 0|A = 0]$$
$$Pr[Y(0) = 0|A = 1] = Pr[Y(0) = 0|A = 0]$$

In other words, it can be asserted that, if the condition of exchangeability holds, the counterfactual outcomes and the treatment subjects actually received are independent:

$$(Y(1), Y(0)) \coprod A \qquad \text{for all a} \in \text{A}$$

This is a stronger condition than the condition of unconfoundedness that was previously put forth, as exchangeability holds unconditionally from the values of the covariates. In fact, unconfoundedness can also be referred to as *conditional exchangeability*, especially in an epidemiology context.

Under exchangeability (either unconditional or conditional) the selection bias is null, so that ATE and ATT are the same and associational measures can be given a causal interpretation. Note that exchangeability relates to the potential outcomes and not to the factual outcomes and it does not imply independence of the factual outcomes from the treatment assignment. For instance, in a randomized experiment in which exchangeability holds and the treatment plays a causal role, the actual outcomes are *dependent* from the assignment of the treatment. An experiment in which exchangeability holds can also be defined as a *marginally randomized experiment*, because an unconditional (marginal) probabilistic rule is used in order to assign participants either to treatment or to control. These are experiments in which the randomization probabilities depend on the values of one or more covariates and conditional exchangeability is expected to hold. Let's turn back to the previous example and imagine to find that 73% treated versus 51% controls suffer from high blood pressure. Obviously, you are not allowed to interpret the results of this experiment without considering blood pressure as a covariate, i.e. you have to consider your study as a conditional randomized experiment.

The same effect measures that were put forth for the case of marginally randomized experiments can also be used in a conditionally randomized experiment. The basic difference is that in the latter case, these measures can be given a causal interpretation only *within each stratum*. Two main methodologies have been put forth in order to compute average causal effects from strata to the entire population: i) *standardization*; ii) *inverse probability weighting*.

The standardization method asserts that the risk in a population, stratified with respect to a certain variable X (that we assume as dichotomic), can be calculated as a weighted average of the stratum specific risks, provided conditional exchangeability holds. This condition can be developed in the following way:

$$(Y(0), Y(1)) \coprod A|X = 0 \leftrightarrow$$

$$\begin{cases} Pr[Y(1) = 1|X = 0, A = 1] = Pr[Y(1) = 1|X = 0, A = 0] = \\ = Pr[((Y(1) = 1|A = 1) + (Y(1) = 1|A = 0)|X = 0] \\ Pr[Y(0) = 1|X = 0, A = 0] = Pr[Y(0) = 1|X = 0, A = 1] \\ = Pr[(Y(0) = 1|A = 0) + (Y(0) = 1|A = 1))|X = 0] \end{cases}$$

and:

$$(Y(0), Y(1)) \coprod A|X = 1 \leftrightarrow$$

$$\begin{cases} Pr[Y(1) = 1|X = 1, A = 1] = Pr[Y(1) = 1|X = 1, A = 0] \\ = Pr[(Y(1) = 1|A = 1) + (Y(1) = 1)|A = 0)|X = 1] \\ Pr[Y(0) = 1|X = 1, A = 0] = Pr[Y(0) = 1|X = 1, A = 1] \\ = Pr[((Y(0) = 1|A = 0) + (Y(1) = 1|A = 1))|X = 1] \end{cases}$$

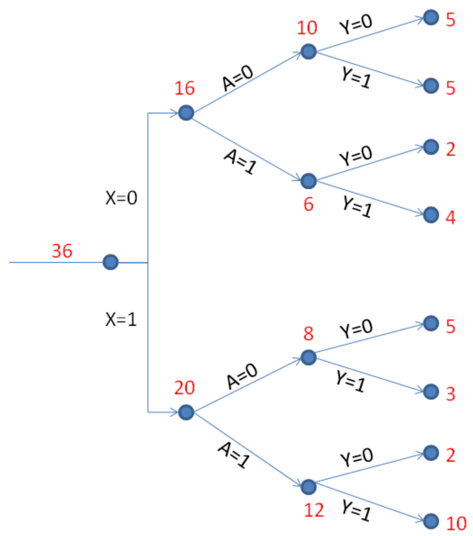

Figure 2.1: Example of a Standardization and Inverse Probability Weighting

Standardization is given by the following equations:

$$
\begin{aligned}
Pr[Y = 1|A = 1] &= Pr[Y = 1|X = 0, A = 1] \cdot Pr[X = 0]+ \\
&+ Pr[Y = 1|X = 1, A = 1] \cdot Pr[X = 1] \\
&= \sum_{X=x} Pr[Y = 1|X = x, A = 1] \cdot Pr[X = x]
\end{aligned}
$$

$$
\begin{aligned}
Pr[Y = 1|A = 0] &= Pr[Y = 1|X = 0, A = 0] \cdot Pr[X = 0]+ \\
&+ Pr[Y = 1|X = 1, A = 0] \cdot Pr[X = 1] \\
&= \sum_{X=x} Pr[Y = 1|X = x, A = 0] \cdot Pr[X = x]
\end{aligned}
$$

In the previous example the focus was on the effect of an anti-cholesterol drug ($Y = 1$: effective; $Y = 0$: not effective) and the sample was stratified according to the values of a covariate X ($X = 1$: high blood pressure; $X = 0$: not high blood pressure). Imagine now that in your 36-units sample, 20 units have high values of pressure and 10 units have low values of pressure and that 18 units are treated whereas 18 are untreated (see Figure 2.1). Our objective is to estimate the *causal risk difference*, defined as:

$$Pr[Y(1) = 1] - Pr[Y(0) = 1]$$

where $Y(1)$ indicates the counterfactual outcome of all the subjects had they been treated and $Y(0)$ indicates the counterfactual outcome of all the subjects had not they been treated. For $X = 1$ we have:

$$Pr[Y = 1|X = 1, A = 1] = \frac{10}{12} = 0.833$$

$$Pr[Y = 1|X = 1, A = 0] = \frac{3}{8} = 0.375$$

and, by the unconfoundedness hypothesis,

$$Pr[Y(1) = 1|X = 1, A = 1] = Pr[Y(1) = 1|X = 1, A = 0]$$

For $X = 0$ we have:

$$Pr[Y = 1|X = 0, A = 1] = \frac{4}{6} = 0.667$$

$$Pr[Y = 1|X = 0, A = 0] = \frac{5}{10} = 0.5$$

and, by the unconfoundedness hypothesis:

$$Pr[Y(1) = 1|X = 0, A = 1] = Pr[Y(1) = 1|X = 0, A = 0]$$

Standardization is given by:

$$\begin{aligned} Pr[Y(1) = 1] &= Pr[Y = 1|X = 1, A = 1] \cdot Pr[X = 1] + \\ &+ Pr[Y = 1|X = 0, A = 1] \cdot Pr[X = 0] \\ &= \frac{10}{12} \times \frac{20}{36} + \frac{4}{6} \times \frac{16}{36} = 0.463 + 0.296 = 0.759 \end{aligned}$$

and:

$$\begin{aligned} Pr[Y(0) = 1] &= Pr[Y = 1|X = 1, A = 0] \cdot Pr[X = 1] \\ &+ Pr[Y = 1|X = 0, A = 0] \cdot Pr[X = 0] \\ &= \frac{3}{8} \times \frac{20}{36} + \frac{5}{10} \times \frac{16}{36} = 0.208 + 0.222 = 0.43 \end{aligned}$$

Hence, the risk difference can be calculated as:

$$Pr[Y(1) = 1] - Pr[Y(0) = 1] = 0.759 - 0.43 = 0.329$$

Let's now analyze the second method that we mentioned, i.e. *inverse probability weighting*. In this context, we have to consider two theoretical *pseudo-populations*, the first defined in the case had all the participants remained untreated (Figure 2.2) and the second defined in the case had all the participants been treated (Figure 2.3). The expected outcomes are calculated according to the proportion of outcomes in the observed sub-populations. For the subpopulation for which $X = 0$, we have:

$$Pr[Y = 0|A = 0] = \frac{5}{10} = 0.5$$
$$Pr[Y = 1|A = 0] = \frac{5}{10} = 0.5$$
$$Pr[Y = 0|A = 1] = \frac{2}{6} = 0.333$$
$$Pr[Y = 1|A = 1] = \frac{4}{6} = 0.667$$

For the subpopulation for which $X = 1$, we have:

$$Pr[Y = 0|A = 0] = \frac{5}{8} = 0.625$$
$$Pr[Y = 1|A = 0] = \frac{3}{8} = 0.375$$
$$Pr[Y = 0|A = 1] = \frac{2}{12} = 0.167$$
$$Pr[Y = 1|A = 1] = \frac{10}{12} = 0.833$$

We can now consider a *total* pseudopopulation (see Figure 2.4), that combines the two pseudopopulation and in which the expected outcomes are weighted for a function $W = f(A|X) = pr(A|X)$ calculated in the observed sample:

$$pr(A = 0|X = 0) = \frac{10}{16} = 0.625$$
$$pr(A = 1|X = 0) = \frac{6}{16} = 0.375$$
$$pr(A = 0|X = 1) = \frac{8}{20} = 0.4$$
$$pr(A = 1|X = 1) = \frac{12}{20} = 0.6$$

In practice, the pseudopopulation is created by weighting each individual in the population by the inverse of the conditional probability of receiving the treatment level he/she actually received. We can now consider our overall pseudopopolation and calculate the risk difference:

$$Pr[Y(1) = 1] - Pr[Y(0) = 0]$$
$$Pr[Y(1) = 1] = \frac{10.56 + 16.66}{36} = 0.757$$
$$Pr[Y(0) = 1] = \frac{8 + 7.5}{36} = 0.430$$

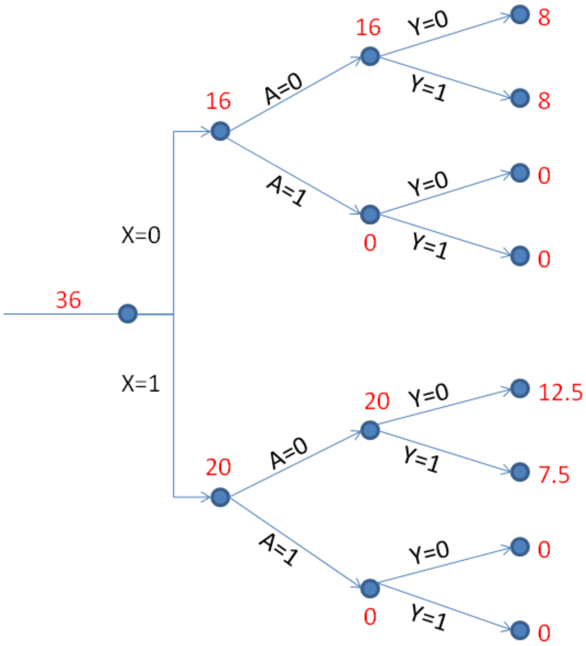

Figure 2.2: Inverse Probability Weighting: Pseudopopulation had all subjects remained untreated

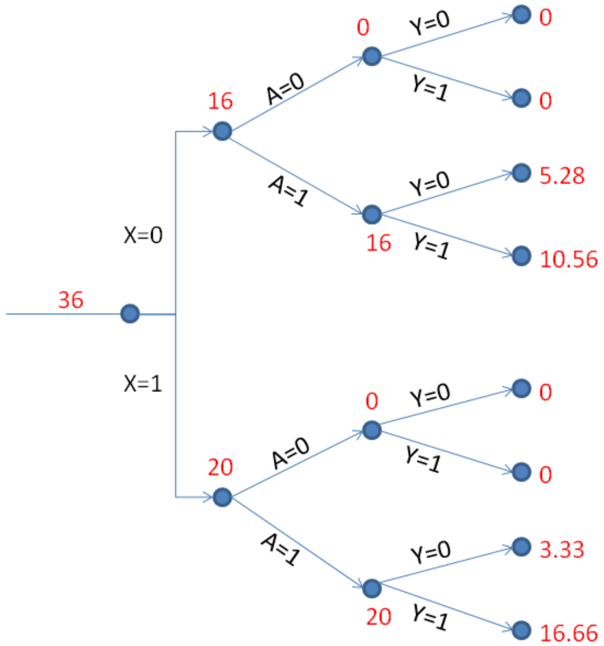

Figure 2.3: Inverse Probability Weighting: Pseudopopulation had all subjects been treated

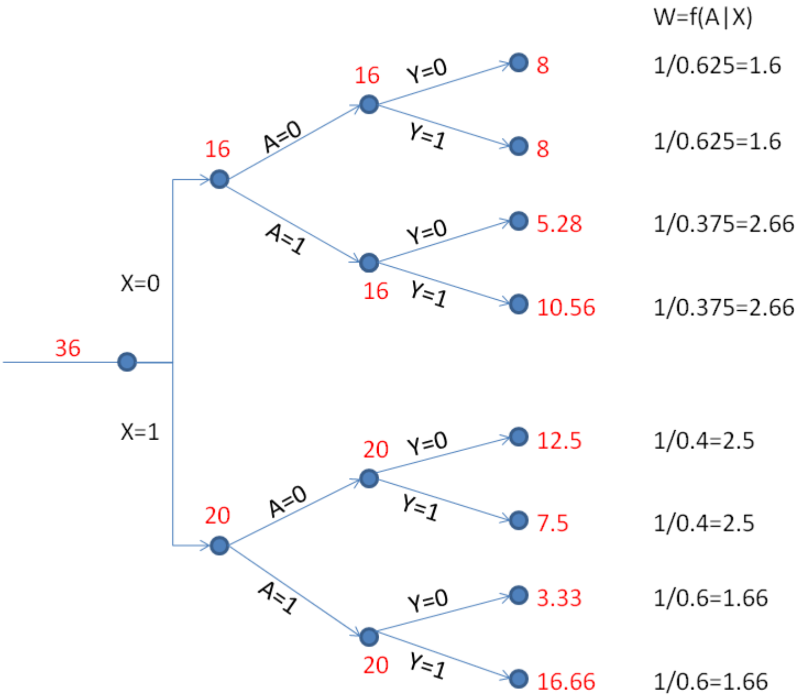

Figure 2.4: Inverse Probability Weighting: Overall Pseudopopulation

It follows that $Pr[Y(1) = 1] - Pr[Y(0) = 1] = 0.327 \cong 0.329$. If we now apply the standardization method in the overall pseudopopulation, it can be shown that the two methods are mathematically equivalent:

$$Pr[Y(1) = 1] = \frac{10.56}{16} \cdot \frac{16}{36} + \frac{16.66}{20} \cdot \frac{20}{36} = 0.293 + 0.46300.756$$
$$Pr[Y(0) = 1] = \frac{8}{16} \cdot \frac{16}{36} + \frac{7.5}{20} \cdot \frac{20}{36} = 0.222 + 0.208 = 0.430$$

It follows that $Pr[Y(1) = 1] - Pr[Y(0) = 1] = 0.756 - 0.430 = 0.326 \cong 0.329$

2.8 Testing Statistical Hypotheses

Testing statistical hypotheses in the Program Evaluation context has not been yet extensively studied. Most of the literature focus on verifying the hypothesis of a null average treatment effect in the population. Many estimators for average treatment effects (whose exact distribution is generally not known) are asymptotically normally distributed and the region of acceptance can be determined by inverting standard confidence intervals. Also hypotheses on the entire outcome distributions have been considered (e.g. Abadie (2002)) by means of Kolmogorov-Smirnov type testing procedures.

Furthermore, some authors have analyzed the problem of testing hypotheses on the heterogeneity of the effects (e.g. Hotz *et al.* (2008)) for which there may be subgroups of individuals with a significant effect of treatment though the overall treatment effect is not significant.

The problem of testing statistical hypotheses in randomized experiments has been treated since the seminal work of Fisher (1925) on the design of experiments, with focus on calculating p-values for hypotheses regarding the effect of a certain treatment. Consider the following system of hypotheses:

$$H_0 : Y_i(0) = Y_i(1) \qquad \forall i = 1...N \qquad H_a : \exists i \text{ such that } Y_i(0) \neq Y_i(1)$$

Fisher's approach to testing statistical hypotheses allows a researcher to verify whether a treatment has *any* effect, and not an average or median effect, as it has been clearly explained by Imbens and Wooldridge (2009). According to Fisher, it is not essential that the treatment assignment probabilities are equal for all units, but that these probabilities are known. In this case, under the null hypothesis H_0, the values of all the potential outcomes are supposed to be known. Consequently, the distribution of *any* test statistic, a function of the realized values $(Y_i, A_i)_{i=1}^N$ generated by randomization, can be computed, as it does not depend from unknown nuisance parameters.

Consider, for instance, the average outcome difference between treated and not treated units as a test statistic:

$$T(A,Y) = \bar{Y}_1 - \bar{Y}_0$$

where

$$\bar{Y}_a = \sum_{i:A_i=a} \frac{Y_i}{N_a} \qquad \text{for } a = 0,1$$

In a completely randomized study, for which $N = n$, $N_1 = n_1$, $N_0 = N - N_1 = n - n_1$, we have:

$$Pr(A_i = 1|\mathbf{X}, \mathbf{Y}_0, \mathbf{Y}_1) = \frac{N_1}{N}$$

the number of possible assignments is given by:

$$\binom{N}{N_1} = \frac{N!}{N_1!(N - N_1!)}$$

and:

$$Pr(\mathbf{A}|\mathbf{X}, \mathbf{Y}_0, \mathbf{Y}_1) = 1/\binom{N}{N_1}$$

The so-called *randomization distribution* for the test statistic can be exactly calculated by considering all the possible values of the assignment vector A. Thus, exact p-values are given by the probability of a value of the statistic of being at least as large, in absolute value, as that of the observed statistic $T(A,Y)$. (Imbens and Rubin (2011)).

Definition 12. *A statistic T is a known, real-valued function* $T(\mathbf{A}, \mathbf{Y}^{obs}, \mathbf{X})$ *of: the vector of assignments,* $\mathbf{A}$*, the vector of the observed outcomes,* $\mathbf{Y}^{obs}$ *(itself a function of* $\mathbf{A}$ *and the potential outcomes* $\mathbf{Y}(0)$ *and* $\mathbf{Y}(1)$*), and the matrix of pretreatment variables,* $\mathbf{X}$*).*

> The test statistic is stochastic solely through the stochastic nature of the assignment vector. We refer to the distribution of the statistic determined by the randomization as the *randomization distribution* of the test statistic. Using this distribution, we can compare the actually observed value of test statistic, T^{obs}, against its distribution under the null hypothesis. An observed value that is "very unlikely", given the null hypothesis and the distribution of the test statistic, will be taken as evidence against the null hypothesis in what is, essentially, a stochastic version of the mathematician's "proof by contradiction". How unusual the observed value is under the null hypothesis will be measured by the probability that a value as extreme or more extreme would be observed – the significance level or p-value. [Imbens and Rubin (2011), Ch. 5, p. 3]

Under the null hypothesis of no treatment effect, the observed average treatment effect $\hat{\tau}_{ATE}$ is an *unbiased* estimator of the average treatment effect in the population. Alternatively, in the case of a constant multiplicative effect of the treatment the average outcomes difference can be compared on a logarithmic scale:

$$T_{log} = \frac{1}{N_t} \sum_{i:A_i=1} ln(Y_i^{obs}) - \frac{1}{N_c} \sum_{i:A_i=0} ln(Y_i^{obs})$$

Note that:

> Such a transformation could also be sensible if the raw data have a quite skewed distribution, which is typically the case for nonnegative variables such as earnings or wealth, or levels of a pathogen, and treatment effects are more likely to be multiplicative than additive. In that case, the test based on taking the average difference, after transforming to logarithms would likely be more powerful than the test based on the simple average difference. [Imbens and Rubin (2011), Ch. 5, p. 10]

Other test statistics that are less affected by the presence of outliers are the difference between medians and the rank statistic:

$$\hat{\tau}_{Med} = Med(Y_1^{obs}) - Med(Y_0^{obs})$$

$$\hat{\tau}_{rank} = \bar{R}_1 - \bar{R}_0 = \frac{\sum_{i:A_i=1} R_i}{N_1} - \frac{\sum_{i:A_i=0} R_i}{N_0}$$

where, if there are no ties in outcomes within the population:

$$R_i(Y_1^{obs}, ..., Y_N^{obs}) = \sum_{j=1}^{N} \mathbb{1}(Y_j^{obs} \le Y_i^{obs})$$

and, if there are ties in outcomes within the population:

$$R_i(Y_1^{obs}, ..., Y_N^{obs}) = \sum_{j=1}^{N} \mathbb{1}(Y_j^{obs} \le Y_i^{obs}) + \frac{1}{2}(1 + \sum_{j=1}^{N} \mathbb{1}(Y_j^{obs} = Y_i^{obs}))$$

Last, the conventional standardized difference between means (the distribution of which can be exactly calculated) can be used:

$$T = \frac{Y_1^{obs} - Y_0^{obs}}{\sqrt{s_0^2/N_0 + s_1^2/N_1}}$$

where

$$s_A^2 = \sum_{i:A_i=a} (Y_i^{obs} - \bar{Y}_a^{obs})^2/(N_a - 1)$$

It can be easily shown that exact distribution functions for each of the previous test statistics can be calculated by means of the randomization distributions. Alternatively, when the total sample size is large enough, asymptotic results can be applied. As observed by Imbens and Rubin (2011):

> An important characteristic of this approach is that it is truly nonparametric, in the sense that it does not rely on a model specified in terms of a set of unknown parameters. In particular, we do not model the distribution of the outcomes; the vectors of potential outcomes $\mathbf{Y}(0)$ and $\mathbf{Y}(1)$ are regarded as fixed quantities. The only reason that the observed outcome, $\mathbf{Y}^{obs}$, and thus the test statistic, T^{obs}, are random is that a stochastic assignment mechanism determines which of the two potential outcomes are observed for each unit. Given the randomization used, this assignment mechanism is by definition known. In addition, given the null hypothesis, all potential outcomes are known. Thus we do not need modeling assumptions to calculate the randomization distribution of any test statistic; instead the assignment mechanism completely determines the randomization distribution of the test statistic. The validity of any resulting p-value is therefore *not* dependent on assumptions concerning the distribution of the potential outcomes. This freedom of reliance on modeling assumptions does not mean, of course, that the values of the potential outcomes do not affect the properties of the test. These values will certainly affect the expectation of the p-value when the null hypothesis is false (the statistical power of the test). They will not, however, affect the validity of the test, which depends solely on randomization. [Imbens and Rubin (2011), Ch. 5, pp. 4-5]

In addition, Fisher's approach to testing statistical hypotheses can keep into account different null hypotheses; for instance, the hypothesis of a *constant additive treatment effect* (see Imbens and Rubin (2011) for a discussion):

$$Y_i(1) = Y_i(0) + c$$

The main alternative to the Fisher's perspective is given by the Neyman (1923)'s repeated sampling approach. This work has been long put aside by the statistical community, but has been recently rediscovered by Dorota Dabrowska and Terry Speed in a new translation on the journal *Statistical Science* in 1990 and has been remarkably commented in Rubin (1990).

> During the same period in which Fisher was developing this method, Jersey Neyman was instead focusing on methods for the estimation of, and inference for, average treatment effects, also using the distribution induced by randomization and repeated sampling from a population. In particular, he was interested in the long-run operating characteristics of statistical procedures under repeating sampling and randomizations. Thus, he attempted to find point estimators that were unbiased, and also interval estimators that had the specified nominal coverage in large samples. As noted before, focusing on average effects is different from the focus of Fisher; the average effect across a population may be equal to zero even when some or even all unit-level treatment effects differ from zero. [Imbens and Rubin (2011), Ch. 6, p. 1]

Indeed, Neyman aimed to construct a measure in order to compare the two average outcomes, had all the subjects been treated $\bar{Y}(1)$ or had all the subjects remained untreated $\bar{Y}(0)$. He considered the so-called *superpopulation* (the potential outcomes, generally not known), the *randomization distribution* (the assignment vector $\mathbf{A}$) and the distribution of the test statistics under the randomization distribution, with all potential outcomes regarded as fixed (Imbens and Rubin (2011)). Differing from Fisher, Neyman considered the following system of hypotheses:

$$H_0^{Neyman} : \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = 0$$
$$H_1^{Neyman} : \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) \neq 0$$

Note that H_0^{Neyman} is a weaker hypothesis than the Fisher's null hypothesis, since the average treatment effect can be zero though for some units the treatment has a positive effect, provided for other units it has a negative effect. Moreover, H_0^{Neyman} is not a *sharp* null hypothesis, as it does not specify values for all potential outcomes under the null hypothesis. Consequently, differing from the Fisherian approach, the exact randomization distribution of the statistics of interest cannot be calculated. Hence, Neyman focused on deriving good estimators of some aspects of this distribution, for instance the first- and the second- order moments. Consider a completely randomized experiment in which we get information on N units, $N_1 = \sum_{i=1}^{N} A_i$ units are assigned to the treatment and $N_0 = \sum_{i=1}^{N}(1-A_i)$ units are assigned to control. For each unit there exist two potential outcomes, $Y_i(0)$ and $Y_i(1)$ and a further random variable is given by the treatment assignment, which is supposed to have a known distribution. The randomization distribution defines which potential outcome is observed for each unit. As it was underlined, Neyman aimed to estimate the population average treatment effect:

$$\tau = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = \bar{Y}(1) - \bar{Y}(0)$$

In a completely randomized experiment an *estimator* for the average treatment effect is given by the difference in average outcomes for those assigned to treatment versus those assigned to control:

$$\hat{\tau} = \frac{1}{N_1}\sum_{i:A_i=1} Y_i^{obs} - \frac{1}{N_0}\sum_{i:A_i=0} Y_i^{obs} = \bar{Y}_1^{obs} - \bar{Y}_0^{obs}$$

Theorem 1. *The estimator $\hat{\tau}$ is unbiased for τ.*

Proof. The observations can be written as:

$$Y_i^{obs} = Y_i(1)|A_i = 1$$
$$Y_i^{obs} = Y_i(0)|A_i = 0$$

and the estimator:

$$\hat{\tau} = \frac{1}{N}\sum_{i=1}^{N}\Big(\frac{A_i \cdot Y_i(1)}{N_1/N} - \frac{(1 - A_i) \cdot Y_i(0)}{N_0/N}\Big)$$

The potential outcomes are conceived as fixed and the only random component of the statistic is the treatment assignment A_i. Since the experiment is completely randomized (N units, N_1 of which are randomly assigned to the treatment), $Pr_A(A_i = 1) = \mathbb{E}_A[A_i] = N_1/N$. It follows that $\hat{\tau}$ is unbiased for the average treatment effect τ:

$$\mathbb{E}_A[\hat{\tau}] = \frac{1}{N}\sum_{i=1}^{N}\Big(\frac{\mathbb{E}_A[A_i]\cdot Y_i(1)}{N_1/N} - \frac{\mathbb{E}_A[1-A_i]\cdot Y_i(0)}{N_0/N}\Big)$$
$$= \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = \bar{Y}(1) - \bar{Y}(0) = \tau$$

□

Let's now turn our attention to the derivation of a confidence interval for τ. This construction involves three steps: i) deriving the sampling variance of the estimator for the average treatment effect; ii) developing estimators for such a sampling variance; iii) applying asymptotic results for the calculation of the confidence interval. The first step is not trivial, as in a completely randomized experiment the assignment to treatment of unit i is not independent of assignment to treatment of unit j. Consider a simple case with one treated unit and one control unit; the average treatment effect is given by:

$$\tau = \frac{1}{2}[(Y_1(1) - Y_1(0)) + (Y_2(1) - Y_2(0))]$$

and $A_1 = 1 - A_2$. The estimator for the ATE is

$$\hat{\tau} = A_1\cdot(Y_1(1) - Y_2(0)) + (1 - A_1)\cdot(Y_2(1) - Y_1(0))$$

Let's now introduce a variable D such that:

$$D = 2\cdot A_1 - 1 \quad A_1 = \frac{D+1}{2} \quad D \in \{-1, 1\} \text{ and } D^2 = 1$$

It follows:

$$\mathbb{E}[A_1] = \frac{1}{2} \qquad \mathbb{E}[D] = 0$$
$$\mathbb{V}_A[D] = \mathbb{E}_A[D^2] = 1$$

We can now write:

$$\hat{\tau} = \frac{D+1}{2}\cdot(Y_1(1) - Y_2(0)) + \frac{1-D}{2}\cdot(Y_2(1) - Y_1(0))$$

which can be rearranged as:

$$\begin{aligned}\hat{\tau} &= \frac{1}{2}[(Y_1(1) - Y_1(0)) + (Y_2(1) - Y_1(0))] + \\ &+ \frac{D}{2}[(Y_1(1) + Y_1(0)) - (Y_2(1) + Y_2(0))] \\ &= \tau + \frac{D}{2}[(Y_1(1) + Y_1(0)) - (Y_2(1) + Y_2(0))]\end{aligned} \tag{2.8}$$

Since $\mathbb{E}[D] = 0$, $\hat{\tau}$ is unbiased for τ (which it was already established by Theorem 1). Moreover, 2.8 also makes the calculation of the variance of $\hat{\tau}$ straightforward:

$$\begin{aligned}\mathbb{V}_A[\hat{\tau}] &= \mathbb{V}_A[\tau + \frac{D}{2} \cdot [(Y_1(1) + Y_1(0)) - (Y_2(1) + Y_2(0))]] \\ &= \frac{1}{4} \cdot \mathbb{V}_A[D] \cdot [(Y_1(1) + Y_1(0)) - (Y_2(1) + Y_2(0))]^2 \\ &= \frac{1}{4} \cdot [(Y_1(1) + Y_1(0)) - (Y_2(1) + Y_2(0))]^2\end{aligned} \tag{2.9}$$

$\mathbb{V}[\hat{\tau}]$ thus depends on all the potential outcomes, including products of potential outcomes for the same unit that are never jointly observed.

We now examine the general case with N units, N_1 of which are randomly assigned to the treatment. In order to calculate the sampling variance of $\bar{Y}_1^{obs} - \bar{Y}_0^{obs}$, we need the expectations of the second and the cross moments of the treatment indicators A_i, for $i = 1, ..., N$. Because $A_i \in \{0, 1\}$ is binary, $A_i^2 = A_i$, and thus:

$$\mathbb{E}_A[A_i^2] = \mathbb{E}_A[A_i] = \frac{N_1}{N}$$

$$\mathbb{V}_A[A_i] = \frac{N_1}{N} \cdot \left(1 - \frac{N_1}{N}\right)$$

Recall now that in a completely randomized experiment where the number of treated units is fixed at N_1, the two events: unit i being treated and unit j being treated, are *not* independent. Therefore:

$$\mathbb{E}_A[A_i \cdot A_j] \neq \mathbb{E}_A[A_i] \cdot \mathbb{E}_A[A_j] = (N_1/N)^2$$

$$\mathbb{E}_A[A_i \cdot A_j] = Pr_A[A_i = 1] \cdot Pr_A[A_j = 1 | A_i = 1] = \frac{N_1}{N} \cdot \frac{N_1 - 1}{N - 1} \qquad \text{for } i \neq j$$

Theorem 2.

$$\mathbb{V}(\hat{\tau}) = \mathbb{V}_A[\bar{Y}_1^{obs} - \bar{Y}_0^{obs}] = \frac{S_0^2}{N_0} + \frac{S_1^2}{N_1} - \frac{S_{01}^2}{N}$$

where S_0^2 and S_1^2 are the variances of $Y_i(0)$ and $Y_i(1)$ in the population, defined as:

$$
\begin{aligned}
S_0^2 &= \frac{1}{N-1}\sum_{i=1}^{N}(Y_i(0)-\bar{Y}(0))^2 \\
S_1^2 &= \frac{1}{N-1}\sum_{i=1}^{N}(Y_i(1)-\bar{Y}(1))^2
\end{aligned}
$$

and S_{01}^2 is the population variance of the unit-level treatment effects, defined as:

$$
S_{01}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(Y_i(1)-Y_i(0)-(\bar{Y}(1)-\bar{Y}(0)))^2 = \frac{1}{N-1}\sum_{i=1}^{N}(Y_i(1)-Y_i(0)-\tau)^2
$$

Proof. The objective is to calculate the sampling variance of the estimator $\hat{\tau} = \bar{Y}_1^{obs} - \bar{Y}_0^{obs}$. N units are given, N_1 receiving treatment and N_0 not receiving treatment. The average treatment effect in the population is:

$$
\bar{Y}(1) - \bar{Y}(0) = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1)-Y_i(0)) = \tau
$$

The standard estimator of τ is:

$$
\begin{aligned}
\hat{\tau} = \bar{Y}_1^{obs} - \bar{Y}_0^{obs} &= \frac{1}{N_1}\sum_{i=1}^{N} A_i \cdot Y_i^{obs} - \frac{1}{N_0}\sum_{i=1}^{N}(1-A_i)\cdot Y_i^{obs} \\
&= \frac{1}{N}\sum_{i=1}^{N}\Big(\frac{N}{N_1}\cdot A_i \cdot Y_i(1) - \frac{N}{N_0}\cdot(1-A_i)\cdot Y_i(0)\Big)
\end{aligned} \tag{2.10}
$$

For the variance calculation, it is useful to define a centered treatment indicator D_i, defined as:

$$
D_i = A_i - \frac{N_1}{N} = \begin{cases} \frac{N_0}{N} & \text{if } A_i = 1 \\ -\frac{N_1}{N} & \text{if } A_i = 0 \end{cases}
$$

$$
\mathbb{E}[D_i] = \mathbb{E}\Big[A_i - \frac{N_1}{N}\Big] = \mathbb{E}[A_i] - \frac{N_1}{N} = \frac{N_1}{N} - \frac{N_1}{N} = 0
$$

$$
\begin{aligned}
\mathbb{V}[D_i] = \mathbb{E}[D_i^2] &= \mathbb{E}\Big[A_i^2 + \frac{N_1^2}{N^2} - 2\frac{N_1}{N}A_i\Big] \\
&= \frac{N_1 \cdot N_0}{N^2}
\end{aligned}
$$

We consider now the cross moment:

$$\mathbb{E}_A[D_i \cdot D_j] = \mathbb{E}_A\Big[\Big(A_i - \frac{N_1}{N}\Big)\cdot\Big(A_j - \frac{N_1}{N}\Big)\Big] = \mathbb{E}_A\Big[A_iA_j - \frac{N_1}{N}A_i - \frac{N_1}{N}A_j + \frac{N_1^2}{N^2}\Big]$$

For $i \neq j$,

$$\mathbb{E}_A[D_i \cdot D_j] = \frac{-N_1 \cdot N_0}{N^2(N-1)}$$

For $i = j$,

$$\mathbb{E}_A[D_i \cdot D_j] = \frac{N_1 \cdot N_0}{N^2}$$

By substituting D_i in 2.10, the estimate of the average treatment effect is:

$$\begin{aligned}\hat{\tau} = \bar{Y}_1^{obs} - \bar{Y}_0^{obs} &= \frac{1}{N}\sum_{i=1}^{N}\Big(\frac{N}{N_1}\cdot\Big(D_i + \frac{N_1}{N}\Big)\cdot Y_i(1) - \frac{N}{N_0}\cdot\Big(\frac{N_0}{N} - D_i\Big)\cdot Y_i(0)\Big) \\ &= \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) + \frac{1}{N}\sum_{i=1}^{N} D_i \cdot \Big(\frac{N}{N_1}\cdot Y_i(1) + \frac{N}{N_0}\cdot Y_i(0)\Big) \\ &= \tau + \frac{1}{N}\sum_{i=1}^{N} D_i \cdot \Big(\frac{N}{N_1}\cdot Y_i(1) + \frac{N}{N_0}\cdot Y_i(0)\Big)\end{aligned} \tag{2.11}$$

Since $\mathbb{E}_A[D_i] = 0$ and all the potential outcomes are fixed, the estimator $\bar{Y}_1^{obs} - \bar{Y}_0^{obs}$ is unbiased for the average treatment effect, $\tau = \bar{Y}(1) - \bar{Y}(0)$. Furthermore, since the only random element in Equation 2.11 is D_i, the variance of $\hat{\tau} = \bar{Y}_1^{obs} - \bar{Y}_0^{obs}$, is equal to the variance of the second term in Equation 2.11. Using now Y_i^+ as shorthand for $\Big(\frac{N}{N_1}\cdot Y_i(1) + \frac{N}{N_0}\cdot Y_i(0)\Big)$, the variance is equal to:

$$\mathbb{V}_A[\bar{Y}_1^{obs} - \bar{Y}_0^{obs}] = \frac{1}{N^2}\cdot\mathbb{E}_A[(\sum_{i=1}^{N} D_i \cdot Y_i^+)^2] \tag{2.12}$$

Expanding Equation 2.12, we obtain:

$$\begin{aligned}\mathbb{V}_A[\bar{Y}_1^{obs} - \bar{Y}_0^{obs}] &= \mathbb{E}_A\Big[\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} D_i \cdot D_j \cdot Y_i^+ \cdot Y_j^+\Big] \\ &= \frac{1}{N^2}\sum_{i=1}^{N}(Y_i^+)^2 \cdot \mathbb{E}_A[D_i^2] + \frac{1}{N^2}\sum_{i=1}^{N}\sum_{i\neq j}\mathbb{E}_A[D_i \cdot D_j]\cdot Y_i^+ \cdot Y_j^+ \\ &= \frac{N_1 \cdot N_0}{N^4}\cdot\sum_{i=1}^{N}(Y_i^+)^2 - \frac{N_1 \cdot N_0}{N^4 \cdot (N-1)}\cdot\sum_{i=1}^{N}\sum_{i\neq j} Y_i^+ \cdot Y_j^+ \\ &= \frac{N_0 \cdot N_1[(N-1)\sum_{i=1}^{N}(Y_i^+)^2 - \sum_{i=1}^{N}\sum_{i\neq j} Y_i^+ Y_j^+]}{N^4(N-1)}\end{aligned}$$

$$
\begin{aligned}
&= \frac{N_0 \cdot N_1 [(N-1)\sum_{i=1}^{N}(Y_i^+)^2 + \sum_{i=1}^{N}(Y_i^+)^2 - \sum_{i=1}^{N}(Y_i^+)^2 - \sum_{i=1}^{N}\sum_{i \neq j} Y_i Y_j]}{N^4(N-1)} \\
&= \frac{N_0 \cdot N_1 [N \sum_{i=1}^{N}(Y_i^+)^2 - \sum_{i=1}^{N}\sum_{j=1}^{N} Y_i Y_j]}{N^4(N-1)} \\
&= \frac{N_0 \cdot N_1}{N^3(N-1)} \cdot [\sum_{i=1}^{N}(Y_i^+)^2 - \sum_{i=1}^{N} Y_i \bar{Y}] \\
&= \frac{N_0 \cdot N_1}{N^3(N-1)} \cdot \sum_{i=1}^{N}(Y_i^+ - \bar{Y}^+)^2 \\
&= \frac{N_0 \cdot N_1}{N^3(N-1)} \cdot \sum_{i=1}^{N}\Big(\frac{N}{N_1}Y_i(1) + \frac{N}{N_0}Y_i(0) - \Big(\frac{N}{N_1}\bar{Y}(1) + \frac{N}{N_0}\bar{Y}(0)\Big)\Big)^2 \\
&= \frac{N_0 \cdot N_1}{N^3(N-1)} \cdot \sum_{i=1}^{N}\Big(\frac{N}{N_1}Y_i(1) - \frac{N}{N_1}\bar{Y}(1)\Big)^2 + \\
&+ \frac{N_0 \cdot N_1}{N^3(N-1)} \cdot \sum_{i=1}^{N}\Big(\frac{N}{N_0} \cdot Y_i(0) - \frac{N}{N_0}\bar{Y}_0\Big)^2 \\
&+ 2\frac{N_0 \cdot N_1}{N^3(N-1)} \cdot \sum_{i=1}^{N}\Big(\frac{N}{N_1} \cdot Y_i(1) - \frac{N}{N_1} \cdot \bar{Y}(1)\Big) \cdot \Big(\frac{N}{N_0} \cdot Y_i(0) - \frac{N}{N_0} \cdot \bar{Y}(0)\Big) \\
&= \frac{N_0}{N \cdot N_1 \cdot (N-1)} \sum_{i=1}^{N}(Y_i(1) - \bar{Y}(1))^2 + \frac{N_1}{N \cdot N_0 \cdot (N-1)} \cdot \sum_{i=1}^{N}(Y_i(0) - \bar{Y}(0))^2 + \\
&+ \frac{2}{N \cdot (N-1)} \sum_{i=1}^{N}(Y_i(1) - \bar{Y}(1)) \cdot (Y_i(0) - \bar{Y}(0))
\end{aligned}
\tag{2.13}
$$

Recall now that the definition of S_{01}^2 implies that:

$$
\begin{aligned}
S_{01}^2 &= \frac{1}{N-1} \cdot \sum_{i=1}^{N}(Y_i(1) - \bar{Y}(1) - (Y_i(0) - \bar{Y}(0))^2 \\
&= \frac{1}{N-1} \cdot \sum_{i=1}^{N}(Y_i(1) - \bar{Y}_1)^2 + \frac{1}{N-1} \cdot \sum_{i=1}^{N}(Y_i(0) - \bar{Y}(0))^2 - \\
&- \frac{2}{N-1} \cdot \sum_{i=1}^{N}(Y_i(1) - \bar{Y}(1)) \cdot (Y_i(0) - \bar{Y}(0)) \\
&= S_1^2 + S_0^2 - \frac{2}{N-1} \sum_{i=1}^{N}(Y_i(1) - \bar{Y}(1)) \cdot (Y_i(0) - \bar{Y}_0)
\end{aligned}
$$

Hence, the expression in 2.13 is equal to:

$$\begin{aligned}
\mathbb{V}_A[\bar{Y}_1^{obs} - \bar{Y}_0^{obs}] &= \frac{N_0}{N \cdot N_1} \cdot S_1^2 + \frac{N_1}{N \cdot N_0} \cdot S_0^2 + \frac{1}{N}(S_1^2 + S_0^2 - S_{01}^2) \\
&= \frac{N_0 S_1^2 + N_1 S_1^2}{N N_1} + \frac{N_1 S_0^2 + N_0 S_0^2}{N N_0} - \frac{S_{01}^2}{N} \\
&= \frac{S_1^2}{N_1} + \frac{S_0^2}{N_0} - \frac{S_{01}^2}{N}
\end{aligned}$$

□

Note that both S_0^2 and S_1^2 are population-level variances, hence for a sample of size N_1 drawn from the group of the treated, the sampling variance is given by:

$$S_1^2/N_1 = \sum_i (Y_i(1) - \bar{Y}(1))^2/(N_1(N-1))$$

and similarly for a sample of size N_0 drawn from the control group, the sampling variance is given by:

$$S_0^2/N_0 = \sum_i (Y_i(0) - \bar{Y}(0))^2/(N_0(N-1))$$

The third term, S_{01}^2/N, is the population variance of the unit-level treatment effects, $Y_i(1) - Y_i(0)$, and is equal to zero if the treatment effect is constant in the population. If now we define:

$$\begin{aligned}
S_0 &= \frac{1}{\sqrt{N-1}} \sum_{i=1}^{N} (Y_i(0) - \bar{Y}(0)) \\
S_1 &= \frac{1}{\sqrt{N-1}} \sum_{i=1}^{N} (Y_i(1) - \bar{Y}(1)) \\
S_{01}^2 &= \frac{1}{N-1} \sum_{i=1}^{N} (Y_i(1) - Y_i(0) - (\bar{Y}(1) - \bar{Y}(0)))^2 \\
&= \frac{1}{N-1} [\sum_{i=1}^{N} (Y_i(1) - \bar{Y}(1))^2 + \sum_{i=1}^{N} (Y_i(0) - \bar{Y}(0))^2 - \\
&- 2 \sum_{i=1}^{N} (Y_i(1) - \bar{Y}(1))(Y_i(0) - \bar{Y}(0))] \\
\rho_{01} &= \frac{1}{(N-1) \cdot S_0 \cdot S_1} \sum_{i=1}^{N} (Y_i(1) - \bar{Y}(1))(Y_i(0) - \bar{Y}(0))
\end{aligned}$$

we have:

$$S_{01}^2 = S_0^2 + S_1^2 - 2\rho_{01} \cdot S_0 \cdot S_1$$

and it follows that:

$$\mathbb{V}_A(\bar{Y}_1^{obs} - \bar{Y}_0^{obs}) = \frac{N_1}{N \cdot N_0} S_0^2 + \frac{N_0}{N \cdot N_1} S_1^2 + \frac{2}{N} \cdot \rho_{01} \cdot S_0 \cdot S_1$$

Different proposals have been suggested for the estimation of this variance (see Imbens and Rubin (2011)); among them we mention the so-called Neyman's variance estimator, in which the treatment effects are supposed to be constant and additive $(Y_i(1) - Y_i(0)) = c$ for all i, so that the third component of the sampling variance vanishes. Such an estimator is given by:

$$\hat{\mathbb{V}}_{Neyman} = \frac{s_0^2}{N_0} + \frac{s_1^2}{N_1}$$

where:

$$s_0^2 = \frac{1}{N_0 - 1} \sum_{i:A_i=0} (Y_i(0) - \bar{Y}_0^{obs})^2$$
$$s_1^2 = \frac{1}{N_1 - 1} \sum_{i:A_i=1} (Y_i(1) - \bar{Y}_1^{obs})^2$$

As noted by Imbens and Rubin (2011):

> This estimator for the sampling variance is widely used, even when the assumption of an additive treatment effect may be inaccurate. There are two main reasons for the popularity of this estimator for the sampling variance. First, by implicitly setting the third element of the estimated sampling variance equal to zero, the expected value of $\hat{\mathbb{V}}_{Neyman}$ is at least as large as the true sampling variance of $\bar{Y}_1^{obs} - \bar{Y}_1^{obs}$, irrespective of the heterogeneity in the treatment effect. Hence, in large samples, confidence intervals generated using this estimator of the sampling variance will have coverage at least as large, but not necessarily equal to, this nominal coverage. [...] The second reason for using this estimator for the sampling variance of $\bar{Y}_1^{obs} - \bar{Y}_0^{obs}$ is that it is always unbiased for the sampling variance of τ as an estimator of the average treatment effect. [Imbens and Rubin (2011), Ch.6, p. 12]

Also the following estimators have been proposed (for a comparative approach see Imbens and Rubin (2011)):

$$\hat{\mathbb{V}}_{\rho_{10}} = s_0^2 \cdot \frac{N_1}{N \cdot N_0} + s_1^2 \cdot \frac{N_0}{N \cdot N_1} + \rho_{10} \cdot s_0 \cdot s_1 \cdot \frac{2}{N}$$
$$\hat{\mathbb{V}}_{\rho_{10=1}} = s_0^2 \cdot \frac{N_1}{N \cdot N_0} + s_1^2 \cdot \frac{N_0}{N \cdot N_1} + s_0 \cdot s_1 \cdot \frac{2}{N}$$
$$= \frac{s_0^2}{N_0} + \frac{s_1^2}{N_1} - \frac{(s_1 - s_0)^2}{N}$$

Since $\mathbb{V}_{\text{Neyman}}$ can be approximated by a chi-squared distribution and the distribution of the estimator $\hat{\tau}$ can be approximated by a normal distribution, the ratio $\frac{\hat{\tau}}{\sqrt{\hat{\mathbb{V}}_{Neyman}}}$ has a t-distribution. Hence, it can be calculated a confidence interval $[C_L(\mathbf{Y}^{obs}, \mathbf{A}), C_U(\mathbf{Y}^{obs}, \mathbf{A})]$ at a level $(1 - \alpha)$, such that:

$$Pr_A(C_L(\mathbf{Y}^{obs}, \mathbf{A}) \le \tau \le C_U(\mathbf{Y}^{obs}, \mathbf{A})) \ge 1 - \alpha$$

Consequently, the hypotheses:

$$H_0^{Neyman} : \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) = 0$$
$$H_1^{Neyman} : \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_i(0)) \neq 0$$

can be compared by means of the test statistic with t- distribution:

$$t = \frac{\bar{Y}_1^{obs} - \bar{Y}_0^{obs}}{\sqrt{\hat{\mathbb{V}}_{Neyman}}}$$

2.9 The Structural Approach to causal inference

As it was mentioned in the second paragraph, both the statistical and the econometric literature have been extensively concerned with causal inference. From a historical perspective, renowned statisticians such as Fisher (1925) and Neyman (1923) dealt with the problem of causality in randomized experiments. While Fisher's contribute was given a wide credit in the statisticians' community, Neyman's approach stand in the background. As it was mentioned, in 1990 a portion of Neyman (1923)'s paper was retranslated in the journal *Statistical Science* and remarkably commented by Donald Rubin. This was extremely useful in order to re-consider Neyman's approach to the analysis of randomized experiments. With respect to observational studies, a comprehensive framework for causality was put forth by Rubin in a series of very influential papers (Rubin (1973a, 1974, 1977), see Chapter 3) and is now commonly referred to as the *Rubin Causal Model* or the *Program Evaluation Approach*. Another important approach to causation in statistics is given by the so-called Granger-Sims model of causality, developed in the context of time series analysis. According to these authors, causality can be conceived as a sort of *prediction property*, for which a time series A can *cause* another time series B if, conditional on the past values of B, and possibly conditional on other variables, past values of A predict future values of B. As we have seen, Rubin –according to the Lewis' perspective on causality– put forward a different theoretical framework based on the concept of potential outcomes. In this author's opinion, inference can be causally interpreted only comparing the potential and not the observed outcomes. In this perspective, randomized experiments are conceived as a sort of *gold standard* to draw causal inference. Nevertheless, this approach has been criticized by econometricians such as James Heckman who, in a recent influential paper commented:

> Rubin and Holland argue that causal effects are defined only if an experiment can be performed. This conflation of the separate tasks of defining causality and identifying causal parameters from data is a signature feature of the program evaluation approach. It is a consequence of the absence of clearly formulated economic models. The probability limits of estimators, and not the parameters of well-defined economic models, are often used to define causal effects or policy effects. [...] The "causal models" advocated in the program evaluation literature are motivated by the experiment as an ideal. They do not clearly specify the theoretical mechanisms determining the set of possible counterfactual outcomes, how hypothetical counterfactuals are realized or how hypothetical interventions are implemented except to compare "randomized" with "nonrandomized" interventions. They focus on outcomes, leaving the model for selecting outcomes and preferences of agents over expected outcomes unspecified. [Heckman (2010), p. 358-360]

The core of Heckman's criticism to the Rubin Causal Model is that it does not keep into account the individual choices that participants can make on participating / not participating to a program, based on their prior information. A second argument is that the Rubin's approach does not consider any parametrical model as strictly necessary in order to define either the assumptions or the parameters of interest. On this point, Heckman (2010) remarkably notes:

> Any estimator makes assumptions (often implicit) about the behavior of the agents being analyzed. For example, the ability of a randomized controlled trial to identify parameters of interest depends on assumptions about the agent subject to randomization. The structural approach is explicit about this assumptions. The program evaluation approach is often not. Some economists confuse the absence of explicit statements of assumptions with the absence of assumptions. The models in the program evaluation literature do not specify the sources of randomness generating variability among agents, i.e., they do not specify why otherwise observationally identical people make different choices. They do not distinguish what is in the agent's information set from what is in the observing economist's information set, although the distinction is fundamental in justifying the properties of any estimator for solving selection and evaluation problems. They do not allow for interpersonal interactions inside and outside of markets in determining outcomes that are the heart of game theory, general equilibrium theory, and models of social interaction and contagion. [Heckman (2010), p. 360- 361]

In the previous paragraphs, our attention has been exclusively focused on the Program Evaluation Approach. In the following I'll give a brief overview on the Structural Approach for causal inference. This has been developed by econometricians such as James Heckman, Joshua D. Angrist and Edward J. Vytlacil and historically derives from the literature on the evaluation of labor market programs (e.g. Ashenfelter (1978), Ashenfelter and Card (1985), Heckman and Robb Jr (1985), LaLonde (1986)). These authors directed their attention on issues such as endogeneity and self-selection, that normally are not treated in the Program Evaluation Approach. The Structural Approach focuses on understanding the relation among social variables, primarily in order to forecast the effects of new policies. Heckman and Vytlacil (2007) put forth three reasons for policy evaluation:

1. P-1. Evaluating the impact of historical interventions on outcomes including their impact in term of welfare:

> P-1 is the problem of *internal validity*. It is the problem of identifying a given treatment parameter or a set of parameters in a given environment. Focusing exclusively on objective outcomes, this is the problem addressed in the epidemiological and statistical literature on causal inference. A drug trial for a particular patient population is a prototypical problem in the literature. The econometric approach emphasizes valuation of the objective outcome of the trial (e.g. health status) as well as subjective evaluation of outcomes (patient's welfare), and the latter may be *ex post* or *ex ante*. Most policy evaluation is designed with an eye toward the future and towards informing decisions about new policies and application of old policies to new environments. [Heckman and Vytlacil (2007), p. 4791]

2. P-2. Forecasting the impacts (constructing counterfactual states) of interventions implemented in one environment in other environments, including their impacts in terms of welfare.

> Included in these interventions are policies described by generic characteristics (e.g., tax or benefit rates, etc.) that are applied to different groups of people or in different time periods from those studied in implementations of the policies on which data are available. This is the problem of *external validity*: taking a treatment parameter or a set of parameters estimated in one environment to another environment. The environment includes the characteristics of individuals and of the treatments. [Heckman and Vytlacil (2007), p. 4791]

3. Forecasting the impacts of interventions (constructing counterfactual states associated with interventions) never historically experienced to various environments, including their impact in terms of welfare.

The Structural Approach is centered on estimating models for the potential outcomes $Y(0)$ and $Y(1)$ and of costs C under different economic environments. From this perspective –differing from the Program Evaluation Approach– researchers try to *model* the counterfactual distribution, keeping into account both *preferences* and *choices* of participants and *objective outcomes*. Indeed, econometricians have developed a three-steps approach to causal inference: i) defining a set of counterfactuals; ii) developing an hypothetical model of such counterfactuals; iii) identifying a model (parameter estimation) from sample surveys. Consider, for instance, the following specification of a structural model:

$$\begin{aligned} Y(1) &= \mu_1(X) + U(1) \\ Y(0) &= \mu_0(X) + U(0) \\ C &= \mu_C(Z) + U(C) \end{aligned}$$

where (X, Z) are observed variables whereas $U(0)$, $U(1)$ and $U(C)$ are unobserved variables. Theoretical issues (either made implicit or explicit) lead to the specification of X and Z. $Y(0)$ and $Y(1)$ are the two potential outcomes that, as we said, are random variables with joint distribution $F_{Y(0),Y(1)}(y(0), y(1))$. As observed by Heckman (2010):

> The central question recognized in this literature is that analysts observe either $Y(0)$ or $Y(1)$, but not both, for any person. In the program evaluation literature, this is called the **evaluation problem**. In addition to this problem, there is the **selection problem**. The values of $Y(0)$ or $Y(1)$ that are observed are not necessarily a random sample of the potential $Y(0)$ or $Y(1)$ distributions. [Heckman (2010), p. 361]

As it was remarked, this approach derives from the analysis of economic and social problems, in which the subjective evaluation is as important as the objective outcome. To keep subjective evaluation into account, a decision rule D expressed by an indicator function is introduced, such that an agent selects into sector 1 if $Y(1) > Y(0)$:

$$D = \mathbb{1}(Y(1) > Y(0))$$

or, adding the cost C:

$$D = \mathbb{1}(Y(1) - Y(0) - C > 0) \tag{2.14}$$

Hence, participation to a program is not externally determined but is chosen by agents according to individual expected outcomes. From one side this leads to selection bias, but, from the other side, it also provides information on subjective evaluations. Equation 2.14 expresses a set of counterfactual outcomes and costs $(Y(0), Y(1), C)$ with distribution $F_{Y(0),Y(1),C}(y(0), y(1), c)$ and a mechanism for selecting which element of $Y(0), Y(1)$ is observed for each person. The observed outcome for unit i can be expressed by the equation:

$$Y_i = D_i Y_i(1) + (1 - D_i) Y_i(0) \tag{2.15}$$

For, the structural approach to causal inference keeps into account the choices made by participants:

> Agents make their choices under imperfect information. Let $\mathscr{I}$ denote the agent's information. In advance of participation, the agent may be uncertain about all components of $(Y(0), Y(1), C)$. The expected benefit is $I_D = E(Y(1) - Y(0) - C|\mathscr{I})$. Then $D = \mathbb{1}(I_D > 0)$. Moreover, the decision maker selecting "treatment" may be different than the person who experiences the outcomes (Y(0),Y(1)). Thus parents may make school decisions for their children: doctors may make treatment decisions for their patients. More generally, decisions to participate may entail joint approval of all parties. The ex post objective outcomes are $(Y(0), Y(1))$. Associated with each outcome there is also an evaluation $(V_i(1), (0))$ by the agent. The ex ante outcomes are $E(Y(0)|\mathscr{I})$ and $E(Y(1)|\mathscr{I})$. The ex ante subjective evaluation is I_D. The ex post subjective evaluation is $Y(1) - Y(0) - C$. Agents may regret their choices because realizations may differ from anticipations. The ex ante versus ex post distinction is essential for understanding behavior. In environments of uncertainty, agent choices are made in terms of ex ante calculations. Yet the treatment effect literature largely reports ex post returns. [Heckman (2010), p. 363-364]

We will not further deal with the problems of causality from an econometric perspective; we underline only that one of the main features of this approach is that it tries to put forward theoretical hypotheses on the distribution of the potential outcomes. As it will be shown in the next chapter, this is not the case for the Rubin Causal Model, as stated by Heckman:

> The discussion of Holland (1986) illustrates this point and the central role of randomized controlled trial to the Holland-Rubin analysis. After explicating the "Rubin model", Holland makes a very revealing claim: there can be no causal effect of gender on earnings because analysts cannot randomly assign gender. This statement confuses the act of defining a causal effect (a purely mental act performed within a model) with empirical difficulties in estimating it. [Heckman (2010), p. 363-364]

2.10 Conclusions

In this chapter, after commenting two examples on the informal representation of causal concepts, two formal approaches to causal inference have been discussed: the Structural Approach (developed by authors such as James Heckman) and the Program Evaluation approach (developed by authors such as Donald Rubin). The former approach has not been discussed in depth; the main goal in this context was only to show the usefulness of Heckman's framework to keep into account subjective factors (such as individual choices) in the analysis of causality. Our attention has been focused on the latter approach; let's briefly sum up the main steps we've done. First, some fundamental concepts have been introduced, such as unit, treatment, target population, dichotomous outcome, assignment mechanism and potential outcomes. Second, some important issues on the assignment mechanism have been highlighted, such as the definitions of individualistic, probabilistic, ignorable, strongly ignorable and unconfounded assignment mechanisms. Third, the assignment mechanism defines the type of a study: a randomized study, a classical randomized study, a completely randomized study and an observational study. Fourth, we have focused on the main assumptions for causal inference: SUTVA and consistency. Fifth, we have defined different measures for the average causal effects: ATE, ATT, CATE, CATT and we introduced the selection bias and the fundamental Equation 2.4. Sixth, alternative measures for causal inference have been put forth: risk differences, risk ratio and odds ratio, each of which can be given a different interpretation. Seventh, the attention has been focused on randomized experiments, and on the hypotheses of exchangeability and conditional exchangeability. Eighth, two methodologies for drawing causal inference when conditional exchangeability holds have been explained: standardization and inverse probability weighting. An example showed that these two methodologies are equivalent from a mathematical point of view. Ninth, a brief investigation on testing statistical hypotheses has been put forward and the alternative approaches of Fisher and Neyman have been presented. In the next chapter, we will shift our attention from randomized studies to observational studies, and different methodologies for drawing causal inference when either conditional exchangeability is supposed / not supposed to hold will be presented.

Chapter 3

Observational Studies

3.1 Overview

In this chapter we shift our attention from randomized experiments to observational studies. In the Program Evaluation Approach randomized experiments are conceived as a sort of *gold standard*. Consequently, causal inference in non-experimental settings should imitate the conditions of a complete randomized experiment. Authors such as Paul Holland and Donald Rubin also proposed that, in contexts where a certain variable cannot be explicitly manipulated (for instance race or gender), it is hard to draw causal inference. On this issue, Angrist and Pischke (2008) note:

> Research questions that cannot be answered by an experiment are FUQs: fundamentally unidentified questions. What does exactly look like? At first blush, questions about the causal effect of race or gender seem good candidates because these things are hard to manipulate in isolation ("imagine your chromosomes were switched at birth"). On the other hand, the issue economists care most about in the realm of race and sex, labor market discrimination, turns on whether someone treats you differently because they *believe* you to be black or white, male or female. The notion of a counterfactual world where men are perceived as women or vice versa has a long history and does not require Douglas-Adams style outlandishness to entertain (Rosalind disguised as Ganymede fools everyone in Shakespeare's *As You Like It*). The idea of changing race is similarly near-fetched: in *The Human Stain*, Philip Roth imagines the world of Coleman Silk, a black literature professor who passes as white in professional life. Labor economists imagine this sort of thing all time. Sometimes we even construct such scenarios for the advancement of science, as in audit studies involving fake job applicants and resumes. [Angrist and Pischke (2008), p. 6]

Causal inference from observational studies can be obtained by "miming" the conditions of a randomized study and different methodologies to achieve this objective have been proposed:

> We hope to find natural or quasi-experiments that mimic a randomized trial by changing the variable of interest while other factors are kept balanced. Can we always find a convincing natural experiment? Of course, not. Nevertheless, we take the position that a notional randomized trial is our benchmark. Not all researchers share this view, but many do. [Angrist and Pischke (2008), p. 21]

In this chapter we analyze how an observational study can "mimic" a randomized experiment. Consider N units, indexed by $i = 1, ..., N$, drawn randomly from a large population. Each unit is characterized by a pair of potential outcomes $Y_i(0)$ and $Y_i(1)$ and by a vector of characteristics, referred to as covariates, that are pretreatment variables not affected by the treatment itself, and denoted by X_i. A single treatment is given to each unit: $A_i = 0$ indicates the non treated units and $A_i = 1$ indicates the treated units. For each unit, we therefore observe the triplet (A_i, Y_i, X_i), such that:

$$Y_i^{obs} = Y_i(1) \cdot A_i + Y_i(0) \cdot (1 - A_i)$$

As we've seen in the previous chapter, causal estimands of interest are usually average treatment effects on subpopulations:

$$\begin{aligned}
\tau_{ATE} &= \mathbb{E}[Y(1) - Y(0)] \\
\tau_{ATT} &= \mathbb{E}[Y(1) - Y(0)|A = 1] \\
\tau_{CATE} &= \mathbb{E}[Y(1) - Y(0)|X = x] \\
\tau_{CATT} &= \mathbb{E}[Y(1) - Y(0)|A = 1, X = x]
\end{aligned}$$

In general, τ_{ATE} is not equal to τ_{ATT} due to the presence of the selection bias:

$$\begin{gathered}
\mathbb{E}[Y(1)|A = 1] - \mathbb{E}[Y(0)|A = 0] = \\
\mathbb{E}[Y(1)|A = 1] - \mathbb{E}[Y(0)|A = 1] + \mathbb{E}[Y(0)|A = 1] - \mathbb{E}[Y(0)|A = 0]
\end{gathered}$$

Such a bias can be originated by three main causes: (i) non overlapping with the respect to the covariates' values on the support between treated and non treated units; (ii) the presence of observed confounders (selection on observables); (iii) the presence of unobserved counfounders (selection on unobservables). In an observational study, the assignment mechanism A_i is generally not known. A usual assumption on the selection mechanism is that it is *strongly ignorable* (unconfounded + overlap on the covariates' support). If this assumption holds, observational studies can be interpreted as a completely randomized study, within subpopulations of units with the "same" values for the covariates.

The first assumption that has to be kept into account is that of *overlapping*, for which:

$$0 < Pr(A_i = 1|X_i = x) < 1 \qquad \text{for all } x$$

From en econometric perspective, this assumption is also known as *full common support* (see Figure 3.1 a). If we're only interested in examining the causal effect of the treatment on the treated units (e.g. τ_{ATT}), the assumption can be relaxed as:

$$0 < Pr(A(1)|A = 1, X = x) < 1$$

In the case the overlapping assumption holds only for a subsample of the treated / not treated units, the analysis of causal relations should be narrowed only to the subset of values which share a common support. This assumption can be not satisfied in different ways: let's indicate as X_1 the covariate domain of the treated units and as X_0 the covariate domain of the control units with respect to a covariate X; the following cases can be given:

1. Full common support with respect to X_1 (see Figure 3.1 b)
2. Partial common support with respect to X_1 (see Figure 3.1 c)
3. Common support at the threshold (a discontinuity point) of X_1 (see Figure 3.1 d)
4. No common support with respect to X_1 (see Figure 3.1 e)

Second, the main statistical methods to draw causal inference from observational studies depends on relying or not on the *unconfoundedness* assumption. As we have seen, unconfoundedness demands that, after conditioning on the observed covariates, there are not unobserved factors that are correlated both with the mechanism of assignment and with the potential outcomes:

$$A \coprod (Y(0), Y(1))|X = x \qquad \text{for all } x$$

In order to unconfoundedness to hold in observational studies, we need a certain set of covariates so that –adjusting for differences in these covariates– causal effects can be estimated. Most of the methods dealing with causality in observational studies make use of the so-called *propensity score*, i.e. the conditional probability of receiving the treatment given the values of the covariates:

$$e(X_i) = Pr(A_i = a|X_i = x) \qquad \text{for } i = 1, ..., N$$

Alternatively, *matching methods*, that are methods that aim to match treated units and control units according to the covariates' values, have been proposed. Furthermore, methods that combine propensity score and matching methods have also been recently put forth.

Before briefly describing some of the main proposal for drawing causal inference in observational studies, it is necessary to discuss a fundamental

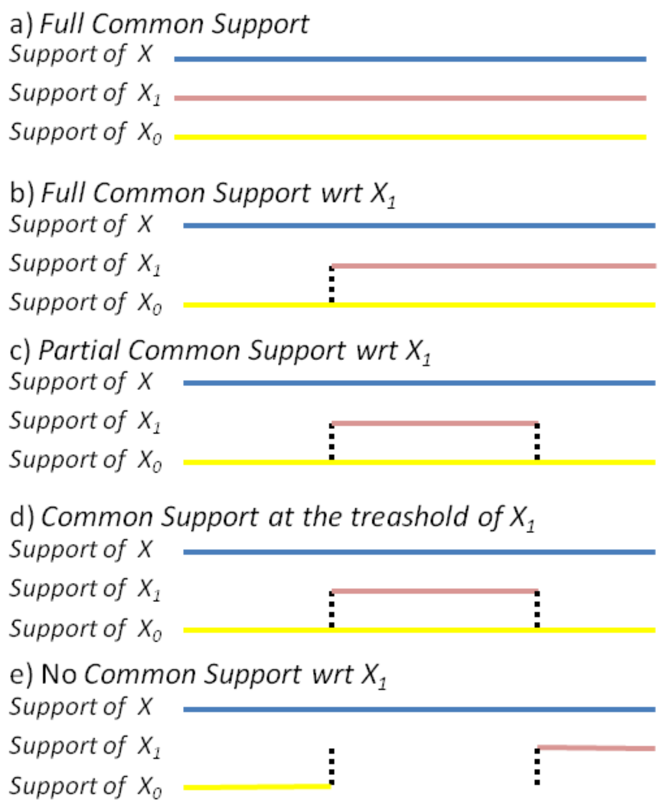

Figure 3.1: Some examples of the common support problem

premise. Using a metaphor, the unconfoundedness assumption shall constitute the *rock* on which we'll build our theoretical house. This assumption was originally proposed by Rosenbaum and Rubin (1983b) and it is a not directly testable assumption. Unconfoundedness states that –beyond the observed covariates X_i– there are no unobserved characteristics of the individuals associated both with the potential outcomes and with the assignment mechanism. In many applications, even if not explicitly declared, the unconfoundedness assumption is routinely used when performing multiple regression analyses. Assume that the treatment effect τ is constant across subjects: $\tau = Y_i(1) - Y_i(0)$ and consider the standard regression model $Y_i(0) = \alpha + \beta' X_i + \epsilon_i$, where $\epsilon_i = Y_i(0) - \mathbb{E}[Y_i(0)|X_i]$ is a residual capturing the unobservable variable actings on the response variable in the absence of the treatment. The observed outcome can be written as:

$$Y_i^{obs} = \alpha + \tau A_i + \beta' X_i + \epsilon_i$$

and, as we know, a common assumption of this model is given by the independence of the residuals ϵ_i from the regressors A_i conditional on the values of the covariates X_i.

Differing from the overlap assumption, the unconfoundedness assumption is a not directly testable assumption, as it involves the unknown values of the potential outcomes $Y(0)$ and $Y(1)$. Since the 1980s, indirect methodologies aimed to verify this hypothesis have been proposed (e.g. Rosenbaum (1987), Heckman and Hotz (1989)).

Think, for instance, you're a clinical psychologist and you want to test the effect of a new brief-cognitive psychotherapy (duration: 3 months) on the attentional symptoms of the Attention Deficit Hyperactivity Disorder (ADHD). A previous study asserted that this brief treatment is not effective on the behavioral symptoms of ADHD. Your objective is to test the effect of this brief therapy not on the behavioural symptoms but on the attentional deficit. For, you select a sample of 30 children for participating at a brief treatment (1-hour sessions, three times a week for three months) on the attentional deficit. The screening of attentional disorders requires a long sequence of examinations composed of neuropsychological and neurophysiological tests. The evaluation of the behavioral symptoms is based on a behavioral questionnaire compiled by the parents. In order to evaluate if the unconfoundedness assumption holds, you evaluate both at the start-up and at the follow-ups the attentional functions and the behavioural symptoms. In the case you find that a psychotherapy has a strong positive effect on both the behavioral and the attentional symptoms, you suspect that the unconfoundedness assumption does not hold in your sample and there exist unobserved covariates that may act as confounders. This is because the null effect of the psychotherapy on the behavioural symptoms is a sort of counterfactual that is known *ex-ante* in your study. If you don't replicate the null effect of the treatment, you cannot exclude that a selection bias is affecting you results.

This clinical example shows the typical *indirect* procedure of assessing the unconfoundedness assumption, i.e. by testing the null hypothesis that an effect is equal to zero when such an effect is *already known* to be equal to zero. If the null hypothesis is rejected, the assumption is suspected of not to hold. Note that, even if we were able to reject the null hypothesis and consequently to weaken the unconfoundedness assumption, we would have no indication on which variables have been playing the role of confounders (that is a theoretical problem, and obviously cannot be solved by means of a statistical procedure).

Consider further the following example, adapted from Heckman *et al.* (1997). Imagine you're a Human Resources specialist and you've been asked by your company to test the effect of a new training program for unemployed people aged 16-24. You announce your program by mail to all the 136 contacts that you received from the local job-placement office. However, only 47 people are actually interested in this proposal. In order to assess the unconfoundedness assumption, you select 50 non-applicants as a control group, but you choose also a sample of 50 ineligible unemployed people (for instance aged 24-29) as a second control group. After a year, you evaluate the effect of your training program by comparing the number of new employed people in both the applicant and non-applicant groups. Moreover, in order to assess the unconfoundedness assumption, you compare the employment status across the populations of non-applicants and ineligibles. By definition, the effect of the treatment on non-applicants should be equal to zero. Nevertheless, it might be the case that non-applicants have found a new job more easily than ineligibles, and this would prove that the two groups are strictly comparable. Consequently, you cannot impute the values of the counterfactual outcomes $Y_i(0)$ for applicants by means of a matching procedure using non-applicants as a control group, because you've verified that non-applicants are not exchangeable with ineligibles, and you've no reason to think that they're exchangeable with applicants. You can only impute the counterfactual values of applicants using those of non applicants only conditioning on age. Nonetheless, this does not guarantee that there are not other covariates that act as a confounder.

Imbens and Wooldridge (2009) comment:

> One can estimate a "pseudo" average treatment effect by analyzing the data from these two control groups as if one of them is the treatment group. In that case the effect of the

> treatment is known to be zero, and statistical evidence of a non-zero effect implies that at least one of the control group is invalid. Again, not rejecting the test does not imply the unconfoundedness assumption is valid (as both the control groups can suffer the same bias), but not rejection in the case where the two control groups could potentially have different biases makes it more plausible that the unconfoundedness assumption holds. The key of the power of this test is to have available control groups that are likely to have different biases, if they have any at all. [Imbens and Wooldridge (2009), p. 43]

Another possibility to indirectly assess the unconfoundedness hypothesis is given by considering geographically distinct comparison groups: for instance, groups from areas bordering different sides of the treatment group (Imbens and Wooldridge (2009)). Formally, an higher-level treatment variable G_i is introduced, such that $G_i \in \{-1, 0, 1\}$ and:

$$A_i = \begin{cases} 0 \text{ if } G_i = -1, 0 \\ 1 \text{ if } G_i = 1 \end{cases}$$

As we know, unconfoundedness only requires that:

$$(Y_i(0), Y_i(1)) \coprod A_i | X_i \tag{3.1}$$

and this is a not directly testable assumption. Consider now the higher-level (and stronger) conditional independence relation:

$$(Y_i(0), Y_i(1)) \coprod G_i | X_i \tag{3.2}$$

We have:

$$(Y_i(0), Y_i(1)) \coprod G_i | X_i \Longrightarrow (Y_i(0), Y_i(1)) \coprod A_i | X_i$$

Since $G_i \in \{-1, 0\}$ implies that $Y_i = Y_i(0)$, we also have:

$$Y_i(0) \coprod G_i | X_i, G_i \in \{-1, 0\} \Longleftrightarrow Y_i \coprod G_i | X_i, G_i \in \{-1, 0\} \tag{3.3}$$

and the right side of the implication is *testable*, as it does not involve potential outcomes. Hence, the conditional independence relation in 3.2 can be split into the two following relations:

$$(Y_i(0), Y_i(1)) \coprod A_i | X_i, G_i \in \{-1, 1\} \tag{3.4}$$

and:

$$(Y_i(0), Y_i(1)) \coprod A_i | X_i, G_i \in \{0, 1\} \tag{3.5}$$

Imbens and Wooldridge (2009) observe:

> If 3.4 holds, then we can estimate the average causal effect by invoking the unconfoundedness assumption using only the first control group. Similarly, if 3.5 holds, then we can estimate the average causal effect by invoking the unconfoundedness assumption using only the second control group. The point is that it is difficult to envision a situation where unconfoundedness based on the two comparison groups holds –that is, 3.1 holds– but it does not hold using only one of the two comparison groups at the time. In practice, it seems likely that if unconfoundedness holds, then so would the stronger condition 3.2, and we have the testable implication 3.3. [Imbens and Wooldridge (2009), p. 44]

Afterwards, an hypotheses testing procedure is implemented in order to verify whether:

$$\mathbb{E}[\mathbb{E}[Y_i|G_i = -1, X_i] - \mathbb{E}[Y_i|G_i = 0, X_i]] = 0$$

or, more generally:

$$\mathbb{E}[\mathbb{E}[Y_i|G_i = -1, X_i = x] - \mathbb{E}[Y_i|G_i = 0, X_i = x]] = 0$$

Last, an important method in order to assess the unconfoundedness assumption is given by considering the effect of a treatment on a *lagged outcome* that acts as a pre-treatment covariate variable. From one side, if the treatment effect on a lagged outcome is not zero, the distribution of $Y_i(0)$ for the treated units is not comparable to the distribution of $Y_i(0)$ for the controls. From the other side, if the treatment effect on a lagged outcome is zero, it is more plausible that the unconfoundedness assumption holds.

Let's analyze the following example (see Imbens and Wooldridge (2009), p. 46): imagine you're a labour economist and you aim to evaluate the effect of a labour market program (A) on annual earnings (Y). Among all the eligible applicants, only a group of them enroll to the program ($A = 1$) whereas the others do not enroll ($A = 0$). For all the subjects, you collect time-series data on pre-treatment earnings in the previous six years: $Y_{i,-1}, ..., Y_{i,-6}$. These lagged observed outcomes act as pre-treatment covariates and are not expected to influence participation to the program.

The overall set of covariates is now split in two subsets: a subset of lagged outcomes, denoted by X_i^p (that Imbens and Wooldridge (2009) defines as a pseudo-outcome) and the set of all the other covariates X_i^r. We now aim to evaluate the following conditional independence relation:

$$X_i^p \coprod A|X_i^r \tag{3.6}$$

Let $Y_{i,-1}$ be X_i^p and $Y_{i,-2}, ..., Y_{i,-5}$ be X_i^r. If it can be shown that the relation in 3.6 holds, it can be reasonably generalized to non lagged outcomes (i.e. ex-post outcomes). Under unconfoundedness, $Y_i(c)$ is independent of A_i given $Y_{i,-1}, Y_{i,-6}$ (and other covariates) that would suggest that it is plausible that $Y_{i,-1}$ is independent of A_i given $Y_{i,-2}, ..., Y_{i,-6}$ (and other covariates). In other words, if we're able to verify that the treated units and control units were exchangeable in the past, we may reasonably argue that such assumption also holds in the present (i.e., when treatment is allocated).

Note that, when we consider the hypothesis of unconfoundedness, we state:

$$(Y_i(0), Y_i(1)) \coprod A_i | X_i = x \qquad \text{for all } x$$

whereas, with this method, only a subset of the covariates is considered, and it might be the case that the hypothesis is valid for a subset of the covariates, but not for all the covariates, and this possibility is not directly testable.

In the previous chapter we stated that, if both unconfoundedness and common support hold, the situation is defined as *strong ignorability* (Rosenbaum and Rubin (1983b)). In this case, the average causal effect can be defined as:

$$\begin{aligned}\tau(x) &= \mathbb{E}[Y_i(1) - Y_i(0) | X_i = x] \\ &= \mathbb{E}[Y_i(1) | A_i = 1, X_i = x] - \mathbb{E}[Y_i(0) | A_i = 0, X_i = x] \\ &= \mathbb{E}[Y_i(1) | X_i = x] - \mathbb{E}[Y_i(0) | X_i = x]\end{aligned}$$

Under overlapping, both terms on the last line can be calculated and so the causal effect τ under different values of the covariate $X = x$ can be estimated. An important estimator is given by $\hat{\tau}_{ATE}$, which it was defined as:

$$\hat{\tau}_{ATE} = \mathbb{E}[Y(1) | A = 1, X = x] - \mathbb{E}[Y(0) | A = 0, X = x]$$

It can be shown that, under both the assumptions of unconfoundedness and overlapping and under some smoothness conditions on the conditional expectations of potential outcomes, this estimator is $\sqrt{N}$-consistent and asymptotically normally distributed. The lower bound for the variance of a $\sqrt{N}$-consistent estimator $\hat{\tau}_{ATE}(x)$ and such that:

$$\hat{\tau}_{ATE} \xrightarrow{d} \mathcal{N}(0, \mathbb{V})$$

has been derived by Hahn (1998):

$$\mathbb{V}_{\hat{\tau}_{ATE}} \geq \mathbb{E}\left[\frac{\sigma_1^2(X_i)}{e(X_1)} + \frac{\sigma_0^2(X_i)}{1 - e(X_i)} + (\tau(X_i) - \tau)^2\right]$$

where $e(X_i)$ is the propensity score, and:

$$\begin{aligned}\sigma_0^2(x) &= \mathbb{V}[Y_i(0) | X_i = x] \\ \sigma_1^2(x) &= \mathbb{V}[Y_i(1) | X_i = x]\end{aligned}$$

In general, there exist estimators that achieve this lower bound and that do not require functional form restrictions on either the conditional means or the propensity score.

In the next sections the main methods of estimation under unconfoundedness will be briefly described. These are: regression methods, methods based on the propensity score, matching methods.

3.2 Selection on Observables

3.2.1 Regression Methods

First of all, *regression* is a basic tool for estimating causal effects. We are interested in estimating τ_{ATE}, that is:

$$\tau_{ATE} = \mathbb{E}[Y(1)|A = 1] - \mathbb{E}[Y(0)|A = 0] \tag{3.7}$$

We consider N individuals and we assume that the effect of treatment is the same across all the subjects: $\rho = Y_i(1) - Y_i(0)$ for $i = 1, ..., N$. We can write the observed outcomes in terms of a regression model:

$$Y_i^{obs} = \alpha + \rho A_i + \eta_i$$

where $\alpha = \mathbb{E}[Y_i(0)]$, $\rho = Y_i(1) - Y_i(0)$ and η_i is the random part of $Y(0)$: $\eta_i = Y_i(0) - \mathbb{E}[Y_i(0)]$. If we consider the conditional expectation to the treatment status, we have:

$$\begin{aligned} \mathbb{E}[Y_i|A_i = 1] &= \alpha + \rho + \mathbb{E}[\eta_i|A_i = 1] \\ \mathbb{E}[Y_i|A_i = 0] &= \alpha + \mathbb{E}[\eta_i|A_i = 0] \end{aligned} \tag{3.8}$$

And, by substituting 3.8 in 3.7:

$$\mathbb{E}[Y_i|A_i = 1] - \mathbb{E}[Y_i|A_i = 0] = \rho + \mathbb{E}[\eta_i|A_i = 1] - \mathbb{E}[\eta_i|A_i = 0]$$

Remember that in the previous chapter, also τ_{CATE} has been defined, i.e. the average treatment effect conditional to the values of a covariate $X = x$:

$$\tau_{CATE} = \mathbb{E}[Y_i(1)|A_i = 1, X_i = x] - \mathbb{E}[Y_i(0)|A_i = 0, X_i = x]$$

We can now define the two regression functions for the potential outcomes:

$$\mu_0(x) = \mathbb{E}[Y_i(0)|X_i = x] \qquad \mu_1(x) = \mathbb{E}[Y_i(1)|X_i = x]$$

Under the unconfoundedness assumption, we have that:

$$\begin{aligned}\tau_{CATE} &= \mu_1(x) - \mu_0(x)\\ &= \mathbb{E}[Y_i(1)|X_i = x] - \mathbb{E}[Y_i(0)|X_i = x]\end{aligned}$$

as, by hypothesis, $Y_i(1) = Y_i(1)|A_i = 1$ and $(Y_i(0) = Y_i(0))|A_i = 0$. Our objective is to estimate τ_{CATE}. To this purpose, consider two subsamples of the treated units and of non-treated units in order to estimate μ_0 and μ_1. It can be shown that a consistent estimator for τ_{ATE} is given by:

$$\hat{\tau}_{reg} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i))$$

The problem is how to choose a *parametrical model* for $\mu_1(\cdot)$ and $\mu_0(\cdot)$ in order to estimate τ_{reg}. For, each conditional mean can be expressed by a function *linear in the parameters*:

$$\begin{aligned}\mu_0(x) &= \alpha_0 + \beta_0'(x - \psi_X)\\ \mu_1(x) &= \alpha_1 + \beta_1'(x - \psi_X)\end{aligned}$$

where ψ_X is the overall population covariate mean, that is rarely known, but that can be replaced by the sample average across units $\hat{\psi}_X$. In this case, the effect of the treatment is given by the difference between intercepts (as, by hypothesis, the effect of the treatment is considered to be constant across subjects, see Figure 3.2):

$$\hat{\tau}_{reg} = \hat{\alpha}_1 - \hat{\alpha}_0$$

These estimates can be obtained by means of a standard least squares regression. Furthermore, it can be shown that, under the linear model:

$$\hat{\tau}_{reg} = \bar{Y}_1 - \bar{Y}_0 - \Big(\frac{N_0}{N_0 + N_1}\cdot\hat{\beta}_1 + \frac{N_1}{N_0 + N_1}\cdot\hat{\beta}_0\Big)'(\bar{X}_1 - \bar{X}_0)$$

This equation shows that, the bigger is the difference in covariate means, the more the simple difference $\bar{Y}_1 - \bar{Y}_0$ is adjusted.

A serious problem that can raise with the regression methods in causal inference is that the estimates can be *biased*, if the linear approximation to the regression function is not globally accurate. Furthermore, if the averages of the covariates in the two treatment arms are very different, the correlation between the covariates and the treatment indicator is relatively high (multicollinearity problem). This problem can be evaluated, for instance, by considering the normalized differences $\bar{X}_1 - \bar{X}_0/\sqrt{S_0^2 + S_1^2}$.

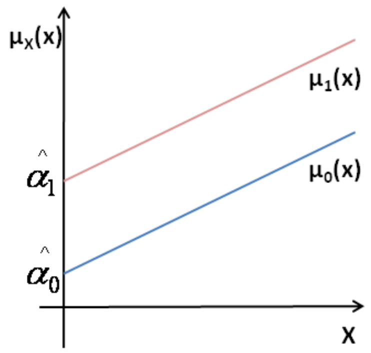

Figure 3.2: Example of a regression method in causal inference. The effect of the treatment is evaluated as an estimated difference in intercepts between the regression function for the treated ($\mu_1(x)$) and for the non treated units ($\mu_0(x)$).

We now mention some important asymptotic results for the estimates of τ_{ATE} and τ_{CATE}. By standard regression, we have:

$$\sqrt{N}(\hat{\tau}_{reg} - \tau_{CATE}) \xrightarrow{d} \mathcal{N}(0, \mathbb{V}_0 + \mathbb{V}_1)$$

where:

$$\mathbb{V}_a = N \cdot \mathbb{E}[(\hat{\alpha}_a - \alpha_a)^2] \qquad a = 0, 1$$

Also if we consider the estimator of τ_{ATE}, it can be shown that:

$$\sqrt{N}(\hat{\tau}_{reg} - \tau_{ATE}) \xrightarrow{d} \mathcal{N}(0, \mathbb{V}_0 + \mathbb{V}_1 + \mathbb{V}_\tau)$$

where

$$\mathbb{V}_\tau = (\beta_1 - \beta_0)' \mathbb{E}[(X_i - \mathbb{E}[X_i])(X_i - \mathbb{E}[X_i])'](\beta_1 - \beta_0)$$

which can be estimated as:

$$\hat{\mathbb{V}}_\tau = (\hat{\beta}_1 - \hat{\beta}_0)' \frac{1}{N} \sum_{i=1}^{N} (X_i - \bar{X})(X_i - \bar{X})'(\hat{\beta}_1 - \hat{\beta}_0)$$

As we know, for many applications simple parametric models can represent a naive assumption. Two main solutions to face this problem have been proposed: i) the use of local smoothing methods (e.g. Heckman *et al.* (1997); Heckman *et al.* (1998)); ii) the use of global smoothing methods (e.g. Hahn (1998), Imbens *et al.* (2003)).

The most important among local smoothing methods is given by *kernel regression*. Given a kernel $K(\cdot)$, i.e. a non-negative real-valued integrable function satisfying the following two requirements:

(i) $\int_{-\infty}^{+\infty} K(u)du = 1$

(ii) $K(-u) = K(u)$

and given a bandwidth h, the kernel estimator for $\mu_a(x)$ is:

$$\hat{\mu}_a(x) = \sum_{i:A_i=a} Y_i \cdot \lambda_i \tag{3.9}$$

with weights:

$$\lambda_i = K\left(\frac{x - X_i}{h}\right) \Big/ \sum_{i:A_i=a} K\left(\frac{x - X_i}{h}\right)$$

Indeed, a kernel regression is a well-known non-parametric technique in order to estimating the conditional expectation of a random variable $\mathbb{E}[Y(1)|X = x]$ or $\mathbb{E}[Y(0)|X = x]$ when a non-linear relation between X and Y is supposed to hold. The objective of kernel regression is to find a regression function $\hat{\mu}_a(x)$, such that it can be considered as a best-fit match to the data points. This approach is nonparametric since no underlying distributional assumption is put forth in estimating the regression functions. In this technique, a set of identical *symmetric* functions known as *kernel* is assigned to each observed datum (X_i, Y_i). A weight λ_i proportional to the distance from the data point (X_i, Y_i) can be assigned to each value of $x \in \mathfrak{R}$. Different kernel functions –each of which can vary with respect to the width (scale) parameter– have been proposed in the literature, for instance:

- Uniform kernel

$$K(u) = \frac{1}{2} \cdot \mathbb{1}_{\{|u| \le 1\}}$$

- Triangular kernel

$$K(u) = (1 - |u|) \cdot \mathbb{1}_{\{|u| \le 1\}}$$

- Epanechnikov's kernel

$$K(u) = \frac{3}{4}(1 - u^2) \cdot \mathbb{1}_{\{|u| \le 1\}}$$

- Quadratic kernel

$$K(u) = \frac{15}{16}(1 - u^2) \cdot \mathbb{1}_{\{|u| \leq 1\}}$$

- Tricube kernel

$$K(u) = \frac{35}{32}(1 - u^2)^3 \cdot \mathbb{1}_{\{|u| \leq 1\}}$$

- Gaussian kernel

$$K(u) = \frac{1}{\sqrt{2\pi h}} e^{-1/2u^2}$$

- Cosine kernel

$$K(u) = \frac{\pi}{4} cos\left(\frac{\pi}{2}u\right) \mathbb{1}_{\{|u| \leq 1\}}$$

Note the use of the different variable names: X_i is referred to your original data ($i = 1, ..., N$); x is a real-valued variable and u represents the standardized x variable (with mean X_i and standard deviation h). By means of a kernel function, you can extend the value of the original data X_i to the potentially infinite values of x at a certain step dx from X_i. Consequently, you can estimate your nonlinear regression function by considering the kernel regression formula (also called Nadaraya-Watson kernel weighted average), that, as we've seen, is given by Equation 3.9. To this purpose, the conditional expectation can be written as:

$$\mathbb{E}[Y|X] = \mu_a(x)$$

where $\mu_a(x)$ is an unknown function and can be estimated by using a kernel as a weighting function (Nadaraya-Watson estimator):

$$\hat{\mu}_a(x) = \frac{\sum_{i=1}^{N} K[(x - X_i)/h]Y_i}{\sum_{i=1}^{N} K[(x - X_i)/h]}$$

where $K(\cdot)$ is a kernel with bandwidth h. The derivation of this estimator can be obtained by considering:

$$\mathbb{E}[Y|X] = \int yf(y|x)dx = \int y\frac{f(x;y)}{f(x)}dy$$

and the following kernel density estimations for the joint distribution $f(x;y)$ and $f(x)$:

$$\hat{f}(x;y) = \sum_{i=1}^{N} K\left(\frac{x - X_i}{h}\right) K\left(\frac{y - Y_i}{h}\right) \Big/ n \cdot h^2$$

$$\hat{f}(x) = \sum_{i=1}^{N} K\left(\frac{x - X_i}{h}\right) \Big/ n \cdot h$$

As noted by Imbens and Wooldridge (2009), although the rate of convergence of the kernel estimator to the regression function is slower than the conventional parametric rate $N^{-1/2}$, the rate of convergence of the implied estimator for the average treatment effect $\hat{\tau}_{reg}$ is the regular parametric rate under regularity conditions. These conditions include smoothness of the regression functions and require the use of higher order kernels (the order of kernel depends on the dimension of the covariates).

Heckman *et al.* (1997) and Heckman *et al.* (1998) used an alternative method, that is based on locally fitting a polynomial regression function. Instead of Equation 3.9, these authors considered local least square estimates, based on locally fitting a linear regression function:

$$(\hat{\alpha}(x), \hat{\beta}(x)) = \underset{\alpha,\beta}{argmin} \sum_{i=1}^{N} \lambda_i \cdot (Y_i - \alpha - \beta'(x - X_i))^2$$

where λ_i are the same weights as in the standard kernel regression estimator. Consequently, the regression function at x is estimated as $\hat{\mu}(x) = \hat{\alpha}(x)$.

A common problem for both the standard kernel estimation and the local linear estimation is given by the choice of an optimal bandwidth h. In the nonparametric regression literature, there exist optimization algorithms aimed to minimize a global criterion such as the expected value of the squared difference between the estimated and the regression model, with the expectation taken with respect to the marginal distribution of the covariate. These criteria cannot be directly used in the nonparametric estimation of causal effects, but the debate on this issue is still open.

As it was mentioned, some authors have put forward the use of *global smoothing* methods instead of local smoothing methods. Following this approach, the regression function $\mu_a(x)$ is approximated by a K-th order polynomial:

$$\hat{\mu}_{a,k}(x) = \sum_{k=0}^{K} \beta_{a,k} \cdot x^k \tag{3.10}$$

The coefficients $\beta_{a,k}$ are estimated by least square regression and then the average treatment effect is estimated by:

$$\hat{\tau}_{reg} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i))$$

For a discussion on the choice of the number of terms in the series 3.10 see Imbens *et al.* (2003).

Before concluding this discussion, it is very useful to mention a general remark by Imbens and Wooldridge (2009):

> Generally, methods based on global approximations suffer from the same drawbacks of linear regression. If the covariate distributions are substantially different in both treatment groups, estimates based on such methods rely, perhaps more than desired, on extrapolation. Using these methods in cases with substantial differences in covariate distributions is therefore not recommended (except possibly in cases where the sample has been trimmed so that the covariates across the two treatment regimes have sufficient considerable overlap). [Imbens and Wooldridge (2009), p.27]

3.2.2 Methods based on the Propensity Score

Rosenbaum and Rubin (1983b) demonstrated this important implication:

$$(Y_i(0), Y_i(1)) \coprod A_i|X_i \Rightarrow (Y_i(0), Y_i(1)) \coprod A_i|e(X_i) \quad \forall i \tag{3.11}$$

where $e(X_i) = Pr(A_i = 1|X_i)$ is the *propensity score*, i.e. the probability of receiving the treatment given the covariates. By definition, a *balancing score* $b(x)$ is a function of the covariates such that: $X_i \coprod A_i|b(x)$. It can be shown that the propensity score is a balancing score (see Rosenbaum and Rubin (1983b)). The proof can informally be summed up in the following way:

$$Pr[A_i = 1|X_i, e(X_i)] = Pr[A_i = 1|X_i] = e(X_i)$$

and

$$Pr[A_i = 1|e(X_i)] = \mathbb{E}[A_i|e(X_i)] =$$
$$= \mathbb{E}[\mathbb{E}[A_i|X_i, e(X_i)]|e(X_i)] = \mathbb{E}[e(X_i)|e(X_i)] = e(X_i)$$

It follows:

$$e(X_i) = Pr[A_i = 1|X_i, e(X_i)] = Pr[A_i = 1|e(X_i)]$$

implying that A_i is independent of X_i given the propensity score. The result of Rosenbaum and Rubin (1983b) expressed by the Equation 3.11, shows that it is not necessary to simultaneously conditioning on all the covariates, but all the bias due to *observable* covariates can be removed by conditioning solely on the propensity score. The proof consists in showing that:

$$Pr[A_i = 1|Y_i(0), Y_i(1), e(X_i)] = Pr[A_i = 1|e(X_i)] = e(X_i)$$

implying independence of $(Y_i(0), Y_i(1))$ and A_i conditional on $e(X_i)$.

$$\begin{aligned}
&Pr[A_i = 1|Y_i(0), Y_i(1), e(X_i)] = \mathbb{E}[A_i|Y_i(0), Y_i(1), e(X_i)] = \\
&= \mathbb{E}[\mathbb{E}[A_i|Y_i(0), Y_i(1), e(X_i), X_i]|Y_i(0), Y_i(1), e(X_i)] = \\
&= \mathbb{E}[\mathbb{E}[A_i|Y_i(0), Y_i(1), X_i]|Y_i(0), Y_i(1), e(X_i)] = \\
&= \mathbb{E}[\mathbb{E}[A_i|X_i]|Y_i(0), Y_i(1), e(X_i)] = \\
&= \mathbb{E}[e(X_i)|Y_i(0), Y_i(1), e(X_i)] = e(X_i)
\end{aligned}$$

Moreover,

$$\begin{aligned}
&Pr[A_i = 1|e(X_i)] = \mathbb{E}[A_i|X_i] = \\
&= \mathbb{E}[\mathbb{E}[A_i|X_i]|e(X_i)] = \mathbb{E}[e(X_i)|e(X_i)] = e(X_i)
\end{aligned}$$

It follows:

$$Pr[A_i = 1|Y_i(0), Y_i(1), e(X_i)] = Pr[A_i = 1|e(X_i)] = e(X_i)$$

i.e. $(Y_i(0), Y_i(1)) \amalg A_i|e(X_i)$. Under unconfoundedness, confounding is kept under control by regulating differences in the covariates, and consequently, according to the relation 3.11, by considering groups homogeneous with respect to the propensity score; covariates are independent of the treatment and treated units can be compared with control units. Among methods based on the propensity score, it is useful to list three main approaches.

First, the propensity score can be used in place of the covariates in the regression analysis, defining:

$$\nu_a(e) = \mathbb{E}[Y_i|A_i, e(X_i) = e]$$

By means of 3.11 and unconfoundedness, it follows:

$$\nu_a(e) = \mathbb{E}[Y_i(a)|e(X_i) = e]$$

and $\nu_a(e)$ can be estimated by means of the kernel methods that were mentioned in the previous section applied to the values of the propensity score instead of the values of the covariates.

Second, a methodology known as *blocking*, *stratification* or *subclassifications* has been proposed. The sample space is partitioned into strata, according to the values of the propensity score. Data are separately analyzed within each stratum, that is homogeneous with respect to the covariates used to construct the propensity score. Hence, for each stratum, data are analyzed as if they were collected in a completely randomized experiment and the key-hypotheses (unconfoundedness and overlapping) to draw causal inference are assumed to hold.

A third method based on the propensity score is known as *weighting*. As we've seen, $\tau_{ATE} = \mathbb{E}[Y(1)|Y=1] - \mathbb{E}[Y(0)|Y=0]$; consider now the two terms separately: it can be shown that weighting the treated population by the inverse of the propensity score recovers the expectation of the unconditional response under treatment. Since A_i is a treatment indicator, we have: $A_i \cdot Y_i = A_i \cdot Y_i(1)$ for the treated and $(1-A_i)\cdot Y_i = (1-A_i)\cdot Y_i(0)$, and consequently:

$$\begin{aligned}\mathbb{E}\left[\frac{A_i \cdot Y_i}{e(X_i)}\right] = \mathbb{E}\left[\frac{A_i \cdot Y_i(1)}{e(X_i)}\right] = \mathbb{E}\left[\mathbb{E}\left[\frac{A_i \cdot Y_i(1)}{e(X_i)}\right]\Big|X_i\right] = \\ = \mathbb{E}\left[\frac{\mathbb{E}[A_i|X_i]\cdot\mathbb{E}[Y_i(1)|X_i]}{e(X_i)}\right] = \\ = \mathbb{E}[\mathbb{E}[Y_i(1)|X_i]] = \mathbb{E}[Y_i(1)]\end{aligned}$$

$$\begin{aligned}\mathbb{E}\left[\frac{(1-A_i)\cdot Y_i}{(1-e(X_i))}\right] = \mathbb{E}\left[\frac{(1-A_i)\cdot Y_i(0)}{(1-e(X_i))}\right] = \mathbb{E}\left[\mathbb{E}\left[\frac{(1-A_i)\cdot Y_i(0)}{(1-e(X_i))}\right]\Big|X_i\right] = \\ = \mathbb{E}\left[\frac{\mathbb{E}[(1-A_i)|X_i]\cdot\mathbb{E}[Y_i(0)|X_i]}{(1-e(X_i))}\right] = \\ = \mathbb{E}[\mathbb{E}[Y_i(0)|X_i]] = \mathbb{E}[Y_i(0)]\end{aligned}$$

Hence, we have:

$$\tau_{ATE} = \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)] = \mathbb{E}\left[\frac{A_i \cdot Y_i}{e(X_i)} - \frac{(1-A_i)\cdot Y_i}{(1-e(X_i))}\right]$$

And the following *weighting estimator* for τ_{ATE} has been proposed:

$$\hat{\tau}_{weight} = \frac{1}{N}\cdot\sum_{i=1}^{N}\left[\frac{A_i \cdot Y_i}{e(X_i)} - \frac{(1-A_i)\cdot Y_i}{1-e(X_i)}\right]$$

This is a sample average from a random sample and it can be shown that it is consistent for τ_{ATE} and $\sqrt{N}$-asymptotically normally distributed. The problem in calculating this estimator is that it depends on the propensity score function, which is rarely known. However, a fundamental disadvantage of this estimator is that it does not achieve the efficiency bound. In order to calculate the weighting estimator, the propensity score function $e(\cdot)$ can be replaced with a *logistic sieve estimator*, to obtain the so-called *inverse probability weighting* estimator:

$$\hat{\tau}_{ipw} = \sum_{i=1}^{N} \frac{A_i \cdot Y_i}{\hat{e}(X_i)} \Big/ \sum_{i=1}^{N} \frac{A_i}{\hat{e}(X_i)} - \sum_{i=1}^{N} \frac{(1 - A_i) \cdot Y_i}{\hat{e}(X_i)} \Big/ \sum_{i=1}^{N} \frac{A_i}{\hat{e}(X_i)}$$

Imbens and Wooldridge (2009) remarkably comment:

> A particular concern with IPW estimators arises again when the two covariate distributions are substantially different for the two treatment groups. That implies that the propensity score gets close to zero or one for some values of the covariates. Small or large values of the propensity score raises a number of issues. One concern is that alternative parametric models for the binary data, such as probit and logit models that can provide similar approximations in terms of estimated probabilities over the middle ranges of their arguments, tend to be more different when the probability are close to zero or one. Thus the choice of model and specification becomes more important, and it is often difficult to make well motivated choices in treatment effect settings. A second concern is that for units with propensity score close to zero or one, the weights can be large, making those units particularly influential in the estimates of the average treatment effects, and thus making the estimator imprecise. These concerns are less serious than those regarding regression estimators because at least the IPW estimates will accurately reflect uncertainty. Still, the concerns make the simple ipw estimators less attractive (As for regression cases, the problem can be less severe for the ATT parameters because propensity score values close to zero play no role). Problems for estimating ATT arise when some units, as described by their observed covariates, are almost certain to receive treatment). [Imbens and Wooldridge (2009), p.31]

Another important method that can be either based or not based on the propensity score is *matching*. By means of this methodology the values of the missing outcomes are imputed using only the outcomes of a few nearest neighbours of the opposite treatment group. In a certain sense, matching might be compared with non-parametric kernel regression, with the number of neighbours considered in order to match, playing the role of the bandwidth in the kernel regression. Hence, the asymptotic distribution for matching estimators is derived conditional on the implicit bandwidth, i.e. the number of neighbours, often fixed at a small number. Note that the implicit estimate $\hat{\mu}_a(x)$ is unbiased, but not consistent, in contrast to the kernel estimators. With regard to the advantages of this methodology, Imbens and Wooldridge (2009) observe:

> Matching estimators have the attractive feature that smoothing parameters are easily interpretable. Given the matching metric, the researcher only has to choose the number of matches. Using only a single match leads to the most credible inference with the least bias, at the cost of sacrificing such precision. This sits well with the focus in the literature to reducing bias rather than variance. It also can make the matching estimator easier to use than those estimators that require more complex choices of smoothing parameters, and this may be another explanation for its popularity. Matching estimators have been widely studied in practice and theory (e.g. Gu and Rosenbaum (1993), Rosenbaum (1989), Rosenbaum (1995), Rosenbaum (2002), Rubin (1973b), Rubin (1979), Rubin and Thomas (1992a), Rubin and Thomas (1992b), Rubin and Thomas (1996), Rubin and Thomas (2000), Heckman *et al.* (1998), Dehejia and Wahba (1999), Abadie and Imbens (2008)). Most often they have been applied in settings where, (i) the interest is in the average treatment effect for the treated, and (ii) there is a large reservoir of potential controls, although recent work (Abadie and Imbens (2006)) shows that matching estimators can be modified to estimate the overall average effect. [Imbens and Wooldridge (2009), p. 32].

Matching methods require the choice of an algorithm in order to conveniently match the observations. As observed by Imbens and Wooldridge (2009), there are not –at the actual state of the art– fully efficient matching algorithms that take into account the effect of a particular choice of match on treated unit i on the pool of the potential matches for unit j. In practice, units are matched *sequentially* by current algorithms, i.e. they are ordered by the value of covariates or the propensity score with highest propensity score units matched first (see Gu and Rosenbaum (1993) and Rosenbaum (1995) for discussion). The most important algorithms used in the literature are the Nearest Neighbour Matching, the Caliper Matching, the Radius Matching and the Kernel Matching.

In the following, we briefly formalize these concepts with respect to the Nearest Neighbour Matching (see Abadie and Imbens (2006)). Let $\{(Y_i, X_i, A_i)\}_{i=1}^N$ be a sample, let $l_1(i)$ be the nearest neighbour to the unit i, i.e. $l_1(i)$ is equal to the nonnegative integer j, for $j \in \{1, ..., N\}$, if $A_i \neq A_j$, and:

$$\|X_j - X_i\| = \underset{k:A_k \neq A_i}{argmin} \|X_k - X_i\|$$

More generally, let $l_m(i)$ be the index that satisfies: $A_{l_m(i)} \neq A_i$ and that is the m-th unit closest to unit i:

$$\sum_{l:A_l \neq A_i} \mathbb{1}\{\|X_l - X_i\| \leq \left\|X_{l_m(i)} - X_i\right\|\} = m$$

where $\mathbb{1}(\cdot)$ is the indicator function, that is equal to one if the expression in brackets is true and zero otherwise. In other words, $l_m(i)$ is the index of the unit in the opposite treatment group that is the m-th closest to unit i in terms of distance measure based on the norm $\|\cdot\|$. Let now $\mathbb{J}_M(i) \subset \{1, ..., N\}$ denote the set of indexes for the first M matches for unit i: $\mathbb{J}_M(i) = \{l_1(i), ..., l_m(i)\}$. The basic idea underlying matching methods is to impute the missing potential outcomes for the the matches, by defining $\hat{Y}_i(0)$ and $\hat{Y}_i(1)$ as:

$$\hat{Y}_i(0) = \begin{cases} Y_i & \text{if } A_i = 0 \\ 1/M \sum_{j \in \mathbb{J}(i)} Y_j & \text{if } A_i = 1 \end{cases}$$

$$\hat{Y}_i(1) = \begin{cases} 1/M \sum_{j \in \mathbb{J}(i)} Y_j & \text{if } A_i = 0 \\ Y_i & \text{if } A_i = 1 \end{cases}$$

The matching estimator proposed by Abadie and Imbens (2006) is given by:

$$\hat{\tau}_{match} = \frac{1}{N} \sum_{i=1}^{N} (\hat{Y}_i(1) - \hat{Y}_i(0))$$

This estimator has been shown to have a bias of order $O(N^{-1/K})$, where K is the dimension of the covariates. Imbens and Wooldridge (2009) comment:

> There are three caveats to the Abadie-Imbens results. First, it is only the continuous covariates that should be counted in the dimension of the covariates. With discrete covariates, the matching will be exact in large samples, and as a result such covariates do not contribute to the order of the bias. Second, if one matches only the treated, and the number of potential controls is much larger than the number of treated units, one can justify ignoring the bias by appealing to an asymptotic sequence where the number of potential controls increases faster with the sample size than the number of treated units. Specifically, if the number of controls, N_0, and the number of treated, N_1, satisfy $N_1/N_0^{4/k} \to 0$, then the bias disappears in large samples after normalization by $\sqrt{N_1}$. Third, even though the order of the bias may be high, the actual bias may still be small if the coefficients in the leading term are small. This is possible, if the biases for different units are at least partially offsetting. For example, the leading term in the bias relies on the regression function being nonlinear, and the density of the covariates having a nonzero slope. If either, the regression function is well approximated by a linear function, or the density is approximately flat, the bias may be fairly limited. [Imbens and Wooldridge (2009), p. 33]

The variance of this estimator has been calculated using standard methods for differences in means or methods for paired randomized experiments. It has been shown that this estimator is not efficient and it does not reach the efficiency bound given a fixed number of matches (and the number would need to increase with the sample size in order to reach the bound). In the case $M \to \infty$, with $M/N \to 0$, then the matching estimator can be interpreted as a nonparametric regression estimator. Abadie and Imbens (2006) have shown that, under certain conditions, the Nearest Neighbour Matching estimator (with a fixed number of neighbours and matching with replacement), is $\sqrt{N}$ consistent and asymptotically normally distributed with zero asymptotic bias. Abadie and Imbens (2010) have also derived the asymptotic distribution of the matching estimator when matching is carried out without replacement. Furthermore, in the absence of exact or large sample approximation results to the distribution of matching estimators, bootstrap procedures have been used. However, Abadie and Imbens (2008) have recently shown that, in general, the bootstrap does not provide valid large sample inference for matching estimators.

An additional problem deals with the number of nearest neighbours that should be used. In general, it has been shown that, from one side matching just one nearest neighbour minimizes the bias but increases the bias; on the other side, using additional neighbours increases the bias, but decreases the variance. As suggested by Imbens and Wooldridge (2009), at the actual state of the art it is not clear that using an approximation based on a sequence with an increasing number of matches improves the accuracy of the approximation. Furthermore, the discussion on the optimal number of matches or regarding data-dependent methods to choose the matches, is far to be conclusive.

The debate is open also with respect to either matching with replacement or matching without replacement. From one side, matching with replacement keeps the bias low but increases the variance; from the other side, matching without replacement keeps the variance low at the cost of a potential bias.

Nearest Neighbour Matching is not the only matching method that has been proposed in the literature. With Nearest Neighbour Matching, unit i is matched with unit j in the opposite group such that:

$$\|X_i - X_j\| = \min_{k \in \{A=0\}} \|X_i - X_k\|$$

Nearest Neighbour Matching always finds a neighbour j for each unit i in the treated sample, even if the covariates values are not strictly "equal".

With Caliper Matching, we pre-specify a real value $\delta > 0$ (that is fixed by means of theoretical issues) so that treated unit i is matched with untreated unit j only if:

$$\delta > \|X_i - X_j\| = \min_{k \in \{A=0\}} \|X_i - X_k\|$$

If no untreated unit j is within δ from treated unit i, this is left unmatched.

Radius Matching does not involve a minimum problem with respect to a distance measure, but it only fixes a *radius* r, and then matches to unit i all the control units with X_j falling within a radius r from X_j:

$$\|X_i - X_j\| < r$$

Last, also a method based on a Kernel function has been proposed. Given a kernel $K(\cdot)$, a bandwidth h, and given a treated unit i, the counterfactual outcome $Y_i(0)$ is imputed by considering a kernel-weighted average of the outcomes of all the non-treated units, where the weight attributed to non-treated unit j is in proportion to the closeness between i and j:

$$\hat{Y}_i = \frac{\sum_{j \in \{A=0\}} K\left(\frac{X_i - X_j}{h}\right) \cdot Y_j}{\sum_{j \in \{A=0\}} K\left(\frac{X_i - X_j}{h}\right)}$$

Let's now briefly consider the problem of which distance metrics to choose with respect to the covariates. Until today, three main approaches have been proposed:
(i) the use of an Euclidean metric:

$$\|X_i - X_j\| = (X_i - X_j)'(X_i - X_j)$$

(ii) the use of the Mahalanobis metric, which is based on the inverse of the full covariate matrix Σ_X:

$$\|X_i - X_j\| = (X_i - X_j)'\Sigma_X^{-1}(X_i - X_j)$$

(iii) the use of the diagonal matrix $diag\Sigma_X$, with each diagonal element equal to the inverse of the corresponding covariate variance:

$$\|X_i - X_j\| = (X_i - X_j)' diag\Sigma_X^{-1}(X_i - X_j)$$

Other proposals (not used in the econometric or statistical literature) have been reviewed in Zhao (2004).

Note that, in the presence of many covariates of different types, it is not easy to find an "optimal" metric. For, it has been suggested to use matching methods with respect to the propensity score. The objective is to match each treated unit with a control unit characterized by a similar propensity score's value. The advantage of this procedure is that the dimensionality of matching is reduced from k (the number of the covariates), to 1. Similarly to other propensity-score based methods, the main problem of this approach is that the propensity score is rarely known and has to be estimated. Asymptotic theory shows that matching on the "true" propensity score value leads to a $\sqrt{N}$-consistent asymptotically normally distributed estimator for τ_{ATE} (see Abadie and Imbens (2009)).

3.2.3 Combining the Regression and the Propensity Score Methods

In the previous section, we've seen that two main methods in causal inference are given by *regression methods* and by methods based on the *propensity score*.

The first, is based on the estimation of the regression functions:

$$\mu_a(x) = \mathbb{E}[Y_i(a)|X_i = x] \quad \text{for } a = 0, 1$$

and then averaging the difference:

$$\hat{\tau}_{reg} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\mu}_1(X_i) - \hat{\mu}_0(X_i))$$

The second class of methods are based on the estimation of the propensity score, $e(x) = pr(A_i = 1|X_i = x)$ and using this estimated propensity score for weighting the outcomes (inverse probability weighting estimator):

$$\hat{\tau}_{ipw} = \sum_{i=1}^{N}\frac{A_i \cdot Y_i}{\hat{e}(X_i)} \Big/ \sum_{i=1}^{N}\frac{A_i}{\hat{e}(X_i)} - \sum_{i=1}^{N}\frac{(1 - A_i)\cdot Y_i}{1 - \hat{e}(X_i)} \Big/ \sum_{i=1}^{N}\frac{A_i}{1 - \hat{e}(X_i)}$$

Asymptotic efficient estimators have been searched by contemporary authors. Two main suggestions have been proposed to this purpose: (i) if large samples –with respect to the dimension of X_i– are available, then nonparametric estimators of the conditional means or propensity score are asymptotically efficient; (ii) if such large samples are not available, it is necessary to invoke flexible parametric hypotheses.

In this second case, estimates are sensible to misspecification of the parametric model. For this, strategies that combine regression and propensity score methods in order to achieve some robustness have been discussed. Imbens and Wooldridge (2009) put forth the following analogy. Think at a linear regression model and at the problem of omitted variables; consider the following full regression model:

$$Y_i^f = \alpha + \beta A_i + \gamma X_i + \epsilon_i$$

where A_i indicates a dichotomous treatment and X_i a full set of covariates. Imagine now to omit this set of covariates from your model and to run a short regression on the constant and on the treatment indicator:

$$Y_i^s = \alpha' + \beta' A_i + \epsilon_i'$$

then the omitted variable can be considered as a function of A_i in a conditional or auxiliary regression:

$$X_i = \alpha'' + \beta'' A_i + \epsilon_i''$$

it follows:

$$\begin{aligned} Y_i^f &= \alpha + \beta A_i + \gamma[\alpha'' + \beta'' A_i + \epsilon_i''] + \epsilon_i \\ Y_i^f &= [\alpha + \alpha''\gamma] + [\beta + \beta'']A_i + [\epsilon_i + \gamma\epsilon_i''] \\ Y_i^f &= \delta_0 + \delta_1 A_i + u_i \end{aligned}$$

it can be shown that the estimated parameter in the short model $\hat{\beta}'$ is biased:

$$\mathbb{E}[\hat{\beta}'] = \beta' + \beta'' \left[\frac{\sum a_i x_i}{\sum a_i^2} \right]$$

and the bias picks up the part of the influence of A_i that is correlated with X_i. Weighting can be interpreted as removing the correlation between A_i and X_i and regression as removing the direct effect of X_i. Weighting therefore removes the bias from omitting X_i from the regression. As a result, combining regression and weighting can lead to *additional robustness* by both removing the correlation between the omitted covariates, and by reducing the correlation between the omitted and included variables. This is the general idea underlying the *doubly robust estimators* developed in Robins and Rotnitzky (1995), Robins *et al.* (1995), van der Laan and Robins (2003).

Let's now formalize these concepts. Consider the following two regression functions:

$$\mu_a(x) = \alpha_a + \beta_a'(x - \bar{X}) \quad \text{for } a = 0, 1$$

Note that we substituted the covariate population mean ψ_X with the sample average $\bar{X}$. More generally, either a more flexible linear approximation or a nonlinear model could be used instead of the linear model. Suppose now we model the propensity score as a known probability density function:

$$e(x) = p(x; \gamma)$$

for instance, a logit model:

$$p(x, \gamma) = \frac{exp(\gamma_0 + x'\gamma_1)}{1 + exp(\gamma_0 + x'\gamma_1)}$$

First, γ is estimated by maximum likelihood, and consequently the propensity scores can be estimated as:

$$\hat{e}(X_i) = p(x; \hat{\gamma})$$

Second, least squares are used in the two regression models in order to estimate the parameters, and the objective functions are weighted by the inverse of the probability of treatment / not treatment. Formally, to estimate (α_0, β_0) and (α_1, β_1), we would solve the following least squares problem:

$$\min_{\alpha_0, \beta_0} \sum_{i: A_i = 0} \frac{(Y_i - \alpha_0 - \beta_0'(X_i - \bar{X}))^2}{p(X_i, \hat{\gamma})}$$

$$\min_{\alpha_1, \beta_1} \sum_{i: A_i = 1} \frac{(Y_i - \alpha_1 - \beta_1'(X_i - \bar{X}))^2}{1 - p(X_i, \hat{\gamma})}$$

Once the conditional mean functions are determined, τ_{ATE} is calculated by considering:

$$\hat{\tau} = \hat{\alpha}_1 - \hat{\alpha}_0$$

The motivation of weighting by the inverse of the propensity score is given by the double robustness result (see Robins and Rotnitzky (1995); Scharfstein *et al.* (1999)). We add now two additional remarks. First, consider the consistency of the least squares estimates: Is it affected by weighting? Wooldridge (2007) shows that, if the conditional expectation is indeed linear:

$$\mathbb{E}[Y_i(a) | X_i = x] = \alpha_a + \beta_a'(x - \bar{X})$$

then, weighting the objective function by any nonnegative function of X_i does not affect *consistency*. Moreover, even if the model for the propensity score are misspecified for the true propensity score but the conditional means $\mathbb{E}[Y(a)|X = x]$ are correctly specified, then least squares lead to a consistent estimator of τ_{ATE}. With regard to efficiency, Wooldridge (2007) shows that, assuming homoskedasticity of $Y_i(a)$ so that $\sigma_a^2 = \sigma_a^2(x)$, the inverse probability weighting estimator of α_a, β_a is less efficient than the unweighted estimator. The optimal weights would be given by the inverse of the variances.

Consider now the case in which the logit model (or any alternative binary response model) is correctly specified for the propensity score, but the conditional mean functions are misspecified. By double robustness it can be shown that:

$$\hat{\alpha}_a \to \mathbb{E}[Y_i(a)]$$

$$\hat{\tau}_{REG} = \hat{\alpha}_1 - \hat{\alpha}_0 \to \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)] = \tau_{ATE}$$

So, also in this case, the estimator is *consistent*. Actually, the linearity assumption $\mathbb{E}[Y_i(a)|X_i = x]$ is a poor assumption for certain kinds of responses (e.g. binary responses, fractional responses, and count responses). Hence, we need to correctly specify the functional form for the propensity score so that, even when the mean functions are misspecified, $\mathbb{E}[Y_i(a)] = \mathbb{E}[\mu(x_i, \delta_a^*)]$, where δ_a^* is the probability limit of $\hat{\delta}_a$, that is a functional form for the propensity score (see Wooldridge (2007)). In summary, it can be said that combining weighting and regression is more attractive than either regression or weighting on their own, but it still requires at least one of the specifications to be accurate to have consistent estimates.

Another possibility is given by combining subclassification with regression. The outcome is regressed on a constant, an indicator for the treatment, and the covariates within each stratum j:

$$Y_i = \alpha_j + \tau_j A_i + \beta_j' X_i + \epsilon_i$$

And, by least squares, we can obtain the estimates of τ_j for each stratum and the estimates of the variances $\mathbb{V}_j$. Moreover, the estimated stratum-specific average treatment effects are then averaged and weighted by the relative stratum size:

$$\hat{\tau} = \sum_{j=1}^{J} \left(\frac{N_{j0} + N_{j1}}{N} \right) \cdot \hat{\tau}_j$$

$$\hat{\mathbb{V}} = \sum_{j=1}^{J} \left(\frac{N_{j0} + N_{j1}}{N} \right) \cdot \hat{\mathbb{V}}_j$$

The important advantage of this method compared to the use of regression alone or subclassification alone is that, by definition, within each stratum the propensity scores should be relatively similar. As a consequence, this leads to more flexible and more robust estimators.

Last, it has also been proposed to combine matching and regression. As we've seen, matching techniques entail the choice of an algorithm in order to match the treated units with the controls. Once we've N pairs $(\hat{Y}_i(0), \hat{Y}_i(1))$, we can calculate the following estimator:

$$\hat{\tau}_{match} = \frac{1}{N}\sum_{i=1}^{N}(\hat{Y}_i(1) - \hat{Y}_i(0))$$

which averages the difference. A serious concern with this estimator is that it can be biased, and it has been suggested that regression methods can be a useful tool in order to reduce the bias. Missing potential outcomes are imputed in the following way:

$$\hat{Y}_i(0) = \begin{cases} Y_i & \text{if } A_i = 0 \\ \dfrac{1}{M}\sum_{j \in \mathbb{J}(i)} (Y_j + \beta_0'(X_i - X_j)) & \text{if } A_i = 1 \end{cases}$$

$$\hat{Y}_i(1) = \begin{cases} \dfrac{1}{M}\sum_{j \in \mathbb{J}(i)} (Y_j + \beta_1'(X_i - X_j)) & \text{if } A_i = 0 \\ Y_i & \text{if } A_i = 1 \end{cases}$$

In this way, the average of the matched outcomes is adjusted by the difference in covariates relative to the matched observations. Quade (1982) and Rubin (1979) suggested two different ways in order to estimate the regression parameters (β_0, β_1).

Abadie and Imbens (2006) proposed a regression adjustment with respect to the covariates. Given the set of matching indexes $\mathbb{J}_M(i)$, these authors defined:

$$\hat{X}_i(0) = \begin{cases} X_i & \text{if } A_i = 0 \\ \dfrac{1}{M}\sum_{j \in \mathbb{J}(i)} X_j & \text{if } A_i = 1 \end{cases}$$

$$\hat{X}_i(1) = \begin{cases} \dfrac{1}{M}\sum_{j \in \mathbb{J}(i)} X_j & \text{if } A_i = 0 \\ X_i & \text{if } A_i = 1 \end{cases}$$

and the parameters are estimated as:

$$\begin{pmatrix} \hat{\alpha}_a \\ \hat{\beta}_a \end{pmatrix} = \left(\sum_{i=1}^{N}\begin{pmatrix} 1 & \hat{X}_i(a)' \\ \hat{X}_i(a) & \hat{X}_i(a)\hat{X}_i(a)' \end{pmatrix}\right)^{-1} \begin{pmatrix} \hat{Y}_i(a) \\ \hat{X}_i(a)\hat{Y}_i(a) \end{pmatrix}$$

3.3 Selection on Unobservables

At the beginning of this chapter, it was underlined that the unconfoundedness assumption can be considered as the "rock" on which building causal inference. Nevertheless, this assumption may be relaxed or may be not totally realistic in many applications. The reason for which it can be not realistic is that there can exist many factors or variables that cannot be observed, but that can confound the relation between the treatment indicator and the potential outcomes, so that the unconfoundedness assumption does not hold. This problem cannot be definitely solved, but many possibilities in order to keep it under control have been suggested.

A first approach (Rosenbaum and Rubin (1983b), Rosenbaum (1995)) is given by the *sensitivity analysis*. This considers mild violations of the unconfoundedness assumption and investigates changes in the results under these violations. In fact, the presence of these violations might be interpreted as an indirect proof of the presence of unobserved components correlated with both the potential outcomes and the treatment indicator.

A second method is given by the *bound analysis* (Manski (1990), Manski (1995), Manski (2003),), Manski (2005), Manski (2007)). As sensitivity analysis, this is an indirect method aimed to rule out the values of the parameters that are not realistic. Parameters and ranges for the parameters are estimated according to available data and the limited assumptions that are put forth.

Third, it has been proposed to introduce in the analyses the use of the so-called *instrumental variables* (Imbens and Angrist (1994), Angrist *et al.* (1996)), that have to be conceived as a sort of additional treatment variables, satisfying specific exogeneity and exclusion restrictions.

Fourth, when the assignment is a deterministic function of the covariates and thus overlapping is completely absent, it has been suggested to use a particular technique known as *regression discontinuity design* (Hahn *et al.* (2000), Shadish *et al.* (2002), Cook (2008)).

Fifth, if sampling data of treated and control units before and after the treatment are available, a technique known as *difference in differences* can be used (Ashenfelter and Card (1985), Abadie (2005), Athey and Imbens (2006), Donald and Lang (2007)).

3.3.1 Sensitivity Analysis

The basic principle underlying sensitivity analysis is not to drop the unconfoundedness assumption, but to relax it to some extent. If there are unobserved covariates that are correlated with both the potential outcomes and the treatment indicator, these can lead to violations of the unconfoundedness assumption. Note that this violation may be mild or deep, depending on the strength of the correlations. The question is: Which is the size of the *bias* in the results between a situation in which unconfoundedness is assumed to hold and a situation in which modest violations of the assumption are put forth?

The formal methods to answer the previous question were originally developed in Rosenbaum and Rubin (1983a) and, for instance, applied in Imbens (2003) in the analysis of labour market training programs. An alternative approach to sensitivity analysis was developed by Rosenbaum (1995).

In order to introduce these methodologies, consider the following example. Imagine you're a developmental psychologist and you're studying the effect of a new training program aimed to improve the text-writing abilities in a group of teenagers. The program consists of three-hours lessons twice a week, conducted by a professional writer and with voluntary enrollment. You consider the performance of the students on text writing (evaluated by three external judges) before and after the program. Previous investigations suggest you to further consider in your analyses the effect of the *motivation* of the students in participating at the program. This can be thought as a latent variable, that is supposed to be correlated with both the treatment indicator and the potential outcomes. A sensitivity analysis, as developed in Rosenbaum and Rubin (1983a), is performed in order to compare the robustness of the results when the unconfoundedness hypothesis is not supposed to hold.

Let's now formalize this approach following Imbens and Wooldridge (2009), who recall the original work of Rosenbaum and Rubin (1983a) on binary outcomes. Remember the previous example and define as A_i the treatment (1: enrolling in the text-writing program; 0: not enrolling in the text-writing program), as $Y_i(0), Y_i(1)$ the potential outcomes, with U_i the motivation of the participants to join the program, and with X_i the other covariates. If the unconfoundedness assumption is supposed to hold only by considering both the observed and the unobserved covariates, we have:

$$Y_i(0), Y_i(1) \coprod A_i | X_i, U_i$$

Imbens and Wooldridge (2009) remarkably define the theoretical underpinning of the sensitivity analysis in the following way:

> Consider both the distribution of the potential outcomes given observed and unobserved covariates and the conditional probability of assignment given observed and observed covariates. Rather than attempting to estimate both these conditional distributions, the idea behind the sensitivity analysis is to specify the form and the amount of dependence of these conditional distributions on the unobserved covariate, and estimate only the dependence on the observed covariate. Conditional on the specification of the first part of the

estimation of the latter is typically straightforward. The idea is then to vary the amount of dependence of the conditional distributions on the unobserved covariate and assess how much this changes the point estimate of the average treatment effect. [Imbens and Wooldridge (2009), p.51]

For instance, in Rosenbaum and Rubin (1983a) the marginal distribution of the unobserved covariate is fixed as a Binomial variable with parameter $p = pr(U_i = 1)$, and independence is supposed to hold between U_i and X_i. Consequently, a logistic distribution for the treatment is specified:

$$pr(A_i = 1|X_i = x, U_i = u) = \frac{exp(\alpha_0 + \alpha_1' x + \alpha_2 \cdot u)}{1 + exp(\alpha_0 + \alpha_1' x + \alpha_2 \cdot u)}$$

A logistic distribution for the two potential outcomes is also specified:

$$pr(Y_i(a) = 1|X_i = x, U_i = u) = \frac{exp(\beta_{a0} + \beta_{a1}' x + \beta_{a2}' \cdot u)}{1 + exp(\beta_{a0} + \beta_{a1}' x + \beta_{a2}' \cdot u)}$$

The conditional average treatment effect with respect to $X_i = x$ and $U_i = u$ is given by:

$$\begin{aligned}\mathbb{E}[Y_i(1) - Y_i(0)|X_i = x, U_i = u] = &\frac{exp(\beta_{10} + \beta_{11}' x + \beta_{12}' \cdot u)}{1 + exp(\beta_{10} + \beta_{11}' x + \beta_{12}' \cdot u)} - \\ &- \frac{exp(\beta_{00} + \beta_{01}' x + \beta_{02}' \cdot u)}{1 + exp(\beta_{00} + \beta_{01}' x + \beta_{02}' \cdot u)}\end{aligned}$$

τ_{CATE} is now expressed in terms of the parameters of this model and the distribution of the observable covariates, by averaging over X_i and integrating out the unobserved covariate U_1:

$$\begin{aligned}\tau &\equiv \tau(p, \alpha_0, \alpha_1, \alpha_2, \beta_{00}, \beta_{01}, \beta_{02}, \beta_{10}, \beta_{11}, \beta_{12}) \\ &= \frac{1}{N}\left\{\sum_{i=1}^{N} p\left(\frac{exp(\beta_{10} + \beta_{11}' X_i + \beta_{12})}{1 + exp(\beta_{10} + \beta_{11}' X_i + \beta_{12})} - \frac{exp(\beta_{00} + \beta_{01}' X_i + \beta_{02})}{1 + exp(\beta_{00} + \beta_{01}' X_i + \beta_{02})}\right) + \right. \\ &\left. + (1 - p)\left(\frac{exp(\beta_{10} + \beta_{11}' X_i)}{1 + exp(\beta_{10} + \beta_{11}' X_i)} - \frac{exp(\beta_{00} + \beta_{01}' X_i)}{1 + exp(\beta_{00} + \beta_{01}' X_i)}\right)\right\}\end{aligned}$$

Consider that all the parameters are not known and have to be estimated in order to estimate τ_{CATE}. Contrary to this, Rosenbaum and Rubin (1983a) proposed to divide the parameters in two sets:

$$\tau_{sens} = (p, \alpha_2, \beta_{02}, \beta_{12})$$

and:

$$\tau_{other} = (\alpha_0, \alpha_1, \beta_{00}, \beta_{01}, \beta_{10}, \beta_{11})$$

τ_{sens} includes the parameters that would be set to boundary values under unconfoundedness, $(\alpha_2, \beta_{02}, \beta_{12})$ and the parameter p capturing the marginal distribution of the unobserved covariate U_i. Hence, under unconfoundedness, estimation of τ_{other} can be obtained by fixing $\alpha_2 = \beta_{02} = \beta_{12} = 0$ and p at an arbitrary value. The values of τ_{sens} are fixed, and afterwards the remaining parameters are estimated through maximum likelihood:

$$\hat{\tau}_{other}(\tau_{sens}) = \underset{\tau_{other}}{argmax}\ l\ (\tau_{other}|\tau_{sens})$$

where $l(\cdot)$ is the logarithm of the likelihood function.

Second, the following function is considered:

$$\tau(\theta_{sens}) = \tau(\theta_{sens}, \hat{\theta}_{other}(\theta_{sens}))$$

and different values of this function –according to different values of θ_{sens}– are compared. In this way, a set of values for τ_{CATE} can be obtained. Normally, when choosing the values of τ_{sens}, p is fixed at 1/2, while the effect of the unobserved covariate is assumed to be equal in both treatment arms: $\beta_2 = \beta_{02} = \beta_{21}$, so that only α_2 and β_2 have to be fixed.

Let's now briefly consider the approach developed by Rosenbaum (1995). The unconfoundedness assumption can be stated by affirming that, for each couple of units i and j in the population, given $x_i = x_j$, both units have the same probability of assignment to the treatment: $e(x_i) = e(x_j)$. In the case unconfoundedness only holds conditional on both X_i and a binary observed covariate U_i, the probabilities of assignment may differ. The following odds ratio is considered:

$$\frac{e(x_i) \cdot (1 - e(x_j))}{(1 - e(x_i)) \cdot e(x_j)}$$

that is equal to 1 if unconfoundedness, unconditional to unobserved covariates, holds. Rosenbaum (1995) fixes different values of γ for the odds ratio and investigates the effect of this on the p-value of a test of no effect of the treatment based on the unconfoundedness assumption.

3.3.2 Bound Analysis

This approach has been developed by Manski, in a series of papers dating back the beginning of the nineties (Manski, 1990, 1995, 2003, 2005, 2007). This is a comprehensive approach, that can be applied not only in causal inference, but also in more general settings. Following Imbens and Wooldridge (2009), we're describing the simplest of these cases. Consider a setting with a binary outcome $Y_i \in \{0,1\}$ and there are no covariates. As we've seen, τ_{ATE} is given by:

$$\tau_{ATE} = \mathbb{E}[Y_i(1)|A_i = 1] - \mathbb{E}[Y_i(0)|A_i = 0]$$

If unconfoundedness unconditional of the covariates holds, we have:

$$(Y_i(1), Y_i(0)) \coprod A_i$$

so that:

$$\begin{aligned}
&\mathbb{E}[Y_i(1)|A_i = 1] = \mathbb{E}[Y_i(1)|A_i = 0] \\
&\mathbb{E}[Y_i(0)|A_i = 0] = \mathbb{E}[Y_i(0)|A_i = 0]
\end{aligned}$$

and:

$$\begin{aligned}
&\mathbb{E}[Y_i(1)] = \mathbb{E}[Y_i(1)|A_i = 1] \cdot pr(A_i = 1) + \mathbb{E}[Y_i(1)|A_i = 0] \cdot pr(A_i = 0) \\
&\mathbb{E}[Y_i(0)] = \mathbb{E}[Y_i(0)|A_i = 0] \cdot pr(A_i = 0) + \mathbb{E}[Y_i(0)|A_i = 1] \cdot pr(A_i = 1)
\end{aligned}$$

so that τ_{ATE} can be developed as:

$$\begin{aligned}
\tau_{ATE} &= \mathbb{E}[Y_i(1)] = \mathbb{E}[Y_i(1)|A_i = 1] \cdot pr(A_i = 1) + \\
&+ \mathbb{E}[Y_i(1)|A_i = 0] \cdot pr(A_i = 0) - [\mathbb{E}[Y_i(0)] \\
&= \mathbb{E}[Y_i(0)|A_i = 0] \cdot pr(A_i = 0) + \mathbb{E}[Y_i(0)|A_i = 1] \cdot pr(A_i = 1)]
\end{aligned}$$

Since data are not informative about the counterfactuals $\mathbb{E}[Y_i(1)|A_i = 0]$ and $\mathbb{E}[Y_i(0)|A_i = 1]$, we can only estimate six of the previous eight terms. Nevertheless, since the outcome is binary, we can deduce that these two conditional expectations must lie inside the interval $[0,1]$. In other words, we can write τ_{ATE} in terms of an interval, the bounds of which are estimable:

$$\tau_{ATE} \in [\tau_l, \tau_u]$$

and:

$$\begin{aligned}
\tau_l &= \mathbb{E}[Y_i(1)|A_i = 1] \cdot pr(A_i = 1) - pr(A_i = 1) - \mathbb{E}[Y_i(0)|A_i = 0] \cdot pr(A_i = 0) \\
\tau_u &= \mathbb{E}[Y_i(1)|A_i = 1] \cdot pr(A_i = 1) + pr(A_i = 0) - \mathbb{E}[Y_i(0)|A_i = 0] \cdot pr(A_i = 0)
\end{aligned}$$

The problem of the identification and estimation of these bounds has been recently faced by many authors (e.g. Horowitz and Manski (2000), Imbens and Manski (2004), Chernozhukov *et al.* (2007)).

3.3.3 Instrumental Variables

We now introduce in our reasoning a variable, that we define as an *instrumental variable* and that we indicate as Z_i. Treatment status for each subject is now conceived as depending from the value of the instrument: $A_i(0)$ denotes the value of the treatment if the instrument takes on value 0; $A_i(1)$ denotes the value of the treatment if the instrument takes on value 1. $Y_i(0)$ and $Y_i(1)$ indicate the values of the potential outcomes. We can use, for the observed treatment, the same notation we used for the observed outcome:

$$A_i = A_i(0) \cdot (1 - Z_i) + A_i(1) \cdot Z_i = \begin{cases} A_i(0) \text{ if } Z_i = 0 \\ A_i(1) \text{ if } Z_i = 1 \end{cases}$$

We now put forward a basic assumption on the independence of all the potential outcomes and treatments from the instrument:

$$(Y_i(0), Y_i(1), A_i(0), A_i(1)) \coprod Z_i$$

As suggested by Imbens and Wooldridge (2009), this assumption can be summed up in two different statements: i) the instrument is explicitly randomized; ii) there is not a direct effect of the instrument on the potential outcomes.

Let's further introduce the concept of *compliance type* of an individual. Imagine you're investigating the effect of a new drug on the cognitive symptoms of the Alzheimer's disease. You divide your sample according to the treatment status of the individuals: $A_i = 1$ indicates individuals taking the active treatment and $A_i = 0$ indicates individuals receiving placebo. You can expect that the results of your study will be affected by the real motivation of the participants in assuming the treatment during the entire period of the study. This information can be formally stated by introducing an instrumental variable indicating the *real* treatment values for each subject, for whom you define the couple of the two potential values $(A_i(0), A_i(1))$. Hence, individuals can now be classified according to the treatment status T_i, defined as a function of the variable A_i.

In particular, four types of responses for the potential treatment can be identified: i) *never-takers* are those who never take the treatment, either they are assigned to active treatment or to control treatment; ii) *compliers* are those who take active treatment if they are assigned to active treatment and they take control treatment if they are assigned to control treatment; iii) *defiers* are those who take active treatment if they are assigned to control treatment and take control treatment if they are assigned to active treatment; iv) *always takers* are those who always take the active treatment, either they are assigned to the active treatment or to the control group. The notation is the following:

$$T_i = \begin{cases} \text{never-taker} & \text{if } A_i(0) = A_i(1) = 0 \\ \text{complier} & \text{if } A_i(0) = 0, A_i(1) = 1 \\ \text{defier} & \text{if } A_i(0) = 1, A_i(1) = 0 \\ \text{always-taker} & \text{if } A_i(0) = A_i(1) = 1 \end{cases}$$

As we can see, in this context the variable A_i indicates the random assignment of the individuals to the treatment/control groups whereas T_i represents an endogenous indicator for the actual receipt of the treatment. Note that only the actual treatment status is observed, so we cannot infer from the data if an individual is a never-taker, a complier, a defier or an always-taker. To draw causal inference from studies where unobservable variables (as in this case of the regressor T_i) affect the real treatment status, an important assumption is commonly invoked: *monotonicity*. This requires that we exclude the presence of defiers in our population and can be formalized as:

$$A_i(1) \geq A_i(0) \quad \text{for all i}$$

Angrist *et al.* (1996) show that, under the assumption of independence of all four potential outcomes from the instrument Z_i and monotonicity, the average treatment effect can be identified for the subpopulation of compliers. First, the population proportions of never-takers, always-takers and compliers can be identified: $P_t = pr(T_i = t)$ for $t \in \{n, a, c\}$. For the subpopulation with $Z_i = 0$, given the monotonicity assumption, we observe $W_i = 1$ only for always takers. Hence:

$$P_n = pr(A_i = 0|Z_i = 1)$$

It follows:

$$P_c = 1 - P_n - P_a$$

Second, we analyze the distribution of Y_i given (Z_i, A_i). Consider the subpopulation of individuals for which $(Z_i, A_i) = (1, 0)$; as it was underlined, under the monotonicity assumption we know that these individuals are never-takers. So, we can calculate the distribution of $Y_i|A_i = 0, T_i = n$:

$$pr(Y_i = y_i|A_i = 0, T_i = n)$$

Furthermore, we consider the distribution of $Y_i|Z_i = 0, A_i = 0$, that is a mixture of the distributions of $Y_i|A_i = 0, T_i = n$ and $Y_i|A_i = 0, T_i = c$ with mixture probabilities equal to the relative population shares: $P_n/(P_c + P_n)$ and

$P_c/(P_c+P_n)$. It is now possible to back out the distributions of $Y_i|A_i = 0, T_i = c$ and $Y_i|A_i = 1, T_i = c$. Consequently, we can calculate the so-called Local Average Treatment Effect (Late, Imbens and Angrist (1994)):

$$\tau_{late} = \mathbb{E}[Y_i(1) - Y_i(0)|A_i(0) = 0, A_i(1) = 1] = \mathbb{E}[Y_i(1) - Y_i(0)|T_i = c]$$

However, this important theoretical result have to face important practical problems, as one should calculate mixture distributions in order to estimate τ_{late}. This problem is solved by means of the following theoretical result, due to Imbens and Angrist (1994), who showed that τ_{late} equals the standard instrumental variable estimand, i.e. the ratio of the covariance of Y_i and Z_i and the covariance of A_i and Z_i:

$$\tau_{late} = \frac{\mathbb{E}[Y_i|Z_i = 1] - \mathbb{E}[Y_i|Z_i = 0]}{\mathbb{E}[A_i|Z_i = 1] - \mathbb{E}[A_i|Z_i = 0]} = \frac{\mathbb{E}[Y_i \cdot [Z_i - \mathbb{E}[Z_i]]]}{\mathbb{E}[A_i \cdot [Z_i - \mathbb{E}[Z_i]]]}$$

Consider now that, as it is not possible to consistently estimate the average effect for either never-takers or always-takers, it would seem impossible to estimate the average treatment effect for the entire population in this setting. However, we can use the approach developed by Manski (and that was previously summed up) in order to bound the average treatment effect for the full population. If we maintain the monotonicity assumption, τ_{ATE} can be decomposed by compliance-type:

$$\begin{aligned}\tau_{ATE} = {} & P_n \cdot \mathbb{E}[Y_i(1) - Y_i(0)|T_i = n] + P_a \cdot \mathbb{E}[Y_i(1) - Y_i(0)|T_i = a] \\ & + P_c \cdot \mathbb{E}[Y_i(1) - Y_i(0)|T_i = c]\end{aligned}$$

and we can use the bound approach to estimate the terms for which data are uninformative.

3.3.4 Regression Discontinuity Design

This is a method for causal inference that can be only used in a specific situation: the case in which participants are deterministically assigned to the treatment according to the values of one or more covariates. Consider, for instance, the covariate X_i: annual income of a family, and the possibility for a student to get a grant from the university ($A_i = 1$: receiving the grant; $A_i = 0$: not receiving the grant). The government establishes the rules under which a student can receive the grant, according to the annual income of the family he/she belongs to (for instance, $A_i = 1$ if $X_i \leq 20000$ euros). The discontinuity is given from the fact that there is a point (in our example $X_i = 20000$) on the domain of one or more covariates around which subjects are explicitly divided in participants / not participants. This variable (commonly known as forcing variable) is often associated with the potential outcomes, but such an association is assumed to be smooth (Imbens and Wooldridge (2009)).

Regression Discontinuity Design is one of the "oldest" methods in causal inference, dating back to applied works in psychology and statistics during the sixties (see Thistlethwaite and Campbell (1960), Trochim (1984), Shadish *et al.* (2002), Cook (2008)). More recently, this method has been used also in many economics applications (e.g. Van der Klaauw (2002), Lee (2008)).

Remember that Regression Discontinuity Design is indeed a design, and not a method for data analysis. Consequently, in order to apply this technique, there must be a point on a covariate's domain such that it divides subjects in participants / not participants to a certain program.

> The design often arises from administrative decisions, where the incentives for individuals to participate in a program are rationed for reasons of resource constraints, and clear transparent rules, rather than discretion, by administrators are used for the allocation of the incentives. [Imbens and Wooldridge (2009), p. 59]

Regression Discontinuity Design techniques can be divided in two general frameworks: the *Sharp* and the *Fuzzy* Regression Discontinuity Design. We first analyze the Sharp Discontinuity Design. As it was previously mentioned, the assignment mechanism A_i is defined as a deterministic function of one of the covariates, the forcing variable X_i:

$$A_i = \mathbb{1}[X_i \geq c]$$

Consider now the following estimand:

$$\tau_{srd} = \mathbb{E}[Y_i(1) - Y_i(0)|X_i = c] = \mathbb{E}[Y_i(1)|X_i = c] - \mathbb{E}[Y_i(0)|X_i = c]$$

τ_{srd} cannot be estimated since, by design, there are no units with $X_i = c$ for which $Y_i(0)$ is observed. Hence, the basic idea underlying this technique is to consider units with covariate values arbitrarily close to c, under the assumption that the conditional expectations $\mathbb{E}[Y_i(a)|X_i = x]$ for $a = 0, 1$, are continuous functions in $X_i = x$. Under this assumption, we have:

$$\mathbb{E}[Y_i(0)|X_i = x] = \lim_{x \uparrow c} \mathbb{E}[Y_i(0)|X_i = x] = \lim_{x \uparrow c} \mathbb{E}[Y_i|X_i = c]$$

so that:

$$\tau_{srd} = \lim_{x \downarrow c} \mathbb{E}[Y_i|X_i = x] - \lim_{x \uparrow c} \mathbb{E}[Y_i|X_i = x]$$

The problem is now that of non-parametrically estimating a regression function at a boundary point (see Lee and Lemieux (2009) for a discussion).

As we've seen, in the Sharp Regression Discontinuity Design the probability of receiving the treatment changes from zero to one at the threshold. This is not the case for the Fuzzy Regression Discontinuity Design, that only requires a discontinuity in the probability of assignment to the treatment at the threshold:

$$\lim_{x \downarrow c} \quad pr(A_i = 1|X_i = x) \neq \lim_{x \uparrow c} \quad pr(A_i = 1|X_i = x)$$

For instance, this may be the case for some training programs or benefit programs, where the incentives to participate change discontinuously at a threshold, without being powerful enough to move all units from non participation to participation.

The estimand of interest in this case is given by the ratio of the jump in the regression of the outcome (on the covariate) to the jump in the regression of the treatment indicator (on the covariate):

$$\tau_{frd} = \frac{\lim_{x \downarrow c} \mathbb{E}[Y_i|X_i = x] - \lim_{x \uparrow c} \mathbb{E}[Y_i|X_i = x]}{\lim_{x \downarrow c} \mathbb{E}[A_i|X_i = x] - \lim_{x \uparrow c} \mathbb{E}[A_i|X_i = x]}$$

Consider now the problems of estimation and inference for both the Sharp and the Fuzzy Regression Discontinuity Design. In the former case, τ_{srd} has to be estimated, i.e. a difference in two regression functions at a particular point, in the latter case τ_{frd} has to be estimated, i.e. the ratio of two differences of regression functions. In both cases, these estimands have to be calculated without functional form assumptions, and in general by means of nonparametric regression methods. Among these methods, it has been already introduced the use of local smoothing methods, such as kernel regression. Given a kernel function $K(\cdot)$ and a bandwidth h, a regression function at x, $m(x) = \mathbb{E}[Y_i|X_i = x]$ is estimated as:

$$\hat{m}(x) = \sum_{i=1}^{N} Y_i \cdot \lambda_i$$

with weights:

$$\lambda_i = \frac{K(X_i - x/h)}{\sum_{i=1}^{N} K(X_i - x/h)}$$

Note that, in a Regression Discontinuity Design the interest is not focused on estimating a regression function by itself, but rather in evaluating the difference between two regression functions at a boundary point. So, it can be used a *local linear regression* method, which leads to an estimator for the regression function at x equals to:

$$\hat{m}(x) = \hat{\alpha}$$

where

$$(\hat{\alpha}, \hat{\beta}) = \underset{\alpha,\beta}{argmin} \sum_{i=1}^{N} \lambda_i \cdot (Y_i - \alpha - \beta \cdot (X_i - x))^2$$

with the same weights of the previous case.

Furthermore, a basic problem is given by the choice of the bandwidth h, that leads to drop all observations such that $X_i \notin [c - h, c + h]$. A criterion is to choose h such that it minimizes:

$$\mathbb{E}[(\hat{m}(c) - m(c))^2]$$

Imbens and Kalyanaramang (2009) have recently shown that the optimal bandwidth depends on the second derivatives of the regression functions at the threshold and such that:

$$h_{opt} = N^{-1/5} \cdot C_k \cdot \sigma^2 \cdot \left(\frac{\frac{1}{p} + \frac{1}{1-p}}{\underset{x \downarrow c}{lim}(\frac{\partial^2 m}{\partial x^2}(x)) + \underset{x \uparrow c}{lim}(\frac{\partial^2 m}{\partial x^2}(x))^2} \right)^{1/5}$$

where p is the fraction of observations with $X_i \geq c$ and C_k is a constant that depends on a kernel.

3.3.5 Difference-in-differences Methods

Consider an empirical problem in which we have two groups (G_1 and G_2) and we consider two time periods (T_1 and T_2). Individuals of group A are exposed to control on time 1 and to treatment on time 2, whereas individuals of group B are always exposed to control. In such a situation, a method, known as *difference-in-differences* method can be applied [Ashenfelter (1978), Ashenfelter and Card (1985)].

This method is based on subtracting the average gain over time in the non-exposed (control) group from the gain over time in the exposed (treatment) group. Such a double difference removes the bias on the second period comparisons between the treatment and the control group. In fact, this could originate from permanent differences between the two groups, as well as from biases in the comparisons over time in the treatment group, that could be the result of time trends unrelated to the treatment [Imbens and Wooldridge (2009)].

Let's now formalize these concepts. Consider a random sample of N individuals from a population; for $i = 1, ..., N$ individual i belongs to a group $G_i \in \{0, 1\}$ (where group 1 is the treatment group), and is observed in time period $T_i \in \{0, 1\}$. The outcome for individual i in the absence of intervention can be written as:

$$Y_i(0) = \alpha + \beta \cdot T_i + \gamma \cdot G_i + \epsilon_i$$

with unknown parameters α, β, γ. The error term ϵ represents unobservable characteristics of the individual and this term is assumed to be independent of the group indicator and has the same distribution over time (i.e. $\epsilon_i \coprod (G_i, T_i)$) and is normalized to have mean zero. The equation for the outcome without the treatment is now combined with an equation for the outcome given the treatment:

$$Y_i(1) = Y_i(0) + \tau_{did}$$

where τ_{did} is equal to:

$$\begin{aligned}\tau_{did} &= \mathbb{E}[Y_i(1)] - \mathbb{E}[Y_i(0)] \\ &= [\mathbb{E}[Y_i|G_i = 1, T_i = 1] - \mathbb{E}[Y_i|G_i = 1, T_i = 0]] \\ &- [\mathbb{E}[Y_i|G_i = 0, T_i = 1] - \mathbb{E}[Y_i|G_i = 0, T_i = 0]]\end{aligned}$$

τ_{did} is obtained by subtracting the population average difference over time in the control group ($G_i = 0$) from the population average difference over time in the treatment group ($G_i = 1$) to remove biases associated with a common time trend unrelated to the intervention.

τ_{did} can be estimated by least squares methods on the regression function for the observed outcome:

$$Y_i = \alpha + \beta_1 \cdot T_i + \gamma_1 \cdot G_i + \tau_{did} \cdot W_i + \epsilon_i$$

where the treatment indicator W_i is equal to the interaction of the group and time indicators, $W_i = T_i \cdot G_i$. τ_{did} is estimated as:

$$\hat{\tau}_{did} = (\bar{Y}_{11} - \bar{Y}_{10}) - (\bar{Y}_{01} - \bar{Y}_{00})$$

where $\bar{Y}_{gt} = \sum_{i|G_i=g,T_i=t} Y_i / N_{gt}$ is the average outcome among units in group g and time period t.

The difference-in-differences method can be also generalized to the case of multiple time periods or multiple treatments. If we define two variables T

and G to indicate multiple times and groups, the outcome under control can be indicated as:

$$Y_i(0) = \alpha + \sum_{t=1}^{T} \beta_t \cdot \mathbb{1}_{T_i=t} + \sum_{g=1}^{G} \gamma_g \cdot \mathbb{1}_{G_i=g} + \epsilon_i$$

for $g = 1, ..., G$ and $t = 1, ..., T$. Moreover, as in the case of two time periods, we consider an additive model for the treatment effect:

$$Y_i(1) = Y_i(0) + \tau_{did}$$

and the regression function:

$$Y_i = \alpha_i + \sum_{t=1}^{T} \beta_t \cdot \mathbb{1}_{T_i=t} + \sum_{g=1}^{G} \gamma_g \cdot \mathbb{1}_{G_i=g} + \tau_{did} \cdot I_i + \epsilon_i$$

where I_i is an indicator function for unit i being in a group and time period that was exposed to the treatment. The parameters of this model can be still estimated by ordinary least squares.

Let's now analyze the estimation of the standard errors in the regression models. Bertrand *et al.* (2004), Donald and Lang (2007), Hansen (2007a), Hansen (2007b) has faced the problem for which, as underlined by Imbens and Wooldridge (2009), ordinary least squares standard errors for $\hat{\tau}_{did}$ may not be accurate in the presence of correlations between outcomes within groups and between time periods. Define the error term as:

$$\epsilon_i = \eta_{G_i,T_i} + \nu_i$$

where ν_i is an individual-level error term, and η_{gt} is a group/time specific component. The hypotheses that have to be put forth are: i) the unit-level error term ν_i is independent across units; ii) $\mathbb{E}[\nu_i, \nu_j] = 0$ if $i \neq j$; iii) $\mathbb{E}[\nu_i^2] = \sigma_\nu^2$; iv) $\eta_{g,t} \sim \mathcal{N}(0, \sigma_\eta^2)$; v) $\eta_{g,t}$ are independent. If we consider the case with two groups and two time periods, it can be shown that the estimator for τ_{did} is not consistent. Hence, we have:

$$\bar{Y}_{gt} \to \alpha + \beta_t + \gamma_g + \mathbb{1}_{g=1,t=1} \cdot \tau_{did} + \eta_{g,t}$$

so that:

$$\begin{aligned} \hat{\tau}_{did} &= (\bar{Y}_{11} - \bar{Y}_{10}) - (\bar{Y}_{01} - \bar{Y}_{00}) \\ &\to \tau_{did} + (\eta_{11} - \eta_{10}) - (\eta_{01} - \eta_{00}) \sim \mathcal{N}(\tau_{did}, 4 \cdot \sigma_\eta^2) \end{aligned}$$

The estimator for τ_{did} is not consistent since the error term depends from an unobserved component η_{gt}. If data are available from more than two groups or from more than two time periods, σ_η^2 can be estimated and confidence intervals for τ_{did} can be constructed.

If we consider the case with multiple time periods, the assumption that the parameters $\eta_{g,t}$ are independent over time can be relaxed, and an autoregressive model for $\eta_{g,t}$ can be put forth:

$$\eta_{g,t} = \alpha \cdot \eta_{g,t-1} + \omega_{g,t}$$

with a serially uncorrelated ω_{gt}.

The previous discussion refers to the case of two independent groups. We now briefly examine the case of *panel data*, i.e. we have N individuals, for whom we observe $(G_i, Y_{i0}, Y_{i1}, X_{i0}, X_{i1})$, where G_i indicates group membership. Note that, whereas in the previous case we had observations coming from repeated cross sections, in this case the observations in different time periods come from the same individuals.

Imbens and Wooldridge (2009) focus on two approaches aimed to analyze these data. The first approach considers estimation as in the case of repeated cross sections, ignoring the fact that the observations in different time periods come from the same units. The second approach assumes unconfoundedness given lagged outcomes:

$$(Y_{i,t_{1i}}, Y_{i,t_j}) \coprod G_i | Y_{i,t_{i-1}}, Y_{i,t_{j-1}}$$

In this case, the unconfoundedness assumption would suggest the regression of the difference $Y_{i1} - Y_{i0}$ on the group indicator and the lagged outcome Y_{i0}:

$$Y_{i1} - Y_{i0} = \beta + \tau_{unconf} \cdot G_i + \delta \cdot Y_{i0} + \epsilon_i$$

3.4 The Structural Approach: A Brief Note

In this section, we briefly introduce the econometric approach to observational studies, as developed by authors such as James Heckman and Edward Vytlacil. In the previous chapter, it was underlined that, whereas the Program Evaluation Approach does not use models for the potential outcomes (hence, authors such as James Robins and Miguel Hernan define it as "counterfactual without models"'), econometricians start from another perspective, that of generating the counterfactual distribution. In fact, three objectives are put forth in the econometric analysis of causality: i) defining the set of counterfactuals; ii) identifying causal models from hypothetical data; iii) identifying causal models from real data [see Heckman and Vytlacil (2007)].

The fundamental feature of the econometric approach is that it tries to keep into account the individual choices that an agent can take. If we indicate with $\mathcal{S}$ the set of all possible treatments an agent can choose, we can define the individual treatment effect for agent i, by comparing the outcome under treatment s with the outcome under treatment s':

$$Y(s,i) - Y(s',i) \qquad s \neq s'$$

for two elements s and s' (individual causal effect). In this approach the participant is conceived as an active *decision maker*, who is able to produce an evaluation V associated with each potential outcome:

$$V(Y(i,s))$$

For each unit i, the evaluation depends on which treatment s is either chosen or assigned. So, in this context, we can formally define a treatment as a rule:

$$\tau : \mathcal{I} \rightarrow \mathcal{S}$$

which assigns treatment to each individual i. Consequently, we indicate with τ, where $\tau \in \mathcal{T}$ the collection of possible assignment rules, and we indicate with $Y(i,s)$, $i \in \mathcal{I}$ the consequences of the treatment to each individual.

In addition, we can introduce the so-called *benefits*, that are incentives (for instance, on taxation) that can be assigned to subjects and that can affect their selection of the treatment. For individual i, we can define a rule $a \in \mathcal{A}$ mapping individual i into constraints or benefits $b \in \mathcal{B}$ under different mechanisms $a : \mathcal{I} \rightarrow \mathcal{B}$ as a deterministic rule or a random assignment.

Two important *invariance assumptions* are put forth by the literature: i) for the same treatment s and agent i, different constraint assignment mechanisms a and a' and associated constraint state assignment b and b' produce the same outcome; ii) for a fixed a and b, the outcomes are the same, independent of the treatment assignment mechanism (social interaction and contagion are ruled out). After these assumptions have been posed, the problem faced by econometricians is to identify the counterfactual distributions. Obviously, the problem is that we do not observe the outcome of each subjects under different treatment states. Moreover, as it was underlined before, subjects are supposed to self-select themselves into treatment, in order to obtain the maximum benefit.

A last feature of the econometric approach that is useful to be underlined in this context, is that we can distinguish between *ex-ante* and *ex-post* evaluation of both subjective and objective outcomes (and this is very useful in order to understanding behaviour). Formally, if we indicate as D_i the informations available to agents in order to compare policy j with policy k, we have that, under an expected utility criterion $\mathcal{U}$, policy j is preferred to policy k if:

$$\mathbb{E}[\mathcal{U}(Y(j,i),i)|D_i] > \mathbb{E}[\mathcal{U}(Y(k,i),i)|D_i]$$

After unit i experiences either policy j or k, there is also an ex-post evaluation of the treatment, but also this one is subjected to uncertainty, because people do not know the outcome associated with the policy they did not experience (see Heckman (2010) for a detailed analysis of this approach).

3.5 Final Remarks

In this chapter, the literature on the identification of causal effects in observational studies has been briefly reviewed. A fundamental distinction has been proposed between methods assuming unconfoundedness or methods not assuming unconfoundedness. In the former case, we're dealing with *selection on observables*, and the methods that have been reviewed are regression methods and methods based on the propensity score (and their combination). In the latter case, we're dealing with the *selection on unobservables*, as unobserved factors influencing the relation between treatment assignment and potential outcomes are supposed to exist. The methods that have been reviewed in this case are: sensitivity analysis, bound analysis, instrumental variables, regression discontinuity design, difference-in-differences. Last, a brief note on the structural approach to causality has been sketched.

Since the next chapter, causal inference methods will not further be analyzed in general, but the analysis will be narrowed on inference from risk differences. We will see that the theoretical background that has been built in the first three chapter can be applied on the specific case of the analysis of risk differences. The attention shall be focused on testing statistical hypothesis, and, after a general review of the literature (chapter 4), we will consider the proposal of Suissa and Shuster (1985) of an unconditional test. A development of this test and the derivation of the critical values and p-values will be proposed in Chapter 6. Application of this test for causal analysis in the Program Evaluation Approach will be proposed as a further development of the present work.

Chapter 4

Exact Analysis of 2×2 Binomial Trials

4.1 Overview

This chapter presents the exact methods for testing statistical hypotheses in a 2×2 binomial trial, that is the case in which the row marginal sums are fixed in a 2×2 table. Let's consider the following question from psycholinguistics: how can we identify and read words? Which is the "code" allowing us to identify that, for instance, SNAKE is a word whereas SNATE is not a word? The psychologist John Morton proposed a seminal theory on this issue (Morton (1969)). In this author's opinion, each word is stored as a "file" (which he defined a *logogen*) in our reading system. When we perceive a visual object matching the visual features of a word, we identify it as a whole word. Alternatively, if we perceive a string of letters like SNATE, we have no *logogen* activation, and we classify that string as a nonword. Think now at a morphologically complex language such as Italian, where a single root (e.g. LAMP-) can be suffixed in different ways in order to obtain words (e.g. LAMPADA, LAMPADINA, LAMPADARIO...). According to the Morton's original model, each of these words is stored as a distinct *logogen*. An alternative theory, put forth by the psycholinguist Ken Forster, states that there is not a single *logogen* for each word, but morphologically complex words are routinely decomposed into roots and suffixes in order to assemble the words (Forster (1976)).

Baldi and Traficante (1992) compared these two theories by means of a letter recognition task. Participants were randomly presented with roots (e.g. LAMP-, CAMP-) and non-roots (e.g. PLAM-, APML-, MAPL-). Stimuli were tachistoscopically projected at the center of a black screen and lasted for 40 msec. Afterwards, subjects were presented with two letters, one of which belonged to the stimulus previously appeared, whereas the other was a distracter. For instance, the string LAMP was presented at the center of a black screen for 40 msec, followed by a perceptual mask (####). Subsequently, the consonants M and C were presented and subjects were asked to choose in 2 seconds which of them belonged to the original stimulus (the correct answer was randomly put either on the left side or on the right side of the screen). Overall accuracy in this task was measured. From one side, according to the Morton's original model, no difference in accuracy between roots and anagrams is expected, since both roots and anagrams have no *logogen* representation. From the other side, Forster's decomposition model clearly predicts a superiority in accuracy for roots over anagrams since the latter have no abstract representation, and are expected to be recognized less accurately than roots. Data collected in this experiment are reported in Table 4.1.

	Correct Answers	Incorrect Answers	Total
Roots	147	13	160
Anagrams	151	9	160
Total	298	22	320

Table 4.1: Association between Type of stimulus (root or anagram) and accuracy in a letter recognition task (Baldi and Traficante (1992)).

Authors tested the null hypothesis of independence by means of a χ^2 test. This statistical test is adequate when large samples are available, but it represents a rough approximation in cases of small samples. In this experiment, subjects were presented with 320 recognition trials, and an asymptotic analysis of the 2×2 table can be considered acceptable. This kind of analysis is defined *analysis by item*, since the statistical units are the items presented to participants. If we had considered subjects instead of items as statistical units (*analysis by subjects*), the asymptotic approximation would have been rough and imprecise, since only 15 subjects took part in the experiment. Hence, analysis *by subjects* would have lead the researcher to choose an exact rather than an asymptotic test. Note that the modern psychometric theory uses random effect models in order to simultaneously consider both the subjects' and the items' random effects.

Another case of incorrect application of the asymptotic approximation is given by the research of Pfirrmann *et al.* (2005). These authors prospectively examined magnetic resonance imaging (MRI) of abductor tendons and muscles in asymptomatic and symptomatic patients after lateral transgluteal total hip arthroplasty (THA). Two musculoskeletal radiologists (blinded to clinical information) analyzed triplanar MR images of the greater trochanter obtained in 25 patients without and 39 patients with trochanteric pain and abductor weakness after THA. Tendon defects, diameter, signal intensity and ossification, fatty atrophy and bursal fluid collections were assessed. Differences in the frequencies of findings between the two groups of symptomatic and asymptomatic patients were tested for significance using χ^2 analyses. As it is commonly known, the use of this test in the presence of small samples may conduct into fallacy. Table 4.2 reports the association between abductor tendon defect at the *Gluteus minimus* in asymptomatic vs not asymptomatic patients.

	Tendon defect	No tendon defect	Total
Asymptomatic patients	2	33	25
Symptomatic patients	22	17	39
	24	40	64

Table 4.2: Association between tendon defect and symptoms reported by patients (Pfirrmann *et al.* (2005)).

Authors report a significant p-value associated to a χ^2 test ($p < 0.001$) and I've replicated this result by means of a Fisher's exact test using the software SPSS 17.0 ($p < 0.001$) (see also Liao *et al.* (2006) for a discussion on the use of the Fisher's exact test). Hence, in this case, both the asymptotic test and the exact test would have conducted the researcher to the same conclusions (i.e. reject the null hypothesis of no association). Physicians also investigated the presence of Bursal fluid collection in asymptomatic and symptomatic patients (see Table 4.3). Also in this case, authors report a significant value of the χ^2 statistic ($p = 0.21$); I've replicated this result by means of a Fisher's exact test, but obtaining a higher p-value ($p = 0.39$). This example shows that, even in the case of *medium* sample size ($N = 69$), the use of an asymptotic approximation may lead into fallacy.

	Fluid	No Fluid	Total
Asymptomatic patients	8	17	25
Symptomatic patients	24	15	39
	32	32	64

Table 4.3: Association between presence of bursal fluid collection and symptoms reported by patients (Pfirrmann *et al.* (2005)).

In the present chapter, the main tests for comparing statistical hypotheses in a 2×2 binomial trial shall be reviewed. First, we'll emphasize that a 2×2 table can represent a way to summarize data collected in three different experimental designs: i) all-margin fixed design; ii) one-margin fixed design; iii) total-sum fixed design. These cases should be analyzed by means of different statistical techniques, but only the second case will be discussed in this chapter, i.e. the case of two independent binomial trials. Second, we'll consider the main test statistics used in this analysis, as the Pearson's statistic, the likelihood ratio statistic, the z-unpooled and the z-pooled statistics. Third, we'll analyze how to compute the p-values in these cases. Fourth, we'll compare these tests with respect to the power they can achieve.

Before considering these four points, a general review on the theory of testing statistical hypotheses will be given. This review is adapted from Quatto (2008), Casella and Berger (2001), Lehmann and Romano (2005), Landenna *et al.* (1998), Shao (1999) and Rohatgi and Saleh (2008). This will be particularly useful in order to introduce some notation to be used in this chapter and to recall some important definitions and theorems.

4.2 Optimal and suboptimal testing of statistical hypotheses: a brief review

In the Neyman and Pearson (1936)'s theory, a problem of testing statistical hypotheses is conceived as an *optimization* problem, the solution of which (whenever exists), is called an *optimal test.* The Neyman and Pearson's theory, developed in the 1930s, constituted a fundamental step in the progress of the theory of testing statistical hypotheses. In the previous decades, there was not a formal and congruent theory, but a lot of approaches had been proposed.

An optimal test can be informally defined as a test for which the power function is maximized under the alternative hypothesis ($(1-\beta)$ is maximum) provided that, under the null hypothesis, the power function does not exceed a fixed level α. If an optimal test does not exist, we search for a *suboptimal test*, i.e. an optimal test under some constraints. Among suboptimal tests, two main classes can be defined: unbiased most powerful tests (UMPU tests) and invariant most powerful tests (UMPI). Note that optimal tests –whenever they exist– might be not unique. This is a basic difference with respect to some theorems in the theory of point estimation. For instance, it can be proved that, if a uniformly minimum-variance unbiased estimator (UMVUE) exists, it is unique. This is not the case for optimal testing, where, if a most powerful test exists, it might be not unique.

Let now X be a random variable (either discrete or continuous), such that $\mathbb{X} \subseteq \mathfrak{R}$ and distribution function $\varphi_{\boldsymbol{\theta}}$ belonging to the class of the parametrical models:

$$H = \{\varphi_{\boldsymbol{\theta}} : \boldsymbol{\theta} \in \boldsymbol{\Theta}\} \tag{4.1}$$

Consider the partition of the m-dimensional parametrical space $\boldsymbol{\Theta} \subseteq \mathfrak{R}^m$ determining a partition of H in the subclasses:

$$H_0 = \{\varphi_{\boldsymbol{\theta}} : \boldsymbol{\theta} \in \boldsymbol{\Theta}_0\} \tag{4.2}$$

$$H_1 = \{\varphi_{\boldsymbol{\theta}} : \boldsymbol{\theta} \in \boldsymbol{\Theta}_1\} \tag{4.3}$$

such that $\boldsymbol{\Theta}_0 \cap \boldsymbol{\Theta}_1 = \varnothing$, $\boldsymbol{\Theta}_0 \cup \boldsymbol{\Theta}_1 = \boldsymbol{\Theta}$. Expressions 4.2 and 4.3 are respectively called **null** and **alternative** hypotheses. Let $X_1, ..., X_n$ be n i.i.d. random variables and identically distributed to X, so that:

$$\varphi(\mathbf{x}, \boldsymbol{\theta}) = \prod_{i=1}^{n} \varphi_{\boldsymbol{\theta}}(\mathbf{x}_i)$$

defined on all the points $\mathbf{x} = (x_1, ...x_n)$ of the sample space $\mathbb{X}$. A test for comparing the hypothesis H_{θ_0} vs H_{θ_1} is defined as a partition of the sample space $\mathcal{X}$ in the two subsets Ω_0 and Ω_1 such that:

$$\Omega_0 \cup \Omega_1 = \mathcal{X}$$
$$\Omega_0 \cap \Omega_1 = \varnothing$$

Ω_0 is called acceptance region, whereas Ω_1 is called reject region. A statistical **test function** for comparing H_0 vs H_1 can be defined as a measurable function τ:

$$\tau : \mathbb{X}^n \to [0, 1]$$

associating to each $\mathbf{x} = (x_1, ..., x_n) \in \mathbb{X}^n$ the probability of rejecting H_0, given the observed sample $\mathbf{x}$.

Example 1. *Let X be a continuous random variable with distribution function:*

$$\varphi_X(\theta) = \begin{cases} \theta e^{-\theta x} & x > 0 \\ 0 & elsewhere \end{cases}$$

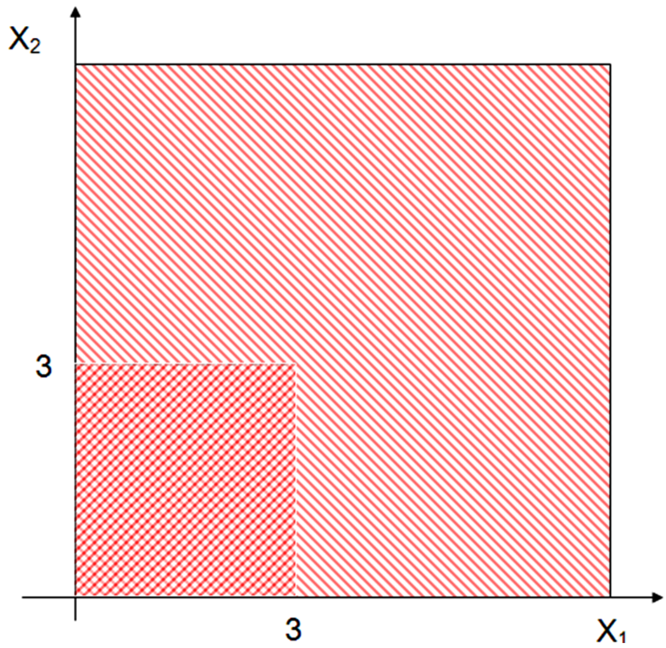

Figure 4.1: Example of a critical region for the test τ in Equation 4.4.

It follows that:

$$\mathbb{E}[X] = \int_0^\infty \theta e^{-\theta x} x dx = \frac{1}{\theta}$$

Consider the following hypotheses:

$$\begin{cases} H_0 : \theta \le \theta_0 \\ H_1 : \theta > \theta_0 \end{cases}$$

i.e.:

$$\begin{cases} H_0 : \mathbb{E}[X] \ge 1/\theta_0 \\ H_1 : \mathbb{E}[X] < 1/\theta_0 \end{cases}$$

Suppose that $n = 2$ and $\theta_0 = 10$. A statistical test is a function connecting each couple of observations (x_1, x_2) with the probability of rejecting H_0. For instance τ is such that (see Figure 4.1):

$$\tau : \begin{cases} 1 & \text{if } x_1 < 3 \text{ and } x_2 < 3 \\ 0 & \text{elsewhere} \end{cases} \tag{4.4}$$

but τ' can also be such that (see Figure 4.3):

$$\tau' : \begin{cases} 1 & \text{if } x_1 + x_2 < t \\ 0 & \text{elsewhere} \end{cases} \tag{4.5}$$

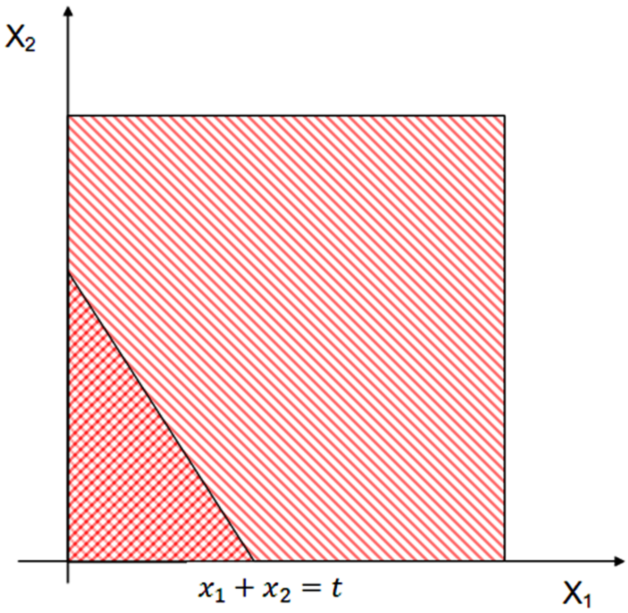

Figure 4.2: Example of a critical region for the test τ' in Equation 4.5.

For each statistical test we define a **power function** π_τ:

$$\pi_\tau : \boldsymbol{\Theta} \to [0,1]$$

such that to each

$$\boldsymbol{\theta} = (\theta_1, ..., \theta_m) \in \boldsymbol{\Theta}$$

corresponds the probability of rejecting H_0, given $\boldsymbol{\theta}$ as a true parameter value:

$$\pi_\tau(\boldsymbol{\theta}) = \int_{\mathbb{X}^n} \tau(\mathbf{x})\varphi(\mathbf{x};\boldsymbol{\theta})dx = \mathbb{E}_{\boldsymbol{\theta}}[\tau(X_1, ..., X_n)]$$

We fix now a significance level $\alpha \in [0,1]$ and we define the class of **level $\boldsymbol{\alpha}$ tests** for H_0:

$$L_\alpha(H_0) = \{\tau : \forall \boldsymbol{\theta}_0 \in \boldsymbol{\Theta}_0, \pi_\tau(\boldsymbol{\theta}_0) \leq \alpha\}$$

We also define the subset of the **similar $\boldsymbol{\alpha}$ tests** for H_0:

$$S_\alpha(H_0) = \{\tau : \forall \boldsymbol{\theta}_0 \in \boldsymbol{\Theta}_0, \pi_\tau(\boldsymbol{\theta}_0) = \alpha\} \subseteq L_\alpha(H_0)$$

A test τ is called **most powerful** at level α for H_0 vs the simple hypothesis $H_{\boldsymbol{\theta}_1} = \{\varphi_{\boldsymbol{\theta}_1} \subseteq H_1\}$ whether $\tau \in L_\alpha(H_0)$ and:

$$\forall \tau' \in L_\alpha(H_0), \pi_\tau(\boldsymbol{\theta}_1) \geq \pi'_\tau(\boldsymbol{\theta}_1)$$

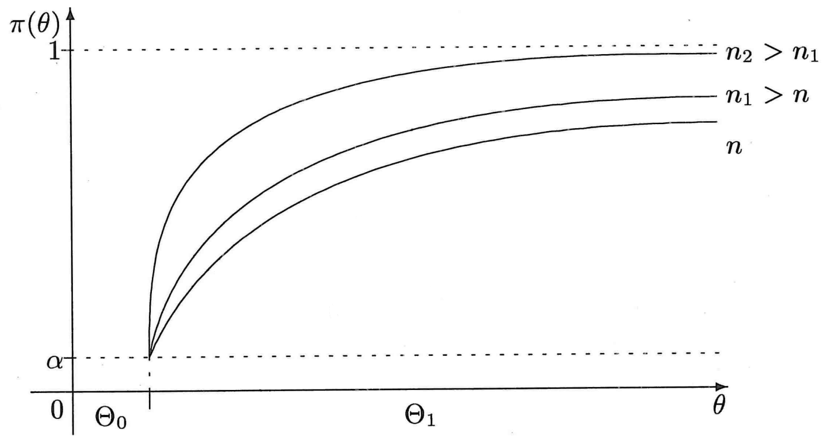

Figure 4.3: Consistency of a statistical test; as n increases, the power function under the alternative hypothesis is higher.

A test is called **uniformly most powerful** at level α for H_0 vs the composite hypothesis H_1, whether it is powerful at level α for the hypothesis in 4.2 against every simple hypothesis $H_{\boldsymbol{\theta}_1}$ in 4.3, i.e.:

$$\tau \in L_\alpha(H_0) \qquad \text{and} \qquad \forall \tau' \in L_\alpha(H_0), \forall \boldsymbol{\theta}_1 \in \boldsymbol{\Theta}_1, \pi_\tau(\boldsymbol{\theta}_1) \geq \pi'_\tau(\boldsymbol{\theta}_1)$$

We define a test τ to be **consistent**, if, fixed α:

$$\lim_{n\to\infty} \pi(\theta) = 1 \quad \text{for all } \theta \in \boldsymbol{\Theta}$$

We now introduce the Neyman-Pearson's fundamental Lemma, proposed in 1933 and that can be applied in order to find a most powerful test, when simple hypotheses are compared. This Lemma allows a researcher to construct an optimal critical region by considering the sample points for which the likelihood ratio is higher, provided that the power function under the null hypothesis does not exceed a fixed value α.

Theorem 3. *Let Φ_0 and Φ_1 be probability distributions possessing densities $\varphi_{\boldsymbol{\theta}_0}$ and $\varphi_{\boldsymbol{\theta}_1}$ respectively with respect to a measure μ. Consider the following hypotheses: $H_{\boldsymbol{\theta}_0} = \{\varphi_{\boldsymbol{\theta}_0}\} \subseteq H_0$ and $H_{\boldsymbol{\theta}_1} = \{\varphi_{\boldsymbol{\theta}_1}\} \subseteq H_1$.*

Existence *For testing $H_{\boldsymbol{\theta}_0}$ vs $H_{\boldsymbol{\theta}_1}$, there exists a test τ and a constant k such that:*

$$\mathbb{E}_0\{\tau(\mathbf{x})\} = \alpha \tag{4.6}$$

and

$$\tau_{\boldsymbol{\theta}_0,\boldsymbol{\theta}_1} : \mathbb{X}^n \to [0,1] \tag{4.7}$$

$$\tau(x) = \begin{cases} 1 & \textit{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) > k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \\ \gamma(x) & \textit{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) = k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \\ 0 & \textit{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) < k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \end{cases} \tag{4.8}$$

Sufficient condition for a most powerful test *If a test satisfies 4.6 and 4.8 for some k, then it is most powerful for testing $\varphi_{\boldsymbol{\theta}_0}$ vs $\varphi_{\boldsymbol{\theta}_1}$ at a level α;*

Necessary condition for a most powerful test *If τ is most powerful at level α for testing $\varphi_{\boldsymbol{\theta}_0}$ vs $\varphi_{\boldsymbol{\theta}_1}$, then for some k it satisfies 4.8 a.e. μ. It also satisfies 4.6 unless there exists a test of size α and with power 1.*

Proof. For $\alpha = 0$ and $\alpha = 1$ the theorem is easily seen to be true provided the value $k = +\infty$ is admitted in 4.8 and $0 \cdot \infty$ is interpreted as 0. Throughout the proof we shall therefore assume $0 < \alpha < 1$.

Existence Let $\alpha(c) = P_0\{\varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) > c\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})\}$. Since the probability is computed under P_0, the inequality need to be considered only for the set where $\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) > 0$, so that $\alpha(c)$ is the probability that the random variable $\frac{\varphi_{\boldsymbol{\theta}_1}(\mathbf{x})}{\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})} > c$. Thus, $1 - \alpha(c)$ is a cumulative distribution function and $\alpha(c)$ is non-increasing and continuous on the right:

$$\alpha(c-0) - \alpha(c) = P_0\Big\{\frac{\varphi_{\boldsymbol{\theta}_1}(\mathbf{x})}{\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})} = c\Big\}, \qquad \alpha(-\infty) = 1, \qquad \alpha(+\infty) = 0$$

Given any $0 < \alpha < 1$, let c_0 be such that $\alpha(c_0) \le \alpha \le \alpha(c_0 - 0)$ and consider the test τ defined by:

$$\tau(\mathbf{x}) = \begin{cases} 1 & \text{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) > c_0\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \\ \frac{\alpha - \alpha(c_0)}{\alpha(c_0-0) - \alpha(c_0)} & \text{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) = c_0\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \\ 0 & \text{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) < c_0\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \end{cases}$$

Here the middle expression is meaningful unless $\alpha(c_0) = \alpha(c_0 - 0)$; since then:

$$P_0\{\varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) = c_0\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})\} = 0$$

and τ is defined almost everywhere. The size of τ is:

$$\mathbb{E}_0\{\tau(\mathbf{x})\} = P_0\Big\{\frac{\varphi_{\boldsymbol{\theta}_1}(\mathbf{x})}{\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})} > c_0\Big\} + \frac{\alpha - \alpha(c_0)}{\alpha(c_0 - 0) - \alpha(c_0)} P_0\Big\{\frac{\varphi_{\boldsymbol{\theta}_1}(\mathbf{x})}{\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})} = c_0\Big\} = \alpha \tag{4.9}$$

so that c_0 can be taken as the k of the theorem.

Sufficiency Let $\tau(\mathbf{x})$ be the test function of a size α test satisfying 4.8. Let $\tau'(\mathbf{x})$ be the test function of any other level α test and let $\pi_\tau(\theta)$ and $\pi'_\tau(\theta)$ be the power functions corresponding to the tests τ and τ' respectively. Because $0 \le \tau' \le 1$, 4.8 implies that:

$$(\tau(\mathbf{x}) - \tau'(\mathbf{x}))(\varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) - k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})) \ge 0 \quad \forall \mathbf{x} \tag{4.10}$$

since $\tau = 1$ if $\varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) > k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})$ and $\tau = 0$ if $\varphi_{\theta_1}(\mathbf{x}) < k\varphi_{\theta_0}(\mathbf{x})$. Thus:

$$\begin{aligned} 0 &\le \int [\tau(\mathbf{x}) - \tau'(\mathbf{x})][\varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) - k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x})]dx \\ &= \pi_\tau(\boldsymbol{\theta}_1) - \pi_{\tau'}(\boldsymbol{\theta}_1) - k(\pi_\tau(\boldsymbol{\theta}_0) - \pi_{\tau'}(\boldsymbol{\theta}_0)) \end{aligned} \tag{4.11}$$

Sufficiency is proved noting that, since τ' is a level α test and τ is a size α test, $\pi_\tau(\boldsymbol{\theta}_0) - \pi_{\tau'}(\boldsymbol{\theta}_0) = \alpha - \pi_{\tau'}(\boldsymbol{\theta}_0) \ge 0$. Thus, 4.11 and $k > 0$ imply that:

$$0 \le \pi_\tau(\boldsymbol{\theta}_1) - \pi_{\tau'}(\boldsymbol{\theta}_1) - k(\pi_\tau(\boldsymbol{\theta}_0) - \pi_{\tau'}(\boldsymbol{\theta}_0)) \le \pi_\tau(\boldsymbol{\theta}_1) - \pi_{\tau'}(\boldsymbol{\theta}_1)$$

showing that $\pi_\tau(\boldsymbol{\theta}_1) \ge \pi_{\tau'}(\boldsymbol{\theta}_1)$, and thus τ has greater power than τ'. Since τ' was an arbitrary level α test, τ is an UMP level α test.

Necessity Let now τ' be the test function for any UMP level α test. By sufficiency, τ, the test satisfying 4.6 and 4.8 is also an UMP level α test, thus $\pi_\tau(\boldsymbol{\theta}_1) = \pi_{\tau'}(\boldsymbol{\theta}_1)$. This fact, 4.11 and $k > 0$ imply:

$$\alpha - \pi_{\tau'}(\boldsymbol{\theta}_0) = \pi_\tau(\boldsymbol{\theta}_0) - \pi_{\tau'}(\boldsymbol{\theta}_0) \le 0$$

Now, since τ' is a level α test, $\pi_{\tau'}(\theta_0) \le \alpha$. Thus, $\pi_{\tau'}(\theta_0) = \alpha$ that is, τ' is a size α test, and also it implies that 4.11 is an equality in this case. But the non-negative integrand:

$$(\tau(\mathbf{x}) - \tau'(\mathbf{x}))(\varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) - k\varphi_{\boldsymbol{\theta}_0}(\mathbf{x}))$$

will also have zero integral only if τ' satisfies 4.8 except perhaps a set A with $\int_A \varphi_{\boldsymbol{\theta}_1}(\mathbf{x})d\mathbf{x} = 0$ □

The following examples are given in Landenna *et al.* (1998), p. 327–.

Example 2. *As a first application of the Neyman-Pearson's theorem, consider a continuous r.v. X such that:*

$$\varphi(x;\theta) = \theta e^{-\theta x} \quad x > 0 \quad \theta > 0$$

The following problem is given:

$$H_0 : \theta = 1 \qquad H_1 : \theta = 2$$

The values of α and n are fixed. First, we derive the likelihood ratio:

$$\lambda = \frac{L(x;2)}{L(x;1)} = \frac{\prod_{i=1}^{n} 2\cdot e^{-2x_i}}{\prod_{i=1}^{n} e^{-x_i}} = \frac{2^n \cdot e^{-2\sum_{i=1}^{n} x_i}}{e^{-\sum_{i=1}^{n} x_i}} = 2^n \cdot e^{-\sum_{i=1}^{n} x_i}$$

Applying the Neyman-Pearson's Lemma, the test function $\tau(\mathbf{x})$ is given by:

$$\tau(\mathbf{x}) = \begin{cases} 1 & 2^n \cdot e^{-\sum_{i=1}^{n} x_i} \geq k \\ 0 & elsewhere \end{cases}$$

$$\tau(\mathbf{x}) = \begin{cases} 1 & \sum_{i=1}^{n} x_i \leq ln\frac{2^n}{k} \\ 0 & elsewhere \end{cases}$$

where k is such that:

$$\mathbb{E}_{\theta_0}[\tau(x)] = \pi(1) = P\Big[\sum_{i=1}^{n} X_i \leq ln\frac{2^n}{k}|\theta = 1\Big] = \alpha$$

Since $X \sim Ga(1,\theta)$, for the summation property of the Gamma distribution, it follows: $Y = \sum_{i=1}^{n} X_i \sim Ga(n,\theta)$.

Under H_0:

$$\varphi(y|\theta = 1) = \frac{1}{\Gamma(n)} \cdot e^{-y} \cdot y^{n-1} \qquad y > 0$$

If we now consider the transformation of r.v. $W = 2Y$, $dw = 2dy$, it follows:

$$\begin{aligned} \eta(w|\theta = 1) &= \frac{1}{\Gamma(n)} \cdot e^{-1/2w} \cdot \left(\frac{1}{2}\right)^{n-1} \cdot 2 \cdot w^{n-1} \qquad w > 0 \\ &= \frac{1}{\Gamma(n)} \cdot e^{-1/2w} \cdot \left(\frac{1}{2}\right)^{n} \cdot w^{n-1} \qquad w > 0 \end{aligned}$$

that is the density function of a χ^2_{2n}. Hence:

$$P\left[Y \leq ln\frac{2^n}{k}\right] = P\left[2Y \leq 2ln\frac{2^n}{k}\right] = P\left[\chi^2_{2n} \leq 2ln\frac{2^n}{k}\right] = \alpha$$

Indicating with χ^2_α the α-order quantile of the r.v. χ^2_{2n}, the Neyman-Pearson's most powerful test has critical region:

$$\Omega_1 = \{y = \sum_{i=1}^{n} x_i : y \leq 1/2\chi^2_\alpha\}$$

and power function:

$$\pi(\theta) = \int_0^{1/2\chi^2_\alpha} \varphi(y|\theta)dy \qquad \theta = 1,2$$

where $\varphi(y|\theta)$ indicates the density function of a Gamma r.v. (n, θ).

We can now obtain a value for k, by fixing $n = 1$, $\alpha = 0.05$:

$$\chi^2_\alpha = 2ln\frac{2^n}{k}$$
$$k = 2^n \cdot e^{-1/2\chi^2_\alpha}$$

and we obtain $k = 4.506$.

Note that the Neyman-Pearson's Lemma does not require that the hypotheses are identified by the same functional form. The only condition on the distributions that has to be satisfied is that the functional form must be *known*, so that the likelihood functions can be calculated. This concept is illustrated by the following example (Landenna *et al.* (1998), p. 331).

Example 3. *Let X be an unknown distribution function and consider the following hypotheses:*

$$H_0: \quad \varphi_0(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \qquad -\infty < x < \infty$$
$$H_1: \quad \varphi_1(x) = \frac{1}{\pi(1+x^2)} \qquad -\infty < x < \infty$$

for which $\varphi_0(x)$ is a $\mathcal{N}(0,1)$ and $\varphi_1(x)$ is a Cauchy random variable. In order to compare the previous hypotheses, a sample such that $n = 1$ is drawn. The likelihood ratio is calculated as:

$$\frac{L(x, \varphi_1(x))}{L(x, \varphi_0(x))} = \frac{1}{\pi(1+x^2)} \cdot \frac{\sqrt{2\pi}}{e^{-\frac{x^2}{2}}} = \sqrt{\frac{2}{\pi}} \cdot \frac{e^{\frac{x^2}{2}}}{(1+x^2)}$$

and, applying the Neyman-Pearson's Lemma, the non-randomized most powerful test is given by:

$$\tau(\mathbf{x}) = \begin{cases} 1 & \lambda = \sqrt{\frac{2}{\pi}} \cdot \frac{e^{\frac{x^2}{2}}}{(1+x^2)} \geq k \\ 0 & elsewhere \end{cases}$$

Note now that λ is a monotonically increasing function of $|x|$, for which:

$$\tau(\mathbf{x}) = \begin{cases} 1 & |x| \geq k_1 \\ 0 & |x| < k_1 \end{cases}$$

and k_1 is such that $\mathbb{E}_{\varphi_0}[\tau(\mathbf{x})] = \alpha$, i.e.:

$$\int_{-k_1}^{k_1} \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{x^2}{2}} dx = 1 - \alpha$$

and it follows that $k_1 = z_{1-\frac{\alpha}{2}}$ *so that the power function is given by:*

$$\mathbb{E}_{\varphi_1}[\tau(\mathbf{x})] = 1 - \int_{z_{\frac{\alpha}{2}}}^{z_{1-\frac{\alpha}{2}}} \frac{1}{\pi(1+x^2)} dx = 1 - \frac{2}{\pi} arctan(z_{1-\frac{\alpha}{2}})$$

For the Neyman-Pearson's test, in the particular case for which the domain of the random variable X does not depend on the unknown parameter values, the following corollary holds.

Corollary 1. *The Neyman-Pearson's test is unique, as the constant k for which it holds is unique.*

Proof. Suppose, in the continuous case, there exist more than one positive value satisfying:

$$\tau(\mathbf{x}) = \begin{cases} 1 & \text{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) > c_0 \varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \\ \frac{\alpha - \alpha(c_0)}{\alpha(c_0 - 0) - \alpha(c_0)} & \text{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) = c_0 \varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \\ 0 & \text{when} \quad \varphi_{\boldsymbol{\theta}_1}(\mathbf{x}) < c_0 \varphi_{\boldsymbol{\theta}_0}(\mathbf{x}) \end{cases}$$

and:

$$\mathbb{E}_{\boldsymbol{\theta}_0}[\tau(\mathbf{x})] = \alpha$$

Suppose there exists a set of values (k', k'') for which $\alpha(k) = \alpha$. Consider the following set:

$$A = \left\{ \mathbf{x} : L(\mathbf{x}, \boldsymbol{\theta}_0) > 0, k' < \frac{L(\mathbf{x}, \boldsymbol{\theta}_1)}{L(\mathbf{x}, \boldsymbol{\theta}_0)} < k'' \right\}$$

it follows:

$$P_{\theta_0}(A) = \underset{\epsilon \to 0^+}{lim} [\alpha(k') - \alpha(k'' - \epsilon)] = 0$$

But, since in these points $L(\mathbf{x}, \boldsymbol{\theta}_0 > 0)$, it follows that the measure of the set A is null, and therefore $P_{\boldsymbol{\theta}_1}(A) = 0$. □

As it was mentioned, the previous Corollary does not hold in the case the domain of the r.v. X depends on the parameter values. This is illustrated by the following example:

Example 4. *Let* $(x_1, ..., x_n)$ *be a sample drawn from a r.v. with probability density function:*

$$\varphi(x;\theta) = \begin{cases} 1/\theta & 0 \le x \le \theta \\ 0 & elsewhere \end{cases}$$

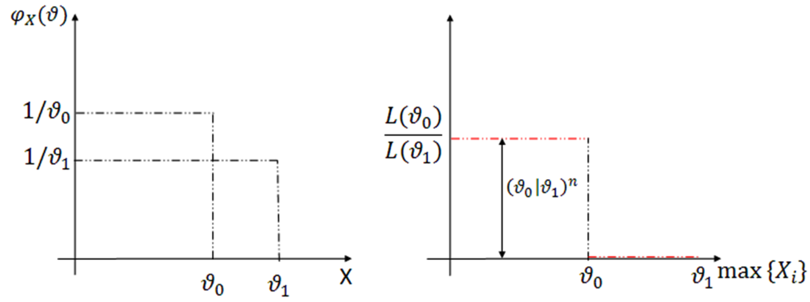

Figure 4.4: Pdfs under the null and alternative hypotheses (on the left), and likelihood ratio given the observed sample (on the right).

The following simple hypotheses are compared:

$$H_0 : \theta = \theta_0 > 0$$
$$H_1 : \theta = \theta_1 > \theta_0$$

The likelihood function is given by:

$$L(\theta) = \begin{cases} (1/\theta)^n & \text{if } max\{X_i\} \le \theta \\ 0 & \text{if } max\{X_i\} > \theta \end{cases}$$

In order to apply the Neyman-Pearson's Lemma, the likelihood ratio is calculated:

$$\frac{L(\theta_0)}{L(\theta_1)} = \frac{(1/\theta_0)^n}{(1/\theta_1)^n} = \begin{cases} (\theta_1/\theta_0)^n & \text{if } 0 \le max\{X_i\} \le \theta_0 \\ 0 & \text{if } \theta_0 < max\{X_i\} \le \theta_1 \end{cases}$$

If $\theta_0 < max\{X_i\} \le \theta_1$, the sample cannot be drawn from a distribution such as $\theta = \theta_0$ (i.e. H_0 is not true, see Figure 4.4).

So the set B such that:

$$B = \left\{ (x_1, ..., x_n) : \theta_0 < max\{X_i\} \le \theta_1 \;\; i.e. \; \frac{L(\theta_0)}{L(\theta_1)} = 0 \right\}$$

is part of the critical region. Since $P\{B|H_0\} = 0$, the set B cannot be the only set that defines the critical region, as $\alpha > 0$.

In the following, we'll show that, in this specific case, there exist two disjoint subregions B' and B'' that both satisfy the Neyman-Pearson's Lemma, but that are equivalent in terms of power.

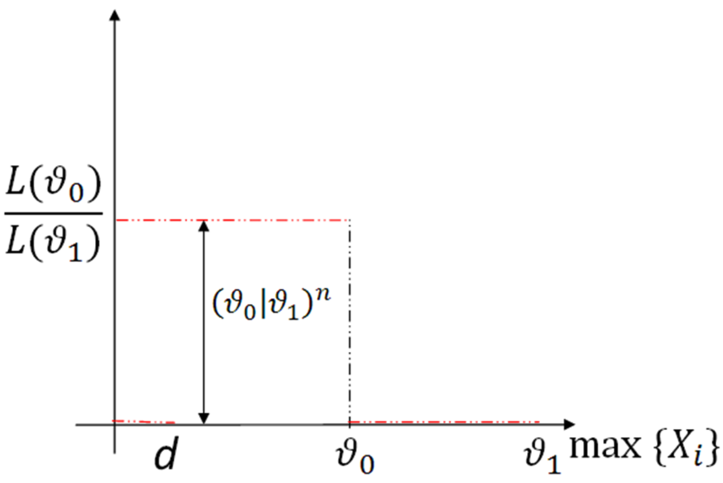

Figure 4.5: Critical region determined by the set B'.

B' is defined as (see Figure 4.5):

$$B' = \left\{ (x_1, ..., x_n) : 0 < max\{X_i\} < d \text{ i.e. } \frac{L(\theta_0)}{L(\theta_1)} = \left(\frac{\theta_1}{\theta_0}\right)^n \right\}$$

The critical region is $C = B \cup B'$ and, as B and B' are disjoint, the probability of reject of H_0 given θ_0 is given by:

$$P\{C|H_0\} = P\{0 \leq max\{X_i\} \leq d|\theta_0\} + P\{\theta_0 \leq max\{X_i\} \leq \theta_1|\theta_0\}$$

and:

$$P\{\theta_0 \leq max\{X_i\} \leq \theta_1|\theta_0\} = 0$$

$$P\{0 \leq max\{X_i\} \leq d|\theta_0\} = P\{0 \leq X_i \leq d|\theta_0\} \cdot ... \cdot P\{0 \leq X_n \leq d|\theta_0\} = \left(\frac{d}{\theta}\right)^n$$

By defining a test of size α, we obtain:

$$\alpha = \left(\frac{d}{\theta_0}\right)^n \qquad \alpha^{1/n} = \frac{d}{\theta_0} \qquad d = \theta_0 \cdot \alpha^{1/n}$$

The power of the test is given by:

$$\pi(\theta_1) = P\{0 \leq max\{X_i\} \leq d|\theta_1\} + P\{\theta_0 \leq max\{X_i\} \leq \theta_1|\theta_1\}$$

$$P\{0 \leq max\{X_i\} \leq d|\theta_1\} = \left(\frac{d}{\theta_1}\right)^n$$

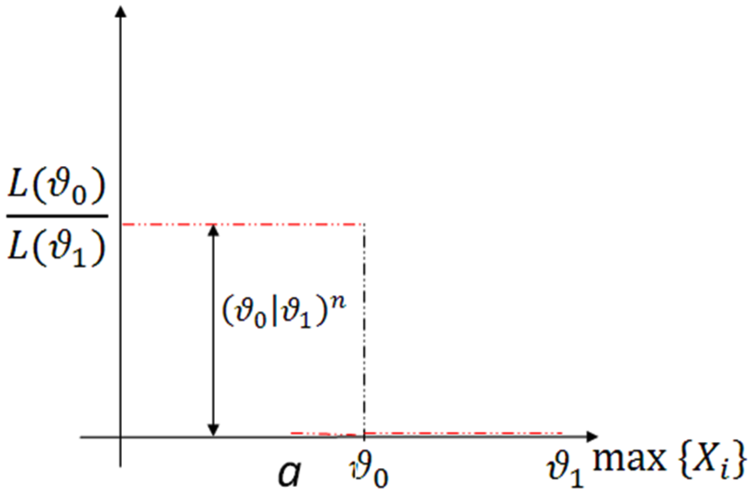

Figure 4.6: Critical region determined by the set B''.

$$P\{\theta_0 \le max\{X_i\} \le \theta_1|\theta_1\} = 1 - \left(\frac{\theta_0}{\theta_1}\right)^n$$

$$\pi(\theta_1) = \left(\frac{d}{\theta_1}\right)^n + \left[1 - \left(\frac{\theta_0}{\theta_1}\right)^n\right]$$

And, by substituting $d = \theta_0 \cdot \alpha^{1/n}$*:*

$$\pi(\theta_1) = \left(\frac{\theta_0 \cdot \alpha^{1/n}}{\theta_1}\right)^n + \left[1 - \left(\frac{\theta_0}{\theta_1}\right)^n\right]$$

$$= \alpha \cdot \left(\frac{\theta_0}{\theta_1}\right)^n + 1 - \left(\frac{\theta_0}{\theta_1}\right)^n = 1 - \left(\frac{\theta_0}{\theta_1}\right)^n \cdot (1 - \alpha)$$

and the probability of a second type error β *is:*

$$\beta = (1 - \alpha)\left(\frac{\theta_0}{\theta_1}\right)^n = \left(\frac{\theta_0}{\theta_1}\right)^n - \alpha\left(\frac{\theta_0}{\theta_1}\right)^n$$

Consider now another region B'' *(see Figure 4.6):*

$$B'' = \{(x_1, ..., x_n) : a \le max\{X_i\} \le \theta_0\}$$

The critical region is given by:

$$C = \{(x_1, ..., x_n) : a \le max\{X_i\} \le \theta_0\} \cup \{(x_1, ..., x_n) : \theta_0 \le max\{X_i\} \le \theta_1\}$$

Hence:

$$P(C|H_0) = P\{(x_1, ..., x_n) : a \le max\{X_i\} \le \theta_0|\theta_0\} + P\{(x_1, ..., x_n) : \theta_0 \le max\{X_i\} \le \theta_1|\theta_0\}$$

$$P\{(x_1,...,x_n) : \theta_0 \le max\{X_i\} \le \theta_1 | H_0\} = 0$$
$$P\{(x_1,...,x_n) : a \le max\{X_i\} \le \theta_0 | \theta_0\} = 1 - \left(\frac{a}{\theta_0}\right)^n$$

and:

$$1 - \alpha = \left(\frac{a}{\theta_0}\right)^n \longleftrightarrow (1-\alpha)^{1/n} = \frac{a}{\theta_0} \longleftrightarrow a = \theta_0(1-\alpha)^{1/n}$$

The power of the test is given by:

$$\begin{aligned}\pi(\theta_1) &= P\{(x_1,...,x_n) : a \le max\{X_i\} \le \theta_0 | \theta_1\} \\ &\quad + P\{(x_1,...,x_n) : \theta_0 \le max\{X_i\} \le \theta_1 | \theta_1\} \\ &= P\{(x_1,...,x_n) : a \le max\{X_i\} \le \theta_1 | \theta_1\} = 1 - \left(\frac{a}{\theta_1}\right)^n\end{aligned}$$

And, by substituting $a = \theta_0(1-\alpha)^{1/n}$:

$$\pi(\theta_1) = 1 - \left(\frac{\theta_0(1-\alpha)^{1/n}}{\theta - 1}\right)^n = 1 - (1-\alpha)\left(\frac{\theta_0}{\theta_1}\right)^n$$

that is equivalent to the power that can be achieved with the region B'.

Consider now the following theorem, associating the notion of sufficient statistic to the construction of a statistical test.

Theorem 4. *Let X be a random variable with distribution function $\varphi(x;\boldsymbol{\theta})$ depending from an unknown vector of parameters $\boldsymbol{\theta}$ and let $S = s(X_1,...,X_n)$ be a sufficient statistic for $\boldsymbol{\theta}$. It follows that for each test function $\tau(x)$:*

$$\tau : \mathbb{X}^n \to [0,1]$$

defined on $\mathcal{X}$, there exists a test function $\tau'(s)$ defined on $\mathcal{S}$ such that:

$$\pi_\tau(\boldsymbol{\theta}) = \pi_{\tau'}(\boldsymbol{\theta}) \qquad \text{for all } \boldsymbol{\theta} \in \boldsymbol{\Theta}$$

Proof. For sufficiency, it follows that each function of X conditioned to $S = s$ is independent of $\boldsymbol{\theta}$. Therefore:

$$\tau'(s) = \mathbb{E}[\tau(X)|S = s]$$

is independent of $\boldsymbol{\theta}$. Since $0 \le \mathbb{E}[\tau(x)|S = s] \le 1$, $\tau'(s)$ is a test function, rejecting H_0 with probability $\tau'(s)$, if $S = s$. By the properties of the conditioned expected value, it follows:

$$\begin{aligned}\pi_{\tau'}(\boldsymbol{\theta}) &= \mathbb{E}_{\boldsymbol{\theta}}[\tau'(s)] = \\ &= \mathbb{E}_{\boldsymbol{\theta}}[\mathbb{E}[\tau(x)|S = s]] \\ &= \mathbb{E}_{\boldsymbol{\theta}}[\tau(x)] = \pi_\tau(x)\end{aligned}$$

that is the power function of $\tau(x)$. □

Sufficiency leads to reduct the dimension of the sample space with no loss of information about $\boldsymbol{\theta} = (\theta_1, ..., \theta_n)$. This implies that, if there exists a sufficient statistic for the unknown parameter vector, the research of an optimal test can be narrowed to the test built on such a sufficient statistic.

Theorem 5. *If $S = s(X_1, ..., X_n)$ is a sufficient statistic for θ and τ^s and τ are the LRT statistics based on S and $\boldsymbol{X}$, respectively, then $\tau^s = \tau$ for every $\boldsymbol{x}$ in the sample space.*

Proof. From the Factorization Theorem, the pdf of $\mathbf{X}$ can be written as:

$$f(\mathbf{x}|\theta) = g(S(\mathbf{x})|\theta)h(\mathbf{x})$$

where $g(s|\theta)$ is the pdf of S and $h(\mathbf{x})$ does not depend on θ. Thus:

$$\begin{aligned}\tau &= \frac{\sup_{\Theta_0} L(\theta|\mathbf{x})}{\sup_{\Theta} L(\theta|\mathbf{x})} = \frac{\sup_{\Theta_0} f(\mathbf{x}|\theta)}{\sup_{\Theta} f(\mathbf{x}|\theta)}\\ &= \frac{\sup_{\Theta_0} g(S(\mathbf{x}|\theta))}{\sup_{\Theta} g(S(\mathbf{x})|\theta)} = \frac{\sup_{\Theta_0} L^s(\theta|S(\mathbf{x}))}{\sup_{\Theta} L^s(\theta|S(\mathbf{x}))}\\ &= \tau^s\end{aligned}$$

□

Let now $H = \{\varphi_{\boldsymbol{\theta}}, \theta \in \boldsymbol{\Theta}\}$ be an uniparametrical model and let the parametrical space $\Theta \subseteq \mathfrak{R}$ be an interval containing θ_0 and θ_1 and $\theta_0 < \theta_1$. Consider the likelihood ratio:

$$\frac{\varphi(X_1, ..., X_n; \theta_1)}{\varphi(X_1, ..., X_n; \theta_0)}$$

as a strictly increasing function of the 1-dimensional statistic:

$$T = t(X_1, ..., X_n) \tag{4.12}$$

with domain the real interval $\mathbb{T}$.
The Neyman-Pearson's test in order to test the hypotheses:

$$H_{\theta_0} = \{\varphi_{\theta_0}\} \qquad vs \qquad H_{\theta_1} = \{\varphi_{\theta_1}\} \tag{4.13}$$

is given by:

$$\begin{aligned}\tau_{\theta_0,\theta_1} &: \mathbb{T} \to [0,1]\\ &: t = \begin{cases} 1 & \text{when} \quad t > c\\ \gamma(x) & \text{when} \quad t = c\\ 0 & \text{when} \quad t < c\end{cases}\end{aligned}$$

with constants c and γ determined by the α-similarity condition: $\pi_{\theta_0,\theta_1}(\theta_0) = \alpha$.

Consider now the unidirectional hypotheses:

$$H_0 = \{\varphi_\theta : \theta \leq \theta_0\} \qquad \text{vs} \qquad H_1 = \{\varphi_\theta : \theta > \theta_1\}$$

including the simple hypotheses in 4.13. If the statistic 4.12 is an increasing function of T for all $\theta_1 > \theta_0$, we have:

$$\forall \theta_1 \in \Theta_1 \qquad \tau_{\theta_0,\theta_1} = \tau_{\theta_0}$$

and τ_{θ_0} is uniformly most powerful at level α for H_0 vs each H_1. This concept is formalized by the following theorem and lemma:

Theorem 6. *Suppose that the distribution of X is in a parametric family $\mathcal{P}$ indexed by a real-valued parameter θ and that $\mathcal{P}$ has a monotone likelihood ratio in $Y(X)$. Consider the problem of testing $H_0 : \theta \leq \theta_0$ vs $H_1 : \theta > \theta_0$, where θ_0 is a given constant.*

- *There exists a UMP test of size α, which is given by:*

$$\tau_*(Y) = \begin{cases} 1 & Y(X) > c \\ \gamma & Y(X) = c \\ 0 & Y(X) < c \end{cases} \tag{4.14}$$

  where c and γ are determined by $\pi_{\tau_*}(\theta_0) = \alpha$ and $\pi_\tau(\theta)$ is the power function of a test τ.

- *The power function $\pi_{\tau_*}(\theta)$ is strictly increasing for all θ's for which $0 < \pi_{\tau_*}(\theta) < 1$.*

- *For any $\theta < \theta_0$, τ_* minimizes $\pi_\tau(\theta)$ (the type I error probability of τ) among all tests τ satisfying $\pi_\tau(\theta_0) = \alpha$.*

- *For any θ_1, τ_* is UMP for testing $H_0 : \theta \leq \theta_1$ vs $H_1 : \theta > \theta_1$ with size $\pi_{\tau_*}(\theta_1)$.*

Lemma 1. *Suppose that there is a test τ_* of size α such that for every $P_1 \in \mathcal{P}_1$, τ_* is UMP for testing H_0 vs the hypothesis $P = P_1$. Then τ_* is UMP for testing H_0 vs H_1.*

Let now a parametrical model H be represented by a canonical uniparametrical exponential family:

$$\varphi_\theta(x_i) = exp[\theta B(x_i) - C(\theta)]D(x_i)$$

so that:

$$\begin{aligned}\varphi(\mathbf{x};\theta) &= \prod_{i=1}^{n} \varphi_\theta(x_i) \\ &= \exp[\theta \sum_{i=1}^{n} B(x_i) - nC(\theta)] \prod_{i=1}^{n} D(x_i)\end{aligned}$$

Let $t(x) = \sum_{i=1}^{n} B(x_i)$; we can conclude that, $\forall\theta \in \Theta$, $\forall\theta' > \theta$,

$$\frac{\varphi(\mathbf{x};\theta')}{\varphi(\mathbf{x};\theta)} = \{(\theta' - \theta)t(\mathbf{x}) - n[c(\theta') - c(\theta)]\}$$

is a strictly increasing function in $t(x)$ so that Theorem 6 applies.

Consider now a 1-dimensional parameter θ and the problem of finding an optimal test for the following system of hypotheses:

$$H_0 : \theta \in \Theta_0 \qquad H_{\theta_1} : \theta = \theta_1 \tag{4.15}$$

H_0 can be summed up by a simple functional hypothesis H_λ and the Neyman-Pearson's Lemma can be applied in order to construct the level α most powerful test for H_λ vs H_{θ_1}. In this view, the pdf defining H_λ is computed as a mixture of the pdfs under H_0, assigning a distribution λ on Θ_0 called *least favorable distribution*, for which the power of τ_{λ,θ_1} is minimum. This is what is expressed by the following Lehmann & Stein's theorem.

Theorem 7. *Let a σ-field be defined over ω such that the densities $\varphi_\theta(x)$ are jointly measurable in θ and x. Suppose over this σ-field there exists a probability distribution Λ such that the most powerful level α test τ_λ for testing H_λ against H_{θ_1} is of size $\leq \alpha$ also with respect to the original hypothesis H_0.*

- *The test τ_λ is most powerful for testing H_0 against H_{θ_1};*
- *If τ_λ is the unique most powerful level α test for comparing H_λ against H_{θ_1}, it is also the unique most powerful test of H_0 against H_{θ_1};*
- *The distribution Λ is least favorable.*

Observation 8. *If the Neyman-Pearson's test τ_{λ,θ_1} preserves a level α on the original hypothesis H_0, it is most powerful at level α for H_0 vs H_{θ_1} and λ is least favorable.*

Corollary 2. *Suppose that Λ is a probability distribution over ω and that ω' is a subset of ω with $\Lambda(\omega') = 1$. Let τ_λ be a test such that:*

$$\tau_\lambda(x) = \begin{cases} 1 & when \quad \varphi_{\theta_1}(x) > k\varphi_{\theta_0}(x) \\ \gamma(x) & when \quad \varphi_{\theta_1}(x) = k\varphi_{\theta_0}(x) \\ 0 & when \quad \varphi_{\theta_1}(x) < k\varphi_{\theta_0}(x) \end{cases} \tag{4.16}$$

Then τ_λ is a most powerful α-level test for comparing H_{θ_0} against H_{θ_1}.

Observation 9. *If the Lehmann and Stein's Theorem is applied to the Neyman-Pearson's τ_{θ_0,θ_1} test, for:*

$$H_{\theta_0} : \theta = \theta_0 \qquad vs \qquad H_{\theta_1} : \theta = \theta_1 \qquad \theta_0 \in \Theta_0 \tag{4.17}$$

and if τ_{θ_0,θ_1} has a level α on H_0, it is most powerful at level α for H_0 vs H_{θ_1} and $\theta = \theta_0$ identifies a least favorable distribution.

The Lehmann and Stein's theorem allows us to find a general solution for the search of an optimal test in the case of composite hypotheses. If an optimal solution does not exist, we can look for a *suboptimal* test, i.e. a constrained optimal test. We will impose a reasonable restriction on the tests to be considered and we will look for an optimal test in the class of tests under the restriction. Two types of restrictions are *unbiasedness* and *invariance*; in this context we can narrow our attention to the class of *unbiased tests*.

Consider a random variable X with domain $\mathbb{X} \subseteq \mathfrak{R}$ and pdf belonging to the parametrical model $H = \{\varphi_\theta : \theta \in \Theta\}$. Consider the partition (Θ_0, Θ_1) of the m-dimensional space and the system of hypotheses:

$$H_0 = \{\varphi_\theta : \theta \in \Theta_0\} \qquad H_1 = \{\varphi_\theta : \theta \in \Theta_1\}$$

A test τ is called *unbiased* if the following inequality holds:

$$\forall \theta_1 \in \Theta_1, \qquad \pi_\tau(\theta_1) \geq \alpha$$

A test τ is called *admissible* whether there does not exist a level α test $\tau' \in L_\alpha(H_0)$ such that:

$$\forall \theta_1 \in \Theta_1, \qquad \pi_{\tau'}(\theta_1) \geq \pi_\tau(\theta_1)$$

and

$$\exists \theta_1' \in \Theta_1, \qquad \pi_{\tau'}(\theta_1') > \pi_\tau(\theta')$$

A simple example of unbiased test is given by the *purely random test*:

$$\begin{aligned} \tau_\alpha &: \mathbb{X}^n \to [0,1] \\ &: x \to \alpha \end{aligned}$$

for which the power function is constant:

$$\forall \theta \in \Theta, \pi_{\tau_\alpha} = \mathbb{E}_\theta[\alpha] = \alpha$$

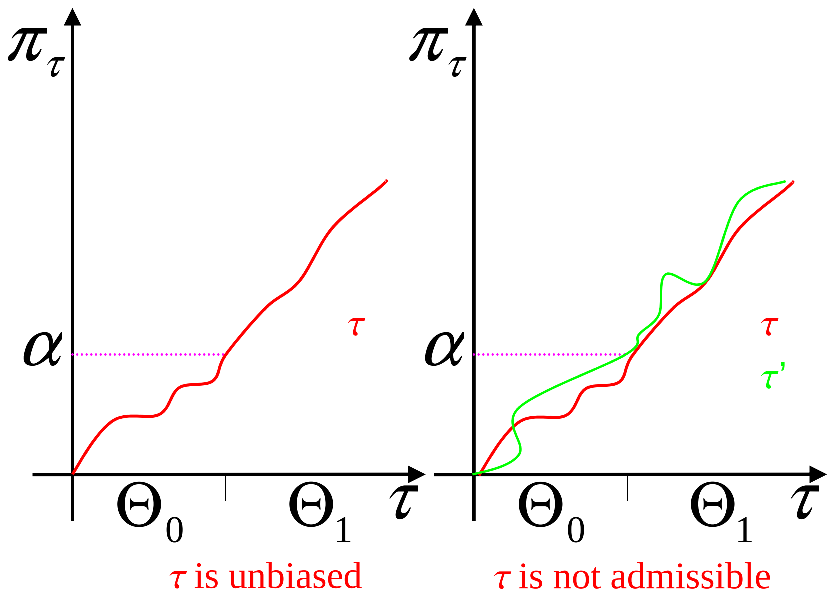

Figure 4.7: Examples of an unbiased and of a not admissible test.

Let U_α be the set of unbiased tests:

$$\begin{aligned} U_\alpha &= \{\tau \in L_\alpha(H_0) : \forall \theta_1 \in \Theta_1, \pi_\tau(\theta_1) \geq \alpha\} \\ &= \{\tau : \forall \theta_0 \in \Theta_0, \pi_\tau(\theta_0) \leq \alpha \leq \pi_\tau(\theta_1)\} \end{aligned}$$

A test is called *uniformly most powerful unbiased (UMPU)* at level α in order to compare a null hypothesis H_0 vs an alternative hypothesis H_1 if:

$$\tau \in U_\alpha$$

and:

$$\forall \tau' \in U_\alpha, \forall \theta_1 \in \Theta_1, \qquad \pi_\tau(\theta_1) \geq \pi_{\tau'}(\theta_1)$$

Observation 10. *If a test is uniformly most powerful (UMP), then it is uniformly most powerful unbiased (UMPU), since its power cannot fall below that of the purely random test* $\tau(x) = \alpha$.

A very important Lemma is now introduced and proved.

Lemma 2. *If a test is uniformly most powerful unbiased (UMPU), then it is admissible.*

Proof. Let τ be a uniformly most powerful unbiased (UMPU) test. Suppose now, there exists another test τ' so that τ is not admissible:

$$\exists \tau' \in L_\alpha(H_0)$$
$$\forall \theta_1 \in \Theta_1, \pi_{\tau'}(\theta_1) \geq \pi_\tau(\theta_1)$$
$$\exists \theta_1' \in \Theta_1, \pi_{\tau'}(\theta_1') > \pi_\tau(\theta_1')$$

It follows that:

$$\tau \in U_\alpha \Rightarrow \forall \theta_1 \in \Theta_1, \pi_\tau(\theta_1) \geq \alpha \Rightarrow \forall \theta_1 \in \Theta_1, \pi_{\tau'}(\theta_1) \geq \alpha$$
$$\Rightarrow \tau' \in U_\alpha \Rightarrow \forall \theta_1 \in \Theta_1, \pi_\tau(\theta_1) \geq \pi_{\tau'}(\theta_1)$$
$$\pi_{\tau'}(\theta_1') > \pi_\tau(\theta_1') \geq \pi_{\tau'}(\theta_1')$$

that is a contradiction. So, the UMPU test τ is admissible. □

Observation 11. *For a large class of problems for which a UMP test does not exist, there does exist a UMP unbiased test. This is the case, in particular, for certain hypotheses such as $\theta \leq \theta_0$ or $\theta = \theta_0$, where the distribution of the random observables depends on other parameters besides θ.*

Let's consider a parametrical model $H = \{\varphi_\theta : \theta \in \Theta\}$ and the hypotheses:

$$H_0 : \theta \in \Theta_0 \quad vs \quad H_1 : \theta \in \Theta_1$$

the set of **boundary $\boldsymbol{\alpha}$-similar** tests is defined as:

$$S_\alpha = \{\tau \in L_\alpha(H_0) : \forall \theta \in \partial\Theta_0, \quad \pi_\tau(\theta) = \alpha\}$$

Theorem 12. *If a test τ has a continuous power function π_τ, then:*

$$\tau \in U_\alpha \Rightarrow \tau \in S_\alpha$$

Proof. Consider $\tau \in L_\alpha(H_0)$ and consider a point θ^* on the boundary:

$$\theta^* \in \partial\Theta_0 \qquad \partial\Theta_0 = \bar{\Theta}_0 \cap \bar{\Theta}_1$$

there do exist two sequences : $\{\theta_{0n}\} \subseteq \Theta_0$ and $\{\theta_{1n}\} \subseteq \Theta_1$ for which:

$$\theta_{0n} \to \theta^* \leftarrow \theta_{1n}$$

and so, for the continuity of the power function:

$$\alpha \geq \pi_\tau(\theta_{0n}) \to \pi_\tau(\theta^*) \leftarrow \pi_\tau(\theta_{1n}) \geq \alpha$$

and it follows $\pi_\tau(\theta^*) = \alpha$ □

A test $\tau \in S_\alpha$ is called **α-similar uniformly most powerful** in order to compare H_0 vs H_1, whether:

$$\forall \tau' \in S_\alpha, \quad \forall \theta_1 \in \Theta_1, \quad \pi_\tau(\theta_1) \geq \pi_{\tau'}(\theta_1)$$

Lemma 3. *A α-similar uniformly most powerful test is also UMPU (in the case that all the UMPU tests have continuous power function). Indeed, $U_\alpha \subseteq S_\alpha$.*

Let S be a sufficient statistic for $\theta \in \partial\Theta_0$. The set of tests:

$$NS_\alpha = \{\tau \in L_\alpha(H_0) : \forall \theta \in \partial\Theta_0, \mathbb{E}[\tau(x)|S] = \alpha\} \tag{4.18}$$

is called a **Neyman-structure** test.

Observation 13. *A Neyman-structure test is characterized by the fact that the conditional probability of rejection is α on each of the surfaces $S = s$.*

Observation 14. *$NS_\alpha \subseteq S_\alpha$; indeed, if $\tau \in NS_\alpha$, by definition $\tau \in L_\alpha(H_0)$ and:*

$$\forall \theta \in \partial\Theta_0, \pi_\tau(\theta) = \mathbb{E}_\theta[\tau(x)] = \mathbb{E}_\theta[E[\tau|S]] = \alpha$$

Observation 15. *Since the distribution on each surface is independent of θ for $\theta \in \partial\Theta_0$, the condition 4.18 essentially reduces the problem to that of testing a simple hypothesis for each value of s. Frequently, it is easy to obtain a most powerful test among those having Neyman structure, by solving the optimum problem for each face separately. The resulting test is then most powerful among all similar tests provided each similar test has a Neyman structure.*

We now introduce another important definition. A family $\mathcal{P}$ of probability distributions is said to be **complete** if:

$$\mathbb{E}_p[f(x)] = 0 \qquad \text{for all } p \in \mathcal{P}$$

implies $f(x) = 0$ a.e. $\mathcal{P}$

Let's analyze the following two examples.

Example 5. *Consider n independent trials with probability p of success, and let X_i be either 1 or 0 according to the i-th trial is a success or a failure. Then $T = X_1 + ... + X_n$ is a sufficient statistic for p, and the family of its possible distributions is $\mathcal{P} = \{Bi(n,p), 0 < p < 1\}$. For this family:*

$$\mathbb{E}_p[f(t)] = \sum_{t=0}^{n} f(t)\binom{n}{t}p^t(1-p)^{n-t} = \sum_{t=0}^{n} f(t)\binom{n}{t}(1-p)^n\rho^t$$

where $\rho = \frac{p}{1-p}$. *Hence, this expected value is a polynomial function in* ρ. *This expected value is null if and only if all the polynomial coefficients are fixed at 0. It follows that* $f(t) = 0$, *for* $t = 0, ..., n$ *and the binomial distribution of* T *is complete.*

Example 6. *Let* $X_1, ..., X_n$ *be a sample from the Uniform distribution* $U(0, \theta)$, $0 < \theta < \infty$. *Then* $T = \max\{X_1, ..., X_n\}$ *is a sufficient statistic for* θ. T *is complete if*

$$\mathbb{E}_\theta[f(t)] = 0 \Rightarrow f(t) = 0 \ a.e. \ \mathcal{P}$$

The distribution function of t *can be derived:*

$$\Phi_T(t) = \left[\frac{t}{\theta}\right]^n \qquad 0 \le t \le \theta \qquad \varphi_T(t) = \frac{n}{\theta}\left[\frac{t}{\theta}\right]^{n-1} \qquad 0 \le t \le \theta$$

Following the definition of completeness, the expected value is set to 0:

$$\mathbb{E}_\theta[f(t)] = \int_0^\theta f(t)\frac{n}{\theta}\left[\frac{1}{\theta}\right]^{n-1} t^{n-1} dt = n\theta^{-n}\int_0^\theta f(t)t^{n-1}dt = 0$$

Consider now $f(t) = f^+(t) - f^-(t)$,

$$\mathbb{E}_\theta[f(t)] \propto \int_0^\theta [f^+(t) - f^-(t)]t^{n-1}dt = 0$$

Define now:

$$v^+(A) = \int_A f^+(t)t^{n-1} \qquad v^-(A) = \int_A f^-(t)t^{n-1}dt$$

It follows:

$$v^+(A) = v^-(A) \longleftrightarrow f^+(t) = f^-(t) \longleftrightarrow f(t) = 0$$

Also the slightly weaker property of bounded completeness can be introduced: a family of probability distributions is said to be **boundedly complete** if, for all bounded functions f,

$$\mathbb{E}_p[f(x)] = 0 \qquad \text{for all } P \in \mathcal{P}$$

implies $f(x) = 0$ a.e. $\mathcal{P}$. The following theorem holds:

Theorem 16. *Let* X *be a random variable with distribution* $P \in \mathcal{P}$, *and let* S *be a sufficient statistic for* P. *Then, a necessary and sufficient condition for all similar tests to have Neyman's structure with respect to* S *is that the family* $\mathcal{P}^s$ *of distributions of* S *is boundedly complete.*

Theorem 16 is a fundamental theorem allowing statisticians to identify the Neyman's structure of a similar test by verifying the completeness of a family of distributions. In the following, we define and prove another fundamental theorem (Theorem 18), allowing us to identify an UMPU test in exponential families. The proof of this theorem is quite complicated, and only a draft of such a proof will be given. In order to prove this theorem, other theorems and definitions have now to be introduced.

Theorem 17. *Let $\mathcal{P}$ be a natural exponential family given by:*

$$\tilde{f}_\eta(\omega) = exp\{T(\omega)\eta' - \zeta(\eta)\}h(\omega) \qquad \omega \in \Omega$$

1. *The random vector T has the following pdf in an exponential family dominated by some measure on $(\mathcal{R}^p, \mathcal{B}^p)$:*

   $$exp\{t\eta^t - \zeta(\eta)\}g(t) \qquad t \in \mathcal{R}^p$$

   where g is a nonnegative Borel function;

2. *If η_0 is an interior point of the natural parameter space, then the moment generating function ψ_{η_0} of $\mathcal{P} \circ T^{-1}$ is finite in a neighbourhood of 0 and is given by:*

   $$\psi_{\eta_0}(t) = exp\{\zeta(\eta_0 + t) - \zeta(\eta_0)\}$$

   Furthermore, if f is a Borel function satisfying $\int |f| d\mathcal{P}_{\eta_0} < \infty$, then the function:

   $$\int f(\omega) exp\{T(\omega)\eta'\}h(\omega)d\nu(\omega)$$

   is infinitely often differentiable in a neighborhood of η_0 and the derivatives can be computed under the integral sign.

Proposition 1. *(Generalized Neyman-Pearson's Lemma) Let $f_1, ..., f_{m+1}$ be real-valued functions on $\mathcal{R}^p$ that are integrable with respect to a σ-finite measure ν. For given constants $t_1, ..., t_m$, let T be the class of Borel functions ϕ (from $\mathcal{R}^p$ to $[0,1]$) satisfying:*

$$\int \phi f_i d\nu \le t_i \qquad i = 1, ..., m \tag{4.19}$$

and T_0 be the set of ϕ's in T satisfying 4.19, with all inequalities replaced by equalities. If there are constants $c_1, ..., c_m$ such that:

$$\phi_*(x) = \begin{cases} 1 & f_{m+1}(x) > c_1 f_1(x) + ... + c_m f_m(x) \\ 0 & f_{m+1}(x) < c_1 f_1(x) + ... + c_m f_m(x) \end{cases} \tag{4.20}$$

is a member of T_0, then $\phi_*(x)$ maximizes $\int \phi f_{m+1} d\nu$ over $\phi \in T_0$. If $c_i \ge 0$ for all i, then ϕ_* maximizes $\phi f_{m+1} d\nu$ over $\phi \in T$.

Lemma 4. *Let $f_1, ..., f_m$ and ν given by Proposition . Then the set:*

$$M = \left\{ \int \phi f_1 d\nu, ..., \int \phi f_m d\nu \quad : \phi \text{ is from } \mathcal{R}^p \text{ to } [0,1] \right\}$$

is closed and convex. If $(t_1, ..., t_m)$ is an interior point of M, then there exist constants $c_1, ..., c_m$ such that the function defined in 4.20 is in T_0.

Suppose now that the distribution of a r.v. X belongs to a multiparameter exponential family with the following pdf with respect to a σ-finite measure ν:

$$f_{\theta,\omega}(x) = exp\{\theta YTx) + U(x) - \zeta(\theta, \omega)\} \tag{4.21}$$

where θ is a real-valued parameter, ω is a vector valued parameter, and T (real-valued) and U (vector-valued) are statistics. It can be shown that (Y, U) has the pdf:

$$exp\{\theta t + u\omega' - \zeta(\theta, \omega)\}$$

with respect to some measure and, given $U = u$, the conditional distribution of T has the pdf $exp\{\theta t\}$ with respect to some measure ν_u, which also belongs to a natural exponential family. We now introduce and prove a fundamental theorem (see Shao (1999), p. 358- for details).

Theorem 18. *Suppose that the distribution of X is in a multiparametric exponential family given by 4.35.*

1. *For testing $H_0 : \theta \le \theta_0$ vs $H_1 : \theta > \theta_0$, a UMPU test of size α is:*

$$\tau_*(T, U) = \begin{cases} 1 & T > c(u) \\ \gamma(u) & T = c(u) \\ 0 & T < c(u) \end{cases} \tag{4.22}$$

where $c(u)$ and $\gamma(u)$ are Borel functions determined by:

$$\mathbb{E}_{\theta_0}[\tau_*(T, U) | U = u] = \alpha \tag{4.23}$$

for every u, and $\mathbb{E}_{\theta_0}$ is the expectation with respect to $f_{\theta_0,\omega}$.

2. *For testing two-sided hypotheses:*

$$H_0 : \theta \le \theta_1 \;\; or \;\; \theta \ge \theta_0 \qquad vs \qquad H_1 : \theta_1 < \theta < \theta_2 \tag{4.24}$$

a UMPU test of size α is:

$$\tau_*(T,U) = \begin{cases} 1 & c_1(u) < T < c_2(u) \\ \gamma_i(u) & T = c_i(u),\ i = 1,2 \\ 0 & T < c_1 \ or\ T > c_2 \end{cases} \tag{4.25}$$

where $c_i(u)$'s and $\gamma_i(u)$'s are Borel functions determined by:

$$\mathbb{E}_{\theta_1}[\tau_*(T,U)|U = u] = \alpha \tag{4.26}$$

for every u.

3. *For testing two-sided hypotheses:*

$$H_0 : \theta_1 \leq \theta \leq \theta_2 \qquad vs \qquad H_1 : \theta < \theta_1 \ or\ \theta > \theta_2 \tag{4.27}$$

a UMPU test of size α is:

$$\tau_*(T,U) = \begin{cases} 1 & T < c_1(u) \quad or\ T > c_2(u) \\ \gamma_i(u) & T = c_i(u)\ i{=}1{,}2 \\ 0 & c_1(u) < T < c_2(u) \end{cases} \tag{4.28}$$

4. *For testing hypotheses*

$$H_0 : \theta = \theta_0 \qquad vs \qquad H_1 : \theta \neq \theta_0 \tag{4.29}$$

a UMPU test of size α is given by 4.28, where $c_i(u)$'s and $\gamma_i(i)$'s are Borel functions determined by 4.23 and:

$$\mathbb{E}_{\theta_0}[\tau_*(T,U)|U = u] = \alpha \mathbb{E}_{\theta_0}(T|U = u) \tag{4.30}$$

for every u.

Proof. Since (T,U) is sufficient for (θ,ω), we only need to consider tests that are functions of (T,U). Hypotheses in $1-4$ are in the form:

$$H_0 : \theta \in \Theta_0 \qquad \text{vs} \qquad H_1 : \theta \in \Theta_1$$

with:

$$\bar{\Theta}_{01} = \{(\theta,\omega) : \theta = \theta_0\} \text{ or } \{(\theta,\omega) : \theta = \theta_i, i = 1,2\}$$

In any case, U is sufficient and complete for $P \in \bar{\mathcal{P}}$ and, thus, Theorem 16 applies. By Theorem 17, the power function of all tests are continuous and

Lemma 3, applies. Then for points 1 – 3, we only need to show that τ_* is UMP among all tests τ satisfying 4.23 (for part 1) or 4.26 (for part 2 or 3), with τ_* replaced by τ. For point 4, any unbiased T should satisfy 4.23 with τ_* replaced by τ and:

$$\frac{\partial}{\partial\theta}\mathbb{E}_{\theta,\omega}[\tau(T,U)] = 0 \qquad \theta \in \bar{\Theta}_{01} \tag{4.31}$$

By Theorem 17, the differentiation can be carried out under the expectation sign. Hence, it can be shown that 4.31 is equivalent to:

$$\mathbb{E}_{\theta,\omega}[\tau(T,U)Y - \alpha T] = 0 \qquad \theta \in \bar{\Theta}_{01} \tag{4.32}$$

Using the argument in the proof of Theorem 16 it can be shown that 4.32 is equivalent to 4.30 with τ_* replaced by τ. The power function of any test $\tau(T,U)$ is:

$$\pi_\tau(\theta,\omega) = \int\left[\int \tau(t,u)dP_{T|U=u}(t)\right]dP_U(u)$$

Thus, it suffices to show that, for every fixed u and $\theta \in \Theta_1$, τ_* maximizes:

$$\int \tau(t,u)dP_{T|U=u}(t)$$

over all τ subject to the given side conditions. Since $P_{T|U=u}$ is in a one-parameter exponential family, the results in points 1 and 3 follow from Theorem (see Theorem 6.3, Shao) by considering τ_* with τ_* given by:

$$\tau_*(X) = \begin{cases} 1 & c_1 < T(X) < c_2 \\ \gamma_i & T(X) = c_i \ i = 1,2 \\ 0 & T(X) < c_1 \text{ or } T(X) > c_2 \end{cases} \tag{4.33}$$

To prove the result in point 4, it suffices to show that if f has a pdf given by:

$$f_\theta(x) = exp\{\eta(\theta)T(x) - \xi(\theta)\}h(x) \tag{4.34}$$

and if U is treated as a constant in 4.23, 4.28, 4.30, τ_* in 4.28 is UMP subject to conditions 4.23 and 4.30. We now omit U in the following proof for point 4, which is very similar to the proof of Theorem 6.3 (Shao (1999), p.353).

First, $(\alpha, \alpha\mathbb{E}_{\theta_0}(T))$ is an interior point on the set of points:

$$(\mathbb{E}[\tau(T)], \mathbb{E}[\tau(T)T])$$

as τ ranges over all sets of the form $\tau(T)$. By Lemma 4 and Proposition 1, for testing $\theta = \theta_0$ vs $\theta = \theta_1$, the UMP test is equal to 1 when:

$$(k_1 + k_2 y)e^{\theta_0 y} < C(\theta_0, \theta_1)e^{\theta_1 y} \tag{4.35}$$

where k_i's and $C(\theta_0, \theta_1)$ are constants. Note that 4.35 is equivalent to:

$$\theta_1 + \theta_2 y < e^{bt}$$

for some constants θ_1, θ_2 and b. This region is either one-sided or the outside of an interval.

By Theorem 6, a one-sided test has a strictly monotone power function and therefore cannot satisfy 4.30. Thus, this test must have the form 4.28. Since τ_* in 4.28 does not depend on θ_1, by Lemma 1, it is UMP over all tests satisfying 4.23 and 4.30, in particular the test $\equiv \alpha$. Thus, τ_* is UMPU. Finally, it can be shown that all the $c-$ and $\gamma-$ functions in 1-4 are Borel functions. □

We can further comment this theorem. Consider a parametrical model H represented by a full-rank minimal canonical exponential family:

$$\varphi_{\theta,\omega}(x) = \exp\{\theta A(x) + \sum_{i=1}^{m} \omega_i B_i(x) - C(\theta, \omega_1, ..., \omega_m)\}D(x) \tag{4.36}$$

where the parametrical space contains an open set of R^{m+1} and no linear relationships exist both among $A, B_1, ..., B_m$ and among $\theta, \omega_1, ..., \omega_m$. Let $X_1, ..., X_n$ be i.i.d. r.v. with density function belonging to 4.36. Consider the following statistics:

$$T = \sum_{j=1}^{n} A(X_j)$$
$$U_1 = \sum_{j=1}^{n} B_1(X_j)$$
$$\dots$$
$$U_m = \sum_{j=1}^{n} B_m(X_j)$$

The statistic $S = (T, U_1, ..., U_m)$ is complete and sufficient for the parameter vector $(\theta, \omega_1, ...\omega_m)$. Fix θ and consider the statistic $U = U_1, ..., U_m$, that is sufficient and complete for the nuisance parameters $\omega = (\omega_1, ..., \omega_m)$. Consider now the hypotheses:

$$H_0 : \theta \le \theta_0 \qquad vs \qquad H_1 : \theta > \theta_0$$

The test τ_* defined as:

$$\tau_*(t,u) = \begin{cases} 1 & : t > c(u) \\ \gamma(u) & : t = c(u) \\ 0 & : t < c(u) \end{cases} \tag{4.37}$$

is UMPU at level α whether the functions $c(u)$ and $\gamma(u)$ satisfy:

$$\forall u \in U, E_\theta[\tau_*(T,U)|U = u] = \alpha$$

that is a functional equation in τ_*.

As we've seen, the proof of this theorem is quite complicated, but can be informally summed up as it follows: in the case of a family such as 4.36, the power function of a test τ is continue, and, fixed $\theta > \theta_0$ and ω,

$$\begin{aligned} \pi_\tau(\theta,\omega) &= \mathbb{E}_{\theta,\omega}[\tau(s)] \\ &= \int \int \tau(t,u)\varphi(t,u;\theta,\omega)dtdu \\ &= \int \int \tau(t,u)\varphi(t|u;\theta)\varphi(u;\theta,\omega)dtdu \\ &= \int \Big[\int \tau(t,u)\varphi(t|u;\theta)dt\Big]\varphi(u;\theta,\omega)du \end{aligned}$$

and has a maximum with respect to τ if, for each u, the internal integral is maximized. In conclusion, the UMPU test is the uniformly most powerful test in the class of the Neyman's structure family of tests with respect to the statistic U and such a test is τ_* as $\varphi(t|u;\theta)$ belongs to the exponential family. In this way, the Neyman-Pearson's Lemma can be applied, as $\varphi(t|u;\theta)$ does not depend on the nuisance parameter ω. The basic problem of the test defined in Theorem 18 is that such a test cannot be used unless $c(u)$ and $\gamma(u)$ are determined. This problem can be solved in the case that there exists a statistic $V = h(T,U)$ that is a strictly increasing function of T and independent from U in $\theta = \theta_0$. In this case, the test is equivalent to τ':

$$\tau'(v) = \begin{cases} 1 & : v > c \\ \gamma(u) & : v = c \\ 0 & : v < c \end{cases} \tag{4.38}$$

and γ and c are constants such that:

$$\mathbb{E}_{\theta_0}[\tau'(V)] = \alpha$$

and

$$P_{\theta_0}[V > c(u)|U = u] + \gamma(u)P[V = c(u)|U = u] = \alpha$$

and, since V is independent from U,

$$P_{\theta_0}[V > c(u)] + \gamma(u)P[V = c(u)] = \alpha$$

Theorem 18 can be applied in the case of the Binomial distribution functions to give a UMPU test.

Example 7. *Let X and Y be independent observations from the binomial distribution with sizes n_1 and n_2 and probabilities p_1 and p_2 respectively, where n_i's are known and p_i's are unknown. Let $T = Y$, $U = X + Y$, it can be shown that:*

$$P(T = t|U = u) = K_u(\theta)\binom{n_1}{u-t}\binom{n_2}{t}e^{\theta t}\mathbb{1}_A(t) \quad u = 0, 1, ..., n_1 + n_2$$

where:

$$A = \{t : t = 0, 1, ..., min\{u, n_2\}, u - t \leq n_1\}$$

$$\theta = log\frac{p_2(1-p_1)}{p_1(1-p_2)}$$

and:

$$K_u(\theta) = \left[\sum_{t\in A}\binom{n_1}{u-t}\binom{n_2}{t}e^{\theta t}\right]^{-1}$$

In fact, when $u = 0, 1, ..., n_1 + n_2$ and $t \in A$,

$$P(T = t) = \binom{n_2}{t}p_2^t(1-p_2)^{n_2-t}$$

$$P(X = x, T = t) = \binom{n_1}{x}\binom{n_2}{t}p_1^x(1-p_1)^{n_1-x}p_2^t(1-p_2)^{n_2-t}$$

And, by substituting $X = U - T$:

$$P(T = t, U = u) = \binom{n_1}{u-t}\binom{n_2}{t}p_1^{u-t}(1-p_1)^{n_1-u+t}p_2^t(1-p_2)^{n_2-t}$$

and, integrating out $T = t$,

$$P(U = u) = \sum_{t\in A}\binom{n_1}{u-t}\binom{n_2}{t}p_1^{u-t}(1-p_1)^{n_1-u+t}p_2^y(1-p_2)^{n_2-t}$$

Then, if $t \in A$,

$$P(T = t|U = u) = \frac{P(T = t, U = u)}{P(U = u)}$$
$$= \frac{\binom{n_1}{u-t}\binom{n_2}{t}\left(\frac{1-p_1}{p_1}\right)^t\left(\frac{p_2}{1-p_2}\right)^t}{\sum_{t\in A}\binom{n_1}{u-t}\binom{n_2}{t}\left(\frac{1-p_1}{p_1}\right)^t\left(\frac{p_2}{1-p_2}\right)^t}$$

and it follows:

$$P(T = t|U = u) = K_u(\theta)\binom{n_1}{u-t}\binom{n_2}{t}e^{\theta t}\mathbb{1}_A(t) \quad u = 0, 1, ..., n_1 + n_2$$

We now search for a UMPU test of size α *for testing:*

$$H_0 : p_1 \geq p_2 \qquad vs \qquad H_1 : p_1 < p_2$$

Since $\theta = log\frac{p_2(1-p_1)}{p_1(1-p_2)}$*, the testing problem is equivalent to testing* $H_0 : \theta \leq 0$ *vs* $H_1 : \theta > 0$*. By the previous theorem, the UMPU test is:*

$$\tau_*(T, U) = \begin{cases} 1 & T > c(U) \\ \gamma(U) & T = c(U) \\ 0 & T < c(U) \end{cases}$$

where C and U are functions of U such that $\mathbb{E}[\tau_*|U] = \alpha$ *when* $\theta = 0$ *(i.e.* $p_1 = p_2$*), which can be determined using the conditional distribution of T given U. When* $\theta = 0$*, the conditional distribution is:*

$$P(T = t|U = u) = \binom{n_1 + n_2}{u}^{-1}\binom{n_1}{u-t}\binom{n_2}{t}\mathbb{1}_A(t) \quad u = 0, 1, ..., n_1 + n_2$$

In the previous pages, some of the most important optimality properties of testing statistical hypotheses have been mentioned. Two milestones in this literature are given by the Neyman-Pearson's Lemma for testing simple statistical hypotheses and by the Lehmann and Stein's theorem for testing composite hypotheses. Then, it has been mentioned that, in the case an optimal solution cannot be found, we can narrow our attention to the search of a suboptimal test. Theorem 18 identifies a UMPU test in the case of a multiparameter exponential family and can be applied to the case of the Binomial random variable to give a UMPU (and hence, admissible) test. In the following paragraph, the discussion will be narrowed to a wide class of statistical tests, aimed to compare hypotheses in a 2×2 table. The main references for the next section will be the recent review of Lydersen *et al.* (2009), and the books of Hirji (2006) and Agresti (2002).

		j		
		1	2	Sum
i	1	n_{11}	n_{12}	n_{1+}
	2	n_{21}	n_{22}	n_{2+}
	Sum	n_{+1}	n_{+2}	N

Figure 4.8: The general count of a 2×2 table.

4.3 The analysis of 2×2 tables

In section 4.3.1, we'll first describe three different experimental designs in the analysis of a 2×2 table, that should be independently treated from a theoretical point of view. In the following sections, we'll concentrate our attention on the case of a 2×2 binomial trial and we'll analyze the main test statistics that have been proposed in the literature (§ 4.3.2). These are: the Pearson's chi-squared statistic, the likelihood ratio statistic, the Fisher's statistic, the Leibermeister's statistic, the Lancaster's mid-P statistic, the z-pooled and the z-unpooled statistics. Subsequently, we'll mention several problems with respect to the derivation of the p-values in these cases (§ 4.3.3). Last (§ 4.3.4) we'll propose some relevant results in the power computation and power comparisons of these tests.

4.3.1 Experimental Designs

A first important point to be focused is that a 2×2 table can collect data drawn from three different experimental designs: i) both-margin fixed design; ii) one-margin fixed design; iii) total-number fixed design (see Figure 4.8).

The case of *both-margins fixed design* can be illustrated by the famous example of the *lady tasting a cup of tea* (Fisher (1925)). A woman claims she can taste whether milk or tea was added first to her cup. Consequently, four tea-first and four milk-first cups are presented to her in a randomized order. The woman knows in advance that there are four of each kind of cups and is asked to identify them. Hence, in this experiment, the row sums as well as the column sums are fixed by design (see Figure 4.9).

An example of *one-margin fixed design* is reported in Lydersen *et al.* (2009) and concerns the treatment of children with cardiac arrest (Perondi *et al.* (2004)). The problem considered by these authors is that the attempts to resuscitate a child after cardiac arrest with the administration of an initial dose of epinephrine can be unsuccessful. In particular, it is not clear

	Guess poured first		
Poured first	Milk	Tea	Sum
Milk	3	1	4*
Tea	1	3	4*
Sum	4*	4*	8*

Figure 4.9: Fisher's tea tasting example.

	Survival at 24 h		
Treatment	Yes	No	Sum
High dose	1	33	34*
Standard dose	7	27	34*
Sum	8	60	68*

Figure 4.10: Treatment of children with cardiac arrest. High dose versus standard dose epinephrine Perondi *et al.* (2004).

whether the next dose of epinephrine should be the same dose or a higher dose. In order to analyze this issue more in depth, a prospective, randomized, double-blind trial study has been performed. Outcomes from 68 children either treated with high-dose epinephrine therapy or with standard-dose epinephrine therapy have been considered. High-dose epinephrine therapy represents a rescue therapy for in-hospital cardiac arrest in children, after failure of an initial, standard dose of epinephrine. The outcome measure considered by the authors was survival rate, 24 hours after the arrest (see Figure 4.10). The design underlying this research project is a one-margin fixed design, since only the row sums (i.e. the number of children that have to the receive the standard vs the experimental treatment) are fixed *a priori* by the researchers.

Last, it can be the case that only *the total number N* is fixed by design. Lydersen *et al.* (2009) report the example of the research of Ritland *et al.* (2007). These authors studied the effect of the genotype on eyes' exfoliative syndrome by investigating the influence of the CHRNA4 and APOE genotypes on the development of the syndrome. A sample of 88 healthy adults (aged from 50 to 75 years) genotyped for polymorphisms of APOE and CHRNA4 underwent an eye examination including slit-lamp examination and fundus photography, as well as measurements of visual acuity, refraction, IOP and RNFL thickness at the optic disc by optical coherence tomography. The result of this study are reported in Figure 4.11. This study exemplifies the case of a

	XFS		
	Yes	No	Sum
CHRNA4-CC	0	16	16
CHRNA4-TC/TT	15	57	72
Sum	15	73	88*

Figure 4.11: Effect of Genotype on Eyes' Exofoliative Syndrome, Ritland *et al.* (2007).

total-number fixed design, since only the total number of patients has been fixed before genotype determination and eye examination.

Let's now go back to Figure 4.8; we indicated with **n** the observed table, with n_{1+}, n_{2+} the row sums, with n_{+1}, n_{+2} the column sums and with N the total sum. Consider a testing statistical hypotheses problem in a 2×2 table, in which the null hypothesis of independence is compared with an alternative hypothesis of presence of association between two phenomena.

If both the row sums and the column sums are fixed by design and if the null hypothesis of independence holds, the probability model under which the observed table has to be considered is that of the hypergeometric distribution:

$$P(n_{11} = t | n_{+1}, n_{+2}, n_{1+}, n_{2+}) = \frac{\binom{n_{1+}}{t}\binom{n_{2+}}{n_{+1}-t}}{\binom{N}{n_{+1}}}$$

If only the row margins, i.e. n_{1+} and n_{2+} and $N = n_{1+} + n_{2+}$ are fixed by design, the situation is that of a 2×2 binomial trial, where each trial is characterized by an unknown probability of success that can be respectively indicated with p_1 and p_2. The joint probability distribution of observing the table **n** is given by:

$$P(\mathbf{n}) = \binom{n_{1+}}{n_{11}} p_1^{n_{11}} (1-p_1)^{n_{1+}-n_{11}} \binom{n_{2+}}{n_{21}} p_2^{n_{21}} (1-p_2)^{n_{2+}-n_{21}}$$

Last, in the case only the total N of cases is fixed by design, we have four unknown parameters that are represented by the probability cells p_{11}, p_{21}, p_{12} and p_{21}, so that the probability model to be considered is multinomial:

$$P(\mathbf{n}) = \frac{N!}{n_{11}! n_{12}! n_{21}! n_{22}!} p_{11}^{n_{11}} p_{21}^{n_{21}} p_{12}^{n_{12}} p_{22}^{n_{22}}$$

4.3.2 Test statistics

In this section we briefly review the classical test statistics that are used in the analysis of a 2×2 table. Since the next section, we'll consider how these statistics are applied in order to obtain tests for comparing statistical hypotheses. A test statistic for the analysis of a 2 × 2 table can be defined as a function of the observations, providing a measure of the observed table's compliance with the null hypothesis of no association. Let **n** denote the observed table with marginal sums $\mathbf{n}_+ = (n_{1+}, n_{2+}, n_{+1}, n_{+2})$. In the case of all the margins fixed design, it was shown that the probability that $n_{11} = t$ is given by the hypergeometric distribution, which coincides with the probability of observing the table **n**. This is what is expressed by the Fisher's statistic $T_F = N_{11}$ that considers the number of successes in the first sample as a test statistic and where:

$$P(\mathbf{n}|\mathbf{n}_+) = p(n_{11}; n_{1+}, n_{2+}, n_{+1}, n_{+2}) = \binom{n_{+1}}{n_{11}}\binom{n_{+2}}{n_{1+} - n_{11}}\Big/\binom{N}{n_{1+}}$$

In 1877, Carl Liebermeister (a statistician from the school of Tubingen), proposed to use the same Fisher's statistic: $T_L = T_F = N_{11}$, but with the following probability function:

$$\begin{aligned} P(\mathbf{n}|\mathbf{n}_+) &= p(n_{11}; n_{1+}, n_{2+}, n_{+1}, n_{+2}) \\ &= \binom{n_{+1} + 1}{n_{11}}\binom{n_{+2} + 1}{n_{1+} + 1 - n_{11}}\Big/\binom{N + 2}{n_{1+} + 1} \end{aligned}$$

As we shall see, the Liebermeister's test adjusts the p-values of the Fisher's exact test in order to obtain a less conservative test.

If we now consider a null hypothesis H_0 of no association, the estimated expected counts are:

$$m_{ij} = n_{i+}n_{j+}/N$$

The *Pearson's chi-squared* test statistic T_{Pe} is given by:

$$T_{Pe}(\mathbf{n}) = \sum_{i,j} \frac{(n_{ij} - m_{ij})^2}{m_{ij}} = \frac{N(n_{11}n_{22} - n_{12}n_{21})}{n_{1+}n_{2+}n_{+1}n_{+2}}$$

As it is commonly known, the Pearson's statistic is one of the most used statistics in the applications in a lot of fields, as well as the *likelihood ratio* statistic T_{LR}:

$$T_{LR}(\mathbf{n}) = -2log\frac{L_0}{L_1} = 2\sum_{i,j} n_{i,j} log\left(\frac{n_{ij}}{m_{ij}}\right)$$

Furthermore, in the case of one margin fixed design, a common test statistic is given by the normalized difference between the observed proportions, z-pooled and z-unpooled. Let $X \sim Bi(n_1, p_1)$ and let $Y \sim Bi(n_2, p_2)$; two estimators for p_1 and p_2 are given by:

$$\hat{p}_1 = \frac{x}{n_1} \qquad \hat{p}_2 = \frac{y}{n_2}$$

where x indicates the number of successes in the sample of size n_1 drawn from X whereas y indicates the number of successes in a sample of size n_2 drawn from Y. It follows:

$$\mathbb{E}[\hat{p}_1] = \frac{1}{n_1}\mathbb{E}[X] = \frac{1}{n_1}n_1 p_1 = p_1$$

$$\mathbb{V}[\hat{p}_1] = \frac{1}{{n_1}^2}\mathbb{V}[X] = \frac{1}{{n_1}^2}n_1 p_1(1-p_1) = \frac{p_1(1-p_1)}{n_1}$$

and

$$\mathbb{E}[\hat{p}_2] = \frac{1}{n_2}\mathbb{E}[Y] = \frac{1}{n_2}n_2 p_2 = p_2$$

$$\mathbb{V}[\hat{p}_2] = \frac{1}{{n_2}^2}\mathbb{V}[Y] = \frac{1}{{n_2}^2}n_2 p_2(1-p_2) = \frac{p_2(1-p_2)}{n_2}$$

Consider now a null hypothesis $H_0 : p_1 = p_2 \leftrightarrow p_2 - p_1 = 0$. An estimator for $(p_2 - p_1)$ is given by: $\hat{p_2} - \hat{p_1} = \frac{y}{n_2} - \frac{x}{n_1}$. It follows:

$$\mathbb{E}[\hat{p}_2 - \hat{p}_1] = p_2 - p_1$$

$$\begin{aligned}\mathbb{V}[\hat{p}_2 - \hat{p}_1] &= \mathbb{V}[\hat{p}_1] + \mathbb{V}[\hat{p}_2] - 2Cov(\hat{p}_1, \hat{p}_2) \\ &= \frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}\end{aligned}$$

Hence, the standardized estimator for risk differences is given by:

$$\frac{(\hat{p}_2 - \hat{p}_1) - (p_2 - p_1)}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}}$$

that, under H_0, becomes:

$$\frac{\hat{p}_2 - \hat{p}_1}{\sqrt{\frac{p_1(1-p_1)}{n_1} + \frac{p_2(1-p_2)}{n_2}}}$$

There are two ways to estimate the variance at the denominator of the ratio:

1. Unpooled variance estimator:

$$\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}$$

2. Pooled variance estimator:

$$\hat{p}(1-\hat{p})\left(\frac{1}{n_1}+\frac{1}{n_2}\right)$$

where $\hat{p} = \frac{(x+y)}{n_1+n_2}$. It follows that the z-unpooled statistic (Wald's) is given by:

$$\begin{aligned} z - unpooled &= \frac{\hat{p}_2 - \hat{p}_1}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{n_1} + \frac{\hat{p}_2(1-\hat{p}_2)}{n_2}}} \\ &= \frac{\frac{n_{21}}{n_{2+}} - \frac{n_{11}}{n_{1+}}}{\sqrt{\frac{\frac{n_{11}}{n_{1+}}(1-\frac{n_{11}}{n_{1+}})}{n_{1+}} + \frac{\frac{n_{22}}{n_{2+}}(1-\frac{n_{22}}{n_{2+}})}{n_{2+}}}} \\ &= \frac{\frac{n_{21}}{n_{2+}} - \frac{n_{11}}{n_{1+}}}{\sqrt{\frac{n_{11}n_{12}}{n_{1+}^3} + \frac{n_{21}n_{22}}{n_{2+}^3}}} \end{aligned}$$

and z-pooled (score) is given by:

$$\begin{aligned} z - pooled &= \frac{(\hat{p}_2 - \hat{p}_1)}{\sqrt{\hat{p}(1-\hat{p})\frac{n_1+n_2}{n_1 n_2}}} \\ &= \frac{\frac{n_{21}}{n_{2+}} - \frac{n_{21}}{n_{2+}}}{\sqrt{\frac{n_{1+}}{N} \cdot \frac{n_{2+}}{N}(\frac{1}{n_{1+}} + \frac{1}{n_{2+}})}} \end{aligned}$$

4.3.3 Defining and Computing the p-value

A p-value can be defined as the probability of the test statistic T being equal to or more extreme than its value for the observed table (t_{obs}) under the null hypothesis:

$$p - value = P(T \geq t_{obs}|H_0)$$

In general, H_0 is rejected if the p-value does not exceed α, the nominal significance level, fixed *a priori* by the researcher. The calculated p-value depends on the design of the study, as well as on the value(s) of the unknown parameter(s), or nuisance parameter(s), under H_0. Note that in a one-margin fixed design on a 2×2 binomial trial we have one nuisance parameter, the common success probability in rows 1 and 2: $p_1 = p_2 = p$. In the total sum fixed design there are two nuisance parameters, the row and column probabilities, that are unknown: p_{1+} and p_{+1}.

A test is said to preserve the test size if the actual significance level does not exceed the nominal significance level, for any value of the nuisance parameter(s). If the actual significance level is lower than α, the test is called *conservative*. Similarly, we define a *valid p-value* as a statistic p_* such that, under the null hypothesis H_0:

$$P[p_* \leq \alpha | H_0] \leq \alpha \qquad \alpha \in [0,1] \tag{4.39}$$

A statistic that satisfies 4.39 is said a valid p-value because it can be used in the standard way to define a level α test. Consider the test that rejects the null hypothesis if and only if $p_* \leq \alpha$. Hence, under the null hypothesis, $P(\text{reject null}) = P(p_* \leq \alpha) \leq \alpha$; that is, the test so defined is a level α test.

A p-value can be exactly calculated or asymptotically approximated. An exact p-value is the exact probability of observing a table at least as extreme as the observed one, under the null hypothesis. In 2×2 tables this probability typically depends on one or more unknown parameters, such as the common success probability in comparing two binomials in the one-margin fixed design. This obstacle vanishes if we condition on the marginals (observed row and column sums), as these were fixed by design like in the Fisher's tea drinker example. In this case, the conditional probability of a table given the marginals does not depend on any unknown parameters.

We now briefly recall the fundamental Theorem 18. In the present context we narrow our attention to the comparison of the hypotheses $H_0 : \theta \leq \theta_0$ vs $H_1 : \theta > \theta_0$. In the previous pages it was shown that, given a real-valued statistic T and a vector-valued statistic U, a UMPU test of size α is:

$$\tau_*(T,U) = \begin{cases} 1 & T > c(u) \\ \gamma(u) & T = c(u) \\ 0 & T < c(u) \end{cases}$$

where $c(u)$ and $\gamma(u)$ are Borel functions determined by the α-similarity condition:

$$\mathbb{E}_{\theta_0}[\tau_*(T,U)|U = u] = \alpha$$

for every u, and $\mathbb{E}_{\theta_0}$ is the expectation with respect to $f_{\theta_0,\omega}$. This test is admissible, but is not eligible for applications due to the randomization procedure. All the statistical tests for comparing hypotheses on the 2×2 binomial trials can be conceived as non-randomized tests aimed to approximate the UMPU test expressed in Theorem 18. In the following, we'll compare the properties of these test, with respect to the p-values. Ideally, we search a test suitable for applications provided with the following properties:

1. it is a non-randomized test;

2. it is a test with valid p-values;

3. it is a test with power as close as possible to the power of the UMPU test;

Consider now that the expected value of the UMPU test under the null hypothesis can be developed in the following way:

$$\alpha = \mathbb{E}_{\theta_0}[\tau_*|U = u] = P_{\theta_0}[T > c(u)|U = u] + \gamma(u)P_{\theta_0}[T = c(u)|U = u]$$

Furthermore, since $0 \leq \gamma(u) \leq 1$, the following inequalities hold:

$$\begin{aligned} \alpha &= \mathbb{E}_{\theta_0}[\tau_*|U = u] = P_{\theta_0}[T > c(u)|U = u] + \gamma(u)P_{\theta_0}[T = c(u)|U = u] \\ &\leq P_{\theta_0}[T \geq c(u)|U = u] \qquad (\gamma = 1) \\ &\geq P_{\theta_0}[T > c(u)|U = u] \qquad (\gamma = 0) \end{aligned}$$

Following Tocher (1950), who proposed a randomized version of a Fisher's exact test as a most powerful test, we now consider a discrete statistic $T = t$ and we define the following p-value $\hat{\alpha}$ associated to a value $T = t$:

$$\hat{\alpha} = P_{\theta_0}[T \geq t|U = u]$$

If $\hat{\alpha} < \alpha$, in terms of the statistic T compared to the unknown function $c(u)$, this means: $t > c(u)$, and it follows the decision that we reject H_0.

Consider two independent binomial r.v.: $X \sim Bi(p_1, n_1)$ and $Y \sim Bi(p_2, n_2)$ and consider the following system of hypotheses:

$$H_0 : p_2 \leq p_1 \quad \text{vs} \quad H_1 : p_2 > p_1$$

Consider the statistic $U = X + Y$ that, on the boundary points $p_2 = p_1$, is such that $U \sim Bi(n_1 + n_2, p_2 = p_1 = p)$. We'll now show that $\hat{\alpha} = P[Y \geq y|U = u] = \hat{\alpha}(y, u)$ is a valid p-value. Given the definition of valid p-value, the following inequality has to be shown:

$$P[\hat{\alpha}(y, u) \leq \alpha|U = u] \leq \alpha$$

Proof $\forall u \leq m + n$:

$$\begin{aligned} A_u &= \{y \in \mathbb{N} : P[Y \geq y|U = u] \leq \alpha\} \subseteq \mathbb{N} \\ y_u &= min\{A_u\} \in A_u \\ A_u &= \{y_u, y_{u+1}, ..., n\} \\ p_u &= P[A_u|U = u] = P[Y \geq y_u|U = u] \leq \alpha \end{aligned}$$

Furthermore:

$$P[\hat{\alpha} \leq \alpha] = P[\hat{\alpha}(Y,U) \leq \alpha] = \sum_{u=0}^{m+n} P[\hat{\alpha}(Y,U) \leq \alpha | U = u] P(U = u)$$
$$\leq \alpha \sum_{u=0}^{m+n} P(U = u) = \alpha$$

Let's now define the p-value $\tilde{\alpha}$ associated at the value $T = t$ of the statistic and such that:

$$\tilde{\alpha} = P_{\theta_0}[Y > y | U = u]$$

In the case that $\tilde{\alpha} > \alpha$, in terms of the statistic T compared to the unknown function $c(u)$, this means: $t < c(u)$ and we accept H_0.

Consider two independent binomial r.v.: $X \sim Bi(p_1, n_1)$ and $Y \sim Bi(p_2, n_2)$ and consider the following system of hypotheses:

$$H_0 : p_2 \leq p_1 \quad \text{vs} \quad H_1 : p_2 > p_1$$

Consider the statistic $U = X + Y$ that, on the boundary points $p_2 = p_1$, is such that $U \sim Bi(n_1 + n_2, p_2 = p_1 = p)$.

We'll now show that $\tilde{\alpha} = \tilde{\alpha}(y,u) = P[Y > y | U = u] \leq \hat{\alpha}$ is not a valid p-value. *Proof* Fix $\alpha_0 = \tilde{\alpha}(y_0, u_0) \in (0,1)$, $y_0 \in \mathbb{N}$, $\epsilon_0 = P(Y = y_0 | U = u_0) > 0$. Consider the set A_0 such that:

$$A_0 = \{y \in \mathbb{N} : \tilde{\alpha}(y, u_0) \leq \alpha_0\} = \{y_0, y_0 + 1, ..., n\}$$

It follows:

$$P[\tilde{\alpha}(Y, u_0) \leq \alpha_0 | U = u_0] = P(A_0 | U = u_0) = P(Y \geq y_0 | U = u_0) =$$
$$= P(Y = y_0 | U = u_0) + P(Y > y_0 | U = u_0)$$
$$= \epsilon_0 + \alpha_0 = \alpha_1 > \alpha_0$$

Consider now the values of the sample space that lead to values of the statistic T for which:

1. $\hat{\alpha}$ [associated to the value of the statistic T such that $T \geq t$] is bigger or equal to alpha;

2. $\tilde{\alpha}$ [associated to the value of the statistic T such that $T > t$] is less or equal to alpha;

If we now compare the value of the T statistic with the unknown value of the function $c(u)$, it follows that both $t \leq c(u)$ and $t \geq c(u)$ (i.e. $t = c(u)$) and, by Theorem 18, in order to obtain an unbiased most powerful test, a decision should be taken only after an extra-experiment is performed. These values of the sample space define the so-called **randomization region**.

Most of the literature on the 2×2 binomial trial focus on the proposal of **non-randomized** tests which can achieve **the best performance in terms of power**. The Fisher's exact test is the most famous test for comparing hypotheses on the 2×2 binomial trial, and it is a test such that, if $X \sim Bi(n_{1+}, p_1)$ and $Y \sim Bi(n_{2+}, p_2)$, the distribution of the statistic $t = n_{11}$ is hypergeometric. This test is commonly applied in fields such as medicine, biometry and psychology in cases of small sample sizes n_{1+} and n_{2+}. The p-value of the test is calculated as:

$$p_F(n_{11}; n_{+1}, n_{1+}, n_{2+}) = \sum_{t \geq n_{11}} = \frac{\binom{n_{1+}}{t}\binom{n_{2+}}{n_{+1}-t}}{\binom{N}{n_{+1}}}$$

where $0 < n_{+1} < n_{1+} + n_{2+} + 1$. This test rejects H_0 at a nominal level α if:

$$p_F(n_{11}; n_{+1}, n_{1+}, n_{2+}) \leq \alpha$$

Consider $T = t_{\text{obs}} = n_{11}$ as a test statistic. The test function of a size α test is defined as:

$$\tau(T) = \begin{cases} 1 & T \geq t_\alpha \\ 0 & T < t_\alpha \end{cases}$$

Compared with the UMPU test, Fisher's exact test adds a sample point to the reject region (the point that in the UMPU test corresponds to $t = c(u)$), but it compels the test to have level α, since t_α is determined by the α-similarity condition: $\mathbb{E}[\tau(T)] = \alpha$. The p-value is calculated as:

$$p_F(n_{11}; n_{+1}, n_{1+}, n_{2+}) = P_0[T \geq t_{obs}] = \sum_{t \geq n_{11}} = \frac{\binom{n_{1+}}{t}\binom{n_{2+}}{n_{+1}-t}}{\binom{N}{n_{+1}}}$$

where $0 < n_{+1} < n_{1+} + n_{2+} + 1$ and, since the test is of level α, it is a valid p-value. Nevertheless, Fisher's exact test is widely known to be a conservative procedure, i.e. the p-value $p_F(n_{11}; n_{+1}, n_{1+}, n_{2+})$ tends to be too large. Barnard (1989) suggested that this is due to the discreteness of the hypergeometric distribution (i.e. the conditional distribution of X, given $X + Y = n_{+1}$).

A solution that has been proposed in order to obtain a less conservative test is to use the so-called Lancaster's (1961) mid-p test. This test reduces the conservatorism of the p-value using the following adjusted p-value:

$$p_m = P_0(T > t_{obs}) + \frac{1}{2}P_0(T = t_{obs})$$

Remember that $p_F = P(T \geq t_{obs})$, so that:

$$\begin{aligned} p_m &= p_F - P_0(t = t_{obs}) + \frac{1}{2}[p_F - P_0(t > t_{obs})] \\ &= p_F(n_{11} + 1) + \frac{1}{2}p_F - \frac{1}{2}p_F(n_{11} + 1) \\ &= \frac{p_F(n_{11}) + p_F(n_{11} + 1)}{2} \end{aligned}$$

In other words, the Lancaster's mid-p test, is a non-randomized test that rejects the null hypothesis when $p_m = \frac{p_F(n_{11})+p_F(n_{11}+1)}{2} \leq \alpha$.

We now consider the Leibermeister's test, the p-value of which is calculated as:

$$p_L(n_{11}; n_{+1}, n_{1+}, n_{2+}) = \sum_{s \geq n_{11}+1} \frac{\binom{n_{1+}+1}{s}\binom{n_{2+}+1}{n_{+1}+1-s}}{\binom{N+2}{n_{+1}+1}}$$

This is a test which has similar properties to those of the mid-p test. In particular, following Seneta and Phipps (2001) it can be shown that, under reasonable conditions:

$$p_F(n_{11} + 1; n_{+1}, n_{1+}, n_{2+}) < p_L(n_{11}; n_{+1}, n_{1+}, n_{2+}) < p_F(n_{11}; n_{+1}, n_{1+}, n_{2+})$$

for a integer $n_{11} \in [max(0, n_{+1} - n_{2+}), min(n_{1+}, n_{+1})]$. Consequently, p_L is more suitable than the Fisher's exact p-value in the analysis of a 2×2 binomial trial.

For sake of simplicity, in order to show the previous inequality, we now consider Table 4.12. In the new notation, the inequality that has to be proved is the following:

$$p_F(a + 1; z, m, n) < p_L(a; z, m, n) < p_F(a; z, m, n)$$

for a integer a satisfying $a \in [max(0, z - n), min(m, z)]$, where:

$$\begin{aligned} p_L(a; z, m, n) &= \sum_{s \geq a+1} \frac{\binom{m+1}{s}\binom{n+1}{z+1-s}}{\binom{m+n+2}{z+1}} \\ &= \sum_{r \geq a} \frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}} \end{aligned}$$

	Success	Failure	Total
Sample 1	a	b	m
Sample 2	c	d	n
	z	v	m+n

Figure 4.12: Contingency Table to show the inequality: $p_F(a+1; z, m, n) < p_L(a; z, m, n) < p_F(a; z, m, n)$.

and:

$$p_F(a; z, m, n) = \sum_{r \geq a} \frac{\binom{m}{r}\binom{n}{z-r}}{\binom{m+n}{z}}$$

We will also use the following substitutions: $l = max(0, z - n)$ and $u = min(m, z)$ for the lower and the upper bounds respectively for a, and we'll write $p_L(a)$, $p_F(a)$ for $p_L(a; z, m, n)$ and $p_F(a; z, m, n)$ respectively. The expressions $p_L(a)$ and $p_F(a)$ have the same number of summands, and we'll separately prove the following two inequalities:

$$p_L(a) < p_F(a) \tag{4.40}$$

and:

$$p_F(a+1) < p_L(a) \tag{4.41}$$

for $a = l, l+1, ..., u$. Remember that Hájek and Havránek (1978) have proved the inequality:

$$p_F(a; z, m, n) \geq p_F(a+1; z+1, m+1, n)$$

providing $ad > bc$. This inequality can be manipulated to give $p_L(a) \leq p_F(a)$, providing $ad > bc$. Nevertheless, Seneta and Phipps (2001) have proved the strict inequality 4.40 without imposing the condition $ad > bc$. This fundamental result is used to obtain 4.41. In order to prove inequality 4.40 we search which r is large enough to satisfy:

$$\frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}} < \frac{\binom{m}{r}\binom{n}{z-r}}{\binom{m+n}{z}}$$

i.e.:

$$\frac{(m+1)(n+1)}{(r+1)(n+1-z+r)} < \frac{(m+n+2)(m+n+1)}{(z+1)(m+n+1-z)} \tag{4.42}$$

The denominator parabola $f(x) = (x+1)(n+1-z+x)$ is strictly positive and strictly increasing for all x where $l \le x \le u$. This ensures that:

$$\frac{(m+1)(n+1)}{(r+1)(n+1-z+r)}$$

decreases as r increases for $r = l, l+1, ..., u$. It can be easily shown that 4.42 holds for $r = m$ (when $z \ge m$):

$$\frac{(m+1)(n+1)}{(m+1)(n+1-z+m)} < \frac{(m+n+2)(m+n+1)}{(z+1)(m+n+1-z)}$$
$$(n+1)(z+1) < (m+n+2)(m+n+1)$$

But the previous inequality holds, as $(n+1) < (n+2+m)$ and $(z+1) < (m+n+1)$. Moreover, inequality 4.42 holds for $r = z$ (when $z < m$):

$$\frac{(m+1)(n+1)}{(z+1)(n+1)} < \frac{(m+n+2)(m+n+1)}{(z+1)(m+n+1-z)}$$
$$(m+n+1-z) < (m+n+1)$$

But the previous inequality holds, as $(m+1) < (m+n+2)$ and $(m+n+1-z) < (m+n+1)$. Hence, 4.42 holds for $r = min(m, z) = u$. Suppose a' is the smallest integer value of r, $l \le r \le u$, for which 4.42 holds. Since:

$$\frac{(m+1)(n+1)}{(r+1)(n+1-z+r)}$$

decreases as r increases for $r = l, l+1, ..., u$ and since 4.42 holds for $r = a'$, it follows that 4.42 holds for $r = a', a'+1, ..., u$. Further, since $p_L(a)$ and $p_F(a)$ have the same number of summands, for each of which 4.42 is satisfied, it follows that 4.40 holds for $a = a', a'+1, ..., u$.

To show that 4.40 holds for $a = l, l+1, ..., a'-1$, consider:

$$q_F(a) = 1 - p_F(a) = \sum_{l \le r < a} \frac{\binom{m}{r}\binom{n}{z-r}}{\binom{m+n}{z}} \tag{4.43}$$

and:

$$\begin{aligned} q_L(a) = 1 - p_L(a) &= \sum_{l \le s < a+1} \frac{\binom{m+1}{s}\binom{n+1}{z+1-s}}{\binom{m+n+2}{z+1}} \\ &= \sum_{l-1 \le r < a} \frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}} \\ &= \frac{\binom{m+1}{l}\binom{n+1}{z+1-l}}{\binom{m+n+2}{z+1}} + \sum_{l \le r < a} \frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}} \end{aligned} \tag{4.44}$$

We note from 4.43 and 4.44 that $q_L(a)$ has one more positive summand than $q_F(a)$. Recall that a' is the smallest integer r satisfying 4.42, so that:

$$\frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}} \ge \frac{\binom{m}{r}\binom{n}{z-r}}{\binom{m+n}{z}}$$

for $r = a' - 1$. Moreover,

$$\frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}}$$

strictly increases as r decreases, and therefore the remaining corresponding summands of $q_L(a)$ and $q_F(a)$ satisfy 4.42 with the inequality reversed. Adding over these summands gives $q_L(a) > q_F(a)$ and it follows immediately that $p_L(a) < p_F(a)$, thus establishing inequality 4.40 for $a = l, l+1, ..., u$.

We now have to prove inequality 4.41: $p_F(a+1) < p_L(a)$; we shall simplify notation by writing $p'_F(\cdot)$ and $p'_L(\cdot)$. Expressions for $p_F(a+1)$ and $p_L(a)$ in terms of $p'_F(\cdot)$ and $p'_L(\cdot)$ can be derived:

$$p_F(a+1) = \sum_{r \ge a+1} \frac{\binom{m}{r}\binom{n}{z-r}}{\binom{m+n}{z}}$$

and, substituting $t = z - r$,

$$\begin{aligned} p_F(a+1) &= \sum_{z-t \ge a+1} \frac{\binom{m}{z-t}\binom{m}{t}}{\binom{m+n}{z}} \\ &= 1 - \sum_{t > z-a-1} \frac{\binom{n}{t}\binom{m}{z-t}}{\binom{m+n}{z}} \\ &= 1 - \sum_{t \ge z-a} \frac{\binom{n}{t}\binom{m}{z-t}}{\binom{m+n}{z}} \\ &= 1 - p'_F(z-a) \end{aligned}$$

Similarly,

$$\begin{aligned} p_L(a) &= \sum_{s \geq a+1} \frac{\binom{m+1}{s}\binom{n+1}{z+1-s}}{\binom{m+n+2}{z+1}} \\ &= \sum_{r \geq a} \frac{\binom{m+1}{r+1}\binom{n+1}{z-r}}{\binom{m+n+2}{z+1}} \end{aligned}$$

Substituting $t = z - r$

$$\begin{aligned} p_L(a) &= \sum_{t \leq z-a} \frac{\binom{m+1}{z-t+1}\binom{n+1}{t}}{\binom{m+n+2}{z+1}} \\ &= 1 - \sum_{t > z-a} \frac{\binom{n+1}{t}\binom{m+1}{z-t+1}}{\binom{m+n+2}{z+1}} \\ &= 1 - \sum_{t \geq z-a+1} \frac{\binom{n+1}{t}\binom{m+1}{z-t+1}}{\binom{m+n+2}{z+1}} \\ &= 1 - p'_L(z-a) \end{aligned}$$

From 4.42, it follows:

$$p'_L(z-a) < p'_F(z-a)$$

for $(z-a) = l', l'+1, ..., u$, i.e.:

$$p_F(a+1) < p_L(a)$$

This establishes inequality 4.41 for $a = l, l+1, ..., u$. Together, 4.40 and 4.41 imply that:

$$p_F(a+1) < p_L(a) < p_F(a)$$

Let's now sum up the main results achieved in this section. We've searched for a non-randomized test that can attain the highest level of power under the alternative (i.e. it is the closest test to the UMPU test in terms of power). Fisher's conditional test is unnecessarily conservative, with actual significance level notably less than α. There are several approaches for reducing this conservatism, for instance using adjusted versions of the Fisher's p-values (Liebermeister's test, Lancaster's mid-p test). These tests reduce the conservatorism of the Fisher's procedure (thus achieving more power), but the size of the test may be violated (even if typically not much). For, this approach is called *quasi-exact* approach.

Another possibility to reduce the conservatorism consists in applying an *asymptotic method*, like the asymptotic Pearson's chi-squared test. Consider the hypotheses $H_0 : p_1 = p_2$ vs $H_1 : p_1 \neq p_2$. Let $\mathbf{n}$ denote the observed table with marginal sums $\mathbf{n}_+ = (n_{1+}, n_{2+}, n_{+1}, n_{+2})$. Testing $p_1 = p_2$ is equivalent to test the independence of the classification in the table $\mathbf{n}$. The independence frequency of each cell is the expected frequency under H_0. For instance, consider the upper-left cell; the observed frequency is n_{11} and, under $p_1 = p_2$, the expected frequency is:

$$n_{1+}\hat{P} = n_{1+}\frac{n_{11} + n_{21}}{n_{1+} + n_{2+}} = \frac{n_{1+} \cdot n_{+1}}{N}$$

Define $m_{ij} = \frac{n_{i+} \cdot n_{+j}}{N}$; the Pearson's statistic (which has an asymptotic null chi-squared distribution) is given by:

$$T_{Pe}(\mathbf{n}) = \sum_{i,j} \frac{(n_{ij} - m_{ij})^2}{m_{ij}} = \frac{N(n_{11}n_{22} - n_{12}n_{21})}{n_{1+}n_{2+}n_{+1}n_{+2}}$$

However, also this approach may seriously violate test size for small samples. As it is widely known, Pearson's chi-squared statistic and LR statistic approximate the p-value as:

$$\text{asym p-value } = P(\chi_1^2 \geq t_{obs})$$

where χ_1^2 is a chi-squared distribution with one degree of freedom. These asymptotic tests can be used for all designs described above (both-margins fixed design, one-margin fixed design, no-margin fixed design). It has also been proposed to correct the value of the statistic, using the so-called Yates' correction:

$$T_{Pe,CC}(\mathbf{n}) = \sum_{i,j} \frac{(|n_{ij} - m_{ij}| - 1/2)^2}{m_{ij}} = \frac{N(|n_{11}n_{22} - n_{12}n_{21}| - \frac{N}{2})^2}{n_{1+}n_{2+}n_{+1}n_{+2}}$$

The main disadvantage of the asymptotic approach is that it is a rough approximation in cases of small samples. Consequently, a more suitable possibility consists in considering test statistics with known asymptotic distribution function, such as the z-unpooled and the z-pooled and in calculating the *unconditional exact* distribution function. As far as the *design* of the study is concerned, the unconditional approach represents a more appropriate statistical tool for the analysis of a 2 × 2 tables in cases of one-margin fixed design. As we've seen, the exact distribution of the Fisher's test is calculated conditioning on both the marginal row and column sums:

$$\mathbf{n}_+ = (n_{1+}, n_{2+}, n_{+1}, n_{+2})$$

In one-margin fixed designs, it is not totally appropriate to use a double conditioning approach and the unconditional approach assumes that no marginal sums are fixed, save those fixed by design.

However, a noteworthy complication concerning the unconditional p-value is that $P(T \geq t_{obs})$ depends on the unknown nuisance parameter(s) under H_0 (see Basu (1977) for a discussion on this issue). The main methods in order to solve this problem can be summarized as following:

1. Plan the experiment in a way such that the probability model interpreting the phenomenon that is being studied depends only upon the parameter of interest and is relatively free of the disturbing nuisance parameter;

2. Replace the basic probability model $(\mathscr{X}, \mathscr{A}, \mathscr{P})$, depending on both the parameter of interest $\theta \in \Theta$ and the nuisance parameter $\phi \in \Phi$, with a θ-oriented model $(\mathscr{T}, \mathscr{B}, \mathscr{Z})$, where the family $\mathscr{Z}$ is indexed by θ alone. This can be done by means of a marginalization or conditioning procedure;

3. Construct a pivotal quantity involving the sample $\mathbf{x}$ and the parameter of interest θ;

4. Delimit the problem to a smaller class of decision procedures, for instance unbiased estimators, fixed confidence intervals, similar tests, whose average performance characteristics are, at least in part, free of nuisance parameters;

5. Use the so-called maximization (or minimax) principle to eliminate the nuisance parameter from the risk function $r_\delta(\theta, \phi)$ of the decision procedure δ. The recommendation for the choice δ is then made on the basis of the eliminated risk function:

   $$R_\delta(\theta) = \underset{\phi}{sup}\ \mathrm{r}_\delta(\theta, \phi)$$

   In Lehmann (1959), the size of a test in the presence of a nuisance parameter is frequently obtained by means of the maximization principle.

6. Justify the elimination of the nuisance parameter directly from the likelihood function $L(\theta, \phi | x)$ generated by the particular data (ϵ, x). In this approach, the new likelihood function $L_e(\theta, x)$ is created for a direct comparison of the amount of support that the data provide for various values of θ. A classic example in this case is given by the maximization of the likelihood with the respect of the nuisance parameter ϕ;

7. Substitute the unknown nuisance parameter ϕ, with its estimate $\hat{\phi}$, for instance its likelihood estimation;

8. Follow a Bayesian procedure by fixing a *prior*, compute the *posterior* and integrate out the nuisance parameter from the posterior to arrive at the posterior marginal distribution of the parameter of interest;

An example of an unconditional approach to testing statistical hypotheses in the 2 × 2 binomial trial is given by the test proposed by Suissa and Shuster (1985), that uses the z-unpooled and z-pooled statistics. The derivations proposed by these authors will be developed in the next chapter. Note that this test is implemented by the software StatXact, but it is misleadingly named as Barnard's test, which is not an unconditional test, but uses a more complex algorithm for building the reject region (Barnard (1947)). The Suissa and Shuster (1985)'s test uses the Lehmann (1959)'s procedure of maximization of the null power function over the nuisance parametric space. Hence, the p-value, defined as:

$$\underset{0 \le p \le 1}{P}(T \ge t_{obs}; p|H_0)$$

is maximized over all values of p.

The Z-pooled (also called *score statistic*) is given by:

$$Z_p(x,y) = \frac{\hat{p}_2 - \hat{p}_1}{\sqrt{\frac{\hat{p}(1-\hat{p})}{m} + \frac{\hat{p}(1-\hat{p})}{n}}}$$

where $\hat{p}_1 = x/m$, $\hat{p}_2 = y/n$ and $\hat{p} = (x+y)/(m+n)$, the pooled estimate of $p_1 = p_2 = p$. Then:

$$\begin{aligned} p_P(x,y) &= sup_{0 \le p \le 1} P_p(Z_p(X,Y) \ge Z_p(x,y)) \\ &= sup_{0 \le p \le 1} \sum_{(a,b) \in R_P(x,y)} Bi(a;m,p)Bi(b;n,p) \end{aligned}$$

where $R_P(x,y) = \{(a,b) : (a,b) \in \mathcal{X} \text{ and } Z_p(a,b) \ge Z_p(x,y)\}$.

The Z-unpooled statistic is given by:

$$Z_u(x,y) = \frac{\hat{p}_2 - \hat{p}_1}{\sqrt{\frac{\hat{p}_1(1-\hat{p}_1)}{m} + \frac{\hat{p}_2(1-\hat{p}_2)}{n}}}$$

where $\hat{p}_1 = x/m$, $\hat{p}_2 = y/n$ and $\hat{p}_1$ and $\hat{p}_2$ are the unpooled estimate of $p_1 = p_2 = p$. Hence:

$$\begin{aligned} p_U(x,y) &= sup_{0 \le p \le 1} P_u(Z_p(X,Y) \ge Z_u(x,y)) \\ &= sup_{0 \le p \le 1} \sum_{(a,b) \in R_U(x,y)} Bi(a;m,p)Bi(b;n,p) \end{aligned}$$

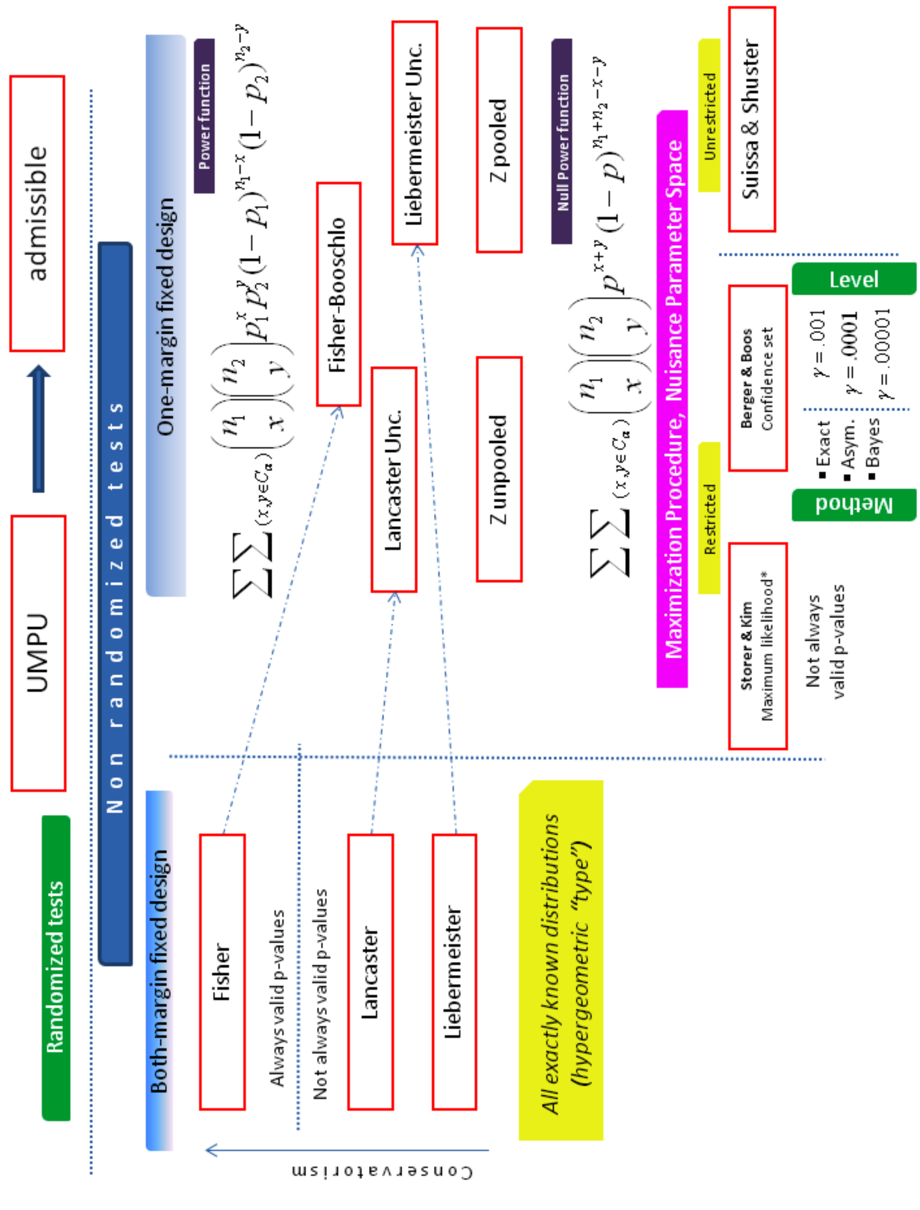

Figure 4.13: General diagram of testing statistical hypotheses on the 2 × 2 binomial trial.

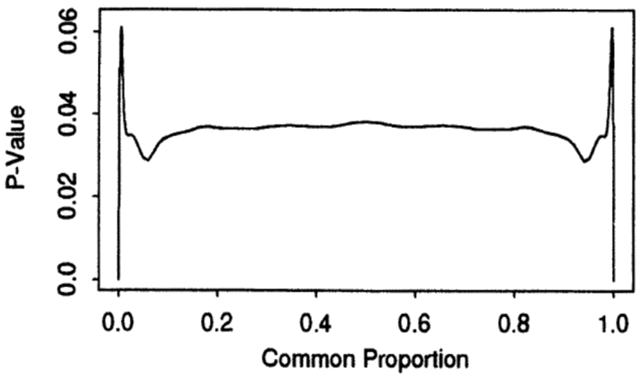

Figure 4.14: Exact p-values for the 2 × 2 table using the Chi-squared statistic: $Z^2 = \frac{(\hat{p}_2 - \hat{p}_1)}{\hat{p}(1-\hat{p})(\frac{1}{n_1} + \frac{1}{n_2})}$. Calculations are from independent binomial distributions with common proportion p. Note that the maximum is achieved for values of the parameter that are highly unlikely in light of the observations.

where $R_U(x,y) = \{(a,b) : (a,b) \in \mathcal{X} \text{ and } Z_u(a,b) \geq Z_u(x,y)\}$.

Another possibility is given by the so-called Boschloo (1970) test. Assume $p_1 = p_2 = p$.

$$\begin{aligned} p_B(x,y) &= sup_{0 \leq p \leq 1} P_f(p_F(X,Y) \geq p_F(x,y)) \\ &= sup_{0 \leq p \leq 1} \sum_{(a,b) \in R_B(x,y)} Bi(a;m,p)Bi(b;n,p) \end{aligned}$$

where $R_B(x,y) = \{(a,b) : (a,b) \in \mathcal{X} \text{ and } p_F(a,b) \geq p_F(x,y)\}$. Here, Fisher's p-value is used as the test statistic, not the p-value.

Nevertheless, the procedure of maximizing the null power function over the nuisance parameter space can lead to values of the nuisance parameter that are highly unlikely in the light of the observations (see Figure 4.14 for an example on the chi-squared statistic).

Such a drawback can be reduced by using the so-called *Berger and Boos procedure* (Berger and Boos (1994)). This procedure narrows the set of values in the domain of parameter value p, by considering a confidence set before taking the maximum:

$$\max_{p \in C_\gamma} P(T \geq t_{obs}; p) + \gamma$$

where C_γ is a $100(1-\gamma)$ per cent confidence interval for p. Normally, γ is taken to be very small, for instance 0.001. Consequently, the p-value of the Confidence-Interval Modified Boschloo Test can be defined in the following way. Fix $\gamma, 0 \le \gamma \le 1$:

$$\begin{aligned} p_{B_c}(x,y) &= sup_{p \in C_\gamma} P_p(p_F(X,Y) \le p_F(x,y)) + \gamma \\ &= sup_{p \in C_\gamma} \sum_{(a,b) \in R_B(x,y)} Bi(a;m,p)Bi(b;n,p) + \gamma \end{aligned}$$

where $R_B(x,y)$ is the same as in definition of the Boschloo's statistic and C_γ is a $100(1-\gamma)\%$ confidence interval for p calculated from the data (x,y) and assuming $p_1 = p_2 = p$. Berger and Boos (1994) have shown that this modification of the usual definition of a p-value yields a valid p-value.

Lemma 5. *Let p_γ be given by:*

$$p_\gamma = sup_{\theta \in C_\gamma} p(\theta) + \gamma$$

and suppose that $p(\theta)$ is a valid p-value for any assumed known value of θ. Let C_γ satisfy: $P(\theta \in C_\gamma) \ge 1 - \gamma$ if the null hypothesis is true. Then p_γ is a valid p-value.

Proof. Suppose that the null hypothesis is true. Denote the true and unknown θ by θ_0.

- If $\gamma > \alpha$, then because p_γ is never smaller than γ,

$$P(p_\gamma \le \alpha) = 0 \le \alpha$$

- If $\gamma \le \alpha$

$$P(p_\gamma \le \alpha) = P(p_\gamma \le \alpha, \theta_0 \in C_\gamma) + P(p_\gamma \le \alpha, \theta_0 \in \bar{C}_\gamma)$$

  Since $sup_{\theta \in C_\gamma} p(\theta) \ge p(\theta_0)$ when $\theta_0 \in C_\gamma$, we have:

$$\begin{aligned} P(p_\gamma \le \alpha) &\le P(p(\theta_0) + \gamma \le \alpha, \theta_0 \in C_\gamma) + P(\theta_0 \in \bar{C}_\gamma) \\ &\le P(p(\theta_0) \le \alpha - \gamma) + \gamma \\ &\le \alpha - \gamma + \gamma = \alpha \end{aligned}$$

□

In alternative to the use of a maximization procedure over a confidence set, it has also been proposed to consider the *maximum likelihood estimate* of p (Storer and Kim (1990)). The main problem of this approach is that the p-value is typically not valid (Berger and Boos, 1994).

We can now conclude this section analyzing Figure 4.13 that sums up the main results discussed above. The test function defined in Theorem 18 defines a level α optimum test among unbiased tests. From an applicative point of view, the disadvantage of this test is that it is a randomized test (very unsuitable for applied research). Hence, other non-randomized test functions have been proposed in the literature. The major challenge is to find a non-randomized test that is as close as possible to the UMPU test in terms of powers. As we've seen, this problem cannot be definitely solved due to the discreteness of the test statistics. Fisher's exact test represented the milestone in this search for a best test. The main drawback of this test is that it is too conservative. We've seen that this problem has been faced by two other conditional tests, proposed by Liebermeister (1877) and Lancaster (1961). Both the Lancaster's test and the Liebermeister's test use a Fisher's modified p-value, obtaining a less conservative test but with not always valid p-values. Hence, the problem of the conservatorism of the Fisher's exact test cannot be definitely solved only considering conditional tests.

An alternative approach, that was not taken into account until few decades ago due to computational problems, consists in changing the test statistic, considering for instance the z-pooled (score) and z-unpooled (Wald's) statistics, with known asymptotic distribution, but unknown exact distribution. The disadvantage of this approach is that the null power function depends on an unknown nuisance parameter (the common probability of success) that has to be eliminated in order to calculate the p-values. The main elimination technique suggested by the literature consists in maximizing the null power function over the domain of the nuisance parameter (Lehmann (1959)). This approach can also be used considering the critical regions of the Fisher, Lancaster and Liebermeister tests, thus obtaining the so-called Fisher-Boschloo test, Lancaster unconditional test and Liebermeister unconditional test. The main problem of the maximization approach, is that the maximum can be achieved for values of the unknown common success probability that are very atypical in applications. For, Berger and Boos (1994) proposed to restrict the maximization procedure over a confidence set for the nuisance parameter. These authors demonstrated that the p-values calculated with this procedure are valid. Nevertheless, at the current state of the art, neither the methods for the construction of the confidence interval, nor the levels of confidence have been yet compared.

4.3.4 Comparing the tests

The issue of the conservativeness of the Fisher's exact test and, more in general, of the conditional tests is commonly known. The research of less conservative approaches in the analysis of the 2×2 binomial trial has been also motivated by the wide range of applications of statistical methodologies.

As it was mentioned, a first approach in order to reduce the conservativeness of the Fisher's exact test has been given by the mid-p-value approach. However, the problem of such an approach is that the conditional mid-p test does not always preserve the size of the test. Note that, as we've seen, the test based on the mid-p-value is not computationally more intensive than the Fisher's exact test, as it only requires a correction to the Fisher's exact test. A systematic comparison of the Fisher's exact test, mid-p test and asymptotic chi-squared test has been conducted by Hirji *et al.* (1991). These authors have shown that, for both one-sided and two-sided tests, and for a wide range of sample sizes, the actual significance level of the mid-p test tends to be closer to the nominal level as compared with various classical tests. Moreover, Hirji (2006) has shown that the performance of a conditional mid-p test resembles that of an unconditional test.

From an historical point of view, before than the Lancaster's proposal of the mid-p tests, the main approach to the analysis of 2×2 tables was that of using an asymptotic approximation. Cochran (1954) has shown that an asymptotic chi-squared test is inaccurate in a 2×2 table if any of the expected counts are less than five ($m_{ij} \leq 5$). As it was stated in the introduction of this chapter, this criterion is still widely used in the applications. In the previous lines, it has also been introduced the correction proposed by Yates for the chi-squared test. Note that such a correction assumes that the marginal sums $\mathbf{n}_{+} = (n_{1+}, n_{2+}, n_{+1}, n_{+2})$ are fixed, and in this sense the use of the Yates' correction in the Pearson's chi-squared test is similar to a conditional approach. However, Haviland (1990) has shown that the use of the Yates' correction does not solve the problem of the conservatorism. Indeed, this correction reduces the numerical value of the test statistic, and consequently it reduces the power of the test, making it overly conservative.

The use of unconditional rather than conditional tests can be recommended, as the former are generally more powerful than the latter. Boschloo (1970) originally showed that the Fisher-Boschloo's test is uniformly more powerful than the Fisher's exact test, since its reject region always includes that of the Fisher's exact test. Seneta and Phipps (2001) show that, while the p-values of the Fisher-Boschloo test are valid, both the unconditional Liebermeister's and Lancaster's unconditional procedures do not preserve the test size (see Figure 4.15).

Authors show that, for other choices of small m and n and for a range of values of p, the exceedance of the nominal level is consistently closer to α when the Liebermeister unconditional procedure is used. The procedures are judged by closeness of the step function to the diagonal line. A test is level α (and conservative) for those α for which the step function is below the diagonal and the test is anti-conservative when the step function is above

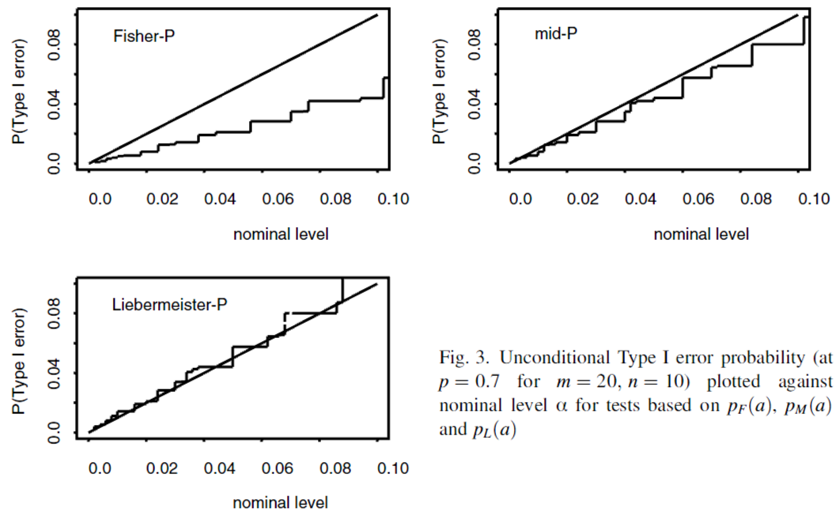

Figure 4.15: At p=0.7, m=20, n=10, the p-values of the Fisher-Boschloo test are valid, whereas both the unconditional Liebermeister's and Lancaster's unconditional procedures (respectively called Liebermeister-P and mid-P) do not preserve the test size

the diagonal. The first frame of Figure 4.15 shows that, although the Fisher-Boschloo procedure is strictly level α (as is well known theoretically) there is a price to pay. The Type I error is always far below and often half the value of α, as observed by Boschloo (1970), in contrast with the mid-P and Liebermeister unconditional procedures.

Let's now consider the problem of maximizing the null power function under unrestricted / restricted parameter space. The use of the Berger and Boos' procedure has been studied for unconditional Pearson's and Fisher-Boschloo's statistics (Mehrotra *et al.* (2003)); these authors found that this procedure gives a slight improvement in test power. The point is that this result has been obtained only for γ fixed as 0.001. Normally, in the application of this technique, γ is fixed either at 0.001 or 0.0001 (Lydersen *et al.* (2009))and no research has been conducted to find optimal values of γ. This issue will be further considered and deepened in the next chapters.

Berger (1994) studied the power function of six unconditional tests for comparing binomial proportions. Authors report that, although no test is uniformly better than all the rest in all situations, Boschloo's (1970) test, with confidence interval modification of Berger and Boos (1994), generally has the best properties. The Suissa and Shuster (1985) test, using the pooled variance estimate and the confidence interval modification of Berger and Boos (1994), also has generally good power properties. Fisher's exact test shows

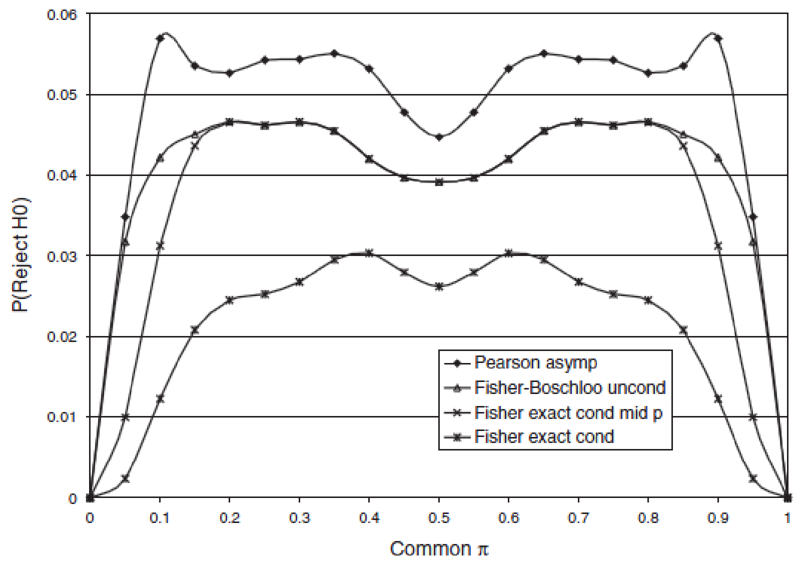

Figure 4.16: Actual significance level, two binomials (one-margin fixed design), row sums 34, $\alpha = 0.05$, Lydersen *et al.* (2009), p. 1169.

to reach poor unconditional power and is not recommended for applications.

Lydersen *et al.* (2009) compared two groups with fixed row sums $n_{1+} = n_{2+} = 34$ using different test statistics: the Pearson's asymptotic statistic, the Fisher-Boschloo's unconditional statistic, the Fisher's exact mid-p and the Fisher's exact conditional statistic. The study of the conservativeness of the tests based on these test statistics is shown in Figure 4.16. It appears that the Fisher's exact test is far more conservative than the Fisher-Boschloo's unconditional test that, by definition, preserves the test size.

Moreover, authors compared the power of these tests, considered as a function of the sample size for two equal groups with success probabilities $\pi_1 = 0.03$ and $\pi_2 = 0.2$ and with nominal significance level α fixed at 0.05 (see Figure 4.17).

It has also been showed that the conservatism of conditional tests is more pronounced in balanced designs than in unbalanced design (Duchateau and Janssen (1999)). Sample size reduction generally provokes a loosing of power in conditional mid-p tests as well as in unconditional tests.

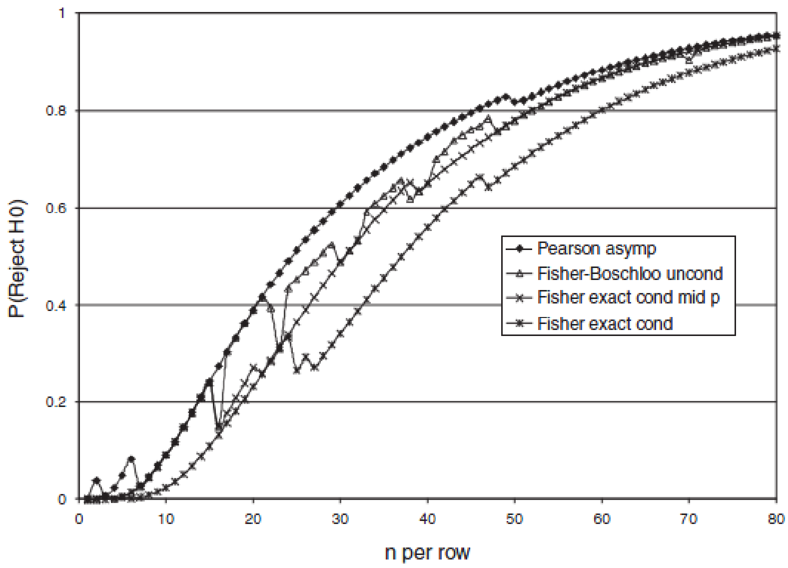

Figure 4.17: Power, two binomials (one margin fixed design), equal row sums, $\pi_1 = 0.03$, $\pi_2 = 0.2$, $\alpha = 0.05$ Lydersen *et al.* (2009), p. 1169.

4.4 Unbiased Estimation of Risk Differences in the Potential Outcomes Framework

In this section we consider the problem of finding an unbiased estimator for risk differences in the potential outcomes framework (the main reference for this section will be Borgoni *et al.* (2011)). We focus on this issue since we search for a non-randomized test with best powerful properties for testing statistical hypotheses in the potential outcomes framework.

Consider two dichotomous variables A (a treatment) and Y (an outcome). We aim to measure the causal relationship between A and Y. Various measures have been proposed in the literature, as risk differences, relative risk, odds ratio, and were briefly reviewed in the second chapter. In the present context, we will first consider associational risks difference, that can be defined as:

$$d = \bar{Y}_1 - \bar{Y}_0 = P(Y = 1|A = 1) - P(Y = 1|A = 0) \tag{4.45}$$

Consider a finite population U such that it can be divided into two subgroups E ($A = 1$, treated, or experimental group) of size N and C ($A = 0$, untreated or control group) of size M. The two probabilities in 4.45 measure the risks in the populations E and C, respectively. We consider now the problem of the estimation of the associative parameter in 4.45. At this point, the assumptions in order to draw causal inference from our data are not yet considered; as a consequence, our results will only be given an associative interpretation. For these purposes, a sample (without replacement) of size $t = n + m$ is selected from $U = E \cup C$;

Let s_1 be a sample of n units drawn from E and let s_0 be a sample of m units drawn from C and let $s = s_1 \cup s_0$ be the union of two independent samples. Each sample of size n from the population E has a probability of $1/\binom{N}{n}$ to be selected whereas each sample of size m from the population C has a probability of $1/\binom{M}{m}$ to be selected. From independence, it follows that $p(s) = 1/\binom{N}{n}\binom{M}{m}$.

An unbiased estimator for d is given by:

$$\hat{d} = \sum_{i \in s_1} \frac{y_i}{n} - \sum_{j \in s_0} \frac{y_j}{m} = \hat{\bar{y}}_1 - \hat{\bar{y}}_0$$

where $\hat{\bar{y}}_1$ and $\hat{\bar{y}}_0$ are the usual estimates of the means $\bar{Y}_1$ and $\bar{Y}_0$, respectively. The correspondent estimator $\hat{D}$ is unbiased and:

$$Var(\hat{d}) = \frac{\hat{\bar{y}}_1}{(1 - \hat{\bar{y}}_1)} \frac{N - n}{N} + \frac{\hat{\bar{y}}_0}{(1 - \hat{\bar{y}}_0)} \frac{M - m}{M}$$

represents an unbiased estimate of the variance of $\hat{D}$:

$$Var(\hat{D}) = \frac{\hat{\bar{Y}}_1}{(1 - \hat{\bar{Y}}_1)} \frac{N - n}{N} + \frac{\hat{\bar{Y}}_0}{(1 - \hat{\bar{Y}}_0)} \frac{M - m}{M}$$

Let $Y(1)$ and $Y(0)$ be the potential outcomes of the outcome variable Y. The **causal risk difference** can be defined as:

$$\delta = P(Y(1) = 1) - P(Y(0) = 1)$$

In general, the causal risk difference is not equal to the associative risks difference (for the presence of the selection bias). The two conditions that have to be met in order to give a causal interpretation to associative risks difference are, as we've seen, the consistency condition:

$$\forall a = 0, 1 \quad A = a \Rightarrow Y(a) = Y$$

and exchangeability:

$$\forall a = 0, 1 \quad Y(a) \coprod A$$

Under exchangeability:

$$P(Y(a) = 1) = P(Y(a) = 1|A = a)$$

and, under consistency:

$$P(Y(a) = 1|A = a) = P(Y = 1|A = a)$$

so that:

$$P(Y(a) = 1) = P(Y = 1|A = a)$$

and then:

$$\delta = P(Y(1) = 1) - P(Y(0) = 1) = P(Y = 1|A = 1) - P(Y = 1|A = 0) = d$$

It follows that, under consistency and exchangeability, the causal risk difference equals the associational risk difference. Nevertheless, the exchangeability condition is rarely met in observational designs. Hence, we introduce a covariate X, and exchangeability is assumed only within the strata defined by X:

$$\forall a = 0, 1 \quad Y(a) \coprod A|X$$

Causal risk difference under conditional exchangeability is given by:

$$d_x = \bar{Y}_{1x} - \bar{Y}_{0x} = P(Y = 1|A = 1, X = h) - P(Y = 1|A = 0, X = h)$$

and can be generalized to the weighted mean:

$$d = \sum_{h=1}^{H} w_h d_h = \sum_{h=1}^{H} w_h (\bar{Y}_{1h} - \bar{Y}_{0h}) \tag{4.46}$$

where

$$w_h = P(X = h) = \frac{N_h + M_h}{N + M}$$

represents the stratum weight and N_h is the number of those units having $X = 1$ while M_h is the number of those units having $X = 0$.

Borgoni *et al.* (2011) prove that the parameter in 4.46 is equal to the causal risk difference, if the assumptions of consistency and conditional exchangeability hold. Under conditional exchangeability:

$$P(Y(a)|X = h) = P(Y(a)|A = a, X = h)$$

and, under consistency:

$$P(Y(a)|A = a, X = h) = P(Y = 1|A = a, X = h)$$

so that,

$$P(Y(a) = 1|X = h) = P(Y = 1|A = a, X = h)$$

and then:

$$\begin{aligned}
\delta &= P(Y(1) = 1) - P(Y(0) = 1) \\
&= \sum_{h=1}^{H} P(X = h)[P(Y(1)|A = 1, X = h) - P(Y(0)|A = 1, X = h)] \\
&= \sum_{h=1}^{H} P(X = h)[P(Y = 1|A = 1, X = h) - P(Y = 0|A = 1, X = h)] = d
\end{aligned}$$

The plug-in estimator of 4.46 becomes:

$$\hat{D} = \sum_{h=1}^{H} w_h \hat{D}_h = \sum_{h=1}^{H} w_h (\hat{\bar{Y}}_{1h} - \hat{\bar{Y}}_{0h}) \tag{4.47}$$

It can be proved that the estimator 4.47 is unbiased and has variance:

$$Var(\hat{D}) = \sum_{h=1}^{H} w_h^2 \Big[\frac{\sigma_{1h}^2}{N_h - 1}\Big(\frac{N_h}{n_h} - 1\Big) + \frac{\sigma_{0h}^2}{M_h - 1}\Big(\frac{M_h}{m_h} - 1\Big)\Big] \tag{4.48}$$

with

$$\begin{aligned}
\sigma_{1h}^2 &= \bar{Y}_{1h}(1 - \bar{Y}_{1h}) \\
\sigma_{0h}^2 &= \bar{Y}_{0h}(1 - \bar{Y}_{0h})
\end{aligned}$$

It has also been derived an optimal allocation of sample sizes, by finding the minimum of 4.48 subject to the constraint:

$$\sum_{h=1}^{H} (n_h + m_h) = t$$

where t represents the total sample size. For this purpose, the method of Lagrange multipliers provides the optimal sample size:

$$\begin{aligned}
n_h &= \frac{w_h \sigma_{1h}}{\sum_{k=1}^{H} w_k(\sigma_{1k} + \sigma_{0k})} t \\
m_h &= \frac{w_h \sigma_{0h}}{\sum_{k=1}^{H} w_k(\sigma_{1k} + \sigma_{0k})} t
\end{aligned}$$

In the following, we'll consider the following hypotheses:

$$H_0 : d \geq 0 \qquad \text{vs } H_1 : d < 0$$

In Chapter 5, an unconditional method for testing these hypotheses, originally proposed by Suissa and Shuster (1985), will be reviewed. We'll focus on both the advantages of this method and the computational limitations of the Fortran algorithm originally developed by these authors.

Chapter 5

An Unconditional Approach to the Analysis of the 2×2 Binomial Trials

5.1 Overview

In the previous chapter it has been shown that it is possible to draw inference from the analysis of a 2×2 binomial trial by conditioning the distribution of the test statistic (under the null hypothesis) on an observable statistic, so that this distribution does not depend on nuisance parameter(s). This is what we do when we use the Fisher's exact test. Alternatively, it is possible to use the asymptotic theory and to derive an approximate p-value for the test statistic. The main problem of the conditional approach is that, in most cases, the conditional test is conservative, and loses power. It has been suggested that a possible solution to the problem of conservativeness is that of using a randomized statistical test (e.g. Bishop *et al.* (1975)). The main problem of the asymptotic approach is that it constitutes a good approximation only in the case of large sample sizes.

Furthermore, as recently reviewed in Hirji (2006), an unconditional approach to the exact analysis of the 2×2 binomial trial has been proposed. The main problem of this approach is that, normally, the null power function depends on an unknown nuisance parameter and consequently the p-values cannot be calculated. Many solutions to solve this problem have been put forward (see Basu (1977) for a review). The most popular *elimination method* in the applications is given by the maximization of the null power function over the domain of the nuisance parameter (Lehmann, 1959). Using this method, the attained size of the test is not the nominal one (i.e. that externally fixed by the researcher), but the conservatism of the test is consistently reduced (Lehmann and Romano (2005)).

Nevertheless, the unconditional methods for testing statistical hypotheses can raise many mathematical and computational problems in the determination of the distribution of the test statistic under the null hypothesis. This practical trouble contrasts with the importance of unconditional methods in the applications, as underlined by Suissa and Shuster (1985):

> A strong motivation of unconditional methods over the admittedly more popular conditional methods for this problem is the ease of explanation of results. An unconditional p-value of 0.038 means that if the study was replicated in a target population where the null hypothesis is true, there is at most 3.8 per cent chance of finding evidence "at least convincing" as that observed. The conditional inference clouds this very clear picture by conditioning on the total number of successes and producing conditional p-values which non-statisticians have significant difficulty in correctly interpreting. [Suissa and Shuster (1985), p. 318]

From the next paragraph, an unconditional test for the analysis of the 2×2 binomial trial will be developed and deepen (Suissa and Shuster (1985)).

5.2 The Null Power Function

Let $\varphi_X(\theta,\omega)$ be a parametrical model for a r.v. X and consider the following hypotheses testing problem:

$$H_0 : \theta \in \Theta_0 \qquad H_1 : \theta \in \Theta_1$$

Since the probability density function (pdf) depends from θ (parameter of interest) and also from ω, ω is a **nuisance parameter**. The power function π_τ of a test $\tau : \mathbb{X}^n \to [0,1]$ is given by:

$$\pi_\tau(\theta,\omega) : \Theta \to [0,1]$$
$$\pi_\tau(\theta,\omega) = \int_{\mathbb{X}^n} \tau(x)\varphi(x;\theta,\omega)dx = \mathbb{E}_{\theta,\omega}[\tau(X_1,...,X_n)]$$

The attained size of the test (p-value) can be defined as:

$$\pi_\tau(\theta_0,\omega) = \int_{\mathbb{X}^n} \tau(x)\varphi(x;\theta_0,\omega)dx = \mathbb{E}_{\theta_0,\omega}[\tau(X_1,...,X_n)]$$

and, fixed $\theta_0 \in \Theta_0$, the power function depends on the nuisance parameter ω. The test proposed in 1985 by Samy Suissa and Jonathan Shuster in order to testing statistical hypotheses for the 2×2 binomial trial applies to this problem the maximization method proposed in Lehmann (1959) (see also Lehmann and Romano (2005)).

Consider two independent r.v. X and Y such that $X \sim Bi(n, p_1)$ and $Y \sim Bi(n, p_2)$ and consider the following hypotheses testing problem:

$$H_0 : p_2 = p_1 \quad \text{vs} \quad H_1 : p_2 > p_1$$

Remember the Wald's statistic Z_u:

$$Z_u = \frac{(\hat{p}_2 - \hat{p}_1)}{\sqrt{\frac{(\hat{p}_2\hat{q}_2 + \hat{p}_1\hat{q}_1)}{n}}}$$

which is a Z statistic with unpooled variance estimator, where $\hat{p}_1 = \frac{x}{n} = 1 - \hat{q}_1$ and $\hat{p}_2 = \frac{y}{n} = 1 - \hat{q}_2$.

The *test function* can be expressed as:

$$\tau : \mathbb{X}^n \to [0,1]$$

$$\tau : \mathbb{X}^n \to \begin{cases} 1 & \text{when} \left\{ (x,y) : y - x > z_u \sqrt{\frac{y(n-y)+x(n-x)}{n}} \right\} \\ 0 & \text{when} \left\{ (x,y) : y - x \leq z_u \sqrt{\frac{y(n-y)+x(n-x)}{n}} \right\} \end{cases}$$

If z_u is the value of the Z_u statistic that we set as a critical value), then the set of the outcomes as extremes or more extremes than the observed one for the one-sided alternative hypothesis is given by:

$$C = \left\{ (x,y) : \frac{y/n - x/n}{\sqrt{\frac{y/n(1-y/n)+x/n(1-x/n)}{n}}} > z_u \right\}$$

$$C = \left\{ (x,y) : \frac{y - x}{\sqrt{\frac{y(n-y)+x(n-x)}{n}}} > z_u \right\} \tag{5.1}$$

and the *power function*:

$$\pi_\tau(p_1, p_2) = \langle \tau, \varphi_{p_1,p_2} \rangle = \int_{\mathbb{X}^n} \tau(x)\varphi_{p_1,p_2}(x)dx$$

$$\pi_\tau(p_1, p_2) = \sum \sum_{(x,y)\in C} 1 \cdot \varphi_{p_1,p_2}(x,y)$$

$$\varphi_{p_1}(x) = \binom{n}{x} p_1^x \cdot (1-p_1)^{n-x}$$

$$\varphi_{p_2}(y) = \binom{n}{y} p_2^y \cdot (1-p_2)^{n-y}$$

$$\varphi_{p_1,p_2}(x,y) = \binom{n}{x}\binom{n}{y} p_1^x \cdot (1-p_1)^{n-x} p_2^y \cdot (1-p_2)^{n-y}$$

so that the **attained power function of the test** is given by:

$$\pi(p_1, p_2) = \sum\sum_{(x,y)\in C} \binom{n}{x} {p_1}^x (1-p_1)^{n-x} \binom{n}{y} {p_2}^y (1-p_2)^{n-y} \tag{5.2}$$

and, under $H_0 : p_1 = p_2$ $(= p)$, the **attained null power function** is given by:

$$\pi(p) = \sum\sum_{(x,y)\in C} \binom{n}{x} p^{x+y} \binom{n}{y} (1-p)^{2n-x-y} \tag{5.3}$$

that is a function of the unknown nuisance parameter p. Following Lehmann (1959), the **attained size** of Z_u on the basis of z_u is given by $\sup_p\{\pi_\tau(p)\}$, $0 < p < 1$.

The function $\pi_\tau(p)$ can be reduced to a single summation:

$$(y-x) > z_u \sqrt{\frac{y(n-y) + x(n-x)}{n}}$$
$$y^2 \left(1 + \frac{{z_u}^2}{n}\right) - y\left(2x + {z_u}^2\right) + \left(1 + \frac{{z_u}^2}{n}\right) x^2 - {z_u}^2 x > 0$$

Consider now the following substitutions:

$$a = \left(1 + \frac{z_u^2}{n}\right) \qquad b = (2x + z_u^2) \qquad c = ax^2 - z_u^2 x$$

and thus:

$$ay^2 - by + c > 0$$

and so we have:

$$y > h(x) = \frac{b + \sqrt{b^2 - 4ac}}{2a}$$

The critical region C can be re-written as:

$$C = \{(x,y) : y \geq h(x), \quad x = 0(1)...n, \quad y = 0(1)...n\}$$

In the case $h(x) = 0$, we have:

$$h(x) = \left\{\frac{b + \sqrt{b^2 - 4ac}}{2a}\right\}$$
$$x = \frac{n{z_u}^2}{n + {z_u}^2}$$

and 5.2 can be rewritten as:

$$\pi(p) = \sum_{x=0}^{v} \sum_{y \geq h(x)} \binom{n}{x} p^{x+y} \binom{n}{y} (1-p)^{2n-x-y}$$

where $v = int\left\{\frac{n{z_u}^2}{(n+{z_u}^2)}\right\}$. It follows:

$$\pi(p) = \sum_{x=0}^{v} f(x)[1 - F\{h(x)\}]$$

where $f(x)$ is the density of a Binomial (n, p) and $F(\cdot)$ is the cumulative distribution function. Following Lehmann (1959), the attained size of Z_u on the basis of z_u is $\sup\{\pi_\tau(p)\}$, $0 < p < 1$. In order to calculate the *sup*, 5.3 is derived (we set from now $\sum_C = \sum\sum_{(x,y)\in C}$)

5.3 The Derivative of $\pi_\tau(p)$

$$\begin{aligned}\frac{\partial\pi(p)}{\partial p} &= \sum_C \binom{n}{x}\binom{n}{y}(x+y)p^{x+y-1}(1-p)^{2n-x-y} - \\ &- \sum_C \binom{n}{x}\binom{n}{y} p^{x+y}(1-p)^{2n-x-y-1}(2n-x-y) \\ &= \sum_C \binom{n}{x}\binom{n}{y}(x+y)p^{x+y-1}(1-p)^{2n-x-y} - \\ &- \sum_C \binom{n}{x}\binom{n}{y}(n-x+n-y)p^{x+y}(1-p)^{2n-x-y-1}\end{aligned}$$

The following expressions can be calculated:

$$\binom{n}{x}\binom{n}{y}(x+y) = n\binom{n-1}{x-1}\binom{n}{y} + n\binom{n-1}{y-1}\binom{n}{x}$$

$$\binom{n}{x}\binom{n}{y}(n-x+n-y) = n\binom{n-1}{x}\binom{n}{y} + n\binom{n-1}{y}\binom{n}{x}$$

and the derivative can be rewritten as the sum of four addends:

$$\begin{aligned}\frac{\partial\pi(p)}{\partial p} &= \sum_C n\binom{n-1}{x-1}\binom{n}{y}p^{x+y-1}(1-p)^{2n-x-y} + \\ &+ \sum_C n\binom{n}{x}\binom{n-1}{y-1}p^{x+y-1}(1-p)^{2n-x-y} - \\ &- \sum_C n\binom{n-1}{x}\binom{n}{y}p^{x+y}(1-p)^{2n-x-y-1} - \\ &- \sum_C n\binom{n}{x}\binom{n-1}{y}p^{x+y}(1-p)^{2n-x-y-1}\end{aligned} \tag{5.4}$$

Consider now the first and the third addends:

$$\underbrace{\sum_C n\binom{n-1}{x-1}\binom{n}{y}p^{x+y-1}(1-p)^{2n-x-y}}_{A} - \underbrace{\sum_C n\binom{n-1}{x}\binom{n}{y}p^{x+y}(1-p)^{2n-x-y-1}}_{B} \quad (5.5)$$

A strict relationship between the terms A and B holds: if x is fixed in B, there exists an identical term (but opposite signed) in A corresponding to $x+1$. Moreover, consider that in A the term corresponding to $x = 0$ vanishes, as we have $\binom{n-1}{-1}$ and, by definition, $\binom{n}{k} = 0$, $n, k \in \mathbb{Z}$, $n > 0, k < 0$. The only non-simplified term in 5.5 is the addend in the B sum corresponding to the x points located on the boundary W of the set C (critical region):

$$W = \{(x, y) : (x, y) \in C \wedge (x+1, y) \notin C\}$$

Hence, the sum of the first and of the third term in 5.4 becomes, after cancellation of opposite signed terms:

$$\pi_1^{'}(p) = -\sum_W n\binom{n-1}{x}\binom{n}{y}p^{x+y}(1-p)^{2n-x-y-1}$$

Consider now the second and the fourth addends:

$$\underbrace{\sum_C n\binom{n}{x}\binom{n-1}{y-1}p^{x+y-1}(1-p)^{2n-x-y}}_{C} - \underbrace{\sum_C n\binom{n}{x}\binom{n-1}{y}p^{x+y}(1-p)^{2n-x-y-1}}_{D}$$

In analogy with the previous case, a strict relationship between the terms in the sums C and D holds: set y in C, there exists an identical term (but opposite signed) in D corresponding to the term $(y-1)$. All the terms in C are simplified with a corresponding term in D. The only non-simplified term is the term in the C sum corresponding to the y on the boundary V of the critical region:

$$V = \{(x, y) : (x, y) \in C \wedge (x, y-1) \notin C\}$$

Hence, the sum of the second and the fourth terms in 5.4 becomes, after cancellation of opposite signed terms:

$$\pi_2^{'}(p) = \sum_V n\binom{n}{x}\binom{n-1}{y-1}p^{x+y-1}(1-p)^{2n-x-y} \quad (5.6)$$

Upon combining 5.5 and 5.6 it follows:

$$\pi^{'}(p) = \pi_1^{'}(p) + \pi_2^{'}(p)$$

It can now be easily noted that in 5.1 the following relationship holds:

$$(x_0, y_0) \in C \iff (n - y_0, n - x_0) \in C \tag{5.7}$$

Set now a point (x_1, y_1) belonging to the boundary V of C. By definition of V:

$$V = \{(x, y) : (x, y) \in C \wedge (x, y - 1) \notin C\}$$

And, applying the implication in 5.7 we have:

$$(n - y_1, n - x_1) \in C$$

but we also have $(n - y_1, n - x_1) \in W$, as $(n - y_1 + 1, n - x_1) \notin C$. The following implication holds:

$$(x_1, y_1) \in V \iff (n - y_1, n - x_1) \in W$$

The derivative $\pi(p)$ can be computed as sum of points on the boundary V:

$$\pi'(p) = \sum_V n\binom{n}{x}\binom{n-1}{y-1} p^{x+y-1}(1-p)^{2n-x-y} - \sum_V n\binom{n-1}{n-y}\binom{n}{n-x} p^{2n-x-y}(1-p)^{x+y-1}$$

For the properties of the binomial coefficients we have: $\binom{n}{n-x} = \binom{n}{x}$ and $\binom{n-1}{n-y} = \binom{n-1}{y-1}$, so that:

$$\pi'(p) = \sum_V n\binom{n}{x}\binom{n-1}{y-1}\left[p^{x+y-1}(1-p)^{2n-x-y} - p^{2n-x-y}(1-p)^{x+y-1}\right] \tag{5.8}$$

Note that 5.8 is a linear combination of terms of the form:

$$h(p) = p^r(1-p)^{s-r}$$

so that:

$$\frac{\partial h(p)}{\partial p} = rp^{r-1}(1-p)^{s-r} - (s-r)(1-p)^{s-r-1}p^r$$

and it can be calculated that:

$$\frac{\partial h(p)}{\partial p} = 0 \qquad \text{for } \tilde{p} = r/s$$
$$\frac{\partial h(p)}{\partial p} > 0 \qquad \text{for } \tilde{p} < r/s$$
$$\frac{\partial h(p)}{\partial p} < 0 \qquad \text{for } \tilde{p} > r/s$$

Hence, it follows that, for any given Interval $I = (a, b)$ with $0 < a < b < 1$:

$$\begin{aligned} \sup_{p \in I} h(p) &= h(b) \quad \text{if} \quad \frac{r}{s} > b \\ &= h(a) \quad \text{if} \quad \frac{r}{s} < a \\ &= h(\tilde{p}) \quad \text{if} \quad \frac{r}{s} \in I \end{aligned} \tag{5.9}$$

and

$$\inf_{p \in I} h(p) = \min\{h(a), h(b)\} \tag{5.10}$$

An upper bound for $\pi'(p)$ is obtained on (a, b) by substituting the right hand side of 5.9 in each positive term of 5.8 and the right side of 5.10 in each negative term of 5.8. Similarly, a lower bound for $\pi'(p)$ is obtained on (a, b) by reversing the substitutions. Finally, a bound M for $|\pi'(p)|$ on (a, b) is taken as the largest of the two bounds, in absolute value.

5.4 Exact Attained Size of the Test

Consider $p \in (0, 1)$ and let $I_1 = (0, 0.01), I_2 = (0.01, 0.02), ..., I_{50} = (0.49, 0.50)$; for each I_j, $j = 1(1)50$, we can find an M_j:

$$|\pi'(\theta_j)| < M_j \quad \forall \theta_j \in I_j$$

By the Mean Value Theorem of Calculus, we can conclude:

$$\pi(\theta_j) \in (\pi(p_j) - .005M_j, \pi(p_j) + .005M_j)$$

where $p_j = \frac{j-0.5}{100}$, the midpoint of I_j. Consider now, since $\pi(p) = \pi(1-p)$, the function $\pi(p)$ can be bounded above by:

$$\pi(p) < \max_{j=1...50} \{\pi(p_j) + .005Mj\}, p \in (0, 1) \tag{5.11}$$

The bound 5.11 has been improved by means of a numerical routine in order to produce a least upper bound of precision δ. An exact size of the test (with approximation δ) has been determined for any value z_u of Z_u. Attained significant levels using the Fisher's exact test and the exact Z test were compared in Table 1 in the case of $n = 10$. Notice that the exact unconditional p-values are smaller than the respective p-values from the exact conditional test for each outcome with $n = 10$;

TABLE 1

Comparison of one-sided exact significance levels for the case n = 10.
(Upper value is from Fisher's exact test. Lower value is from the exact unconditional test.)

$y = 10$	5×10^{-6} 9×10^{-7}										–
9	6×10^{-5} 1×10^{-5}	0.0005 0.0002			See entry for $(10 - y,\ 10 - x)$					–	–
8	4×10^{-4} 8×10^{-5}	0.0027 0.0012	0.0115 0.0059						–	–	–
7	0.0015 0.0004	0.0099 0.0039	0.0348 0.0206	0.0894 0.0578				–	–	–	–
6	0.0054 0.0017	0.0286 0.0113	0.0849 0.0474	0.1849 0.1316	0.3281 0.2617		–	–	–	–	–
5	0.0162 0.0063	0.0704 0.0311	0.1749 0.1103	0.3249 0.2617	0.5000 0.4119	–	–	–	–	–	–
4	0.0433 0.0211	0.1517 0.0755	0.3142 0.2617	0.5000 0.3883	–	–	–	–	–	–	–
3	0.1052 0.0438	0.2910 0.1647	0.5000 0.3702	–	–	–	–	–	–	–	–
2	0.2368 0.1074	0.5000 0.3367	–	–	–	–	–	–	–	–	–
1	0.5000 0.2610	–	–	–	–	–	–	–	–	–	–
0	–	–	–	–	–	–	–	–	–	–	–
	$x = 0$	1	2	3	4	5	6	7	8	9	10

Figure 5.1: Table 1, from Suissa and Shuster (1985), p. 322

We now fix a significance level α and compute the power of the test. For a level α test, the critical value of Z_u, namely z_u^*, satisfies the equation:

$$z_u^* = \inf\{z_u : \sup_p\{\pi(p)\} \leq \alpha\}$$

Authors considered the $100(1-\alpha)$ percentile point of the normal standard distribution as a starting value for z_u. This value was incremented until the attained size (precision 0.001), $\alpha^* \leq \alpha$ was achieved, and z_u^* was taken as the smallest of such values.

Remember now the expression of the power function:

$$\pi(p_1, p_2) = \sum\sum\nolimits_{(x,y)\in C}\binom{n}{x}{p_1}^x(1-p_1)^{n-x}\binom{n}{y}{p_2}^y(1-p_2)^{n-y}$$

$$C = \left\{(x,y) : \frac{y-x}{\sqrt{\frac{y(n-y)+x(n-x)}{n}}} > z_u\right\}$$

Notice that $\pi(p_1, p_2)$ is a function of n and α through z_u (and hence the fixed value z_u^*). The critical values in Table 2 have been used to compute the minimal sample sizes (n^*) required per group to attain a power of at least

TABLE 2

Critical values and exact attained significance levels of Z tests for comparing two independent binomial proportions

	α = .05				α = .025			α = .01		
n	α_1	α^*	z_u^*	z_p^*	α^*	z_u^*	z_p^*	α^*	z_u^*	z_p^*
10	.0068	.0476	1.96	1.80	.0212	2.17	1.96	.0064	2.76	2.35
11	.0086	.0456	1.92	1.78	.0208	2.40	2.14	.0087	2.63	2.29
12	.0105	.0471	1.86	1.74	.0225	2.26	2.06	.0087	2.83	2.45
13	.0125	.0484	1.81	1.71	.0200	2.26	2.07	.0097	2.67	2.37
14	.0146	.0495	1.77	1.68	.0209	2.19	2.03	.0083	2.65	2.37
15	.0125	.0417	1.94	1.83	.0218	2.14	2.00	.0089	2.57	2.33
16	.0188	.0421	1.92	1.82	.0252	2.10	1.97	.0100	2.72	2.45
17	.0209	.0426	1.90	1.81	.0233	2.21	2.07	.0099	2.66	2.42
18	.0230	.0430	1.88	1.80	.0241	2.14	2.02	.0084	2.63	2.41
19	.0251	.0435	1.86	1.78	.0246	2.14	2.03	.0092	2.59	2.39

p = common probability of success
n = sample size per group
α = desired significance level
$1-\beta^*$ = attained power
α^* = upper bound (precision 0.001) for exact attained significance level
α_1 = lower bound for $\pi(p)$ in (0.05, 0.95)
z_u^* = critical value of Z statistic with unpooled variance estimator
z_p^* = critical value of Z statistic with pooled variance estimator
p_i = probability of success for group i, $i = 1, 2$

The following denote samples sizes determined by
n_e = Fisher's exact test, Casagrande *et al.* (1978a), Haseman (1978)
n_c = corrected chi-squared approximation, Kramer and Greenhouse (1959) and tabulated in Fleiss (1973)
n_r = recorrected chi-squared approximation, Casagrande *et al.*, (1978b) and tabulated in Fleiss (1981)
n_p = uncorrected chi-squared approximation, Fleiss (1981)
n_{as} = arcsine formula, Cochran and Cox (1957)

Figure 5.2: Table 2, from Suissa and Shuster (1985), p. 324

$(1-\beta)$ and significance level of at most α^*. These values were determined by solving the equation:

$$n^* = \min\{n : \pi(p_1, p_2) \geq (1-\beta)\}$$

Last, authors **computed the exact unconditional attained significance levels** and these have been found to be smaller than the corresponding exact conditional attained significance levels for every possible outcomes of $n = 10$.

TABLE 3

Comparison of minimum sample sizes to achieve 80% power and one-sided $\alpha \leqslant 0.05$ for comparing two independent binomial proportions

p_1	p_2	n_e	n_c	n_r	n_p	n_{as}	n^*	$1-\beta^*$	α^*	z_u^*	z_p^*
.05	.15	126	148	130	111	105	107	.8009	.0495	1.69	1.68
	.20	67	84	72	59	55	56	.8016	.0498	1.73	1.71
	.25	45	57	48	39	35	38	.8098	.0476	1.74	1.71
	.30	34	42	36	28	25	28	.8095	.0458	1.78	1.74
	.35	25	33	28	21	19	22	.8095	.0484	1.83	1.77
	.40	20	27	22	17	15	18	.8190	.0430	1.88	1.80
	.45	17	23	19	14	12	13	.8142	.0484	1.81	1.71
.10	.25	89	104	92	79	76	79	.8026	.0489	1.70	1.69
	.30	56	67	58	49	47	49	.8071	.0486	1.72	1.70
	.35	39	49	42	34	32	35	.8063	.0476	1.75	1.72
	.40	30	37	31	25	24	26	.8088	.0449	1.79	1.74
	.45	24	30	25	20	19	21	.8057	.0445	1.84	1.77
	.50	19	25	20	16	15	17	.8213	.0426	1.90	1.81
	.55	16	21	17	13	12	13	.8016	.0484	1.81	1.71
	.60	13	18	14	11	10	10	.8016	.0476	1.96	1.80

p = common probability of success
n = sample size per group
α = desired significance level
$1-\beta^*$ = attained power
α^* = upper bound (precision 0.001) for exact attained significance level
α_1 = lower bound for $\pi(p)$ in (0.05, 0.95)
z_u^* = critical value of Z statistic with unpooled variance estimator
z_p^* = critical value of Z statistic with pooled variance estimator
p_i = probability of success for group i, $i = 1, 2$

The following denote samples sizes determined by
n_e = Fisher's exact test, Casagrande *et al.* (1978a), Haseman (1978)
n_c = corrected chi-squared approximation, Kramer and Greenhouse (1959) and tabulated in Fleiss (1973)
n_r = recorrected chi-squared approximation, Casagrande *et al.*, (1978b) and tabulated in Fleiss (1981)
n_p = uncorrected chi-squared approximation, Fleiss (1981)
n_{as} = arcsine formula, Cochran and Cox (1957)

Figure 5.3: Table 3, from Suissa and Shuster (1985), p. 325

Chapter 6

New developments on the Suissa & Shuster's test

6.1 Introduction

In this chapter, we consider the problem of calculating the attained sizes for unconditional tests when the power function depends on nuisance parameters. In Chapters 4 and 5 it has been shown that using unconditional methods for testing statistical hypotheses on the 2×2 binomial trial represents an appropriate approach for, at least, three reasons. First, the unconditional approach allows a researcher to handle data in a pertinent way when only the marginal rows are fixed by design (see, for instance, Perondi *et al.* (2004)). The use of the conditional approach to testing statistical hypotheses (e.g. the Fisher's exact test) would not been totally appropriate in these situations, since it would *ex-post* violate the marginal assumptions under which data have been collected. Second, as claimed by Suissa and Shuster (1985), the use of an unconditional approach permits a more natural and intuitive interpretation of the results (also for the non statisticians) than the conditional approach. Hence, in these authors' opinion, the unconditional approach represents the *best practice* for testing statistical hypotheses in the applications. Third, as reviewed for instance in Hirji (2006) and in Lydersen *et al.* (2009), the unconditional tests generally lead to achieve more power than the conditional tests.

In the case of the 2×2 binomial trial, the main problem of the unconditional approach is that the power function depends on a nuisance parameter (p, the common success probability under the null hypothesis), which has to be eliminated in order to calculate the attained sizes. Curiously, even if from an historical point of view several approaches have been proposed to solve the elimination problem (see Basu (1977) for a classic review), normally only the method proposed in Lehmann (1959) is used in the applications. This approach eliminates the dependence upon the nuisance parameter by maximizing the null power function over the entire nuisance parameter space. In this way, *valid* attained sizes can be calculated (see Lehmann and Romano (2005) for a definition of attained size, Berger and Boos (1994) for a definition of validity).

Nevertheless, it has been shown by Berger and Boos (1994) that the Lehmann (1959)'s method calculates the attained sizes using values of the nuisance parameter which can be very unusual on the light of the observations. Occasionally, the maximum of the null power function on the nuisance parameter space is reached for values of p that are strictly close to 0 or to 1 (see, for instance, Example 2 from Berger and Boos (1994), which refers to real data appeared in Emerson and Moses (1985)). Consequently, Berger and Boos (1994) proposed a new approach for the computation of the attained sizes, for which these are obtained maximizing the null power function over a confidence set (calculated at a fixed level $(1-\gamma)$) for the nuisance parameter space and summing up the result of this maximization with the value of γ. Authors demonstrate that the attained sizes calculated with this restricted maximization procedure are *valid*. Moreover, it is shown by several examples that these attained sizes are improved (in the sens of less conservatorism) with respect to those calculated with the original unrestricted maximization procedure.

Several authors have compared the degree of conservatorism and the power achieved by the conditional and unconditional tests calculated with different methods (see Lydersen *et al.* (2009) and Hirji (2006) for general reviews). Among these work, the comparison proposed by Berger (1994) is particularly valuable. This author compared the power of six exact, unconditional tests for comparing two binomial proportions with total sample sizes ranging from 20 to 100 and including balanced and imbalanced designs. Previous works (see Hirji (2006)) had reported that unconditional tests generally achieve more power than conditional tests, but also unconditional tests are found to have poor power for imbalanced designs. Using the procedure of constrained maximization of the null power function over the nuisance parameter space proposed in Berger and Boos (1994), Berger (1994) shows that the confidence interval modifications of both the Boschloo's and the Suissa and Shuster's tests have the best power properties.

Nevertheless, as recently stated in Lydersen *et al.* (2009), no research has been yet conducted on: i) the use of different procedures aimed to calculate the confidence interval for the nuisance parameter and ii) the use of different confidence levels. With respect to the latter point, in the seminal work by

Berger and Boos (1994), it is suggested to fix γ at 0.001. Lydersen *et al.* (2009) claim that in the applications most authors fix γ at either 0.001 or 0.0001 (with the relevant exception of the popular software StatXact 8, which sets 0.000001 as default value). All these proposal appear as cryptic suggestions, since no investigation has been so far conducted in order to find optimal values of γ.

In this chapter, we first propose a new R's algorithm aimed to calculate the attained sizes and the power for the original Suissa & Shuster's test. In fact, although several softwares allow to perform this tests, at our knowledge the algorithms aimed to compute these values have not ever been discussed and published, with the exception of the original Fortran's algorithm. Furthermore, it has been correctly claimed (Lydersen *et al.* (2009)) that in the most popular software for exact statistics (StatXact 8), the Suissa & Shuster's original test has been misleadingly named Barnard's test.

We've previously mentioned that the original Suissa and Shuster (1985)'s article proposes a Fortran's algorithm to calculate the attained sizes. Nevertheless, these are typed only for the cases of balanced sample sizes. Since a comparison on the power of the unconditional tests is particularly relevant in cases of imbalanced sample sizes, we have written a new R's algorithm in order to compute both the attained sizes and the power of the test for both balanced and imbalanced sample sizes. Note that we've both considered the unpooled Z test, which is directly treated in Suissa and Shuster (1985), and the pooled Z test, which has been found to achieve higher levels of power than the unpooled test (Berger (1994)).

In Section 6.2, we briefly describe the algorithm we've built for computing the Suissa & Shuster's test (the full codes are reported in Appendix A). In Section 6.3, we report the main findings we've obtained using this algorithm, and we compare them with those originally obtained with the Fortran's algorithm. In Section 6.4 we propose a new algorithm aimed to compute the attained sizes for both the unpooled and pooled unconditional tests using the Berger & Boos' procedure. The structure of the algorithm is equivalent to that used for the Suissa & Shuster's test, unless the optimization procedure is constrained to a confidence interval for the nuisance parameter space. In the original Berger and Boos (1994)'s work the confidence interval is calculated on a real dataset, whereas in Berger (1994) it is calculated basing on the total number of successes in the two sample $X + Y$, which is a binomial $(m + n, p)$ random variable if $p_1 = p_2 = p$.

We calculated the confidence interval using Monte Carlo simulations from binomial random variables with unequal sample sizes parameter (n_1, n_2) but equal success probability parameter (p). Clearly, this simulation procedure is not representative of all the possible datasets can be obtained in applied research. Nevertheless, this point does not narrows the generality of the procedure we've used to the purposes of the computation of both the critical values and the power of the test, since the Monte Carlo simulations are only employed in order to derive a confidence set on the nuisance parameter space. In section 6.5 we present and comment the results we've obtained, which are comprehensively reported in Appendix B and Appendix C. Last, in section 6.6, we critically discuss the results on the light of the literature.

6.2 A new R algorithm for the Suissa & Shuster's test

In the previous chapter, a two-step procedure aimed to compute the exact size of a test for comparing two binomial proportions has been described (Suissa and Shuster, 1985). The first step of this procedure is an analytical calculation on the derivative of a null power function; the second step consists in a numerical routine aimed to produce a least upper bound on the null power function. This was originally implemented in 1985 by means of a Fortran's algorithm, thus obtaining both the critical values and the sample sizes necessary to achieve a fixed level of power.

A first objective of the present work has been that of implementing an R's algorithm in order to directly calculate the attained sizes of the test. Consider first the case of the unpooled Z statistic (that's the case treated in Suissa and Shuster (1985)). The **R Code 1** (see Appendix A) has been written to calculate the attained sizes of the test. This code has been used for the computation of the attained sizes for the relevant cases of $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$.

Let's briefly comment the code that has been written for the case $\alpha = 0.05$. The "core" of the computation is a function, that has been called *null.power*, which takes the two sample sizes (n_1 and n_2) as arguments:

```
null.power<-function(n1,n2){

}
```

First, this function defines a bidimensional critical region (*dataframe.crit$X, dataframe.crit$Y*) in the follwoing way (the critical value *quant* is arbitrarily set at 1.64):

```
quant<-1.64
  x<-0:n1
  y<-0:n2
```

```
comb<-(expand.grid(x,y))
d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
(comb[,1]/n1*(1-comb[,1]/n1))/n1+
(comb[,2]/n2*(1-comb[,2]/n2)/n2))
quant.vec<-rep(quant, length(d))
dataframe.all<-data.frame(comb,d,quant.vec)
names(dataframe.all)[1] <- "X"
names(dataframe.all)[2]<-"Y"
dataframe.crit<-dataframe.all[
dataframe.all$d > dataframe.all$quant.vec,
]
dataframe.crit<-dataframe.crit[
complete.cases(dataframe.crit),
]
```

Second, we defined the null power function (which is a function of an unknown parameter p) and that has been called *opt.object*:

```
opt.object<-function(p){
  for(i in 1:length(dataframe.crit$X)){
  expr[i]<-(choose(n1,dataframe.crit$X[i])*
  p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
  choose(n2,dataframe.crit$Y[i])*(1-p)^
  (n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
  }
  }
```

Third, the attained size of the test is calculated by means of the built-in *optimization* function, which calculates the maximum of the null power function on the nuisance parameter space:

```
pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
```

Since the critical value is not generally known, the algorithm we've developed considers the asymptotic critical value of the normal distribution (e.g. quant←1.64) as a starting value and calculates the attained size of the test:

```
null.power<-function(n1,n2){
quant<-1.64
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
```

```
(comb[,2]/n2*(1-comb[,2]/n2)/n2))
quant.vec<-rep(quant, length(d))
dataframe.all<-data.frame(comb,d,quant.vec)
names(dataframe.all)[1] <- "X"
names(dataframe.all)[2]<-"Y"
dataframe.crit<-dataframe.all[
dataframe.all$d > dataframe.all$quant.vec,
]
dataframe.crit<-dataframe.crit[
complete.cases(dataframe.crit),
]
expr<-rep(0,length(dataframe.crit$X))
opt.object<-function(p){
for(i in 1:length(dataframe.crit$X)){
expr[i]<-(choose(n1,dataframe.crit$X[i])*
p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
choose(n2,dataframe.crit$Y[i])*(1-p)^
(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
}
somma<-sum(expr)
return(somma)
}
pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
}
```

If this attained size is less or equal to 0.05, the algorithm moves back to the value of the statistic: *quant* ← 1.00 and then moves on the right side (*quant* ← *quant* + 0.01) up to the first value for which the attained size is less than α. This has been implemented by means of a *if* statement and a *while* loop:

```
if(pvalue$objective <= 0.05){
quant<-1.00
  while(quant){
  quant<-quant+0.01
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
  (comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
```

```
  dataframe.all<-data.frame(comb,d,quant.vec)
  names(dataframe.all)[1] <- "X"
  names(dataframe.all)[2]<-"Y"
  dataframe.crit<-dataframe.all[
  dataframe.all$d > dataframe.all$quant.vec,
  ]
  dataframe.crit<-dataframe.crit[complete.cases(dataframe.crit),
  ]
  expr<-rep(0,length(dataframe.crit$X))
  opt.object<-function(p){
  for(i in 1:length(dataframe.crit$X)){
    expr[i]<-(choose(n1,dataframe.crit$X[i])*
    p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
    choose(n2,dataframe.crit$Y[i])*
    (1-p)^(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
  }
  somma<-sum(expr)
  return(somma)
  }
  pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
  if(pvalue$objective<0.05) break
  }
        return(c(quant,pvalue$maximum,pvalue$objective))
}
```

Otherwise, if the attained size of the test associated to the starting value is strictly more than 0.05, we directly move on the right side (quant←quant+0.01) in order to obtain a attained size less or equal to 0.05. This pattern has also been implemented by means of conditional *if/if else* statements and by means of a *while* loop (see Figure 6.1):

```
else if (pvalue$objective>0.05) {
while(quant){
  quant<-quant+0.01
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
  (comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
  dataframe.all<-data.frame(comb,d,quant.vec)
```

```
    names(dataframe.all)[1] <- "X"
    names(dataframe.all)[2]<-"Y"
    dataframe.crit<-dataframe.all[
    dataframe.all$d > dataframe.all$quant.vec,
    ]
    dataframe.crit<-dataframe.crit[
    complete.cases(dataframe.crit),
    ]
    expr<-rep(0,length(dataframe.crit$X))
    opt.object<-function(p){
    for(i in 1:length(dataframe.crit$X)){
    expr[i]<-(choose(n1,dataframe.crit$X[i])*
    p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
    choose(n2,dataframe.crit$Y[i])*(1-p)^
    (n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
    }
    somma<-sum(expr)
    return(somma)
    }
    pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
    if(pvalue$objective<0.05) break
    }
    return(c(quant,pvalue$maximum,pvalue$objective))
}
```

Last, in order to calculate the power of the test, we've written the R function *AttPower* (see Appendix A, **R Code 2**), which takes four arguments: the sample sizes, the critical value, and fixed values of p1 and p2:

```
AttPower<-function(n1,n2,CritVal,p1,p2){

}
```

and computes the power of the test for these cases of p_1 and p_2, which have been fixed as:

```
p1<-c(rep(.05,7),rep(.10,8),rep(.15,8),rep(.20,8),
rep(.25,8),rep(.30,6),rep(.35,4),rep(.40,2))
p2<-c(seq(.15,.45,.05),seq(.25,.60,.05),seq(.30,.65,.05),
seq(.35,.70,.05),seq(.40,.75,.05),seq(.45,.70,.05),
seq(.50,.65,.05),.55,.60)
```

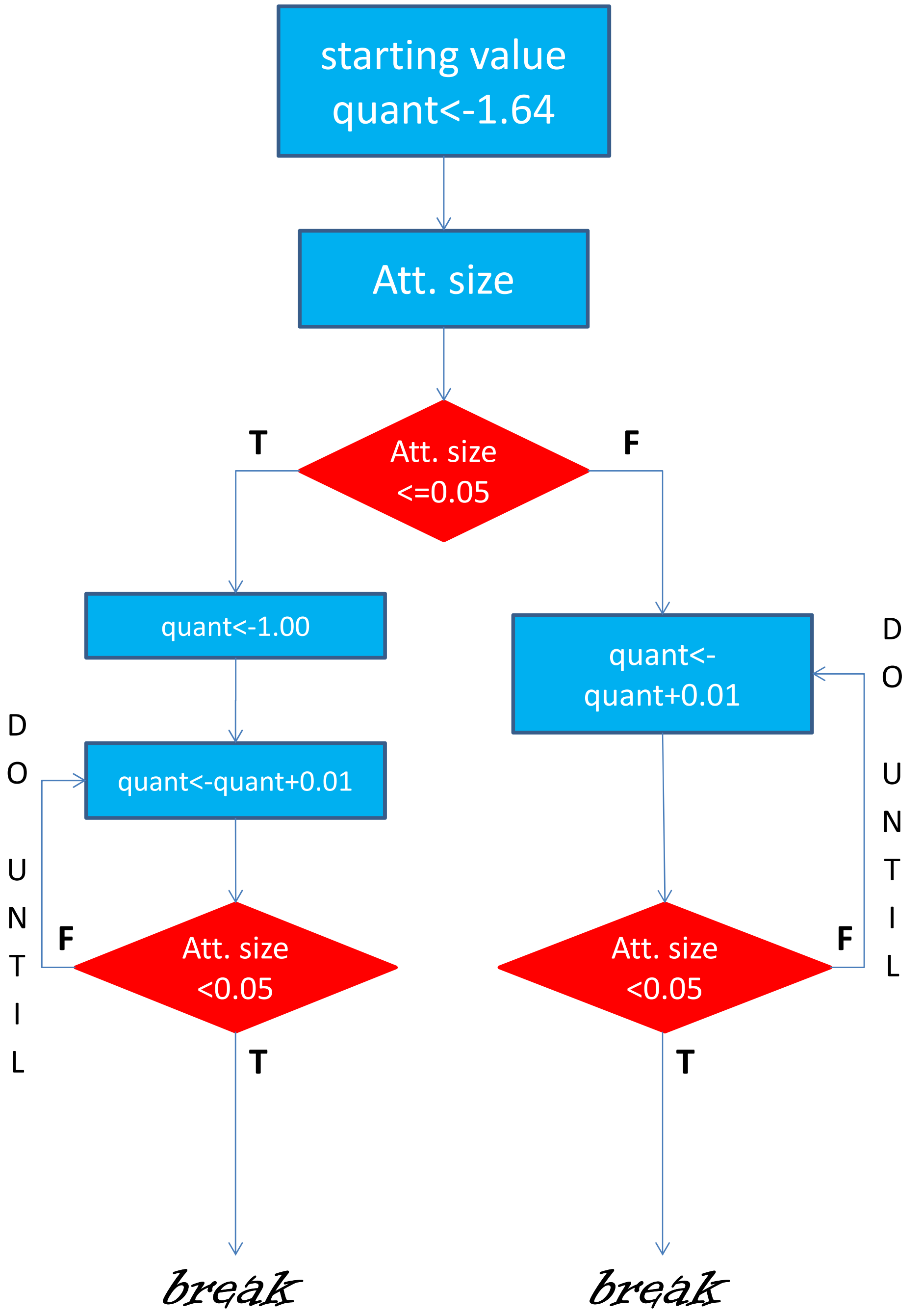

Figure 6.1: Structure of the R's algorithm used to compute the attained sizes of the Suissa and Shuster (1985)'s test, in case of different sample sizes for $\alpha = 0.05$.

6.3 Results on the Suissa & Shuster's test

We've first considered the case of *balanced sample sizes* for which we fixed $n1$ and $n1$ as:

```
n2<-c(seq(10,40, by=1), seq(50,100,by=10), 150)
n1<-c(seq(10,40, by=1), seq(50,100,by=10), 150)
```

Table B.1, Table B.2, and Table B.3 (see Appendix B) report the critical values calculated for these sample sizes for the unpooled Z statistic whereas Table B.4, Table B.5 and Table B.6 show the power values achieved when $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$ respectively.

Table B.7, Table B.8, Table B.9 report the critical values calculated for these sample sizes for the pooled Z statistic whereas Table B.10, Table B.11, Table B.12 show the power values achieved when $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$ respectively.

Suissa and Shuster (1985) claim that, in case of equal sample sizes, the unpooled Z test and the pooled Z tests are equivalent. Our results basically confirm this statement. In Figure C.1, Figure C.2 and Figure C.3 (see Appendix C) we've compared the attained size of the unpooled and pooled test. Apart from some exceptions, the two tests prove to have the same attained size under the null hypothesis.

Furthermore, we've considered the case of imbalanced sample sizes, for which we fixed $n1$ and $n2$ as:

```
n1<-c(rep(10, length(seq(20,100, by=10))),
rep(20, length(seq(30,100,by=10))),
rep(30, length(seq(40,100, by=10))),
rep(40, length( seq(50,100,by=10))))
n2<-c(seq(20,100, by=10), seq(30,100,by=10),
 seq(40,100, by=10), seq(50,100,by=10))
```

Table B.13, Table B.14, and Table B.15 report the critical values calculated for these sample sizes for the unpooled Z statistic whereas Table B.16, Table B.17 and Table B.18 show the power values calculated when $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$ respectively.

Table B.19, Table B.20, Table B.21 report the critical values calculated for these sample sizes for the pooled Z statistic whereas Table B.22, Table B.23, Table B.24 show the power values when $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$ respectively.

In Figure **??**, Figure **??**, Figure **??** is shown a comparison of the attained sizes for the unpooled and the pooled Z statistics for the cases of $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$ respectively. Note that the attained size from the pooled

Z statistic shows to be less conservative than the attained size calculated from the unpooled Z statistic in the 63.33%, 56.67%, 56.67% of the times respectively when $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$. Hence, the use of the pooled estimation insted of the unpooled estimation of the variance should be preferred in order to obtain a less conservative test (at least in the relevant cases we've examined).

In Figure C.7, Figure C.8, Figure C.9 we've compared the power achieved by the Z exact tests, calculated with either the unpooled or the pooled statistics respectively for $\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$. Results show that generally the pooled test achieve more power than the unpooled test (Berger (1994)). Nevertheless, we show that the pooled test is not uniformly more powerful than the unpooled test. In fact, we find that the unpooled Z test achieve more power than the pooled Z test in the following cases:

- $n_1 = 10$ $n_2 = 20$ ($\alpha = 0.05$);
- $n_1 = 30$ $n_2 = 40$ ($\alpha = 0.025$);
- $n_1 = 40$ $n_2 = 50$ ($\alpha = 0.025$);
- $n_1 = 40$ $n_2 = 60$ ($\alpha = 0.025$);
- $n_1 = 30$ $n_2 = 40$ ($\alpha = 0.01$);
- $n_1 = 40$ $n_2 = 50$ ($\alpha = 0.01$);

The results reviewed in this section comprehensively indicate that the pooled Z test is eligible for application in case of imbalanced sample sizes, but the unpooled Z test can also be considered when the imbalance is slight (e.g. $n_1 = 10, n_2 = 20$; $n_1 = 10, n_2 = 40$). In these cases, the unpooled test prove to be more powerful than the pooled test.

6.4 A new R algorithm to compute the Berger & Boos' Modified Z test

We've modified the algorithm described in the previous section in order to implement the maximization procedure proposed by Berger and Boos (1994) and that has been summed up in Chapter 4. Consider a Binomial random variable X of parameters $(p_1; n_1)$ and a Binomial random variable Y of parameters $(p_2; n_2)$. Consider the null hypothesis $H_0 : p_1 = p_2 = P$ and let's independently extract N Monte Carlo random vectors of size n_1 and n_2 respectively from X and Y:

```
xmc <- rbinom(N, size = n1, prob = P)
ymc <- rbinom(N, size = n2, prob = P)
```

By independence, it follows:

$$Pr(X = x, Y = y) = L(p) = \prod_{i=1}^{N}\prod_{i=1}^{N}\binom{n_1}{x_i}\binom{n_2}{y_i}p^{x_i+y_i}\cdot(1-p)^{n_1+n_2-(x_i+y_i)}$$

$$L(p) \propto p^{\sum_{i=1}^{N} x_i+y_i}\cdot(1-p)^{\sum_{i=1}^{N}(n_1+n_2-x_i-y_i)}$$
$$l(p) \propto \sum_{i=1}^{N}(x_i+y_i)lnp + \sum_{i=1}^{N}(n_1+n_2-x_i-y_i)ln(1-p)$$

And it follows that the maximum likelihood estimation $\hat{p}$ is given by:

$$\hat{p}_{MLE} = \frac{\sum_{i=1}^{N}(x_i+y_i)}{N(n_1+n_2)}$$

This estimator is unbiased:

$$\mathbb{E}[\hat{p}_{MLE}] = \frac{1}{N(n_1+n_2)}Nn_1p + Nn_2p = \frac{Np(n_1+n_2)}{N(n_1+n_2)} = p$$

and has variance:

$$\mathbb{V}[\hat{p}_{MLE}] = \frac{p(1-p)}{N(n_1+n_2)}$$

which can be estimated as:

$$\frac{\hat{p}_{MLE}(1-\hat{p}_{MLE})}{N(n_1+n_2)}$$

Hence, a Wald's type confidence set for the parameter p at confidence level $(1-\gamma)$ is given by:

$$Pr\left[\hat{p} - z_{\gamma/2}\frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{N(n_1+n_2)}} \leq p \leq \hat{p} + z_{\gamma/2}\frac{\sqrt{\hat{p}(1-\hat{p})}}{\sqrt{N(n_1+n_2)}}\right] \leq 1-\gamma$$

We've implemented the calculation of this confidence set in R (see Appendix A, **R Code 3**), fixing N at 1000. Afterwards, we've defined a function, *null.power*, which takes four arguments: the sample sizes $(n1, n2)$, the value of γ (*gamma.value*), the lower and the upper bounds of the asymptotic confidence set previously calculated (*low.bound*, *upp.bound*):

```
null.power<-function(n1,n2, gamma.value,
low.bound, upp.bound){

}
```

The "core" of this function is closed to the core of the previously described function, which calculated the attained sizes for the Suissa & Shuster's test:

```
null.power<-function(n1,n2, gamma.value,
low.bound, upp.bound){
quant<-1.64
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
  (comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
  dataframe.all<-data.frame(comb,d,quant.vec)
  names(dataframe.all)[1] <- "X"
  names(dataframe.all)[2]<-"Y"
  dataframe.crit<-dataframe.all[
  dataframe.all$d > dataframe.all$quant.vec,
  ]
  dataframe.crit<-dataframe.crit[
  complete.cases(dataframe.crit),
  ]
  expr<-rep(0,length(dataframe.crit$X))
  opt.object<-function(p){
    for(i in 1:length(dataframe.crit$X)){
    expr[i]<-(choose(n1,dataframe.crit$X[i])*
    p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
    choose(n2,dataframe.crit$Y[i])*
    (1-p)^(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
    }
  somma<-sum(expr)
  return(somma)
  }
pvalue<-optimize(opt.object, c(low.bound,upp.bound),
maximum=TRUE)
}
```

Note that *opt.object* is now optimized over the confidence set:

$$c(low.bound, upp.bound)$$

and not over the entire parametric space $c(0, 1)$. Furthermore, following Berger and Boos (1994), the attained size is defined as:

```
pvalue$objective + gamma.value
```

and, consequently, the loops of the algorithm and the conditional statements are defined as:

```
if(pvalue$objective + gamma.value <= 0.05){
quant<-1.00
while(quant){
  quant<-quant+0.01
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
  (comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
  dataframe.all<-data.frame(comb,d,quant.vec)
  names(dataframe.all)[1] <- "X"
  names(dataframe.all)[2]<-"Y"
  dataframe.crit<-dataframe.all[
  dataframe.all$d > dataframe.all$quant.vec,
  ]
  dataframe.crit<-dataframe.crit[
  complete.cases(dataframe.crit),
  ]
  expr<-rep(0,length(dataframe.crit$X))
  opt.object<-function(p){
    for(i in 1:length(dataframe.crit$X)){
    expr[i]<-(choose(n1,dataframe.crit$X[i])*
    p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
    choose(n2,dataframe.crit$Y[i])*
    (1-p)^(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
  }
somma<-sum(expr)
return(somma)
}
```

```
pvalue<-optimize(opt.object, c(low.bound,upp.bound),
 maximum=TRUE)
   if(pvalue$objective + gamma.value < 0.05) break
   }
   return(c(quant,pvalue$maximum,pvalue$objective + gamma.value))
   }
else if (pvalue$objective + gamma.value > 0.05) {
while(quant){
quant<-quant+0.01
   x<-0:n1
   y<-0:n2
   comb<-(expand.grid(x,y))
   d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
   (comb[,1]/n1*(1-comb[,1]/n1))/n1+
   (comb[,2]/n2*(1-comb[,2]/n2)/n2))
   quant.vec<-rep(quant, length(d))
   dataframe.all<-data.frame(comb,d,quant.vec)
   names(dataframe.all)[1] <- "X"
   names(dataframe.all)[2]<-"Y"
   dataframe.crit<-dataframe.all[
   dataframe.all$d >dataframe.all$quant.vec,
   ]
   dataframe.crit<-dataframe.crit[
   complete.cases(dataframe.crit),
   ]
   expr<-rep(0,length(dataframe.crit$X))
   opt.object<-function(p){
      for(i in 1:length(dataframe.crit$X)){
      expr[i]<-(choose(n1,dataframe.crit$X[i])*
      p^(dataframe.crit$X[i]+dataframe.crit$Y[i])*
      choose(n2,dataframe.crit$Y[i])*
      (1-p)^(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
   }
somma<-sum(expr)
return(somma)
}
pvalue<-optimize(opt.object, c(low.bound,upp.bound),
maximum=TRUE)
   if(pvalue$objective + gamma.value < 0.05) break
   }
return(c(quant,pvalue$maximum,pvalue$objective + gamma.value))
```

```
}
```

We've calculated the attained sizes and the achieved power of the test for:

```
n1<-c(rep(10, length(seq(20,100, by=10))),
rep(20, length(seq(30,100,by=10))),
rep(30, length(seq(40,100, by=10))),
rep(40, length( seq(50,100,by=10))))
n2<-c(seq(20,100, by=10), seq(30,100,by=10),
 seq(40,100, by=10), seq(50,100,by=10))
```

constructing the confidence set under the hypotheses that:

```
P<-c(rep(.10,30), rep(.25,30), rep(.50,30),
rep(.75,30), rep(.90,30))
```

and fixing γ at 0.001; 0.0001; 0.00001.

6.5 Results on the Berger & Boos' Modified Z test

6.5.1 Comparison of sizes

In this section, we compare the attained sizes obtained either with the Suissa & Shuster's procedure or with the Berger & Boos' procedure.

In Figure C.10 we compare the attained sizes for the **unpoooled** Z test calculated when $\boldsymbol{\alpha}$= **0.05**. This figure displays the ranking of the four tests with respect to the attained size that they achieve. Ideally, the true size should be closed to the nominal value of α.As it was reviewed in Chapter 4, the Fisher's exact test is known to be very conservative. Moreover, Berger (1994) shows that, even if used unconditionally, the Fisher's exact test is extremely conservative. In fact, when α is fixed at 0.10, the true size of the test ranges from 0.04 to 0.07. In Figure C.10 cells have been depicted in green, yellow, orange or pink according to the degree of conservatorism of the attained sizes (the less conservative attained size is in the green cell, the second less conservative test is in the yellow cell, the third less conservative test is in the orange cell whereas the most conservative test is in the pink cell).

When the confidence set for the nuisance parameter has been built with Monte Carlo simulations with success probability parameter P fixed at 0.10, we note that the classic Suissa & Shuster's test gives the less conservative test at 53.33 percent chance whereas the Berger & Boos' test when γ = 0.001

gives the less conservative test at 36.33 percent chance. The Berger & Boos' test when either $\gamma = 0.0001$ or $\gamma = 0.00001$ are less recommendable for applications. In particular, the Berger & Boos' test when $\gamma = 0.0001$ is the most conservative test at 40 percent chance whereas the Berger & Boos' test when $\gamma = 0.00001$ is the most conservative test at 13.3 percent chance. There does not hold a simple relation between the degree of conservatorism of the tests and the imbalance of the sample sizes. Note, for instance, that the Suissa & Shuster's test is the *less* conservative test when sample sizes are very imbalanced (e.g. $n_1 = 20$, $n_2 = 70, 80, 90, 100$) but in other similar imbalanced cases it is the *most* conservative test (e.g. $n_1 = 30$, $n_2 = 70, 80, 90, 100$). We obtained a different pattern of results when $P = 0.25$. In this case, the less conservative test is the Berger & Boos' test when $\gamma = 0.001$; indeed, this test has the more similar size with respect to the nominal size at 50 percent chance. The Suissa & Shuster's test is the less conservative test at 30 percent chance but it is also the most conservative test at 46.67 percent chance. The Berger & Boos' test when both $\gamma = 0.0001$ and $\gamma = 0.00001$ show intermediate degrees of conservatorism. Results completely change when $P = 0.50$; in this case, the Berger & Boos' procedure shows a clear superiority on the Suissa & Shuster's procedure in terms of less conservatorism. In fact, the Berger & Boos' procedure when $\gamma = 0.001$ is the less conservative procedure at 56.67 percent chance, whereas the Suissa & Shuster's procedure is the most conservative procedure at 73.33 percent chance. Similarly to the case of $P = 0.25$, both the Berger & Boos' test when $\gamma = 0.0001$ and when $\gamma = 0.00001$ show intermediate degrees of conservatorism, but are explicitly less conservative than the classic Suissa & Shuster's test. When $P = 0.75$, the Berger & Boos' test when $\gamma = 0.0001$ is the less conservative test, ranking first and second respectively at 30 percent chance and at 36.67 percent chance. This finding is very closed to that obtained with the Berger & Boos' test when $\gamma = 0.001$, which ranks first and second at 46.67 percent chance and at 16.67 percent chance respectively. The Suissa & Shuster's test is still the most conservative test, ranking fourth at 70 percent chance. When $P = 0.90$ results are similar to those obtained when $P = 0.10$. In fact, the Suissa & Shuster's test is the less conservative test at 43.33 percent chance but it is also the most conservative test at 53.33 percent chance. The Berger & Boos' procedure shows an intermediate pattern of performance, with an advantage using a lower confidence level (i.e. $\gamma = 0.001$).

These results comprehensively indicate that, in general, the Berger & Boos' procedure leads to a less conservative test, especially when the success probability in the population is not extreme ($P = 0.25; 0.50; 0.75$). In many cases, when the success probability in the population used to simulate the confidence interval is rather extreme ($P = 0.10; 0.90$), the classic Suissa &

Shuster's procedure seems to be eligible for applications.

Figure C.11 reports the results obtained for $\boldsymbol{\alpha}=\mathbf{0.025}$. When P = 0.10, the Berger & Boos' procedure with γ = 0.001 leads to the less conservative test, which ranks first and second at 36.67 and at 43.33 percent chance respectively. The classic Suissa & Shuster's procedure is the less conservative method at 46.67 percent chance but it is also the most conservative procedure at 36.67 percent chance. The Berger & Boos' test when either γ = 0.0001 or γ = 0.00001 show intermediate degrees of conservatorism. Results significantly change when P = 0.25: the Berger & Boos' procedure when γ = 0.001 is clearly the less conservative test, ranking first at 46.67 percent chance. The Suissa & Shuster's original procedure leads to a clear disadvantage in terms of conservatorism, giving the most conservative test at 46.67 percent chance. Moreover, note that it does not seem useful to set a large confidence level for the nuisance parameter, since the use of the Berger & Boos' procedure when γ = 0.0001 leads to a less conservative test with respect to that obtained when γ = 0.00001 (the former ranks second at 53.33 percent chance whereas the latter ranks third at 50 percent chance). When P = 0.50 results clearly show that the use of the Berger & Boos' procedure is eligible for applications. Indeed, the use of this procedure when γ = 0.0001 ranks first and second at 36.67 and at 40 percent chance respectively. The use of the confidence set with either γ = 0.001 or γ = 0.0001 leads to intermediate degrees of conservatorism whereas the use of the Suissa & Shuster's test clearly gives the most conservative attained sizes, since this procedure ranks fourth at 60 percent chance. When P = 0.75, the use of the Berger & Boos' procedure with either γ = 0.001 or γ = 0.0001 leads to the less conservative attained sizes. The former procedure ranks first and second at 40 percent chance and at 20 percent chance respectively, whereas the latter procedure ranks first and second at 36.67 percent chance and at 36.67 percent chance respectively. The Suissa & Shuster's procedure gives the most conservative attained sizes at 60 percent chance whereas the use of the Berger & Boos' procedure with γ = 0.00001 gives an intermediate performance. A similar pattern of results is obtained when p = 0.90, with the use of the Berger & Boos' procedure giving the less conservative attained sizes with 60 percent chance whereas the use of the Suissa & Shuster's test leading to the most conservative attained sizes at 53.33 percent chance.

Also when α = 0.025, we can sum up these results by stating that the use of the Berger & Boos' procedure leads to obtain less conservative attained sizes in all the cases that have been considered, with the only exception of the case of P = 0.10 (where, in some cases, the use of the original Suissa & Shuster's procedure can be more adequate). With respect to the use of different confidence levels, similarly to the case of $\alpha = 0.05$, the choice of $\gamma = 0.001$ seems to be the most appropriate, thus leading to the less conservative attained sizes.

Figure C.12 reports the results obtained for these tests when $\boldsymbol{\alpha} = \mathbf{0.01}$. When $P = 0.10$, both the use of the Suissa & Shuster's procedure and the use of the Berger & Boos' procedure with $\gamma = 0.001$ seem to be equivalent and give less conservative attained sizes with respect to the Berger & Boos procedure with γ fixed at either 0.0001 or 0.00001. Indeed, the use of the Suissa & Shuster's procedure ranks first at 46.67 percent chance and ranks second at 30 percent chance. When $P = 0.25$ the use of the Suissa & Shuster's test is not advisable, ranking fourth at 53.33 percent chance. The use of the Berger & Boos' test with $\gamma = 0.0001$ leads to the less conservative attained sizes, ranking first at 33.33 percent chance and ranking second at 23.33 percent chance. When $P = 0.50$, the use of the Berger & Boos' procedures with γ fixed at either 0.001 or 0.0001 seem to be equivalent, leading to less conservative attained sizes. Differently, fixing γ at 0.0001 does not lead to any consistent advantage, whereas the use of the Suissa & Shuster's procedure is no doubt the most conservative method, ranking fourth at 80 percent chance. The pattern of results when $P = 0.75$ or $P = 0.90$ are very closed to those obtained when $P = 0.50$. Indeed, in these cases, the use of use of the Berger & Boos' procedure fixing γ either equal to 0.001 or 0.0001 is the most appropriate choice.

Comprehensively, when $\alpha = 0.01$, we can draw the same conclusions previously put forth for the case of $\alpha = 0.025$ with the following *caveat*: when $\alpha = 0.01$, fixing γ at 0.001 or 0.0001 does not lead to considerable differences in the results with respect to the degree of conservatorism.

Overall, the results so far discussed suggest that in the unpooled case the use of the Berger & Boos' procedure in order to calculate the attained sizes leads to less conservative tests, especially when the probability in the population on which is calculated the confidence set is not extreme ($P = 0.25; 0.50; 0.75$). With respect to the use of different Berger & Boos' procedures, we can conclude that, in terms of conservatorism, it is not useful to calculate an interval at a larger confidence level (i.e. $\gamma = 0.00001$), but the best performances are obtained when $\gamma = 0.001$ or $\gamma = 0.0001$. Last, we aimed to investigate the relation between the conservatorism of the procedures and the degree of imbalance of the sample sizes. Nevertheless, as it has been previously mentioned, from our results it is not possible to infer any regularity pattern.

Let's now analyze the results for the **pooled** Z test calculated with either the Suissa & Shuster's procedure or the Berger & Boos' procedure. Let's begin with the case of $\boldsymbol{\alpha}$= **0.05**, which is reported in Figure C.13. When P = 0.10 the Suissa & Shuster's test is certainly the less conservative test, ranking first in the 76.67 percent of cases. Among the Berger & Boos' procedures, the test calculated fixing γ = 0.001 ranks second in 63.33 percent of cases. The use of the Berger & Boos' procedures with either γ = 0.0001 or γ = 0.00001 leads to the most conservative attained sizes. When P = 0.25, the use of the Berger & Boos' procedure when γ = 0.001 leads to the less conservative attained sizes in the 40 percent of cases, whereas both the use of larger confidence sets and of the classic Suissa & Shuster's procedures give more conservative attained sizes. When P = 0.50, using the Berger & Boos' procedure with γ = 0.001 leads to the less conservative attained sizes with the 53.33 percent chance of occurrence. However, both fixing other confidence levels and the use of the Suissa & Shuster's test lead to the most conservative attained sizes, with the latter ranking fourth 60 percent of the time. Similar results have been obtained in the case P = 0.75. Contrary to this, when P = 0.90, the use of the Suissa & Shuster's test leads to the less conservative attained sizes at 50 percent chance, and the use of this test is more adequate with respect to the use of the constrained optimization procedure proposed by Berger & Boos.

On the whole, we can state that the use of the Suissa & Shuster's procedure is only adequate when P = 0.10 or P = 0.90. In all the other cases, the Berger & Boos' procedure leads to less conservative attained sizes and the best practice is to fix γ at 0.001.

In Figure C.14 we compare the attained sizes for the **poooled** Z test calculated when $\boldsymbol{\alpha}$= **0.025**. Similarly to the case of α = 0.05, when P = 0.10 the Suissa & Shuster's test is the less conservative test at 63.33 percent chance. Among the three Berger & Boos' procedures, the most appropriate is that with the lowest confidence level (i.e. γ = 0.001), which ranks second at 63.33 percent chance. When P = 0.25 the pattern of results is substantially different. Indeed, the ranking of the Suissa & Shuster's test and of the Berger & Boos' test is reversed. The Berger & Boos' test when γ = 0.001 ranks first at 40 percent chance whereas the Berger & Boos' test when γ = 0.0001 ranks first at 23.33 percent chance and ranks second at 26.66 percent chance respectively. The Berger & Boos' test when γ = 0.00001 shows an intermediate pattern of results, ranking second and third at 40 percent chance and at 36.67 percent chance respectively. The Suissa & Shuster's test is definitely the most conservative test, ranking fourth at 50 percent chance. Similar conclusions can be drawn when P = 0.50. In particular, note that in this case the Suissa & Shuster's procedure is both the less conservative and the most conservative procedure at 40 percent chance and at 56.67 percent chance respectively. As previously commented, there does not hold a clear relation between the degree of conservatorism and the degree of imbalance of the sample sizes.

With respect to the Berger & Boos' procedures, the use of a lower confidence level (i.e. $\gamma = 0.001$) leads to a more suitable test in terms of conservatorism. In fact, this test ranks first and second at 30 percent chance and at 26.67 percent chance respectively. Also the use of the Berger & Boos' procedure when $\gamma = 0.0001$ has to be kept into consideration, ranking first and second at 30 percent chance and at 43.33 percent chance respectively. When $P = 0.75$, the use of the Berger & Boos' procedure when $\gamma = 0.0001$ leads to the less conservative test and the second less conservative test respectively at 40 percent chance and at 30 percent chance. Both the Berger & Boos' test when $\gamma = 0.001$ and when $\gamma = 0.00001$ show an intermediate pattern of results whereas the Suissa & Shuster's test is certainly the most conservative test, ranking fourth at 50 percent chance. When $P = 0.90$, similarly to the case of $\alpha = 0.05$, the Suissa & Shuster's test can be kept into consideration, being the less conservative test at 43.33 percent chance. Among the Berger & Boos' procedures, the most suitable for applications is the one which fixes $\gamma = 0.001$.

The overall conclusions that can be drawn for $\alpha = 0.025$ are similar to those obtained for the case of $\alpha = 0.05$. Generally, the Berger & Boos' procedure leads to a less conservative test, especially when the success probability in the population is not extreme ($P = 0.25; 0.50; 0.75$). In many cases, when the success probability in the population is rather extreme ($P = 0.10; 0.90$), the classic Suissa & Shuster's procedure is adequate. Nevertheless, it is not easy to extrapolate regularity patterns with respect to the role of the balance of the sample sizes.

Let's now discuss the results when $\boldsymbol{\alpha} = \mathbf{0.01}$, which are not substantially different from those previously commented. When $P = 0.10$, the Suissa & Shuster's test is the most suitable test, being the less conservative at 56.67 percent chance. With respect to the Berger & Boos' procedures, the most suitable is that with the largest value of γ (i.e. $\gamma = 0.001$), which ranks first and second at 30 percent chance and at 53.33 percent chance respectively. When $P = 0.25$, the Berger & Boos' tests when $\gamma = 0.001$ and $\gamma = 0.0001$ are the less conservative tests, ranking first at 43.33 and at 30 percent chance respectively. The Suissa & Shuster's procedure is the most conservative procedure at 56.67 percent chance. Similar results have been found when $P = 0.50$, with the Berger & Boos' procedures leading to less conservative tests, and the Suissa & Shuster's test ranking fourth at 60 percent chance. Also when $P = 0.75$, the Berger & Boos' procedure when $\gamma = 0.001$ and $\gamma = 0.0001$ lead to the most suitable tests, whereas the Suissa & Shuster's test ranks fourth at 50 percent chance. In the case of $P = 0.90$, the Berger & Boos' test when $\gamma = 0.0001$ leads to the less conservative test, which ranks first and second at 33.33 and at 46.67 percent chance respectively.

Overall, the results for the pooled Z statistic indicate that the use of the Berger & Boos' procedure to calculate the attained sizes leads to less conservative tests when the probability in the population is not extreme ($P = 0.25; 0.50; 0.75$). On the contrary, when $P = 0.10$ or $P = 0.90$ the use of the classic Suissa & Shuster's procedure is more appropriate. With respect to the Berger & Boos' procedures, it is not relevant (in terms of conservatorism) to fix a larger confidence level (i.e. $\gamma = 0.00001$), since the best performances have been obtained when $\gamma = 0.001$ or $\gamma = 0.0001$. Last, with respect to the relation between sample sizes and degree of conservatorism, we are not able to draw any conclusion, as in the case of the unpooled Z statistic previously discussed.

6.5.2 Power Comparison

In Figure C.16 we compare the power achieved by the four different **unpooled** tests we've considered for $\boldsymbol{\alpha} = \mathbf{0.05}$. Diagrams represent the power difference between the power achieved by the Berger & Boos' test and the Suissa & Shuster's test, respectively when $\gamma = 0.001$ (red bars), $\gamma = 0.0001$ (green dots) and $\gamma = 0.00001$ (blue dots). When $P = 0.10$, the four tests achieve the same level of power when $n_1 = 10, n_2 = 20$; $n_1 = 20, n_2 = 40$; $n_1 = 20, n_2 = 50$; $n_1 = 20, n_2 = 60$; $n_1 = 20, n_2 = 80$; $n_1 = 20, n_2 = 90$ and $n_1 = 20, n_2 = 100$; $n_1 = 30, n_2 = 60$. In the other cases, the use of the Berger & Boos' modified test can lead to either more or less power than the original Suissa & Shuster's procedure. In particular, it can be noted that the use of the latter procedure achieve higher power where the sample sizes are less imbalanced (when $n_1 = 20, n_2 = 30$; $n_1 = 30, n_2 = 40$; $n_1 = 30, n_2 = 50$; $n_1 = 40, n_2 = 50$; $n_1 = 40, n_2 = 60$; $n_1 = 40, n_2 = 70$). Except from the case in which $n_1 = 20, n_2 = 70$, in all the other cases the power we've calculated does not vary using different confidence levels. When $P = 0.25$, the four tests achieve the same level of power in the following cases: $n_1 = 10, n_2 = 20$; $n_1 = 10, n_2 = 30$; $n_1 = 20, n_2 = 50$; $n_1 = 10, n_2 = 60$; $n_1 = 10, n_2 = 70$; $n_1 = 10, n_2 = 100$. In all the other cases we've considered, the use of the Berger & Boos' procedure leads to achieve more power with respect to the use of the Suissa & Shuster's procedure, but not significant differences are found with respect to the use of different confidence level, with the exceptions of the cases when $n_1 = 40, n_2 = 50$; $n_1 = 40, n_2 = 60$; $n_1 = 40, n_2 = 70$; $n_1 = 40, n_2 = 80$, where both the use of $\gamma = 0.0001$ and $\gamma = 0.00001$ prove to be more powerful with the respect to the use of a confidence interval at level $\gamma = 0.001$. When $P = 0.50$, the use of the Berger & Boos' procedure always shows to achieve more power with respect to the original Suissa & Shuster's procedure. Note that the power improvement in using the Berger & Boos' procedure can be very small (e.g. $n_1 = 20, n_2 = 30$; $n_1 = 30, n_2 = 40$), but also very large, especially when the sizes of the samples are imbalanced (e.g. $n_1 = 10, n_2 = 80$; $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$), with a power improvement ranging from 0.20 to 0.60. Slight differences are found with respect to the use of different confidence levels; in particular when $n_1 = 30, n_2 = 50$; $n_1 = 30, n_2 = 80$; $n_1 = 40, n_2 = 70$, both fixing γ at 0.0001 and at 0.00001 lead to achieve more power with respect to fixing γ at 0.001. Furthermore, note that, when $n_1 = 30, n_2 = 70$, the use of a larger confidence level (i.e. $\gamma = 0.00001$) does not prove to achieve more power than fixing γ at both 0.0001 and 0.001. Also when $P = 0.75$, the use of the Berger & Boos' procedure leads to achieve more power with respect to the use of the Suissa & Shuster's procedure in all the cases we've considered. Note that it is equivalent to fix γ at 0.0001 or 0.00001, whereas these procedure prove to achieve a higher level of power when γ is fixed at 0.001 in these cases: $n_1 = 30, n_2 = 50$; $n_1 = 30, n_2 = 70$; $n_1 = 40, n_2 = 70$. Last, also when the Monte Carlo simulations for calculating the confidence interval have been performed fixing $P = 0.90$, the use of the Berger & Boos' procedure leads to achieve more power with respect to the original unconstrained maximization on the nuisance parameter space. Similarly to the cases of $P = 0.50$ and of $P = 0.75$, the improvement in power is larger when the sample sizes are very imbalanced (e.g. $n_1 = 10, n_2 = 70$; $n_1 = 10, n_2 = 80$; $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). Note that, from one side, fixing γ at either 0.0001 or at 0.00001 does not lead to any difference in power; from the other side the us of these confidence levels leads to achieve more power with respect to fixing γ at 0.001 only when $n_1 = 30, n_2 = 40$.

In Figure C.17 we compare the power achieved by the four different **unpooled** tests we've considered for $\boldsymbol{\alpha} = \mathbf{0.025}$. When $P = 0.10$, in several cases all the four tests achieve the same level of power ($n_1 = 20, n_2 = 30$; $n_1 = 20, n_2 = 40$; $n_1 = 20, n_2 = 50$; $n_1 = 20, n_2 = 60$; $n_1 = 20, n_2 = 90$; $n_1 = 30, n_2 = 50$; $n_1 = 30, n_2 = 60$; $n_1 = 30, n_2 = 70$; $n_1 = 30, n_2 = 80$; $n_1 = 30, n_2 = 90$; $n_1 = 30, n_2 = 100$). Note that these are mostly cases with relatively low imbalanced sample sizes. Furthermore, in other three cases of relatively low imbalanced sample sizes, the Suissa & Shuster's test prove to achieve more power with respect to the Berger & Boos' test ($n_1 = 40, n_2 = 50$; $n_1 = 40, n_2 = 60$; $n_1 = 40, n_2 = 70$). Differences can be highlighted with respect to the use of different values of γ. From one side, when both $n_1 = 40, n_2 = 50$ and $n_1 = 40, n_2 = 60$, the Suissa & Shuster's original test achieves more power than all the three Berger & Boos' procedures. From the other side, when $n_1 = 40, n_2 = 70$, the Suissa & Shuster's test is more powerful only than the Berger & Boos' test when $\gamma = 0.001$, whereas achieve the same level of power of the Berger & Boos' test when $\gamma = 0.0001$ or $\gamma = 0.00001$. In all the other cases that we've studied, all the Berger & Boos' tests prove to be more powerful than the Suissa & Shuster's test. In particular, we note that the difference in power is higher when the sample sizes are more imbalanced (e.g. $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). No differences emerge with respect the values of γ we've fixed. Let's now comment the case of $P = 0.25$. As in the previous case, the four tests show to be equally powerful in several cases (e.g. $n_1 = 10, n_2 = 30$; $n_1 = 10, n_2 = 40$). Furthermore, the Suissa & Shuster's test proves to be more powerful than the Berger & Boos' test (only when γ is fixed at 0.001) in three cases ($n_1 = 10, n_2 = 20$; $n_1 = 10, n_2 = 60$; $n_1 = 40, n_2 = 50$) but these power differences are very low. In all the other cases, the Berger & Boos' procedure leads to achieve more power with respect to the original Suissa & Shuster's procedure. In most cases, these differences are particularly relevant in cases of very imbalanced sample sizes (e.g. $n_1 = 20, n_2 = 80$; $n_1 = 20, n_2 = 90$). The use of a larger confidence level (i.e. $\gamma = 0.0001$, $\gamma = 0.00001$) leads to a more powerful test with respect to the use of a lower confidence level (i.e. $\gamma = 0.001$) in the following cases: $n_1 = 20, n_2 = 40$; $n_1 = 20, n_2 = 50$; $n_1 = 20, n_2 = 60$; $n_1 = 30, n_2 = 50$; $n_1 = 20, n_2 = 60$, but these differences are not particularly relevant. When $P = 0.50$, the Berger & Boos' test is always more powerful than the Suissa & Shuster's test; this is particularly relevant, for instance, when $n_1 = 10, n_2 = 80$; $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$. When $n_1 = 20, n_2 = 30$, the use of a larger confidence set ($\gamma = 0.0001$ or $\gamma = 0.00001$) leads to achieve more power with respect to the use of a lower confidence level. Curiously, when $n_1 = 20, n_2 = 90$, fixing γ at 0.0001 leads to a slight improvement in power with respect to fixing γ at both 0.001 and 0.00001. We find a similar pattern of results also when $p = 0.75$, where the Berger & Boos' test always achieve more power than the Suissa & Shuster's test, with the only exception of the case when $n_1 = 40, n_2 = 50$, where the four tests achieve a very similar level of power. No relevent differences emerge with respect to the use of different levels of γ. When $P = 0.90$, the Berger & Boos' test is always more powerful than the Suissa & Shuster's test, with stronger differences in cases of very imbalanced sample sizes. No differences are found among the use of the three different confidence sets.

Let's now discuss the results we've obtained for the **unpooled** test when $\boldsymbol{\alpha}$= **0.01**. When $P = 0.10$, in eleven cases that we've considered, the four tests achieve the same level of power (e.g. $n_1 = 20, n_2 = 30$; $n_1 = 30, n_2 = 50$; $n_1 = 40, n_2 = 60$). When $n_1 = 40, n_2 = 50$, using the Suissa & Shuster's procedure leads to achieve more power with respect to the use of all the Berger & Boos' procedures. This pattern is found also when $n_1 = 30, n_2 = 40$, but this difference in power is higher when $\gamma = 0.001$. In the case $n_1 = 40, n_2 = 70$, the Suissa & Shuster's test is only more powerful with respect to the Berger & Boos' procedure when $\gamma = 0.001$. In all the other cases, the use of all the Berger & Boos' procedures leads to achieve more power with respect to the unconstrained maximization on the nuisance parameter space. When $P = 0.25$, in four cases all the tests show to achieve the same level of power ($n_1 = 10, n_2 = 20$; $n_1 = 10, n_2 = 30$; $n_1 = 10, n_2 = 40$; $n_1 = 10, n_2 = 50$). In only two cases the Suissa & Shuster's test is more powerful than the Berger & Boos' test, but only when γ is set at 0.001 ($n_1 = 30, n_2 = 40$; $n_1 = 40, n_2 = 50$). In all the other cases, the Berger & Boos' procedures show to achieve more power with respect to the Suissa & Shuster's procedure. This power difference is higher in cases of high imbalanced sample sizes (e.g. $n_1 = 20, n_2 = 90$; $n_1 = 20, n_2 = 100$; $n_1 = 30, n_2 = 100$). Differences emerge also with respect to the use of different levels of γ. Indeed, the use of both $\gamma = 0.0001$ and $\gamma = 0.00001$ leads to achieve more power when $n_1 = 10, n_2 = 100$; $n_1 = 20, n_2 = 50$; $n_1 = 30, n_2 = 50$; $n_1 = 30, n_2 = 60$; $n_1 = 40, n_2 = 60$; $n_1 = 40, n_2 = 70$; $n_1 = 40, n_2 = 80$. In two cases, when $n_1 = 30, n_2 = 90$ and $n_1 = 30, n_2 = 100$, the use of both $\gamma = 0.001$ and $\gamma = 0.0001$ leads to achieve more power with respect to the use of $\gamma = 0.00001$. When $P = 0.50$ the Berger & Boos' tests lead to achieve more power with respect to the Suissa & Shuster's test, with the only exception of the case when $n_1 = 30, n_2 = 40$, where the four tests show to achieve similar levels of power. As in previous cases, also when $P = 0.90$ power differences are more relevant in cases of high imbalanced sample sizes (e.g. $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). The use of the three Berger & Boos' procedures does not lead to relevant differences in power, with two exceptions. First, when $n_1 = 10, n_2 = 40$, fixing γ at 0.001 or 0.0001 leads to a more powerful test with respect to fixing γ at 0.00001. Second, when $n_1 = 40, n_2 = 50$ or when $n_1 = 40, n_2 = 60$, using the Berger & Boos' procedure with γ fixed at 0.0001 leads to the most powerful test; moreover, fixing γ at 0.00001 leads to a more powerful test with respect to fixing γ at 0.001. When $P = 0.75$ the Berger & Boos' tests are always more powerful than the original Suissa & Shuster's test. Also in this case, this power difference is higher in cases of high imbalanced sample sizes (e.g. $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). No relevant differences emerge with respect to the use of different levels of γ. This "state of the art" also holds when $P = 0.90$, with the exceptions of the cases when $n_1 = 30, n_2 = 40$; $n_1 = 40, n_2 = 50$, where the use of $\gamma = 0.0001$ or $\gamma = 0.00001$ leads to more powerful tests with respect to fixing γ at 0.001.

We now comment the results we obtained for the **pooled** test; let's begin with the case when $\boldsymbol{\alpha}$= **0.05** (see Figure C.19). When $P = 0.10$, the Berger &

Boos' test always prove to achieve more power than the Suissa & Shuster's test, with the only two exceptions of low imbalanced sample sizes, such as the cases of $n_1 = 20, n_2 = 30$ and $n_1 = 40, n_2 = 50$. In all the other cases, the Berger & Boos' tests lead to achieve more power, but not significant differences are found with respect to the use of different levels of γ. Furthermore, note that, as previously revealed for the unpooled statistic, the difference in power between the use of the constrained and the unconstrained optimization procedures is found in cases of high imbalanced sample sizes (e.g. $n_1 = 10, n_2 = 70$; $n_1 = 10, n_2 = 80$; $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). When $P = 0.25$, the Berger & Boos' tests alway achieve more power than the Suissa & Shuster's test, with the only exception of the case when $n_1 = 40, n_2 = 50$, where the four tests achieve the same levels of power. Differences are found with respect to the use of different Berger & Boos' procedures. In particular, when $n_1 = 20, n_2 = 60$ and when $n_1 = 40, n_2 = 80$, fixing γ at 0.0001 leads to achieve more power than fixing γ at both 0.001 and 0.00001. Furthermore, in the cases when $n_1 = 30, n_2 = 60$; $n_1 = 30, n_2 = 80$; $n_1 = 40, n_2 = 80$; $n_1 = 40, n_2 = 90$, fixing γ at both 0.0001 and 0.00001 leads to achieve more power than fixing γ at 0.001. Also when $P = 0.50$, the use of the Berger & Boos' procedure leads to a more powerful test than the use of the Suissa & Shuster's procedure, with the only exception of the case when $n_1 = 40, n_2 = 70$. When $n_1 = 20, n_2 = 80$; $n_1 = 30, n_2 = 80$; $n_1 = 30, n_2 = 100$ and $n_1 = 40, n_2 = 90$, fixing γ at both 0.0001 and 0.00001 leads to achieve more power than fixing γ at 0.001. Moreover, when $n_1 = 20, n_2 = 70$ fixing γ at 0.0001 leads to achieve more power with respect to fixing γ at both 0.001 and 0.00001. When $P = 0.75$, the four tests are found to achieve the same level of power in several cases (e.g. $n_1 = 10, n_2 = 30$; $n_1 = 10, n_2 = 50$; $n_1 = 20, n_2 = 80$; $n_1 = 40, n_2 = 100$). In all the other cases, the use of the Berger & Boos' procedure leads to achieve more power with respect to the use of the Suissa & Shuster's procedure. As previously noted, this power difference is higher in cases of high imbalanced sample sizes. No relevant power difference are found with respect to the use of different values of γ, with the exception of the case when $n_1 = 20, n_2 = 70$, where fixing γ at 0.0001 or 0.00001 leads to achieve more power than fixing γ at 0.001. Also when $P = 0.90$, the four tests show to be equivalent in several cases (e.g. $n_1 = 10, n_2 = 80$; $n_1 = 20, n_2 = 60$; $n_1 = 20, n_2 = 70$). In other cases, the Suissa & Shuster's test leads to achieve more power than the Berger & Boos' test, but these differences are slight (e.g. $n_1 = 20, n_2 = 50$; $n_1 = 20, n_2 = 80$). In few cases, the use of the constrained maximization procedure leads to achieve more power than the use of the unconstrained procedure, and typically these are cases of high imbalanced sample sizes (e.g. $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). No differences are found with respect to the use of different values of γ.

Let's now comment the results we've obtained for the **pooled** statistic when **$\boldsymbol{\alpha}$= 0.025**. When P = 0.10, the Berger & Boos' tests always prove to be more powerful with respect to the Suissa & Shuster's test. As previously observed, these differences are particularly relevant when the sample sizes are high imbalanced (note, for instance, that the power difference can also reach 0.7, 0.8 or 0.9 when $n_1 = 20, n_2 = 90$; $n_1 = 10, n_2 = 100$). Slight difference are found with respect to the use of different levels of γ, with the use of $\gamma = 0.0001$ or $\gamma = 0.00001$ leading to more powerful tests with respect to the use of $\gamma = 0.001$. Also when $P = 0.25$, the Berger & Boos' test always prove to be more powerful than the Suissa & Shuster's test. Moreover, slight power differences are found with respect to the use of different levels of γ, but these differences always indicate that using $\gamma = 0.0001$ or $\gamma = 0.00001$ leads to more powerful tests with respect to fixing γ at 0.001. Similar conclusions can be drawn for the case of $P = 0.50$: apart from some exceptions (e.g. $n_1 = 10, n_2 = 20$; $n_1 = 20, n_2 = 30$), generally the use of the Berger & Boos' procedure leads to more powerful test than the Suissa & Shuster's procedure. Also in this case, sligth power differences are found with respect to the use of different levels of γ, but these differences always indicate that fixing $\gamma = 0.0001$ or $\gamma = 0.00001$ leads to more powerful tests with respect to fixing γ at 0.001. Different results are found when $P = 0.75$. In this case, in several situations the four tests show to achieve a similar level of power (e.g. $n_1 = 10, n_2 = 40$; $n_1 = 10, n_2 = 60$), whereas, as previously shed into light, the superiority of the Berger & Boos' procedure in cases of high imbalanced sample sizes is clear (see the cases when $n_1 = 10, n_2 = 90$; $n_1 = 10, n_2 = 100$). Moreover, minor power differences are found with respect to the use of different levels of γ. Similar conclusions to the case of $P = 0.75$ can be drawn for the case of $P = 0.90$.

Last, in Figure C.21 are reported the results obtained for the **pooled** statistic, when **$\boldsymbol{\alpha}$= 0.01**. When $P = 0.10$, the Berger & Boos' tests always prove to be more powerful than the Suissa & Shuster's test. We note that, differently from several cases previously commented, the power difference between the two procedures is relevant also for cases of relatively low imbalanced sample sizes (e.g. $n_1 = 10, n_2 = 20$; $n_1 = 10, n_2 = 30$; $n_1 = 10, n_2 = 40$). Only minor differences are found with respect to the use of different levels of γ. Results are very similar when $P = 0.25$, where the constrained optimization procedure is still more powerful than the unconstrained optimization procedure. In two cases, it is found that the four tests achieve the same level of power ($n_1 = 40, n_2 = 50$; $n_1 = 40, n_2 = 60$). Note that, in several cases, fixing γ at 0.0001 or 0.00001 leads to achieve more power than fixing γ at 0.001 (e.g.

$n_1 = 30, n_2 = 90$; $n_1 = 40, n_2 = 70$;). When $P = 0.50$, the Berger & Boos' procedure is always more powerful than the Suissa & Shuster's procedure, with the exception of some cases of relatively low imbalanced sample sizes ($n_1 = 30, n_2 = 40$; $n_1 = 40, n_2 = 50$; $n_1 = 40, n_2 = 60$; $n_1 = 40, n_2 = 70$). Small differences are found with respect to the use of different levels of γ; for instance, when $n_1 = 10, n_2 = 40$, fixing γ at 0.0001 leads to achieve more power than fixing γ at both 0.001 and 0.00001. When $P = 0.75$, we can note that, in several cases, the four tests achieve the same (or very similar) level of power (e.g. $n_1 = 10, n_2 = 20$; $n_1 = 10, n_2 = 30$; $n_1 = 20, n_2 = 30$). In cases in which the Suissa & Shuster's test achieves more power than the Berger & Boos' test (γ is fixed at 0.001), such a power difference is not relevant (e.g. $n_1 = 40, n_2 = 70$; $n_1 = 40, n_2 = 80$). When $P = 0.90$, graphs show that all the four tests achieve similar levels of power, with only minor differences indicating either a better performance of the Suissa & Shuster's test or a better performance of the Berger & Boos' test.

6.6 Discussion

Exact unconditional tests are a useful tool for testing statistical hypotheses on the 2×2 binomial trial. From a historical point of view, these tests have not been developed for applications until the 1980s. In fact, computational intensive procedures are necessary for the derivation of the attained sizes and, hence, the conditional approach for testing statistical hypotheses has been far and away more popular. Nevertheless, the unconditional approach presents with three fundamental advantages with respect to the conditional approach: i) a better fit to the design of the study when only one margin is fixed by design; ii) a clearer and easier interpretation of the results; iii) stronger power properties.

In this chapter, a new R's algorithm has been developed in order to derive both the attained sizes and the power of the Suissa & Shuster's test. First, we've considered the case of balanced sample sizes, for which Suissa and Shuster (1985) report that the unpooled Z test and the pooled Z tests are equivalent. As shown in Figure C.1, Figure C.2 and Figure C.3 (see Appendix C), we essentially confirm this statement.

Second, we've used the R's algorithm to derive the attained sizes in the case of imbalanced sample sizes. This case has not yet been comprehensively studied, even if several authors (see Hirji (2006)) have reported that in these cases both conditional and unconditional tests have poor power properties. We find that: i) generally the pooled Z test is less conservative than the unpooled Z test; ii) generally the pooled Z test achieve more power than the unpooled Z test, even if the pooled test is not uniformly more powerful than the unpooled test. Hence we suggest that, following Berger (1994), the pooled Z test is appropriate for applications.

Third, we've compared two different procedures aimed to unconditionally compute the attained sizes. Suissa and Shuster (1985) use the classic Lehmann (1959)'s procedure, which maximizes the null power function with respect to the nuisance parameter p over the entire parametric space. As it has been shown by Berger and Boos (1994), sometimes this procedure obtains the attained sizes adopting values of the nuisance parameter which can be very unusual on the light of the observations. In fact, the maximum of the null power function on the nuisance parameter space is achieved for values of p that are strictly closed to 0 or to 1. Hence, a new approach for the computation of the attained sizes has been proposed, for which these are calculated maximizing the null power function over a confidence set (calculated at a fixed level $(1 - \gamma)$) for the nuisance parameter space and summing up the result of this maximization with the value of γ (Berger and Boos (1994)). However, no research has been yet conducted on the use of different confidence levels for calculating the attained sizes. In this chapter, we set different values of γ (0.001, 0.0001, 0.00001) in order to compare the conservatorism and the power achieved by both the pooled and the unpooled Z tests. Berger (1994) reports that the Suissa and Shuster (1985) test, using the pooled variance estimate and the confidence interval modification of Berger and Boos (1994), generally has good power properties. Note that Berger (1994)'s paper has been the first work to propose a thorough comparison of the powers of several unconditional tests. Previous works had mostly focused on the size and not on the power of the tests (e.g. Upton (1982), Storer and Kim (1990), Haber (1986)). However, also the comparison proposed in Berger (1994) has to be considered inadequate since only nine sample sizes have been compared and only one α level (0.10) has been fixed. In the present chapter, we've fixed three different α levels (0.05; 0.025; 0.01) and used 30 different sample sizes varying with respect to the degree of imbalance. Moreover, we've computed the confidence set for the nuisance parameter using Monte Carlo simulations from binomial random variables with different success probability parameter (P=0.10; 0.25; 0.50; 0.75; 0.90).

As far as the unpooled Z statistic is concerned, we report that the use of the Berger & Boos' procedure in order to calculate the attained sizes leads to less conservative tests with respect to the classic Suissa & Shuster's procedure. Note that the degree of conservatorism depends on the probability parameter in the population for which is calculated the confidence set. We report a larger advantage in the use of the Berger & Boos' procedure when $P = 0.25; 0.50; 0.75$. Furthermore, the best performances in terms of less conservatorism are obtained when γ is calculated at level 0.001 and 0.0001. Hence, it does not appear useful to set a too large confidence value for the confidence set (as, for instance, it is implemented in StatXact 8). Last, a no clear relation between the conservatorism of the procedures and the degree of imbalance of the sample sizes is reported.

Similar conclusions can be drawn for the pooled Z statistic when $P = 0.25; 0.50; 0.75$: using the Berger & Boos' procedure leads to less conservative attained sizes. On the contrary, when $P = 0.10$ or $P = 0.90$ the use of the classic Suissa & Shuster's procedure is more appropriate (and this result is stronger for the pooled case with respect to the unpooled case). Also in the pooled case, no advantage is found fixing a larger confidence interval and a no clear relation holds between the conservatorism of the procedures and the degree of imbalance of the sample sizes.

Altogether, we can state that the use of a Berger & Boos' procedure to calculate the attained sizes leads to a substantial advantage in terms of less conservatorism with respect to the classic Suissa & Shuster's procedure, both for the unpooled and for the pooled case. Moreover, our data support the Berger (1994)' s suggestion to fix γ at 0.001. In fact, in most cases we've considered, fixing γ at 0.001 leads to a less conservative test with respect to fixing γ either at 0.0001 or 0.00001. Nevertheless, for purposes of application, the Berger & Boos' procedure should be handled with caution when the success probability in the population is suspected to be either too low or too high. Indeed, in these cases, evidence is obtained on the superiority of the Suissa & Shuster's procedure in terms of less conservatorism.

As far as power is concerned, the results that have been presented in the previous section comprehensively indicate that, commonly, the use of the Berger & Boos' procedure leads to achieve more power with respect to the use of the Suissa & Shuster's procedure. This advantage is related to the degree of imbalance of the sample sizes, with high imbalanced designs (e.g. $n_1 = 10, n_2 = 100$) gaining much more power than low imbalanced designs. Our graphs clearly show that, in cases of low imbalanced designs (e.g. $n_1 = 20, n_2 = 30$; $n_1 = 30, n_2 = 40$), using the Suissa & Shuster's or the Berger & Boos' procedure leads to very similar level of powers. This pattern of results has been obtained with all the levels of α that we've fixed ($\alpha = 0.05$, $\alpha = 0.025$, $\alpha = 0.01$) and both for the pooled and for the unpooled test. Furthermore, we've compared the use of different levels of γ with the Berger & Boos' procedure. No substantial differences emerge in any of the case we've considered. Normally, when there is a difference among the three procedures, this indicates a superiority of either the use of γ at 0.0001 or 0.00001 with respect to $\gamma = 0.001$. However, this difference in power is always very slight and unimportant for application purposes. Consequently, our suggestion is to adopt a not too large level of confidence for the Berger & Boos' procedure (i.e. $\gamma = 0.001$ or $\gamma = 0.0001$), thus obtaining a less conservative test.

Conclusion and Perspectives

The present work has focused on testing hypotheses on the 2×2 binomial trial in the Potential Outcomes Framework. This is a theory for causal inference that was originally developed by Donald Rubin and coworkers during the 1970s. This is more than either a new statistical tool or a new statistical technique, but it is a distinctive way to look at the problem of causality, especially as far as observational studies are concerned. First of all, the Rubin Causal Model is a method of reasoning, that makes explicit and clear assumptions that are only implicitly put forward in classic approaches aimed to study the relation among variables, such as multiple regression. As we've mentioned in Chapter 1, the fundamental purpose of causal inference is to evaluate whether a certain treatment (or program) has / does not have an effect on each unit receiving this treatment (e.g. a pharmacological trail or an educational program). Since each unit can be either exposed or not exposed to the treatment, but cannot be both exposed and not exposed to the same treatment, it is not possible to draw causal inference at an *individual* level. This is the famous statement known as the *fundamental problem of causal inference* (Holland, 1986). This problem can be actually solved only at a population level, i.e. by considering different participants exposed to different levels of treatment or comparing the same units at different times. In order to draw causal inference at a population level, assumptions must be put forward, such as the fundamental *unconfoundedness* assumptions. In the last 30 years, several methods for *estimating causal effects* either under unconfoundedness or under other assumptions have been proposed.

Nevertheless, less interest has been given to the problem of *testing statistical hypotheses* in the Potential Outcomes Framework, which has been mainly treated by Donald Rubin and coworkers (see Imbens and Rubin (2011)). In the present thesis, we've reviewed the main approaches to causal inference –which refer to the Rubin Causal Model– essentially in order to make explicit hypotheses and assumptions that have to be put forth when testing statistical hypotheses in observational studies. We will set this to work in an observational study that shall be briefly presented in this Conclusion.

Let's now sum up the main results that have been achieved in Chapters 4,5 and 6, in which we've considered the problem of testing statistical hypotheses on the 2×2 binomial trial. First, the advantages of the unconditional approach over the widespread conditional approach have been highlighted. Second, the Suissa and Shuster (1985)'s work has been presented and some limitations (from a computational point of view) have been emphasized. Third, a new R algorithm for computing the p-values of the Suissa & Shuster's test (for both balanced and imbalanced sample sizes) has been presented. Fourth, we've computed the p-values using both the classic Lehmann (1959)'s procedure and the restricted Berger and Boos (1994)'s procedure.

At our knowledge (see for instance Lydersen *et al.* (2009)), at the actual "state of the art" there do not exist published works that have investigated on the choice of optimal values of the confidence level $(1 - \gamma)$ to be used in the Berger and Boos (1994)'s procedure. In Chapter 6 we've dealt with this problem using Monte Carlo simulations.

We now recall the main results we've obtained. First, as far as the Suissa & Shuster's test is concerned, we've found that, normally, the pooled Z test is less conservative than the unpooled Z test. Moreover, generally the pooled Z test achieves more power than the unpooled Z test, even if the pooled test is not uniformly more powerful than the unpooled test. This has also been reported by previous works (e.g Berger (1994)), but we've checked more cases, varying the degree of imbalance of the two sample sizes.

Second, we've compared the classic Suissa and Shuster (1985)'s procedure with the Berger and Boos (1994)'s procedure to unconditionally compute the p-values. We've set different values of γ (0.001, 0.0001, 0.00001) and we've computed the confidence set for the nuisance parameter using Monte Carlo simulations from binomial random variables with different success probability parameters (P=0.10; 0.25; 0.50; 0.75; 0.90).

It has been shown that, in the unpooled case, the use of the Berger & Boos' procedure in order to calculate the p-values leads to less conservative tests with respect to the classic Suissa & Shuster's procedure. The degree of conservatorism has proved to be dependent from the probability parameter of the random variable used to simulate and to derive the confidence set.

Larger advantages in the use of the Berger & Boos' procedure have been reported when $P = 0.25; 0.50; 0.75$ rather than when $P = 0.10; 0.90$. Moreover, we've found that fixing γ at 0.001 or 0.0001 leads to less degrees of conservatorism.

Similar results have been found for the pooled Z statistic when $P = 0.25; 0.50; 0.75$. On the contrary, when $P = 0.10$ or $P = 0.90$ we've reported that the use of the classic Suissa & Shuster's procedure is more appropriate. With respect to the Berger & Boos' procedure, we've found that fixing a larger confidence interval does not lead to a less conservative test. In addition, no clear relation has been found between the conservatorism of the procedures and the degree of imbalance of the sample sizes.

With respect to power, our results indicate that, generally, the use of the Berger & Boos' procedure leads to achieve more power than the use of the Suissa & Shuster's procedure. This advantage is related to the degree of imbalance of the sample sizes, with high imbalanced designs achieving higher levels of power than low imbalanced designs.

Furthermore, no substantial differences in terms of power have emerged using different levels of γ in the Berger & Boos' procedure. Consequently, our suggestion is to adopt a not too large level of confidence in the Berger & Boos' procedure (i.e. $\gamma = 0.001$ or $\gamma = 0.0001$), thus obtaining both a less conservative test and good power.

Two future directions of this work stand out: i) a comparison of the Berger and Boos (1994)'s procedure using different methods to construct the confidence set (e.g. Clopper-Pearson, Bayesian); ii) the use of other statistics with respect to the pooled and unpooled Z statistics (e.g. Fisher-Boschloo's test; Lancaster's unconditional test; Liebermeister's unconditional test) and a critical comparison of both the degree of conservatorism of the p-values and the power achieved by these unconditional tests.

Further work

We now present some details of an observational study we're applying the results obtained in the present thesis (Ripamonti *et al.*, 2011). This research project aims to study the *neural correlates* of the major *acquired reading impairments*. Although nowadays there exists a flourishing literature describing in detail the cognitive performance of brain-damaged patients, the neuroanatomical localization of these syndromes is not totally clear and is mostly related to single-case studies, since not many group studies have been yet published.

Ever since the seminal papers by Marshall and Newcombe (1966, 1973), the investigation on acquired reading disorders has played a central role in cognitive neuropsychology. In the previous decades, acquired reading disorders were interpreted in the classical Déjerine (1891, 1892) framework. In 1891, the French neurologist Joseph-Jules Déjerine reported the case of a 63-year-old man, with both a reading and a spelling impairment (cécité verbale avec agraphie, i.e. verbal blindness with agraphia) in the absence of any object-naming deficit. This patient suddenly discovered not being able to read, apparently without any other language impairments (but verbal paraphasias, both in the spontaneous speech and in repetition, were found at a more detailed investigation of the patient's oral language). The post-mortem examination of the brain tissue revealed a cerebral damage to the left parietal lobe (including the angular gyrus). In 1892, Déjerine described the case of a second brain-damaged patient with a reading impairment, but with no associated spelling or oral language impairments (cécité verbale pure, i.e. pure alexia, also known as alexia without agraphia or agnosic alexia). The patient did not show either difficulties in writing or in naming objects, and he presented with right homonymous hemianopia but spared color naming ability. In this case, the autopsy revealed the presence of occipital and inferior temporal lesions, extending to the retroventricular white matter and the callosal splenium. A disconnection of the visual information in the right hemisphere from the intact store of "optical images of letters and words" in the left angular gyrus was proposed by Déjerine as a theoretical explanation of pure alexia. On the other side, a lesion of the left angular gyrus (as in the 1891's patient) would product both a spelling and a reading impairment. As wisely observed by Coslett (2000), although nowadays limited, Déjerine's ground-breaking accounts of acquired dyslexia in some aspects presage contemporary cognitive psychologists' theories. Moreover, note that, in his pioneering model of reading, Déjerine assumed the existence of a written word-form area in the left angular gyrus, while the right hemisphere is conceived as word-blind, so that the visual images of words would have to reach the left angular gyrus to be identified. Déjerine's anatomo-functional account of written language remained undisputed until the second half of the twentieth century, and continues to be considered as the major frame of reference for the clinical description of reading and writing disorders after brain damage.

However, Déjerine's taxonomy could not account for some qualitative aspects of reading disorders that can occur among acquired dyslexic patients following left-hemisphere lesions, left hemispherectomy or cerebral hemispheres dissections (split-brain patients). These aspects include the emergence of semantic, visual and morphological errors; grammatical class (e.g. nouns are read better than verbs), imageability, and word frequency effects. Furthermore, Déjerine's model could not account for the inability of reading irregular words or nonwords commonly found in dyslexic patients. A fundamental contribution to the study of acquired reading disorders came from the Dual-Route cognitive model, originally proposed from both a psycholinguistic and a neurolinguistic perspective in a series of seminal papers such as those by Marshall and Newcombe (1966, 1973), Morton (1969, 1980), Forster and Chambers (1973), Morton *et al.* (1980). These authors suggested that reading is underpinned by two distinct cognitive procedures: the lexical route and the sublexical route. Originally, Marshall and Newcombe (1966, 1973) proposed a detailed investigation of acquired dyslexias from a psycholinguistic perspective and also linked the study of reading disorders with the psycholinguistic theories of normal reading. Moreover, beginning from the mid of the 1970s, normal and disordered reading processes began to be described in encapsulated box-and-arrow type diagrams (see for instance Coltheart *et al.* (1987); Ellis and Young (1988)). Nowadays, many single-cases and some group studies have been published, some peculiar dissociation and psycholinguistic patterns have been reported and increasingly elaborated cognitive theories have been proposed. Although some of the original Marshall and Newcombe's hypotheses have been criticized, the fundamental idea for which reading is mediated by two different procedures has received considerable empirical support (Coslett (2000)). Furthermore, a computational realization of the Dual-Route theory of reading, called the Dual-Route Cascaded (DRC) model, has been recently proposed by Coltheart *et al.* (2001). This model simulates a number of effects that other computational models of reading do not and there appear to be no effects that any other current computational model of reading can simulate but that the DRC model cannot.

Note that in the last thirty years, the Dual-Route model has been challenged by the formulation of other models, such as the parallel-distributed-processing (PDP) model (Seidenberg and McClelland, 1989) and an explicit model of reading by analogy (Sullivan and Damper, 1993). These two models postulate a procedure that can correctly translate both exception words and nonwords from print to phonology. There exists a long debate concerining these alternatives to the Dual-Route model (see Coltheart *et al.* (1993) for a discussion); in the present context we emphasize only that, from a clinical perspective, these alternative models cannot substitute the Dual-Route model.

The main difference between the original Déejerine's model and the Dual-Route model is that the latter provides for the existence of independent orthographic representations (orthographic input and output) and the process of reading aloud is based on two different pathways. According to the Dual Route model, after an early visual analysis, words are processed by means of an orthographic recognition system, that specifies the abstract identity (i.e. non dependent from the letter case, the font...) and the position of each letter within each word. This orthographic information can be converted into the phonological form of the word by means of three routes or processes. First, along the sub-word-level route regular words and non-lexical orthographic strings (nonwords) are processed by means of grapheme-to-phoneme conversion rules. This is a serial and slow procedure, but can provide for reading regular words or words that have a predictable relationship between spelling and sound. Contrary to words, nonwords can only be read via the sub-word-level route (but see Glushko (1979); Marcel (1980) for alternative explanations). Second, along the lexical route words are read through a three-steps procedure, proceeding from the orthographic input lexicon, through the semantic system and to the phonological output lexicon. This route provides for regular and irregular words reading and allows a fast and not laborious reading processing by activating automatically the stored conceptual knowledge (Coltheart *et al.*, 1993, 2001). Third, also the existence of a direct pathway connecting the orthographic input lexicon and the phonologic output lexicon has been put forth (Schwartz and Marin, 1980).

From a clinical perspective, several single cases characterized by dissociations (either strong or not, see Shallice (1988)) in reading performance between irregular words and nonwords have been reported. Patients suffering from *acquired surface dyslexia* show a selective deficit in reading irregular words (e.g. “yacht”, “island”, “colonel”, “have”, “borough”) despite a preserved ability in reading both regular words and nonwords along the grapheme-to-phoneme conversion routine (e.g. Marshall and Newcombe (1973); Warrington *et al.* (1980); Behrmann and Bub (1992)). Actually, these patients fail in reading aloud low-frequency and inconsistent words (for instance, they may read “pint” as though it rhymed with “mint”); in contrast, reading of regular words and nonwords is significantly better and, in the purest cases, is closed to or within normal limits (Lambon Ralph and Patterson, 2005). As reported by Coltheart *et al.* (2001), word frequency affects reading along the lexical route, for both regular and irregular words. Consequently, surface dyslexic patients are expected to report more errors when reading high-frequency irregular words rather than low-frequency irregular words (Lambon Ralph and Patterson, 2005). Furthermore, it has long been observed that the performance of surface dyslexic patients can be highly variable with respect to both accuracy and reading latencies. It has also been proposed that there exist two different subtypes of surface dyslexia (Shallice and McCarthy, 1985). One typical pattern of surface dyslexia would be characterized by effortless and accurate reading of nonwords with poor performance only with irregular words . Another variety of surface dyslexia would be characterized by dissociated performance when reading regular/irregular words, and a generally slow, effortful reading. Surface dyslexia can be associated with fluent aphasia, as Wernicke’s aphasia and Sensorial Transcortical aphasia and the syndrome has been described also in demented patients (e.g. Warrington (1975); Shallice *et al.* (1983); Hodges *et al.* (1992); Patterson and Hodges (1992))

Patients with *acquired phonological dyslexia* (e.g. Beauvois and Derouesne (1979), Dérouesné and Beauvois (1979)) show a marked failure in the ability to read nonwords but are still able to read both irregular and regular words (lexicality effect). Phonological dyslexia can also be defined in terms of a strong dissociation (i.e. a dissociation not requiring the better performance to be in the normal range, Shallice (1988)) between lexical and sublexical reading, with better performance on the lexical route. This dissociation can originate at multiple levels such as: i) an early peripheral deficit; ii) a damage to the grapheme-to-phoneme conversion procedure (classical phonological dyslexia); iii) a deficit of the phonological output buffer (Bisiacchi *et al.*, 1989). Classical phonological dyslexia reflects a selective impairment in applying the grapheme-to-phoneme conversion rules, but usually this disorder is not so severe to affect the reading of real words (that may only be slight impaired). Lexicalization errors (e.g. BEM → “Ben”) are typically interpreted as the patient’s attempt to read nonwords via the lexical reading route (Lambon Ralph and Patterson, 2005). Visual errors (e.g. TOPPLE → “table”) have been reported as well as poor performance in reading aloud morphologically complex words (Funnell, 1983). Furthermore, it has long been observed that phonological dyslexic patients obtain a better performance on concrete words than on abstract or function words (see Coltheart (1996)). Actually, this is a controversial issue, since some phonological dyslexic patients read in the same manner all different types of words (Funnell, 1983; Friedman and Kohn, 1990) whereas other patients are relatively impaired in reading function words (Glosser and Friedman, 1990). Last, as observed by Coslett (2000), phonological dyslexia might be associated with different types of aphasias, ranging from very mild or absent (e.g. Dérouesné and Beauvois (1979)) to severe nonfluent (e.g. Funnell (1983)).

Differently from phonological dyslexia, *undifferentiated dyslexia* is characterized by poor reading both on the lexical and the sublexical route.

In the present project, we aim at identifying the neural correlates of phonological dyslexia. Previous research has currently provided insufficient or not consistent information. Usually, this impairment is caused by large left-hemisphere fronto-parietal perisylvian lesions and damage to the superior temporal lobe; angular and supermarginal gyri lesions have been found in most but not all patients (Coslett, 2000; Ralph and Graham, 2000). Also left frontal regions (e.g. the frontal opercolum) have been identified as key-regions in the pathogenesis of the impairment (Fiez and Petersen, 1998; Fiez *et al.*, 2006). Recently, Rapcsak *et al.* (2009) have reported damage to a variety of perisylvian cortical regions associated with phonological dyslexia, consistent with distributed network models of phonological processing.

The main objective of the present study is to bring further evidence on the localization of the left brain areas that are critically involved in the pathogenesis of phonological dyslexia. No clear predictions can be put forward, since a wide number of critical areas have been identified by previous researches, ranging from inferior frontal, to superior temporal and inferior parietal areas.

Participants were recruited among circumscribed left-hemisphere lesioned patients consecutively admitted from three Northern Italian Rehabilitation Units over a period of one year. All patients had been discharged from the hospitals at the time of the present testing, were stable and were tested at a minimum of 3 months post-stroke. Inclusion Criteria were: i) to be Italian native speakers; ii) to have an educational level of at least 5 years of schooling; iii) to have an evidence of focal brain damage only in the left hemisphere (patients with diffuse/bilateral lesions and patients with no obvious lesions were excluded). These criteria were met in 64 patients (43 males and 21 females), aged 17-82 years (mean=55.65, SD=15.82, median=58,) who participated in the study after giving informed consent. The mean education level of the patients was 9.3 (SD=3.6, median=8) years of schooling. Handedness was tested by means of the Edinburgh Inventory (Oldfield, 1971; 61 Right Handers, 3 Left Handers). The type and severity of the language disorder was assessed by means of the Italian version of the Aachen Aphasia Test (Luzzatti *et al.*, 1996).

Lesions in 61 patients were caused by cerebrovascular diseases (41 ischemic strokes and 20 cerebral hemorrhages) and in 3 patients by traumatic brain injury. Across patients, the damage covered a lot of left hemisphere areas, including the insula, the basal ganglia, left inferior and middle frontal gyri, superior and inferior parietal lobule, superior and middle temporal gyri, the occipital lobe. For all the participants, information on lesion location was only available from clinical CT or MRI.

Lesion data shall be analyzed using a Voxel-based Lesion Symptom Mapping approach (VLSM, Bates *et al.* (2003)). VLSM uses tools similar to those employed in functional neuroimaging studies. In VLSM, at each voxel patients are divided in two groups according to whether their lesions do or do not include that voxel. The performance on a reading task for the two groups is compared by means of a statistical test and the resultant p-values are displayed as a color maps. Analyses will be performed using the softwares MRIcron (Rorden *et al.*, 2000), NPM and R. Exact unconditional test using either the Suissa & Shuster's test or the Berger & Boos' procedures will be performed.

Let's now indicate with $L = 1$ a lesioned voxel, $L = 0$ a not lesioned voxel; and with $D = 1$ a phonological dyslexic patient; $D = 0$ a not phonological dyslexic patient. In terms of the Rubin Causal Model we can define as: $D(1)|L = 1$ the factual outcome for the lesioned patients, i.e. the outcome for the lesioned patients given they have been actually lesioned to a certain voxel. We indicate as $D(0)|L = 0$ the factual outcome for the not lesioned patients, i.e. the outcome for the not lesioned patients given they have been actually not lesioned to a certain voxel. Furthermore, we define as $D(0)|L = 1$ the counterfactual outcome for the lesioned patients, i.e. the outcome for the lesioned patients had they been not lesioned to a certain voxel. We indicate with $D(1)|L = 0$ the counterfactual outcome for the not lesioned patients, i.e. the outcome for the not lesioned patients had they been lesioned to a certain voxel

Let's define as Average Lesion Effect (A.L.E.), the outcome difference between the group of lesioned patients and the group of not lesioned patients. We also define the Average Lesion Effect on Lesioned patients (A.L.L.), that indicates the outcome difference between the group of lesioned patients if factually lesioned and if counterfactually not lesioned.

In these terms, we also define the Selection Bias, that is the outcome difference that would be observed between lesioned patients and not lesioned patients in the case they were all not lesioned, capturing pre-existing differences between the two groups that cannot be attributed to the lesion.

A causal interpretation to the effect of lesions on phonological dyslexia can only be given if the selection bias is eliminated. For, it is necessary to know the lesion generating mechanism for each voxel in order to control for factors determining the selection process. Remember now the following definitions (see Chapter 3):

- *Unconditional exchangeability*: the probability to belong to the group of lesioned patients does not vary with potential outcomes
  $L \perp\!\!\!\perp (D(0), D(1))$

- *Conditional exchangeability*: the probability to belong to the group of lesioned patients does not vary with potential outcomes given the covariate X
  $L \perp\!\!\!\perp (D(0), D(1)) \,|X$

- *Selection on unobservable*: the probability of assignment to the group of lesioned patients has some dependence on the potential outcomes
  $L \perp\!\!\!\perp (D(0), D(1)) \,|X, U$, where U are unobservable variables

In the present project, we'll assume the *conditional exchangeability* of the lesion generating mechanism:

$$Pr(D(0) = 1|L = 0, X = x) = Pr(D(0) = 1|L = 1, X = x)$$

This means that, for each voxel, the probability of suffering from phonological dyslexia in the group of not lesioned patients is equal to the probability of suffering from phonological dyslexia in the group of lesioned patients had not they been lesioned, given a covariate $X = x$. Matching methods will be used in order to pair lesioned and not lesioned patients that are similar with respect one or more covariates that we've considered (handedness, sex, age, etiology, years of school attended). Under a conditional exchangeability assumption and after performing a matching procedure, we'll use VLSM techniques in order to identify those voxel causally related with phonological dyslexia. The unconditional methods both reviewed and developed in this thesis for testing statistical hypotheses on risk differences will be used.

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Appendices

Appendix A

R Codes

Code 1

```
null.power<-function(n1,n2){
quant<-1.64
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
  (comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
  dataframe.all<-data.frame(comb,d,quant.vec)
  names(dataframe.all)[1] <- "X"
  names(dataframe.all)[2]<-"Y"
  dataframe.crit<-dataframe.all[dataframe.all$d >
  dataframe.all$quant.vec,]
  dataframe.crit<-dataframe.crit[
  complete.cases(dataframe.crit),]
  expr<-rep(0,length(dataframe.crit$X))
  opt.object<-function(p){
  for(i in 1:length(dataframe.crit$X)){
  expr[i]<-(choose(n1,dataframe.crit$X[i])*
  p^(dataframe.crit$X[i]+dataframe.crit$Y[i])
  *choose(n2,dataframe.crit$Y[i])*(1-p)^
  (n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
  }
  somma<-sum(expr)
  return(somma)
  }
  pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
if(pvalue$objective <= 0.05){
quant<-1.00
  while(quant){
  quant<-quant+0.01
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+
  (comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
  dataframe.all<-data.frame(comb,d,quant.vec)
```

```
  names(dataframe.all)[1] <- "X"
  names(dataframe.all)[2]<-"Y"
  dataframe.crit<-dataframe.all[dataframe.all$d
  > dataframe.all$quant.vec,]
  dataframe.crit<-dataframe.crit[complete.cases
  (dataframe.crit),]
  expr<-rep(0,length(dataframe.crit$X))
  opt.object<-function(p){
  for(i in 1:length(dataframe.crit$X)){
    expr[i]<-(choose(n1,dataframe.crit$X[i])*
    p^(dataframe.crit$X[i]+dataframe.crit$Y[i])
    *choose(n2,dataframe.crit$Y[i])*
    (1-p)^(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
  }
  somma<-sum(expr)
  return(somma)
  }
  pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
  if(pvalue$objective<0.05) break
  }
        return(c(quant,pvalue$maximum,pvalue$objective))
}
else if (pvalue$objective>0.05) {
while(quant){
  quant<-quant+0.01
  x<-0:n1
  y<-0:n2
  comb<-(expand.grid(x,y))
  d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
  (comb[,1]/n1*(1-comb[,1]/n1))/n1+(comb[,2]/n2*(1-comb[,2]/n2)/n2))
  quant.vec<-rep(quant, length(d))
  dataframe.all<-data.frame(comb,d,quant.vec)
  names(dataframe.all)[1] <- "X"
  names(dataframe.all)[2]<-"Y"
  dataframe.crit<-dataframe.all[dataframe.all$d >
  dataframe.all$quant.vec,]
  dataframe.crit<-dataframe.crit[complete.cases
  (dataframe.crit),]
  expr<-rep(0,length(dataframe.crit$X))
  opt.object<-function(p){
  for(i in 1:length(dataframe.crit$X)){
  expr[i]<-(choose(n1,dataframe.crit$X[i])*
  p^(dataframe.crit$X[i]+dataframe.crit$Y[i])
  *choose(n2,dataframe.crit$Y[i])*(1-p)^
  (n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
  }
  somma<-sum(expr)
  return(somma)
  }
  pvalue<-optimize(opt.object, c(0,1), maximum=TRUE)
  if(pvalue$objective<0.05) break
  }
  return(c(quant,pvalue$maximum,pvalue$objective))
}
}
n2<-c(seq(20,100, by=10), seq(30,100,by=10),
seq(40,100, by=10), seq(50,100,by=10))
n1<-c(rep(10, length(seq(20,100, by=10))),
rep(20, length(seq(30,100,by=10))), rep(30, length(seq(40,100, by=10))),
rep(40, length( seq(50,100,by=10))))

pvalues<-matrix(0, nrow=3, ncol=length(n1))
```

```
for(i in 1:length(n1)){
  pvalues[,i]<-null.power(n1[i],n2[i])
}
pvalues
```

Code 2

```
AttPower<-function(n1,n2,CritVal,p1,p2){
        x<-0:n1
      y<-0:n2
      comb<-(expand.grid(x,y))
      d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
      (comb[,1]/n1*(1-comb[,1]/n1))/n1+(comb[,2]/n2*
      (1-comb[,2]/n2)/n2))
      quant.vec<-rep(CritVal, length(d))
      dataframe.all<-data.frame(comb,d,quant.vec)
      names(dataframe.all)[1] <- "X"
      names(dataframe.all)[2]<-"Y"
      dataframe.crit<-dataframe.all[dataframe.all$d >
      dataframe.all$quant.vec,]
      dataframe.crit<-dataframe.crit[complete.cases
      (dataframe.crit),]
      expr<-rep(0,length(dataframe.crit$X))
            for(i in 1:length(dataframe.crit$X)){
            expr[i]<-choose(n1,dataframe.crit$X[i])*
            p1^(dataframe.crit$X[i])*(1-p1)^(n1-dataframe.crit$X[i])*
            choose(n2,dataframe.crit$Y[i])*p2^(dataframe.crit$Y[i])*
            (1-p2)^(n2-dataframe.crit$Y[i])
           }
      somma<-sum(expr)
      return(somma)
      }
p1<-c(rep(.05,7),rep(.10,8),rep(.15,8),rep(.20,8),
rep(.25,8),rep(.30,6),rep(.35,4),rep(.40,2))
p2<-c(seq(.15,.45,.05),seq(.25,.60,.05),seq(.30,.65,.05),seq(.35,.70,.05),
seq(.40,.75,.05),seq(.45,.70,.05),seq(.50,.65,.05),.55,.60)
n1seq<-rep(n1,length(p1))
n1mat<-matrix(n1seq, nrow=length(p1),ncol=length(n1),byrow=T)
n1vecmat<-as.vector(n1mat)
n2seq<-rep(n2,length(p2))
n2mat<-matrix(n2seq, nrow=length(p2),ncol=length(n2),byrow=T)
n2vecmat<-as.vector(n2mat)
Criticals<-pvalues[1,]
Critseq<-rep(Criticals,51)
Critmat<-matrix(Critseq,nrow=51,ncol=length(Criticals),byrow=T)
Critvecmat<-as.vector(Critmat)
pvaluesseq<-rep(pvalues[3,],51)
pvaluesmat<-matrix(pvaluesseq,nrow=51,ncol=length(pvalues[3,]),byrow=T)
pvaluesvecmat<-as.vector(pvaluesmat)
vecp1<-rep(p1,length(n1))
vecp2<-rep(p2,length(n2))

powerval<-rep(0,length(vecp1))
for(i in 1:length(vecp1)){
  powerval[i]<-AttPower(n1vecmat[i], n2vecmat[i], Critvecmat[i], vecp1[i], vecp2[i])
}
powerval
```

R Code 3

```
MLE<-function(n1,n2,P){
N<-1000
set.seed(1968)
    ymc <- rbinom(N, size = n2, prob = P)
    xmc <- rbinom(N, size = n1, prob = P)
        expr<-rep(0,length(xmc))
                for(i in 1:length(xmc)){
                        expr[i]<-(xmc[i]+ymc[i])
                }
        stima<-sum(expr)/(N*(n1+n2))
    return(stima)
    }
N<-1000
n2<-c(rep(c(seq(20,100, by=10), seq(30,100,by=10),
seq(40,100, by=10), seq(50,100,by=10)),5))
n1<-c(rep(c(rep(10, length(seq(20,100, by=10))),
rep(20, length(seq(30,100,by=10))), rep(30, length(seq(40,100, by=10))),
rep(40, length(seq(50,100,by=10)))),5))
length(n1)
length(n2)
P<-c(rep(.10,30), rep(.25,30), rep(.50,30), rep(.75,30), rep(.90,30))
length(P)
MLE.cal<-matrix(0, nrow=1, ncol=length(n1))
for(i in 1:length(n1)){
  MLE.cal[,i]<-MLE(n1[i],n2[i],P[i])
}
MLE.cal

# Calculating a Confidence Set for the MLE Estimator using the Wald Confidence Interval
low.bound<-rep(0, length(n1))
for(i in 1:length(n1)){
        low.bound[i]<-MLE.cal[i]-qnorm(p = 0.9995)*
        sqrt((MLE.cal[i]*(1-MLE.cal[i]))/(N*(n1[i]+n2[i])))
}
low.bound
upp.bound<-rep(0, length(n1))
for(i in 1:length(n1)){
        upp.bound[i]<-MLE.cal[i]+qnorm(p=0.9995)*
        sqrt((MLE.cal[i]*(1-MLE.cal[i]))/(N*(n1[i]+n2[i])))
}
upp.bound

gamma.value<-rep(0.001, length(n1))

null.power<-function(n1,n2, gamma.value, low.bound, upp.bound){
quant<-1.64
 x<-0:n1
      y<-0:n2
      comb<-(expand.grid(x,y))
      d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
      (comb[,1]/n1*(1-comb[,1]/n1))/n1+(comb[,2]/n2*(1-comb[,2]/n2)/n2))
      quant.vec<-rep(quant, length(d))
      dataframe.all<-data.frame(comb,d,quant.vec)
      names(dataframe.all)[1] <- "X"
      names(dataframe.all)[2]<-"Y"
      dataframe.crit<-dataframe.all[dataframe.all$d > dataframe.all$quant.vec,]
      dataframe.crit<-dataframe.crit[complete.cases(dataframe.crit),]
      expr<-rep(0,length(dataframe.crit$X))
      opt.object<-function(p){
```

```
            for(i in 1:length(dataframe.crit$X)){
              expr[i]<-(choose(n1,dataframe.crit$X[i])*
              p^(dataframe.crit$X[i]+dataframe.crit$Y[i])
              *choose(n2,dataframe.crit$Y[i])*
              (1-p)^(n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
            }
        somma<-sum(expr)
        return(somma)
        }
        pvalue<-optimize(opt.object, c(low.bound,upp.bound), maximum=TRUE)
if(pvalue$objective + gamma.value <= 0.05){
quant<-1.00
     while(quant){
        quant<-quant+0.01
        x<-0:n1
        y<-0:n2
        comb<-(expand.grid(x,y))
        d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
        (comb[,1]/n1*(1-comb[,1]/n1))/n1+(comb[,2]/n2*(1-comb[,2]/n2)/n2))
        quant.vec<-rep(quant, length(d))
        dataframe.all<-data.frame(comb,d,quant.vec)
        names(dataframe.all)[1] <- "X"
        names(dataframe.all)[2]<-"Y"
        dataframe.crit<-dataframe.all[dataframe.all$d
        > dataframe.all$quant.vec,]
        dataframe.crit<-dataframe.crit[complete.cases
        (dataframe.crit),]
        expr<-rep(0,length(dataframe.crit$X))
        opt.object<-function(p){
            for(i in 1:length(dataframe.crit$X)){
              expr[i]<-(choose(n1,dataframe.crit$X[i])*
              p^(dataframe.crit$X[i]+dataframe.crit$Y[i])
              *choose(n2,dataframe.crit$Y[i])*(1-p)^
              (n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
            }
        somma<-sum(expr)
        return(somma)
        }
        pvalue<-optimize(opt.object, c(low.bound,upp.bound), maximum=TRUE)
        if(pvalue$objective + gamma.value < 0.05) break
     }
     return(c(quant,pvalue$maximum,pvalue$objective + gamma.value))
     }
else if (pvalue$objective + gamma.value > 0.05) {
while(quant){
        quant<-quant+0.01
        x<-0:n1
        y<-0:n2
        comb<-(expand.grid(x,y))
        d<-((comb[,2]/n2)-(comb[,1]/n1))/sqrt(
        (comb[,1]/n1*(1-comb[,1]/n1))/n1+(comb[,2]/n2*(1-comb[,2]/n2)/n2))
        quant.vec<-rep(quant, length(d))
        dataframe.all<-data.frame(comb,d,quant.vec)
        names(dataframe.all)[1] <- "X"
        names(dataframe.all)[2]<-"Y"
        dataframe.crit<-dataframe.all[dataframe.all$d > dataframe.all$quant.vec,]
        dataframe.crit<-dataframe.crit[complete.cases(dataframe.crit),]
        expr<-rep(0,length(dataframe.crit$X))
        opt.object<-function(p){
            for(i in 1:length(dataframe.crit$X)){
              expr[i]<-(choose(n1,dataframe.crit$X[i])*
              p^(dataframe.crit$X[i]+dataframe.crit$Y[i])
```

```
            *choose(n2,dataframe.crit$Y[i])*(1-p)^
            (n1+n2-dataframe.crit$X[i]-dataframe.crit$Y[i]))
          }
      somma<-sum(expr)
      return(somma)
      }
      pvalue<-optimize(opt.object, c(low.bound,upp.bound), maximum=TRUE)
      if(pvalue$objective + gamma.value < 0.05) break
    }
    return(c(quant,pvalue$maximum,pvalue$objective + gamma.value))
}
}

pvalues<-matrix(0, nrow=3, ncol=length(n1))
for(i in 1:length(n1)){
  pvalues[,i]<-null.power(n1[i],n2[i],
  gamma.value[i], low.bound[i], upp.bound[i])
}
pvalues
```

Appendix B

Tables

Table B.1: P-values calculated for the z-unpooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.05**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
10	10	1.96	0.7007	0.0474
11	11	1.92	0.8034	0.0454
12	12	1.86	0.8154	0.0468
13	13	1.81	0.8258	0.0480
14	14	1.77	0.8349	0.0491
15	15	1.74	0.5000	0.0495
16	16	1.92	0.1181	0.0416
17	17	1.90	0.8880	0.0420
18	18	1.88	0.1065	0.0424
19	19	1.86	0.7183	0.0415
20	20	1.85	0.5000	0.0404
21	21	1.83	0.5000	0.0442
22	22	1.81	0.5000	0.0481
23	23	1.84	0.6151	0.0438
24	24	1.80	0.3670	0.0455
25	25	1.77	0.3546	0.0472
26	26	1.75	0.3439	0.0489
27	27	1.79	0.2580	0.0413
28	28	1.78	0.7464	0.0423
29	29	1.78	0.7508	0.0432
30	30	1.77	0.7550	0.0440

Table B.1: continue on next page

Table B.1: –continued from previous page

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
31	31	1.72	0.5000	0.0490
32	32	1.80	0.5966	0.0458
33	33	1.77	0.6118	0.0471
34	34	1.75	0.6289	0.0488
35	35	1.75	0.3468	0.0470
36	36	1.75	0.1520	0.0435
37	37	1.70	0.2186	0.0492
38	38	1.71	0.7884	0.0497
39	39	1.74	0.8539	0.0445
40	40	1.73	0.8556	0.0448
50	50	1.71	0.1289	0.0476
60	60	1.70	0.1608	0.0500
70	70	1.72	0.6132	0.0476
80	80	1.68	0.6877	0.0494
90	90	1.69	0.3616	0.0494
100	100	1.68	0.8758	0.0495
150	150	1.67	0.3544	0.0498

Table B.1: concluded from previous page

Table B.2: P-values calculated for the z-unpooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
10	10	2.17	0.5000	0.0211
11	11	2.40	0.6449	0.0207
12	12	2.26	0.3184	0.0225
13	13	2.16	0.3038	0.0243
14	14	2.19	0.7879	0.0208
15	15	2.14	0.7962	0.0216
16	16	2.29	0.8033	0.0224
17	17	2.21	0.1910	0.0231
18	18	2.14	0.3308	0.0239
19	19	2.14	0.1776	0.0243
20	20	2.10	0.1736	0.0249
21	21	2.17	0.8465	0.0248

Table B.2: continue on next page

Table B.2: –continued from previous page

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
22	22	2.14	0.5000	0.0244
23	23	2.17	0.5585	0.0237
24	24	2.12	0.6050	0.0245
25	25	2.10	0.3416	0.0232
26	26	2.06	0.3330	0.0243
27	27	2.11	0.2867	0.0223
28	28	2.10	0.7180	0.0231
29	29	2.09	0.7224	0.0238
30	30	2.15	0.7875	0.0216
31	31	2.11	0.5936	0.0240
32	32	2.09	0.3606	0.0233
33	33	2.06	0.3530	0.0243
34	34	2.06	0.1975	0.0233
35	35	2.06	0.3043	0.0240
36	36	2.05	0.3002	0.0247
37	37	2.05	0.8105	0.0244
38	38	2.04	0.8114	0.0247
39	39	2.10	0.5987	0.0230
40	40	2.08	0.6084	0.0238
50	50	2.05	0.6056	0.0244
60	60	2.05	0.5875	0.0245
70	70	2.00	0.8245	0.0249
80	80	2.01	0.3210	0.0245
90	90	2.00	0.3654	0.0250
100	100	2.01	0.5967	0.0248
150	150	2.00	0.6112	0.0244

Table B.2: concluded from previous page

Table B.3: P-values calculated for the z-unpooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.01**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
10	10	2.76	0.5000	0.0064
11	11	2.63	0.5000	0.0087
12	12	2.83	0.6114	0.0087

Table B.3: continue on next page

Table B.3: –continued from previous page

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
13	13	2.67	0.6577	0.0096
14	14	2.65	0.2519	0.0083
15	15	2.57	0.7560	0.0088
16	16	2.51	0.7612	0.0094
17	17	2.66	0.7714	0.0099
18	18	2.63	0.6552	0.0084
19	19	2.59	0.3353	0.0091
20	20	2.56	0.5000	0.0084
21	21	2.54	0.5000	0.0098
22	22	2.59	0.5519	0.0097
23	23	2.55	0.3287	0.0091
24	24	2.49	0.3236	0.0097
25	25	2.51	0.7387	0.0093
26	26	2.47	0.7534	0.0098
27	27	2.50	0.5000	0.0100
28	28	2.55	0.5908	0.0091
29	29	2.50	0.6087	0.0096
30	30	2.48	0.3498	0.0092
31	31	2.44	0.3434	0.0097
32	32	2.46	0.7043	0.0091
33	33	2.43	0.7063	0.0094
34	34	2.54	0.4659	0.0093
35	35	2.50	0.5821	0.0095
36	36	2.48	0.7760	0.0094
37	37	2.44	0.3649	0.0098
38	38	2.44	0.2197	0.0098
39	39	2.45	0.7277	0.0093
40	40	2.44	0.7304	0.0096
50	50	2.48	0.5818	0.0091
60	60	2.44	0.5839	0.0096
70	70	2.42	0.5838	0.0097
80	80	2.39	0.7375	0.0097
90	90	2.38	0.7609	0.0097
100	100	2.37	0.1185	0.0099
150	150	2.37	0.6167	0.0097

Table B.3: concluded from previous page

Table B.4: Achieved power and p-values calculated for the z-unpooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha} = \mathbf{0.05}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	10	1.96	0.0474	0.05	0.15	0.1109	29	29	1.78	0.0432	0.05	0.15	0.3151
10	10	1.96	0.0474	0.05	0.20	0.2037	29	29	1.78	0.0432	0.05	0.20	0.5053
10	10	1.96	0.0474	0.05	0.25	0.3101	29	29	1.78	0.0432	0.05	0.25	0.6861
10	10	1.96	0.0474	0.05	0.30	0.4205	29	29	1.78	0.0432	0.05	0.30	0.8247
10	10	1.96	0.0474	0.05	0.35	0.5276	29	29	1.78	0.0432	0.05	0.35	0.9137
10	10	1.96	0.0474	0.05	0.40	0.6267	29	29	1.78	0.0432	0.05	0.40	0.9627
10	10	1.96	0.0474	0.05	0.45	0.7151	29	29	1.78	0.0432	0.05	0.45	0.9860
10	10	1.96	0.0474	0.10	0.25	0.1995	29	29	1.78	0.0432	0.10	0.25	0.4129
10	10	1.96	0.0474	0.10	0.30	0.2827	29	29	1.78	0.0432	0.10	0.30	0.5864
10	10	1.96	0.0474	0.10	0.35	0.3725	29	29	1.78	0.0432	0.10	0.35	0.7384
10	10	1.96	0.0474	0.10	0.40	0.4655	29	29	1.78	0.0432	0.10	0.40	0.8521
10	10	1.96	0.0474	0.10	0.45	0.5585	29	29	1.78	0.0432	0.10	0.45	0.9254
10	10	1.96	0.0474	0.10	0.50	0.6478	29	29	1.78	0.0432	0.10	0.50	0.9667
10	10	1.96	0.0474	0.10	0.55	0.7298	29	29	1.78	0.0432	0.10	0.55	0.9869
10	10	1.96	0.0474	0.10	0.60	0.8016	29	29	1.78	0.0432	0.10	0.60	0.9956
10	10	1.96	0.0474	0.15	0.30	0.1871	29	29	1.78	0.0432	0.15	0.30	0.3649
10	10	1.96	0.0474	0.15	0.35	0.2587	29	29	1.78	0.0432	0.15	0.35	0.5262
10	10	1.96	0.0474	0.15	0.40	0.3394	29	29	1.78	0.0432	0.15	0.40	0.6770
10	10	1.96	0.0474	0.15	0.45	0.4263	29	29	1.78	0.0432	0.15	0.45	0.8001
10	10	1.96	0.0474	0.15	0.50	0.5160	29	29	1.78	0.0432	0.15	0.50	0.8892
10	10	1.96	0.0474	0.15	0.55	0.6043	29	29	1.78	0.0432	0.15	0.55	0.9461
10	10	1.96	0.0474	0.15	0.60	0.6876	29	29	1.78	0.0432	0.15	0.60	0.9777
10	10	1.96	0.0474	0.15	0.65	0.7629	29	29	1.78	0.0432	0.15	0.65	0.9924
10	10	1.96	0.0474	0.20	0.35	0.1761	29	29	1.78	0.0432	0.20	0.35	0.3304
10	10	1.96	0.0474	0.20	0.40	0.2417	29	29	1.78	0.0432	0.20	0.40	0.4783
10	10	1.96	0.0474	0.20	0.45	0.3168	29	29	1.78	0.0432	0.20	0.45	0.6270
10	10	1.96	0.0474	0.20	0.50	0.3987	29	29	1.78	0.0432	0.20	0.50	0.7595
10	10	1.96	0.0474	0.20	0.55	0.4844	29	29	1.78	0.0432	0.20	0.55	0.8631
10	10	1.96	0.0474	0.20	0.60	0.5707	29	29	1.78	0.0432	0.20	0.60	0.9327
10	10	1.96	0.0474	0.20	0.65	0.6548	29	29	1.78	0.0432	0.20	0.65	0.9722
10	10	1.96	0.0474	0.20	0.70	0.7344	29	29	1.78	0.0432	0.20	0.70	0.9907
10	10	1.96	0.0474	0.25	0.40	0.1675	29	29	1.78	0.0432	0.25	0.40	0.3020
10	10	1.96	0.0474	0.25	0.45	0.2285	29	29	1.78	0.0432	0.25	0.45	0.4454
10	10	1.96	0.0474	0.25	0.50	0.2986	29	29	1.78	0.0432	0.25	0.50	0.5979
10	10	1.96	0.0474	0.25	0.55	0.3763	29	29	1.78	0.0432	0.25	0.55	0.7390
10	10	1.96	0.0474	0.25	0.60	0.4595	29	29	1.78	0.0432	0.25	0.60	0.8512
10	10	1.96	0.0474	0.25	0.65	0.5465	29	29	1.78	0.0432	0.25	0.65	0.9271
10	10	1.96	0.0474	0.25	0.70	0.6353	29	29	1.78	0.0432	0.25	0.70	0.9701
10	10	1.96	0.0474	0.25	0.75	0.7235	29	29	1.78	0.0432	0.25	0.75	0.9902
10	10	1.96	0.0474	0.30	0.45	0.1598	29	29	1.78	0.0432	0.30	0.45	0.2877
10	10	1.96	0.0474	0.30	0.50	0.2168	29	29	1.78	0.0432	0.30	0.50	0.4320
10	10	1.96	0.0474	0.30	0.55	0.2836	29	29	1.78	0.0432	0.30	0.55	0.5875
10	10	1.96	0.0474	0.30	0.60	0.3598	29	29	1.78	0.0432	0.30	0.60	0.7320
10	10	1.96	0.0474	0.30	0.65	0.4448	29	29	1.78	0.0432	0.30	0.65	0.8473

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	10	1.96	0.0474	0.30	0.70	0.5373	29	29	1.78	0.0432	0.30	0.70	0.9256
10	10	1.96	0.0474	0.35	0.50	0.1526	29	29	1.78	0.0432	0.35	0.50	0.2849
10	10	1.96	0.0474	0.35	0.55	0.2078	29	29	1.78	0.0432	0.35	0.55	0.4293
10	10	1.96	0.0474	0.35	0.60	0.2746	29	29	1.78	0.0432	0.35	0.60	0.5850
10	10	1.96	0.0474	0.35	0.65	0.3536	29	29	1.78	0.0432	0.35	0.65	0.7304
10	10	1.96	0.0474	0.40	0.55	0.1481	29	29	1.78	0.0432	0.40	0.55	0.2856
10	10	1.96	0.0474	0.40	0.60	0.2043	29	29	1.78	0.0432	0.40	0.60	0.4292
11	11	1.92	0.0454	0.05	0.15	0.1311	30	30	1.77	0.0440	0.05	0.15	0.3237
11	11	1.92	0.0454	0.05	0.20	0.2344	30	30	1.77	0.0440	0.05	0.20	0.5203
11	11	1.92	0.0454	0.05	0.25	0.3483	30	30	1.77	0.0440	0.05	0.25	0.7029
11	11	1.92	0.0454	0.05	0.30	0.4621	30	30	1.77	0.0440	0.05	0.30	0.8389
11	11	1.92	0.0454	0.05	0.35	0.5687	30	30	1.77	0.0440	0.05	0.35	0.9233
11	11	1.92	0.0454	0.05	0.40	0.6640	30	30	1.77	0.0440	0.05	0.40	0.9681
11	11	1.92	0.0454	0.05	0.45	0.7461	30	30	1.77	0.0440	0.05	0.45	0.9886
11	11	1.92	0.0454	0.10	0.25	0.2166	30	30	1.77	0.0440	0.10	0.25	0.4269
11	11	1.92	0.0454	0.10	0.30	0.3013	30	30	1.77	0.0440	0.10	0.30	0.6036
11	11	1.92	0.0454	0.10	0.35	0.3898	30	30	1.77	0.0440	0.10	0.35	0.7550
11	11	1.92	0.0454	0.10	0.40	0.4790	30	30	1.77	0.0440	0.10	0.40	0.8652
11	11	1.92	0.0454	0.10	0.45	0.5662	30	30	1.77	0.0440	0.10	0.45	0.9341
11	11	1.92	0.0454	0.10	0.50	0.6489	30	30	1.77	0.0440	0.10	0.50	0.9715
11	11	1.92	0.0454	0.10	0.55	0.7253	30	30	1.77	0.0440	0.10	0.55	0.9893
11	11	1.92	0.0454	0.10	0.60	0.7939	30	30	1.77	0.0440	0.10	0.60	0.9966
11	11	1.92	0.0454	0.15	0.30	0.1902	30	30	1.77	0.0440	0.15	0.30	0.3779
11	11	1.92	0.0454	0.15	0.35	0.2579	30	30	1.77	0.0440	0.15	0.35	0.5422
11	11	1.92	0.0454	0.15	0.40	0.3325	30	30	1.77	0.0440	0.15	0.40	0.6934
11	11	1.92	0.0454	0.15	0.45	0.4122	30	30	1.77	0.0440	0.15	0.45	0.8147
11	11	1.92	0.0454	0.15	0.50	0.4953	30	30	1.77	0.0440	0.15	0.50	0.9005
11	11	1.92	0.0454	0.15	0.55	0.5798	30	30	1.77	0.0440	0.15	0.55	0.9537
11	11	1.92	0.0454	0.15	0.60	0.6634	30	30	1.77	0.0440	0.15	0.60	0.9818
11	11	1.92	0.0454	0.15	0.65	0.7434	30	30	1.77	0.0440	0.15	0.65	0.9942
11	11	1.92	0.0454	0.20	0.35	0.1648	30	30	1.77	0.0440	0.20	0.35	0.3415
11	11	1.92	0.0454	0.20	0.40	0.2226	30	30	1.77	0.0440	0.20	0.40	0.4935
11	11	1.92	0.0454	0.20	0.45	0.2893	30	30	1.77	0.0440	0.20	0.45	0.6451
11	11	1.92	0.0454	0.20	0.50	0.3645	30	30	1.77	0.0440	0.20	0.50	0.7776
11	11	1.92	0.0454	0.20	0.55	0.4473	30	30	1.77	0.0440	0.20	0.55	0.8780
11	11	1.92	0.0454	0.20	0.60	0.5357	30	30	1.77	0.0440	0.20	0.60	0.9427
11	11	1.92	0.0454	0.20	0.65	0.6268	30	30	1.77	0.0440	0.20	0.65	0.9775
11	11	1.92	0.0454	0.20	0.70	0.7164	30	30	1.77	0.0440	0.20	0.70	0.9929
11	11	1.92	0.0454	0.25	0.40	0.1439	30	30	1.77	0.0440	0.25	0.40	0.3139
11	11	1.92	0.0454	0.25	0.45	0.1962	30	30	1.77	0.0440	0.25	0.45	0.4633
11	11	1.92	0.0454	0.25	0.50	0.2595	30	30	1.77	0.0440	0.25	0.50	0.6196
11	11	1.92	0.0454	0.25	0.55	0.3341	30	30	1.77	0.0440	0.25	0.55	0.7603
11	11	1.92	0.0454	0.25	0.60	0.4192	30	30	1.77	0.0440	0.25	0.60	0.8681
11	11	1.92	0.0454	0.25	0.65	0.5126	30	30	1.77	0.0440	0.25	0.65	0.9381
11	11	1.92	0.0454	0.25	0.70	0.6106	30	30	1.77	0.0440	0.25	0.70	0.9759
11	11	1.92	0.0454	0.25	0.75	0.7083	30	30	1.77	0.0440	0.25	0.75	0.9925
11	11	1.92	0.0454	0.30	0.45	0.1287	30	30	1.77	0.0440	0.30	0.45	0.3024
11	11	1.92	0.0454	0.30	0.50	0.1790	30	30	1.77	0.0440	0.30	0.50	0.4528
11	11	1.92	0.0454	0.30	0.55	0.2419	30	30	1.77	0.0440	0.30	0.55	0.6112
11	11	1.92	0.0454	0.30	0.60	0.3181	30	30	1.77	0.0440	0.30	0.60	0.7543

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
11	11	1.92	0.0454	0.30	0.65	0.4067	30	30	1.77	0.0440	0.30	0.65	0.8647
11	11	1.92	0.0454	0.30	0.70	0.5056	30	30	1.77	0.0440	0.30	0.70	0.9368
11	11	1.92	0.0454	0.35	0.50	0.1195	30	30	1.77	0.0440	0.35	0.50	0.3013
11	11	1.92	0.0454	0.35	0.55	0.1698	30	30	1.77	0.0440	0.35	0.55	0.4511
11	11	1.92	0.0454	0.35	0.60	0.2341	30	30	1.77	0.0440	0.35	0.60	0.6092
11	11	1.92	0.0454	0.35	0.65	0.3132	30	30	1.77	0.0440	0.35	0.65	0.7529
11	11	1.92	0.0454	0.40	0.55	0.1154	30	30	1.77	0.0440	0.40	0.55	0.3024
11	11	1.92	0.0454	0.40	0.60	0.1670	30	30	1.77	0.0440	0.40	0.60	0.4512
12	12	1.86	0.0468	0.05	0.15	0.1510	31	31	1.72	0.0490	0.05	0.15	0.3952
12	12	1.86	0.0468	0.05	0.20	0.2638	31	31	1.72	0.0490	0.05	0.20	0.5898
12	12	1.86	0.0468	0.05	0.25	0.3845	31	31	1.72	0.0490	0.05	0.25	0.7502
12	12	1.86	0.0468	0.05	0.30	0.5020	31	31	1.72	0.0490	0.05	0.30	0.8649
12	12	1.86	0.0468	0.05	0.35	0.6096	31	31	1.72	0.0490	0.05	0.35	0.9360
12	12	1.86	0.0468	0.05	0.40	0.7037	31	31	1.72	0.0490	0.05	0.40	0.9739
12	12	1.86	0.0468	0.05	0.45	0.7827	31	31	1.72	0.0490	0.05	0.45	0.9909
12	12	1.86	0.0468	0.10	0.25	0.2350	31	31	1.72	0.0490	0.10	0.25	0.4531
12	12	1.86	0.0468	0.10	0.30	0.3248	31	31	1.72	0.0490	0.10	0.30	0.6253
12	12	1.86	0.0468	0.10	0.35	0.4184	31	31	1.72	0.0490	0.10	0.35	0.7723
12	12	1.86	0.0468	0.10	0.40	0.5121	31	31	1.72	0.0490	0.10	0.40	0.8775
12	12	1.86	0.0468	0.10	0.45	0.6028	31	31	1.72	0.0490	0.10	0.45	0.9418
12	12	1.86	0.0468	0.10	0.50	0.6878	31	31	1.72	0.0490	0.10	0.50	0.9758
12	12	1.86	0.0468	0.10	0.55	0.7649	31	31	1.72	0.0490	0.10	0.55	0.9913
12	12	1.86	0.0468	0.10	0.60	0.8322	31	31	1.72	0.0490	0.10	0.60	0.9974
12	12	1.86	0.0468	0.15	0.30	0.2026	31	31	1.72	0.0490	0.15	0.30	0.3919
12	12	1.86	0.0468	0.15	0.35	0.2758	31	31	1.72	0.0490	0.15	0.35	0.5581
12	12	1.86	0.0468	0.15	0.40	0.3568	31	31	1.72	0.0490	0.15	0.40	0.7092
12	12	1.86	0.0468	0.15	0.45	0.4438	31	31	1.72	0.0490	0.15	0.45	0.8285
12	12	1.86	0.0468	0.15	0.50	0.5342	31	31	1.72	0.0490	0.15	0.50	0.9110
12	12	1.86	0.0468	0.15	0.55	0.6251	31	31	1.72	0.0490	0.15	0.55	0.9604
12	12	1.86	0.0468	0.15	0.60	0.7127	31	31	1.72	0.0490	0.15	0.60	0.9853
12	12	1.86	0.0468	0.15	0.65	0.7929	31	31	1.72	0.0490	0.15	0.65	0.9956
12	12	1.86	0.0468	0.20	0.35	0.1750	31	31	1.72	0.0490	0.20	0.35	0.3526
12	12	1.86	0.0468	0.20	0.40	0.2394	31	31	1.72	0.0490	0.20	0.40	0.5089
12	12	1.86	0.0468	0.20	0.45	0.3147	31	31	1.72	0.0490	0.20	0.45	0.6631
12	12	1.86	0.0468	0.20	0.50	0.3999	31	31	1.72	0.0490	0.20	0.50	0.7950
12	12	1.86	0.0468	0.20	0.55	0.4928	31	31	1.72	0.0490	0.20	0.55	0.8917
12	12	1.86	0.0468	0.20	0.60	0.5897	31	31	1.72	0.0490	0.20	0.60	0.9514
12	12	1.86	0.0468	0.20	0.65	0.6854	31	31	1.72	0.0490	0.20	0.65	0.9819
12	12	1.86	0.0468	0.20	0.70	0.7744	31	31	1.72	0.0490	0.20	0.70	0.9946
12	12	1.86	0.0468	0.25	0.40	0.1550	31	31	1.72	0.0490	0.25	0.40	0.3264
12	12	1.86	0.0468	0.25	0.45	0.2156	31	31	1.72	0.0490	0.25	0.45	0.4817
12	12	1.86	0.0468	0.25	0.50	0.2895	31	31	1.72	0.0490	0.25	0.50	0.6410
12	12	1.86	0.0468	0.25	0.55	0.3758	31	31	1.72	0.0490	0.25	0.55	0.7803
12	12	1.86	0.0468	0.25	0.60	0.4719	31	31	1.72	0.0490	0.25	0.60	0.8834
12	12	1.86	0.0468	0.25	0.65	0.5735	31	31	1.72	0.0490	0.25	0.65	0.9475
12	12	1.86	0.0468	0.25	0.70	0.6747	31	31	1.72	0.0490	0.25	0.70	0.9805
12	12	1.86	0.0468	0.25	0.75	0.7693	31	31	1.72	0.0490	0.25	0.75	0.9943
12	12	1.86	0.0468	0.30	0.45	0.1429	31	31	1.72	0.0490	0.30	0.45	0.3176
12	12	1.86	0.0468	0.30	0.50	0.2027	31	31	1.72	0.0490	0.30	0.50	0.4735
12	12	1.86	0.0468	0.30	0.55	0.2770	31	31	1.72	0.0490	0.30	0.55	0.6341

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
12	12	1.86	0.0468	0.30	0.60	0.3650	31	31	1.72	0.0490	0.30	0.60	0.7751
12	12	1.86	0.0468	0.30	0.65	0.4639	31	31	1.72	0.0490	0.30	0.65	0.8803
12	12	1.86	0.0468	0.30	0.70	0.5691	31	31	1.72	0.0490	0.30	0.70	0.9463
12	12	1.86	0.0468	0.35	0.50	0.1370	31	31	1.72	0.0490	0.35	0.50	0.3177
12	12	1.86	0.0468	0.35	0.55	0.1971	31	31	1.72	0.0490	0.35	0.55	0.4725
12	12	1.86	0.0468	0.35	0.60	0.2724	31	31	1.72	0.0490	0.35	0.60	0.6323
12	12	1.86	0.0468	0.35	0.65	0.3621	31	31	1.72	0.0490	0.35	0.65	0.7737
12	12	1.86	0.0468	0.40	0.55	0.1350	31	31	1.72	0.0490	0.40	0.55	0.3191
12	12	1.86	0.0468	0.40	0.60	0.1957	31	31	1.72	0.0490	0.40	0.60	0.4725
13	13	1.81	0.0480	0.05	0.15	0.1703	32	32	1.80	0.0458	0.05	0.15	0.3414
13	13	1.81	0.0480	0.05	0.20	0.2914	32	32	1.80	0.0458	0.05	0.20	0.5495
13	13	1.81	0.0480	0.05	0.25	0.4178	32	32	1.80	0.0458	0.05	0.25	0.7334
13	13	1.81	0.0480	0.05	0.30	0.5381	32	32	1.80	0.0458	0.05	0.30	0.8622
13	13	1.81	0.0480	0.05	0.35	0.6461	32	32	1.80	0.0458	0.05	0.35	0.9374
13	13	1.81	0.0480	0.05	0.40	0.7384	32	32	1.80	0.0458	0.05	0.40	0.9751
13	13	1.81	0.0480	0.05	0.45	0.8142	32	32	1.80	0.0458	0.05	0.45	0.9913
13	13	1.81	0.0480	0.10	0.25	0.2518	32	32	1.80	0.0458	0.10	0.25	0.4459
13	13	1.81	0.0480	0.10	0.30	0.3468	32	32	1.80	0.0458	0.10	0.30	0.6214
13	13	1.81	0.0480	0.10	0.35	0.4455	32	32	1.80	0.0458	0.10	0.35	0.7682
13	13	1.81	0.0480	0.10	0.40	0.5437	32	32	1.80	0.0458	0.10	0.40	0.8741
13	13	1.81	0.0480	0.10	0.45	0.6379	32	32	1.80	0.0458	0.10	0.45	0.9403
13	13	1.81	0.0480	0.10	0.50	0.7248	32	32	1.80	0.0458	0.10	0.50	0.9759
13	13	1.81	0.0480	0.10	0.55	0.8016	32	32	1.80	0.0458	0.10	0.55	0.9919
13	13	1.81	0.0480	0.10	0.60	0.8660	32	32	1.80	0.0458	0.10	0.60	0.9978
13	13	1.81	0.0480	0.15	0.30	0.2144	32	32	1.80	0.0458	0.15	0.30	0.3787
13	13	1.81	0.0480	0.15	0.35	0.2937	32	32	1.80	0.0458	0.15	0.35	0.5447
13	13	1.81	0.0480	0.15	0.40	0.3820	32	32	1.80	0.0458	0.15	0.40	0.7016
13	13	1.81	0.0480	0.15	0.45	0.4768	32	32	1.80	0.0458	0.15	0.45	0.8283
13	13	1.81	0.0480	0.15	0.50	0.5745	32	32	1.80	0.0458	0.15	0.50	0.9149
13	13	1.81	0.0480	0.15	0.55	0.6703	32	32	1.80	0.0458	0.15	0.55	0.9643
13	13	1.81	0.0480	0.15	0.60	0.7593	32	32	1.80	0.0458	0.15	0.60	0.9876
13	13	1.81	0.0480	0.15	0.65	0.8366	32	32	1.80	0.0458	0.15	0.65	0.9964
13	13	1.81	0.0480	0.20	0.35	0.1862	32	32	1.80	0.0458	0.20	0.35	0.3406
13	13	1.81	0.0480	0.20	0.40	0.2582	32	32	1.80	0.0458	0.20	0.40	0.5057
13	13	1.81	0.0480	0.20	0.45	0.3431	32	32	1.80	0.0458	0.20	0.45	0.6696
13	13	1.81	0.0480	0.20	0.50	0.4385	32	32	1.80	0.0458	0.20	0.50	0.8060
13	13	1.81	0.0480	0.20	0.55	0.5404	32	32	1.80	0.0458	0.20	0.55	0.9010
13	13	1.81	0.0480	0.20	0.60	0.6429	32	32	1.80	0.0458	0.20	0.60	0.9565
13	13	1.81	0.0480	0.20	0.65	0.7395	32	32	1.80	0.0458	0.20	0.65	0.9836
13	13	1.81	0.0480	0.20	0.70	0.8239	32	32	1.80	0.0458	0.20	0.70	0.9948
13	13	1.81	0.0480	0.25	0.40	0.1685	32	32	1.80	0.0458	0.25	0.40	0.3289
13	13	1.81	0.0480	0.25	0.45	0.2384	32	32	1.80	0.0458	0.25	0.45	0.4925
13	13	1.81	0.0480	0.25	0.50	0.3232	32	32	1.80	0.0458	0.25	0.50	0.6549
13	13	1.81	0.0480	0.25	0.55	0.4205	32	32	1.80	0.0458	0.25	0.55	0.7907
13	13	1.81	0.0480	0.25	0.60	0.5255	32	32	1.80	0.0458	0.25	0.60	0.8877
13	13	1.81	0.0480	0.25	0.65	0.6318	32	32	1.80	0.0458	0.25	0.65	0.9476
13	13	1.81	0.0480	0.25	0.70	0.7323	32	32	1.80	0.0458	0.25	0.70	0.9795
13	13	1.81	0.0480	0.25	0.75	0.8206	32	32	1.80	0.0458	0.25	0.75	0.9938
13	13	1.81	0.0480	0.30	0.45	0.1600	32	32	1.80	0.0458	0.30	0.45	0.3259
13	13	1.81	0.0480	0.30	0.50	0.2299	32	32	1.80	0.0458	0.30	0.50	0.4820

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
13	13	1.81	0.0480	0.30	0.55	0.3154	32	32	1.80	0.0458	0.30	0.55	0.6373
13	13	1.81	0.0480	0.30	0.60	0.4139	32	32	1.80	0.0458	0.30	0.60	0.7719
13	13	1.81	0.0480	0.30	0.65	0.5205	32	32	1.80	0.0458	0.30	0.65	0.8744
13	13	1.81	0.0480	0.30	0.70	0.6290	32	32	1.80	0.0458	0.30	0.70	0.9424
13	13	1.81	0.0480	0.35	0.50	0.1574	32	32	1.80	0.0458	0.35	0.50	0.3166
13	13	1.81	0.0480	0.35	0.55	0.2274	32	32	1.80	0.0458	0.35	0.55	0.4643
13	13	1.81	0.0480	0.35	0.60	0.3133	32	32	1.80	0.0458	0.35	0.60	0.6186
13	13	1.81	0.0480	0.35	0.65	0.4124	32	32	1.80	0.0458	0.35	0.65	0.7613
13	13	1.81	0.0480	0.40	0.55	0.1571	32	32	1.80	0.0458	0.40	0.55	0.3039
13	13	1.81	0.0480	0.40	0.60	0.2271	32	32	1.80	0.0458	0.40	0.60	0.4539
14	14	1.77	0.0491	0.05	0.15	0.1888	33	33	1.77	0.0471	0.05	0.15	0.3505
14	14	1.77	0.0491	0.05	0.20	0.3173	33	33	1.77	0.0471	0.05	0.20	0.5639
14	14	1.77	0.0491	0.05	0.25	0.4484	33	33	1.77	0.0471	0.05	0.25	0.7478
14	14	1.77	0.0491	0.05	0.30	0.5710	33	33	1.77	0.0471	0.05	0.30	0.8731
14	14	1.77	0.0491	0.05	0.35	0.6788	33	33	1.77	0.0471	0.05	0.35	0.9441
14	14	1.77	0.0491	0.05	0.40	0.7692	33	33	1.77	0.0471	0.05	0.40	0.9785
14	14	1.77	0.0491	0.05	0.45	0.8416	33	33	1.77	0.0471	0.05	0.45	0.9929
14	14	1.77	0.0491	0.10	0.25	0.2675	33	33	1.77	0.0471	0.10	0.25	0.4579
14	14	1.77	0.0491	0.10	0.30	0.3678	33	33	1.77	0.0471	0.10	0.30	0.6353
14	14	1.77	0.0491	0.10	0.35	0.4717	33	33	1.77	0.0471	0.10	0.35	0.7814
14	14	1.77	0.0491	0.10	0.40	0.5745	33	33	1.77	0.0471	0.10	0.40	0.8847
14	14	1.77	0.0491	0.10	0.45	0.6719	33	33	1.77	0.0471	0.10	0.45	0.9474
14	14	1.77	0.0491	0.10	0.50	0.7599	33	33	1.77	0.0471	0.10	0.50	0.9797
14	14	1.77	0.0491	0.10	0.55	0.8350	33	33	1.77	0.0471	0.10	0.55	0.9936
14	14	1.77	0.0491	0.10	0.60	0.8951	33	33	1.77	0.0471	0.10	0.60	0.9984
14	14	1.77	0.0491	0.15	0.30	0.2263	33	33	1.77	0.0471	0.15	0.30	0.3895
14	14	1.77	0.0491	0.15	0.35	0.3123	33	33	1.77	0.0471	0.15	0.35	0.5598
14	14	1.77	0.0491	0.15	0.40	0.4086	33	33	1.77	0.0471	0.15	0.40	0.7183
14	14	1.77	0.0491	0.15	0.45	0.5113	33	33	1.77	0.0471	0.15	0.45	0.8431
14	14	1.77	0.0491	0.15	0.50	0.6152	33	33	1.77	0.0471	0.15	0.50	0.9252
14	14	1.77	0.0491	0.15	0.55	0.7140	33	33	1.77	0.0471	0.15	0.55	0.9700
14	14	1.77	0.0491	0.15	0.60	0.8016	33	33	1.77	0.0471	0.15	0.60	0.9900
14	14	1.77	0.0491	0.15	0.65	0.8733	33	33	1.77	0.0471	0.15	0.65	0.9973
14	14	1.77	0.0491	0.20	0.35	0.1987	33	33	1.77	0.0471	0.20	0.35	0.3537
14	14	1.77	0.0491	0.20	0.40	0.2793	33	33	1.77	0.0471	0.20	0.40	0.5241
14	14	1.77	0.0491	0.20	0.45	0.3742	33	33	1.77	0.0471	0.20	0.45	0.6894
14	14	1.77	0.0491	0.20	0.50	0.4791	33	33	1.77	0.0471	0.20	0.50	0.8226
14	14	1.77	0.0491	0.20	0.55	0.5879	33	33	1.77	0.0471	0.20	0.55	0.9121
14	14	1.77	0.0491	0.20	0.60	0.6929	33	33	1.77	0.0471	0.20	0.60	0.9623
14	14	1.77	0.0491	0.20	0.65	0.7869	33	33	1.77	0.0471	0.20	0.65	0.9861
14	14	1.77	0.0491	0.20	0.70	0.8642	33	33	1.77	0.0471	0.20	0.70	0.9957
14	14	1.77	0.0491	0.25	0.40	0.1842	33	33	1.77	0.0471	0.25	0.40	0.3440
14	14	1.77	0.0491	0.25	0.45	0.2640	33	33	1.77	0.0471	0.25	0.45	0.5115
14	14	1.77	0.0491	0.25	0.50	0.3594	33	33	1.77	0.0471	0.25	0.50	0.6734
14	14	1.77	0.0491	0.25	0.55	0.4661	33	33	1.77	0.0471	0.25	0.55	0.8051
14	14	1.77	0.0491	0.25	0.60	0.5772	33	33	1.77	0.0471	0.25	0.60	0.8969
14	14	1.77	0.0491	0.25	0.65	0.6850	33	33	1.77	0.0471	0.25	0.65	0.9524
14	14	1.77	0.0491	0.25	0.70	0.7818	33	33	1.77	0.0471	0.25	0.70	0.9818
14	14	1.77	0.0491	0.25	0.75	0.8619	33	33	1.77	0.0471	0.25	0.75	0.9947
14	14	1.77	0.0491	0.30	0.45	0.1794	33	33	1.77	0.0471	0.30	0.45	0.3394

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
14	14	1.77	0.0491	0.30	0.50	0.2594	33	33	1.77	0.0471	0.30	0.50	0.4967
14	14	1.77	0.0491	0.30	0.55	0.3551	33	33	1.77	0.0471	0.30	0.55	0.6504
14	14	1.77	0.0491	0.30	0.60	0.4622	33	33	1.77	0.0471	0.30	0.60	0.7818
14	14	1.77	0.0491	0.30	0.65	0.5740	33	33	1.77	0.0471	0.30	0.65	0.8813
14	14	1.77	0.0491	0.30	0.70	0.6830	33	33	1.77	0.0471	0.30	0.70	0.9467
14	14	1.77	0.0491	0.35	0.50	0.1794	33	33	1.77	0.0471	0.35	0.50	0.3246
14	14	1.77	0.0491	0.35	0.55	0.2591	33	33	1.77	0.0471	0.35	0.55	0.4724
14	14	1.77	0.0491	0.35	0.60	0.3545	33	33	1.77	0.0471	0.35	0.60	0.6264
14	14	1.77	0.0491	0.35	0.65	0.4614	33	33	1.77	0.0471	0.35	0.65	0.7689
14	14	1.77	0.0491	0.40	0.55	0.1804	33	33	1.77	0.0471	0.40	0.55	0.3067
14	14	1.77	0.0491	0.40	0.60	0.2594	33	33	1.77	0.0471	0.40	0.60	0.4586
15	15	1.74	0.0495	0.05	0.15	0.2064	34	34	1.75	0.0488	0.05	0.15	0.3598
15	15	1.74	0.0495	0.05	0.20	0.3415	34	34	1.75	0.0488	0.05	0.20	0.5787
15	15	1.74	0.0495	0.05	0.25	0.4768	34	34	1.75	0.0488	0.05	0.25	0.7634
15	15	1.74	0.0495	0.05	0.30	0.6010	34	34	1.75	0.0488	0.05	0.30	0.8859
15	15	1.74	0.0495	0.05	0.35	0.7084	34	34	1.75	0.0488	0.05	0.35	0.9529
15	15	1.74	0.0495	0.05	0.40	0.7966	34	34	1.75	0.0488	0.05	0.40	0.9834
15	15	1.74	0.0495	0.05	0.45	0.8655	34	34	1.75	0.0488	0.05	0.45	0.9950
15	15	1.74	0.0495	0.10	0.25	0.2824	34	34	1.75	0.0488	0.10	0.25	0.4815
15	15	1.74	0.0495	0.10	0.30	0.3882	34	34	1.75	0.0488	0.10	0.30	0.6670
15	15	1.74	0.0495	0.10	0.35	0.4975	34	34	1.75	0.0488	0.10	0.35	0.8122
15	15	1.74	0.0495	0.10	0.40	0.6049	34	34	1.75	0.0488	0.10	0.40	0.9070
15	15	1.74	0.0495	0.10	0.45	0.7049	34	34	1.75	0.0488	0.10	0.45	0.9599
15	15	1.74	0.0495	0.10	0.50	0.7928	34	34	1.75	0.0488	0.10	0.50	0.9852
15	15	1.74	0.0495	0.10	0.55	0.8648	34	34	1.75	0.0488	0.10	0.55	0.9955
15	15	1.74	0.0495	0.10	0.60	0.9192	34	34	1.75	0.0488	0.10	0.60	0.9989
15	15	1.74	0.0495	0.15	0.30	0.2386	34	34	1.75	0.0488	0.15	0.30	0.4269
15	15	1.74	0.0495	0.15	0.35	0.3320	34	34	1.75	0.0488	0.15	0.35	0.6012
15	15	1.74	0.0495	0.15	0.40	0.4366	34	34	1.75	0.0488	0.15	0.40	0.7528
15	15	1.74	0.0495	0.15	0.45	0.5468	34	34	1.75	0.0488	0.15	0.45	0.8659
15	15	1.74	0.0495	0.15	0.50	0.6554	34	34	1.75	0.0488	0.15	0.50	0.9376
15	15	1.74	0.0495	0.15	0.55	0.7548	34	34	1.75	0.0488	0.15	0.55	0.9756
15	15	1.74	0.0495	0.15	0.60	0.8385	34	34	1.75	0.0488	0.15	0.60	0.9921
15	15	1.74	0.0495	0.15	0.65	0.9030	34	34	1.75	0.0488	0.15	0.65	0.9979
15	15	1.74	0.0495	0.20	0.35	0.2128	34	34	1.75	0.0488	0.20	0.35	0.3861
15	15	1.74	0.0495	0.20	0.40	0.3027	34	34	1.75	0.0488	0.20	0.40	0.5555
15	15	1.74	0.0495	0.20	0.45	0.4073	34	34	1.75	0.0488	0.20	0.45	0.7147
15	15	1.74	0.0495	0.20	0.50	0.5204	34	34	1.75	0.0488	0.20	0.50	0.8401
15	15	1.74	0.0495	0.20	0.55	0.6337	34	34	1.75	0.0488	0.20	0.55	0.9223
15	15	1.74	0.0495	0.20	0.60	0.7384	34	34	1.75	0.0488	0.20	0.60	0.9674
15	15	1.74	0.0495	0.20	0.65	0.8273	34	34	1.75	0.0488	0.20	0.65	0.9882
15	15	1.74	0.0495	0.20	0.70	0.8962	34	34	1.75	0.0488	0.20	0.70	0.9965
15	15	1.74	0.0495	0.25	0.40	0.2021	34	34	1.75	0.0488	0.25	0.40	0.3652
15	15	1.74	0.0495	0.25	0.45	0.2917	34	34	1.75	0.0488	0.25	0.45	0.5327
15	15	1.74	0.0495	0.25	0.50	0.3968	34	34	1.75	0.0488	0.25	0.50	0.6916
15	15	1.74	0.0495	0.25	0.55	0.5110	34	34	1.75	0.0488	0.25	0.55	0.8184
15	15	1.74	0.0495	0.25	0.60	0.6256	34	34	1.75	0.0488	0.25	0.60	0.9053
15	15	1.74	0.0495	0.25	0.65	0.7321	34	34	1.75	0.0488	0.25	0.65	0.9572
15	15	1.74	0.0495	0.25	0.70	0.8232	34	34	1.75	0.0488	0.25	0.70	0.9841
15	15	1.74	0.0495	0.25	0.75	0.8944	34	34	1.75	0.0488	0.25	0.75	0.9956

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
15	15	1.74	0.0495	0.30	0.45	0.2005	34	34	1.75	0.0488	0.30	0.45	0.3530
15	15	1.74	0.0495	0.30	0.50	0.2900	34	34	1.75	0.0488	0.30	0.50	0.5109
15	15	1.74	0.0495	0.30	0.55	0.3947	34	34	1.75	0.0488	0.30	0.55	0.6631
15	15	1.74	0.0495	0.30	0.60	0.5084	34	34	1.75	0.0488	0.30	0.60	0.7922
15	15	1.74	0.0495	0.30	0.65	0.6232	34	34	1.75	0.0488	0.30	0.65	0.8891
15	15	1.74	0.0495	0.30	0.70	0.7306	34	34	1.75	0.0488	0.30	0.70	0.9516
15	15	1.74	0.0495	0.35	0.50	0.2024	34	34	1.75	0.0488	0.35	0.50	0.3325
15	15	1.74	0.0495	0.35	0.55	0.2911	34	34	1.75	0.0488	0.35	0.55	0.4814
15	15	1.74	0.0495	0.35	0.60	0.3948	34	34	1.75	0.0488	0.35	0.60	0.6364
15	15	1.74	0.0495	0.35	0.65	0.5080	34	34	1.75	0.0488	0.35	0.65	0.7787
15	15	1.74	0.0495	0.40	0.55	0.2040	34	34	1.75	0.0488	0.40	0.55	0.3114
15	15	1.74	0.0495	0.40	0.60	0.2917	34	34	1.75	0.0488	0.40	0.60	0.4661
16	16	1.92	0.0416	0.05	0.15	0.2026	35	35	1.75	0.0470	0.05	0.15	0.3691
16	16	1.92	0.0416	0.05	0.20	0.3197	35	35	1.75	0.0470	0.05	0.20	0.5918
16	16	1.92	0.0416	0.05	0.25	0.4363	35	35	1.75	0.0470	0.05	0.25	0.7746
16	16	1.92	0.0416	0.05	0.30	0.5509	35	35	1.75	0.0470	0.05	0.30	0.8925
16	16	1.92	0.0416	0.05	0.35	0.6608	35	35	1.75	0.0470	0.05	0.35	0.9555
16	16	1.92	0.0416	0.05	0.40	0.7606	35	35	1.75	0.0470	0.05	0.40	0.9841
16	16	1.92	0.0416	0.05	0.45	0.8439	35	35	1.75	0.0470	0.05	0.45	0.9952
16	16	1.92	0.0416	0.10	0.25	0.2370	35	35	1.75	0.0470	0.10	0.25	0.4810
16	16	1.92	0.0416	0.10	0.30	0.3381	35	35	1.75	0.0470	0.10	0.30	0.6620
16	16	1.92	0.0416	0.10	0.35	0.4545	35	35	1.75	0.0470	0.10	0.35	0.8063
16	16	1.92	0.0416	0.10	0.40	0.5765	35	35	1.75	0.0470	0.10	0.40	0.9039
16	16	1.92	0.0416	0.10	0.45	0.6918	35	35	1.75	0.0470	0.10	0.45	0.9595
16	16	1.92	0.0416	0.10	0.50	0.7903	35	35	1.75	0.0470	0.10	0.50	0.9858
16	16	1.92	0.0416	0.10	0.55	0.8668	35	35	1.75	0.0470	0.10	0.55	0.9960
16	16	1.92	0.0416	0.10	0.60	0.9211	35	35	1.75	0.0470	0.10	0.60	0.9991
16	16	1.92	0.0416	0.15	0.30	0.2049	35	35	1.75	0.0470	0.15	0.30	0.4117
16	16	1.92	0.0416	0.15	0.35	0.3042	35	35	1.75	0.0470	0.15	0.35	0.5903
16	16	1.92	0.0416	0.15	0.40	0.4185	35	35	1.75	0.0470	0.15	0.40	0.7505
16	16	1.92	0.0416	0.15	0.45	0.5370	35	35	1.75	0.0470	0.15	0.45	0.8693
16	16	1.92	0.0416	0.15	0.50	0.6492	35	35	1.75	0.0470	0.15	0.50	0.9417
16	16	1.92	0.0416	0.15	0.55	0.7474	35	35	1.75	0.0470	0.15	0.55	0.9779
16	16	1.92	0.0416	0.15	0.60	0.8279	35	35	1.75	0.0470	0.15	0.60	0.9929
16	16	1.92	0.0416	0.15	0.65	0.8902	35	35	1.75	0.0470	0.15	0.65	0.9981
16	16	1.92	0.0416	0.20	0.35	0.1948	35	35	1.75	0.0470	0.20	0.35	0.3803
16	16	1.92	0.0416	0.20	0.40	0.2872	35	35	1.75	0.0470	0.20	0.40	0.5585
16	16	1.92	0.0416	0.20	0.45	0.3914	35	35	1.75	0.0470	0.20	0.45	0.7222
16	16	1.92	0.0416	0.20	0.50	0.4998	35	35	1.75	0.0470	0.20	0.50	0.8462
16	16	1.92	0.0416	0.20	0.55	0.6058	35	35	1.75	0.0470	0.20	0.55	0.9251
16	16	1.92	0.0416	0.20	0.60	0.7044	35	35	1.75	0.0470	0.20	0.60	0.9682
16	16	1.92	0.0416	0.20	0.65	0.7920	35	35	1.75	0.0470	0.20	0.65	0.9886
16	16	1.92	0.0416	0.20	0.70	0.8655	35	35	1.75	0.0470	0.20	0.70	0.9967
16	16	1.92	0.0416	0.25	0.40	0.1851	35	35	1.75	0.0470	0.25	0.40	0.3685
16	16	1.92	0.0416	0.25	0.45	0.2670	35	35	1.75	0.0470	0.25	0.45	0.5368
16	16	1.92	0.0416	0.25	0.50	0.3606	35	35	1.75	0.0470	0.25	0.50	0.6929
16	16	1.92	0.0416	0.25	0.55	0.4621	35	35	1.75	0.0470	0.25	0.55	0.8176
16	16	1.92	0.0416	0.25	0.60	0.5677	35	35	1.75	0.0470	0.25	0.60	0.9050
16	16	1.92	0.0416	0.25	0.65	0.6727	35	35	1.75	0.0470	0.25	0.65	0.9582
16	16	1.92	0.0416	0.25	0.70	0.7711	35	35	1.75	0.0470	0.25	0.70	0.9852

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
16	16	1.92	0.0416	0.25	0.75	0.8563	35	35	1.75	0.0470	0.25	0.75	0.9961
16	16	1.92	0.0416	0.30	0.45	0.1706	35	35	1.75	0.0470	0.30	0.45	0.3495
16	16	1.92	0.0416	0.30	0.50	0.2443	35	35	1.75	0.0470	0.30	0.50	0.5044
16	16	1.92	0.0416	0.30	0.55	0.3327	35	35	1.75	0.0470	0.30	0.55	0.6576
16	16	1.92	0.0416	0.30	0.60	0.4345	35	35	1.75	0.0470	0.30	0.60	0.7911
16	16	1.92	0.0416	0.30	0.65	0.5461	35	35	1.75	0.0470	0.30	0.65	0.8915
16	16	1.92	0.0416	0.30	0.70	0.6613	35	35	1.75	0.0470	0.30	0.70	0.9542
16	16	1.92	0.0416	0.35	0.50	0.1559	35	35	1.75	0.0470	0.35	0.50	0.3225
16	16	1.92	0.0416	0.35	0.55	0.2270	35	35	1.75	0.0470	0.35	0.55	0.4743
16	16	1.92	0.0416	0.35	0.60	0.3167	35	35	1.75	0.0470	0.35	0.60	0.6352
16	16	1.92	0.0416	0.35	0.65	0.4246	35	35	1.75	0.0470	0.35	0.65	0.7812
16	16	1.92	0.0416	0.40	0.55	0.1472	35	35	1.75	0.0470	0.40	0.55	0.3048
16	16	1.92	0.0416	0.40	0.60	0.2206	35	35	1.75	0.0470	0.40	0.60	0.4631
17	17	1.90	0.0420	0.05	0.15	0.2141	36	36	1.75	0.0435	0.05	0.15	0.3785
17	17	1.90	0.0420	0.05	0.20	0.3346	36	36	1.75	0.0435	0.05	0.20	0.6053
17	17	1.90	0.0420	0.05	0.25	0.4560	36	36	1.75	0.0435	0.05	0.25	0.7870
17	17	1.90	0.0420	0.05	0.30	0.5764	36	36	1.75	0.0435	0.05	0.30	0.9011
17	17	1.90	0.0420	0.05	0.35	0.6907	36	36	1.75	0.0435	0.05	0.35	0.9604
17	17	1.90	0.0420	0.05	0.40	0.7910	36	36	1.75	0.0435	0.05	0.40	0.9864
17	17	1.90	0.0420	0.05	0.45	0.8706	36	36	1.75	0.0435	0.05	0.45	0.9960
17	17	1.90	0.0420	0.10	0.25	0.2498	36	36	1.75	0.0435	0.10	0.25	0.4923
17	17	1.90	0.0420	0.10	0.30	0.3609	36	36	1.75	0.0435	0.10	0.30	0.6748
17	17	1.90	0.0420	0.10	0.35	0.4865	36	36	1.75	0.0435	0.10	0.35	0.8180
17	17	1.90	0.0420	0.10	0.40	0.6133	36	36	1.75	0.0435	0.10	0.40	0.9124
17	17	1.90	0.0420	0.10	0.45	0.7280	36	36	1.75	0.0435	0.10	0.45	0.9644
17	17	1.90	0.0420	0.10	0.50	0.8213	36	36	1.75	0.0435	0.10	0.50	0.9880
17	17	1.90	0.0420	0.10	0.55	0.8906	36	36	1.75	0.0435	0.10	0.55	0.9967
17	17	1.90	0.0420	0.10	0.60	0.9377	36	36	1.75	0.0435	0.10	0.60	0.9993
17	17	1.90	0.0420	0.15	0.30	0.2214	36	36	1.75	0.0435	0.15	0.30	0.4229
17	17	1.90	0.0420	0.15	0.35	0.3295	36	36	1.75	0.0435	0.15	0.35	0.6047
17	17	1.90	0.0420	0.15	0.40	0.4501	36	36	1.75	0.0435	0.15	0.40	0.7640
17	17	1.90	0.0420	0.15	0.45	0.5711	36	36	1.75	0.0435	0.15	0.45	0.8784
17	17	1.90	0.0420	0.15	0.50	0.6821	36	36	1.75	0.0435	0.15	0.50	0.9460
17	17	1.90	0.0420	0.15	0.55	0.7769	36	36	1.75	0.0435	0.15	0.55	0.9794
17	17	1.90	0.0420	0.15	0.60	0.8530	36	36	1.75	0.0435	0.15	0.60	0.9933
17	17	1.90	0.0420	0.15	0.65	0.9104	36	36	1.75	0.0435	0.15	0.65	0.9982
17	17	1.90	0.0420	0.20	0.35	0.2111	36	36	1.75	0.0435	0.20	0.35	0.3907
17	17	1.90	0.0420	0.20	0.40	0.3091	36	36	1.75	0.0435	0.20	0.40	0.5684
17	17	1.90	0.0420	0.20	0.45	0.4176	36	36	1.75	0.0435	0.20	0.45	0.7279
17	17	1.90	0.0420	0.20	0.50	0.5290	36	36	1.75	0.0435	0.20	0.50	0.8479
17	17	1.90	0.0420	0.20	0.55	0.6369	36	36	1.75	0.0435	0.20	0.55	0.9255
17	17	1.90	0.0420	0.20	0.60	0.7361	36	36	1.75	0.0435	0.20	0.60	0.9689
17	17	1.90	0.0420	0.20	0.65	0.8220	36	36	1.75	0.0435	0.20	0.65	0.9894
17	17	1.90	0.0420	0.20	0.70	0.8912	36	36	1.75	0.0435	0.20	0.70	0.9972
17	17	1.90	0.0420	0.25	0.40	0.1981	36	36	1.75	0.0435	0.25	0.40	0.3689
17	17	1.90	0.0420	0.25	0.45	0.2848	36	36	1.75	0.0435	0.25	0.45	0.5334
17	17	1.90	0.0420	0.25	0.50	0.3838	36	36	1.75	0.0435	0.25	0.50	0.6889
17	17	1.90	0.0420	0.25	0.55	0.4914	36	36	1.75	0.0435	0.25	0.55	0.8170
17	17	1.90	0.0420	0.25	0.60	0.6023	36	36	1.75	0.0435	0.25	0.60	0.9079
17	17	1.90	0.0420	0.25	0.65	0.7097	36	36	1.75	0.0435	0.25	0.65	0.9617

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
17	17	1.90	0.0420	0.25	0.70	0.8062	36	36	1.75	0.0435	0.25	0.70	0.9874
17	17	1.90	0.0420	0.25	0.75	0.8848	36	36	1.75	0.0435	0.25	0.75	0.9969
17	17	1.90	0.0420	0.30	0.45	0.1815	36	36	1.75	0.0435	0.30	0.45	0.3408
17	17	1.90	0.0420	0.30	0.50	0.2615	36	36	1.75	0.0435	0.30	0.50	0.4986
17	17	1.90	0.0420	0.30	0.55	0.3579	36	36	1.75	0.0435	0.30	0.55	0.6594
17	17	1.90	0.0420	0.30	0.60	0.4677	36	36	1.75	0.0435	0.30	0.60	0.7992
17	17	1.90	0.0420	0.30	0.65	0.5851	36	36	1.75	0.0435	0.30	0.65	0.9003
17	17	1.90	0.0420	0.30	0.70	0.7012	36	36	1.75	0.0435	0.30	0.70	0.9597
17	17	1.90	0.0420	0.35	0.50	0.1678	36	36	1.75	0.0435	0.35	0.50	0.3196
17	17	1.90	0.0420	0.35	0.55	0.2465	36	36	1.75	0.0435	0.35	0.55	0.4802
17	17	1.90	0.0420	0.35	0.60	0.3450	36	36	1.75	0.0435	0.35	0.60	0.6481
17	17	1.90	0.0420	0.35	0.65	0.4601	36	36	1.75	0.0435	0.35	0.65	0.7947
17	17	1.90	0.0420	0.40	0.55	0.1608	36	36	1.75	0.0435	0.40	0.55	0.3121
17	17	1.90	0.0420	0.40	0.60	0.2416	36	36	1.75	0.0435	0.40	0.60	0.4760
18	18	1.88	0.0424	0.05	0.15	0.2246	37	37	1.70	0.0492	0.05	0.15	0.4416
18	18	1.88	0.0424	0.05	0.20	0.3489	37	37	1.70	0.0492	0.05	0.20	0.6521
18	18	1.88	0.0424	0.05	0.25	0.4759	37	37	1.70	0.0492	0.05	0.25	0.8142
18	18	1.88	0.0424	0.05	0.30	0.6023	37	37	1.70	0.0492	0.05	0.30	0.9162
18	18	1.88	0.0424	0.05	0.35	0.7199	37	37	1.70	0.0492	0.05	0.35	0.9684
18	18	1.88	0.0424	0.05	0.40	0.8190	37	37	1.70	0.0492	0.05	0.40	0.9900
18	18	1.88	0.0424	0.05	0.45	0.8936	37	37	1.70	0.0492	0.05	0.45	0.9974
18	18	1.88	0.0424	0.10	0.25	0.2640	37	37	1.70	0.0492	0.10	0.25	0.5241
18	18	1.88	0.0424	0.10	0.30	0.3850	37	37	1.70	0.0492	0.10	0.30	0.7096
18	18	1.88	0.0424	0.10	0.35	0.5183	37	37	1.70	0.0492	0.10	0.35	0.8464
18	18	1.88	0.0424	0.10	0.40	0.6479	37	37	1.70	0.0492	0.10	0.40	0.9299
18	18	1.88	0.0424	0.10	0.45	0.7601	37	37	1.70	0.0492	0.10	0.45	0.9727
18	18	1.88	0.0424	0.10	0.50	0.8476	37	37	1.70	0.0492	0.10	0.50	0.9912
18	18	1.88	0.0424	0.10	0.55	0.9098	37	37	1.70	0.0492	0.10	0.55	0.9977
18	18	1.88	0.0424	0.10	0.60	0.9507	37	37	1.70	0.0492	0.10	0.60	0.9995
18	18	1.88	0.0424	0.15	0.30	0.2386	37	37	1.70	0.0492	0.15	0.30	0.4610
18	18	1.88	0.0424	0.15	0.35	0.3543	37	37	1.70	0.0492	0.15	0.35	0.6416
18	18	1.88	0.0424	0.15	0.40	0.4796	37	37	1.70	0.0492	0.15	0.40	0.7919
18	18	1.88	0.0424	0.15	0.45	0.6019	37	37	1.70	0.0492	0.15	0.45	0.8962
18	18	1.88	0.0424	0.15	0.50	0.7116	37	37	1.70	0.0492	0.15	0.50	0.9559
18	18	1.88	0.0424	0.15	0.55	0.8033	37	37	1.70	0.0492	0.15	0.55	0.9841
18	18	1.88	0.0424	0.15	0.60	0.8752	37	37	1.70	0.0492	0.15	0.60	0.9952
18	18	1.88	0.0424	0.15	0.65	0.9279	37	37	1.70	0.0492	0.15	0.65	0.9988
18	18	1.88	0.0424	0.20	0.35	0.2266	37	37	1.70	0.0492	0.20	0.35	0.4203
18	18	1.88	0.0424	0.20	0.40	0.3296	37	37	1.70	0.0492	0.20	0.40	0.5986
18	18	1.88	0.0424	0.20	0.45	0.4422	37	37	1.70	0.0492	0.20	0.45	0.7551
18	18	1.88	0.0424	0.20	0.50	0.5569	37	37	1.70	0.0492	0.20	0.50	0.8688
18	18	1.88	0.0424	0.20	0.55	0.6671	37	37	1.70	0.0492	0.20	0.55	0.9386
18	18	1.88	0.0424	0.20	0.60	0.7665	37	37	1.70	0.0492	0.20	0.60	0.9755
18	18	1.88	0.0424	0.20	0.65	0.8500	37	37	1.70	0.0492	0.20	0.65	0.9920
18	18	1.88	0.0424	0.20	0.70	0.9137	37	37	1.70	0.0492	0.20	0.70	0.9980
18	18	1.88	0.0424	0.25	0.40	0.2103	37	37	1.70	0.0492	0.25	0.40	0.3959
18	18	1.88	0.0424	0.25	0.45	0.3024	37	37	1.70	0.0492	0.25	0.45	0.5650
18	18	1.88	0.0424	0.25	0.50	0.4079	37	37	1.70	0.0492	0.25	0.50	0.7187
18	18	1.88	0.0424	0.25	0.55	0.5220	37	37	1.70	0.0492	0.25	0.55	0.8393
18	18	1.88	0.0424	0.25	0.60	0.6377	37	37	1.70	0.0492	0.25	0.60	0.9213

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
18	18	1.88	0.0424	0.25	0.65	0.7461	37	37	1.70	0.0492	0.25	0.65	0.9683
18	18	1.88	0.0424	0.25	0.70	0.8386	37	37	1.70	0.0492	0.25	0.70	0.9900
18	18	1.88	0.0424	0.25	0.75	0.9094	37	37	1.70	0.0492	0.25	0.75	0.9977
18	18	1.88	0.0424	0.30	0.45	0.1932	37	37	1.70	0.0492	0.30	0.45	0.3679
18	18	1.88	0.0424	0.30	0.50	0.2807	37	37	1.70	0.0492	0.30	0.50	0.5283
18	18	1.88	0.0424	0.30	0.55	0.3857	37	37	1.70	0.0492	0.30	0.55	0.6857
18	18	1.88	0.0424	0.30	0.60	0.5033	37	37	1.70	0.0492	0.30	0.60	0.8186
18	18	1.88	0.0424	0.30	0.65	0.6250	37	37	1.70	0.0492	0.30	0.65	0.9124
18	18	1.88	0.0424	0.30	0.70	0.7401	37	37	1.70	0.0492	0.30	0.70	0.9660
18	18	1.88	0.0424	0.35	0.50	0.1818	37	37	1.70	0.0492	0.35	0.50	0.3415
18	18	1.88	0.0424	0.35	0.55	0.2691	37	37	1.70	0.0492	0.35	0.55	0.5037
18	18	1.88	0.0424	0.35	0.60	0.3763	37	37	1.70	0.0492	0.35	0.60	0.6700
18	18	1.88	0.0424	0.35	0.65	0.4980	37	37	1.70	0.0492	0.35	0.65	0.8125
18	18	1.88	0.0424	0.40	0.55	0.1770	37	37	1.70	0.0492	0.40	0.55	0.3293
18	18	1.88	0.0424	0.40	0.60	0.2658	37	37	1.70	0.0492	0.40	0.60	0.4967
19	19	1.86	0.0415	0.05	0.15	0.2342	38	38	1.71	0.0497	0.05	0.15	0.4488
19	19	1.86	0.0415	0.05	0.20	0.3628	38	38	1.71	0.0497	0.05	0.20	0.6620
19	19	1.86	0.0415	0.05	0.25	0.4962	38	38	1.71	0.0497	0.05	0.25	0.8238
19	19	1.86	0.0415	0.05	0.30	0.6283	38	38	1.71	0.0497	0.05	0.30	0.9231
19	19	1.86	0.0415	0.05	0.35	0.7479	38	38	1.71	0.0497	0.05	0.35	0.9720
19	19	1.86	0.0415	0.05	0.40	0.8444	38	38	1.71	0.0497	0.05	0.40	0.9915
19	19	1.86	0.0415	0.05	0.45	0.9131	38	38	1.71	0.0497	0.05	0.45	0.9979
19	19	1.86	0.0415	0.10	0.25	0.2793	38	38	1.71	0.0497	0.10	0.25	0.5359
19	19	1.86	0.0415	0.10	0.30	0.4098	38	38	1.71	0.0497	0.10	0.30	0.7220
19	19	1.86	0.0415	0.10	0.35	0.5493	38	38	1.71	0.0497	0.10	0.35	0.8562
19	19	1.86	0.0415	0.10	0.40	0.6798	38	38	1.71	0.0497	0.10	0.40	0.9360
19	19	1.86	0.0415	0.10	0.45	0.7883	38	38	1.71	0.0497	0.10	0.45	0.9758
19	19	1.86	0.0415	0.10	0.50	0.8697	38	38	1.71	0.0497	0.10	0.50	0.9924
19	19	1.86	0.0415	0.10	0.55	0.9256	38	38	1.71	0.0497	0.10	0.55	0.9980
19	19	1.86	0.0415	0.10	0.60	0.9611	38	38	1.71	0.0497	0.10	0.60	0.9996
19	19	1.86	0.0415	0.15	0.30	0.2560	38	38	1.71	0.0497	0.15	0.30	0.4713
19	19	1.86	0.0415	0.15	0.35	0.3782	38	38	1.71	0.0497	0.15	0.35	0.6529
19	19	1.86	0.0415	0.15	0.40	0.5071	38	38	1.71	0.0497	0.15	0.40	0.8010
19	19	1.86	0.0415	0.15	0.45	0.6301	38	38	1.71	0.0497	0.15	0.45	0.9013
19	19	1.86	0.0415	0.15	0.50	0.7383	38	38	1.71	0.0497	0.15	0.50	0.9579
19	19	1.86	0.0415	0.15	0.55	0.8271	38	38	1.71	0.0497	0.15	0.55	0.9847
19	19	1.86	0.0415	0.15	0.60	0.8950	38	38	1.71	0.0497	0.15	0.60	0.9954
19	19	1.86	0.0415	0.15	0.65	0.9427	38	38	1.71	0.0497	0.15	0.65	0.9989
19	19	1.86	0.0415	0.20	0.35	0.2412	38	38	1.71	0.0497	0.20	0.35	0.4264
19	19	1.86	0.0415	0.20	0.40	0.3490	38	38	1.71	0.0497	0.20	0.40	0.6026
19	19	1.86	0.0415	0.20	0.45	0.4659	38	38	1.71	0.0497	0.20	0.45	0.7557
19	19	1.86	0.0415	0.20	0.50	0.5844	38	38	1.71	0.0497	0.20	0.50	0.8681
19	19	1.86	0.0415	0.20	0.55	0.6967	38	38	1.71	0.0497	0.20	0.55	0.9389
19	19	1.86	0.0415	0.20	0.60	0.7956	38	38	1.71	0.0497	0.20	0.60	0.9765
19	19	1.86	0.0415	0.20	0.65	0.8751	38	38	1.71	0.0497	0.20	0.65	0.9928
19	19	1.86	0.0415	0.20	0.70	0.9325	38	38	1.71	0.0497	0.20	0.70	0.9984
19	19	1.86	0.0415	0.25	0.40	0.2223	38	38	1.71	0.0497	0.25	0.40	0.3910
19	19	1.86	0.0415	0.25	0.45	0.3205	38	38	1.71	0.0497	0.25	0.45	0.5586
19	19	1.86	0.0415	0.25	0.50	0.4331	38	38	1.71	0.0497	0.25	0.50	0.7155
19	19	1.86	0.0415	0.25	0.55	0.5536	38	38	1.71	0.0497	0.25	0.55	0.8413

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
19	19	1.86	0.0415	0.25	0.60	0.6728	38	38	1.71	0.0497	0.25	0.60	0.9258
19	19	1.86	0.0415	0.25	0.65	0.7801	38	38	1.71	0.0497	0.25	0.65	0.9719
19	19	1.86	0.0415	0.25	0.70	0.8671	38	38	1.71	0.0497	0.25	0.70	0.9917
19	19	1.86	0.0415	0.25	0.75	0.9296	38	38	1.71	0.0497	0.25	0.75	0.9982
19	19	1.86	0.0415	0.30	0.45	0.2062	38	38	1.71	0.0497	0.30	0.45	0.3599
19	19	1.86	0.0415	0.30	0.50	0.3017	38	38	1.71	0.0497	0.30	0.50	0.5270
19	19	1.86	0.0415	0.30	0.55	0.4153	38	38	1.71	0.0497	0.30	0.55	0.6927
19	19	1.86	0.0415	0.30	0.60	0.5396	38	38	1.71	0.0497	0.30	0.60	0.8292
19	19	1.86	0.0415	0.30	0.65	0.6637	38	38	1.71	0.0497	0.30	0.65	0.9211
19	19	1.86	0.0415	0.30	0.70	0.7760	38	38	1.71	0.0497	0.30	0.70	0.9707
19	19	1.86	0.0415	0.35	0.50	0.1976	38	38	1.71	0.0497	0.35	0.50	0.3441
19	19	1.86	0.0415	0.35	0.55	0.2936	38	38	1.71	0.0497	0.35	0.55	0.5150
19	19	1.86	0.0415	0.35	0.60	0.4090	38	38	1.71	0.0497	0.35	0.60	0.6858
19	19	1.86	0.0415	0.35	0.65	0.5361	38	38	1.71	0.0497	0.35	0.65	0.8265
19	19	1.86	0.0415	0.40	0.55	0.1950	38	38	1.71	0.0497	0.40	0.55	0.3406
19	19	1.86	0.0415	0.40	0.60	0.2918	38	38	1.71	0.0497	0.40	0.60	0.5129
20	20	1.85	0.0404	0.05	0.15	0.2430	39	39	1.74	0.0445	0.05	0.15	0.4071
20	20	1.85	0.0404	0.05	0.20	0.3755	39	39	1.74	0.0445	0.05	0.20	0.6436
20	20	1.85	0.0404	0.05	0.25	0.5133	39	39	1.74	0.0445	0.05	0.25	0.8203
20	20	1.85	0.0404	0.05	0.30	0.6474	39	39	1.74	0.0445	0.05	0.30	0.9231
20	20	1.85	0.0404	0.05	0.35	0.7649	39	39	1.74	0.0445	0.05	0.35	0.9720
20	20	1.85	0.0404	0.05	0.40	0.8563	39	39	1.74	0.0445	0.05	0.40	0.9914
20	20	1.85	0.0404	0.05	0.45	0.9197	39	39	1.74	0.0445	0.05	0.45	0.9978
20	20	1.85	0.0404	0.10	0.25	0.2842	39	39	1.74	0.0445	0.10	0.25	0.5249
20	20	1.85	0.0404	0.10	0.30	0.4132	39	39	1.74	0.0445	0.10	0.30	0.7111
20	20	1.85	0.0404	0.10	0.35	0.5483	39	39	1.74	0.0445	0.10	0.35	0.8496
20	20	1.85	0.0404	0.10	0.40	0.6747	39	39	1.74	0.0445	0.10	0.40	0.9338
20	20	1.85	0.0404	0.10	0.45	0.7821	39	39	1.74	0.0445	0.10	0.45	0.9755
20	20	1.85	0.0404	0.10	0.50	0.8656	39	39	1.74	0.0445	0.10	0.50	0.9925
20	20	1.85	0.0404	0.10	0.55	0.9248	39	39	1.74	0.0445	0.10	0.55	0.9981
20	20	1.85	0.0404	0.10	0.60	0.9627	39	39	1.74	0.0445	0.10	0.60	0.9996
20	20	1.85	0.0404	0.15	0.30	0.2454	39	39	1.74	0.0445	0.15	0.30	0.4553
20	20	1.85	0.0404	0.15	0.35	0.3616	39	39	1.74	0.0445	0.15	0.35	0.6430
20	20	1.85	0.0404	0.15	0.40	0.4890	39	39	1.74	0.0445	0.15	0.40	0.7965
20	20	1.85	0.0404	0.15	0.45	0.6167	39	39	1.74	0.0445	0.15	0.45	0.8995
20	20	1.85	0.0404	0.15	0.50	0.7338	39	39	1.74	0.0445	0.15	0.50	0.9574
20	20	1.85	0.0404	0.15	0.55	0.8312	39	39	1.74	0.0445	0.15	0.55	0.9849
20	20	1.85	0.0404	0.15	0.60	0.9039	39	39	1.74	0.0445	0.15	0.60	0.9957
20	20	1.85	0.0404	0.15	0.65	0.9518	39	39	1.74	0.0445	0.15	0.65	0.9991
20	20	1.85	0.0404	0.20	0.35	0.2219	39	39	1.74	0.0445	0.20	0.35	0.4152
20	20	1.85	0.0404	0.20	0.40	0.3307	39	39	1.74	0.0445	0.20	0.40	0.5934
20	20	1.85	0.0404	0.20	0.45	0.4560	39	39	1.74	0.0445	0.20	0.45	0.7503
20	20	1.85	0.0404	0.20	0.50	0.5870	39	39	1.74	0.0445	0.20	0.50	0.8675
20	20	1.85	0.0404	0.20	0.55	0.7106	39	39	1.74	0.0445	0.20	0.55	0.9410
20	20	1.85	0.0404	0.20	0.60	0.8153	39	39	1.74	0.0445	0.20	0.60	0.9787
20	20	1.85	0.0404	0.20	0.65	0.8944	39	39	1.74	0.0445	0.20	0.65	0.9940
20	20	1.85	0.0404	0.20	0.70	0.9469	39	39	1.74	0.0445	0.20	0.70	0.9987
20	20	1.85	0.0404	0.25	0.40	0.2105	39	39	1.74	0.0445	0.25	0.40	0.3802
20	20	1.85	0.0404	0.25	0.45	0.3178	39	39	1.74	0.0445	0.25	0.45	0.5535
20	20	1.85	0.0404	0.25	0.50	0.4434	39	39	1.74	0.0445	0.25	0.50	0.7186

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	20	1.85	0.0404	0.25	0.55	0.5759	39	39	1.74	0.0445	0.25	0.55	0.8490
20	20	1.85	0.0404	0.25	0.60	0.7018	39	39	1.74	0.0445	0.25	0.60	0.9328
20	20	1.85	0.0404	0.25	0.65	0.8091	39	39	1.74	0.0445	0.25	0.65	0.9759
20	20	1.85	0.0404	0.25	0.70	0.8908	39	39	1.74	0.0445	0.25	0.70	0.9933
20	20	1.85	0.0404	0.25	0.75	0.9456	39	39	1.74	0.0445	0.25	0.75	0.9986
20	20	1.85	0.0404	0.30	0.45	0.2088	39	39	1.74	0.0445	0.30	0.45	0.3592
20	20	1.85	0.0404	0.30	0.50	0.3157	39	39	1.74	0.0445	0.30	0.50	0.5353
20	20	1.85	0.0404	0.30	0.55	0.4407	39	39	1.74	0.0445	0.30	0.55	0.7064
20	20	1.85	0.0404	0.30	0.60	0.5728	39	39	1.74	0.0445	0.30	0.60	0.8423
20	20	1.85	0.0404	0.30	0.65	0.6990	39	39	1.74	0.0445	0.30	0.65	0.9299
20	20	1.85	0.0404	0.30	0.70	0.8075	39	39	1.74	0.0445	0.30	0.70	0.9751
20	20	1.85	0.0404	0.35	0.50	0.2110	39	39	1.74	0.0445	0.35	0.50	0.3543
20	20	1.85	0.0404	0.35	0.55	0.3168	39	39	1.74	0.0445	0.35	0.55	0.5312
20	20	1.85	0.0404	0.35	0.60	0.4406	39	39	1.74	0.0445	0.35	0.60	0.7033
20	20	1.85	0.0404	0.35	0.65	0.5722	39	39	1.74	0.0445	0.35	0.65	0.8407
20	20	1.85	0.0404	0.40	0.55	0.2128	39	39	1.74	0.0445	0.40	0.55	0.3546
20	20	1.85	0.0404	0.40	0.60	0.3175	39	39	1.74	0.0445	0.40	0.60	0.5307
21	21	1.83	0.0442	0.05	0.15	0.2945	40	40	1.73	0.0448	0.05	0.15	0.4166
21	21	1.83	0.0442	0.05	0.20	0.4580	40	40	1.73	0.0448	0.05	0.20	0.6557
21	21	1.83	0.0442	0.05	0.25	0.6081	40	40	1.73	0.0448	0.05	0.25	0.8302
21	21	1.83	0.0442	0.05	0.30	0.7330	40	40	1.73	0.0448	0.05	0.30	0.9293
21	21	1.83	0.0442	0.05	0.35	0.8289	40	40	1.73	0.0448	0.05	0.35	0.9751
21	21	1.83	0.0442	0.05	0.40	0.8975	40	40	1.73	0.0448	0.05	0.40	0.9927
21	21	1.83	0.0442	0.05	0.45	0.9432	40	40	1.73	0.0448	0.05	0.45	0.9982
21	21	1.83	0.0442	0.10	0.25	0.3490	40	40	1.73	0.0448	0.10	0.25	0.5355
21	21	1.83	0.0442	0.10	0.30	0.4759	40	40	1.73	0.0448	0.10	0.30	0.7227
21	21	1.83	0.0442	0.10	0.35	0.6009	40	40	1.73	0.0448	0.10	0.35	0.8592
21	21	1.83	0.0442	0.10	0.40	0.7154	40	40	1.73	0.0448	0.10	0.40	0.9399
21	21	1.83	0.0442	0.10	0.45	0.8125	40	40	1.73	0.0448	0.10	0.45	0.9786
21	21	1.83	0.0442	0.10	0.50	0.8875	40	40	1.73	0.0448	0.10	0.50	0.9936
21	21	1.83	0.0442	0.10	0.55	0.9397	40	40	1.73	0.0448	0.10	0.55	0.9984
21	21	1.83	0.0442	0.10	0.60	0.9717	40	40	1.73	0.0448	0.10	0.60	0.9997
21	21	1.83	0.0442	0.15	0.30	0.2788	40	40	1.73	0.0448	0.15	0.30	0.4665
21	21	1.83	0.0442	0.15	0.35	0.3947	40	40	1.73	0.0448	0.15	0.35	0.6559
21	21	1.83	0.0442	0.15	0.40	0.5219	40	40	1.73	0.0448	0.15	0.40	0.8077
21	21	1.83	0.0442	0.15	0.45	0.6491	40	40	1.73	0.0448	0.15	0.45	0.9072
21	21	1.83	0.0442	0.15	0.50	0.7639	40	40	1.73	0.0448	0.15	0.50	0.9618
21	21	1.83	0.0442	0.15	0.55	0.8564	40	40	1.73	0.0448	0.15	0.55	0.9870
21	21	1.83	0.0442	0.15	0.60	0.9223	40	40	1.73	0.0448	0.15	0.60	0.9965
21	21	1.83	0.0442	0.15	0.65	0.9633	40	40	1.73	0.0448	0.15	0.65	0.9993
21	21	1.83	0.0442	0.20	0.35	0.2411	40	40	1.73	0.0448	0.20	0.35	0.4254
21	21	1.83	0.0442	0.20	0.40	0.3555	40	40	1.73	0.0448	0.20	0.40	0.6055
21	21	1.83	0.0442	0.20	0.45	0.4865	40	40	1.73	0.0448	0.20	0.45	0.7623
21	21	1.83	0.0442	0.20	0.50	0.6207	40	40	1.73	0.0448	0.20	0.50	0.8774
21	21	1.83	0.0442	0.20	0.55	0.7434	40	40	1.73	0.0448	0.20	0.55	0.9475
21	21	1.83	0.0442	0.20	0.60	0.8430	40	40	1.73	0.0448	0.20	0.60	0.9819
21	21	1.83	0.0442	0.20	0.65	0.9146	40	40	1.73	0.0448	0.20	0.65	0.9952
21	21	1.83	0.0442	0.20	0.70	0.9595	40	40	1.73	0.0448	0.20	0.70	0.9990
21	21	1.83	0.0442	0.25	0.40	0.2281	40	40	1.73	0.0448	0.25	0.40	0.3901
21	21	1.83	0.0442	0.25	0.45	0.3433	40	40	1.73	0.0448	0.25	0.45	0.5674

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
21	21	1.83	0.0442	0.25	0.50	0.4756	40	40	1.73	0.0448	0.25	0.50	0.7336
21	21	1.83	0.0442	0.25	0.55	0.6112	40	40	1.73	0.0448	0.25	0.55	0.8613
21	21	1.83	0.0442	0.25	0.60	0.7357	40	40	1.73	0.0448	0.25	0.60	0.9405
21	21	1.83	0.0442	0.25	0.65	0.8376	40	40	1.73	0.0448	0.25	0.65	0.9795
21	21	1.83	0.0442	0.25	0.70	0.9115	40	40	1.73	0.0448	0.25	0.70	0.9946
21	21	1.83	0.0442	0.25	0.75	0.9584	40	40	1.73	0.0448	0.25	0.75	0.9990
21	21	1.83	0.0442	0.30	0.45	0.2277	40	40	1.73	0.0448	0.30	0.45	0.3717
21	21	1.83	0.0442	0.30	0.50	0.3424	40	40	1.73	0.0448	0.30	0.50	0.5521
21	21	1.83	0.0442	0.30	0.55	0.4736	40	40	1.73	0.0448	0.30	0.55	0.7233
21	21	1.83	0.0442	0.30	0.60	0.6084	40	40	1.73	0.0448	0.30	0.60	0.8555
21	21	1.83	0.0442	0.30	0.65	0.7330	40	40	1.73	0.0448	0.30	0.65	0.9379
21	21	1.83	0.0442	0.30	0.70	0.8360	40	40	1.73	0.0448	0.30	0.70	0.9789
21	21	1.83	0.0442	0.35	0.50	0.2306	40	40	1.73	0.0448	0.35	0.50	0.3685
21	21	1.83	0.0442	0.35	0.55	0.3439	40	40	1.73	0.0448	0.35	0.55	0.5488
21	21	1.83	0.0442	0.35	0.60	0.4736	40	40	1.73	0.0448	0.35	0.60	0.7205
21	21	1.83	0.0442	0.35	0.65	0.6078	40	40	1.73	0.0448	0.35	0.65	0.8540
21	21	1.83	0.0442	0.40	0.55	0.2327	40	40	1.73	0.0448	0.40	0.55	0.3691
21	21	1.83	0.0442	0.40	0.60	0.3447	40	40	1.73	0.0448	0.40	0.60	0.5484
22	22	1.81	0.0481	0.05	0.15	0.3067	50	50	1.71	0.0476	0.05	0.15	0.5071
22	22	1.81	0.0481	0.05	0.20	0.4739	50	50	1.71	0.0476	0.05	0.20	0.7566
22	22	1.81	0.0481	0.05	0.25	0.6256	50	50	1.71	0.0476	0.05	0.25	0.9045
22	22	1.81	0.0481	0.05	0.30	0.7499	50	50	1.71	0.0476	0.05	0.30	0.9700
22	22	1.81	0.0481	0.05	0.35	0.8437	50	50	1.71	0.0476	0.05	0.35	0.9925
22	22	1.81	0.0481	0.05	0.40	0.9092	50	50	1.71	0.0476	0.05	0.40	0.9985
22	22	1.81	0.0481	0.05	0.45	0.9517	50	50	1.71	0.0476	0.05	0.45	0.9998
22	22	1.81	0.0481	0.10	0.25	0.3590	50	50	1.71	0.0476	0.10	0.25	0.6308
22	22	1.81	0.0481	0.10	0.30	0.4904	50	50	1.71	0.0476	0.10	0.30	0.8151
22	22	1.81	0.0481	0.10	0.35	0.6192	50	50	1.71	0.0476	0.10	0.35	0.9245
22	22	1.81	0.0481	0.10	0.40	0.7357	50	50	1.71	0.0476	0.10	0.40	0.9751
22	22	1.81	0.0481	0.10	0.45	0.8321	50	50	1.71	0.0476	0.10	0.45	0.9935
22	22	1.81	0.0481	0.10	0.50	0.9039	50	50	1.71	0.0476	0.10	0.50	0.9987
22	22	1.81	0.0481	0.10	0.55	0.9513	50	50	1.71	0.0476	0.10	0.55	0.9998
22	22	1.81	0.0481	0.10	0.60	0.9786	50	50	1.71	0.0476	0.10	0.60	1.0000
22	22	1.81	0.0481	0.15	0.30	0.2884	50	50	1.71	0.0476	0.15	0.30	0.5516
22	22	1.81	0.0481	0.15	0.35	0.4115	50	50	1.71	0.0476	0.15	0.35	0.7479
22	22	1.81	0.0481	0.15	0.40	0.5453	50	50	1.71	0.0476	0.15	0.40	0.8846
22	22	1.81	0.0481	0.15	0.45	0.6763	50	50	1.71	0.0476	0.15	0.45	0.9576
22	22	1.81	0.0481	0.15	0.50	0.7904	50	50	1.71	0.0476	0.15	0.50	0.9875
22	22	1.81	0.0481	0.15	0.55	0.8783	50	50	1.71	0.0476	0.15	0.55	0.9970
22	22	1.81	0.0481	0.15	0.60	0.9376	50	50	1.71	0.0476	0.15	0.60	0.9995
22	22	1.81	0.0481	0.15	0.65	0.9723	50	50	1.71	0.0476	0.15	0.65	0.9999
22	22	1.81	0.0481	0.20	0.35	0.2543	50	50	1.71	0.0476	0.20	0.35	0.5077
22	22	1.81	0.0481	0.20	0.40	0.3773	50	50	1.71	0.0476	0.20	0.40	0.7079
22	22	1.81	0.0481	0.20	0.45	0.5153	50	50	1.71	0.0476	0.20	0.45	0.8549
22	22	1.81	0.0481	0.20	0.50	0.6525	50	50	1.71	0.0476	0.20	0.50	0.9400
22	22	1.81	0.0481	0.20	0.55	0.7732	50	50	1.71	0.0476	0.20	0.55	0.9798
22	22	1.81	0.0481	0.20	0.60	0.8670	50	50	1.71	0.0476	0.20	0.60	0.9947
22	22	1.81	0.0481	0.20	0.65	0.9311	50	50	1.71	0.0476	0.20	0.65	0.9990
22	22	1.81	0.0481	0.20	0.70	0.9692	50	50	1.71	0.0476	0.20	0.70	0.9999
22	22	1.81	0.0481	0.25	0.40	0.2451	50	50	1.71	0.0476	0.25	0.40	0.4784

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
22	22	1.81	0.0481	0.25	0.45	0.3685	50	50	1.71	0.0476	0.25	0.45	0.6700
22	22	1.81	0.0481	0.25	0.50	0.5068	50	50	1.71	0.0476	0.25	0.50	0.8231
22	22	1.81	0.0481	0.25	0.55	0.6445	50	50	1.71	0.0476	0.25	0.55	0.9225
22	22	1.81	0.0481	0.25	0.60	0.7663	50	50	1.71	0.0476	0.25	0.60	0.9735
22	22	1.81	0.0481	0.25	0.65	0.8621	50	50	1.71	0.0476	0.25	0.65	0.9932
22	22	1.81	0.0481	0.25	0.70	0.9284	50	50	1.71	0.0476	0.25	0.70	0.9988
22	22	1.81	0.0481	0.25	0.75	0.9683	50	50	1.71	0.0476	0.25	0.75	0.9999
22	22	1.81	0.0481	0.30	0.45	0.2468	50	50	1.71	0.0476	0.30	0.45	0.4445
22	22	1.81	0.0481	0.30	0.50	0.3689	50	50	1.71	0.0476	0.30	0.50	0.6372
22	22	1.81	0.0481	0.30	0.55	0.5053	50	50	1.71	0.0476	0.30	0.55	0.8029
22	22	1.81	0.0481	0.30	0.60	0.6417	50	50	1.71	0.0476	0.30	0.60	0.9142
22	22	1.81	0.0481	0.30	0.65	0.7636	50	50	1.71	0.0476	0.30	0.65	0.9711
22	22	1.81	0.0481	0.30	0.70	0.8606	50	50	1.71	0.0476	0.30	0.70	0.9928
22	22	1.81	0.0481	0.35	0.50	0.2503	50	50	1.71	0.0476	0.35	0.50	0.4258
22	22	1.81	0.0481	0.35	0.55	0.3705	50	50	1.71	0.0476	0.35	0.55	0.6247
22	22	1.81	0.0481	0.35	0.60	0.5052	50	50	1.71	0.0476	0.35	0.60	0.7970
22	22	1.81	0.0481	0.35	0.65	0.6410	50	50	1.71	0.0476	0.35	0.65	0.9124
22	22	1.81	0.0481	0.40	0.55	0.2525	50	50	1.71	0.0476	0.40	0.55	0.4221
22	22	1.81	0.0481	0.40	0.60	0.3712	50	50	1.71	0.0476	0.40	0.60	0.6227
23	23	1.84	0.0438	0.05	0.15	0.2673	60	60	1.70	0.0500	0.05	0.15	0.5849
23	23	1.84	0.0438	0.05	0.20	0.4168	60	60	1.70	0.0500	0.05	0.20	0.8290
23	23	1.84	0.0438	0.05	0.25	0.5731	60	60	1.70	0.0500	0.05	0.25	0.9475
23	23	1.84	0.0438	0.05	0.30	0.7162	60	60	1.70	0.0500	0.05	0.30	0.9879
23	23	1.84	0.0438	0.05	0.35	0.8291	60	60	1.70	0.0500	0.05	0.35	0.9979
23	23	1.84	0.0438	0.05	0.40	0.9069	60	60	1.70	0.0500	0.05	0.40	0.9997
23	23	1.84	0.0438	0.05	0.45	0.9542	60	60	1.70	0.0500	0.05	0.45	1.0000
23	23	1.84	0.0438	0.10	0.25	0.3270	60	60	1.70	0.0500	0.10	0.25	0.7116
23	23	1.84	0.0438	0.10	0.30	0.4748	60	60	1.70	0.0500	0.10	0.30	0.8802
23	23	1.84	0.0438	0.10	0.35	0.6204	60	60	1.70	0.0500	0.10	0.35	0.9615
23	23	1.84	0.0438	0.10	0.40	0.7477	60	60	1.70	0.0500	0.10	0.40	0.9905
23	23	1.84	0.0438	0.10	0.45	0.8476	60	60	1.70	0.0500	0.10	0.45	0.9982
23	23	1.84	0.0438	0.10	0.50	0.9175	60	60	1.70	0.0500	0.10	0.50	0.9997
23	23	1.84	0.0438	0.10	0.55	0.9607	60	60	1.70	0.0500	0.10	0.55	1.0000
23	23	1.84	0.0438	0.10	0.60	0.9838	60	60	1.70	0.0500	0.10	0.60	1.0000
23	23	1.84	0.0438	0.15	0.30	0.2860	60	60	1.70	0.0500	0.15	0.30	0.6313
23	23	1.84	0.0438	0.15	0.35	0.4220	60	60	1.70	0.0500	0.15	0.35	0.8207
23	23	1.84	0.0438	0.15	0.40	0.5658	60	60	1.70	0.0500	0.15	0.40	0.9310
23	23	1.84	0.0438	0.15	0.45	0.7010	60	60	1.70	0.0500	0.15	0.45	0.9796
23	23	1.84	0.0438	0.15	0.50	0.8134	60	60	1.70	0.0500	0.15	0.50	0.9955
23	23	1.84	0.0438	0.15	0.55	0.8954	60	60	1.70	0.0500	0.15	0.55	0.9993
23	23	1.84	0.0438	0.15	0.60	0.9478	60	60	1.70	0.0500	0.15	0.60	0.9999
23	23	1.84	0.0438	0.15	0.65	0.9769	60	60	1.70	0.0500	0.15	0.65	1.0000
23	23	1.84	0.0438	0.20	0.35	0.2658	60	60	1.70	0.0500	0.20	0.35	0.5733
23	23	1.84	0.0438	0.20	0.40	0.3976	60	60	1.70	0.0500	0.20	0.40	0.7747
23	23	1.84	0.0438	0.20	0.45	0.5407	60	60	1.70	0.0500	0.20	0.45	0.9070
23	23	1.84	0.0438	0.20	0.50	0.6772	60	60	1.70	0.0500	0.20	0.50	0.9705
23	23	1.84	0.0438	0.20	0.55	0.7919	60	60	1.70	0.0500	0.20	0.55	0.9928
23	23	1.84	0.0438	0.20	0.60	0.8775	60	60	1.70	0.0500	0.20	0.60	0.9987
23	23	1.84	0.0438	0.20	0.65	0.9346	60	60	1.70	0.0500	0.20	0.65	0.9998
23	23	1.84	0.0438	0.20	0.70	0.9690	60	60	1.70	0.0500	0.20	0.70	1.0000

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
23	23	1.84	0.0438	0.25	0.40	0.2599	60	60	1.70	0.0500	0.25	0.40	0.5426
23	23	1.84	0.0438	0.25	0.45	0.3871	60	60	1.70	0.0500	0.25	0.45	0.7487
23	23	1.84	0.0438	0.25	0.50	0.5241	60	60	1.70	0.0500	0.25	0.50	0.8884
23	23	1.84	0.0438	0.25	0.55	0.6553	60	60	1.70	0.0500	0.25	0.55	0.9603
23	23	1.84	0.0438	0.25	0.60	0.7686	60	60	1.70	0.0500	0.25	0.60	0.9891
23	23	1.84	0.0438	0.25	0.65	0.8581	60	60	1.70	0.0500	0.25	0.65	0.9979
23	23	1.84	0.0438	0.25	0.70	0.9228	60	60	1.70	0.0500	0.25	0.70	0.9997
23	23	1.84	0.0438	0.25	0.75	0.9647	60	60	1.70	0.0500	0.25	0.75	1.0000
23	23	1.84	0.0438	0.30	0.45	0.2552	60	60	1.70	0.0500	0.30	0.45	0.5191
23	23	1.84	0.0438	0.30	0.50	0.3736	60	60	1.70	0.0500	0.30	0.50	0.7182
23	23	1.84	0.0438	0.30	0.55	0.5023	60	60	1.70	0.0500	0.30	0.55	0.8655
23	23	1.84	0.0438	0.30	0.60	0.6305	60	60	1.70	0.0500	0.30	0.60	0.9503
23	23	1.84	0.0438	0.30	0.65	0.7486	60	60	1.70	0.0500	0.30	0.65	0.9867
23	23	1.84	0.0438	0.30	0.70	0.8484	60	60	1.70	0.0500	0.30	0.70	0.9976
23	23	1.84	0.0438	0.35	0.50	0.2440	60	60	1.70	0.0500	0.35	0.50	0.4864
23	23	1.84	0.0438	0.35	0.55	0.3555	60	60	1.70	0.0500	0.35	0.55	0.6906
23	23	1.84	0.0438	0.35	0.60	0.4830	60	60	1.70	0.0500	0.35	0.60	0.8524
23	23	1.84	0.0438	0.35	0.65	0.6184	60	60	1.70	0.0500	0.35	0.65	0.9471
23	23	1.84	0.0438	0.40	0.55	0.2327	60	60	1.70	0.0500	0.40	0.55	0.4687
23	23	1.84	0.0438	0.40	0.60	0.3463	60	60	1.70	0.0500	0.40	0.60	0.6826
24	24	1.80	0.0455	0.05	0.15	0.3293	70	70	1.72	0.0476	0.05	0.15	0.6228
24	24	1.80	0.0455	0.05	0.20	0.5034	70	70	1.72	0.0476	0.05	0.20	0.8649
24	24	1.80	0.0455	0.05	0.25	0.6577	70	70	1.72	0.0476	0.05	0.25	0.9667
24	24	1.80	0.0455	0.05	0.30	0.7806	70	70	1.72	0.0476	0.05	0.30	0.9941
24	24	1.80	0.0455	0.05	0.35	0.8699	70	70	1.72	0.0476	0.05	0.35	0.9992
24	24	1.80	0.0455	0.05	0.40	0.9295	70	70	1.72	0.0476	0.05	0.40	0.9999
24	24	1.80	0.0455	0.05	0.45	0.9656	70	70	1.72	0.0476	0.05	0.45	1.0000
24	24	1.80	0.0455	0.10	0.25	0.3789	70	70	1.72	0.0476	0.10	0.25	0.7528
24	24	1.80	0.0455	0.10	0.30	0.5197	70	70	1.72	0.0476	0.10	0.30	0.9111
24	24	1.80	0.0455	0.10	0.35	0.6560	70	70	1.72	0.0476	0.10	0.35	0.9766
24	24	1.80	0.0455	0.10	0.40	0.7752	70	70	1.72	0.0476	0.10	0.40	0.9956
24	24	1.80	0.0455	0.10	0.45	0.8679	70	70	1.72	0.0476	0.10	0.45	0.9994
24	24	1.80	0.0455	0.10	0.50	0.9313	70	70	1.72	0.0476	0.10	0.50	0.9999
24	24	1.80	0.0455	0.10	0.55	0.9688	70	70	1.72	0.0476	0.10	0.55	1.0000
24	24	1.80	0.0455	0.10	0.60	0.9879	70	70	1.72	0.0476	0.10	0.60	1.0000
24	24	1.80	0.0455	0.15	0.30	0.3102	70	70	1.72	0.0476	0.15	0.30	0.6712
24	24	1.80	0.0455	0.15	0.35	0.4480	70	70	1.72	0.0476	0.15	0.35	0.8602
24	24	1.80	0.0455	0.15	0.40	0.5934	70	70	1.72	0.0476	0.15	0.40	0.9551
24	24	1.80	0.0455	0.15	0.45	0.7275	70	70	1.72	0.0476	0.15	0.45	0.9893
24	24	1.80	0.0455	0.15	0.50	0.8355	70	70	1.72	0.0476	0.15	0.50	0.9982
24	24	1.80	0.0455	0.15	0.55	0.9111	70	70	1.72	0.0476	0.15	0.55	0.9998
24	24	1.80	0.0455	0.15	0.60	0.9572	70	70	1.72	0.0476	0.15	0.60	1.0000
24	24	1.80	0.0455	0.15	0.65	0.9817	70	70	1.72	0.0476	0.15	0.65	1.0000
24	24	1.80	0.0455	0.20	0.35	0.2835	70	70	1.72	0.0476	0.20	0.35	0.6150
24	24	1.80	0.0455	0.20	0.40	0.4212	70	70	1.72	0.0476	0.20	0.40	0.8169
24	24	1.80	0.0455	0.20	0.45	0.5674	70	70	1.72	0.0476	0.20	0.45	0.9351
24	24	1.80	0.0455	0.20	0.50	0.7027	70	70	1.72	0.0476	0.20	0.50	0.9835
24	24	1.80	0.0455	0.20	0.55	0.8126	70	70	1.72	0.0476	0.20	0.55	0.9971
24	24	1.80	0.0455	0.20	0.60	0.8919	70	70	1.72	0.0476	0.20	0.60	0.9996
24	24	1.80	0.0455	0.20	0.65	0.9435	70	70	1.72	0.0476	0.20	0.65	1.0000

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
24	24	1.80	0.0455	0.20	0.70	0.9739	70	70	1.72	0.0476	0.20	0.70	1.0000
24	24	1.80	0.0455	0.25	0.40	0.2766	70	70	1.72	0.0476	0.25	0.40	0.5801
24	24	1.80	0.0455	0.25	0.45	0.4082	70	70	1.72	0.0476	0.25	0.45	0.7939
24	24	1.80	0.0455	0.25	0.50	0.5464	70	70	1.72	0.0476	0.25	0.50	0.9239
24	24	1.80	0.0455	0.25	0.55	0.6755	70	70	1.72	0.0476	0.25	0.55	0.9790
24	24	1.80	0.0455	0.25	0.60	0.7849	70	70	1.72	0.0476	0.25	0.60	0.9957
24	24	1.80	0.0455	0.25	0.65	0.8702	70	70	1.72	0.0476	0.25	0.65	0.9994
24	24	1.80	0.0455	0.25	0.70	0.9311	70	70	1.72	0.0476	0.25	0.70	0.9999
24	24	1.80	0.0455	0.25	0.75	0.9697	70	70	1.72	0.0476	0.25	0.75	1.0000
24	24	1.80	0.0455	0.30	0.45	0.2682	70	70	1.72	0.0476	0.30	0.45	0.5675
24	24	1.80	0.0455	0.30	0.50	0.3886	70	70	1.72	0.0476	0.30	0.50	0.7774
24	24	1.80	0.0455	0.30	0.55	0.5176	70	70	1.72	0.0476	0.30	0.55	0.9100
24	24	1.80	0.0455	0.30	0.60	0.6449	70	70	1.72	0.0476	0.30	0.60	0.9724
24	24	1.80	0.0455	0.30	0.65	0.7618	70	70	1.72	0.0476	0.30	0.65	0.9940
24	24	1.80	0.0455	0.30	0.70	0.8597	70	70	1.72	0.0476	0.30	0.70	0.9992
24	24	1.80	0.0455	0.35	0.50	0.2513	70	70	1.72	0.0476	0.35	0.50	0.5435
24	24	1.80	0.0455	0.35	0.55	0.3641	70	70	1.72	0.0476	0.35	0.55	0.7498
24	24	1.80	0.0455	0.35	0.60	0.4933	70	70	1.72	0.0476	0.35	0.60	0.8946
24	24	1.80	0.0455	0.35	0.65	0.6306	70	70	1.72	0.0476	0.35	0.65	0.9686
24	24	1.80	0.0455	0.40	0.55	0.2359	70	70	1.72	0.0476	0.40	0.55	0.5147
24	24	1.80	0.0455	0.40	0.60	0.3524	70	70	1.72	0.0476	0.40	0.60	0.7348
25	25	1.77	0.0472	0.05	0.15	0.3399	80	80	1.68	0.0494	0.05	0.15	0.7021
25	25	1.77	0.0472	0.05	0.20	0.5171	80	80	1.68	0.0494	0.05	0.20	0.9128
25	25	1.77	0.0472	0.05	0.25	0.6726	80	80	1.68	0.0494	0.05	0.25	0.9829
25	25	1.77	0.0472	0.05	0.30	0.7946	80	80	1.68	0.0494	0.05	0.30	0.9977
25	25	1.77	0.0472	0.05	0.35	0.8817	80	80	1.68	0.0494	0.05	0.35	0.9998
25	25	1.77	0.0472	0.05	0.40	0.9382	80	80	1.68	0.0494	0.05	0.40	1.0000
25	25	1.77	0.0472	0.05	0.45	0.9712	80	80	1.68	0.0494	0.05	0.45	1.0000
25	25	1.77	0.0472	0.10	0.25	0.3889	80	80	1.68	0.0494	0.10	0.25	0.8078
25	25	1.77	0.0472	0.10	0.30	0.5347	80	80	1.68	0.0494	0.10	0.30	0.9439
25	25	1.77	0.0472	0.10	0.35	0.6746	80	80	1.68	0.0494	0.10	0.35	0.9887
25	25	1.77	0.0472	0.10	0.40	0.7941	80	80	1.68	0.0494	0.10	0.40	0.9984
25	25	1.77	0.0472	0.10	0.45	0.8839	80	80	1.68	0.0494	0.10	0.45	0.9998
25	25	1.77	0.0472	0.10	0.50	0.9425	80	80	1.68	0.0494	0.10	0.50	1.0000
25	25	1.77	0.0472	0.10	0.55	0.9753	80	80	1.68	0.0494	0.10	0.55	1.0000
25	25	1.77	0.0472	0.10	0.60	0.9909	80	80	1.68	0.0494	0.10	0.60	1.0000
25	25	1.77	0.0472	0.15	0.30	0.3224	80	80	1.68	0.0494	0.15	0.30	0.7353
25	25	1.77	0.0472	0.15	0.35	0.4675	80	80	1.68	0.0494	0.15	0.35	0.9047
25	25	1.77	0.0472	0.15	0.40	0.6174	80	80	1.68	0.0494	0.15	0.40	0.9758
25	25	1.77	0.0472	0.15	0.45	0.7514	80	80	1.68	0.0494	0.15	0.45	0.9958
25	25	1.77	0.0472	0.15	0.50	0.8549	80	80	1.68	0.0494	0.15	0.50	0.9995
25	25	1.77	0.0472	0.15	0.55	0.9243	80	80	1.68	0.0494	0.15	0.55	1.0000
25	25	1.77	0.0472	0.15	0.60	0.9647	80	80	1.68	0.0494	0.15	0.60	1.0000
25	25	1.77	0.0472	0.15	0.65	0.9854	80	80	1.68	0.0494	0.15	0.65	1.0000
25	25	1.77	0.0472	0.20	0.35	0.2993	80	80	1.68	0.0494	0.20	0.35	0.6831
25	25	1.77	0.0472	0.20	0.40	0.4434	80	80	1.68	0.0494	0.20	0.40	0.8736
25	25	1.77	0.0472	0.20	0.45	0.5922	80	80	1.68	0.0494	0.20	0.45	0.9635
25	25	1.77	0.0472	0.20	0.50	0.7256	80	80	1.68	0.0494	0.20	0.50	0.9924
25	25	1.77	0.0472	0.20	0.55	0.8306	80	80	1.68	0.0494	0.20	0.55	0.9989
25	25	1.77	0.0472	0.20	0.60	0.9044	80	80	1.68	0.0494	0.20	0.60	0.9999

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
25	25	1.77	0.0472	0.20	0.65	0.9513	80	80	1.68	0.0494	0.20	0.65	1.0000
25	25	1.77	0.0472	0.20	0.70	0.9784	80	80	1.68	0.0494	0.20	0.70	1.0000
25	25	1.77	0.0472	0.25	0.40	0.2924	80	80	1.68	0.0494	0.25	0.40	0.6492
25	25	1.77	0.0472	0.25	0.45	0.4278	80	80	1.68	0.0494	0.25	0.45	0.8444
25	25	1.77	0.0472	0.25	0.50	0.5668	80	80	1.68	0.0494	0.25	0.50	0.9493
25	25	1.77	0.0472	0.25	0.55	0.6943	80	80	1.68	0.0494	0.25	0.55	0.9886
25	25	1.77	0.0472	0.25	0.60	0.8008	80	80	1.68	0.0494	0.25	0.60	0.9983
25	25	1.77	0.0472	0.25	0.65	0.8828	80	80	1.68	0.0494	0.25	0.65	0.9999
25	25	1.77	0.0472	0.25	0.70	0.9401	80	80	1.68	0.0494	0.25	0.70	1.0000
25	25	1.77	0.0472	0.25	0.75	0.9749	80	80	1.68	0.0494	0.25	0.75	1.0000
25	25	1.77	0.0472	0.30	0.45	0.2801	80	80	1.68	0.0494	0.30	0.45	0.6128
25	25	1.77	0.0472	0.30	0.50	0.4028	80	80	1.68	0.0494	0.30	0.50	0.8213
25	25	1.77	0.0472	0.30	0.55	0.5332	80	80	1.68	0.0494	0.30	0.55	0.9413
25	25	1.77	0.0472	0.30	0.60	0.6615	80	80	1.68	0.0494	0.30	0.60	0.9869
25	25	1.77	0.0472	0.30	0.65	0.7779	80	80	1.68	0.0494	0.30	0.65	0.9981
25	25	1.77	0.0472	0.30	0.70	0.8730	80	80	1.68	0.0494	0.30	0.70	0.9998
25	25	1.77	0.0472	0.35	0.50	0.2591	80	80	1.68	0.0494	0.35	0.50	0.5984
25	25	1.77	0.0472	0.35	0.55	0.3750	80	80	1.68	0.0494	0.35	0.55	0.8143
25	25	1.77	0.0472	0.35	0.60	0.5076	80	80	1.68	0.0494	0.35	0.60	0.9389
25	25	1.77	0.0472	0.35	0.65	0.6471	80	80	1.68	0.0494	0.35	0.65	0.9865
25	25	1.77	0.0472	0.40	0.55	0.2420	80	80	1.68	0.0494	0.40	0.55	0.5963
25	25	1.77	0.0472	0.40	0.60	0.3626	80	80	1.68	0.0494	0.40	0.60	0.8129
26	26	1.75	0.0489	0.05	0.15	0.3500	90	90	1.69	0.0494	0.05	0.15	0.7328
26	26	1.75	0.0489	0.05	0.20	0.5304	90	90	1.69	0.0494	0.05	0.20	0.9369
26	26	1.75	0.0489	0.05	0.25	0.6869	90	90	1.69	0.0494	0.05	0.25	0.9907
26	26	1.75	0.0489	0.05	0.30	0.8079	90	90	1.69	0.0494	0.05	0.30	0.9991
26	26	1.75	0.0489	0.05	0.35	0.8926	90	90	1.69	0.0494	0.05	0.35	0.9999
26	26	1.75	0.0489	0.05	0.40	0.9460	90	90	1.69	0.0494	0.05	0.40	1.0000
26	26	1.75	0.0489	0.05	0.45	0.9761	90	90	1.69	0.0494	0.05	0.45	1.0000
26	26	1.75	0.0489	0.10	0.25	0.3991	90	90	1.69	0.0494	0.10	0.25	0.8504
26	26	1.75	0.0489	0.10	0.30	0.5501	90	90	1.69	0.0494	0.10	0.30	0.9637
26	26	1.75	0.0489	0.10	0.35	0.6932	90	90	1.69	0.0494	0.10	0.35	0.9942
26	26	1.75	0.0489	0.10	0.40	0.8123	90	90	1.69	0.0494	0.10	0.40	0.9994
26	26	1.75	0.0489	0.10	0.45	0.8985	90	90	1.69	0.0494	0.10	0.45	1.0000
26	26	1.75	0.0489	0.10	0.50	0.9521	90	90	1.69	0.0494	0.10	0.50	1.0000
26	26	1.75	0.0489	0.10	0.55	0.9805	90	90	1.69	0.0494	0.10	0.55	1.0000
26	26	1.75	0.0489	0.10	0.60	0.9932	90	90	1.69	0.0494	0.10	0.60	1.0000
26	26	1.75	0.0489	0.15	0.30	0.3354	90	90	1.69	0.0494	0.15	0.30	0.7786
26	26	1.75	0.0489	0.15	0.35	0.4875	90	90	1.69	0.0494	0.15	0.35	0.9322
26	26	1.75	0.0489	0.15	0.40	0.6409	90	90	1.69	0.0494	0.15	0.40	0.9858
26	26	1.75	0.0489	0.15	0.45	0.7735	90	90	1.69	0.0494	0.15	0.45	0.9980
26	26	1.75	0.0489	0.15	0.50	0.8720	90	90	1.69	0.0494	0.15	0.50	0.9998
26	26	1.75	0.0489	0.15	0.55	0.9353	90	90	1.69	0.0494	0.15	0.55	1.0000
26	26	1.75	0.0489	0.15	0.60	0.9708	90	90	1.69	0.0494	0.15	0.60	1.0000
26	26	1.75	0.0489	0.15	0.65	0.9883	90	90	1.69	0.0494	0.15	0.65	1.0000
26	26	1.75	0.0489	0.20	0.35	0.3154	90	90	1.69	0.0494	0.20	0.35	0.7251
26	26	1.75	0.0489	0.20	0.40	0.4650	90	90	1.69	0.0494	0.20	0.40	0.9018
26	26	1.75	0.0489	0.20	0.45	0.6153	90	90	1.69	0.0494	0.20	0.45	0.9765
26	26	1.75	0.0489	0.20	0.50	0.7461	90	90	1.69	0.0494	0.20	0.50	0.9963
26	26	1.75	0.0489	0.20	0.55	0.8463	90	90	1.69	0.0494	0.20	0.55	0.9996

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
26	26	1.75	0.0489	0.20	0.60	0.9153	90	90	1.69	0.0494	0.20	0.60	1.0000
26	26	1.75	0.0489	0.20	0.65	0.9583	90	90	1.69	0.0494	0.20	0.65	1.0000
26	26	1.75	0.0489	0.20	0.70	0.9824	90	90	1.69	0.0494	0.20	0.70	1.0000
26	26	1.75	0.0489	0.25	0.40	0.3075	90	90	1.69	0.0494	0.25	0.40	0.6897
26	26	1.75	0.0489	0.25	0.45	0.4459	90	90	1.69	0.0494	0.25	0.45	0.8829
26	26	1.75	0.0489	0.25	0.50	0.5854	90	90	1.69	0.0494	0.25	0.50	0.9692
26	26	1.75	0.0489	0.25	0.55	0.7117	90	90	1.69	0.0494	0.25	0.55	0.9944
26	26	1.75	0.0489	0.25	0.60	0.8164	90	90	1.69	0.0494	0.25	0.60	0.9993
26	26	1.75	0.0489	0.25	0.65	0.8955	90	90	1.69	0.0494	0.25	0.65	1.0000
26	26	1.75	0.0489	0.25	0.70	0.9489	90	90	1.69	0.0494	0.25	0.70	1.0000
26	26	1.75	0.0489	0.25	0.75	0.9797	90	90	1.69	0.0494	0.25	0.75	1.0000
26	26	1.75	0.0489	0.30	0.45	0.2911	90	90	1.69	0.0494	0.30	0.45	0.6680
26	26	1.75	0.0489	0.30	0.50	0.4165	90	90	1.69	0.0494	0.30	0.50	0.8622
26	26	1.75	0.0489	0.30	0.55	0.5496	90	90	1.69	0.0494	0.30	0.55	0.9594
26	26	1.75	0.0489	0.30	0.60	0.6797	90	90	1.69	0.0494	0.30	0.60	0.9922
26	26	1.75	0.0489	0.30	0.65	0.7957	90	90	1.69	0.0494	0.30	0.65	0.9991
26	26	1.75	0.0489	0.30	0.70	0.8872	90	90	1.69	0.0494	0.30	0.70	0.9999
26	26	1.75	0.0489	0.35	0.50	0.2676	90	90	1.69	0.0494	0.35	0.50	0.6355
26	26	1.75	0.0489	0.35	0.55	0.3881	90	90	1.69	0.0494	0.35	0.55	0.8431
26	26	1.75	0.0489	0.35	0.60	0.5253	90	90	1.69	0.0494	0.35	0.60	0.9544
26	26	1.75	0.0489	0.35	0.65	0.6669	90	90	1.69	0.0494	0.35	0.65	0.9916
26	26	1.75	0.0489	0.40	0.55	0.2510	90	90	1.69	0.0494	0.40	0.55	0.6211
26	26	1.75	0.0489	0.40	0.60	0.3766	90	90	1.69	0.0494	0.40	0.60	0.8389
27	27	1.79	0.0413	0.05	0.15	0.2986	100	100	1.68	0.0495	0.05	0.15	0.7782
27	27	1.79	0.0413	0.05	0.20	0.4752	100	100	1.68	0.0495	0.05	0.20	0.9572
27	27	1.79	0.0413	0.05	0.25	0.6505	100	100	1.68	0.0495	0.05	0.25	0.9951
27	27	1.79	0.0413	0.05	0.30	0.7932	100	100	1.68	0.0495	0.05	0.30	0.9997
27	27	1.79	0.0413	0.05	0.35	0.8910	100	100	1.68	0.0495	0.05	0.35	1.0000
27	27	1.79	0.0413	0.05	0.40	0.9490	100	100	1.68	0.0495	0.05	0.40	1.0000
27	27	1.79	0.0413	0.05	0.45	0.9789	100	100	1.68	0.0495	0.05	0.45	1.0000
27	27	1.79	0.0413	0.10	0.25	0.3846	100	100	1.68	0.0495	0.10	0.25	0.8852
27	27	1.79	0.0413	0.10	0.30	0.5508	100	100	1.68	0.0495	0.10	0.30	0.9773
27	27	1.79	0.0413	0.10	0.35	0.7023	100	100	1.68	0.0495	0.10	0.35	0.9972
27	27	1.79	0.0413	0.10	0.40	0.8221	100	100	1.68	0.0495	0.10	0.40	0.9998
27	27	1.79	0.0413	0.10	0.45	0.9046	100	100	1.68	0.0495	0.10	0.45	1.0000
27	27	1.79	0.0413	0.10	0.50	0.9543	100	100	1.68	0.0495	0.10	0.50	1.0000
27	27	1.79	0.0413	0.10	0.55	0.9806	100	100	1.68	0.0495	0.10	0.55	1.0000
27	27	1.79	0.0413	0.10	0.60	0.9928	100	100	1.68	0.0495	0.10	0.60	1.0000
27	27	1.79	0.0413	0.15	0.30	0.3384	100	100	1.68	0.0495	0.15	0.30	0.8189
27	27	1.79	0.0413	0.15	0.35	0.4923	100	100	1.68	0.0495	0.15	0.35	0.9523
27	27	1.79	0.0413	0.15	0.40	0.6416	100	100	1.68	0.0495	0.15	0.40	0.9920
27	27	1.79	0.0413	0.15	0.45	0.7682	100	100	1.68	0.0495	0.15	0.45	0.9992
27	27	1.79	0.0413	0.15	0.50	0.8637	100	100	1.68	0.0495	0.15	0.50	0.9999
27	27	1.79	0.0413	0.15	0.55	0.9282	100	100	1.68	0.0495	0.15	0.55	1.0000
27	27	1.79	0.0413	0.15	0.60	0.9670	100	100	1.68	0.0495	0.15	0.60	1.0000
27	27	1.79	0.0413	0.15	0.65	0.9872	100	100	1.68	0.0495	0.15	0.65	1.0000
27	27	1.79	0.0413	0.20	0.35	0.3076	100	100	1.68	0.0495	0.20	0.35	0.7684
27	27	1.79	0.0413	0.20	0.40	0.4478	100	100	1.68	0.0495	0.20	0.40	0.9295
27	27	1.79	0.0413	0.20	0.45	0.5909	100	100	1.68	0.0495	0.20	0.45	0.9856
27	27	1.79	0.0413	0.20	0.50	0.7221	100	100	1.68	0.0495	0.20	0.50	0.9981

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
27	27	1.79	0.0413	0.20	0.55	0.8301	100	100	1.68	0.0495	0.20	0.55	0.9999
27	27	1.79	0.0413	0.20	0.60	0.9087	100	100	1.68	0.0495	0.20	0.60	1.0000
27	27	1.79	0.0413	0.20	0.65	0.9580	100	100	1.68	0.0495	0.20	0.65	1.0000
27	27	1.79	0.0413	0.20	0.70	0.9840	100	100	1.68	0.0495	0.20	0.70	1.0000
27	27	1.79	0.0413	0.25	0.40	0.2798	100	100	1.68	0.0495	0.25	0.40	0.7288
27	27	1.79	0.0413	0.25	0.45	0.4113	100	100	1.68	0.0495	0.25	0.45	0.9065
27	27	1.79	0.0413	0.25	0.50	0.5546	100	100	1.68	0.0495	0.25	0.50	0.9792
27	27	1.79	0.0413	0.25	0.55	0.6937	100	100	1.68	0.0495	0.25	0.55	0.9972
27	27	1.79	0.0413	0.25	0.60	0.8124	100	100	1.68	0.0495	0.25	0.60	0.9998
27	27	1.79	0.0413	0.25	0.65	0.8998	100	100	1.68	0.0495	0.25	0.65	1.0000
27	27	1.79	0.0413	0.25	0.70	0.9546	100	100	1.68	0.0495	0.25	0.70	1.0000
27	27	1.79	0.0413	0.25	0.75	0.9832	100	100	1.68	0.0495	0.25	0.75	1.0000
27	27	1.79	0.0413	0.30	0.45	0.2604	100	100	1.68	0.0495	0.30	0.45	0.7012
27	27	1.79	0.0413	0.30	0.50	0.3911	100	100	1.68	0.0495	0.30	0.50	0.8949
27	27	1.79	0.0413	0.30	0.55	0.5380	100	100	1.68	0.0495	0.30	0.55	0.9762
27	27	1.79	0.0413	0.30	0.60	0.6827	100	100	1.68	0.0495	0.30	0.60	0.9967
27	27	1.79	0.0413	0.30	0.65	0.8064	100	100	1.68	0.0495	0.30	0.65	0.9997
27	27	1.79	0.0413	0.30	0.70	0.8976	100	100	1.68	0.0495	0.30	0.70	1.0000
27	27	1.79	0.0413	0.35	0.50	0.2529	100	100	1.68	0.0495	0.35	0.50	0.6947
27	27	1.79	0.0413	0.35	0.55	0.3848	100	100	1.68	0.0495	0.35	0.55	0.8909
27	27	1.79	0.0413	0.35	0.60	0.5335	100	100	1.68	0.0495	0.35	0.60	0.9750
27	27	1.79	0.0413	0.35	0.65	0.6803	100	100	1.68	0.0495	0.35	0.65	0.9966
27	27	1.79	0.0413	0.40	0.55	0.2519	100	100	1.68	0.0495	0.40	0.55	0.6928
27	27	1.79	0.0413	0.40	0.60	0.3839	100	100	1.68	0.0495	0.40	0.60	0.8897
28	28	1.78	0.0423	0.05	0.15	0.3068	150	150	1.67	0.0498	0.05	0.15	0.9039
28	28	1.78	0.0423	0.05	0.20	0.4902	150	150	1.67	0.0498	0.05	0.20	0.9931
28	28	1.78	0.0423	0.05	0.25	0.6686	150	150	1.67	0.0498	0.05	0.25	0.9998
28	28	1.78	0.0423	0.05	0.30	0.8095	150	150	1.67	0.0498	0.05	0.30	1.0000
28	28	1.78	0.0423	0.05	0.35	0.9030	150	150	1.67	0.0498	0.05	0.35	1.0000
28	28	1.78	0.0423	0.05	0.40	0.9563	150	150	1.67	0.0498	0.05	0.40	1.0000
28	28	1.78	0.0423	0.05	0.45	0.9828	150	150	1.67	0.0498	0.05	0.45	1.0000
28	28	1.78	0.0423	0.10	0.25	0.3988	150	150	1.67	0.0498	0.10	0.25	0.9679
28	28	1.78	0.0423	0.10	0.30	0.5688	150	150	1.67	0.0498	0.10	0.30	0.9977
28	28	1.78	0.0423	0.10	0.35	0.7208	150	150	1.67	0.0498	0.10	0.35	0.9999
28	28	1.78	0.0423	0.10	0.40	0.8378	150	150	1.67	0.0498	0.10	0.40	1.0000
28	28	1.78	0.0423	0.10	0.45	0.9157	150	150	1.67	0.0498	0.10	0.45	1.0000
28	28	1.78	0.0423	0.10	0.50	0.9609	150	150	1.67	0.0498	0.10	0.50	1.0000
28	28	1.78	0.0423	0.10	0.55	0.9840	150	150	1.67	0.0498	0.10	0.55	1.0000
28	28	1.78	0.0423	0.10	0.60	0.9944	150	150	1.67	0.0498	0.10	0.60	1.0000
28	28	1.78	0.0423	0.15	0.30	0.3518	150	150	1.67	0.0498	0.15	0.30	0.9324
28	28	1.78	0.0423	0.15	0.35	0.5095	150	150	1.67	0.0498	0.15	0.35	0.9924
28	28	1.78	0.0423	0.15	0.40	0.6598	150	150	1.67	0.0498	0.15	0.40	0.9996
28	28	1.78	0.0423	0.15	0.45	0.7847	150	150	1.67	0.0498	0.15	0.45	1.0000
28	28	1.78	0.0423	0.15	0.50	0.8769	150	150	1.67	0.0498	0.15	0.50	1.0000
28	28	1.78	0.0423	0.15	0.55	0.9376	150	150	1.67	0.0498	0.15	0.55	1.0000
28	28	1.78	0.0423	0.15	0.60	0.9727	150	150	1.67	0.0498	0.15	0.60	1.0000
28	28	1.78	0.0423	0.15	0.65	0.9901	150	150	1.67	0.0498	0.15	0.65	1.0000
28	28	1.78	0.0423	0.20	0.35	0.3191	150	150	1.67	0.0498	0.20	0.35	0.8997
28	28	1.78	0.0423	0.20	0.40	0.4631	150	150	1.67	0.0498	0.20	0.40	0.9852
28	28	1.78	0.0423	0.20	0.45	0.6090	150	150	1.67	0.0498	0.20	0.45	0.9989

Table B.4: continue on next page

Table B.4: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
28	28	1.78	0.0423	0.20	0.50	0.7410	150	150	1.67	0.0498	0.20	0.50	1.0000
28	28	1.78	0.0423	0.20	0.55	0.8471	150	150	1.67	0.0498	0.20	0.55	1.0000
28	28	1.78	0.0423	0.20	0.60	0.9214	150	150	1.67	0.0498	0.20	0.60	1.0000
28	28	1.78	0.0423	0.20	0.65	0.9658	150	150	1.67	0.0498	0.20	0.65	1.0000
28	28	1.78	0.0423	0.20	0.70	0.9878	150	150	1.67	0.0498	0.20	0.70	1.0000
28	28	1.78	0.0423	0.25	0.40	0.2907	150	150	1.67	0.0498	0.25	0.40	0.8715
28	28	1.78	0.0423	0.25	0.45	0.4280	150	150	1.67	0.0498	0.25	0.45	0.9786
28	28	1.78	0.0423	0.25	0.50	0.5761	150	150	1.67	0.0498	0.25	0.50	0.9981
28	28	1.78	0.0423	0.25	0.55	0.7168	150	150	1.67	0.0498	0.25	0.55	0.9999
28	28	1.78	0.0423	0.25	0.60	0.8326	150	150	1.67	0.0498	0.25	0.60	1.0000
28	28	1.78	0.0423	0.25	0.65	0.9144	150	150	1.67	0.0498	0.25	0.65	1.0000
28	28	1.78	0.0423	0.25	0.70	0.9631	150	150	1.67	0.0498	0.25	0.70	1.0000
28	28	1.78	0.0423	0.25	0.75	0.9871	150	150	1.67	0.0498	0.25	0.75	1.0000
28	28	1.78	0.0423	0.30	0.45	0.2736	150	150	1.67	0.0498	0.30	0.45	0.8514
28	28	1.78	0.0423	0.30	0.50	0.4113	150	150	1.67	0.0498	0.30	0.50	0.9709
28	28	1.78	0.0423	0.30	0.55	0.5630	150	150	1.67	0.0498	0.30	0.55	0.9971
28	28	1.78	0.0423	0.30	0.60	0.7081	150	150	1.67	0.0498	0.30	0.60	0.9999
28	28	1.78	0.0423	0.30	0.65	0.8279	150	150	1.67	0.0498	0.30	0.65	1.0000
28	28	1.78	0.0423	0.30	0.70	0.9127	150	150	1.67	0.0498	0.30	0.70	1.0000
28	28	1.78	0.0423	0.35	0.50	0.2687	150	150	1.67	0.0498	0.35	0.50	0.8300
28	28	1.78	0.0423	0.35	0.55	0.4072	150	150	1.67	0.0498	0.35	0.55	0.9664
28	28	1.78	0.0423	0.35	0.60	0.5598	150	150	1.67	0.0498	0.35	0.60	0.9967
28	28	1.78	0.0423	0.35	0.65	0.7062	150	150	1.67	0.0498	0.35	0.65	0.9999
28	28	1.78	0.0423	0.40	0.55	0.2687	150	150	1.67	0.0498	0.40	0.55	0.8254
28	28	1.78	0.0423	0.40	0.60	0.4068	150	150	1.67	0.0498	0.40	0.60	0.9655

Table B.4: concluded from previous page

Table B.5: Achieved power and p-values calculated for the z-unpooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	10	2.17	0.0211	0.05	0.15	0.0304	29	29	2.09	0.0238	0.05	0.15	0.2090
10	10	2.17	0.0211	0.05	0.20	0.0744	29	29	2.09	0.0238	0.05	0.20	0.3775
10	10	2.17	0.0211	0.05	0.25	0.1407	29	29	2.09	0.0238	0.05	0.25	0.5637
10	10	2.17	0.0211	0.05	0.30	0.2255	29	29	2.09	0.0238	0.05	0.30	0.7304
10	10	2.17	0.0211	0.05	0.35	0.3230	29	29	2.09	0.0238	0.05	0.35	0.8533
10	10	2.17	0.0211	0.05	0.40	0.4265	29	29	2.09	0.0238	0.05	0.40	0.9300
10	10	2.17	0.0211	0.05	0.45	0.5298	29	29	2.09	0.0238	0.05	0.45	0.9709
10	10	2.17	0.0211	0.10	0.25	0.0865	29	29	2.09	0.0238	0.10	0.25	0.3005
10	10	2.17	0.0211	0.10	0.30	0.1427	29	29	2.09	0.0238	0.10	0.30	0.4687
10	10	2.17	0.0211	0.10	0.35	0.2116	29	29	2.09	0.0238	0.10	0.35	0.6356
10	10	2.17	0.0211	0.10	0.40	0.2911	29	29	2.09	0.0238	0.10	0.40	0.7761
10	10	2.17	0.0211	0.10	0.45	0.3786	29	29	2.09	0.0238	0.10	0.45	0.8774
10	10	2.17	0.0211	0.10	0.50	0.4713	29	29	2.09	0.0238	0.10	0.50	0.9406
10	10	2.17	0.0211	0.10	0.55	0.5660	29	29	2.09	0.0238	0.10	0.55	0.9747
10	10	2.17	0.0211	0.10	0.60	0.6590	29	29	2.09	0.0238	0.10	0.60	0.9907
10	10	2.17	0.0211	0.15	0.30	0.0886	29	29	2.09	0.0238	0.15	0.30	0.2646
10	10	2.17	0.0211	0.15	0.35	0.1365	29	29	2.09	0.0238	0.15	0.35	0.4162
10	10	2.17	0.0211	0.15	0.40	0.1961	29	29	2.09	0.0238	0.15	0.40	0.5749
10	10	2.17	0.0211	0.15	0.45	0.2673	29	29	2.09	0.0238	0.15	0.45	0.7180
10	10	2.17	0.0211	0.15	0.50	0.3490	29	29	2.09	0.0238	0.15	0.50	0.8311
10	10	2.17	0.0211	0.15	0.55	0.4393	29	29	2.09	0.0238	0.15	0.55	0.9103
10	10	2.17	0.0211	0.15	0.60	0.5352	29	29	2.09	0.0238	0.15	0.60	0.9589
10	10	2.17	0.0211	0.15	0.65	0.6321	29	29	2.09	0.0238	0.15	0.65	0.9843
10	10	2.17	0.0211	0.20	0.35	0.0866	29	29	2.09	0.0238	0.20	0.35	0.2407
10	10	2.17	0.0211	0.20	0.40	0.1301	29	29	2.09	0.0238	0.20	0.40	0.3765
10	10	2.17	0.0211	0.20	0.45	0.1857	29	29	2.09	0.0238	0.20	0.45	0.5257
10	10	2.17	0.0211	0.20	0.50	0.2540	29	29	2.09	0.0238	0.20	0.50	0.6709
10	10	2.17	0.0211	0.20	0.55	0.3343	29	29	2.09	0.0238	0.20	0.55	0.7959
10	10	2.17	0.0211	0.20	0.60	0.4248	29	29	2.09	0.0238	0.20	0.60	0.8896
10	10	2.17	0.0211	0.20	0.65	0.5221	29	29	2.09	0.0238	0.20	0.65	0.9493
10	10	2.17	0.0211	0.20	0.70	0.6216	29	29	2.09	0.0238	0.20	0.70	0.9809
10	10	2.17	0.0211	0.25	0.40	0.0847	29	29	2.09	0.0238	0.25	0.40	0.2190
10	10	2.17	0.0211	0.25	0.45	0.1267	29	29	2.09	0.0238	0.25	0.45	0.3455
10	10	2.17	0.0211	0.25	0.50	0.1811	29	29	2.09	0.0238	0.25	0.50	0.4933
10	10	2.17	0.0211	0.25	0.55	0.2487	29	29	2.09	0.0238	0.25	0.55	0.6448
10	10	2.17	0.0211	0.25	0.60	0.3288	29	29	2.09	0.0238	0.25	0.60	0.7792
10	10	2.17	0.0211	0.25	0.65	0.4196	29	29	2.09	0.0238	0.25	0.65	0.8810
10	10	2.17	0.0211	0.25	0.70	0.5178	29	29	2.09	0.0238	0.25	0.70	0.9459
10	10	2.17	0.0211	0.25	0.75	0.6190	29	29	2.09	0.0238	0.25	0.75	0.9800
10	10	2.17	0.0211	0.30	0.45	0.0845	29	29	2.09	0.0238	0.30	0.45	0.2054
10	10	2.17	0.0211	0.30	0.50	0.1260	29	29	2.09	0.0238	0.30	0.50	0.3307
10	10	2.17	0.0211	0.30	0.55	0.1801	29	29	2.09	0.0238	0.30	0.55	0.4807
10	10	2.17	0.0211	0.30	0.60	0.2474	29	29	2.09	0.0238	0.30	0.60	0.6359
10	10	2.17	0.0211	0.30	0.65	0.3273	29	29	2.09	0.0238	0.30	0.65	0.7740

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	10	2.17	0.0211	0.30	0.70	0.4184	29	29	2.09	0.0238	0.30	0.70	0.8789
10	10	2.17	0.0211	0.35	0.50	0.0852	29	29	2.09	0.0238	0.35	0.50	0.2017
10	10	2.17	0.0211	0.35	0.55	0.1266	29	29	2.09	0.0238	0.35	0.55	0.3274
10	10	2.17	0.0211	0.35	0.60	0.1803	29	29	2.09	0.0238	0.35	0.60	0.4780
10	10	2.17	0.0211	0.35	0.65	0.2473	29	29	2.09	0.0238	0.35	0.65	0.6342
10	10	2.17	0.0211	0.40	0.55	0.0860	29	29	2.09	0.0238	0.40	0.55	0.2021
10	10	2.17	0.0211	0.40	0.60	0.1269	29	29	2.09	0.0238	0.40	0.60	0.3274
11	11	2.40	0.0207	0.05	0.15	0.0404	30	30	2.15	0.0216	0.05	0.15	0.1732
11	11	2.40	0.0207	0.05	0.20	0.0957	30	30	2.15	0.0216	0.05	0.20	0.3639
11	11	2.40	0.0207	0.05	0.25	0.1750	30	30	2.15	0.0216	0.05	0.25	0.5702
11	11	2.40	0.0207	0.05	0.30	0.2725	30	30	2.15	0.0216	0.05	0.30	0.7444
11	11	2.40	0.0207	0.05	0.35	0.3801	30	30	2.15	0.0216	0.05	0.35	0.8656
11	11	2.40	0.0207	0.05	0.40	0.4901	30	30	2.15	0.0216	0.05	0.40	0.9375
11	11	2.40	0.0207	0.05	0.45	0.5962	30	30	2.15	0.0216	0.05	0.45	0.9744
11	11	2.40	0.0207	0.10	0.25	0.1048	30	30	2.15	0.0216	0.10	0.25	0.3087
11	11	2.40	0.0207	0.10	0.30	0.1697	30	30	2.15	0.0216	0.10	0.30	0.4792
11	11	2.40	0.0207	0.10	0.35	0.2482	30	30	2.15	0.0216	0.10	0.35	0.6433
11	11	2.40	0.0207	0.10	0.40	0.3371	30	30	2.15	0.0216	0.10	0.40	0.7793
11	11	2.40	0.0207	0.10	0.45	0.4329	30	30	2.15	0.0216	0.10	0.45	0.8780
11	11	2.40	0.0207	0.10	0.50	0.5314	30	30	2.15	0.0216	0.10	0.50	0.9406
11	11	2.40	0.0207	0.10	0.55	0.6278	30	30	2.15	0.0216	0.10	0.55	0.9752
11	11	2.40	0.0207	0.10	0.60	0.7175	30	30	2.15	0.0216	0.10	0.60	0.9913
11	11	2.40	0.0207	0.15	0.30	0.1038	30	30	2.15	0.0216	0.15	0.30	0.2632
11	11	2.40	0.0207	0.15	0.35	0.1592	30	30	2.15	0.0216	0.15	0.35	0.4105
11	11	2.40	0.0207	0.15	0.40	0.2275	30	30	2.15	0.0216	0.15	0.40	0.5672
11	11	2.40	0.0207	0.15	0.45	0.3074	30	30	2.15	0.0216	0.15	0.45	0.7130
11	11	2.40	0.0207	0.15	0.50	0.3963	30	30	2.15	0.0216	0.15	0.50	0.8313
11	11	2.40	0.0207	0.15	0.55	0.4902	30	30	2.15	0.0216	0.15	0.55	0.9136
11	11	2.40	0.0207	0.15	0.60	0.5847	30	30	2.15	0.0216	0.15	0.60	0.9622
11	11	2.40	0.0207	0.15	0.65	0.6753	30	30	2.15	0.0216	0.15	0.65	0.9860
11	11	2.40	0.0207	0.20	0.35	0.1000	30	30	2.15	0.0216	0.20	0.35	0.2299
11	11	2.40	0.0207	0.20	0.40	0.1500	30	30	2.15	0.0216	0.20	0.40	0.3663
11	11	2.40	0.0207	0.20	0.45	0.2125	30	30	2.15	0.0216	0.20	0.45	0.5219
11	11	2.40	0.0207	0.20	0.50	0.2864	30	30	2.15	0.0216	0.20	0.50	0.6747
11	11	2.40	0.0207	0.20	0.55	0.3697	30	30	2.15	0.0216	0.20	0.55	0.8027
11	11	2.40	0.0207	0.20	0.60	0.4594	30	30	2.15	0.0216	0.20	0.60	0.8941
11	11	2.40	0.0207	0.20	0.65	0.5522	30	30	2.15	0.0216	0.20	0.65	0.9501
11	11	2.40	0.0207	0.20	0.70	0.6449	30	30	2.15	0.0216	0.20	0.70	0.9799
11	11	2.40	0.0207	0.25	0.40	0.0961	30	30	2.15	0.0216	0.25	0.40	0.2126
11	11	2.40	0.0207	0.25	0.45	0.1424	30	30	2.15	0.0216	0.25	0.45	0.3447
11	11	2.40	0.0207	0.25	0.50	0.2003	30	30	2.15	0.0216	0.25	0.50	0.4970
11	11	2.40	0.0207	0.25	0.55	0.2694	30	30	2.15	0.0216	0.25	0.55	0.6474
11	11	2.40	0.0207	0.25	0.60	0.3489	30	30	2.15	0.0216	0.25	0.60	0.7762
11	11	2.40	0.0207	0.25	0.65	0.4373	30	30	2.15	0.0216	0.25	0.65	0.8735
11	11	2.40	0.0207	0.25	0.70	0.5329	30	30	2.15	0.0216	0.25	0.70	0.9387
11	11	2.40	0.0207	0.25	0.75	0.6333	30	30	2.15	0.0216	0.25	0.75	0.9763
11	11	2.40	0.0207	0.30	0.45	0.0923	30	30	2.15	0.0216	0.30	0.45	0.2040
11	11	2.40	0.0207	0.30	0.50	0.1354	30	30	2.15	0.0216	0.30	0.50	0.3280
11	11	2.40	0.0207	0.30	0.55	0.1900	30	30	2.15	0.0216	0.30	0.55	0.4712
11	11	2.40	0.0207	0.30	0.60	0.2568	30	30	2.15	0.0216	0.30	0.60	0.6176

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
11	11	2.40	0.0207	0.30	0.65	0.3365	30	30	2.15	0.0216	0.30	0.65	0.7524
11	11	2.40	0.0207	0.30	0.70	0.4289	30	30	2.15	0.0216	0.30	0.70	0.8625
11	11	2.40	0.0207	0.35	0.50	0.0884	30	30	2.15	0.0216	0.35	0.50	0.1920
11	11	2.40	0.0207	0.35	0.55	0.1297	30	30	2.15	0.0216	0.35	0.55	0.3070
11	11	2.40	0.0207	0.35	0.60	0.1836	30	30	2.15	0.0216	0.35	0.60	0.4474
11	11	2.40	0.0207	0.35	0.65	0.2520	30	30	2.15	0.0216	0.35	0.65	0.6023
11	11	2.40	0.0207	0.40	0.55	0.0858	30	30	2.15	0.0216	0.40	0.55	0.1794
11	11	2.40	0.0207	0.40	0.60	0.1275	30	30	2.15	0.0216	0.40	0.60	0.2958
12	12	2.26	0.0225	0.05	0.15	0.0515	31	31	2.11	0.0240	0.05	0.15	0.2246
12	12	2.26	0.0225	0.05	0.20	0.1180	31	31	2.11	0.0240	0.05	0.20	0.4073
12	12	2.26	0.0225	0.05	0.25	0.2098	31	31	2.11	0.0240	0.05	0.25	0.6025
12	12	2.26	0.0225	0.05	0.30	0.3183	31	31	2.11	0.0240	0.05	0.30	0.7670
12	12	2.26	0.0225	0.05	0.35	0.4341	31	31	2.11	0.0240	0.05	0.35	0.8802
12	12	2.26	0.0225	0.05	0.40	0.5488	31	31	2.11	0.0240	0.05	0.40	0.9459
12	12	2.26	0.0225	0.05	0.45	0.6555	31	31	2.11	0.0240	0.05	0.45	0.9787
12	12	2.26	0.0225	0.10	0.25	0.1230	31	31	2.11	0.0240	0.10	0.25	0.3242
12	12	2.26	0.0225	0.10	0.30	0.1967	31	31	2.11	0.0240	0.10	0.30	0.4971
12	12	2.26	0.0225	0.10	0.35	0.2846	31	31	2.11	0.0240	0.10	0.35	0.6616
12	12	2.26	0.0225	0.10	0.40	0.3826	31	31	2.11	0.0240	0.10	0.40	0.7957
12	12	2.26	0.0225	0.10	0.45	0.4858	31	31	2.11	0.0240	0.10	0.45	0.8905
12	12	2.26	0.0225	0.10	0.50	0.5884	31	31	2.11	0.0240	0.10	0.50	0.9489
12	12	2.26	0.0225	0.10	0.55	0.6846	31	31	2.11	0.0240	0.10	0.55	0.9798
12	12	2.26	0.0225	0.10	0.60	0.7695	31	31	2.11	0.0240	0.10	0.60	0.9934
12	12	2.26	0.0225	0.15	0.30	0.1193	31	31	2.11	0.0240	0.15	0.30	0.2739
12	12	2.26	0.0225	0.15	0.35	0.1828	31	31	2.11	0.0240	0.15	0.35	0.4260
12	12	2.26	0.0225	0.15	0.40	0.2602	31	31	2.11	0.0240	0.15	0.40	0.5865
12	12	2.26	0.0225	0.15	0.45	0.3486	31	31	2.11	0.0240	0.15	0.45	0.7333
12	12	2.26	0.0225	0.15	0.50	0.4439	31	31	2.11	0.0240	0.15	0.50	0.8490
12	12	2.26	0.0225	0.15	0.55	0.5408	31	31	2.11	0.0240	0.15	0.55	0.9265
12	12	2.26	0.0225	0.15	0.60	0.6342	31	31	2.11	0.0240	0.15	0.60	0.9699
12	12	2.26	0.0225	0.15	0.65	0.7204	31	31	2.11	0.0240	0.15	0.65	0.9897
12	12	2.26	0.0225	0.20	0.35	0.1142	31	31	2.11	0.0240	0.20	0.35	0.2406
12	12	2.26	0.0225	0.20	0.40	0.1712	31	31	2.11	0.0240	0.20	0.40	0.3841
12	12	2.26	0.0225	0.20	0.45	0.2408	31	31	2.11	0.0240	0.20	0.45	0.5459
12	12	2.26	0.0225	0.20	0.50	0.3207	31	31	2.11	0.0240	0.20	0.50	0.7011
12	12	2.26	0.0225	0.20	0.55	0.4078	31	31	2.11	0.0240	0.20	0.55	0.8268
12	12	2.26	0.0225	0.20	0.60	0.4988	31	31	2.11	0.0240	0.20	0.60	0.9126
12	12	2.26	0.0225	0.20	0.65	0.5909	31	31	2.11	0.0240	0.20	0.65	0.9619
12	12	2.26	0.0225	0.20	0.70	0.6816	31	31	2.11	0.0240	0.20	0.70	0.9859
12	12	2.26	0.0225	0.25	0.40	0.1085	31	31	2.11	0.0240	0.25	0.40	0.2265
12	12	2.26	0.0225	0.25	0.45	0.1595	31	31	2.11	0.0240	0.25	0.45	0.3676
12	12	2.26	0.0225	0.25	0.50	0.2217	31	31	2.11	0.0240	0.25	0.50	0.5279
12	12	2.26	0.0225	0.25	0.55	0.2942	31	31	2.11	0.0240	0.25	0.55	0.6819
12	12	2.26	0.0225	0.25	0.60	0.3761	31	31	2.11	0.0240	0.25	0.60	0.8083
12	12	2.26	0.0225	0.25	0.65	0.4665	31	31	2.11	0.0240	0.25	0.65	0.8983
12	12	2.26	0.0225	0.25	0.70	0.5641	31	31	2.11	0.0240	0.25	0.70	0.9541
12	12	2.26	0.0225	0.25	0.75	0.6664	31	31	2.11	0.0240	0.25	0.75	0.9836
12	12	2.26	0.0225	0.30	0.45	0.1011	31	31	2.11	0.0240	0.30	0.45	0.2226
12	12	2.26	0.0225	0.30	0.50	0.1467	31	31	2.11	0.0240	0.30	0.50	0.3577
12	12	2.26	0.0225	0.30	0.55	0.2037	31	31	2.11	0.0240	0.30	0.55	0.5102

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
12	12	2.26	0.0225	0.30	0.60	0.2733	31	31	2.11	0.0240	0.30	0.60	0.6602
12	12	2.26	0.0225	0.30	0.65	0.3566	31	31	2.11	0.0240	0.30	0.65	0.7907
12	12	2.26	0.0225	0.30	0.70	0.4541	31	31	2.11	0.0240	0.30	0.70	0.8903
12	12	2.26	0.0225	0.35	0.50	0.0931	31	31	2.11	0.0240	0.35	0.50	0.2156
12	12	2.26	0.0225	0.35	0.55	0.1360	31	31	2.11	0.0240	0.35	0.55	0.3426
12	12	2.26	0.0225	0.35	0.60	0.1924	31	31	2.11	0.0240	0.35	0.60	0.4919
12	12	2.26	0.0225	0.35	0.65	0.2653	31	31	2.11	0.0240	0.35	0.65	0.6482
12	12	2.26	0.0225	0.40	0.55	0.0878	31	31	2.11	0.0240	0.40	0.55	0.2061
12	12	2.26	0.0225	0.40	0.60	0.1317	31	31	2.11	0.0240	0.40	0.60	0.3337
13	13	2.16	0.0243	0.05	0.15	0.0634	32	32	2.09	0.0233	0.05	0.15	0.2325
13	13	2.16	0.0243	0.05	0.20	0.1410	32	32	2.09	0.0233	0.05	0.20	0.4224
13	13	2.16	0.0243	0.05	0.25	0.2443	32	32	2.09	0.0233	0.05	0.25	0.6212
13	13	2.16	0.0243	0.05	0.30	0.3625	32	32	2.09	0.0233	0.05	0.30	0.7839
13	13	2.16	0.0243	0.05	0.35	0.4849	32	32	2.09	0.0233	0.05	0.35	0.8923
13	13	2.16	0.0243	0.05	0.40	0.6024	32	32	2.09	0.0233	0.05	0.40	0.9531
13	13	2.16	0.0243	0.05	0.45	0.7080	32	32	2.09	0.0233	0.05	0.45	0.9822
13	13	2.16	0.0243	0.10	0.25	0.1412	32	32	2.09	0.0233	0.10	0.25	0.3369
13	13	2.16	0.0243	0.10	0.30	0.2237	32	32	2.09	0.0233	0.10	0.30	0.5136
13	13	2.16	0.0243	0.10	0.35	0.3208	32	32	2.09	0.0233	0.10	0.35	0.6790
13	13	2.16	0.0243	0.10	0.40	0.4270	32	32	2.09	0.0233	0.10	0.40	0.8110
13	13	2.16	0.0243	0.10	0.45	0.5358	32	32	2.09	0.0233	0.10	0.45	0.9020
13	13	2.16	0.0243	0.10	0.50	0.6400	32	32	2.09	0.0233	0.10	0.50	0.9561
13	13	2.16	0.0243	0.10	0.55	0.7336	32	32	2.09	0.0233	0.10	0.55	0.9835
13	13	2.16	0.0243	0.10	0.60	0.8125	32	32	2.09	0.0233	0.10	0.60	0.9949
13	13	2.16	0.0243	0.15	0.30	0.1351	32	32	2.09	0.0233	0.15	0.30	0.2843
13	13	2.16	0.0243	0.15	0.35	0.2067	32	32	2.09	0.0233	0.15	0.35	0.4415
13	13	2.16	0.0243	0.15	0.40	0.2926	32	32	2.09	0.0233	0.15	0.40	0.6054
13	13	2.16	0.0243	0.15	0.45	0.3884	32	32	2.09	0.0233	0.15	0.45	0.7520
13	13	2.16	0.0243	0.15	0.50	0.4886	32	32	2.09	0.0233	0.15	0.50	0.8639
13	13	2.16	0.0243	0.15	0.55	0.5873	32	32	2.09	0.0233	0.15	0.55	0.9356
13	13	2.16	0.0243	0.15	0.60	0.6799	32	32	2.09	0.0233	0.15	0.60	0.9740
13	13	2.16	0.0243	0.15	0.65	0.7630	32	32	2.09	0.0233	0.15	0.65	0.9911
13	13	2.16	0.0243	0.20	0.35	0.1286	32	32	2.09	0.0233	0.20	0.35	0.2513
13	13	2.16	0.0243	0.20	0.40	0.1923	32	32	2.09	0.0233	0.20	0.40	0.4007
13	13	2.16	0.0243	0.20	0.45	0.2684	32	32	2.09	0.0233	0.20	0.45	0.5653
13	13	2.16	0.0243	0.20	0.50	0.3541	32	32	2.09	0.0233	0.20	0.50	0.7179
13	13	2.16	0.0243	0.20	0.55	0.4459	32	32	2.09	0.0233	0.20	0.55	0.8373
13	13	2.16	0.0243	0.20	0.60	0.5405	32	32	2.09	0.0233	0.20	0.60	0.9171
13	13	2.16	0.0243	0.20	0.65	0.6349	32	32	2.09	0.0233	0.20	0.65	0.9631
13	13	2.16	0.0243	0.20	0.70	0.7260	32	32	2.09	0.0233	0.20	0.70	0.9862
13	13	2.16	0.0243	0.25	0.40	0.1206	32	32	2.09	0.0233	0.25	0.40	0.2368
13	13	2.16	0.0243	0.25	0.45	0.1765	32	32	2.09	0.0233	0.25	0.45	0.3799
13	13	2.16	0.0243	0.25	0.50	0.2440	32	32	2.09	0.0233	0.25	0.50	0.5375
13	13	2.16	0.0243	0.25	0.55	0.3222	32	32	2.09	0.0233	0.25	0.55	0.6858
13	13	2.16	0.0243	0.25	0.60	0.4102	32	32	2.09	0.0233	0.25	0.60	0.8078
13	13	2.16	0.0243	0.25	0.65	0.5066	32	32	2.09	0.0233	0.25	0.65	0.8968
13	13	2.16	0.0243	0.25	0.70	0.6088	32	32	2.09	0.0233	0.25	0.70	0.9536
13	13	2.16	0.0243	0.25	0.75	0.7123	32	32	2.09	0.0233	0.25	0.75	0.9837
13	13	2.16	0.0243	0.30	0.45	0.1104	32	32	2.09	0.0233	0.30	0.45	0.2255
13	13	2.16	0.0243	0.30	0.50	0.1601	32	32	2.09	0.0233	0.30	0.50	0.3564

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
13	13	2.16	0.0243	0.30	0.55	0.2225	32	32	2.09	0.0233	0.30	0.55	0.5037
13	13	2.16	0.0243	0.30	0.60	0.2988	32	32	2.09	0.0233	0.30	0.60	0.6517
13	13	2.16	0.0243	0.30	0.65	0.3896	32	32	2.09	0.0233	0.30	0.65	0.7842
13	13	2.16	0.0243	0.30	0.70	0.4942	32	32	2.09	0.0233	0.30	0.70	0.8873
13	13	2.16	0.0243	0.35	0.50	0.1003	32	32	2.09	0.0233	0.35	0.50	0.2073
13	13	2.16	0.0243	0.35	0.55	0.1474	32	32	2.09	0.0233	0.35	0.55	0.3292
13	13	2.16	0.0243	0.35	0.60	0.2098	32	32	2.09	0.0233	0.35	0.60	0.4770
13	13	2.16	0.0243	0.35	0.65	0.2901	32	32	2.09	0.0233	0.35	0.65	0.6364
13	13	2.16	0.0243	0.40	0.55	0.0940	32	32	2.09	0.0233	0.40	0.55	0.1918
13	13	2.16	0.0243	0.40	0.60	0.1426	32	32	2.09	0.0233	0.40	0.60	0.3169
14	14	2.19	0.0208	0.05	0.15	0.0756	33	33	2.06	0.0243	0.05	0.15	0.2907
14	14	2.19	0.0208	0.05	0.20	0.1632	33	33	2.06	0.0243	0.05	0.20	0.4923
14	14	2.19	0.0208	0.05	0.25	0.2749	33	33	2.06	0.0243	0.05	0.25	0.6760
14	14	2.19	0.0208	0.05	0.30	0.3974	33	33	2.06	0.0243	0.05	0.30	0.8167
14	14	2.19	0.0208	0.05	0.35	0.5192	33	33	2.06	0.0243	0.05	0.35	0.9091
14	14	2.19	0.0208	0.05	0.40	0.6318	33	33	2.06	0.0243	0.05	0.40	0.9608
14	14	2.19	0.0208	0.05	0.45	0.7300	33	33	2.06	0.0243	0.05	0.45	0.9855
14	14	2.19	0.0208	0.10	0.25	0.1521	33	33	2.06	0.0243	0.10	0.25	0.3624
14	14	2.19	0.0208	0.10	0.30	0.2347	33	33	2.06	0.0243	0.10	0.30	0.5358
14	14	2.19	0.0208	0.10	0.35	0.3286	33	33	2.06	0.0243	0.10	0.35	0.6978
14	14	2.19	0.0208	0.10	0.40	0.4292	33	33	2.06	0.0243	0.10	0.40	0.8260
14	14	2.19	0.0208	0.10	0.45	0.5318	33	33	2.06	0.0243	0.10	0.45	0.9127
14	14	2.19	0.0208	0.10	0.50	0.6318	33	33	2.06	0.0243	0.10	0.50	0.9626
14	14	2.19	0.0208	0.10	0.55	0.7250	33	33	2.06	0.0243	0.10	0.55	0.9866
14	14	2.19	0.0208	0.10	0.60	0.8072	33	33	2.06	0.0243	0.10	0.60	0.9961
14	14	2.19	0.0208	0.15	0.30	0.1330	33	33	2.06	0.0243	0.15	0.30	0.2963
14	14	2.19	0.0208	0.15	0.35	0.1990	33	33	2.06	0.0243	0.15	0.35	0.4577
14	14	2.19	0.0208	0.15	0.40	0.2781	33	33	2.06	0.0243	0.15	0.40	0.6244
14	14	2.19	0.0208	0.15	0.45	0.3690	33	33	2.06	0.0243	0.15	0.45	0.7705
14	14	2.19	0.0208	0.15	0.50	0.4686	33	33	2.06	0.0243	0.15	0.50	0.8782
14	14	2.19	0.0208	0.15	0.55	0.5728	33	33	2.06	0.0243	0.15	0.55	0.9445
14	14	2.19	0.0208	0.15	0.60	0.6756	33	33	2.06	0.0243	0.15	0.60	0.9784
14	14	2.19	0.0208	0.15	0.65	0.7706	33	33	2.06	0.0243	0.15	0.65	0.9929
14	14	2.19	0.0208	0.20	0.35	0.1157	33	33	2.06	0.0243	0.20	0.35	0.2628
14	14	2.19	0.0208	0.20	0.40	0.1732	33	33	2.06	0.0243	0.20	0.40	0.4183
14	14	2.19	0.0208	0.20	0.45	0.2460	33	33	2.06	0.0243	0.20	0.45	0.5861
14	14	2.19	0.0208	0.20	0.50	0.3340	33	33	2.06	0.0243	0.20	0.50	0.7373
14	14	2.19	0.0208	0.20	0.55	0.4349	33	33	2.06	0.0243	0.20	0.55	0.8520
14	14	2.19	0.0208	0.20	0.60	0.5436	33	33	2.06	0.0243	0.20	0.60	0.9264
14	14	2.19	0.0208	0.20	0.65	0.6531	33	33	2.06	0.0243	0.20	0.65	0.9684
14	14	2.19	0.0208	0.20	0.70	0.7554	33	33	2.06	0.0243	0.20	0.70	0.9888
14	14	2.19	0.0208	0.25	0.40	0.1039	33	33	2.06	0.0243	0.25	0.40	0.2490
14	14	2.19	0.0208	0.25	0.45	0.1582	33	33	2.06	0.0243	0.25	0.45	0.3967
14	14	2.19	0.0208	0.25	0.50	0.2294	33	33	2.06	0.0243	0.25	0.50	0.5559
14	14	2.19	0.0208	0.25	0.55	0.3177	33	33	2.06	0.0243	0.25	0.55	0.7030
14	14	2.19	0.0208	0.25	0.60	0.4205	33	33	2.06	0.0243	0.25	0.60	0.8225
14	14	2.19	0.0208	0.25	0.65	0.5322	33	33	2.06	0.0243	0.25	0.65	0.9079
14	14	2.19	0.0208	0.25	0.70	0.6454	33	33	2.06	0.0243	0.25	0.70	0.9605
14	14	2.19	0.0208	0.25	0.75	0.7516	33	33	2.06	0.0243	0.25	0.75	0.9869
14	14	2.19	0.0208	0.30	0.45	0.0980	33	33	2.06	0.0243	0.30	0.45	0.2354

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
14	14	2.19	0.0208	0.30	0.50	0.1517	33	33	2.06	0.0243	0.30	0.50	0.3698
14	14	2.19	0.0208	0.30	0.55	0.2231	33	33	2.06	0.0243	0.30	0.55	0.5201
14	14	2.19	0.0208	0.30	0.60	0.3121	33	33	2.06	0.0243	0.30	0.60	0.6699
14	14	2.19	0.0208	0.30	0.65	0.4160	33	33	2.06	0.0243	0.30	0.65	0.8014
14	14	2.19	0.0208	0.30	0.70	0.5295	33	33	2.06	0.0243	0.30	0.70	0.9001
14	14	2.19	0.0208	0.35	0.50	0.0963	33	33	2.06	0.0243	0.35	0.50	0.2153
14	14	2.19	0.0208	0.35	0.55	0.1501	33	33	2.06	0.0243	0.35	0.55	0.3423
14	14	2.19	0.0208	0.35	0.60	0.2216	33	33	2.06	0.0243	0.35	0.60	0.4951
14	14	2.19	0.0208	0.35	0.65	0.3109	33	33	2.06	0.0243	0.35	0.65	0.6565
14	14	2.19	0.0208	0.40	0.55	0.0962	33	33	2.06	0.0243	0.40	0.55	0.2004
14	14	2.19	0.0208	0.40	0.60	0.1499	33	33	2.06	0.0243	0.40	0.60	0.3311
15	15	2.14	0.0216	0.05	0.15	0.0884	34	34	2.06	0.0233	0.05	0.15	0.2489
15	15	2.14	0.0216	0.05	0.20	0.1859	34	34	2.06	0.0233	0.05	0.20	0.4526
15	15	2.14	0.0216	0.05	0.25	0.3063	34	34	2.06	0.0233	0.05	0.25	0.6569
15	15	2.14	0.0216	0.05	0.30	0.4348	34	34	2.06	0.0233	0.05	0.30	0.8146
15	15	2.14	0.0216	0.05	0.35	0.5593	34	34	2.06	0.0233	0.05	0.35	0.9132
15	15	2.14	0.0216	0.05	0.40	0.6714	34	34	2.06	0.0233	0.05	0.40	0.9648
15	15	2.14	0.0216	0.05	0.45	0.7667	34	34	2.06	0.0233	0.05	0.45	0.9877
15	15	2.14	0.0216	0.10	0.25	0.1670	34	34	2.06	0.0233	0.10	0.25	0.3619
15	15	2.14	0.0216	0.10	0.30	0.2558	34	34	2.06	0.0233	0.10	0.30	0.5455
15	15	2.14	0.0216	0.10	0.35	0.3561	34	34	2.06	0.0233	0.10	0.35	0.7117
15	15	2.14	0.0216	0.10	0.40	0.4627	34	34	2.06	0.0233	0.10	0.40	0.8388
15	15	2.14	0.0216	0.10	0.45	0.5702	34	34	2.06	0.0233	0.10	0.45	0.9218
15	15	2.14	0.0216	0.10	0.50	0.6732	34	34	2.06	0.0233	0.10	0.50	0.9676
15	15	2.14	0.0216	0.10	0.55	0.7664	34	34	2.06	0.0233	0.10	0.55	0.9888
15	15	2.14	0.0216	0.10	0.60	0.8452	34	34	2.06	0.0233	0.10	0.60	0.9968
15	15	2.14	0.0216	0.15	0.30	0.1439	34	34	2.06	0.0233	0.15	0.30	0.3053
15	15	2.14	0.0216	0.15	0.35	0.2162	34	34	2.06	0.0233	0.15	0.35	0.4720
15	15	2.14	0.0216	0.15	0.40	0.3034	34	34	2.06	0.0233	0.15	0.40	0.6406
15	15	2.14	0.0216	0.15	0.45	0.4034	34	34	2.06	0.0233	0.15	0.45	0.7840
15	15	2.14	0.0216	0.15	0.50	0.5117	34	34	2.06	0.0233	0.15	0.50	0.8865
15	15	2.14	0.0216	0.15	0.55	0.6218	34	34	2.06	0.0233	0.15	0.55	0.9481
15	15	2.14	0.0216	0.15	0.60	0.7262	34	34	2.06	0.0233	0.15	0.60	0.9796
15	15	2.14	0.0216	0.15	0.65	0.8174	34	34	2.06	0.0233	0.15	0.65	0.9933
15	15	2.14	0.0216	0.20	0.35	0.1259	34	34	2.06	0.0233	0.20	0.35	0.2717
15	15	2.14	0.0216	0.20	0.40	0.1911	34	34	2.06	0.0233	0.20	0.40	0.4290
15	15	2.14	0.0216	0.20	0.45	0.2740	34	34	2.06	0.0233	0.20	0.45	0.5945
15	15	2.14	0.0216	0.20	0.50	0.3732	34	34	2.06	0.0233	0.20	0.50	0.7413
15	15	2.14	0.0216	0.20	0.55	0.4841	34	34	2.06	0.0233	0.20	0.55	0.8534
15	15	2.14	0.0216	0.20	0.60	0.5992	34	34	2.06	0.0233	0.20	0.60	0.9279
15	15	2.14	0.0216	0.20	0.65	0.7095	34	34	2.06	0.0233	0.20	0.65	0.9703
15	15	2.14	0.0216	0.20	0.70	0.8066	34	34	2.06	0.0233	0.20	0.70	0.9903
15	15	2.14	0.0216	0.25	0.40	0.1160	34	34	2.06	0.0233	0.25	0.40	0.2508
15	15	2.14	0.0216	0.25	0.45	0.1793	34	34	2.06	0.0233	0.25	0.45	0.3954
15	15	2.14	0.0216	0.25	0.50	0.2617	34	34	2.06	0.0233	0.25	0.50	0.5526
15	15	2.14	0.0216	0.25	0.55	0.3616	34	34	2.06	0.0233	0.25	0.55	0.7022
15	15	2.14	0.0216	0.25	0.60	0.4740	34	34	2.06	0.0233	0.25	0.60	0.8263
15	15	2.14	0.0216	0.25	0.65	0.5913	34	34	2.06	0.0233	0.25	0.65	0.9142
15	15	2.14	0.0216	0.25	0.70	0.7042	34	34	2.06	0.0233	0.25	0.70	0.9655
15	15	2.14	0.0216	0.25	0.75	0.8039	34	34	2.06	0.0233	0.25	0.75	0.9893

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
15	15	2.14	0.0216	0.30	0.45	0.1128	34	34	2.06	0.0233	0.30	0.45	0.2290
15	15	2.14	0.0216	0.30	0.50	0.1761	34	34	2.06	0.0233	0.30	0.50	0.3641
15	15	2.14	0.0216	0.30	0.55	0.2586	34	34	2.06	0.0233	0.30	0.55	0.5209
15	15	2.14	0.0216	0.30	0.60	0.3587	34	34	2.06	0.0233	0.30	0.60	0.6790
15	15	2.14	0.0216	0.30	0.65	0.4714	34	34	2.06	0.0233	0.30	0.65	0.8143
15	15	2.14	0.0216	0.30	0.70	0.5895	34	34	2.06	0.0233	0.30	0.70	0.9103
15	15	2.14	0.0216	0.35	0.50	0.1132	34	34	2.06	0.0233	0.35	0.50	0.2120
15	15	2.14	0.0216	0.35	0.55	0.1764	34	34	2.06	0.0233	0.35	0.55	0.3463
15	15	2.14	0.0216	0.35	0.60	0.2586	34	34	2.06	0.0233	0.35	0.60	0.5079
15	15	2.14	0.0216	0.35	0.65	0.3583	34	34	2.06	0.0233	0.35	0.65	0.6728
15	15	2.14	0.0216	0.40	0.55	0.1142	34	34	2.06	0.0233	0.40	0.55	0.2052
15	15	2.14	0.0216	0.40	0.60	0.1769	34	34	2.06	0.0233	0.40	0.60	0.3419
16	16	2.29	0.0224	0.05	0.15	0.1014	35	35	2.06	0.0240	0.05	0.15	0.2573
16	16	2.29	0.0224	0.05	0.20	0.2082	35	35	2.06	0.0240	0.05	0.20	0.4676
16	16	2.29	0.0224	0.05	0.25	0.3364	35	35	2.06	0.0240	0.05	0.25	0.6738
16	16	2.29	0.0224	0.05	0.30	0.4699	35	35	2.06	0.0240	0.05	0.30	0.8284
16	16	2.29	0.0224	0.05	0.35	0.5961	35	35	2.06	0.0240	0.05	0.35	0.9221
16	16	2.29	0.0224	0.05	0.40	0.7072	35	35	2.06	0.0240	0.05	0.40	0.9695
16	16	2.29	0.0224	0.05	0.45	0.7991	35	35	2.06	0.0240	0.05	0.45	0.9898
16	16	2.29	0.0224	0.10	0.25	0.1813	35	35	2.06	0.0240	0.10	0.25	0.3741
16	16	2.29	0.0224	0.10	0.30	0.2763	35	35	2.06	0.0240	0.10	0.30	0.5608
16	16	2.29	0.0224	0.10	0.35	0.3830	35	35	2.06	0.0240	0.10	0.35	0.7271
16	16	2.29	0.0224	0.10	0.40	0.4956	35	35	2.06	0.0240	0.10	0.40	0.8516
16	16	2.29	0.0224	0.10	0.45	0.6075	35	35	2.06	0.0240	0.10	0.45	0.9305
16	16	2.29	0.0224	0.10	0.50	0.7119	35	35	2.06	0.0240	0.10	0.50	0.9724
16	16	2.29	0.0224	0.10	0.55	0.8027	35	35	2.06	0.0240	0.10	0.55	0.9909
16	16	2.29	0.0224	0.10	0.60	0.8755	35	35	2.06	0.0240	0.10	0.60	0.9975
16	16	2.29	0.0224	0.15	0.30	0.1548	35	35	2.06	0.0240	0.15	0.30	0.3160
16	16	2.29	0.0224	0.15	0.35	0.2339	35	35	2.06	0.0240	0.15	0.35	0.4875
16	16	2.29	0.0224	0.15	0.40	0.3294	35	35	2.06	0.0240	0.15	0.40	0.6581
16	16	2.29	0.0224	0.15	0.45	0.4375	35	35	2.06	0.0240	0.15	0.45	0.7997
16	16	2.29	0.0224	0.15	0.50	0.5515	35	35	2.06	0.0240	0.15	0.50	0.8976
16	16	2.29	0.0224	0.15	0.55	0.6629	35	35	2.06	0.0240	0.15	0.55	0.9547
16	16	2.29	0.0224	0.15	0.60	0.7631	35	35	2.06	0.0240	0.15	0.60	0.9829
16	16	2.29	0.0224	0.15	0.65	0.8456	35	35	2.06	0.0240	0.15	0.65	0.9947
16	16	2.29	0.0224	0.20	0.35	0.1368	35	35	2.06	0.0240	0.20	0.35	0.2828
16	16	2.29	0.0224	0.20	0.40	0.2094	35	35	2.06	0.0240	0.20	0.40	0.4447
16	16	2.29	0.0224	0.20	0.45	0.3005	35	35	2.06	0.0240	0.20	0.45	0.6117
16	16	2.29	0.0224	0.20	0.50	0.4063	35	35	2.06	0.0240	0.20	0.50	0.7570
16	16	2.29	0.0224	0.20	0.55	0.5197	35	35	2.06	0.0240	0.20	0.55	0.8659
16	16	2.29	0.0224	0.20	0.60	0.6320	35	35	2.06	0.0240	0.20	0.60	0.9364
16	16	2.29	0.0224	0.20	0.65	0.7353	35	35	2.06	0.0240	0.20	0.65	0.9751
16	16	2.29	0.0224	0.20	0.70	0.8235	35	35	2.06	0.0240	0.20	0.70	0.9924
16	16	2.29	0.0224	0.25	0.40	0.1274	35	35	2.06	0.0240	0.25	0.40	0.2607
16	16	2.29	0.0224	0.25	0.45	0.1967	35	35	2.06	0.0240	0.25	0.45	0.4091
16	16	2.29	0.0224	0.25	0.50	0.2841	35	35	2.06	0.0240	0.25	0.50	0.5694
16	16	2.29	0.0224	0.25	0.55	0.3861	35	35	2.06	0.0240	0.25	0.55	0.7200
16	16	2.29	0.0224	0.25	0.60	0.4968	35	35	2.06	0.0240	0.25	0.60	0.8421
16	16	2.29	0.0224	0.25	0.65	0.6094	35	35	2.06	0.0240	0.25	0.65	0.9254
16	16	2.29	0.0224	0.25	0.70	0.7174	35	35	2.06	0.0240	0.25	0.70	0.9716

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
16	16	2.29	0.0224	0.25	0.75	0.8141	35	35	2.06	0.0240	0.25	0.75	0.9917
16	16	2.29	0.0224	0.30	0.45	0.1223	35	35	2.06	0.0240	0.30	0.45	0.2380
16	16	2.29	0.0224	0.30	0.50	0.1883	35	35	2.06	0.0240	0.30	0.50	0.3788
16	16	2.29	0.0224	0.30	0.55	0.2718	35	35	2.06	0.0240	0.30	0.55	0.5409
16	16	2.29	0.0224	0.30	0.60	0.3709	35	35	2.06	0.0240	0.30	0.60	0.7007
16	16	2.29	0.0224	0.30	0.65	0.4822	35	35	2.06	0.0240	0.30	0.65	0.8327
16	16	2.29	0.0224	0.30	0.70	0.6002	35	35	2.06	0.0240	0.30	0.70	0.9225
16	16	2.29	0.0224	0.35	0.50	0.1181	35	35	2.06	0.0240	0.35	0.50	0.2229
16	16	2.29	0.0224	0.35	0.55	0.1814	35	35	2.06	0.0240	0.35	0.55	0.3643
16	16	2.29	0.0224	0.35	0.60	0.2636	35	35	2.06	0.0240	0.35	0.60	0.5309
16	16	2.29	0.0224	0.35	0.65	0.3647	35	35	2.06	0.0240	0.35	0.65	0.6961
16	16	2.29	0.0224	0.40	0.55	0.1149	35	35	2.06	0.0240	0.40	0.55	0.2182
16	16	2.29	0.0224	0.40	0.60	0.1785	35	35	2.06	0.0240	0.40	0.60	0.3613
17	17	2.21	0.0231	0.05	0.15	0.1144	36	36	2.05	0.0247	0.05	0.15	0.2658
17	17	2.21	0.0231	0.05	0.20	0.2300	36	36	2.05	0.0247	0.05	0.20	0.4825
17	17	2.21	0.0231	0.05	0.25	0.3652	36	36	2.05	0.0247	0.05	0.25	0.6900
17	17	2.21	0.0231	0.05	0.30	0.5028	36	36	2.05	0.0247	0.05	0.30	0.8412
17	17	2.21	0.0231	0.05	0.35	0.6302	36	36	2.05	0.0247	0.05	0.35	0.9301
17	17	2.21	0.0231	0.05	0.40	0.7397	36	36	2.05	0.0247	0.05	0.40	0.9736
17	17	2.21	0.0231	0.05	0.45	0.8277	36	36	2.05	0.0247	0.05	0.45	0.9915
17	17	2.21	0.0231	0.10	0.25	0.1952	36	36	2.05	0.0247	0.10	0.25	0.3861
17	17	2.21	0.0231	0.10	0.30	0.2965	36	36	2.05	0.0247	0.10	0.30	0.5758
17	17	2.21	0.0231	0.10	0.35	0.4098	36	36	2.05	0.0247	0.10	0.35	0.7419
17	17	2.21	0.0231	0.10	0.40	0.5283	36	36	2.05	0.0247	0.10	0.40	0.8636
17	17	2.21	0.0231	0.10	0.45	0.6437	36	36	2.05	0.0247	0.10	0.45	0.9384
17	17	2.21	0.0231	0.10	0.50	0.7482	36	36	2.05	0.0247	0.10	0.50	0.9765
17	17	2.21	0.0231	0.10	0.55	0.8353	36	36	2.05	0.0247	0.10	0.55	0.9926
17	17	2.21	0.0231	0.10	0.60	0.9012	36	36	2.05	0.0247	0.10	0.60	0.9981
17	17	2.21	0.0231	0.15	0.30	0.1661	36	36	2.05	0.0247	0.15	0.30	0.3268
17	17	2.21	0.0231	0.15	0.35	0.2526	36	36	2.05	0.0247	0.15	0.35	0.5030
17	17	2.21	0.0231	0.15	0.40	0.3567	36	36	2.05	0.0247	0.15	0.40	0.6752
17	17	2.21	0.0231	0.15	0.45	0.4725	36	36	2.05	0.0247	0.15	0.45	0.8143
17	17	2.21	0.0231	0.15	0.50	0.5910	36	36	2.05	0.0247	0.15	0.50	0.9076
17	17	2.21	0.0231	0.15	0.55	0.7019	36	36	2.05	0.0247	0.15	0.55	0.9604
17	17	2.21	0.0231	0.15	0.60	0.7969	36	36	2.05	0.0247	0.15	0.60	0.9856
17	17	2.21	0.0231	0.15	0.65	0.8713	36	36	2.05	0.0247	0.15	0.65	0.9958
17	17	2.21	0.0231	0.20	0.35	0.1487	36	36	2.05	0.0247	0.20	0.35	0.2940
17	17	2.21	0.0231	0.20	0.40	0.2292	36	36	2.05	0.0247	0.20	0.40	0.4600
17	17	2.21	0.0231	0.20	0.45	0.3284	36	36	2.05	0.0247	0.20	0.45	0.6282
17	17	2.21	0.0231	0.20	0.50	0.4400	36	36	2.05	0.0247	0.20	0.50	0.7719
17	17	2.21	0.0231	0.20	0.55	0.5552	36	36	2.05	0.0247	0.20	0.55	0.8776
17	17	2.21	0.0231	0.20	0.60	0.6650	36	36	2.05	0.0247	0.20	0.60	0.9443
17	17	2.21	0.0231	0.20	0.65	0.7626	36	36	2.05	0.0247	0.20	0.65	0.9793
17	17	2.21	0.0231	0.20	0.70	0.8441	36	36	2.05	0.0247	0.20	0.70	0.9941
17	17	2.21	0.0231	0.25	0.40	0.1398	36	36	2.05	0.0247	0.25	0.40	0.2704
17	17	2.21	0.0231	0.25	0.45	0.2153	36	36	2.05	0.0247	0.25	0.45	0.4228
17	17	2.21	0.0231	0.25	0.50	0.3077	36	36	2.05	0.0247	0.25	0.50	0.5861
17	17	2.21	0.0231	0.25	0.55	0.4121	36	36	2.05	0.0247	0.25	0.55	0.7376
17	17	2.21	0.0231	0.25	0.60	0.5224	36	36	2.05	0.0247	0.25	0.60	0.8572
17	17	2.21	0.0231	0.25	0.65	0.6328	36	36	2.05	0.0247	0.25	0.65	0.9354

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
17	17	2.21	0.0231	0.25	0.70	0.7379	36	36	2.05	0.0247	0.25	0.70	0.9767
17	17	2.21	0.0231	0.25	0.75	0.8319	36	36	2.05	0.0247	0.25	0.75	0.9936
17	17	2.21	0.0231	0.30	0.45	0.1325	36	36	2.05	0.0247	0.30	0.45	0.2474
17	17	2.21	0.0231	0.30	0.50	0.2016	36	36	2.05	0.0247	0.30	0.50	0.3942
17	17	2.21	0.0231	0.30	0.55	0.2870	36	36	2.05	0.0247	0.30	0.55	0.5613
17	17	2.21	0.0231	0.30	0.60	0.3872	36	36	2.05	0.0247	0.30	0.60	0.7218
17	17	2.21	0.0231	0.30	0.65	0.4994	36	36	2.05	0.0247	0.30	0.65	0.8498
17	17	2.21	0.0231	0.30	0.70	0.6190	36	36	2.05	0.0247	0.30	0.70	0.9332
17	17	2.21	0.0231	0.35	0.50	0.1237	36	36	2.05	0.0247	0.35	0.50	0.2346
17	17	2.21	0.0231	0.35	0.55	0.1883	36	36	2.05	0.0247	0.35	0.55	0.3828
17	17	2.21	0.0231	0.35	0.60	0.2722	36	36	2.05	0.0247	0.35	0.60	0.5537
17	17	2.21	0.0231	0.35	0.65	0.3766	36	36	2.05	0.0247	0.35	0.65	0.7183
17	17	2.21	0.0231	0.40	0.55	0.1169	36	36	2.05	0.0247	0.40	0.55	0.2316
17	17	2.21	0.0231	0.40	0.60	0.1824	36	36	2.05	0.0247	0.40	0.60	0.3808
18	18	2.14	0.0239	0.05	0.15	0.1274	37	37	2.05	0.0244	0.05	0.15	0.2745
18	18	2.14	0.0239	0.05	0.20	0.2512	37	37	2.05	0.0244	0.05	0.20	0.4973
18	18	2.14	0.0239	0.05	0.25	0.3927	37	37	2.05	0.0244	0.05	0.25	0.7055
18	18	2.14	0.0239	0.05	0.30	0.5338	37	37	2.05	0.0244	0.05	0.30	0.8532
18	18	2.14	0.0239	0.05	0.35	0.6617	37	37	2.05	0.0244	0.05	0.35	0.9373
18	18	2.14	0.0239	0.05	0.40	0.7692	37	37	2.05	0.0244	0.05	0.40	0.9772
18	18	2.14	0.0239	0.05	0.45	0.8531	37	37	2.05	0.0244	0.05	0.45	0.9930
18	18	2.14	0.0239	0.10	0.25	0.2088	37	37	2.05	0.0244	0.10	0.25	0.3979
18	18	2.14	0.0239	0.10	0.30	0.3166	37	37	2.05	0.0244	0.10	0.30	0.5899
18	18	2.14	0.0239	0.10	0.35	0.4367	37	37	2.05	0.0244	0.10	0.35	0.7548
18	18	2.14	0.0239	0.10	0.40	0.5606	37	37	2.05	0.0244	0.10	0.40	0.8727
18	18	2.14	0.0239	0.10	0.45	0.6786	37	37	2.05	0.0244	0.10	0.45	0.9431
18	18	2.14	0.0239	0.10	0.50	0.7816	37	37	2.05	0.0244	0.10	0.50	0.9784
18	18	2.14	0.0239	0.10	0.55	0.8634	37	37	2.05	0.0244	0.10	0.55	0.9931
18	18	2.14	0.0239	0.10	0.60	0.9220	37	37	2.05	0.0244	0.10	0.60	0.9982
18	18	2.14	0.0239	0.15	0.30	0.1779	37	37	2.05	0.0244	0.15	0.30	0.3350
18	18	2.14	0.0239	0.15	0.35	0.2723	37	37	2.05	0.0244	0.15	0.35	0.5116
18	18	2.14	0.0239	0.15	0.40	0.3848	37	37	2.05	0.0244	0.15	0.40	0.6809
18	18	2.14	0.0239	0.15	0.45	0.5072	37	37	2.05	0.0244	0.15	0.45	0.8165
18	18	2.14	0.0239	0.15	0.50	0.6282	37	37	2.05	0.0244	0.15	0.50	0.9084
18	18	2.14	0.0239	0.15	0.55	0.7370	37	37	2.05	0.0244	0.15	0.55	0.9612
18	18	2.14	0.0239	0.15	0.60	0.8262	37	37	2.05	0.0244	0.15	0.60	0.9866
18	18	2.14	0.0239	0.15	0.65	0.8933	37	37	2.05	0.0244	0.15	0.65	0.9964
18	18	2.14	0.0239	0.20	0.35	0.1616	37	37	2.05	0.0244	0.20	0.35	0.2933
18	18	2.14	0.0239	0.20	0.40	0.2498	37	37	2.05	0.0244	0.20	0.40	0.4563
18	18	2.14	0.0239	0.20	0.45	0.3562	37	37	2.05	0.0244	0.20	0.45	0.6243
18	18	2.14	0.0239	0.20	0.50	0.4724	37	37	2.05	0.0244	0.20	0.50	0.7718
18	18	2.14	0.0239	0.20	0.55	0.5887	37	37	2.05	0.0244	0.20	0.55	0.8815
18	18	2.14	0.0239	0.20	0.60	0.6963	37	37	2.05	0.0244	0.20	0.60	0.9490
18	18	2.14	0.0239	0.20	0.65	0.7898	37	37	2.05	0.0244	0.20	0.65	0.9824
18	18	2.14	0.0239	0.20	0.70	0.8663	37	37	2.05	0.0244	0.20	0.70	0.9953
18	18	2.14	0.0239	0.25	0.40	0.1526	37	37	2.05	0.0244	0.25	0.40	0.2629
18	18	2.14	0.0239	0.25	0.45	0.2337	37	37	2.05	0.0244	0.25	0.45	0.4184
18	18	2.14	0.0239	0.25	0.50	0.3308	37	37	2.05	0.0244	0.25	0.50	0.5899
18	18	2.14	0.0239	0.25	0.55	0.4383	37	37	2.05	0.0244	0.25	0.55	0.7483
18	18	2.14	0.0239	0.25	0.60	0.5501	37	37	2.05	0.0244	0.25	0.60	0.8691

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
18	18	2.14	0.0239	0.25	0.65	0.6607	37	37	2.05	0.0244	0.25	0.65	0.9438
18	18	2.14	0.0239	0.25	0.70	0.7643	37	37	2.05	0.0244	0.25	0.70	0.9808
18	18	2.14	0.0239	0.25	0.75	0.8546	37	37	2.05	0.0244	0.25	0.75	0.9950
18	18	2.14	0.0239	0.30	0.45	0.1427	37	37	2.05	0.0244	0.30	0.45	0.2468
18	18	2.14	0.0239	0.30	0.50	0.2153	37	37	2.05	0.0244	0.30	0.50	0.4027
18	18	2.14	0.0239	0.30	0.55	0.3044	37	37	2.05	0.0244	0.30	0.55	0.5778
18	18	2.14	0.0239	0.30	0.60	0.4082	37	37	2.05	0.0244	0.30	0.60	0.7407
18	18	2.14	0.0239	0.30	0.65	0.5240	37	37	2.05	0.0244	0.30	0.65	0.8652
18	18	2.14	0.0239	0.30	0.70	0.6459	37	37	2.05	0.0244	0.30	0.70	0.9426
18	18	2.14	0.0239	0.35	0.50	0.1304	37	37	2.05	0.0244	0.35	0.50	0.2439
18	18	2.14	0.0239	0.35	0.55	0.1980	37	37	2.05	0.0244	0.35	0.55	0.4000
18	18	2.14	0.0239	0.35	0.60	0.2862	37	37	2.05	0.0244	0.35	0.60	0.5754
18	18	2.14	0.0239	0.35	0.65	0.3959	37	37	2.05	0.0244	0.35	0.65	0.7392
18	18	2.14	0.0239	0.40	0.55	0.1215	37	37	2.05	0.0244	0.40	0.55	0.2449
18	18	2.14	0.0239	0.40	0.60	0.1908	37	37	2.05	0.0244	0.40	0.60	0.4001
19	19	2.14	0.0243	0.05	0.15	0.1402	38	38	2.04	0.0247	0.05	0.15	0.2833
19	19	2.14	0.0243	0.05	0.20	0.2717	38	38	2.04	0.0247	0.05	0.20	0.5118
19	19	2.14	0.0243	0.05	0.25	0.4189	38	38	2.04	0.0247	0.05	0.25	0.7204
19	19	2.14	0.0243	0.05	0.30	0.5628	38	38	2.04	0.0247	0.05	0.30	0.8643
19	19	2.14	0.0243	0.05	0.35	0.6905	38	38	2.04	0.0247	0.05	0.35	0.9439
19	19	2.14	0.0243	0.05	0.40	0.7949	38	38	2.04	0.0247	0.05	0.40	0.9803
19	19	2.14	0.0243	0.05	0.45	0.8738	38	38	2.04	0.0247	0.05	0.45	0.9942
19	19	2.14	0.0243	0.10	0.25	0.2217	38	38	2.04	0.0247	0.10	0.25	0.4096
19	19	2.14	0.0243	0.10	0.30	0.3350	38	38	2.04	0.0247	0.10	0.30	0.6040
19	19	2.14	0.0243	0.10	0.35	0.4594	38	38	2.04	0.0247	0.10	0.35	0.7682
19	19	2.14	0.0243	0.10	0.40	0.5846	38	38	2.04	0.0247	0.10	0.40	0.8828
19	19	2.14	0.0243	0.10	0.45	0.7000	38	38	2.04	0.0247	0.10	0.45	0.9493
19	19	2.14	0.0243	0.10	0.50	0.7975	38	38	2.04	0.0247	0.10	0.50	0.9814
19	19	2.14	0.0243	0.10	0.55	0.8731	38	38	2.04	0.0247	0.10	0.55	0.9943
19	19	2.14	0.0243	0.10	0.60	0.9268	38	38	2.04	0.0247	0.10	0.60	0.9986
19	19	2.14	0.0243	0.15	0.30	0.1866	38	38	2.04	0.0247	0.15	0.30	0.3452
19	19	2.14	0.0243	0.15	0.35	0.2838	38	38	2.04	0.0247	0.15	0.35	0.5255
19	19	2.14	0.0243	0.15	0.40	0.3965	38	38	2.04	0.0247	0.15	0.40	0.6954
19	19	2.14	0.0243	0.15	0.45	0.5159	38	38	2.04	0.0247	0.15	0.45	0.8288
19	19	2.14	0.0243	0.15	0.50	0.6323	38	38	2.04	0.0247	0.15	0.50	0.9171
19	19	2.14	0.0243	0.15	0.55	0.7375	38	38	2.04	0.0247	0.15	0.55	0.9663
19	19	2.14	0.0243	0.15	0.60	0.8261	38	38	2.04	0.0247	0.15	0.60	0.9889
19	19	2.14	0.0243	0.15	0.65	0.8950	38	38	2.04	0.0247	0.15	0.65	0.9972
19	19	2.14	0.0243	0.20	0.35	0.1635	38	38	2.04	0.0247	0.20	0.35	0.3027
19	19	2.14	0.0243	0.20	0.40	0.2492	38	38	2.04	0.0247	0.20	0.40	0.4698
19	19	2.14	0.0243	0.20	0.45	0.3513	38	38	2.04	0.0247	0.20	0.45	0.6401
19	19	2.14	0.0243	0.20	0.50	0.4642	38	38	2.04	0.0247	0.20	0.50	0.7872
19	19	2.14	0.0243	0.20	0.55	0.5808	38	38	2.04	0.0247	0.20	0.55	0.8934
19	19	2.14	0.0243	0.20	0.60	0.6935	38	38	2.04	0.0247	0.20	0.60	0.9561
19	19	2.14	0.0243	0.20	0.65	0.7943	38	38	2.04	0.0247	0.20	0.65	0.9856
19	19	2.14	0.0243	0.20	0.70	0.8762	38	38	2.04	0.0247	0.20	0.70	0.9964
19	19	2.14	0.0243	0.25	0.40	0.1453	38	38	2.04	0.0247	0.25	0.40	0.2726
19	19	2.14	0.0243	0.25	0.45	0.2220	38	38	2.04	0.0247	0.25	0.45	0.4339
19	19	2.14	0.0243	0.25	0.50	0.3173	38	38	2.04	0.0247	0.25	0.50	0.6092
19	19	2.14	0.0243	0.25	0.55	0.4282	38	38	2.04	0.0247	0.25	0.55	0.7669

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
19	19	2.14	0.0243	0.25	0.60	0.5489	38	38	2.04	0.0247	0.25	0.60	0.8830
19	19	2.14	0.0243	0.25	0.65	0.6699	38	38	2.04	0.0247	0.25	0.65	0.9519
19	19	2.14	0.0243	0.25	0.70	0.7804	38	38	2.04	0.0247	0.25	0.70	0.9844
19	19	2.14	0.0243	0.25	0.75	0.8706	38	38	2.04	0.0247	0.25	0.75	0.9962
19	19	2.14	0.0243	0.30	0.45	0.1308	38	38	2.04	0.0247	0.30	0.45	0.2589
19	19	2.14	0.0243	0.30	0.50	0.2029	38	38	2.04	0.0247	0.30	0.50	0.4210
19	19	2.14	0.0243	0.30	0.55	0.2966	38	38	2.04	0.0247	0.30	0.55	0.5994
19	19	2.14	0.0243	0.30	0.60	0.4096	38	38	2.04	0.0247	0.30	0.60	0.7605
19	19	2.14	0.0243	0.30	0.65	0.5354	38	38	2.04	0.0247	0.30	0.65	0.8796
19	19	2.14	0.0243	0.30	0.70	0.6631	38	38	2.04	0.0247	0.30	0.70	0.9508
19	19	2.14	0.0243	0.35	0.50	0.1217	38	38	2.04	0.0247	0.35	0.50	0.2576
19	19	2.14	0.0243	0.35	0.55	0.1931	38	38	2.04	0.0247	0.35	0.55	0.4194
19	19	2.14	0.0243	0.35	0.60	0.2880	38	38	2.04	0.0247	0.35	0.60	0.5974
19	19	2.14	0.0243	0.35	0.65	0.4043	38	38	2.04	0.0247	0.35	0.65	0.7591
19	19	2.14	0.0243	0.40	0.55	0.1180	38	38	2.04	0.0247	0.40	0.55	0.2590
19	19	2.14	0.0243	0.40	0.60	0.1903	38	38	2.04	0.0247	0.40	0.60	0.4196
20	20	2.10	0.0249	0.05	0.15	0.1529	39	39	2.10	0.0230	0.05	0.15	0.2625
20	20	2.10	0.0249	0.05	0.20	0.2915	39	39	2.10	0.0230	0.05	0.20	0.4771
20	20	2.10	0.0249	0.05	0.25	0.4439	39	39	2.10	0.0230	0.05	0.25	0.6888
20	20	2.10	0.0249	0.05	0.30	0.5903	39	39	2.10	0.0230	0.05	0.30	0.8451
20	20	2.10	0.0249	0.05	0.35	0.7175	39	39	2.10	0.0230	0.05	0.35	0.9354
20	20	2.10	0.0249	0.05	0.40	0.8189	39	39	2.10	0.0230	0.05	0.40	0.9775
20	20	2.10	0.0249	0.05	0.45	0.8929	39	39	2.10	0.0230	0.05	0.45	0.9935
20	20	2.10	0.0249	0.10	0.25	0.2348	39	39	2.10	0.0230	0.10	0.25	0.3749
20	20	2.10	0.0249	0.10	0.30	0.3544	39	39	2.10	0.0230	0.10	0.30	0.5765
20	20	2.10	0.0249	0.10	0.35	0.4845	39	39	2.10	0.0230	0.10	0.35	0.7523
20	20	2.10	0.0249	0.10	0.40	0.6128	39	39	2.10	0.0230	0.10	0.40	0.8758
20	20	2.10	0.0249	0.10	0.45	0.7280	39	39	2.10	0.0230	0.10	0.45	0.9470
20	20	2.10	0.0249	0.10	0.50	0.8222	39	39	2.10	0.0230	0.10	0.50	0.9810
20	20	2.10	0.0249	0.10	0.55	0.8927	39	39	2.10	0.0230	0.10	0.55	0.9944
20	20	2.10	0.0249	0.10	0.60	0.9409	39	39	2.10	0.0230	0.10	0.60	0.9987
20	20	2.10	0.0249	0.15	0.30	0.1979	39	39	2.10	0.0230	0.15	0.30	0.3236
20	20	2.10	0.0249	0.15	0.35	0.3015	39	39	2.10	0.0230	0.15	0.35	0.5080
20	20	2.10	0.0249	0.15	0.40	0.4200	39	39	2.10	0.0230	0.15	0.40	0.6846
20	20	2.10	0.0249	0.15	0.45	0.5434	39	39	2.10	0.0230	0.15	0.45	0.8251
20	20	2.10	0.0249	0.15	0.50	0.6614	39	39	2.10	0.0230	0.15	0.50	0.9181
20	20	2.10	0.0249	0.15	0.55	0.7659	39	39	2.10	0.0230	0.15	0.55	0.9685
20	20	2.10	0.0249	0.15	0.60	0.8513	39	39	2.10	0.0230	0.15	0.60	0.9903
20	20	2.10	0.0249	0.15	0.65	0.9151	39	39	2.10	0.0230	0.15	0.65	0.9977
20	20	2.10	0.0249	0.20	0.35	0.1737	39	39	2.10	0.0230	0.20	0.35	0.2886
20	20	2.10	0.0249	0.20	0.40	0.2651	39	39	2.10	0.0230	0.20	0.40	0.4609
20	20	2.10	0.0249	0.20	0.45	0.3735	39	39	2.10	0.0230	0.20	0.45	0.6404
20	20	2.10	0.0249	0.20	0.50	0.4924	39	39	2.10	0.0230	0.20	0.50	0.7940
20	20	2.10	0.0249	0.20	0.55	0.6136	39	39	2.10	0.0230	0.20	0.55	0.9006
20	20	2.10	0.0249	0.20	0.60	0.7279	39	39	2.10	0.0230	0.20	0.60	0.9600
20	20	2.10	0.0249	0.20	0.65	0.8260	39	39	2.10	0.0230	0.20	0.65	0.9867
20	20	2.10	0.0249	0.20	0.70	0.9014	39	39	2.10	0.0230	0.20	0.70	0.9964
20	20	2.10	0.0249	0.25	0.40	0.1549	39	39	2.10	0.0230	0.25	0.40	0.2696
20	20	2.10	0.0249	0.25	0.45	0.2380	39	39	2.10	0.0230	0.25	0.45	0.4393
20	20	2.10	0.0249	0.25	0.50	0.3414	39	39	2.10	0.0230	0.25	0.50	0.6198

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	20	2.10	0.0249	0.25	0.55	0.4607	39	39	2.10	0.0230	0.25	0.55	0.7755
20	20	2.10	0.0249	0.25	0.60	0.5874	39	39	2.10	0.0230	0.25	0.60	0.8856
20	20	2.10	0.0249	0.25	0.65	0.7099	39	39	2.10	0.0230	0.25	0.65	0.9505
20	20	2.10	0.0249	0.25	0.70	0.8161	39	39	2.10	0.0230	0.25	0.70	0.9826
20	20	2.10	0.0249	0.25	0.75	0.8977	39	39	2.10	0.0230	0.25	0.75	0.9955
20	20	2.10	0.0249	0.30	0.45	0.1414	39	39	2.10	0.0230	0.30	0.45	0.2638
20	20	2.10	0.0249	0.30	0.50	0.2215	39	39	2.10	0.0230	0.30	0.50	0.4268
20	20	2.10	0.0249	0.30	0.55	0.3247	39	39	2.10	0.0230	0.30	0.55	0.5993
20	20	2.10	0.0249	0.30	0.60	0.4467	39	39	2.10	0.0230	0.30	0.60	0.7526
20	20	2.10	0.0249	0.30	0.65	0.5778	39	39	2.10	0.0230	0.30	0.65	0.8694
20	20	2.10	0.0249	0.30	0.70	0.7052	39	39	2.10	0.0230	0.30	0.70	0.9445
20	20	2.10	0.0249	0.35	0.50	0.1346	39	39	2.10	0.0230	0.35	0.50	0.2540
20	20	2.10	0.0249	0.35	0.55	0.2147	39	39	2.10	0.0230	0.35	0.55	0.4061
20	20	2.10	0.0249	0.35	0.60	0.3190	39	39	2.10	0.0230	0.35	0.60	0.5756
20	20	2.10	0.0249	0.35	0.65	0.4432	39	39	2.10	0.0230	0.35	0.65	0.7388
20	20	2.10	0.0249	0.40	0.55	0.1326	39	39	2.10	0.0230	0.40	0.55	0.2394
20	20	2.10	0.0249	0.40	0.60	0.2132	39	39	2.10	0.0230	0.40	0.60	0.3930
21	21	2.17	0.0248	0.05	0.15	0.1652	40	40	2.08	0.0238	0.05	0.15	0.2997
21	21	2.17	0.0248	0.05	0.20	0.3101	40	40	2.08	0.0238	0.05	0.20	0.5336
21	21	2.17	0.0248	0.05	0.25	0.4656	40	40	2.08	0.0238	0.05	0.25	0.7363
21	21	2.17	0.0248	0.05	0.30	0.6111	40	40	2.08	0.0238	0.05	0.30	0.8720
21	21	2.17	0.0248	0.05	0.35	0.7339	40	40	2.08	0.0238	0.05	0.35	0.9471
21	21	2.17	0.0248	0.05	0.40	0.8294	40	40	2.08	0.0238	0.05	0.40	0.9818
21	21	2.17	0.0248	0.05	0.45	0.8981	40	40	2.08	0.0238	0.05	0.45	0.9949
21	21	2.17	0.0248	0.10	0.25	0.2408	40	40	2.08	0.0238	0.10	0.25	0.4038
21	21	2.17	0.0248	0.10	0.30	0.3578	40	40	2.08	0.0238	0.10	0.30	0.5996
21	21	2.17	0.0248	0.10	0.35	0.4827	40	40	2.08	0.0238	0.10	0.35	0.7690
21	21	2.17	0.0248	0.10	0.40	0.6062	40	40	2.08	0.0238	0.10	0.40	0.8865
21	21	2.17	0.0248	0.10	0.45	0.7198	40	40	2.08	0.0238	0.10	0.45	0.9529
21	21	2.17	0.0248	0.10	0.50	0.8163	40	40	2.08	0.0238	0.10	0.50	0.9838
21	21	2.17	0.0248	0.10	0.55	0.8910	40	40	2.08	0.0238	0.10	0.55	0.9955
21	21	2.17	0.0248	0.10	0.60	0.9428	40	40	2.08	0.0238	0.10	0.60	0.9990
21	21	2.17	0.0248	0.15	0.30	0.1901	40	40	2.08	0.0238	0.15	0.30	0.3365
21	21	2.17	0.0248	0.15	0.35	0.2874	40	40	2.08	0.0238	0.15	0.35	0.5230
21	21	2.17	0.0248	0.15	0.40	0.4027	40	40	2.08	0.0238	0.15	0.40	0.6999
21	21	2.17	0.0248	0.15	0.45	0.5290	40	40	2.08	0.0238	0.15	0.45	0.8380
21	21	2.17	0.0248	0.15	0.50	0.6556	40	40	2.08	0.0238	0.15	0.50	0.9268
21	21	2.17	0.0248	0.15	0.55	0.7700	40	40	2.08	0.0238	0.15	0.55	0.9731
21	21	2.17	0.0248	0.15	0.60	0.8622	40	40	2.08	0.0238	0.15	0.60	0.9921
21	21	2.17	0.0248	0.15	0.65	0.9273	40	40	2.08	0.0238	0.15	0.65	0.9982
21	21	2.17	0.0248	0.20	0.35	0.1588	40	40	2.08	0.0238	0.20	0.35	0.2990
21	21	2.17	0.0248	0.20	0.40	0.2492	40	40	2.08	0.0238	0.20	0.40	0.4764
21	21	2.17	0.0248	0.20	0.45	0.3635	40	40	2.08	0.0238	0.20	0.45	0.6583
21	21	2.17	0.0248	0.20	0.50	0.4942	40	40	2.08	0.0238	0.20	0.50	0.8097
21	21	2.17	0.0248	0.20	0.55	0.6283	40	40	2.08	0.0238	0.20	0.55	0.9109
21	21	2.17	0.0248	0.20	0.60	0.7511	40	40	2.08	0.0238	0.20	0.60	0.9653
21	21	2.17	0.0248	0.20	0.65	0.8505	40	40	2.08	0.0238	0.20	0.65	0.9888
21	21	2.17	0.0248	0.20	0.70	0.9212	40	40	2.08	0.0238	0.20	0.70	0.9971
21	21	2.17	0.0248	0.25	0.40	0.1453	40	40	2.08	0.0238	0.25	0.40	0.2816
21	21	2.17	0.0248	0.25	0.45	0.2352	40	40	2.08	0.0238	0.25	0.45	0.4566

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
21	21	2.17	0.0248	0.25	0.50	0.3506	40	40	2.08	0.0238	0.25	0.50	0.6380
21	21	2.17	0.0248	0.25	0.55	0.4832	40	40	2.08	0.0238	0.25	0.55	0.7901
21	21	2.17	0.0248	0.25	0.60	0.6195	40	40	2.08	0.0238	0.25	0.60	0.8949
21	21	2.17	0.0248	0.25	0.65	0.7446	40	40	2.08	0.0238	0.25	0.65	0.9554
21	21	2.17	0.0248	0.25	0.70	0.8465	40	40	2.08	0.0238	0.25	0.70	0.9848
21	21	2.17	0.0248	0.25	0.75	0.9195	40	40	2.08	0.0238	0.25	0.75	0.9963
21	21	2.17	0.0248	0.30	0.45	0.1433	40	40	2.08	0.0238	0.30	0.45	0.2757
21	21	2.17	0.0248	0.30	0.50	0.2336	40	40	2.08	0.0238	0.30	0.50	0.4414
21	21	2.17	0.0248	0.30	0.55	0.3489	40	40	2.08	0.0238	0.30	0.55	0.6135
21	21	2.17	0.0248	0.30	0.60	0.4811	40	40	2.08	0.0238	0.30	0.60	0.7642
21	21	2.17	0.0248	0.30	0.65	0.6172	40	40	2.08	0.0238	0.30	0.65	0.8777
21	21	2.17	0.0248	0.30	0.70	0.7430	40	40	2.08	0.0238	0.30	0.70	0.9494
21	21	2.17	0.0248	0.35	0.50	0.1455	40	40	2.08	0.0238	0.35	0.50	0.2621
21	21	2.17	0.0248	0.35	0.55	0.2354	40	40	2.08	0.0238	0.35	0.55	0.4158
21	21	2.17	0.0248	0.35	0.60	0.3496	40	40	2.08	0.0238	0.35	0.60	0.5862
21	21	2.17	0.0248	0.35	0.65	0.4809	40	40	2.08	0.0238	0.35	0.65	0.7492
21	21	2.17	0.0248	0.40	0.55	0.1475	40	40	2.08	0.0238	0.40	0.55	0.2441
21	21	2.17	0.0248	0.40	0.60	0.2363	40	40	2.08	0.0238	0.40	0.60	0.4006
22	22	2.14	0.0244	0.05	0.15	0.1773	50	50	2.05	0.0244	0.05	0.15	0.3460
22	22	2.14	0.0244	0.05	0.20	0.3284	50	50	2.05	0.0244	0.05	0.20	0.6147
22	22	2.14	0.0244	0.05	0.25	0.4878	50	50	2.05	0.0244	0.05	0.25	0.8210
22	22	2.14	0.0244	0.05	0.30	0.6342	50	50	2.05	0.0244	0.05	0.30	0.9335
22	22	2.14	0.0244	0.05	0.35	0.7554	50	50	2.05	0.0244	0.05	0.35	0.9802
22	22	2.14	0.0244	0.05	0.40	0.8475	50	50	2.05	0.0244	0.05	0.40	0.9953
22	22	2.14	0.0244	0.05	0.45	0.9121	50	50	2.05	0.0244	0.05	0.45	0.9991
22	22	2.14	0.0244	0.10	0.25	0.2515	50	50	2.05	0.0244	0.10	0.25	0.4870
22	22	2.14	0.0244	0.10	0.30	0.3734	50	50	2.05	0.0244	0.10	0.30	0.7035
22	22	2.14	0.0244	0.10	0.35	0.5029	50	50	2.05	0.0244	0.10	0.35	0.8606
22	22	2.14	0.0244	0.10	0.40	0.6298	50	50	2.05	0.0244	0.10	0.40	0.9474
22	22	2.14	0.0244	0.10	0.45	0.7446	50	50	2.05	0.0244	0.10	0.45	0.9841
22	22	2.14	0.0244	0.10	0.50	0.8393	50	50	2.05	0.0244	0.10	0.50	0.9962
22	22	2.14	0.0244	0.10	0.55	0.9095	50	50	2.05	0.0244	0.10	0.55	0.9993
22	22	2.14	0.0244	0.10	0.60	0.9554	50	50	2.05	0.0244	0.10	0.60	0.9999
22	22	2.14	0.0244	0.15	0.30	0.1985	50	50	2.05	0.0244	0.15	0.30	0.4165
22	22	2.14	0.0244	0.15	0.35	0.3023	50	50	2.05	0.0244	0.15	0.35	0.6309
22	22	2.14	0.0244	0.15	0.40	0.4254	50	50	2.05	0.0244	0.15	0.40	0.8049
22	22	2.14	0.0244	0.15	0.45	0.5584	50	50	2.05	0.0244	0.15	0.45	0.9150
22	22	2.14	0.0244	0.15	0.50	0.6881	50	50	2.05	0.0244	0.15	0.50	0.9704
22	22	2.14	0.0244	0.15	0.55	0.8006	50	50	2.05	0.0244	0.15	0.55	0.9920
22	22	2.14	0.0244	0.15	0.60	0.8866	50	50	2.05	0.0244	0.15	0.60	0.9984
22	22	2.14	0.0244	0.15	0.65	0.9438	50	50	2.05	0.0244	0.15	0.65	0.9998
22	22	2.14	0.0244	0.20	0.35	0.1687	50	50	2.05	0.0244	0.20	0.35	0.3744
22	22	2.14	0.0244	0.20	0.40	0.2677	50	50	2.05	0.0244	0.20	0.40	0.5783
22	22	2.14	0.0244	0.20	0.45	0.3913	50	50	2.05	0.0244	0.20	0.45	0.7616
22	22	2.14	0.0244	0.20	0.50	0.5292	50	50	2.05	0.0244	0.20	0.50	0.8905
22	22	2.14	0.0244	0.20	0.55	0.6657	50	50	2.05	0.0244	0.20	0.55	0.9602
22	22	2.14	0.0244	0.20	0.60	0.7852	50	50	2.05	0.0244	0.20	0.60	0.9887
22	22	2.14	0.0244	0.20	0.65	0.8772	50	50	2.05	0.0244	0.20	0.65	0.9975
22	22	2.14	0.0244	0.20	0.70	0.9389	50	50	2.05	0.0244	0.20	0.70	0.9996
22	22	2.14	0.0244	0.25	0.40	0.1585	50	50	2.05	0.0244	0.25	0.40	0.3466

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
22	22	2.14	0.0244	0.25	0.45	0.2575	50	50	2.05	0.0244	0.25	0.45	0.5496
22	22	2.14	0.0244	0.25	0.50	0.3820	50	50	2.05	0.0244	0.25	0.50	0.7391
22	22	2.14	0.0244	0.25	0.55	0.5208	50	50	2.05	0.0244	0.25	0.55	0.8751
22	22	2.14	0.0244	0.25	0.60	0.6584	50	50	2.05	0.0244	0.25	0.60	0.9509
22	22	2.14	0.0244	0.25	0.65	0.7796	50	50	2.05	0.0244	0.25	0.65	0.9845
22	22	2.14	0.0244	0.25	0.70	0.8737	50	50	2.05	0.0244	0.25	0.70	0.9963
22	22	2.14	0.0244	0.25	0.75	0.9375	50	50	2.05	0.0244	0.25	0.75	0.9994
22	22	2.14	0.0244	0.30	0.45	0.1589	50	50	2.05	0.0244	0.30	0.45	0.3366
22	22	2.14	0.0244	0.30	0.50	0.2580	50	50	2.05	0.0244	0.30	0.50	0.5327
22	22	2.14	0.0244	0.30	0.55	0.3815	50	50	2.05	0.0244	0.30	0.55	0.7165
22	22	2.14	0.0244	0.30	0.60	0.5192	50	50	2.05	0.0244	0.30	0.60	0.8548
22	22	2.14	0.0244	0.30	0.65	0.6563	50	50	2.05	0.0244	0.30	0.65	0.9400
22	22	2.14	0.0244	0.30	0.70	0.7781	50	50	2.05	0.0244	0.30	0.70	0.9816
22	22	2.14	0.0244	0.35	0.50	0.1622	50	50	2.05	0.0244	0.35	0.50	0.3212
22	22	2.14	0.0244	0.35	0.55	0.2603	50	50	2.05	0.0244	0.35	0.55	0.5047
22	22	2.14	0.0244	0.35	0.60	0.3824	50	50	2.05	0.0244	0.35	0.60	0.6895
22	22	2.14	0.0244	0.35	0.65	0.5190	50	50	2.05	0.0244	0.35	0.65	0.8422
22	22	2.14	0.0244	0.40	0.55	0.1644	50	50	2.05	0.0244	0.40	0.55	0.2991
22	22	2.14	0.0244	0.40	0.60	0.2613	50	50	2.05	0.0244	0.40	0.60	0.4870
23	23	2.17	0.0237	0.05	0.15	0.1621	60	60	2.05	0.0245	0.05	0.15	0.4278
23	23	2.17	0.0237	0.05	0.20	0.2919	60	60	2.05	0.0245	0.05	0.20	0.7165
23	23	2.17	0.0237	0.05	0.25	0.4399	60	60	2.05	0.0245	0.05	0.25	0.8948
23	23	2.17	0.0237	0.05	0.30	0.5922	60	60	2.05	0.0245	0.05	0.30	0.9704
23	23	2.17	0.0237	0.05	0.35	0.7297	60	60	2.05	0.0245	0.05	0.35	0.9937
23	23	2.17	0.0237	0.05	0.40	0.8380	60	60	2.05	0.0245	0.05	0.40	0.9990
23	23	2.17	0.0237	0.05	0.45	0.9125	60	60	2.05	0.0245	0.05	0.45	0.9999
23	23	2.17	0.0237	0.10	0.25	0.2201	60	60	2.05	0.0245	0.10	0.25	0.5792
23	23	2.17	0.0237	0.10	0.30	0.3500	60	60	2.05	0.0245	0.10	0.30	0.7942
23	23	2.17	0.0237	0.10	0.35	0.4953	60	60	2.05	0.0245	0.10	0.35	0.9216
23	23	2.17	0.0237	0.10	0.40	0.6374	60	60	2.05	0.0245	0.10	0.40	0.9769
23	23	2.17	0.0237	0.10	0.45	0.7613	60	60	2.05	0.0245	0.10	0.45	0.9948
23	23	2.17	0.0237	0.10	0.50	0.8579	60	60	2.05	0.0245	0.10	0.50	0.9991
23	23	2.17	0.0237	0.10	0.55	0.9248	60	60	2.05	0.0245	0.10	0.55	0.9999
23	23	2.17	0.0237	0.10	0.60	0.9654	60	60	2.05	0.0245	0.10	0.60	1.0000
23	23	2.17	0.0237	0.15	0.30	0.1908	60	60	2.05	0.0245	0.15	0.30	0.4954
23	23	2.17	0.0237	0.15	0.35	0.3064	60	60	2.05	0.0245	0.15	0.35	0.7174
23	23	2.17	0.0237	0.15	0.40	0.4423	60	60	2.05	0.0245	0.15	0.40	0.8735
23	23	2.17	0.0237	0.15	0.45	0.5848	60	60	2.05	0.0245	0.15	0.45	0.9555
23	23	2.17	0.0237	0.15	0.50	0.7176	60	60	2.05	0.0245	0.15	0.50	0.9880
23	23	2.17	0.0237	0.15	0.55	0.8269	60	60	2.05	0.0245	0.15	0.55	0.9976
23	23	2.17	0.0237	0.15	0.60	0.9056	60	60	2.05	0.0245	0.15	0.60	0.9997
23	23	2.17	0.0237	0.15	0.65	0.9549	60	60	2.05	0.0245	0.15	0.65	1.0000
23	23	2.17	0.0237	0.20	0.35	0.1756	60	60	2.05	0.0245	0.20	0.35	0.4392
23	23	2.17	0.0237	0.20	0.40	0.2848	60	60	2.05	0.0245	0.20	0.40	0.6585
23	23	2.17	0.0237	0.20	0.45	0.4178	60	60	2.05	0.0245	0.20	0.45	0.8327
23	23	2.17	0.0237	0.20	0.50	0.5607	60	60	2.05	0.0245	0.20	0.50	0.9368
23	23	2.17	0.0237	0.20	0.55	0.6960	60	60	2.05	0.0245	0.20	0.55	0.9822
23	23	2.17	0.0237	0.20	0.60	0.8088	60	60	2.05	0.0245	0.20	0.60	0.9964
23	23	2.17	0.0237	0.20	0.65	0.8919	60	60	2.05	0.0245	0.20	0.65	0.9995
23	23	2.17	0.0237	0.20	0.70	0.9460	60	60	2.05	0.0245	0.20	0.70	0.9999

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
23	23	2.17	0.0237	0.25	0.40	0.1712	60	60	2.05	0.0245	0.25	0.40	0.4017
23	23	2.17	0.0237	0.25	0.45	0.2779	60	60	2.05	0.0245	0.25	0.45	0.6240
23	23	2.17	0.0237	0.25	0.50	0.4075	60	60	2.05	0.0245	0.25	0.50	0.8115
23	23	2.17	0.0237	0.25	0.55	0.5465	60	60	2.05	0.0245	0.25	0.55	0.9267
23	23	2.17	0.0237	0.25	0.60	0.6793	60	60	2.05	0.0245	0.25	0.60	0.9781
23	23	2.17	0.0237	0.25	0.65	0.7932	60	60	2.05	0.0245	0.25	0.65	0.9950
23	23	2.17	0.0237	0.25	0.70	0.8812	60	60	2.05	0.0245	0.25	0.70	0.9992
23	23	2.17	0.0237	0.25	0.75	0.9416	60	60	2.05	0.0245	0.25	0.75	0.9999
23	23	2.17	0.0237	0.30	0.45	0.1712	60	60	2.05	0.0245	0.30	0.45	0.3895
23	23	2.17	0.0237	0.30	0.50	0.2737	60	60	2.05	0.0245	0.30	0.50	0.6104
23	23	2.17	0.0237	0.30	0.55	0.3976	60	60	2.05	0.0245	0.30	0.55	0.7970
23	23	2.17	0.0237	0.30	0.60	0.5324	60	60	2.05	0.0245	0.30	0.60	0.9152
23	23	2.17	0.0237	0.30	0.65	0.6659	60	60	2.05	0.0245	0.30	0.65	0.9728
23	23	2.17	0.0237	0.30	0.70	0.7856	60	60	2.05	0.0245	0.30	0.70	0.9940
23	23	2.17	0.0237	0.35	0.50	0.1691	60	60	2.05	0.0245	0.35	0.50	0.3797
23	23	2.17	0.0237	0.35	0.55	0.2672	60	60	2.05	0.0245	0.35	0.55	0.5896
23	23	2.17	0.0237	0.35	0.60	0.3884	60	60	2.05	0.0245	0.35	0.60	0.7765
23	23	2.17	0.0237	0.35	0.65	0.5255	60	60	2.05	0.0245	0.35	0.65	0.9065
23	23	2.17	0.0237	0.40	0.55	0.1657	60	60	2.05	0.0245	0.40	0.55	0.3595
23	23	2.17	0.0237	0.40	0.60	0.2635	60	60	2.05	0.0245	0.40	0.60	0.5728
24	24	2.12	0.0245	0.05	0.15	0.2006	70	70	2.00	0.0249	0.05	0.15	0.5050
24	24	2.12	0.0245	0.05	0.20	0.3629	70	70	2.00	0.0249	0.05	0.20	0.7938
24	24	2.12	0.0245	0.05	0.25	0.5290	70	70	2.00	0.0249	0.05	0.25	0.9395
24	24	2.12	0.0245	0.05	0.30	0.6763	70	70	2.00	0.0249	0.05	0.30	0.9874
24	24	2.12	0.0245	0.05	0.35	0.7937	70	70	2.00	0.0249	0.05	0.35	0.9981
24	24	2.12	0.0245	0.05	0.40	0.8790	70	70	2.00	0.0249	0.05	0.40	0.9998
24	24	2.12	0.0245	0.05	0.45	0.9354	70	70	2.00	0.0249	0.05	0.45	1.0000
24	24	2.12	0.0245	0.10	0.25	0.2724	70	70	2.00	0.0249	0.10	0.25	0.6605
24	24	2.12	0.0245	0.10	0.30	0.4042	70	70	2.00	0.0249	0.10	0.30	0.8601
24	24	2.12	0.0245	0.10	0.35	0.5433	70	70	2.00	0.0249	0.10	0.35	0.9569
24	24	2.12	0.0245	0.10	0.40	0.6765	70	70	2.00	0.0249	0.10	0.40	0.9902
24	24	2.12	0.0245	0.10	0.45	0.7916	70	70	2.00	0.0249	0.10	0.45	0.9984
24	24	2.12	0.0245	0.10	0.50	0.8800	70	70	2.00	0.0249	0.10	0.50	0.9998
24	24	2.12	0.0245	0.10	0.55	0.9393	70	70	2.00	0.0249	0.10	0.55	1.0000
24	24	2.12	0.0245	0.10	0.60	0.9736	70	70	2.00	0.0249	0.10	0.60	1.0000
24	24	2.12	0.0245	0.15	0.30	0.2167	70	70	2.00	0.0249	0.15	0.30	0.5662
24	24	2.12	0.0245	0.15	0.35	0.3352	70	70	2.00	0.0249	0.15	0.35	0.7872
24	24	2.12	0.0245	0.15	0.40	0.4737	70	70	2.00	0.0249	0.15	0.40	0.9218
24	24	2.12	0.0245	0.15	0.45	0.6173	70	70	2.00	0.0249	0.15	0.45	0.9789
24	24	2.12	0.0245	0.15	0.50	0.7478	70	70	2.00	0.0249	0.15	0.50	0.9959
24	24	2.12	0.0245	0.15	0.55	0.8511	70	70	2.00	0.0249	0.15	0.55	0.9994
24	24	2.12	0.0245	0.15	0.60	0.9220	70	70	2.00	0.0249	0.15	0.60	0.9999
24	24	2.12	0.0245	0.15	0.65	0.9640	70	70	2.00	0.0249	0.15	0.65	1.0000
24	24	2.12	0.0245	0.20	0.35	0.1919	70	70	2.00	0.0249	0.20	0.35	0.5080
24	24	2.12	0.0245	0.20	0.40	0.3079	70	70	2.00	0.0249	0.20	0.40	0.7384
24	24	2.12	0.0245	0.20	0.45	0.4470	70	70	2.00	0.0249	0.20	0.45	0.8922
24	24	2.12	0.0245	0.20	0.50	0.5921	70	70	2.00	0.0249	0.20	0.50	0.9664
24	24	2.12	0.0245	0.20	0.55	0.7245	70	70	2.00	0.0249	0.20	0.55	0.9925
24	24	2.12	0.0245	0.20	0.60	0.8305	70	70	2.00	0.0249	0.20	0.60	0.9989
24	24	2.12	0.0245	0.20	0.65	0.9057	70	70	2.00	0.0249	0.20	0.65	0.9999

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
24	24	2.12	0.0245	0.20	0.70	0.9534	70	70	2.00	0.0249	0.20	0.70	1.0000
24	24	2.12	0.0245	0.25	0.40	0.1862	70	70	2.00	0.0249	0.25	0.40	0.4694
24	24	2.12	0.0245	0.25	0.45	0.2994	70	70	2.00	0.0249	0.25	0.45	0.6966
24	24	2.12	0.0245	0.25	0.50	0.4329	70	70	2.00	0.0249	0.25	0.50	0.8664
24	24	2.12	0.0245	0.25	0.55	0.5716	70	70	2.00	0.0249	0.25	0.55	0.9570
24	24	2.12	0.0245	0.25	0.60	0.7001	70	70	2.00	0.0249	0.25	0.60	0.9904
24	24	2.12	0.0245	0.25	0.65	0.8081	70	70	2.00	0.0249	0.25	0.65	0.9986
24	24	2.12	0.0245	0.25	0.70	0.8909	70	70	2.00	0.0249	0.25	0.70	0.9999
24	24	2.12	0.0245	0.25	0.75	0.9477	70	70	2.00	0.0249	0.25	0.75	1.0000
24	24	2.12	0.0245	0.30	0.45	0.1839	70	70	2.00	0.0249	0.30	0.45	0.4402
24	24	2.12	0.0245	0.30	0.50	0.2896	70	70	2.00	0.0249	0.30	0.50	0.6744
24	24	2.12	0.0245	0.30	0.55	0.4141	70	70	2.00	0.0249	0.30	0.55	0.8557
24	24	2.12	0.0245	0.30	0.60	0.5474	70	70	2.00	0.0249	0.30	0.60	0.9534
24	24	2.12	0.0245	0.30	0.65	0.6786	70	70	2.00	0.0249	0.30	0.65	0.9896
24	24	2.12	0.0245	0.30	0.70	0.7968	70	70	2.00	0.0249	0.30	0.70	0.9985
24	24	2.12	0.0245	0.35	0.50	0.1764	70	70	2.00	0.0249	0.35	0.50	0.4336
24	24	2.12	0.0245	0.35	0.55	0.2750	70	70	2.00	0.0249	0.35	0.55	0.6694
24	24	2.12	0.0245	0.35	0.60	0.3966	70	70	2.00	0.0249	0.35	0.60	0.8528
24	24	2.12	0.0245	0.35	0.65	0.5353	70	70	2.00	0.0249	0.35	0.65	0.9525
24	24	2.12	0.0245	0.40	0.55	0.1679	70	70	2.00	0.0249	0.40	0.55	0.4337
24	24	2.12	0.0245	0.40	0.60	0.2673	70	70	2.00	0.0249	0.40	0.60	0.6685
25	25	2.10	0.0232	0.05	0.15	0.2117	80	80	2.01	0.0245	0.05	0.15	0.5728
25	25	2.10	0.0232	0.05	0.20	0.3793	80	80	2.01	0.0245	0.05	0.20	0.8489
25	25	2.10	0.0232	0.05	0.25	0.5482	80	80	2.01	0.0245	0.05	0.25	0.9638
25	25	2.10	0.0232	0.05	0.30	0.6956	80	80	2.01	0.0245	0.05	0.30	0.9941
25	25	2.10	0.0232	0.05	0.35	0.8109	80	80	2.01	0.0245	0.05	0.35	0.9993
25	25	2.10	0.0232	0.05	0.40	0.8926	80	80	2.01	0.0245	0.05	0.40	0.9999
25	25	2.10	0.0232	0.05	0.45	0.9450	80	80	2.01	0.0245	0.05	0.45	1.0000
25	25	2.10	0.0232	0.10	0.25	0.2826	80	80	2.01	0.0245	0.10	0.25	0.7091
25	25	2.10	0.0232	0.10	0.30	0.4198	80	80	2.01	0.0245	0.10	0.30	0.8970
25	25	2.10	0.0232	0.10	0.35	0.5636	80	80	2.01	0.0245	0.10	0.35	0.9747
25	25	2.10	0.0232	0.10	0.40	0.6991	80	80	2.01	0.0245	0.10	0.40	0.9958
25	25	2.10	0.0232	0.10	0.45	0.8129	80	80	2.01	0.0245	0.10	0.45	0.9995
25	25	2.10	0.0232	0.10	0.50	0.8965	80	80	2.01	0.0245	0.10	0.50	1.0000
25	25	2.10	0.0232	0.10	0.55	0.9498	80	80	2.01	0.0245	0.10	0.55	1.0000
25	25	2.10	0.0232	0.10	0.60	0.9789	80	80	2.01	0.0245	0.10	0.60	1.0000
25	25	2.10	0.0232	0.15	0.30	0.2267	80	80	2.01	0.0245	0.15	0.30	0.6214
25	25	2.10	0.0232	0.15	0.35	0.3524	80	80	2.01	0.0245	0.15	0.35	0.8402
25	25	2.10	0.0232	0.15	0.40	0.4971	80	80	2.01	0.0245	0.15	0.40	0.9514
25	25	2.10	0.0232	0.15	0.45	0.6422	80	80	2.01	0.0245	0.15	0.45	0.9896
25	25	2.10	0.0232	0.15	0.50	0.7689	80	80	2.01	0.0245	0.15	0.50	0.9985
25	25	2.10	0.0232	0.15	0.55	0.8650	80	80	2.01	0.0245	0.15	0.55	0.9999
25	25	2.10	0.0232	0.15	0.60	0.9290	80	80	2.01	0.0245	0.15	0.60	1.0000
25	25	2.10	0.0232	0.15	0.65	0.9666	80	80	2.01	0.0245	0.15	0.65	1.0000
25	25	2.10	0.0232	0.20	0.35	0.2032	80	80	2.01	0.0245	0.20	0.35	0.5641
25	25	2.10	0.0232	0.20	0.40	0.3245	80	80	2.01	0.0245	0.20	0.40	0.7942
25	25	2.10	0.0232	0.20	0.45	0.4650	80	80	2.01	0.0245	0.20	0.45	0.9293
25	25	2.10	0.0232	0.20	0.50	0.6065	80	80	2.01	0.0245	0.20	0.50	0.9825
25	25	2.10	0.0232	0.20	0.55	0.7324	80	80	2.01	0.0245	0.20	0.55	0.9969
25	25	2.10	0.0232	0.20	0.60	0.8330	80	80	2.01	0.0245	0.20	0.60	0.9997

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
25	25	2.10	0.0232	0.20	0.65	0.9061	80	80	2.01	0.0245	0.20	0.65	1.0000
25	25	2.10	0.0232	0.20	0.70	0.9539	80	80	2.01	0.0245	0.20	0.70	1.0000
25	25	2.10	0.0232	0.25	0.40	0.1935	80	80	2.01	0.0245	0.25	0.40	0.5257
25	25	2.10	0.0232	0.25	0.45	0.3056	80	80	2.01	0.0245	0.25	0.45	0.7577
25	25	2.10	0.0232	0.25	0.50	0.4347	80	80	2.01	0.0245	0.25	0.50	0.9071
25	25	2.10	0.0232	0.25	0.55	0.5682	80	80	2.01	0.0245	0.25	0.55	0.9748
25	25	2.10	0.0232	0.25	0.60	0.6946	80	80	2.01	0.0245	0.25	0.60	0.9955
25	25	2.10	0.0232	0.25	0.65	0.8043	80	80	2.01	0.0245	0.25	0.65	0.9995
25	25	2.10	0.0232	0.25	0.70	0.8902	80	80	2.01	0.0245	0.25	0.70	1.0000
25	25	2.10	0.0232	0.25	0.75	0.9486	80	80	2.01	0.0245	0.25	0.75	1.0000
25	25	2.10	0.0232	0.30	0.45	0.1810	80	80	2.01	0.0245	0.30	0.45	0.4896
25	25	2.10	0.0232	0.30	0.50	0.2815	80	80	2.01	0.0245	0.30	0.50	0.7265
25	25	2.10	0.0232	0.30	0.55	0.4019	80	80	2.01	0.0245	0.30	0.55	0.8931
25	25	2.10	0.0232	0.30	0.60	0.5350	80	80	2.01	0.0245	0.30	0.60	0.9713
25	25	2.10	0.0232	0.30	0.65	0.6701	80	80	2.01	0.0245	0.30	0.65	0.9950
25	25	2.10	0.0232	0.30	0.70	0.7930	80	80	2.01	0.0245	0.30	0.70	0.9995
25	25	2.10	0.0232	0.35	0.50	0.1647	80	80	2.01	0.0245	0.35	0.50	0.4717
25	25	2.10	0.0232	0.35	0.55	0.2594	80	80	2.01	0.0245	0.35	0.55	0.7165
25	25	2.10	0.0232	0.35	0.60	0.3805	80	80	2.01	0.0245	0.35	0.60	0.8894
25	25	2.10	0.0232	0.35	0.65	0.5221	80	80	2.01	0.0245	0.35	0.65	0.9705
25	25	2.10	0.0232	0.40	0.55	0.1534	80	80	2.01	0.0245	0.40	0.55	0.4698
25	25	2.10	0.0232	0.40	0.60	0.2507	80	80	2.01	0.0245	0.40	0.60	0.7151
26	26	2.06	0.0243	0.05	0.15	0.2226	90	90	2.00	0.0250	0.05	0.15	0.6317
26	26	2.06	0.0243	0.05	0.20	0.3951	90	90	2.00	0.0250	0.05	0.20	0.8904
26	26	2.06	0.0243	0.05	0.25	0.5665	90	90	2.00	0.0250	0.05	0.25	0.9794
26	26	2.06	0.0243	0.05	0.30	0.7138	90	90	2.00	0.0250	0.05	0.30	0.9975
26	26	2.06	0.0243	0.05	0.35	0.8268	90	90	2.00	0.0250	0.05	0.35	0.9998
26	26	2.06	0.0243	0.05	0.40	0.9049	90	90	2.00	0.0250	0.05	0.40	1.0000
26	26	2.06	0.0243	0.05	0.45	0.9534	90	90	2.00	0.0250	0.05	0.45	1.0000
26	26	2.06	0.0243	0.10	0.25	0.2929	90	90	2.00	0.0250	0.10	0.25	0.7668
26	26	2.06	0.0243	0.10	0.30	0.4355	90	90	2.00	0.0250	0.10	0.30	0.9317
26	26	2.06	0.0243	0.10	0.35	0.5841	90	90	2.00	0.0250	0.10	0.35	0.9867
26	26	2.06	0.0243	0.10	0.40	0.7215	90	90	2.00	0.0250	0.10	0.40	0.9983
26	26	2.06	0.0243	0.10	0.45	0.8331	90	90	2.00	0.0250	0.10	0.45	0.9999
26	26	2.06	0.0243	0.10	0.50	0.9117	90	90	2.00	0.0250	0.10	0.50	1.0000
26	26	2.06	0.0243	0.10	0.55	0.9592	90	90	2.00	0.0250	0.10	0.55	1.0000
26	26	2.06	0.0243	0.10	0.60	0.9836	90	90	2.00	0.0250	0.10	0.60	1.0000
26	26	2.06	0.0243	0.15	0.30	0.2374	90	90	2.00	0.0250	0.15	0.30	0.6784
26	26	2.06	0.0243	0.15	0.35	0.3708	90	90	2.00	0.0250	0.15	0.35	0.8815
26	26	2.06	0.0243	0.15	0.40	0.5216	90	90	2.00	0.0250	0.15	0.40	0.9699
26	26	2.06	0.0243	0.15	0.45	0.6685	90	90	2.00	0.0250	0.15	0.45	0.9949
26	26	2.06	0.0243	0.15	0.50	0.7919	90	90	2.00	0.0250	0.15	0.50	0.9994
26	26	2.06	0.0243	0.15	0.55	0.8821	90	90	2.00	0.0250	0.15	0.55	1.0000
26	26	2.06	0.0243	0.15	0.60	0.9399	90	90	2.00	0.0250	0.15	0.60	1.0000
26	26	2.06	0.0243	0.15	0.65	0.9729	90	90	2.00	0.0250	0.15	0.65	1.0000
26	26	2.06	0.0243	0.20	0.35	0.2161	90	90	2.00	0.0250	0.20	0.35	0.6135
26	26	2.06	0.0243	0.20	0.40	0.3441	90	90	2.00	0.0250	0.20	0.40	0.8366
26	26	2.06	0.0243	0.20	0.45	0.4887	90	90	2.00	0.0250	0.20	0.45	0.9526
26	26	2.06	0.0243	0.20	0.50	0.6307	90	90	2.00	0.0250	0.20	0.50	0.9910
26	26	2.06	0.0243	0.20	0.55	0.7541	90	90	2.00	0.0250	0.20	0.55	0.9989

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
26	26	2.06	0.0243	0.20	0.60	0.8508	90	90	2.00	0.0250	0.20	0.60	0.9999
26	26	2.06	0.0243	0.20	0.65	0.9194	90	90	2.00	0.0250	0.20	0.65	1.0000
26	26	2.06	0.0243	0.20	0.70	0.9626	90	90	2.00	0.0250	0.20	0.70	1.0000
26	26	2.06	0.0243	0.25	0.40	0.2056	90	90	2.00	0.0250	0.25	0.40	0.5720
26	26	2.06	0.0243	0.25	0.45	0.3222	90	90	2.00	0.0250	0.25	0.45	0.8092
26	26	2.06	0.0243	0.25	0.50	0.4548	90	90	2.00	0.0250	0.25	0.50	0.9401
26	26	2.06	0.0243	0.25	0.55	0.5906	90	90	2.00	0.0250	0.25	0.55	0.9869
26	26	2.06	0.0243	0.25	0.60	0.7178	90	90	2.00	0.0250	0.25	0.60	0.9981
26	26	2.06	0.0243	0.25	0.65	0.8257	90	90	2.00	0.0250	0.25	0.65	0.9998
26	26	2.06	0.0243	0.25	0.70	0.9068	90	90	2.00	0.0250	0.25	0.70	1.0000
26	26	2.06	0.0243	0.25	0.75	0.9588	90	90	2.00	0.0250	0.25	0.75	1.0000
26	26	2.06	0.0243	0.30	0.45	0.1905	90	90	2.00	0.0250	0.30	0.45	0.5491
26	26	2.06	0.0243	0.30	0.50	0.2958	90	90	2.00	0.0250	0.30	0.50	0.7828
26	26	2.06	0.0243	0.30	0.55	0.4219	90	90	2.00	0.0250	0.30	0.55	0.9247
26	26	2.06	0.0243	0.30	0.60	0.5602	90	90	2.00	0.0250	0.30	0.60	0.9827
26	26	2.06	0.0243	0.30	0.65	0.6972	90	90	2.00	0.0250	0.30	0.65	0.9976
26	26	2.06	0.0243	0.30	0.70	0.8169	90	90	2.00	0.0250	0.30	0.70	0.9998
26	26	2.06	0.0243	0.35	0.50	0.1738	90	90	2.00	0.0250	0.35	0.50	0.5167
26	26	2.06	0.0243	0.35	0.55	0.2750	90	90	2.00	0.0250	0.35	0.55	0.7593
26	26	2.06	0.0243	0.35	0.60	0.4034	90	90	2.00	0.0250	0.35	0.60	0.9170
26	26	2.06	0.0243	0.35	0.65	0.5497	90	90	2.00	0.0250	0.35	0.65	0.9816
26	26	2.06	0.0243	0.40	0.55	0.1639	90	90	2.00	0.0250	0.40	0.55	0.5028
26	26	2.06	0.0243	0.40	0.60	0.2678	90	90	2.00	0.0250	0.40	0.60	0.7543
27	27	2.11	0.0223	0.05	0.15	0.1936	100	100	2.01	0.0248	0.05	0.15	0.6640
27	27	2.11	0.0223	0.05	0.20	0.3482	100	100	2.01	0.0248	0.05	0.20	0.9156
27	27	2.11	0.0223	0.05	0.25	0.5229	100	100	2.01	0.0248	0.05	0.25	0.9874
27	27	2.11	0.0223	0.05	0.30	0.6882	100	100	2.01	0.0248	0.05	0.30	0.9988
27	27	2.11	0.0223	0.05	0.35	0.8188	100	100	2.01	0.0248	0.05	0.35	0.9999
27	27	2.11	0.0223	0.05	0.40	0.9065	100	100	2.01	0.0248	0.05	0.40	1.0000
27	27	2.11	0.0223	0.05	0.45	0.9575	100	100	2.01	0.0248	0.05	0.45	1.0000
27	27	2.11	0.0223	0.10	0.25	0.2731	100	100	2.01	0.0248	0.10	0.25	0.8043
27	27	2.11	0.0223	0.10	0.30	0.4298	100	100	2.01	0.0248	0.10	0.30	0.9516
27	27	2.11	0.0223	0.10	0.35	0.5916	100	100	2.01	0.0248	0.10	0.35	0.9924
27	27	2.11	0.0223	0.10	0.40	0.7351	100	100	2.01	0.0248	0.10	0.40	0.9992
27	27	2.11	0.0223	0.10	0.45	0.8456	100	100	2.01	0.0248	0.10	0.45	1.0000
27	27	2.11	0.0223	0.10	0.50	0.9197	100	100	2.01	0.0248	0.10	0.50	1.0000
27	27	2.11	0.0223	0.10	0.55	0.9629	100	100	2.01	0.0248	0.10	0.55	1.0000
27	27	2.11	0.0223	0.10	0.60	0.9850	100	100	2.01	0.0248	0.10	0.60	1.0000
27	27	2.11	0.0223	0.15	0.30	0.2393	100	100	2.01	0.0248	0.15	0.30	0.7172
27	27	2.11	0.0223	0.15	0.35	0.3797	100	100	2.01	0.0248	0.15	0.35	0.9087
27	27	2.11	0.0223	0.15	0.40	0.5325	100	100	2.01	0.0248	0.15	0.40	0.9811
27	27	2.11	0.0223	0.15	0.45	0.6766	100	100	2.01	0.0248	0.15	0.45	0.9975
27	27	2.11	0.0223	0.15	0.50	0.7958	100	100	2.01	0.0248	0.15	0.50	0.9998
27	27	2.11	0.0223	0.15	0.55	0.8836	100	100	2.01	0.0248	0.15	0.55	1.0000
27	27	2.11	0.0223	0.15	0.60	0.9413	100	100	2.01	0.0248	0.15	0.60	1.0000
27	27	2.11	0.0223	0.15	0.65	0.9746	100	100	2.01	0.0248	0.15	0.65	1.0000
27	27	2.11	0.0223	0.20	0.35	0.2183	100	100	2.01	0.0248	0.20	0.35	0.6568
27	27	2.11	0.0223	0.20	0.40	0.3445	100	100	2.01	0.0248	0.20	0.40	0.8730
27	27	2.11	0.0223	0.20	0.45	0.4858	100	100	2.01	0.0248	0.20	0.45	0.9685
27	27	2.11	0.0223	0.20	0.50	0.6269	100	100	2.01	0.0248	0.20	0.50	0.9950

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
27	27	2.11	0.0223	0.20	0.55	0.7534	100	100	2.01	0.0248	0.20	0.55	0.9995
27	27	2.11	0.0223	0.20	0.60	0.8549	100	100	2.01	0.0248	0.20	0.60	1.0000
27	27	2.11	0.0223	0.20	0.65	0.9260	100	100	2.01	0.0248	0.20	0.65	1.0000
27	27	2.11	0.0223	0.20	0.70	0.9684	100	100	2.01	0.0248	0.20	0.70	1.0000
27	27	2.11	0.0223	0.25	0.40	0.1990	100	100	2.01	0.0248	0.25	0.40	0.6121
27	27	2.11	0.0223	0.25	0.45	0.3132	100	100	2.01	0.0248	0.25	0.45	0.8428
27	27	2.11	0.0223	0.25	0.50	0.4485	100	100	2.01	0.0248	0.25	0.50	0.9585
27	27	2.11	0.0223	0.25	0.55	0.5925	100	100	2.01	0.0248	0.25	0.55	0.9931
27	27	2.11	0.0223	0.25	0.60	0.7286	100	100	2.01	0.0248	0.25	0.60	0.9993
27	27	2.11	0.0223	0.25	0.65	0.8409	100	100	2.01	0.0248	0.25	0.65	1.0000
27	27	2.11	0.0223	0.25	0.70	0.9200	100	100	2.01	0.0248	0.25	0.70	1.0000
27	27	2.11	0.0223	0.25	0.75	0.9668	100	100	2.01	0.0248	0.25	0.75	1.0000
27	27	2.11	0.0223	0.30	0.45	0.1825	100	100	2.01	0.0248	0.30	0.45	0.5895
27	27	2.11	0.0223	0.30	0.50	0.2925	100	100	2.01	0.0248	0.30	0.50	0.8281
27	27	2.11	0.0223	0.30	0.55	0.4288	100	100	2.01	0.0248	0.30	0.55	0.9507
27	27	2.11	0.0223	0.30	0.60	0.5777	100	100	2.01	0.0248	0.30	0.60	0.9906
27	27	2.11	0.0223	0.30	0.65	0.7200	100	100	2.01	0.0248	0.30	0.65	0.9989
27	27	2.11	0.0223	0.30	0.70	0.8374	100	100	2.01	0.0248	0.30	0.70	0.9999
27	27	2.11	0.0223	0.35	0.50	0.1742	100	100	2.01	0.0248	0.35	0.50	0.5715
27	27	2.11	0.0223	0.35	0.55	0.2846	100	100	2.01	0.0248	0.35	0.55	0.8061
27	27	2.11	0.0223	0.35	0.60	0.4227	100	100	2.01	0.0248	0.35	0.60	0.9403
27	27	2.11	0.0223	0.35	0.65	0.5744	100	100	2.01	0.0248	0.35	0.65	0.9889
27	27	2.11	0.0223	0.40	0.55	0.1723	100	100	2.01	0.0248	0.40	0.55	0.5417
27	27	2.11	0.0223	0.40	0.60	0.2832	100	100	2.01	0.0248	0.40	0.60	0.7914
28	28	2.10	0.0231	0.05	0.15	0.2013	150	150	2.00	0.0244	0.05	0.15	0.8320
28	28	2.10	0.0231	0.05	0.20	0.3627	150	150	2.00	0.0244	0.05	0.20	0.9833
28	28	2.10	0.0231	0.05	0.25	0.5435	150	150	2.00	0.0244	0.05	0.25	0.9993
28	28	2.10	0.0231	0.05	0.30	0.7098	150	150	2.00	0.0244	0.05	0.30	1.0000
28	28	2.10	0.0231	0.05	0.35	0.8368	150	150	2.00	0.0244	0.05	0.35	1.0000
28	28	2.10	0.0231	0.05	0.40	0.9190	150	150	2.00	0.0244	0.05	0.40	1.0000
28	28	2.10	0.0231	0.05	0.45	0.9648	150	150	2.00	0.0244	0.05	0.45	1.0000
28	28	2.10	0.0231	0.10	0.25	0.2867	150	150	2.00	0.0244	0.10	0.25	0.9351
28	28	2.10	0.0231	0.10	0.30	0.4494	150	150	2.00	0.0244	0.10	0.30	0.9937
28	28	2.10	0.0231	0.10	0.35	0.6140	150	150	2.00	0.0244	0.10	0.35	0.9997
28	28	2.10	0.0231	0.10	0.40	0.7563	150	150	2.00	0.0244	0.10	0.40	1.0000
28	28	2.10	0.0231	0.10	0.45	0.8624	150	150	2.00	0.0244	0.10	0.45	1.0000
28	28	2.10	0.0231	0.10	0.50	0.9309	150	150	2.00	0.0244	0.10	0.50	1.0000
28	28	2.10	0.0231	0.10	0.55	0.9693	150	150	2.00	0.0244	0.10	0.55	1.0000
28	28	2.10	0.0231	0.10	0.60	0.9882	150	150	2.00	0.0244	0.10	0.60	1.0000
28	28	2.10	0.0231	0.15	0.30	0.2519	150	150	2.00	0.0244	0.15	0.30	0.8780
28	28	2.10	0.0231	0.15	0.35	0.3981	150	150	2.00	0.0244	0.15	0.35	0.9819
28	28	2.10	0.0231	0.15	0.40	0.5542	150	150	2.00	0.0244	0.15	0.40	0.9987
28	28	2.10	0.0231	0.15	0.45	0.6979	150	150	2.00	0.0244	0.15	0.45	1.0000
28	28	2.10	0.0231	0.15	0.50	0.8142	150	150	2.00	0.0244	0.15	0.50	1.0000
28	28	2.10	0.0231	0.15	0.55	0.8976	150	150	2.00	0.0244	0.15	0.55	1.0000
28	28	2.10	0.0231	0.15	0.60	0.9507	150	150	2.00	0.0244	0.15	0.60	1.0000
28	28	2.10	0.0231	0.15	0.65	0.9799	150	150	2.00	0.0244	0.15	0.65	1.0000
28	28	2.10	0.0231	0.20	0.35	0.2296	150	150	2.00	0.0244	0.20	0.35	0.8278
28	28	2.10	0.0231	0.20	0.40	0.3606	150	150	2.00	0.0244	0.20	0.40	0.9679
28	28	2.10	0.0231	0.20	0.45	0.5058	150	150	2.00	0.0244	0.20	0.45	0.9969

Table B.5: continue on next page

Table B.5: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
28	28	2.10	0.0231	0.20	0.50	0.6490	150	150	2.00	0.0244	0.20	0.50	0.9998
28	28	2.10	0.0231	0.20	0.55	0.7751	150	150	2.00	0.0244	0.20	0.55	1.0000
28	28	2.10	0.0231	0.20	0.60	0.8730	150	150	2.00	0.0244	0.20	0.60	1.0000
28	28	2.10	0.0231	0.20	0.65	0.9386	150	150	2.00	0.0244	0.20	0.65	1.0000
28	28	2.10	0.0231	0.20	0.70	0.9754	150	150	2.00	0.0244	0.20	0.70	1.0000
28	28	2.10	0.0231	0.25	0.40	0.2089	150	150	2.00	0.0244	0.25	0.40	0.7887
28	28	2.10	0.0231	0.25	0.45	0.3291	150	150	2.00	0.0244	0.25	0.45	0.9538
28	28	2.10	0.0231	0.25	0.50	0.4706	150	150	2.00	0.0244	0.25	0.50	0.9949
28	28	2.10	0.0231	0.25	0.55	0.6188	150	150	2.00	0.0244	0.25	0.55	0.9997
28	28	2.10	0.0231	0.25	0.60	0.7546	150	150	2.00	0.0244	0.25	0.60	1.0000
28	28	2.10	0.0231	0.25	0.65	0.8621	150	150	2.00	0.0244	0.25	0.65	1.0000
28	28	2.10	0.0231	0.25	0.70	0.9341	150	150	2.00	0.0244	0.25	0.70	1.0000
28	28	2.10	0.0231	0.25	0.75	0.9742	150	150	2.00	0.0244	0.25	0.75	1.0000
28	28	2.10	0.0231	0.30	0.45	0.1935	150	150	2.00	0.0244	0.30	0.45	0.7649
28	28	2.10	0.0231	0.30	0.50	0.3112	150	150	2.00	0.0244	0.30	0.50	0.9446
28	28	2.10	0.0231	0.30	0.55	0.4546	150	150	2.00	0.0244	0.30	0.55	0.9928
28	28	2.10	0.0231	0.30	0.60	0.6073	150	150	2.00	0.0244	0.30	0.60	0.9995
28	28	2.10	0.0231	0.30	0.65	0.7481	150	150	2.00	0.0244	0.30	0.65	1.0000
28	28	2.10	0.0231	0.30	0.70	0.8595	150	150	2.00	0.0244	0.30	0.70	1.0000
28	28	2.10	0.0231	0.35	0.50	0.1876	150	150	2.00	0.0244	0.35	0.50	0.7402
28	28	2.10	0.0231	0.35	0.55	0.3058	150	150	2.00	0.0244	0.35	0.55	0.9324
28	28	2.10	0.0231	0.35	0.60	0.4506	150	150	2.00	0.0244	0.35	0.60	0.9911
28	28	2.10	0.0231	0.35	0.65	0.6050	150	150	2.00	0.0244	0.35	0.65	0.9995
28	28	2.10	0.0231	0.40	0.55	0.1870	150	150	2.00	0.0244	0.40	0.55	0.7223
28	28	2.10	0.0231	0.40	0.60	0.3052	150	150	2.00	0.0244	0.40	0.60	0.9292

Table B.5: concluded from previous page

Table B.6: Achieved power and p-values calculated for the z-unpooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}= \mathbf{0.01}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	10	2.76	0.0064	0.05	0.15	0.0060	29	29	2.50	0.0096	0.05	0.15	0.0816
10	10	2.76	0.0064	0.05	0.20	0.0199	29	29	2.50	0.0096	0.05	0.20	0.2085
10	10	2.76	0.0064	0.05	0.25	0.0479	29	29	2.50	0.0096	0.05	0.25	0.3797
10	10	2.76	0.0064	0.05	0.30	0.0934	29	29	2.50	0.0096	0.05	0.30	0.5620
10	10	2.76	0.0064	0.05	0.35	0.1574	29	29	2.50	0.0096	0.05	0.35	0.7238
10	10	2.76	0.0064	0.05	0.40	0.2379	29	29	2.50	0.0096	0.05	0.40	0.8458
10	10	2.76	0.0064	0.05	0.45	0.3310	29	29	2.50	0.0096	0.05	0.45	0.9244
10	10	2.76	0.0064	0.10	0.25	0.0287	29	29	2.50	0.0096	0.10	0.25	0.1662
10	10	2.76	0.0064	0.10	0.30	0.0568	29	29	2.50	0.0096	0.10	0.30	0.3002
10	10	2.76	0.0064	0.10	0.35	0.0977	29	29	2.50	0.0096	0.10	0.35	0.4601
10	10	2.76	0.0064	0.10	0.40	0.1516	29	29	2.50	0.0096	0.10	0.40	0.6214
10	10	2.76	0.0064	0.10	0.45	0.2179	29	29	2.50	0.0096	0.10	0.45	0.7616
10	10	2.76	0.0064	0.10	0.50	0.2951	29	29	2.50	0.0096	0.10	0.50	0.8673
10	10	2.76	0.0064	0.10	0.55	0.3812	29	29	2.50	0.0096	0.10	0.55	0.9361
10	10	2.76	0.0064	0.10	0.60	0.4740	29	29	2.50	0.0096	0.10	0.60	0.9740
10	10	2.76	0.0064	0.15	0.30	0.0337	29	29	2.50	0.0096	0.15	0.30	0.1426
10	10	2.76	0.0064	0.15	0.35	0.0594	29	29	2.50	0.0096	0.15	0.35	0.2569
10	10	2.76	0.0064	0.15	0.40	0.0949	29	29	2.50	0.0096	0.15	0.40	0.4017
10	10	2.76	0.0064	0.15	0.45	0.1412	29	29	2.50	0.0096	0.15	0.45	0.5602
10	10	2.76	0.0064	0.15	0.50	0.1989	29	29	2.50	0.0096	0.15	0.50	0.7102
10	10	2.76	0.0064	0.15	0.55	0.2684	29	29	2.50	0.0096	0.15	0.55	0.8318
10	10	2.76	0.0064	0.15	0.60	0.3494	29	29	2.50	0.0096	0.15	0.60	0.9152
10	10	2.76	0.0064	0.15	0.65	0.4407	29	29	2.50	0.0096	0.15	0.65	0.9632
10	10	2.76	0.0064	0.20	0.35	0.0352	29	29	2.50	0.0096	0.20	0.35	0.1287
10	10	2.76	0.0064	0.20	0.40	0.0582	29	29	2.50	0.0096	0.20	0.40	0.2337
10	10	2.76	0.0064	0.20	0.45	0.0898	29	29	2.50	0.0096	0.20	0.45	0.3727
10	10	2.76	0.0064	0.20	0.50	0.1318	29	29	2.50	0.0096	0.20	0.50	0.5300
10	10	2.76	0.0064	0.20	0.55	0.1857	29	29	2.50	0.0096	0.20	0.55	0.6817
10	10	2.76	0.0064	0.20	0.60	0.2527	29	29	2.50	0.0096	0.20	0.60	0.8068
10	10	2.76	0.0064	0.20	0.65	0.3330	29	29	2.50	0.0096	0.20	0.65	0.8957
10	10	2.76	0.0064	0.20	0.70	0.4256	29	29	2.50	0.0096	0.20	0.70	0.9510
10	10	2.76	0.0064	0.25	0.40	0.0348	29	29	2.50	0.0096	0.25	0.40	0.1236
10	10	2.76	0.0064	0.25	0.45	0.0560	29	29	2.50	0.0096	0.25	0.45	0.2244
10	10	2.76	0.0064	0.25	0.50	0.0856	29	29	2.50	0.0096	0.25	0.50	0.3571
10	10	2.76	0.0064	0.25	0.55	0.1259	29	29	2.50	0.0096	0.25	0.55	0.5063
10	10	2.76	0.0064	0.25	0.60	0.1787	29	29	2.50	0.0096	0.25	0.60	0.6522
10	10	2.76	0.0064	0.25	0.65	0.2453	29	29	2.50	0.0096	0.25	0.65	0.7789
10	10	2.76	0.0064	0.25	0.70	0.3265	29	29	2.50	0.0096	0.25	0.70	0.8773
10	10	2.76	0.0064	0.25	0.75	0.4214	29	29	2.50	0.0096	0.25	0.75	0.9441
10	10	2.76	0.0064	0.30	0.45	0.0340	29	29	2.50	0.0096	0.30	0.45	0.1213
10	10	2.76	0.0064	0.30	0.50	0.0543	29	29	2.50	0.0096	0.30	0.50	0.2148
10	10	2.76	0.0064	0.30	0.55	0.0833	29	29	2.50	0.0096	0.30	0.55	0.3366
10	10	2.76	0.0064	0.30	0.60	0.1231	29	29	2.50	0.0096	0.30	0.60	0.4775
10	10	2.76	0.0064	0.30	0.65	0.1759	29	29	2.50	0.0096	0.30	0.65	0.6252

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	10	2.76	0.0064	0.30	0.70	0.2433	29	29	2.50	0.0096	0.30	0.70	0.7643
10	10	2.76	0.0064	0.35	0.50	0.0335	29	29	2.50	0.0096	0.35	0.50	0.1144
10	10	2.76	0.0064	0.35	0.55	0.0536	29	29	2.50	0.0096	0.35	0.55	0.1996
10	10	2.76	0.0064	0.35	0.60	0.0824	29	29	2.50	0.0096	0.35	0.60	0.3166
10	10	2.76	0.0064	0.35	0.65	0.1223	29	29	2.50	0.0096	0.35	0.65	0.4627
10	10	2.76	0.0064	0.40	0.55	0.0334	29	29	2.50	0.0096	0.40	0.55	0.1063
10	10	2.76	0.0064	0.40	0.60	0.0534	29	29	2.50	0.0096	0.40	0.60	0.1915
11	11	2.63	0.0087	0.05	0.15	0.0091	30	30	2.48	0.0092	0.05	0.15	0.0887
11	11	2.63	0.0087	0.05	0.20	0.0293	30	30	2.48	0.0092	0.05	0.20	0.2232
11	11	2.63	0.0087	0.05	0.25	0.0678	30	30	2.48	0.0092	0.05	0.25	0.4011
11	11	2.63	0.0087	0.05	0.30	0.1271	30	30	2.48	0.0092	0.05	0.30	0.5867
11	11	2.63	0.0087	0.05	0.35	0.2063	30	30	2.48	0.0092	0.05	0.35	0.7470
11	11	2.63	0.0087	0.05	0.40	0.3011	30	30	2.48	0.0092	0.05	0.40	0.8637
11	11	2.63	0.0087	0.05	0.45	0.4056	30	30	2.48	0.0092	0.05	0.45	0.9359
11	11	2.63	0.0087	0.10	0.25	0.0391	30	30	2.48	0.0092	0.10	0.25	0.1770
11	11	2.63	0.0087	0.10	0.30	0.0752	30	30	2.48	0.0092	0.10	0.30	0.3179
11	11	2.63	0.0087	0.10	0.35	0.1261	30	30	2.48	0.0092	0.10	0.35	0.4832
11	11	2.63	0.0087	0.10	0.40	0.1914	30	30	2.48	0.0092	0.10	0.40	0.6461
11	11	2.63	0.0087	0.10	0.45	0.2699	30	30	2.48	0.0092	0.10	0.45	0.7838
11	11	2.63	0.0087	0.10	0.50	0.3595	30	30	2.48	0.0092	0.10	0.50	0.8840
11	11	2.63	0.0087	0.10	0.55	0.4572	30	30	2.48	0.0092	0.10	0.55	0.9464
11	11	2.63	0.0087	0.10	0.60	0.5590	30	30	2.48	0.0092	0.10	0.60	0.9790
11	11	2.63	0.0087	0.15	0.30	0.0435	30	30	2.48	0.0092	0.15	0.30	0.1519
11	11	2.63	0.0087	0.15	0.35	0.0756	30	30	2.48	0.0092	0.15	0.35	0.2728
11	11	2.63	0.0087	0.15	0.40	0.1198	30	30	2.48	0.0092	0.15	0.40	0.4237
11	11	2.63	0.0087	0.15	0.45	0.1772	30	30	2.48	0.0092	0.15	0.45	0.5850
11	11	2.63	0.0087	0.15	0.50	0.2483	30	30	2.48	0.0092	0.15	0.50	0.7323
11	11	2.63	0.0087	0.15	0.55	0.3327	30	30	2.48	0.0092	0.15	0.55	0.8470
11	11	2.63	0.0087	0.15	0.60	0.4284	30	30	2.48	0.0092	0.15	0.60	0.9231
11	11	2.63	0.0087	0.15	0.65	0.5318	30	30	2.48	0.0092	0.15	0.65	0.9664
11	11	2.63	0.0087	0.20	0.35	0.0444	30	30	2.48	0.0092	0.20	0.35	0.1375
11	11	2.63	0.0087	0.20	0.40	0.0736	30	30	2.48	0.0092	0.20	0.40	0.2480
11	11	2.63	0.0087	0.20	0.45	0.1144	30	30	2.48	0.0092	0.20	0.45	0.3903
11	11	2.63	0.0087	0.20	0.50	0.1685	30	30	2.48	0.0092	0.20	0.50	0.5460
11	11	2.63	0.0087	0.20	0.55	0.2373	30	30	2.48	0.0092	0.20	0.55	0.6922
11	11	2.63	0.0087	0.20	0.60	0.3206	30	30	2.48	0.0092	0.20	0.60	0.8120
11	11	2.63	0.0087	0.20	0.65	0.4166	30	30	2.48	0.0092	0.20	0.65	0.8987
11	11	2.63	0.0087	0.20	0.70	0.5215	30	30	2.48	0.0092	0.20	0.70	0.9536
11	11	2.63	0.0087	0.25	0.40	0.0443	30	30	2.48	0.0092	0.25	0.40	0.1298
11	11	2.63	0.0087	0.25	0.45	0.0723	30	30	2.48	0.0092	0.25	0.45	0.2314
11	11	2.63	0.0087	0.25	0.50	0.1119	30	30	2.48	0.0092	0.25	0.50	0.3617
11	11	2.63	0.0087	0.25	0.55	0.1651	30	30	2.48	0.0092	0.25	0.55	0.5074
11	11	2.63	0.0087	0.25	0.60	0.2333	30	30	2.48	0.0092	0.25	0.60	0.6525
11	11	2.63	0.0087	0.25	0.65	0.3165	30	30	2.48	0.0092	0.25	0.65	0.7816
11	11	2.63	0.0087	0.25	0.70	0.4129	30	30	2.48	0.0092	0.25	0.70	0.8823
11	11	2.63	0.0087	0.25	0.75	0.5191	30	30	2.48	0.0092	0.25	0.75	0.9484
11	11	2.63	0.0087	0.30	0.45	0.0446	30	30	2.48	0.0092	0.30	0.45	0.1209
11	11	2.63	0.0087	0.30	0.50	0.0723	30	30	2.48	0.0092	0.30	0.50	0.2115
11	11	2.63	0.0087	0.30	0.55	0.1116	30	30	2.48	0.0092	0.30	0.55	0.3316
11	11	2.63	0.0087	0.30	0.60	0.1645	30	30	2.48	0.0092	0.30	0.60	0.4748

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
11	11	2.63	0.0087	0.30	0.65	0.2325	30	30	2.48	0.0092	0.30	0.65	0.6276
11	11	2.63	0.0087	0.30	0.70	0.3157	30	30	2.48	0.0092	0.30	0.70	0.7701
11	11	2.63	0.0087	0.35	0.50	0.0453	30	30	2.48	0.0092	0.35	0.50	0.1092
11	11	2.63	0.0087	0.35	0.55	0.0730	30	30	2.48	0.0092	0.35	0.55	0.1935
11	11	2.63	0.0087	0.35	0.60	0.1120	30	30	2.48	0.0092	0.35	0.60	0.3126
11	11	2.63	0.0087	0.35	0.65	0.1646	30	30	2.48	0.0092	0.35	0.65	0.4627
11	11	2.63	0.0087	0.40	0.55	0.0459	30	30	2.48	0.0092	0.40	0.55	0.1013
11	11	2.63	0.0087	0.40	0.60	0.0733	30	30	2.48	0.0092	0.40	0.60	0.1867
12	12	2.83	0.0087	0.05	0.15	0.0132	31	31	2.44	0.0097	0.05	0.15	0.1343
12	12	2.83	0.0087	0.05	0.20	0.0406	31	31	2.44	0.0097	0.05	0.20	0.2713
12	12	2.83	0.0087	0.05	0.25	0.0903	31	31	2.44	0.0097	0.05	0.25	0.4414
12	12	2.83	0.0087	0.05	0.30	0.1634	31	31	2.44	0.0097	0.05	0.30	0.6185
12	12	2.83	0.0087	0.05	0.35	0.2566	31	31	2.44	0.0097	0.05	0.35	0.7711
12	12	2.83	0.0087	0.05	0.40	0.3633	31	31	2.44	0.0097	0.05	0.40	0.8804
12	12	2.83	0.0087	0.05	0.45	0.4760	31	31	2.44	0.0097	0.05	0.45	0.9460
12	12	2.83	0.0087	0.10	0.25	0.0505	31	31	2.44	0.0097	0.10	0.25	0.1915
12	12	2.83	0.0087	0.10	0.30	0.0948	31	31	2.44	0.0097	0.10	0.30	0.3372
12	12	2.83	0.0087	0.10	0.35	0.1555	31	31	2.44	0.0097	0.10	0.35	0.5064
12	12	2.83	0.0087	0.10	0.40	0.2317	31	31	2.44	0.0097	0.10	0.40	0.6701
12	12	2.83	0.0087	0.10	0.45	0.3212	31	31	2.44	0.0097	0.10	0.45	0.8048
12	12	2.83	0.0087	0.10	0.50	0.4202	31	31	2.44	0.0097	0.10	0.50	0.8994
12	12	2.83	0.0087	0.10	0.55	0.5239	31	31	2.44	0.0097	0.10	0.55	0.9556
12	12	2.83	0.0087	0.10	0.60	0.6265	31	31	2.44	0.0097	0.10	0.60	0.9835
12	12	2.83	0.0087	0.15	0.30	0.0538	31	31	2.44	0.0097	0.15	0.30	0.1618
12	12	2.83	0.0087	0.15	0.35	0.0924	31	31	2.44	0.0097	0.15	0.35	0.2893
12	12	2.83	0.0087	0.15	0.40	0.1450	31	31	2.44	0.0097	0.15	0.40	0.4466
12	12	2.83	0.0087	0.15	0.45	0.2120	31	31	2.44	0.0097	0.15	0.45	0.6108
12	12	2.83	0.0087	0.15	0.50	0.2927	31	31	2.44	0.0097	0.15	0.50	0.7560
12	12	2.83	0.0087	0.15	0.55	0.3844	31	31	2.44	0.0097	0.15	0.55	0.8649
12	12	2.83	0.0087	0.15	0.60	0.4830	31	31	2.44	0.0097	0.15	0.60	0.9344
12	12	2.83	0.0087	0.15	0.65	0.5835	31	31	2.44	0.0097	0.15	0.65	0.9725
12	12	2.83	0.0087	0.20	0.35	0.0536	31	31	2.44	0.0097	0.20	0.35	0.1471
12	12	2.83	0.0087	0.20	0.40	0.0885	31	31	2.44	0.0097	0.20	0.40	0.2645
12	12	2.83	0.0087	0.20	0.45	0.1362	31	31	2.44	0.0097	0.20	0.45	0.4126
12	12	2.83	0.0087	0.20	0.50	0.1975	31	31	2.44	0.0097	0.20	0.50	0.5705
12	12	2.83	0.0087	0.20	0.55	0.2720	31	31	2.44	0.0097	0.20	0.55	0.7151
12	12	2.83	0.0087	0.20	0.60	0.3580	31	31	2.44	0.0097	0.20	0.60	0.8309
12	12	2.83	0.0087	0.20	0.65	0.4528	31	31	2.44	0.0097	0.20	0.65	0.9125
12	12	2.83	0.0087	0.20	0.70	0.5532	31	31	2.44	0.0097	0.20	0.70	0.9621
12	12	2.83	0.0087	0.25	0.40	0.0525	31	31	2.44	0.0097	0.25	0.40	0.1390
12	12	2.83	0.0087	0.25	0.45	0.0847	31	31	2.44	0.0097	0.25	0.45	0.2459
12	12	2.83	0.0087	0.25	0.50	0.1287	31	31	2.44	0.0097	0.25	0.50	0.3809
12	12	2.83	0.0087	0.25	0.55	0.1855	31	31	2.44	0.0097	0.25	0.55	0.5302
12	12	2.83	0.0087	0.25	0.60	0.2558	31	31	2.44	0.0097	0.25	0.60	0.6769
12	12	2.83	0.0087	0.25	0.65	0.3391	31	31	2.44	0.0097	0.25	0.65	0.8043
12	12	2.83	0.0087	0.25	0.70	0.4349	31	31	2.44	0.0097	0.25	0.70	0.8995
12	12	2.83	0.0087	0.25	0.75	0.5415	31	31	2.44	0.0097	0.25	0.75	0.9584
12	12	2.83	0.0087	0.30	0.45	0.0508	31	31	2.44	0.0097	0.30	0.45	0.1285
12	12	2.83	0.0087	0.30	0.50	0.0809	31	31	2.44	0.0097	0.30	0.50	0.2242
12	12	2.83	0.0087	0.30	0.55	0.1221	31	31	2.44	0.0097	0.30	0.55	0.3508

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
12	12	2.83	0.0087	0.30	0.60	0.1766	31	31	2.44	0.0097	0.30	0.60	0.5004
12	12	2.83	0.0087	0.30	0.65	0.2460	31	31	2.44	0.0097	0.30	0.65	0.6561
12	12	2.83	0.0087	0.30	0.70	0.3319	31	31	2.44	0.0097	0.30	0.70	0.7953
12	12	2.83	0.0087	0.35	0.50	0.0489	31	31	2.44	0.0097	0.35	0.50	0.1166
12	12	2.83	0.0087	0.35	0.55	0.0776	31	31	2.44	0.0097	0.35	0.55	0.2074
12	12	2.83	0.0087	0.35	0.60	0.1180	31	31	2.44	0.0097	0.35	0.60	0.3346
12	12	2.83	0.0087	0.35	0.65	0.1731	31	31	2.44	0.0097	0.35	0.65	0.4906
12	12	2.83	0.0087	0.40	0.55	0.0476	31	31	2.44	0.0097	0.40	0.55	0.1098
12	12	2.83	0.0087	0.40	0.60	0.0763	31	31	2.44	0.0097	0.40	0.60	0.2019
13	13	2.67	0.0096	0.05	0.15	0.0180	32	32	2.46	0.0091	0.05	0.15	0.1031
13	13	2.67	0.0096	0.05	0.20	0.0535	32	32	2.46	0.0091	0.05	0.20	0.2524
13	13	2.67	0.0096	0.05	0.25	0.1149	32	32	2.46	0.0091	0.05	0.25	0.4431
13	13	2.67	0.0096	0.05	0.30	0.2014	32	32	2.46	0.0091	0.05	0.30	0.6335
13	13	2.67	0.0096	0.05	0.35	0.3071	32	32	2.46	0.0091	0.05	0.35	0.7889
13	13	2.67	0.0096	0.05	0.40	0.4235	32	32	2.46	0.0091	0.05	0.40	0.8942
13	13	2.67	0.0096	0.05	0.45	0.5417	32	32	2.46	0.0091	0.05	0.45	0.9543
13	13	2.67	0.0096	0.10	0.25	0.0627	32	32	2.46	0.0091	0.10	0.25	0.1990
13	13	2.67	0.0096	0.10	0.30	0.1153	32	32	2.46	0.0091	0.10	0.30	0.3533
13	13	2.67	0.0096	0.10	0.35	0.1861	32	32	2.46	0.0091	0.10	0.35	0.5275
13	13	2.67	0.0096	0.10	0.40	0.2732	32	32	2.46	0.0091	0.10	0.40	0.6911
13	13	2.67	0.0096	0.10	0.45	0.3730	32	32	2.46	0.0091	0.10	0.45	0.8214
13	13	2.67	0.0096	0.10	0.50	0.4799	32	32	2.46	0.0091	0.10	0.50	0.9097
13	13	2.67	0.0096	0.10	0.55	0.5874	32	32	2.46	0.0091	0.10	0.55	0.9605
13	13	2.67	0.0096	0.10	0.60	0.6885	32	32	2.46	0.0091	0.10	0.60	0.9853
13	13	2.67	0.0096	0.15	0.30	0.0646	32	32	2.46	0.0091	0.15	0.30	0.1705
13	13	2.67	0.0096	0.15	0.35	0.1104	32	32	2.46	0.0091	0.15	0.35	0.3029
13	13	2.67	0.0096	0.15	0.40	0.1720	32	32	2.46	0.0091	0.15	0.40	0.4621
13	13	2.67	0.0096	0.15	0.45	0.2490	32	32	2.46	0.0091	0.15	0.45	0.6238
13	13	2.67	0.0096	0.15	0.50	0.3388	32	32	2.46	0.0091	0.15	0.50	0.7641
13	13	2.67	0.0096	0.15	0.55	0.4370	32	32	2.46	0.0091	0.15	0.55	0.8689
13	13	2.67	0.0096	0.15	0.60	0.5381	32	32	2.46	0.0091	0.15	0.60	0.9368
13	13	2.67	0.0096	0.15	0.65	0.6367	32	32	2.46	0.0091	0.15	0.65	0.9745
13	13	2.67	0.0096	0.20	0.35	0.0637	32	32	2.46	0.0091	0.20	0.35	0.1520
13	13	2.67	0.0096	0.20	0.40	0.1048	32	32	2.46	0.0091	0.20	0.40	0.2692
13	13	2.67	0.0096	0.20	0.45	0.1599	32	32	2.46	0.0091	0.20	0.45	0.4148
13	13	2.67	0.0096	0.20	0.50	0.2287	32	32	2.46	0.0091	0.20	0.50	0.5708
13	13	2.67	0.0096	0.20	0.55	0.3095	32	32	2.46	0.0091	0.20	0.55	0.7170
13	13	2.67	0.0096	0.20	0.60	0.3995	32	32	2.46	0.0091	0.20	0.60	0.8365
13	13	2.67	0.0096	0.20	0.65	0.4960	32	32	2.46	0.0091	0.20	0.65	0.9199
13	13	2.67	0.0096	0.20	0.70	0.5959	32	32	2.46	0.0091	0.20	0.70	0.9680
13	13	2.67	0.0096	0.25	0.40	0.0614	32	32	2.46	0.0091	0.25	0.40	0.1370
13	13	2.67	0.0096	0.25	0.45	0.0984	32	32	2.46	0.0091	0.25	0.45	0.2417
13	13	2.67	0.0096	0.25	0.50	0.1474	32	32	2.46	0.0091	0.25	0.50	0.3783
13	13	2.67	0.0096	0.25	0.55	0.2089	32	32	2.46	0.0091	0.25	0.55	0.5345
13	13	2.67	0.0096	0.25	0.60	0.2832	32	32	2.46	0.0091	0.25	0.60	0.6897
13	13	2.67	0.0096	0.25	0.65	0.3702	32	32	2.46	0.0091	0.25	0.65	0.8210
13	13	2.67	0.0096	0.25	0.70	0.4696	32	32	2.46	0.0091	0.25	0.70	0.9135
13	13	2.67	0.0096	0.25	0.75	0.5798	32	32	2.46	0.0091	0.25	0.75	0.9663
13	13	2.67	0.0096	0.30	0.45	0.0577	32	32	2.46	0.0091	0.30	0.45	0.1244
13	13	2.67	0.0096	0.30	0.50	0.0906	32	32	2.46	0.0091	0.30	0.50	0.2236

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
13	13	2.67	0.0096	0.30	0.55	0.1349	32	32	2.46	0.0091	0.30	0.55	0.3593
13	13	2.67	0.0096	0.30	0.60	0.1929	32	32	2.46	0.0091	0.30	0.60	0.5195
13	13	2.67	0.0096	0.30	0.65	0.2668	32	32	2.46	0.0091	0.30	0.65	0.6808
13	13	2.67	0.0096	0.30	0.70	0.3588	32	32	2.46	0.0091	0.30	0.70	0.8175
13	13	2.67	0.0096	0.35	0.50	0.0532	32	32	2.46	0.0091	0.35	0.50	0.1183
13	13	2.67	0.0096	0.35	0.55	0.0837	32	32	2.46	0.0091	0.35	0.55	0.2171
13	13	2.67	0.0096	0.35	0.60	0.1268	32	32	2.46	0.0091	0.35	0.60	0.3541
13	13	2.67	0.0096	0.35	0.65	0.1865	32	32	2.46	0.0091	0.35	0.65	0.5166
13	13	2.67	0.0096	0.40	0.55	0.0501	32	32	2.46	0.0091	0.40	0.55	0.1172
13	13	2.67	0.0096	0.40	0.60	0.0809	32	32	2.46	0.0091	0.40	0.60	0.2162
14	14	2.65	0.0083	0.05	0.15	0.0236	33	33	2.43	0.0094	0.05	0.15	0.1105
14	14	2.65	0.0083	0.05	0.20	0.0675	33	33	2.43	0.0094	0.05	0.20	0.2670
14	14	2.65	0.0083	0.05	0.25	0.1401	33	33	2.43	0.0094	0.05	0.25	0.4637
14	14	2.65	0.0083	0.05	0.30	0.2374	33	33	2.43	0.0094	0.05	0.30	0.6556
14	14	2.65	0.0083	0.05	0.35	0.3506	33	33	2.43	0.0094	0.05	0.35	0.8076
14	14	2.65	0.0083	0.05	0.40	0.4696	33	33	2.43	0.0094	0.05	0.40	0.9071
14	14	2.65	0.0083	0.05	0.45	0.5850	33	33	2.43	0.0094	0.05	0.45	0.9615
14	14	2.65	0.0083	0.10	0.25	0.0733	33	33	2.43	0.0094	0.10	0.25	0.2102
14	14	2.65	0.0083	0.10	0.30	0.1306	33	33	2.43	0.0094	0.10	0.30	0.3709
14	14	2.65	0.0083	0.10	0.35	0.2044	33	33	2.43	0.0094	0.10	0.35	0.5490
14	14	2.65	0.0083	0.10	0.40	0.2915	33	33	2.43	0.0094	0.10	0.40	0.7124
14	14	2.65	0.0083	0.10	0.45	0.3879	33	33	2.43	0.0094	0.10	0.45	0.8387
14	14	2.65	0.0083	0.10	0.50	0.4892	33	33	2.43	0.0094	0.10	0.50	0.9214
14	14	2.65	0.0083	0.10	0.55	0.5910	33	33	2.43	0.0094	0.10	0.55	0.9670
14	14	2.65	0.0083	0.10	0.60	0.6886	33	33	2.43	0.0094	0.10	0.60	0.9883
14	14	2.65	0.0083	0.15	0.30	0.0692	33	33	2.43	0.0094	0.15	0.30	0.1802
14	14	2.65	0.0083	0.15	0.35	0.1144	33	33	2.43	0.0094	0.15	0.35	0.3188
14	14	2.65	0.0083	0.15	0.40	0.1732	33	33	2.43	0.0094	0.15	0.40	0.4828
14	14	2.65	0.0083	0.15	0.45	0.2454	33	33	2.43	0.0094	0.15	0.45	0.6457
14	14	2.65	0.0083	0.15	0.50	0.3304	33	33	2.43	0.0094	0.15	0.50	0.7834
14	14	2.65	0.0083	0.15	0.55	0.4262	33	33	2.43	0.0094	0.15	0.55	0.8836
14	14	2.65	0.0083	0.15	0.60	0.5296	33	33	2.43	0.0094	0.15	0.60	0.9463
14	14	2.65	0.0083	0.15	0.65	0.6355	33	33	2.43	0.0094	0.15	0.65	0.9796
14	14	2.65	0.0083	0.20	0.35	0.0615	33	33	2.43	0.0094	0.20	0.35	0.1608
14	14	2.65	0.0083	0.20	0.40	0.0987	33	33	2.43	0.0094	0.20	0.40	0.2835
14	14	2.65	0.0083	0.20	0.45	0.1490	33	33	2.43	0.0094	0.20	0.45	0.4341
14	14	2.65	0.0083	0.20	0.50	0.2141	33	33	2.43	0.0094	0.20	0.50	0.5931
14	14	2.65	0.0083	0.20	0.55	0.2949	33	33	2.43	0.0094	0.20	0.55	0.7394
14	14	2.65	0.0083	0.20	0.60	0.3906	33	33	2.43	0.0094	0.20	0.60	0.8553
14	14	2.65	0.0083	0.20	0.65	0.4980	33	33	2.43	0.0094	0.20	0.65	0.9326
14	14	2.65	0.0083	0.20	0.70	0.6113	33	33	2.43	0.0094	0.20	0.70	0.9747
14	14	2.65	0.0083	0.25	0.40	0.0541	33	33	2.43	0.0094	0.25	0.40	0.1448
14	14	2.65	0.0083	0.25	0.45	0.0871	33	33	2.43	0.0094	0.25	0.45	0.2554
14	14	2.65	0.0083	0.25	0.50	0.1336	33	33	2.43	0.0094	0.25	0.50	0.3989
14	14	2.65	0.0083	0.25	0.55	0.1963	33	33	2.43	0.0094	0.25	0.55	0.5604
14	14	2.65	0.0083	0.25	0.60	0.2768	33	33	2.43	0.0094	0.25	0.60	0.7164
14	14	2.65	0.0083	0.25	0.65	0.3745	33	33	2.43	0.0094	0.25	0.65	0.8430
14	14	2.65	0.0083	0.25	0.70	0.4860	33	33	2.43	0.0094	0.25	0.70	0.9278
14	14	2.65	0.0083	0.25	0.75	0.6047	33	33	2.43	0.0094	0.25	0.75	0.9735
14	14	2.65	0.0083	0.30	0.45	0.0490	33	33	2.43	0.0094	0.30	0.45	0.1328

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
14	14	2.65	0.0083	0.30	0.50	0.0803	33	33	2.43	0.0094	0.30	0.50	0.2393
14	14	2.65	0.0083	0.30	0.55	0.1258	33	33	2.43	0.0094	0.30	0.55	0.3831
14	14	2.65	0.0083	0.30	0.60	0.1884	33	33	2.43	0.0094	0.30	0.60	0.5487
14	14	2.65	0.0083	0.30	0.65	0.2700	33	33	2.43	0.0094	0.30	0.65	0.7095
14	14	2.65	0.0083	0.30	0.70	0.3702	33	33	2.43	0.0094	0.30	0.70	0.8403
14	14	2.65	0.0083	0.35	0.50	0.0463	33	33	2.43	0.0094	0.35	0.50	0.1284
14	14	2.65	0.0083	0.35	0.55	0.0773	33	33	2.43	0.0094	0.35	0.55	0.2350
14	14	2.65	0.0083	0.35	0.60	0.1229	33	33	2.43	0.0094	0.35	0.60	0.3797
14	14	2.65	0.0083	0.35	0.65	0.1863	33	33	2.43	0.0094	0.35	0.65	0.5466
14	14	2.65	0.0083	0.40	0.55	0.0454	33	33	2.43	0.0094	0.40	0.55	0.1283
14	14	2.65	0.0083	0.40	0.60	0.0765	33	33	2.43	0.0094	0.40	0.60	0.2348
15	15	2.57	0.0088	0.05	0.15	0.0299	34	34	2.54	0.0093	0.05	0.15	0.1170
15	15	2.57	0.0088	0.05	0.20	0.0828	34	34	2.54	0.0093	0.05	0.20	0.2764
15	15	2.57	0.0088	0.05	0.25	0.1665	34	34	2.54	0.0093	0.05	0.25	0.4699
15	15	2.57	0.0088	0.05	0.30	0.2746	34	34	2.54	0.0093	0.05	0.30	0.6555
15	15	2.57	0.0088	0.05	0.35	0.3960	34	34	2.54	0.0093	0.05	0.35	0.8037
15	15	2.57	0.0088	0.05	0.40	0.5192	34	34	2.54	0.0093	0.05	0.40	0.9035
15	15	2.57	0.0088	0.05	0.45	0.6349	34	34	2.54	0.0093	0.05	0.45	0.9599
15	15	2.57	0.0088	0.10	0.25	0.0852	34	34	2.54	0.0093	0.10	0.25	0.2002
15	15	2.57	0.0088	0.10	0.30	0.1493	34	34	2.54	0.0093	0.10	0.30	0.3547
15	15	2.57	0.0088	0.10	0.35	0.2305	34	34	2.54	0.0093	0.10	0.35	0.5333
15	15	2.57	0.0088	0.10	0.40	0.3252	34	34	2.54	0.0093	0.10	0.40	0.7025
15	15	2.57	0.0088	0.10	0.45	0.4287	34	34	2.54	0.0093	0.10	0.45	0.8344
15	15	2.57	0.0088	0.10	0.50	0.5358	34	34	2.54	0.0093	0.10	0.50	0.9202
15	15	2.57	0.0088	0.10	0.55	0.6412	34	34	2.54	0.0093	0.10	0.55	0.9672
15	15	2.57	0.0088	0.10	0.60	0.7394	34	34	2.54	0.0093	0.10	0.60	0.9888
15	15	2.57	0.0088	0.15	0.30	0.0779	34	34	2.54	0.0093	0.15	0.30	0.1670
15	15	2.57	0.0088	0.15	0.35	0.1284	34	34	2.54	0.0093	0.15	0.35	0.3046
15	15	2.57	0.0088	0.15	0.40	0.1943	34	34	2.54	0.0093	0.15	0.40	0.4710
15	15	2.57	0.0088	0.15	0.45	0.2755	34	34	2.54	0.0093	0.15	0.45	0.6384
15	15	2.57	0.0088	0.15	0.50	0.3706	34	34	2.54	0.0093	0.15	0.50	0.7817
15	15	2.57	0.0088	0.15	0.55	0.4764	34	34	2.54	0.0093	0.15	0.55	0.8864
15	15	2.57	0.0088	0.15	0.60	0.5876	34	34	2.54	0.0093	0.15	0.60	0.9504
15	15	2.57	0.0088	0.15	0.65	0.6968	34	34	2.54	0.0093	0.15	0.65	0.9825
15	15	2.57	0.0088	0.20	0.35	0.0686	34	34	2.54	0.0093	0.20	0.35	0.1507
15	15	2.57	0.0088	0.20	0.40	0.1114	34	34	2.54	0.0093	0.20	0.40	0.2731
15	15	2.57	0.0088	0.20	0.45	0.1699	34	34	2.54	0.0093	0.20	0.45	0.4282
15	15	2.57	0.0088	0.20	0.50	0.2459	34	34	2.54	0.0093	0.20	0.50	0.5959
15	15	2.57	0.0088	0.20	0.55	0.3393	34	34	2.54	0.0093	0.20	0.55	0.7494
15	15	2.57	0.0088	0.20	0.60	0.4473	34	34	2.54	0.0093	0.20	0.60	0.8666
15	15	2.57	0.0088	0.20	0.65	0.5636	34	34	2.54	0.0093	0.20	0.65	0.9403
15	15	2.57	0.0088	0.20	0.70	0.6796	34	34	2.54	0.0093	0.20	0.70	0.9781
15	15	2.57	0.0088	0.25	0.40	0.0614	34	34	2.54	0.0093	0.25	0.40	0.1389
15	15	2.57	0.0088	0.25	0.45	0.1009	34	34	2.54	0.0093	0.25	0.45	0.2544
15	15	2.57	0.0088	0.25	0.50	0.1570	34	34	2.54	0.0093	0.25	0.50	0.4067
15	15	2.57	0.0088	0.25	0.55	0.2321	34	34	2.54	0.0093	0.25	0.55	0.5756
15	15	2.57	0.0088	0.25	0.60	0.3262	34	34	2.54	0.0093	0.25	0.60	0.7322
15	15	2.57	0.0088	0.25	0.65	0.4363	34	34	2.54	0.0093	0.25	0.65	0.8539
15	15	2.57	0.0088	0.25	0.70	0.5557	34	34	2.54	0.0093	0.25	0.70	0.9332
15	15	2.57	0.0088	0.25	0.75	0.6755	34	34	2.54	0.0093	0.25	0.75	0.9758

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
15	15	2.57	0.0088	0.30	0.45	0.0577	34	34	2.54	0.0093	0.30	0.45	0.1345
15	15	2.57	0.0088	0.30	0.50	0.0963	34	34	2.54	0.0093	0.30	0.50	0.2475
15	15	2.57	0.0088	0.30	0.55	0.1522	34	34	2.54	0.0093	0.30	0.55	0.3963
15	15	2.57	0.0088	0.30	0.60	0.2275	34	34	2.54	0.0093	0.30	0.60	0.5622
15	15	2.57	0.0088	0.30	0.65	0.3223	34	34	2.54	0.0093	0.30	0.65	0.7199
15	15	2.57	0.0088	0.30	0.70	0.4338	34	34	2.54	0.0093	0.30	0.70	0.8476
15	15	2.57	0.0088	0.35	0.50	0.0566	34	34	2.54	0.0093	0.35	0.50	0.1331
15	15	2.57	0.0088	0.35	0.55	0.0953	34	34	2.54	0.0093	0.35	0.55	0.2422
15	15	2.57	0.0088	0.35	0.60	0.1511	34	34	2.54	0.0093	0.35	0.60	0.3878
15	15	2.57	0.0088	0.35	0.65	0.2266	34	34	2.54	0.0093	0.35	0.65	0.5553
15	15	2.57	0.0088	0.40	0.55	0.0566	34	34	2.54	0.0093	0.40	0.55	0.1308
15	15	2.57	0.0088	0.40	0.60	0.0952	34	34	2.54	0.0093	0.40	0.60	0.2389
16	16	2.51	0.0094	0.05	0.15	0.0369	35	35	2.50	0.0095	0.05	0.15	0.1243
16	16	2.51	0.0094	0.05	0.20	0.0989	35	35	2.50	0.0095	0.05	0.20	0.2899
16	16	2.51	0.0094	0.05	0.25	0.1934	35	35	2.50	0.0095	0.05	0.25	0.4879
16	16	2.51	0.0094	0.05	0.30	0.3111	35	35	2.50	0.0095	0.05	0.30	0.6745
16	16	2.51	0.0094	0.05	0.35	0.4391	35	35	2.50	0.0095	0.05	0.35	0.8200
16	16	2.51	0.0094	0.05	0.40	0.5651	35	35	2.50	0.0095	0.05	0.40	0.9149
16	16	2.51	0.0094	0.05	0.45	0.6798	35	35	2.50	0.0095	0.05	0.45	0.9662
16	16	2.51	0.0094	0.10	0.25	0.0970	35	35	2.50	0.0095	0.10	0.25	0.2099
16	16	2.51	0.0094	0.10	0.30	0.1678	35	35	2.50	0.0095	0.10	0.30	0.3713
16	16	2.51	0.0094	0.10	0.35	0.2564	35	35	2.50	0.0095	0.10	0.35	0.5546
16	16	2.51	0.0094	0.10	0.40	0.3586	35	35	2.50	0.0095	0.10	0.40	0.7234
16	16	2.51	0.0094	0.10	0.45	0.4690	35	35	2.50	0.0095	0.10	0.45	0.8508
16	16	2.51	0.0094	0.10	0.50	0.5814	35	35	2.50	0.0095	0.10	0.50	0.9307
16	16	2.51	0.0094	0.10	0.55	0.6891	35	35	2.50	0.0095	0.10	0.55	0.9728
16	16	2.51	0.0094	0.10	0.60	0.7856	35	35	2.50	0.0095	0.10	0.60	0.9912
16	16	2.51	0.0094	0.15	0.30	0.0866	35	35	2.50	0.0095	0.15	0.30	0.1767
16	16	2.51	0.0094	0.15	0.35	0.1429	35	35	2.50	0.0095	0.15	0.35	0.3206
16	16	2.51	0.0094	0.15	0.40	0.2166	35	35	2.50	0.0095	0.15	0.40	0.4915
16	16	2.51	0.0094	0.15	0.45	0.3075	35	35	2.50	0.0095	0.15	0.45	0.6602
16	16	2.51	0.0094	0.15	0.50	0.4129	35	35	2.50	0.0095	0.15	0.50	0.8011
16	16	2.51	0.0094	0.15	0.55	0.5278	35	35	2.50	0.0095	0.15	0.55	0.9005
16	16	2.51	0.0094	0.15	0.60	0.6441	35	35	2.50	0.0095	0.15	0.60	0.9587
16	16	2.51	0.0094	0.15	0.65	0.7524	35	35	2.50	0.0095	0.15	0.65	0.9861
16	16	2.51	0.0094	0.20	0.35	0.0763	35	35	2.50	0.0095	0.20	0.35	0.1595
16	16	2.51	0.0094	0.20	0.40	0.1256	35	35	2.50	0.0095	0.20	0.40	0.2881
16	16	2.51	0.0094	0.20	0.45	0.1934	35	35	2.50	0.0095	0.20	0.45	0.4495
16	16	2.51	0.0094	0.20	0.50	0.2811	35	35	2.50	0.0095	0.20	0.50	0.6202
16	16	2.51	0.0094	0.20	0.55	0.3868	35	35	2.50	0.0095	0.20	0.55	0.7715
16	16	2.51	0.0094	0.20	0.60	0.5048	35	35	2.50	0.0095	0.20	0.60	0.8821
16	16	2.51	0.0094	0.20	0.65	0.6262	35	35	2.50	0.0095	0.20	0.65	0.9486
16	16	2.51	0.0094	0.20	0.70	0.7402	35	35	2.50	0.0095	0.20	0.70	0.9814
16	16	2.51	0.0094	0.25	0.40	0.0701	35	35	2.50	0.0095	0.25	0.40	0.1481
16	16	2.51	0.0094	0.25	0.45	0.1171	35	35	2.50	0.0095	0.25	0.45	0.2706
16	16	2.51	0.0094	0.25	0.50	0.1837	35	35	2.50	0.0095	0.25	0.50	0.4290
16	16	2.51	0.0094	0.25	0.55	0.2713	35	35	2.50	0.0095	0.25	0.55	0.5990
16	16	2.51	0.0094	0.25	0.60	0.3779	35	35	2.50	0.0095	0.25	0.60	0.7511
16	16	2.51	0.0094	0.25	0.65	0.4974	35	35	2.50	0.0095	0.25	0.65	0.8658
16	16	2.51	0.0094	0.25	0.70	0.6208	35	35	2.50	0.0095	0.25	0.70	0.9393

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
16	16	2.51	0.0094	0.25	0.75	0.7373	35	35	2.50	0.0095	0.25	0.75	0.9785
16	16	2.51	0.0094	0.30	0.45	0.0681	35	35	2.50	0.0095	0.30	0.45	0.1442
16	16	2.51	0.0094	0.30	0.50	0.1150	35	35	2.50	0.0095	0.30	0.50	0.2623
16	16	2.51	0.0094	0.30	0.55	0.1817	35	35	2.50	0.0095	0.30	0.55	0.4137
16	16	2.51	0.0094	0.30	0.60	0.2693	35	35	2.50	0.0095	0.30	0.60	0.5780
16	16	2.51	0.0094	0.30	0.65	0.3759	35	35	2.50	0.0095	0.30	0.65	0.7320
16	16	2.51	0.0094	0.30	0.70	0.4960	35	35	2.50	0.0095	0.30	0.70	0.8563
16	16	2.51	0.0094	0.35	0.50	0.0686	35	35	2.50	0.0095	0.35	0.50	0.1401
16	16	2.51	0.0094	0.35	0.55	0.1156	35	35	2.50	0.0095	0.35	0.55	0.2512
16	16	2.51	0.0094	0.35	0.60	0.1820	35	35	2.50	0.0095	0.35	0.60	0.3974
16	16	2.51	0.0094	0.35	0.65	0.2693	35	35	2.50	0.0095	0.35	0.65	0.5659
16	16	2.51	0.0094	0.40	0.55	0.0695	35	35	2.50	0.0095	0.40	0.55	0.1338
16	16	2.51	0.0094	0.40	0.60	0.1161	35	35	2.50	0.0095	0.40	0.60	0.2440
17	17	2.66	0.0099	0.05	0.15	0.0444	36	36	2.48	0.0094	0.05	0.15	0.1330
17	17	2.66	0.0099	0.05	0.20	0.1156	36	36	2.48	0.0094	0.05	0.20	0.3109
17	17	2.66	0.0099	0.05	0.25	0.2203	36	36	2.48	0.0094	0.05	0.25	0.5232
17	17	2.66	0.0099	0.05	0.30	0.3466	36	36	2.48	0.0094	0.05	0.30	0.7162
17	17	2.66	0.0099	0.05	0.35	0.4798	36	36	2.48	0.0094	0.05	0.35	0.8553
17	17	2.66	0.0099	0.05	0.40	0.6072	36	36	2.48	0.0094	0.05	0.40	0.9369
17	17	2.66	0.0099	0.05	0.45	0.7197	36	36	2.48	0.0094	0.05	0.45	0.9766
17	17	2.66	0.0099	0.10	0.25	0.1088	36	36	2.48	0.0094	0.10	0.25	0.2436
17	17	2.66	0.0099	0.10	0.30	0.1861	36	36	2.48	0.0094	0.10	0.30	0.4196
17	17	2.66	0.0099	0.10	0.35	0.2817	36	36	2.48	0.0094	0.10	0.35	0.6025
17	17	2.66	0.0099	0.10	0.40	0.3904	36	36	2.48	0.0094	0.10	0.40	0.7591
17	17	2.66	0.0099	0.10	0.45	0.5054	36	36	2.48	0.0094	0.10	0.45	0.8722
17	17	2.66	0.0099	0.10	0.50	0.6191	36	36	2.48	0.0094	0.10	0.50	0.9418
17	17	2.66	0.0099	0.10	0.55	0.7237	36	36	2.48	0.0094	0.10	0.55	0.9778
17	17	2.66	0.0099	0.10	0.60	0.8127	36	36	2.48	0.0094	0.10	0.60	0.9932
17	17	2.66	0.0099	0.15	0.30	0.0950	36	36	2.48	0.0094	0.15	0.30	0.2026
17	17	2.66	0.0099	0.15	0.35	0.1566	36	36	2.48	0.0094	0.15	0.35	0.3504
17	17	2.66	0.0099	0.15	0.40	0.2363	36	36	2.48	0.0094	0.15	0.40	0.5197
17	17	2.66	0.0099	0.15	0.45	0.3322	36	36	2.48	0.0094	0.15	0.45	0.6843
17	17	2.66	0.0099	0.15	0.50	0.4396	36	36	2.48	0.0094	0.15	0.50	0.8196
17	17	2.66	0.0099	0.15	0.55	0.5512	36	36	2.48	0.0094	0.15	0.55	0.9124
17	17	2.66	0.0099	0.15	0.60	0.6592	36	36	2.48	0.0094	0.15	0.60	0.9645
17	17	2.66	0.0099	0.15	0.65	0.7565	36	36	2.48	0.0094	0.15	0.65	0.9881
17	17	2.66	0.0099	0.20	0.35	0.0826	36	36	2.48	0.0094	0.20	0.35	0.1728
17	17	2.66	0.0099	0.20	0.40	0.1352	36	36	2.48	0.0094	0.20	0.40	0.3056
17	17	2.66	0.0099	0.20	0.45	0.2052	36	36	2.48	0.0094	0.20	0.45	0.4702
17	17	2.66	0.0099	0.20	0.50	0.2917	36	36	2.48	0.0094	0.20	0.50	0.6405
17	17	2.66	0.0099	0.20	0.55	0.3911	36	36	2.48	0.0094	0.20	0.55	0.7863
17	17	2.66	0.0099	0.20	0.60	0.4983	36	36	2.48	0.0094	0.20	0.60	0.8898
17	17	2.66	0.0099	0.20	0.65	0.6076	36	36	2.48	0.0094	0.20	0.65	0.9512
17	17	2.66	0.0099	0.20	0.70	0.7135	36	36	2.48	0.0094	0.20	0.70	0.9821
17	17	2.66	0.0099	0.25	0.40	0.0730	36	36	2.48	0.0094	0.25	0.40	0.1571
17	17	2.66	0.0099	0.25	0.45	0.1190	36	36	2.48	0.0094	0.25	0.45	0.2835
17	17	2.66	0.0099	0.25	0.50	0.1810	36	36	2.48	0.0094	0.25	0.50	0.4422
17	17	2.66	0.0099	0.25	0.55	0.2592	36	36	2.48	0.0094	0.25	0.55	0.6077
17	17	2.66	0.0099	0.25	0.60	0.3527	36	36	2.48	0.0094	0.25	0.60	0.7539
17	17	2.66	0.0099	0.25	0.65	0.4596	36	36	2.48	0.0094	0.25	0.65	0.8656

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
17	17	2.66	0.0099	0.25	0.70	0.5764	36	36	2.48	0.0094	0.25	0.70	0.9391
17	17	2.66	0.0099	0.25	0.75	0.6967	36	36	2.48	0.0094	0.25	0.75	0.9788
17	17	2.66	0.0099	0.30	0.45	0.0647	36	36	2.48	0.0094	0.30	0.45	0.1487
17	17	2.66	0.0099	0.30	0.50	0.1051	36	36	2.48	0.0094	0.30	0.50	0.2652
17	17	2.66	0.0099	0.30	0.55	0.1611	36	36	2.48	0.0094	0.30	0.55	0.4118
17	17	2.66	0.0099	0.30	0.60	0.2352	36	36	2.48	0.0094	0.30	0.60	0.5723
17	17	2.66	0.0099	0.30	0.65	0.3297	36	36	2.48	0.0094	0.30	0.65	0.7265
17	17	2.66	0.0099	0.30	0.70	0.4448	36	36	2.48	0.0094	0.30	0.70	0.8537
17	17	2.66	0.0099	0.35	0.50	0.0572	36	36	2.48	0.0094	0.35	0.50	0.1365
17	17	2.66	0.0099	0.35	0.55	0.0944	36	36	2.48	0.0094	0.35	0.55	0.2427
17	17	2.66	0.0099	0.35	0.60	0.1490	36	36	2.48	0.0094	0.35	0.60	0.3857
17	17	2.66	0.0099	0.35	0.65	0.2261	36	36	2.48	0.0094	0.35	0.65	0.5554
17	17	2.66	0.0099	0.40	0.55	0.0525	36	36	2.48	0.0094	0.40	0.55	0.1248
17	17	2.66	0.0099	0.40	0.60	0.0902	36	36	2.48	0.0094	0.40	0.60	0.2316
18	18	2.63	0.0084	0.05	0.15	0.0490	37	37	2.44	0.0098	0.05	0.15	0.1405
18	18	2.63	0.0084	0.05	0.20	0.1196	37	37	2.44	0.0098	0.05	0.20	0.3254
18	18	2.63	0.0084	0.05	0.25	0.2161	37	37	2.44	0.0098	0.05	0.25	0.5423
18	18	2.63	0.0084	0.05	0.30	0.3291	37	37	2.44	0.0098	0.05	0.30	0.7345
18	18	2.63	0.0084	0.05	0.35	0.4508	37	37	2.44	0.0098	0.05	0.35	0.8688
18	18	2.63	0.0084	0.05	0.40	0.5750	37	37	2.44	0.0098	0.05	0.40	0.9448
18	18	2.63	0.0084	0.05	0.45	0.6934	37	37	2.44	0.0098	0.05	0.45	0.9803
18	18	2.63	0.0084	0.10	0.25	0.0958	37	37	2.44	0.0098	0.10	0.25	0.2549
18	18	2.63	0.0084	0.10	0.30	0.1629	37	37	2.44	0.0098	0.10	0.30	0.4358
18	18	2.63	0.0084	0.10	0.35	0.2533	37	37	2.44	0.0098	0.10	0.35	0.6204
18	18	2.63	0.0084	0.10	0.40	0.3658	37	37	2.44	0.0098	0.10	0.40	0.7752
18	18	2.63	0.0084	0.10	0.45	0.4929	37	37	2.44	0.0098	0.10	0.45	0.8843
18	18	2.63	0.0084	0.10	0.50	0.6217	37	37	2.44	0.0098	0.10	0.50	0.9493
18	18	2.63	0.0084	0.10	0.55	0.7385	37	37	2.44	0.0098	0.10	0.55	0.9816
18	18	2.63	0.0084	0.10	0.60	0.8332	37	37	2.44	0.0098	0.10	0.60	0.9947
18	18	2.63	0.0084	0.15	0.30	0.0803	37	37	2.44	0.0098	0.15	0.30	0.2114
18	18	2.63	0.0084	0.15	0.35	0.1408	37	37	2.44	0.0098	0.15	0.35	0.3643
18	18	2.63	0.0084	0.15	0.40	0.2264	37	37	2.44	0.0098	0.15	0.40	0.5379
18	18	2.63	0.0084	0.15	0.45	0.3340	37	37	2.44	0.0098	0.15	0.45	0.7036
18	18	2.63	0.0084	0.15	0.50	0.4550	37	37	2.44	0.0098	0.15	0.50	0.8360
18	18	2.63	0.0084	0.15	0.55	0.5778	37	37	2.44	0.0098	0.15	0.55	0.9234
18	18	2.63	0.0084	0.15	0.60	0.6918	37	37	2.44	0.0098	0.15	0.60	0.9702
18	18	2.63	0.0084	0.15	0.65	0.7898	37	37	2.44	0.0098	0.15	0.65	0.9905
18	18	2.63	0.0084	0.20	0.35	0.0759	37	37	2.44	0.0098	0.20	0.35	0.1810
18	18	2.63	0.0084	0.20	0.40	0.1333	37	37	2.44	0.0098	0.20	0.40	0.3204
18	18	2.63	0.0084	0.20	0.45	0.2121	37	37	2.44	0.0098	0.20	0.45	0.4906
18	18	2.63	0.0084	0.20	0.50	0.3093	37	37	2.44	0.0098	0.20	0.50	0.6621
18	18	2.63	0.0084	0.20	0.55	0.4189	37	37	2.44	0.0098	0.20	0.55	0.8042
18	18	2.63	0.0084	0.20	0.60	0.5340	37	37	2.44	0.0098	0.20	0.60	0.9017
18	18	2.63	0.0084	0.20	0.65	0.6480	37	37	2.44	0.0098	0.20	0.65	0.9579
18	18	2.63	0.0084	0.20	0.70	0.7543	37	37	2.44	0.0098	0.20	0.70	0.9853
18	18	2.63	0.0084	0.25	0.40	0.0737	37	37	2.44	0.0098	0.25	0.40	0.1663
18	18	2.63	0.0084	0.25	0.45	0.1254	37	37	2.44	0.0098	0.25	0.45	0.2989
18	18	2.63	0.0084	0.25	0.50	0.1950	37	37	2.44	0.0098	0.25	0.50	0.4615
18	18	2.63	0.0084	0.25	0.55	0.2821	37	37	2.44	0.0098	0.25	0.55	0.6273
18	18	2.63	0.0084	0.25	0.60	0.3848	37	37	2.44	0.0098	0.25	0.60	0.7712

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
18	18	2.63	0.0084	0.25	0.65	0.4999	37	37	2.44	0.0098	0.25	0.65	0.8789
18	18	2.63	0.0084	0.25	0.70	0.6216	37	37	2.44	0.0098	0.25	0.70	0.9475
18	18	2.63	0.0084	0.25	0.75	0.7409	37	37	2.44	0.0098	0.25	0.75	0.9827
18	18	2.63	0.0084	0.30	0.45	0.0688	37	37	2.44	0.0098	0.30	0.45	0.1571
18	18	2.63	0.0084	0.30	0.50	0.1143	37	37	2.44	0.0098	0.30	0.50	0.2779
18	18	2.63	0.0084	0.30	0.55	0.1773	37	37	2.44	0.0098	0.30	0.55	0.4285
18	18	2.63	0.0084	0.30	0.60	0.2603	37	37	2.44	0.0098	0.30	0.60	0.5918
18	18	2.63	0.0084	0.30	0.65	0.3644	37	37	2.44	0.0098	0.30	0.65	0.7458
18	18	2.63	0.0084	0.30	0.70	0.4872	37	37	2.44	0.0098	0.30	0.70	0.8687
18	18	2.63	0.0084	0.35	0.50	0.0625	37	37	2.44	0.0098	0.35	0.50	0.1432
18	18	2.63	0.0084	0.35	0.55	0.1046	37	37	2.44	0.0098	0.35	0.55	0.2543
18	18	2.63	0.0084	0.35	0.60	0.1663	37	37	2.44	0.0098	0.35	0.60	0.4032
18	18	2.63	0.0084	0.35	0.65	0.2522	37	37	2.44	0.0098	0.35	0.65	0.5764
18	18	2.63	0.0084	0.40	0.55	0.0582	37	37	2.44	0.0098	0.40	0.55	0.1315
18	18	2.63	0.0084	0.40	0.60	0.1009	37	37	2.44	0.0098	0.40	0.60	0.2438
19	19	2.59	0.0091	0.05	0.15	0.0562	38	38	2.44	0.0098	0.05	0.15	0.1482
19	19	2.59	0.0091	0.05	0.20	0.1333	38	38	2.44	0.0098	0.05	0.20	0.3400
19	19	2.59	0.0091	0.05	0.25	0.2366	38	38	2.44	0.0098	0.05	0.25	0.5609
19	19	2.59	0.0091	0.05	0.30	0.3563	38	38	2.44	0.0098	0.05	0.30	0.7519
19	19	2.59	0.0091	0.05	0.35	0.4849	38	38	2.44	0.0098	0.05	0.35	0.8811
19	19	2.59	0.0091	0.05	0.40	0.6141	38	38	2.44	0.0098	0.05	0.40	0.9517
19	19	2.59	0.0091	0.05	0.45	0.7336	38	38	2.44	0.0098	0.05	0.45	0.9834
19	19	2.59	0.0091	0.10	0.25	0.1041	38	38	2.44	0.0098	0.10	0.25	0.2661
19	19	2.59	0.0091	0.10	0.30	0.1789	38	38	2.44	0.0098	0.10	0.30	0.4517
19	19	2.59	0.0091	0.10	0.35	0.2798	38	38	2.44	0.0098	0.10	0.35	0.6376
19	19	2.59	0.0091	0.10	0.40	0.4031	38	38	2.44	0.0098	0.10	0.40	0.7903
19	19	2.59	0.0091	0.10	0.45	0.5374	38	38	2.44	0.0098	0.10	0.45	0.8953
19	19	2.59	0.0091	0.10	0.50	0.6671	38	38	2.44	0.0098	0.10	0.50	0.9557
19	19	2.59	0.0091	0.10	0.55	0.7787	38	38	2.44	0.0098	0.10	0.55	0.9846
19	19	2.59	0.0091	0.10	0.60	0.8646	38	38	2.44	0.0098	0.10	0.60	0.9957
19	19	2.59	0.0091	0.15	0.30	0.0894	38	38	2.44	0.0098	0.15	0.30	0.2201
19	19	2.59	0.0091	0.15	0.35	0.1584	38	38	2.44	0.0098	0.15	0.35	0.3780
19	19	2.59	0.0091	0.15	0.40	0.2539	38	38	2.44	0.0098	0.15	0.40	0.5549
19	19	2.59	0.0091	0.15	0.45	0.3700	38	38	2.44	0.0098	0.15	0.45	0.7200
19	19	2.59	0.0091	0.15	0.50	0.4959	38	38	2.44	0.0098	0.15	0.50	0.8479
19	19	2.59	0.0091	0.15	0.55	0.6194	38	38	2.44	0.0098	0.15	0.55	0.9296
19	19	2.59	0.0091	0.15	0.60	0.7307	38	38	2.44	0.0098	0.15	0.60	0.9726
19	19	2.59	0.0091	0.15	0.65	0.8236	38	38	2.44	0.0098	0.15	0.65	0.9912
19	19	2.59	0.0091	0.20	0.35	0.0859	38	38	2.44	0.0098	0.20	0.35	0.1887
19	19	2.59	0.0091	0.20	0.40	0.1502	38	38	2.44	0.0098	0.20	0.40	0.3321
19	19	2.59	0.0091	0.20	0.45	0.2363	38	38	2.44	0.0098	0.20	0.45	0.5031
19	19	2.59	0.0091	0.20	0.50	0.3401	38	38	2.44	0.0098	0.20	0.50	0.6711
19	19	2.59	0.0091	0.20	0.55	0.4552	38	38	2.44	0.0098	0.20	0.55	0.8088
19	19	2.59	0.0091	0.20	0.60	0.5744	38	38	2.44	0.0098	0.20	0.60	0.9043
19	19	2.59	0.0091	0.20	0.65	0.6901	38	38	2.44	0.0098	0.20	0.65	0.9602
19	19	2.59	0.0091	0.20	0.70	0.7943	38	38	2.44	0.0098	0.20	0.70	0.9870
19	19	2.59	0.0091	0.25	0.40	0.0826	38	38	2.44	0.0098	0.25	0.40	0.1705
19	19	2.59	0.0091	0.25	0.45	0.1396	38	38	2.44	0.0098	0.25	0.45	0.3022
19	19	2.59	0.0091	0.25	0.50	0.2157	38	38	2.44	0.0098	0.25	0.50	0.4625
19	19	2.59	0.0091	0.25	0.55	0.3106	38	38	2.44	0.0098	0.25	0.55	0.6283

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
19	19	2.59	0.0091	0.25	0.60	0.4219	38	38	2.44	0.0098	0.25	0.60	0.7756
19	19	2.59	0.0091	0.25	0.65	0.5442	38	38	2.44	0.0098	0.25	0.65	0.8860
19	19	2.59	0.0091	0.25	0.70	0.6689	38	38	2.44	0.0098	0.25	0.70	0.9535
19	19	2.59	0.0091	0.25	0.75	0.7844	38	38	2.44	0.0098	0.25	0.75	0.9856
19	19	2.59	0.0091	0.30	0.45	0.0763	38	38	2.44	0.0098	0.30	0.45	0.1548
19	19	2.59	0.0091	0.30	0.50	0.1271	38	38	2.44	0.0098	0.30	0.50	0.2748
19	19	2.59	0.0091	0.30	0.55	0.1978	38	38	2.44	0.0098	0.30	0.55	0.4295
19	19	2.59	0.0091	0.30	0.60	0.2906	38	38	2.44	0.0098	0.30	0.60	0.6006
19	19	2.59	0.0091	0.30	0.65	0.4046	38	38	2.44	0.0098	0.30	0.65	0.7597
19	19	2.59	0.0091	0.30	0.70	0.5343	38	38	2.44	0.0098	0.30	0.70	0.8806
19	19	2.59	0.0091	0.35	0.50	0.0698	38	38	2.44	0.0098	0.35	0.50	0.1409
19	19	2.59	0.0091	0.35	0.55	0.1181	38	38	2.44	0.0098	0.35	0.55	0.2573
19	19	2.59	0.0091	0.35	0.60	0.1884	38	38	2.44	0.0098	0.35	0.60	0.4146
19	19	2.59	0.0091	0.35	0.65	0.2840	38	38	2.44	0.0098	0.35	0.65	0.5929
19	19	2.59	0.0091	0.40	0.55	0.0662	38	38	2.44	0.0098	0.40	0.55	0.1347
19	19	2.59	0.0091	0.40	0.60	0.1150	38	38	2.44	0.0098	0.40	0.60	0.2526
20	20	2.56	0.0084	0.05	0.15	0.0635	39	39	2.45	0.0093	0.05	0.15	0.1531
20	20	2.56	0.0084	0.05	0.20	0.1468	39	39	2.45	0.0093	0.05	0.20	0.3425
20	20	2.56	0.0084	0.05	0.25	0.2562	39	39	2.45	0.0093	0.05	0.25	0.5563
20	20	2.56	0.0084	0.05	0.30	0.3818	39	39	2.45	0.0093	0.05	0.30	0.7437
20	20	2.56	0.0084	0.05	0.35	0.5149	39	39	2.45	0.0093	0.05	0.35	0.8755
20	20	2.56	0.0084	0.05	0.40	0.6453	39	39	2.45	0.0093	0.05	0.40	0.9500
20	20	2.56	0.0084	0.05	0.45	0.7612	39	39	2.45	0.0093	0.05	0.45	0.9836
20	20	2.56	0.0084	0.10	0.25	0.1112	39	39	2.45	0.0093	0.10	0.25	0.2512
20	20	2.56	0.0084	0.10	0.30	0.1903	39	39	2.45	0.0093	0.10	0.30	0.4391
20	20	2.56	0.0084	0.10	0.35	0.2948	39	39	2.45	0.0093	0.10	0.35	0.6348
20	20	2.56	0.0084	0.10	0.40	0.4186	39	39	2.45	0.0093	0.10	0.40	0.7953
20	20	2.56	0.0084	0.10	0.45	0.5496	39	39	2.45	0.0093	0.10	0.45	0.9017
20	20	2.56	0.0084	0.10	0.50	0.6745	39	39	2.45	0.0093	0.10	0.50	0.9599
20	20	2.56	0.0084	0.10	0.55	0.7827	39	39	2.45	0.0093	0.10	0.55	0.9863
20	20	2.56	0.0084	0.10	0.60	0.8679	39	39	2.45	0.0093	0.10	0.60	0.9962
20	20	2.56	0.0084	0.15	0.30	0.0919	39	39	2.45	0.0093	0.15	0.30	0.2164
20	20	2.56	0.0084	0.15	0.35	0.1604	39	39	2.45	0.0093	0.15	0.35	0.3820
20	20	2.56	0.0084	0.15	0.40	0.2532	39	39	2.45	0.0093	0.15	0.40	0.5643
20	20	2.56	0.0084	0.15	0.45	0.3661	39	39	2.45	0.0093	0.15	0.45	0.7291
20	20	2.56	0.0084	0.15	0.50	0.4913	39	39	2.45	0.0093	0.15	0.50	0.8534
20	20	2.56	0.0084	0.15	0.55	0.6188	39	39	2.45	0.0093	0.15	0.55	0.9321
20	20	2.56	0.0084	0.15	0.60	0.7373	39	39	2.45	0.0093	0.15	0.60	0.9739
20	20	2.56	0.0084	0.15	0.65	0.8369	39	39	2.45	0.0093	0.15	0.65	0.9920
20	20	2.56	0.0084	0.20	0.35	0.0821	39	39	2.45	0.0093	0.20	0.35	0.1914
20	20	2.56	0.0084	0.20	0.40	0.1430	39	39	2.45	0.0093	0.20	0.40	0.3362
20	20	2.56	0.0084	0.20	0.45	0.2272	39	39	2.45	0.0093	0.20	0.45	0.5056
20	20	2.56	0.0084	0.20	0.50	0.3340	39	39	2.45	0.0093	0.20	0.50	0.6723
20	20	2.56	0.0084	0.20	0.55	0.4583	39	39	2.45	0.0093	0.20	0.55	0.8112
20	20	2.56	0.0084	0.20	0.60	0.5902	39	39	2.45	0.0093	0.20	0.60	0.9085
20	20	2.56	0.0084	0.20	0.65	0.7165	39	39	2.45	0.0093	0.20	0.65	0.9643
20	20	2.56	0.0084	0.20	0.70	0.8243	39	39	2.45	0.0093	0.20	0.70	0.9893
20	20	2.56	0.0084	0.25	0.40	0.0758	39	39	2.45	0.0093	0.25	0.40	0.1687
20	20	2.56	0.0084	0.25	0.45	0.1325	39	39	2.45	0.0093	0.25	0.45	0.2988
20	20	2.56	0.0084	0.25	0.50	0.2136	39	39	2.45	0.0093	0.25	0.50	0.4614

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	20	2.56	0.0084	0.25	0.55	0.3195	39	39	2.45	0.0093	0.25	0.55	0.6340
20	20	2.56	0.0084	0.25	0.60	0.4451	39	39	2.45	0.0093	0.25	0.60	0.7869
20	20	2.56	0.0084	0.25	0.65	0.5800	39	39	2.45	0.0093	0.25	0.65	0.8974
20	20	2.56	0.0084	0.25	0.70	0.7099	39	39	2.45	0.0093	0.25	0.70	0.9607
20	20	2.56	0.0084	0.25	0.75	0.8213	39	39	2.45	0.0093	0.25	0.75	0.9886
20	20	2.56	0.0084	0.30	0.45	0.0728	39	39	2.45	0.0093	0.30	0.45	0.1514
20	20	2.56	0.0084	0.30	0.50	0.1286	39	39	2.45	0.0093	0.30	0.50	0.2760
20	20	2.56	0.0084	0.30	0.55	0.2094	39	39	2.45	0.0093	0.30	0.55	0.4400
20	20	2.56	0.0084	0.30	0.60	0.3155	39	39	2.45	0.0093	0.30	0.60	0.6193
20	20	2.56	0.0084	0.30	0.65	0.4418	39	39	2.45	0.0093	0.30	0.65	0.7795
20	20	2.56	0.0084	0.30	0.70	0.5779	39	39	2.45	0.0093	0.30	0.70	0.8949
20	20	2.56	0.0084	0.35	0.50	0.0728	39	39	2.45	0.0093	0.35	0.50	0.1442
20	20	2.56	0.0084	0.35	0.55	0.1286	39	39	2.45	0.0093	0.35	0.55	0.2690
20	20	2.56	0.0084	0.35	0.60	0.2092	39	39	2.45	0.0093	0.35	0.60	0.4349
20	20	2.56	0.0084	0.35	0.65	0.3150	39	39	2.45	0.0093	0.35	0.65	0.6166
20	20	2.56	0.0084	0.40	0.55	0.0735	39	39	2.45	0.0093	0.40	0.55	0.1434
20	20	2.56	0.0084	0.40	0.60	0.1290	39	39	2.45	0.0093	0.40	0.60	0.2684
21	21	2.54	0.0098	0.05	0.15	0.0708	40	40	2.44	0.0096	0.05	0.15	0.1603
21	21	2.54	0.0098	0.05	0.20	0.1601	40	40	2.44	0.0096	0.05	0.20	0.3553
21	21	2.54	0.0098	0.05	0.25	0.2759	40	40	2.44	0.0096	0.05	0.25	0.5726
21	21	2.54	0.0098	0.05	0.30	0.4084	40	40	2.44	0.0096	0.05	0.30	0.7595
21	21	2.54	0.0098	0.05	0.35	0.5475	40	40	2.44	0.0096	0.05	0.35	0.8872
21	21	2.54	0.0098	0.05	0.40	0.6801	40	40	2.44	0.0096	0.05	0.40	0.9565
21	21	2.54	0.0098	0.05	0.45	0.7933	40	40	2.44	0.0096	0.05	0.45	0.9864
21	21	2.54	0.0098	0.10	0.25	0.1198	40	40	2.44	0.0096	0.10	0.25	0.2622
21	21	2.54	0.0098	0.10	0.30	0.2066	40	40	2.44	0.0096	0.10	0.30	0.4560
21	21	2.54	0.0098	0.10	0.35	0.3201	40	40	2.44	0.0096	0.10	0.35	0.6533
21	21	2.54	0.0098	0.10	0.40	0.4513	40	40	2.44	0.0096	0.10	0.40	0.8105
21	21	2.54	0.0098	0.10	0.45	0.5862	40	40	2.44	0.0096	0.10	0.45	0.9116
21	21	2.54	0.0098	0.10	0.50	0.7108	40	40	2.44	0.0096	0.10	0.50	0.9652
21	21	2.54	0.0098	0.10	0.55	0.8149	40	40	2.44	0.0096	0.10	0.55	0.9886
21	21	2.54	0.0098	0.10	0.60	0.8933	40	40	2.44	0.0096	0.10	0.60	0.9970
21	21	2.54	0.0098	0.15	0.30	0.1004	40	40	2.44	0.0096	0.15	0.30	0.2265
21	21	2.54	0.0098	0.15	0.35	0.1759	40	40	2.44	0.0096	0.15	0.35	0.3970
21	21	2.54	0.0098	0.15	0.40	0.2768	40	40	2.44	0.0096	0.15	0.40	0.5816
21	21	2.54	0.0098	0.15	0.45	0.3977	40	40	2.44	0.0096	0.15	0.45	0.7452
21	21	2.54	0.0098	0.15	0.50	0.5294	40	40	2.44	0.0096	0.15	0.50	0.8657
21	21	2.54	0.0098	0.15	0.55	0.6597	40	40	2.44	0.0096	0.15	0.55	0.9399
21	21	2.54	0.0098	0.15	0.60	0.7762	40	40	2.44	0.0096	0.15	0.60	0.9779
21	21	2.54	0.0098	0.15	0.65	0.8689	40	40	2.44	0.0096	0.15	0.65	0.9936
21	21	2.54	0.0098	0.20	0.35	0.0904	40	40	2.44	0.0096	0.20	0.35	0.1997
21	21	2.54	0.0098	0.20	0.40	0.1580	40	40	2.44	0.0096	0.20	0.40	0.3492
21	21	2.54	0.0098	0.20	0.45	0.2512	40	40	2.44	0.0096	0.20	0.45	0.5222
21	21	2.54	0.0098	0.20	0.50	0.3679	40	40	2.44	0.0096	0.20	0.50	0.6898
21	21	2.54	0.0098	0.20	0.55	0.5006	40	40	2.44	0.0096	0.20	0.55	0.8266
21	21	2.54	0.0098	0.20	0.60	0.6362	40	40	2.44	0.0096	0.20	0.60	0.9194
21	21	2.54	0.0098	0.20	0.65	0.7599	40	40	2.44	0.0096	0.20	0.65	0.9702
21	21	2.54	0.0098	0.20	0.70	0.8594	40	40	2.44	0.0096	0.20	0.70	0.9916
21	21	2.54	0.0098	0.25	0.40	0.0846	40	40	2.44	0.0096	0.25	0.40	0.1760
21	21	2.54	0.0098	0.25	0.45	0.1490	40	40	2.44	0.0096	0.25	0.45	0.3116

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
21	21	2.54	0.0098	0.25	0.50	0.2402	40	40	2.44	0.0096	0.25	0.50	0.4799
21	21	2.54	0.0098	0.25	0.55	0.3567	40	40	2.44	0.0096	0.25	0.55	0.6553
21	21	2.54	0.0098	0.25	0.60	0.4907	40	40	2.44	0.0096	0.25	0.60	0.8061
21	21	2.54	0.0098	0.25	0.65	0.6285	40	40	2.44	0.0096	0.25	0.65	0.9105
21	21	2.54	0.0098	0.25	0.70	0.7549	40	40	2.44	0.0096	0.25	0.70	0.9674
21	21	2.54	0.0098	0.25	0.75	0.8571	40	40	2.44	0.0096	0.25	0.75	0.9911
21	21	2.54	0.0098	0.30	0.45	0.0832	40	40	2.44	0.0096	0.30	0.45	0.1596
21	21	2.54	0.0098	0.30	0.50	0.1472	40	40	2.44	0.0096	0.30	0.50	0.2913
21	21	2.54	0.0098	0.30	0.55	0.2383	40	40	2.44	0.0096	0.30	0.55	0.4619
21	21	2.54	0.0098	0.30	0.60	0.3547	40	40	2.44	0.0096	0.30	0.60	0.6434
21	21	2.54	0.0098	0.30	0.65	0.4885	40	40	2.44	0.0096	0.30	0.65	0.8001
21	21	2.54	0.0098	0.30	0.70	0.6270	40	40	2.44	0.0096	0.30	0.70	0.9085
21	21	2.54	0.0098	0.35	0.50	0.0844	40	40	2.44	0.0096	0.35	0.50	0.1542
21	21	2.54	0.0098	0.35	0.55	0.1485	40	40	2.44	0.0096	0.35	0.55	0.2864
21	21	2.54	0.0098	0.35	0.60	0.2390	40	40	2.44	0.0096	0.35	0.60	0.4583
21	21	2.54	0.0098	0.35	0.65	0.3547	40	40	2.44	0.0096	0.35	0.65	0.6414
21	21	2.54	0.0098	0.40	0.55	0.0858	40	40	2.44	0.0096	0.40	0.55	0.1543
21	21	2.54	0.0098	0.40	0.60	0.1493	40	40	2.44	0.0096	0.40	0.60	0.2863
22	22	2.59	0.0097	0.05	0.15	0.0372	50	50	2.48	0.0091	0.05	0.15	0.2281
22	22	2.59	0.0097	0.05	0.20	0.1118	50	50	2.48	0.0091	0.05	0.20	0.4659
22	22	2.59	0.0097	0.05	0.25	0.2331	50	50	2.48	0.0091	0.05	0.25	0.6948
22	22	2.59	0.0097	0.05	0.30	0.3870	50	50	2.48	0.0091	0.05	0.30	0.8591
22	22	2.59	0.0097	0.05	0.35	0.5499	50	50	2.48	0.0091	0.05	0.35	0.9487
22	22	2.59	0.0097	0.05	0.40	0.6982	50	50	2.48	0.0091	0.05	0.40	0.9855
22	22	2.59	0.0097	0.05	0.45	0.8161	50	50	2.48	0.0091	0.05	0.45	0.9968
22	22	2.59	0.0097	0.10	0.25	0.1098	50	50	2.48	0.0091	0.10	0.25	0.3290
22	22	2.59	0.0097	0.10	0.30	0.2089	50	50	2.48	0.0091	0.10	0.30	0.5537
22	22	2.59	0.0097	0.10	0.35	0.3367	50	50	2.48	0.0091	0.10	0.35	0.7550
22	22	2.59	0.0097	0.10	0.40	0.4791	50	50	2.48	0.0091	0.10	0.40	0.8898
22	22	2.59	0.0097	0.10	0.45	0.6194	50	50	2.48	0.0091	0.10	0.45	0.9597
22	22	2.59	0.0097	0.10	0.50	0.7437	50	50	2.48	0.0091	0.10	0.50	0.9882
22	22	2.59	0.0097	0.10	0.55	0.8431	50	50	2.48	0.0091	0.10	0.55	0.9973
22	22	2.59	0.0097	0.10	0.60	0.9143	50	50	2.48	0.0091	0.10	0.60	0.9995
22	22	2.59	0.0097	0.15	0.30	0.1051	50	50	2.48	0.0091	0.15	0.30	0.2749
22	22	2.59	0.0097	0.15	0.35	0.1893	50	50	2.48	0.0091	0.15	0.35	0.4769
22	22	2.59	0.0097	0.15	0.40	0.2996	50	50	2.48	0.0091	0.15	0.40	0.6774
22	22	2.59	0.0097	0.15	0.45	0.4289	50	50	2.48	0.0091	0.15	0.45	0.8335
22	22	2.59	0.0097	0.15	0.50	0.5659	50	50	2.48	0.0091	0.15	0.50	0.9299
22	22	2.59	0.0097	0.15	0.55	0.6966	50	50	2.48	0.0091	0.15	0.55	0.9768
22	22	2.59	0.0097	0.15	0.60	0.8078	50	50	2.48	0.0091	0.15	0.60	0.9943
22	22	2.59	0.0097	0.15	0.65	0.8914	50	50	2.48	0.0091	0.15	0.65	0.9990
22	22	2.59	0.0097	0.20	0.35	0.0984	50	50	2.48	0.0091	0.20	0.35	0.2372
22	22	2.59	0.0097	0.20	0.40	0.1733	50	50	2.48	0.0091	0.20	0.40	0.4192
22	22	2.59	0.0097	0.20	0.45	0.2753	50	50	2.48	0.0091	0.20	0.45	0.6190
22	22	2.59	0.0097	0.20	0.50	0.3999	50	50	2.48	0.0091	0.20	0.50	0.7924
22	22	2.59	0.0097	0.20	0.55	0.5362	50	50	2.48	0.0091	0.20	0.55	0.9093
22	22	2.59	0.0097	0.20	0.60	0.6693	50	50	2.48	0.0091	0.20	0.60	0.9691
22	22	2.59	0.0097	0.20	0.65	0.7851	50	50	2.48	0.0091	0.20	0.65	0.9920
22	22	2.59	0.0097	0.20	0.70	0.8748	50	50	2.48	0.0091	0.20	0.70	0.9984
22	22	2.59	0.0097	0.25	0.40	0.0936	50	50	2.48	0.0091	0.25	0.40	0.2119

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
22	22	2.59	0.0097	0.25	0.45	0.1647	50	50	2.48	0.0091	0.25	0.45	0.3872
22	22	2.59	0.0097	0.25	0.50	0.2627	50	50	2.48	0.0091	0.25	0.50	0.5907
22	22	2.59	0.0097	0.25	0.55	0.3834	50	50	2.48	0.0091	0.25	0.55	0.7723
22	22	2.59	0.0097	0.25	0.60	0.5166	50	50	2.48	0.0091	0.25	0.60	0.8964
22	22	2.59	0.0097	0.25	0.65	0.6494	50	50	2.48	0.0091	0.25	0.65	0.9621
22	22	2.59	0.0097	0.25	0.70	0.7695	50	50	2.48	0.0091	0.25	0.70	0.9894
22	22	2.59	0.0097	0.25	0.75	0.8672	50	50	2.48	0.0091	0.25	0.75	0.9980
22	22	2.59	0.0097	0.30	0.45	0.0917	50	50	2.48	0.0091	0.30	0.45	0.2035
22	22	2.59	0.0097	0.30	0.50	0.1600	50	50	2.48	0.0091	0.30	0.50	0.3755
22	22	2.59	0.0097	0.30	0.55	0.2539	50	50	2.48	0.0091	0.30	0.55	0.5736
22	22	2.59	0.0097	0.30	0.60	0.3705	50	50	2.48	0.0091	0.30	0.60	0.7524
22	22	2.59	0.0097	0.30	0.65	0.5030	50	50	2.48	0.0091	0.30	0.65	0.8822
22	22	2.59	0.0097	0.30	0.70	0.6406	50	50	2.48	0.0091	0.30	0.70	0.9572
22	22	2.59	0.0097	0.35	0.50	0.0900	50	50	2.48	0.0091	0.35	0.50	0.1982
22	22	2.59	0.0097	0.35	0.55	0.1555	50	50	2.48	0.0091	0.35	0.55	0.3595
22	22	2.59	0.0097	0.35	0.60	0.2470	50	50	2.48	0.0091	0.35	0.60	0.5516
22	22	2.59	0.0097	0.35	0.65	0.3647	50	50	2.48	0.0091	0.35	0.65	0.7386
22	22	2.59	0.0097	0.40	0.55	0.0881	50	50	2.48	0.0091	0.40	0.55	0.1871
22	22	2.59	0.0097	0.40	0.60	0.1532	50	50	2.48	0.0091	0.40	0.60	0.3473
23	23	2.55	0.0091	0.05	0.15	0.0431	60	60	2.44	0.0096	0.05	0.15	0.2907
23	23	2.55	0.0091	0.05	0.20	0.1265	60	60	2.44	0.0096	0.05	0.20	0.5642
23	23	2.55	0.0091	0.05	0.25	0.2584	60	60	2.44	0.0096	0.05	0.25	0.7937
23	23	2.55	0.0091	0.05	0.30	0.4210	60	60	2.44	0.0096	0.05	0.30	0.9262
23	23	2.55	0.0091	0.05	0.35	0.5873	60	60	2.44	0.0096	0.05	0.35	0.9802
23	23	2.55	0.0091	0.05	0.40	0.7329	60	60	2.44	0.0096	0.05	0.40	0.9961
23	23	2.55	0.0091	0.05	0.45	0.8436	60	60	2.44	0.0096	0.05	0.45	0.9994
23	23	2.55	0.0091	0.10	0.25	0.1221	60	60	2.44	0.0096	0.10	0.25	0.4112
23	23	2.55	0.0091	0.10	0.30	0.2294	60	60	2.44	0.0096	0.10	0.30	0.6570
23	23	2.55	0.0091	0.10	0.35	0.3648	60	60	2.44	0.0096	0.10	0.35	0.8432
23	23	2.55	0.0091	0.10	0.40	0.5117	60	60	2.44	0.0096	0.10	0.40	0.9444
23	23	2.55	0.0091	0.10	0.45	0.6524	60	60	2.44	0.0096	0.10	0.45	0.9849
23	23	2.55	0.0091	0.10	0.50	0.7731	60	60	2.44	0.0096	0.10	0.50	0.9969
23	23	2.55	0.0091	0.10	0.55	0.8658	60	60	2.44	0.0096	0.10	0.55	0.9995
23	23	2.55	0.0091	0.10	0.60	0.9291	60	60	2.44	0.0096	0.10	0.60	1.0000
23	23	2.55	0.0091	0.15	0.30	0.1153	60	60	2.44	0.0096	0.15	0.30	0.3413
23	23	2.55	0.0091	0.15	0.35	0.2061	60	60	2.44	0.0096	0.15	0.35	0.5734
23	23	2.55	0.0091	0.15	0.40	0.3231	60	60	2.44	0.0096	0.15	0.40	0.7763
23	23	2.55	0.0091	0.15	0.45	0.4572	60	60	2.44	0.0096	0.15	0.45	0.9070
23	23	2.55	0.0091	0.15	0.50	0.5947	60	60	2.44	0.0096	0.15	0.50	0.9700
23	23	2.55	0.0091	0.15	0.55	0.7208	60	60	2.44	0.0096	0.15	0.55	0.9928
23	23	2.55	0.0091	0.15	0.60	0.8238	60	60	2.44	0.0096	0.15	0.60	0.9988
23	23	2.55	0.0091	0.15	0.65	0.8992	60	60	2.44	0.0096	0.15	0.65	0.9999
23	23	2.55	0.0091	0.20	0.35	0.1069	60	60	2.44	0.0096	0.20	0.35	0.2982
23	23	2.55	0.0091	0.20	0.40	0.1869	60	60	2.44	0.0096	0.20	0.40	0.5144
23	23	2.55	0.0091	0.20	0.45	0.2929	60	60	2.44	0.0096	0.20	0.45	0.7230
23	23	2.55	0.0091	0.20	0.50	0.4179	60	60	2.44	0.0096	0.20	0.50	0.8749
23	23	2.55	0.0091	0.20	0.55	0.5497	60	60	2.44	0.0096	0.20	0.55	0.9572
23	23	2.55	0.0091	0.20	0.60	0.6753	60	60	2.44	0.0096	0.20	0.60	0.9893
23	23	2.55	0.0091	0.20	0.65	0.7845	60	60	2.44	0.0096	0.20	0.65	0.9981
23	23	2.55	0.0091	0.20	0.70	0.8716	60	60	2.44	0.0096	0.20	0.70	0.9998

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
23	23	2.55	0.0091	0.25	0.40	0.0994	60	60	2.44	0.0096	0.25	0.40	0.2678
23	23	2.55	0.0091	0.25	0.45	0.1715	60	60	2.44	0.0096	0.25	0.45	0.4762
23	23	2.55	0.0091	0.25	0.50	0.2673	60	60	2.44	0.0096	0.25	0.50	0.6927
23	23	2.55	0.0091	0.25	0.55	0.3821	60	60	2.44	0.0096	0.25	0.55	0.8576
23	23	2.55	0.0091	0.25	0.60	0.5082	60	60	2.44	0.0096	0.25	0.60	0.9489
23	23	2.55	0.0091	0.25	0.65	0.6367	60	60	2.44	0.0096	0.25	0.65	0.9860
23	23	2.55	0.0091	0.25	0.70	0.7575	60	60	2.44	0.0096	0.25	0.70	0.9972
23	23	2.55	0.0091	0.25	0.75	0.8598	60	60	2.44	0.0096	0.25	0.75	0.9997
23	23	2.55	0.0091	0.30	0.45	0.0914	60	60	2.44	0.0096	0.30	0.45	0.2553
23	23	2.55	0.0091	0.30	0.50	0.1553	60	60	2.44	0.0096	0.30	0.50	0.4611
23	23	2.55	0.0091	0.30	0.55	0.2422	60	60	2.44	0.0096	0.30	0.55	0.6749
23	23	2.55	0.0091	0.30	0.60	0.3517	60	60	2.44	0.0096	0.30	0.60	0.8406
23	23	2.55	0.0091	0.30	0.65	0.4808	60	60	2.44	0.0096	0.30	0.65	0.9391
23	23	2.55	0.0091	0.30	0.70	0.6210	60	60	2.44	0.0096	0.30	0.70	0.9835
23	23	2.55	0.0091	0.35	0.50	0.0821	60	60	2.44	0.0096	0.35	0.50	0.2480
23	23	2.55	0.0091	0.35	0.55	0.1406	60	60	2.44	0.0096	0.35	0.55	0.4415
23	23	2.55	0.0091	0.35	0.60	0.2252	60	60	2.44	0.0096	0.35	0.60	0.6506
23	23	2.55	0.0091	0.35	0.65	0.3394	60	60	2.44	0.0096	0.35	0.65	0.8277
23	23	2.55	0.0091	0.40	0.55	0.0753	60	60	2.44	0.0096	0.40	0.55	0.2325
23	23	2.55	0.0091	0.40	0.60	0.1345	60	60	2.44	0.0096	0.40	0.60	0.4255
24	24	2.49	0.0097	0.05	0.15	0.0924	70	70	2.42	0.0097	0.05	0.15	0.3504
24	24	2.49	0.0097	0.05	0.20	0.1990	70	70	2.42	0.0097	0.05	0.20	0.6530
24	24	2.49	0.0097	0.05	0.25	0.3353	70	70	2.42	0.0097	0.05	0.25	0.8675
24	24	2.49	0.0097	0.05	0.30	0.4887	70	70	2.42	0.0097	0.05	0.30	0.9638
24	24	2.49	0.0097	0.05	0.35	0.6408	70	70	2.42	0.0097	0.05	0.35	0.9928
24	24	2.49	0.0097	0.05	0.40	0.7719	70	70	2.42	0.0097	0.05	0.40	0.9990
24	24	2.49	0.0097	0.05	0.45	0.8701	70	70	2.42	0.0097	0.05	0.45	0.9999
24	24	2.49	0.0097	0.10	0.25	0.1486	70	70	2.42	0.0097	0.10	0.25	0.4900
24	24	2.49	0.0097	0.10	0.30	0.2594	70	70	2.42	0.0097	0.10	0.30	0.7394
24	24	2.49	0.0097	0.10	0.35	0.3973	70	70	2.42	0.0097	0.10	0.35	0.9002
24	24	2.49	0.0097	0.10	0.40	0.5453	70	70	2.42	0.0097	0.10	0.40	0.9719
24	24	2.49	0.0097	0.10	0.45	0.6846	70	70	2.42	0.0097	0.10	0.45	0.9943
24	24	2.49	0.0097	0.10	0.50	0.8010	70	70	2.42	0.0097	0.10	0.50	0.9992
24	24	2.49	0.0097	0.10	0.55	0.8871	70	70	2.42	0.0097	0.10	0.55	0.9999
24	24	2.49	0.0097	0.10	0.60	0.9431	70	70	2.42	0.0097	0.10	0.60	1.0000
24	24	2.49	0.0097	0.15	0.30	0.1281	70	70	2.42	0.0097	0.15	0.30	0.3998
24	24	2.49	0.0097	0.15	0.35	0.2246	70	70	2.42	0.0097	0.15	0.35	0.6501
24	24	2.49	0.0097	0.15	0.40	0.3481	70	70	2.42	0.0097	0.15	0.40	0.8439
24	24	2.49	0.0097	0.15	0.45	0.4875	70	70	2.42	0.0097	0.15	0.45	0.9479
24	24	2.49	0.0097	0.15	0.50	0.6268	70	70	2.42	0.0097	0.15	0.50	0.9872
24	24	2.49	0.0097	0.15	0.55	0.7502	70	70	2.42	0.0097	0.15	0.55	0.9978
24	24	2.49	0.0097	0.15	0.60	0.8475	70	70	2.42	0.0097	0.15	0.60	0.9997
24	24	2.49	0.0097	0.15	0.65	0.9161	70	70	2.42	0.0097	0.15	0.65	1.0000
24	24	2.49	0.0097	0.20	0.35	0.1165	70	70	2.42	0.0097	0.20	0.35	0.3512
24	24	2.49	0.0097	0.20	0.40	0.2029	70	70	2.42	0.0097	0.20	0.40	0.5930
24	24	2.49	0.0097	0.20	0.45	0.3157	70	70	2.42	0.0097	0.20	0.45	0.7989
24	24	2.49	0.0097	0.20	0.50	0.4458	70	70	2.42	0.0097	0.20	0.50	0.9249
24	24	2.49	0.0097	0.20	0.55	0.5798	70	70	2.42	0.0097	0.20	0.55	0.9799
24	24	2.49	0.0097	0.20	0.60	0.7046	70	70	2.42	0.0097	0.20	0.60	0.9963
24	24	2.49	0.0097	0.20	0.65	0.8107	70	70	2.42	0.0097	0.20	0.65	0.9996

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
24	24	2.49	0.0097	0.20	0.70	0.8926	70	70	2.42	0.0097	0.20	0.70	1.0000
24	24	2.49	0.0097	0.25	0.40	0.1081	70	70	2.42	0.0097	0.25	0.40	0.3182
24	24	2.49	0.0097	0.25	0.45	0.1856	70	70	2.42	0.0097	0.25	0.45	0.5518
24	24	2.49	0.0097	0.25	0.50	0.2871	70	70	2.42	0.0097	0.25	0.50	0.7695
24	24	2.49	0.0097	0.25	0.55	0.4074	70	70	2.42	0.0097	0.25	0.55	0.9114
24	24	2.49	0.0097	0.25	0.60	0.5381	70	70	2.42	0.0097	0.25	0.60	0.9750
24	24	2.49	0.0097	0.25	0.65	0.6689	70	70	2.42	0.0097	0.25	0.65	0.9949
24	24	2.49	0.0097	0.25	0.70	0.7878	70	70	2.42	0.0097	0.25	0.70	0.9993
24	24	2.49	0.0097	0.25	0.75	0.8834	70	70	2.42	0.0097	0.25	0.75	0.9999
24	24	2.49	0.0097	0.30	0.45	0.0987	70	70	2.42	0.0097	0.30	0.45	0.3020
24	24	2.49	0.0097	0.30	0.50	0.1674	70	70	2.42	0.0097	0.30	0.50	0.5346
24	24	2.49	0.0097	0.30	0.55	0.2607	70	70	2.42	0.0097	0.30	0.55	0.7527
24	24	2.49	0.0097	0.30	0.60	0.3777	70	70	2.42	0.0097	0.30	0.60	0.8980
24	24	2.49	0.0097	0.30	0.65	0.5133	70	70	2.42	0.0097	0.30	0.65	0.9689
24	24	2.49	0.0097	0.30	0.70	0.6556	70	70	2.42	0.0097	0.30	0.70	0.9937
24	24	2.49	0.0097	0.35	0.50	0.0886	70	70	2.42	0.0097	0.35	0.50	0.2934
24	24	2.49	0.0097	0.35	0.55	0.1526	70	70	2.42	0.0097	0.35	0.55	0.5132
24	24	2.49	0.0097	0.35	0.60	0.2447	70	70	2.42	0.0097	0.35	0.60	0.7289
24	24	2.49	0.0097	0.35	0.65	0.3668	70	70	2.42	0.0097	0.35	0.65	0.8873
24	24	2.49	0.0097	0.40	0.55	0.0821	70	70	2.42	0.0097	0.40	0.55	0.2744
24	24	2.49	0.0097	0.40	0.60	0.1469	70	70	2.42	0.0097	0.40	0.60	0.4946
25	25	2.51	0.0093	0.05	0.15	0.0560	80	80	2.39	0.0097	0.05	0.15	0.4099
25	25	2.51	0.0093	0.05	0.20	0.1575	80	80	2.39	0.0097	0.05	0.20	0.7310
25	25	2.51	0.0093	0.05	0.25	0.3098	80	80	2.39	0.0097	0.05	0.25	0.9182
25	25	2.51	0.0093	0.05	0.30	0.4867	80	80	2.39	0.0097	0.05	0.30	0.9832
25	25	2.51	0.0093	0.05	0.35	0.6555	80	80	2.39	0.0097	0.05	0.35	0.9976
25	25	2.51	0.0093	0.05	0.40	0.7919	80	80	2.39	0.0097	0.05	0.40	0.9998
25	25	2.51	0.0093	0.05	0.45	0.8871	80	80	2.39	0.0097	0.05	0.45	1.0000
25	25	2.51	0.0093	0.10	0.25	0.1472	80	80	2.39	0.0097	0.10	0.25	0.5704
25	25	2.51	0.0093	0.10	0.30	0.2699	80	80	2.39	0.0097	0.10	0.30	0.8152
25	25	2.51	0.0093	0.10	0.35	0.4171	80	80	2.39	0.0097	0.10	0.35	0.9439
25	25	2.51	0.0093	0.10	0.40	0.5685	80	80	2.39	0.0097	0.10	0.40	0.9881
25	25	2.51	0.0093	0.10	0.45	0.7053	80	80	2.39	0.0097	0.10	0.45	0.9983
25	25	2.51	0.0093	0.10	0.50	0.8157	80	80	2.39	0.0097	0.10	0.50	0.9998
25	25	2.51	0.0093	0.10	0.55	0.8954	80	80	2.39	0.0097	0.10	0.55	1.0000
25	25	2.51	0.0093	0.10	0.60	0.9470	80	80	2.39	0.0097	0.10	0.60	1.0000
25	25	2.51	0.0093	0.15	0.30	0.1345	80	80	2.39	0.0097	0.15	0.30	0.4779
25	25	2.51	0.0093	0.15	0.35	0.2353	80	80	2.39	0.0097	0.15	0.35	0.7347
25	25	2.51	0.0093	0.15	0.40	0.3602	80	80	2.39	0.0097	0.15	0.40	0.9011
25	25	2.51	0.0093	0.15	0.45	0.4973	80	80	2.39	0.0097	0.15	0.45	0.9736
25	25	2.51	0.0093	0.15	0.50	0.6325	80	80	2.39	0.0097	0.15	0.50	0.9951
25	25	2.51	0.0093	0.15	0.55	0.7531	80	80	2.39	0.0097	0.15	0.55	0.9994
25	25	2.51	0.0093	0.15	0.60	0.8503	80	80	2.39	0.0097	0.15	0.60	0.9999
25	25	2.51	0.0093	0.15	0.65	0.9203	80	80	2.39	0.0097	0.15	0.65	1.0000
25	25	2.51	0.0093	0.20	0.35	0.1190	80	80	2.39	0.0097	0.20	0.35	0.4182
25	25	2.51	0.0093	0.20	0.40	0.2040	80	80	2.39	0.0097	0.20	0.40	0.6722
25	25	2.51	0.0093	0.20	0.45	0.3138	80	80	2.39	0.0097	0.20	0.45	0.8609
25	25	2.51	0.0093	0.20	0.50	0.4422	80	80	2.39	0.0097	0.20	0.50	0.9572
25	25	2.51	0.0093	0.20	0.55	0.5787	80	80	2.39	0.0097	0.20	0.55	0.9910
25	25	2.51	0.0093	0.20	0.60	0.7100	80	80	2.39	0.0097	0.20	0.60	0.9988

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
25	25	2.51	0.0093	0.20	0.65	0.8224	80	80	2.39	0.0097	0.20	0.65	0.9999
25	25	2.51	0.0093	0.20	0.70	0.9061	80	80	2.39	0.0097	0.20	0.70	1.0000
25	25	2.51	0.0093	0.25	0.40	0.1042	80	80	2.39	0.0097	0.25	0.40	0.3747
25	25	2.51	0.0093	0.25	0.45	0.1791	80	80	2.39	0.0097	0.25	0.45	0.6237
25	25	2.51	0.0093	0.25	0.50	0.2814	80	80	2.39	0.0097	0.25	0.50	0.8301
25	25	2.51	0.0093	0.25	0.55	0.4081	80	80	2.39	0.0097	0.25	0.55	0.9460
25	25	2.51	0.0093	0.25	0.60	0.5497	80	80	2.39	0.0097	0.25	0.60	0.9886
25	25	2.51	0.0093	0.25	0.65	0.6902	80	80	2.39	0.0097	0.25	0.65	0.9985
25	25	2.51	0.0093	0.25	0.70	0.8119	80	80	2.39	0.0097	0.25	0.70	0.9999
25	25	2.51	0.0093	0.25	0.75	0.9024	80	80	2.39	0.0097	0.25	0.75	1.0000
25	25	2.51	0.0093	0.30	0.45	0.0933	80	80	2.39	0.0097	0.30	0.45	0.3484
25	25	2.51	0.0093	0.30	0.50	0.1641	80	80	2.39	0.0097	0.30	0.50	0.6018
25	25	2.51	0.0093	0.30	0.55	0.2650	80	80	2.39	0.0097	0.30	0.55	0.8190
25	25	2.51	0.0093	0.30	0.60	0.3938	80	80	2.39	0.0097	0.30	0.60	0.9421
25	25	2.51	0.0093	0.30	0.65	0.5398	80	80	2.39	0.0097	0.30	0.65	0.9877
25	25	2.51	0.0093	0.30	0.70	0.6854	80	80	2.39	0.0097	0.30	0.70	0.9984
25	25	2.51	0.0093	0.35	0.50	0.0880	80	80	2.39	0.0097	0.35	0.50	0.3446
25	25	2.51	0.0093	0.35	0.55	0.1584	80	80	2.39	0.0097	0.35	0.55	0.5981
25	25	2.51	0.0093	0.35	0.60	0.2600	80	80	2.39	0.0097	0.35	0.60	0.8161
25	25	2.51	0.0093	0.35	0.65	0.3907	80	80	2.39	0.0097	0.35	0.65	0.9411
25	25	2.51	0.0093	0.40	0.55	0.0867	80	80	2.39	0.0097	0.40	0.55	0.3458
25	25	2.51	0.0093	0.40	0.60	0.1574	80	80	2.39	0.0097	0.40	0.60	0.5976
26	26	2.47	0.0098	0.05	0.15	0.1063	90	90	2.38	0.0097	0.05	0.15	0.4697
26	26	2.47	0.0098	0.05	0.20	0.2248	90	90	2.38	0.0097	0.05	0.20	0.7954
26	26	2.47	0.0098	0.05	0.25	0.3758	90	90	2.38	0.0097	0.05	0.25	0.9500
26	26	2.47	0.0098	0.05	0.30	0.5416	90	90	2.38	0.0097	0.05	0.30	0.9920
26	26	2.47	0.0098	0.05	0.35	0.6969	90	90	2.38	0.0097	0.05	0.35	0.9992
26	26	2.47	0.0098	0.05	0.40	0.8208	90	90	2.38	0.0097	0.05	0.40	0.9999
26	26	2.47	0.0098	0.05	0.45	0.9056	90	90	2.38	0.0097	0.05	0.45	1.0000
26	26	2.47	0.0098	0.10	0.25	0.1699	90	90	2.38	0.0097	0.10	0.25	0.6310
26	26	2.47	0.0098	0.10	0.30	0.2957	90	90	2.38	0.0097	0.10	0.30	0.8640
26	26	2.47	0.0098	0.10	0.35	0.4451	90	90	2.38	0.0097	0.10	0.35	0.9667
26	26	2.47	0.0098	0.10	0.40	0.5967	90	90	2.38	0.0097	0.10	0.40	0.9946
26	26	2.47	0.0098	0.10	0.45	0.7312	90	90	2.38	0.0097	0.10	0.45	0.9994
26	26	2.47	0.0098	0.10	0.50	0.8369	90	90	2.38	0.0097	0.10	0.50	1.0000
26	26	2.47	0.0098	0.10	0.55	0.9108	90	90	2.38	0.0097	0.10	0.55	1.0000
26	26	2.47	0.0098	0.10	0.60	0.9569	90	90	2.38	0.0097	0.10	0.60	1.0000
26	26	2.47	0.0098	0.15	0.30	0.1457	90	90	2.38	0.0097	0.15	0.30	0.5355
26	26	2.47	0.0098	0.15	0.35	0.2515	90	90	2.38	0.0097	0.15	0.35	0.7912
26	26	2.47	0.0098	0.15	0.40	0.3815	90	90	2.38	0.0097	0.15	0.40	0.9343
26	26	2.47	0.0098	0.15	0.45	0.5224	90	90	2.38	0.0097	0.15	0.45	0.9861
26	26	2.47	0.0098	0.15	0.50	0.6591	90	90	2.38	0.0097	0.15	0.50	0.9981
26	26	2.47	0.0098	0.15	0.55	0.7783	90	90	2.38	0.0097	0.15	0.55	0.9998
26	26	2.47	0.0098	0.15	0.60	0.8714	90	90	2.38	0.0097	0.15	0.60	1.0000
26	26	2.47	0.0098	0.15	0.65	0.9353	90	90	2.38	0.0097	0.15	0.65	1.0000
26	26	2.47	0.0098	0.20	0.35	0.1270	90	90	2.38	0.0097	0.20	0.35	0.4690
26	26	2.47	0.0098	0.20	0.40	0.2173	90	90	2.38	0.0097	0.20	0.40	0.7326
26	26	2.47	0.0098	0.20	0.45	0.3335	90	90	2.38	0.0097	0.20	0.45	0.9050
26	26	2.47	0.0098	0.20	0.50	0.4684	90	90	2.38	0.0097	0.20	0.50	0.9767
26	26	2.47	0.0098	0.20	0.55	0.6094	90	90	2.38	0.0097	0.20	0.55	0.9962

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
26	26	2.47	0.0098	0.20	0.60	0.7411	90	90	2.38	0.0097	0.20	0.60	0.9996
26	26	2.47	0.0098	0.20	0.65	0.8490	90	90	2.38	0.0097	0.20	0.65	1.0000
26	26	2.47	0.0098	0.20	0.70	0.9248	90	90	2.38	0.0097	0.20	0.70	1.0000
26	26	2.47	0.0098	0.25	0.40	0.1114	90	90	2.38	0.0097	0.25	0.40	0.4295
26	26	2.47	0.0098	0.25	0.45	0.1926	90	90	2.38	0.0097	0.25	0.45	0.6912
26	26	2.47	0.0098	0.25	0.50	0.3032	90	90	2.38	0.0097	0.25	0.50	0.8784
26	26	2.47	0.0098	0.25	0.55	0.4385	90	90	2.38	0.0097	0.25	0.55	0.9674
26	26	2.47	0.0098	0.25	0.60	0.5856	90	90	2.38	0.0097	0.25	0.60	0.9945
26	26	2.47	0.0098	0.25	0.65	0.7258	90	90	2.38	0.0097	0.25	0.65	0.9995
26	26	2.47	0.0098	0.25	0.70	0.8413	90	90	2.38	0.0097	0.25	0.70	1.0000
26	26	2.47	0.0098	0.25	0.75	0.9222	90	90	2.38	0.0097	0.25	0.75	1.0000
26	26	2.47	0.0098	0.30	0.45	0.1015	90	90	2.38	0.0097	0.30	0.45	0.3967
26	26	2.47	0.0098	0.30	0.50	0.1799	90	90	2.38	0.0097	0.30	0.50	0.6591
26	26	2.47	0.0098	0.30	0.55	0.2903	90	90	2.38	0.0097	0.30	0.55	0.8632
26	26	2.47	0.0098	0.30	0.60	0.4279	90	90	2.38	0.0097	0.30	0.60	0.9635
26	26	2.47	0.0098	0.30	0.65	0.5785	90	90	2.38	0.0097	0.30	0.65	0.9939
26	26	2.47	0.0098	0.30	0.70	0.7224	90	90	2.38	0.0097	0.30	0.70	0.9994
26	26	2.47	0.0098	0.35	0.50	0.0980	90	90	2.38	0.0097	0.35	0.50	0.3830
26	26	2.47	0.0098	0.35	0.55	0.1764	90	90	2.38	0.0097	0.35	0.55	0.6507
26	26	2.47	0.0098	0.35	0.60	0.2874	90	90	2.38	0.0097	0.35	0.60	0.8596
26	26	2.47	0.0098	0.35	0.65	0.4259	90	90	2.38	0.0097	0.35	0.65	0.9626
26	26	2.47	0.0098	0.40	0.55	0.0978	90	90	2.38	0.0097	0.40	0.55	0.3827
26	26	2.47	0.0098	0.40	0.60	0.1761	90	90	2.38	0.0097	0.40	0.60	0.6497
27	27	2.50	0.0100	0.05	0.15	0.0678	100	100	2.37	0.0099	0.05	0.15	0.5281
27	27	2.50	0.0100	0.05	0.20	0.1795	100	100	2.37	0.0099	0.05	0.20	0.8462
27	27	2.50	0.0100	0.05	0.25	0.3366	100	100	2.37	0.0099	0.05	0.25	0.9700
27	27	2.50	0.0100	0.05	0.30	0.5116	100	100	2.37	0.0099	0.05	0.30	0.9964
27	27	2.50	0.0100	0.05	0.35	0.6760	100	100	2.37	0.0099	0.05	0.35	0.9997
27	27	2.50	0.0100	0.05	0.40	0.8088	100	100	2.37	0.0099	0.05	0.40	1.0000
27	27	2.50	0.0100	0.05	0.45	0.9009	100	100	2.37	0.0099	0.05	0.45	1.0000
27	27	2.50	0.0100	0.10	0.25	0.1475	100	100	2.37	0.0099	0.10	0.25	0.6899
27	27	2.50	0.0100	0.10	0.30	0.2719	100	100	2.37	0.0099	0.10	0.30	0.9026
27	27	2.50	0.0100	0.10	0.35	0.4271	100	100	2.37	0.0099	0.10	0.35	0.9806
27	27	2.50	0.0100	0.10	0.40	0.5902	100	100	2.37	0.0099	0.10	0.40	0.9976
27	27	2.50	0.0100	0.10	0.45	0.7356	100	100	2.37	0.0099	0.10	0.45	0.9998
27	27	2.50	0.0100	0.10	0.50	0.8470	100	100	2.37	0.0099	0.10	0.50	1.0000
27	27	2.50	0.0100	0.10	0.55	0.9211	100	100	2.37	0.0099	0.10	0.55	1.0000
27	27	2.50	0.0100	0.10	0.60	0.9644	100	100	2.37	0.0099	0.10	0.60	1.0000
27	27	2.50	0.0100	0.15	0.30	0.1338	100	100	2.37	0.0099	0.15	0.30	0.5886
27	27	2.50	0.0100	0.15	0.35	0.2449	100	100	2.37	0.0099	0.15	0.35	0.8379
27	27	2.50	0.0100	0.15	0.40	0.3852	100	100	2.37	0.0099	0.15	0.40	0.9577
27	27	2.50	0.0100	0.15	0.45	0.5367	100	100	2.37	0.0099	0.15	0.45	0.9929
27	27	2.50	0.0100	0.15	0.50	0.6800	100	100	2.37	0.0099	0.15	0.50	0.9993
27	27	2.50	0.0100	0.15	0.55	0.8003	100	100	2.37	0.0099	0.15	0.55	1.0000
27	27	2.50	0.0100	0.15	0.60	0.8899	100	100	2.37	0.0099	0.15	0.60	1.0000
27	27	2.50	0.0100	0.15	0.65	0.9480	100	100	2.37	0.0099	0.15	0.65	1.0000
27	27	2.50	0.0100	0.20	0.35	0.1264	100	100	2.37	0.0099	0.20	0.35	0.5206
27	27	2.50	0.0100	0.20	0.40	0.2241	100	100	2.37	0.0099	0.20	0.40	0.7835
27	27	2.50	0.0100	0.20	0.45	0.3498	100	100	2.37	0.0099	0.20	0.45	0.9343
27	27	2.50	0.0100	0.20	0.50	0.4932	100	100	2.37	0.0099	0.20	0.50	0.9872

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
27	27	2.50	0.0100	0.20	0.55	0.6392	100	100	2.37	0.0099	0.20	0.55	0.9984
27	27	2.50	0.0100	0.20	0.60	0.7704	100	100	2.37	0.0099	0.20	0.60	0.9999
27	27	2.50	0.0100	0.20	0.65	0.8727	100	100	2.37	0.0099	0.20	0.65	1.0000
27	27	2.50	0.0100	0.20	0.70	0.9403	100	100	2.37	0.0099	0.20	0.70	1.0000
27	27	2.50	0.0100	0.25	0.40	0.1170	100	100	2.37	0.0099	0.25	0.40	0.4759
27	27	2.50	0.0100	0.25	0.45	0.2058	100	100	2.37	0.0099	0.25	0.45	0.7453
27	27	2.50	0.0100	0.25	0.50	0.3257	100	100	2.37	0.0099	0.25	0.50	0.9139
27	27	2.50	0.0100	0.25	0.55	0.4694	100	100	2.37	0.0099	0.25	0.55	0.9808
27	27	2.50	0.0100	0.25	0.60	0.6206	100	100	2.37	0.0099	0.25	0.60	0.9974
27	27	2.50	0.0100	0.25	0.65	0.7587	100	100	2.37	0.0099	0.25	0.65	0.9998
27	27	2.50	0.0100	0.25	0.70	0.8669	100	100	2.37	0.0099	0.25	0.70	1.0000
27	27	2.50	0.0100	0.25	0.75	0.9384	100	100	2.37	0.0099	0.25	0.75	1.0000
27	27	2.50	0.0100	0.30	0.45	0.1103	100	100	2.37	0.0099	0.30	0.45	0.4432
27	27	2.50	0.0100	0.30	0.50	0.1969	100	100	2.37	0.0099	0.30	0.50	0.7106
27	27	2.50	0.0100	0.30	0.55	0.3166	100	100	2.37	0.0099	0.30	0.55	0.8971
27	27	2.50	0.0100	0.30	0.60	0.4619	100	100	2.37	0.0099	0.30	0.60	0.9770
27	27	2.50	0.0100	0.30	0.65	0.6154	100	100	2.37	0.0099	0.30	0.65	0.9970
27	27	2.50	0.0100	0.30	0.70	0.7562	100	100	2.37	0.0099	0.30	0.70	0.9998
27	27	2.50	0.0100	0.35	0.50	0.1088	100	100	2.37	0.0099	0.35	0.50	0.4196
27	27	2.50	0.0100	0.35	0.55	0.1954	100	100	2.37	0.0099	0.35	0.55	0.6962
27	27	2.50	0.0100	0.35	0.60	0.3152	100	100	2.37	0.0099	0.35	0.60	0.8926
27	27	2.50	0.0100	0.35	0.65	0.4607	100	100	2.37	0.0099	0.35	0.65	0.9763
27	27	2.50	0.0100	0.40	0.55	0.1095	100	100	2.37	0.0099	0.40	0.55	0.4164
27	27	2.50	0.0100	0.40	0.60	0.1957	100	100	2.37	0.0099	0.40	0.60	0.6945
28	28	2.55	0.0091	0.05	0.15	0.0746	150	150	2.37	0.0097	0.05	0.15	0.7258
28	28	2.55	0.0091	0.05	0.20	0.1940	150	150	2.37	0.0097	0.05	0.20	0.9602
28	28	2.55	0.0091	0.05	0.25	0.3580	150	150	2.37	0.0097	0.05	0.25	0.9975
28	28	2.55	0.0091	0.05	0.30	0.5365	150	150	2.37	0.0097	0.05	0.30	0.9999
28	28	2.55	0.0091	0.05	0.35	0.6991	150	150	2.37	0.0097	0.05	0.35	1.0000
28	28	2.55	0.0091	0.05	0.40	0.8260	150	150	2.37	0.0097	0.05	0.40	1.0000
28	28	2.55	0.0091	0.05	0.45	0.9111	150	150	2.37	0.0097	0.05	0.45	1.0000
28	28	2.55	0.0091	0.10	0.25	0.1557	150	150	2.37	0.0097	0.10	0.25	0.8704
28	28	2.55	0.0091	0.10	0.30	0.2825	150	150	2.37	0.0097	0.10	0.30	0.9827
28	28	2.55	0.0091	0.10	0.35	0.4366	150	150	2.37	0.0097	0.10	0.35	0.9989
28	28	2.55	0.0091	0.10	0.40	0.5956	150	150	2.37	0.0097	0.10	0.40	1.0000
28	28	2.55	0.0091	0.10	0.45	0.7375	150	150	2.37	0.0097	0.10	0.45	1.0000
28	28	2.55	0.0091	0.10	0.50	0.8480	150	150	2.37	0.0097	0.10	0.50	1.0000
28	28	2.55	0.0091	0.10	0.55	0.9231	150	150	2.37	0.0097	0.10	0.55	1.0000
28	28	2.55	0.0091	0.10	0.60	0.9668	150	150	2.37	0.0097	0.10	0.60	1.0000
28	28	2.55	0.0091	0.15	0.30	0.1335	150	150	2.37	0.0097	0.15	0.30	0.7877
28	28	2.55	0.0091	0.15	0.35	0.2410	150	150	2.37	0.0097	0.15	0.35	0.9585
28	28	2.55	0.0091	0.15	0.40	0.3788	150	150	2.37	0.0097	0.15	0.40	0.9959
28	28	2.55	0.0091	0.15	0.45	0.5324	150	150	2.37	0.0097	0.15	0.45	0.9998
28	28	2.55	0.0091	0.15	0.50	0.6819	150	150	2.37	0.0097	0.15	0.50	1.0000
28	28	2.55	0.0091	0.15	0.55	0.8080	150	150	2.37	0.0097	0.15	0.55	1.0000
28	28	2.55	0.0091	0.15	0.60	0.8990	150	150	2.37	0.0097	0.15	0.60	1.0000
28	28	2.55	0.0091	0.15	0.65	0.9544	150	150	2.37	0.0097	0.15	0.65	1.0000
28	28	2.55	0.0091	0.20	0.35	0.1197	150	150	2.37	0.0097	0.20	0.35	0.7214
28	28	2.55	0.0091	0.20	0.40	0.2171	150	150	2.37	0.0097	0.20	0.40	0.9310
28	28	2.55	0.0091	0.20	0.45	0.3481	150	150	2.37	0.0097	0.20	0.45	0.9909

Table B.6: continue on next page

Table B.6: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
28	28	2.55	0.0091	0.20	0.50	0.5004	150	150	2.37	0.0097	0.20	0.50	0.9994
28	28	2.55	0.0091	0.20	0.55	0.6529	150	150	2.37	0.0097	0.20	0.55	1.0000
28	28	2.55	0.0091	0.20	0.60	0.7838	150	150	2.37	0.0097	0.20	0.60	1.0000
28	28	2.55	0.0091	0.20	0.65	0.8805	150	150	2.37	0.0097	0.20	0.65	1.0000
28	28	2.55	0.0091	0.20	0.70	0.9425	150	150	2.37	0.0097	0.20	0.70	1.0000
28	28	2.55	0.0091	0.25	0.40	0.1136	150	150	2.37	0.0097	0.25	0.40	0.6683
28	28	2.55	0.0091	0.25	0.45	0.2073	150	150	2.37	0.0097	0.25	0.45	0.9061
28	28	2.55	0.0091	0.25	0.50	0.3339	150	150	2.37	0.0097	0.25	0.50	0.9862
28	28	2.55	0.0091	0.25	0.55	0.4807	150	150	2.37	0.0097	0.25	0.55	0.9990
28	28	2.55	0.0091	0.25	0.60	0.6287	150	150	2.37	0.0097	0.25	0.60	1.0000
28	28	2.55	0.0091	0.25	0.65	0.7600	150	150	2.37	0.0097	0.25	0.65	1.0000
28	28	2.55	0.0091	0.25	0.70	0.8638	150	150	2.37	0.0097	0.25	0.70	1.0000
28	28	2.55	0.0091	0.25	0.75	0.9357	150	150	2.37	0.0097	0.25	0.75	1.0000
28	28	2.55	0.0091	0.30	0.45	0.1119	150	150	2.37	0.0097	0.30	0.45	0.6389
28	28	2.55	0.0091	0.30	0.50	0.2007	150	150	2.37	0.0097	0.30	0.50	0.8891
28	28	2.55	0.0091	0.30	0.55	0.3193	150	150	2.37	0.0097	0.30	0.55	0.9811
28	28	2.55	0.0091	0.30	0.60	0.4589	150	150	2.37	0.0097	0.30	0.60	0.9984
28	28	2.55	0.0091	0.30	0.65	0.6068	150	150	2.37	0.0097	0.30	0.65	0.9999
28	28	2.55	0.0091	0.30	0.70	0.7475	150	150	2.37	0.0097	0.30	0.70	1.0000
28	28	2.55	0.0091	0.35	0.50	0.1080	150	150	2.37	0.0097	0.35	0.50	0.6082
28	28	2.55	0.0091	0.35	0.55	0.1906	150	150	2.37	0.0097	0.35	0.55	0.8716
28	28	2.55	0.0091	0.35	0.60	0.3046	150	150	2.37	0.0097	0.35	0.60	0.9782
28	28	2.55	0.0091	0.35	0.65	0.4474	150	150	2.37	0.0097	0.35	0.65	0.9983
28	28	2.55	0.0091	0.40	0.55	0.1027	150	150	2.37	0.0097	0.40	0.55	0.5940
28	28	2.55	0.0091	0.40	0.60	0.1848	150	150	2.37	0.0097	0.40	0.60	0.8684

Table B.6: concluded from previous page

Table B.7: P-values calculated for the z-pooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.05**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
10	10	1.79	0.7007	0.0474
11	11	1.78	0.8034	0.0454
12	12	1.74	0.8154	0.0468
13	13	1.70	0.8258	0.0480
14	14	1.68	0.8349	0.0491
15	15	1.66	0.5000	0.0495
16	16	1.82	0.3212	0.0361
17	17	1.80	0.8880	0.0420
18	18	1.79	0.1065	0.0424
19	19	1.78	0.7183	0.0415
20	20	1.78	0.5000	0.0404
21	21	1.76	0.5000	0.0442
22	22	1.75	0.5000	0.0481
23	23	1.78	0.6151	0.0438
24	24	1.74	0.3670	0.0455
25	25	1.71	0.3546	0.0472
26	26	1.70	0.3439	0.0489
27	27	1.74	0.2580	0.0413
28	28	1.73	0.7464	0.0423
29	29	1.73	0.7508	0.0432
30	30	1.73	0.7550	0.0440
31	31	1.68	0.5000	0.0490
32	32	1.76	0.6279	0.0432
33	33	1.73	0.6118	0.0471
34	34	1.71	0.6289	0.0488
35	35	1.71	0.3468	0.0470
36	36	1.71	0.1520	0.0435
37	37	1.67	0.2186	0.0492
38	38	1.68	0.7884	0.0497
39	39	1.70	0.8539	0.0445
40	40	1.70	0.8556	0.0448
50	50	1.69	0.8711	0.0476
60	60	1.68	0.1608	0.0500
70	70	1.70	0.6020	0.0486

Table B.7: continue on next page

Table B.7: –continued from previous page

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
80	80	1.67	0.6877	0.0494
90	90	1.67	0.3616	0.0494
100	100	1.67	0.8758	0.0495
150	150	1.66	0.3544	0.0498

Table B.7: concluded from previous page

Table B.8: P-values calculated for the z-pooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha} = \mathbf{0.025}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
10	10	1.96	0.5000	0.0211
11	11	2.14	0.6449	0.0207
12	12	2.05	0.3184	0.0225
13	13	1.99	0.3038	0.0243
14	14	2.03	0.7879	0.0208
15	15	2.00	0.7962	0.0216
16	16	2.13	0.8033	0.0224
17	17	2.07	0.1910	0.0231
18	18	2.02	0.3308	0.0239
19	19	2.02	0.1776	0.0243
20	20	1.99	0.1736	0.0249
21	21	2.05	0.8465	0.0248
22	22	2.04	0.5000	0.0244
23	23	2.07	0.5585	0.0237
24	24	2.03	0.6050	0.0245
25	25	2.01	0.3416	0.0232
26	26	1.98	0.3330	0.0243
27	27	2.03	0.2867	0.0223
28	28	2.03	0.7180	0.0231
29	29	2.02	0.5000	0.0240
30	30	2.07	0.4471	0.0235
31	31	2.04	0.5936	0.0240
32	32	2.02	0.3606	0.0233
33	33	2.00	0.3530	0.0243
34	34	2.00	0.1975	0.0233

Table B.8: continue on next page

Table B.8: –continued from previous page

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
35	35	2.00	0.3043	0.0240
36	36	1.99	0.3002	0.0247
37	37	1.99	0.8105	0.0244
38	38	1.99	0.8114	0.0247
39	39	2.04	0.4543	0.0248
40	40	2.02	0.6084	0.0238
50	50	2.01	0.6056	0.0244
60	60	2.02	0.6023	0.0238
70	70	1.98	0.8245	0.0249
80	80	1.98	0.3210	0.0245
90	90	1.98	0.3654	0.0250
100	100	1.99	0.5967	0.0248
150	150	1.99	0.6112	0.0244

Table B.8: concluded from previous page

Table B.9: P-values calculated for the z-pooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.01**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
10	10	2.35	0.5000	0.0064
11	11	2.29	0.5000	0.0087
12	12	2.45	0.6114	0.0087
13	13	2.37	0.6577	0.0096
14	14	2.37	0.2519	0.0083
15	15	2.33	0.7560	0.0088
16	16	2.29	0.7612	0.0094
17	17	2.42	0.7714	0.0099
18	18	2.41	0.3519	0.0083
19	19	2.39	0.3353	0.0091
20	20	2.38	0.5000	0.0084
21	21	2.36	0.5000	0.0098
22	22	2.42	0.5519	0.0097
23	23	2.38	0.3287	0.0091
24	24	2.35	0.3236	0.0097
25	25	2.36	0.7387	0.0093

Table B.9: continue on next page

Table B.9: –continued from previous page

n_1	n_2	z_p	p	pvalue
26	26	2.34	0.7534	0.0098
27	27	2.37	0.5000	0.0100
28	28	2.41	0.5908	0.0091
29	29	2.37	0.6087	0.0096
30	30	2.36	0.3498	0.0092
31	31	2.34	0.3434	0.0097
32	32	2.35	0.7043	0.0091
33	33	2.33	0.7063	0.0094
34	34	2.43	0.6136	0.0084
35	35	2.40	0.6215	0.0089
36	36	2.38	0.7760	0.0094
37	37	2.35	0.3649	0.0098
38	38	2.35	0.2197	0.0098
39	39	2.37	0.7277	0.0093
40	40	2.36	0.7304	0.0096
50	50	2.41	0.6033	0.0086
60	60	2.38	0.5839	0.0096
70	70	2.37	0.5684	0.0100
80	80	2.35	0.7375	0.0097
90	90	2.34	0.7609	0.0097
100	100	2.34	0.1185	0.0099
150	150	2.34	0.6121	0.0099

Table B.9: concluded from previous page

Table B.10: Achieved power and p-values calculated for the z-pooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha} = \mathbf{0.05}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
10	10	1.79	0.0474	0.05	0.15	0.1109	29	29	1.73	0.0432	0.05	0.15	0.3151
10	10	1.79	0.0474	0.05	0.20	0.2037	29	29	1.73	0.0432	0.05	0.20	0.5053
10	10	1.79	0.0474	0.05	0.25	0.3101	29	29	1.73	0.0432	0.05	0.25	0.6861
10	10	1.79	0.0474	0.05	0.30	0.4205	29	29	1.73	0.0432	0.05	0.30	0.8247
10	10	1.79	0.0474	0.05	0.35	0.5276	29	29	1.73	0.0432	0.05	0.35	0.9137
10	10	1.79	0.0474	0.05	0.40	0.6267	29	29	1.73	0.0432	0.05	0.40	0.9627
10	10	1.79	0.0474	0.05	0.45	0.7151	29	29	1.73	0.0432	0.05	0.45	0.9860
10	10	1.79	0.0474	0.10	0.25	0.1995	29	29	1.73	0.0432	0.10	0.25	0.4129
10	10	1.79	0.0474	0.10	0.30	0.2827	29	29	1.73	0.0432	0.10	0.30	0.5864
10	10	1.79	0.0474	0.10	0.35	0.3725	29	29	1.73	0.0432	0.10	0.35	0.7384
10	10	1.79	0.0474	0.10	0.40	0.4655	29	29	1.73	0.0432	0.10	0.40	0.8521
10	10	1.79	0.0474	0.10	0.45	0.5585	29	29	1.73	0.0432	0.10	0.45	0.9254
10	10	1.79	0.0474	0.10	0.50	0.6478	29	29	1.73	0.0432	0.10	0.50	0.9667
10	10	1.79	0.0474	0.10	0.55	0.7298	29	29	1.73	0.0432	0.10	0.55	0.9869
10	10	1.79	0.0474	0.10	0.60	0.8016	29	29	1.73	0.0432	0.10	0.60	0.9956
10	10	1.79	0.0474	0.15	0.30	0.1871	29	29	1.73	0.0432	0.15	0.30	0.3649
10	10	1.79	0.0474	0.15	0.35	0.2587	29	29	1.73	0.0432	0.15	0.35	0.5262
10	10	1.79	0.0474	0.15	0.40	0.3394	29	29	1.73	0.0432	0.15	0.40	0.6770
10	10	1.79	0.0474	0.15	0.45	0.4263	29	29	1.73	0.0432	0.15	0.45	0.8001
10	10	1.79	0.0474	0.15	0.50	0.5160	29	29	1.73	0.0432	0.15	0.50	0.8892
10	10	1.79	0.0474	0.15	0.55	0.6043	29	29	1.73	0.0432	0.15	0.55	0.9461
10	10	1.79	0.0474	0.15	0.60	0.6876	29	29	1.73	0.0432	0.15	0.60	0.9777
10	10	1.79	0.0474	0.15	0.65	0.7629	29	29	1.73	0.0432	0.15	0.65	0.9924
10	10	1.79	0.0474	0.20	0.35	0.1761	29	29	1.73	0.0432	0.20	0.35	0.3304
10	10	1.79	0.0474	0.20	0.40	0.2417	29	29	1.73	0.0432	0.20	0.40	0.4783
10	10	1.79	0.0474	0.20	0.45	0.3168	29	29	1.73	0.0432	0.20	0.45	0.6270
10	10	1.79	0.0474	0.20	0.50	0.3987	29	29	1.73	0.0432	0.20	0.50	0.7595
10	10	1.79	0.0474	0.20	0.55	0.4844	29	29	1.73	0.0432	0.20	0.55	0.8631
10	10	1.79	0.0474	0.20	0.60	0.5707	29	29	1.73	0.0432	0.20	0.60	0.9327
10	10	1.79	0.0474	0.20	0.65	0.6548	29	29	1.73	0.0432	0.20	0.65	0.9722
10	10	1.79	0.0474	0.20	0.70	0.7344	29	29	1.73	0.0432	0.20	0.70	0.9907
10	10	1.79	0.0474	0.25	0.40	0.1675	29	29	1.73	0.0432	0.25	0.40	0.3020
10	10	1.79	0.0474	0.25	0.45	0.2285	29	29	1.73	0.0432	0.25	0.45	0.4454
10	10	1.79	0.0474	0.25	0.50	0.2986	29	29	1.73	0.0432	0.25	0.50	0.5979
10	10	1.79	0.0474	0.25	0.55	0.3763	29	29	1.73	0.0432	0.25	0.55	0.7390
10	10	1.79	0.0474	0.25	0.60	0.4595	29	29	1.73	0.0432	0.25	0.60	0.8512
10	10	1.79	0.0474	0.25	0.65	0.5465	29	29	1.73	0.0432	0.25	0.65	0.9271
10	10	1.79	0.0474	0.25	0.70	0.6353	29	29	1.73	0.0432	0.25	0.70	0.9701
10	10	1.79	0.0474	0.25	0.75	0.7235	29	29	1.73	0.0432	0.25	0.75	0.9902
10	10	1.79	0.0474	0.30	0.45	0.1598	29	29	1.73	0.0432	0.30	0.45	0.2877
10	10	1.79	0.0474	0.30	0.50	0.2168	29	29	1.73	0.0432	0.30	0.50	0.4320
10	10	1.79	0.0474	0.30	0.55	0.2836	29	29	1.73	0.0432	0.30	0.55	0.5875
10	10	1.79	0.0474	0.30	0.60	0.3598	29	29	1.73	0.0432	0.30	0.60	0.7320
10	10	1.79	0.0474	0.30	0.65	0.4448	29	29	1.73	0.0432	0.30	0.65	0.8473

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
10	10	1.79	0.0474	0.30	0.70	0.5373	29	29	1.73	0.0432	0.30	0.70	0.9256
10	10	1.79	0.0474	0.35	0.50	0.1526	29	29	1.73	0.0432	0.35	0.50	0.2849
10	10	1.79	0.0474	0.35	0.55	0.2078	29	29	1.73	0.0432	0.35	0.55	0.4293
10	10	1.79	0.0474	0.35	0.60	0.2746	29	29	1.73	0.0432	0.35	0.60	0.5850
10	10	1.79	0.0474	0.35	0.65	0.3536	29	29	1.73	0.0432	0.35	0.65	0.7304
10	10	1.79	0.0474	0.40	0.55	0.1481	29	29	1.73	0.0432	0.40	0.55	0.2856
10	10	1.79	0.0474	0.40	0.60	0.2043	29	29	1.73	0.0432	0.40	0.60	0.4292
11	11	1.78	0.0454	0.05	0.15	0.1311	30	30	1.73	0.0440	0.05	0.15	0.3237
11	11	1.78	0.0454	0.05	0.20	0.2344	30	30	1.73	0.0440	0.05	0.20	0.5203
11	11	1.78	0.0454	0.05	0.25	0.3483	30	30	1.73	0.0440	0.05	0.25	0.7029
11	11	1.78	0.0454	0.05	0.30	0.4621	30	30	1.73	0.0440	0.05	0.30	0.8389
11	11	1.78	0.0454	0.05	0.35	0.5687	30	30	1.73	0.0440	0.05	0.35	0.9233
11	11	1.78	0.0454	0.05	0.40	0.6640	30	30	1.73	0.0440	0.05	0.40	0.9681
11	11	1.78	0.0454	0.05	0.45	0.7461	30	30	1.73	0.0440	0.05	0.45	0.9886
11	11	1.78	0.0454	0.10	0.25	0.2166	30	30	1.73	0.0440	0.10	0.25	0.4269
11	11	1.78	0.0454	0.10	0.30	0.3013	30	30	1.73	0.0440	0.10	0.30	0.6036
11	11	1.78	0.0454	0.10	0.35	0.3898	30	30	1.73	0.0440	0.10	0.35	0.7550
11	11	1.78	0.0454	0.10	0.40	0.4790	30	30	1.73	0.0440	0.10	0.40	0.8652
11	11	1.78	0.0454	0.10	0.45	0.5662	30	30	1.73	0.0440	0.10	0.45	0.9341
11	11	1.78	0.0454	0.10	0.50	0.6489	30	30	1.73	0.0440	0.10	0.50	0.9715
11	11	1.78	0.0454	0.10	0.55	0.7253	30	30	1.73	0.0440	0.10	0.55	0.9893
11	11	1.78	0.0454	0.10	0.60	0.7939	30	30	1.73	0.0440	0.10	0.60	0.9966
11	11	1.78	0.0454	0.15	0.30	0.1902	30	30	1.73	0.0440	0.15	0.30	0.3779
11	11	1.78	0.0454	0.15	0.35	0.2579	30	30	1.73	0.0440	0.15	0.35	0.5422
11	11	1.78	0.0454	0.15	0.40	0.3325	30	30	1.73	0.0440	0.15	0.40	0.6934
11	11	1.78	0.0454	0.15	0.45	0.4122	30	30	1.73	0.0440	0.15	0.45	0.8147
11	11	1.78	0.0454	0.15	0.50	0.4953	30	30	1.73	0.0440	0.15	0.50	0.9005
11	11	1.78	0.0454	0.15	0.55	0.5798	30	30	1.73	0.0440	0.15	0.55	0.9537
11	11	1.78	0.0454	0.15	0.60	0.6634	30	30	1.73	0.0440	0.15	0.60	0.9818
11	11	1.78	0.0454	0.15	0.65	0.7434	30	30	1.73	0.0440	0.15	0.65	0.9942
11	11	1.78	0.0454	0.20	0.35	0.1648	30	30	1.73	0.0440	0.20	0.35	0.3415
11	11	1.78	0.0454	0.20	0.40	0.2226	30	30	1.73	0.0440	0.20	0.40	0.4935
11	11	1.78	0.0454	0.20	0.45	0.2893	30	30	1.73	0.0440	0.20	0.45	0.6451
11	11	1.78	0.0454	0.20	0.50	0.3645	30	30	1.73	0.0440	0.20	0.50	0.7776
11	11	1.78	0.0454	0.20	0.55	0.4473	30	30	1.73	0.0440	0.20	0.55	0.8780
11	11	1.78	0.0454	0.20	0.60	0.5357	30	30	1.73	0.0440	0.20	0.60	0.9427
11	11	1.78	0.0454	0.20	0.65	0.6268	30	30	1.73	0.0440	0.20	0.65	0.9775
11	11	1.78	0.0454	0.20	0.70	0.7164	30	30	1.73	0.0440	0.20	0.70	0.9929
11	11	1.78	0.0454	0.25	0.40	0.1439	30	30	1.73	0.0440	0.25	0.40	0.3139
11	11	1.78	0.0454	0.25	0.45	0.1962	30	30	1.73	0.0440	0.25	0.45	0.4633
11	11	1.78	0.0454	0.25	0.50	0.2595	30	30	1.73	0.0440	0.25	0.50	0.6196
11	11	1.78	0.0454	0.25	0.55	0.3341	30	30	1.73	0.0440	0.25	0.55	0.7603
11	11	1.78	0.0454	0.25	0.60	0.4192	30	30	1.73	0.0440	0.25	0.60	0.8681
11	11	1.78	0.0454	0.25	0.65	0.5126	30	30	1.73	0.0440	0.25	0.65	0.9381
11	11	1.78	0.0454	0.25	0.70	0.6106	30	30	1.73	0.0440	0.25	0.70	0.9759
11	11	1.78	0.0454	0.25	0.75	0.7083	30	30	1.73	0.0440	0.25	0.75	0.9925
11	11	1.78	0.0454	0.30	0.45	0.1287	30	30	1.73	0.0440	0.30	0.45	0.3024
11	11	1.78	0.0454	0.30	0.50	0.1790	30	30	1.73	0.0440	0.30	0.50	0.4528
11	11	1.78	0.0454	0.30	0.55	0.2419	30	30	1.73	0.0440	0.30	0.55	0.6112
11	11	1.78	0.0454	0.30	0.60	0.3181	30	30	1.73	0.0440	0.30	0.60	0.7543

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
11	11	1.78	0.0454	0.30	0.65	0.4067	30	30	1.73	0.0440	0.30	0.65	0.8647
11	11	1.78	0.0454	0.30	0.70	0.5056	30	30	1.73	0.0440	0.30	0.70	0.9368
11	11	1.78	0.0454	0.35	0.50	0.1195	30	30	1.73	0.0440	0.35	0.50	0.3013
11	11	1.78	0.0454	0.35	0.55	0.1698	30	30	1.73	0.0440	0.35	0.55	0.4511
11	11	1.78	0.0454	0.35	0.60	0.2341	30	30	1.73	0.0440	0.35	0.60	0.6092
11	11	1.78	0.0454	0.35	0.65	0.3132	30	30	1.73	0.0440	0.35	0.65	0.7529
11	11	1.78	0.0454	0.40	0.55	0.1154	30	30	1.73	0.0440	0.40	0.55	0.3024
11	11	1.78	0.0454	0.40	0.60	0.1670	30	30	1.73	0.0440	0.40	0.60	0.4512
12	12	1.74	0.0468	0.05	0.15	0.1510	31	31	1.68	0.0490	0.05	0.15	0.3952
12	12	1.74	0.0468	0.05	0.20	0.2638	31	31	1.68	0.0490	0.05	0.20	0.5898
12	12	1.74	0.0468	0.05	0.25	0.3845	31	31	1.68	0.0490	0.05	0.25	0.7502
12	12	1.74	0.0468	0.05	0.30	0.5020	31	31	1.68	0.0490	0.05	0.30	0.8649
12	12	1.74	0.0468	0.05	0.35	0.6096	31	31	1.68	0.0490	0.05	0.35	0.9360
12	12	1.74	0.0468	0.05	0.40	0.7037	31	31	1.68	0.0490	0.05	0.40	0.9739
12	12	1.74	0.0468	0.05	0.45	0.7827	31	31	1.68	0.0490	0.05	0.45	0.9909
12	12	1.74	0.0468	0.10	0.25	0.2350	31	31	1.68	0.0490	0.10	0.25	0.4531
12	12	1.74	0.0468	0.10	0.30	0.3248	31	31	1.68	0.0490	0.10	0.30	0.6253
12	12	1.74	0.0468	0.10	0.35	0.4184	31	31	1.68	0.0490	0.10	0.35	0.7723
12	12	1.74	0.0468	0.10	0.40	0.5121	31	31	1.68	0.0490	0.10	0.40	0.8775
12	12	1.74	0.0468	0.10	0.45	0.6028	31	31	1.68	0.0490	0.10	0.45	0.9418
12	12	1.74	0.0468	0.10	0.50	0.6878	31	31	1.68	0.0490	0.10	0.50	0.9758
12	12	1.74	0.0468	0.10	0.55	0.7649	31	31	1.68	0.0490	0.10	0.55	0.9913
12	12	1.74	0.0468	0.10	0.60	0.8322	31	31	1.68	0.0490	0.10	0.60	0.9974
12	12	1.74	0.0468	0.15	0.30	0.2026	31	31	1.68	0.0490	0.15	0.30	0.3919
12	12	1.74	0.0468	0.15	0.35	0.2758	31	31	1.68	0.0490	0.15	0.35	0.5581
12	12	1.74	0.0468	0.15	0.40	0.3568	31	31	1.68	0.0490	0.15	0.40	0.7092
12	12	1.74	0.0468	0.15	0.45	0.4438	31	31	1.68	0.0490	0.15	0.45	0.8285
12	12	1.74	0.0468	0.15	0.50	0.5342	31	31	1.68	0.0490	0.15	0.50	0.9110
12	12	1.74	0.0468	0.15	0.55	0.6251	31	31	1.68	0.0490	0.15	0.55	0.9604
12	12	1.74	0.0468	0.15	0.60	0.7127	31	31	1.68	0.0490	0.15	0.60	0.9853
12	12	1.74	0.0468	0.15	0.65	0.7929	31	31	1.68	0.0490	0.15	0.65	0.9956
12	12	1.74	0.0468	0.20	0.35	0.1750	31	31	1.68	0.0490	0.20	0.35	0.3526
12	12	1.74	0.0468	0.20	0.40	0.2394	31	31	1.68	0.0490	0.20	0.40	0.5089
12	12	1.74	0.0468	0.20	0.45	0.3147	31	31	1.68	0.0490	0.20	0.45	0.6631
12	12	1.74	0.0468	0.20	0.50	0.3999	31	31	1.68	0.0490	0.20	0.50	0.7950
12	12	1.74	0.0468	0.20	0.55	0.4928	31	31	1.68	0.0490	0.20	0.55	0.8917
12	12	1.74	0.0468	0.20	0.60	0.5897	31	31	1.68	0.0490	0.20	0.60	0.9514
12	12	1.74	0.0468	0.20	0.65	0.6854	31	31	1.68	0.0490	0.20	0.65	0.9819
12	12	1.74	0.0468	0.20	0.70	0.7744	31	31	1.68	0.0490	0.20	0.70	0.9946
12	12	1.74	0.0468	0.25	0.40	0.1550	31	31	1.68	0.0490	0.25	0.40	0.3264
12	12	1.74	0.0468	0.25	0.45	0.2156	31	31	1.68	0.0490	0.25	0.45	0.4817
12	12	1.74	0.0468	0.25	0.50	0.2895	31	31	1.68	0.0490	0.25	0.50	0.6410
12	12	1.74	0.0468	0.25	0.55	0.3758	31	31	1.68	0.0490	0.25	0.55	0.7803
12	12	1.74	0.0468	0.25	0.60	0.4719	31	31	1.68	0.0490	0.25	0.60	0.8834
12	12	1.74	0.0468	0.25	0.65	0.5735	31	31	1.68	0.0490	0.25	0.65	0.9475
12	12	1.74	0.0468	0.25	0.70	0.6747	31	31	1.68	0.0490	0.25	0.70	0.9805
12	12	1.74	0.0468	0.25	0.75	0.7693	31	31	1.68	0.0490	0.25	0.75	0.9943
12	12	1.74	0.0468	0.30	0.45	0.1429	31	31	1.68	0.0490	0.30	0.45	0.3176
12	12	1.74	0.0468	0.30	0.50	0.2027	31	31	1.68	0.0490	0.30	0.50	0.4735
12	12	1.74	0.0468	0.30	0.55	0.2770	31	31	1.68	0.0490	0.30	0.55	0.6341

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
12	12	1.74	0.0468	0.30	0.60	0.3650	31	31	1.68	0.0490	0.30	0.60	0.7751
12	12	1.74	0.0468	0.30	0.65	0.4639	31	31	1.68	0.0490	0.30	0.65	0.8803
12	12	1.74	0.0468	0.30	0.70	0.5691	31	31	1.68	0.0490	0.30	0.70	0.9463
12	12	1.74	0.0468	0.35	0.50	0.1370	31	31	1.68	0.0490	0.35	0.50	0.3177
12	12	1.74	0.0468	0.35	0.55	0.1971	31	31	1.68	0.0490	0.35	0.55	0.4725
12	12	1.74	0.0468	0.35	0.60	0.2724	31	31	1.68	0.0490	0.35	0.60	0.6323
12	12	1.74	0.0468	0.35	0.65	0.3621	31	31	1.68	0.0490	0.35	0.65	0.7737
12	12	1.74	0.0468	0.40	0.55	0.1350	31	31	1.68	0.0490	0.40	0.55	0.3191
12	12	1.74	0.0468	0.40	0.60	0.1957	31	31	1.68	0.0490	0.40	0.60	0.4725
13	13	1.70	0.0480	0.05	0.15	0.1703	32	32	1.76	0.0432	0.05	0.15	0.3414
13	13	1.70	0.0480	0.05	0.20	0.2914	32	32	1.76	0.0432	0.05	0.20	0.5495
13	13	1.70	0.0480	0.05	0.25	0.4178	32	32	1.76	0.0432	0.05	0.25	0.7334
13	13	1.70	0.0480	0.05	0.30	0.5381	32	32	1.76	0.0432	0.05	0.30	0.8622
13	13	1.70	0.0480	0.05	0.35	0.6461	32	32	1.76	0.0432	0.05	0.35	0.9374
13	13	1.70	0.0480	0.05	0.40	0.7384	32	32	1.76	0.0432	0.05	0.40	0.9751
13	13	1.70	0.0480	0.05	0.45	0.8142	32	32	1.76	0.0432	0.05	0.45	0.9913
13	13	1.70	0.0480	0.10	0.25	0.2518	32	32	1.76	0.0432	0.10	0.25	0.4459
13	13	1.70	0.0480	0.10	0.30	0.3468	32	32	1.76	0.0432	0.10	0.30	0.6214
13	13	1.70	0.0480	0.10	0.35	0.4455	32	32	1.76	0.0432	0.10	0.35	0.7682
13	13	1.70	0.0480	0.10	0.40	0.5437	32	32	1.76	0.0432	0.10	0.40	0.8741
13	13	1.70	0.0480	0.10	0.45	0.6379	32	32	1.76	0.0432	0.10	0.45	0.9403
13	13	1.70	0.0480	0.10	0.50	0.7248	32	32	1.76	0.0432	0.10	0.50	0.9758
13	13	1.70	0.0480	0.10	0.55	0.8016	32	32	1.76	0.0432	0.10	0.55	0.9919
13	13	1.70	0.0480	0.10	0.60	0.8660	32	32	1.76	0.0432	0.10	0.60	0.9978
13	13	1.70	0.0480	0.15	0.30	0.2144	32	32	1.76	0.0432	0.15	0.30	0.3787
13	13	1.70	0.0480	0.15	0.35	0.2937	32	32	1.76	0.0432	0.15	0.35	0.5447
13	13	1.70	0.0480	0.15	0.40	0.3820	32	32	1.76	0.0432	0.15	0.40	0.7015
13	13	1.70	0.0480	0.15	0.45	0.4768	32	32	1.76	0.0432	0.15	0.45	0.8281
13	13	1.70	0.0480	0.15	0.50	0.5745	32	32	1.76	0.0432	0.15	0.50	0.9145
13	13	1.70	0.0480	0.15	0.55	0.6703	32	32	1.76	0.0432	0.15	0.55	0.9638
13	13	1.70	0.0480	0.15	0.60	0.7593	32	32	1.76	0.0432	0.15	0.60	0.9871
13	13	1.70	0.0480	0.15	0.65	0.8366	32	32	1.76	0.0432	0.15	0.65	0.9961
13	13	1.70	0.0480	0.20	0.35	0.1862	32	32	1.76	0.0432	0.20	0.35	0.3405
13	13	1.70	0.0480	0.20	0.40	0.2582	32	32	1.76	0.0432	0.20	0.40	0.5051
13	13	1.70	0.0480	0.20	0.45	0.3431	32	32	1.76	0.0432	0.20	0.45	0.6681
13	13	1.70	0.0480	0.20	0.50	0.4385	32	32	1.76	0.0432	0.20	0.50	0.8033
13	13	1.70	0.0480	0.20	0.55	0.5404	32	32	1.76	0.0432	0.20	0.55	0.8975
13	13	1.70	0.0480	0.20	0.60	0.6429	32	32	1.76	0.0432	0.20	0.60	0.9532
13	13	1.70	0.0480	0.20	0.65	0.7395	32	32	1.76	0.0432	0.20	0.65	0.9814
13	13	1.70	0.0480	0.20	0.70	0.8239	32	32	1.76	0.0432	0.20	0.70	0.9938
13	13	1.70	0.0480	0.25	0.40	0.1685	32	32	1.76	0.0432	0.25	0.40	0.3270
13	13	1.70	0.0480	0.25	0.45	0.2384	32	32	1.76	0.0432	0.25	0.45	0.4878
13	13	1.70	0.0480	0.25	0.50	0.3232	32	32	1.76	0.0432	0.25	0.50	0.6465
13	13	1.70	0.0480	0.25	0.55	0.4205	32	32	1.76	0.0432	0.25	0.55	0.7798
13	13	1.70	0.0480	0.25	0.60	0.5255	32	32	1.76	0.0432	0.25	0.60	0.8772
13	13	1.70	0.0480	0.25	0.65	0.6318	32	32	1.76	0.0432	0.25	0.65	0.9400
13	13	1.70	0.0480	0.25	0.70	0.7323	32	32	1.76	0.0432	0.25	0.70	0.9755
13	13	1.70	0.0480	0.25	0.75	0.8206	32	32	1.76	0.0432	0.25	0.75	0.9924
13	13	1.70	0.0480	0.30	0.45	0.1600	32	32	1.76	0.0432	0.30	0.45	0.3176
13	13	1.70	0.0480	0.30	0.50	0.2299	32	32	1.76	0.0432	0.30	0.50	0.4668

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
13	13	1.70	0.0480	0.30	0.55	0.3154	32	32	1.76	0.0432	0.30	0.55	0.6169
13	13	1.70	0.0480	0.30	0.60	0.4139	32	32	1.76	0.0432	0.30	0.60	0.7511
13	13	1.70	0.0480	0.30	0.65	0.5205	32	32	1.76	0.0432	0.30	0.65	0.8584
13	13	1.70	0.0480	0.30	0.70	0.6290	32	32	1.76	0.0432	0.30	0.70	0.9330
13	13	1.70	0.0480	0.35	0.50	0.1574	32	32	1.76	0.0432	0.35	0.50	0.2980
13	13	1.70	0.0480	0.35	0.55	0.2274	32	32	1.76	0.0432	0.35	0.55	0.4380
13	13	1.70	0.0480	0.35	0.60	0.3133	32	32	1.76	0.0432	0.35	0.60	0.5898
13	13	1.70	0.0480	0.35	0.65	0.4124	32	32	1.76	0.0432	0.35	0.65	0.7367
13	13	1.70	0.0480	0.40	0.55	0.1571	32	32	1.76	0.0432	0.40	0.55	0.2784
13	13	1.70	0.0480	0.40	0.60	0.2271	32	32	1.76	0.0432	0.40	0.60	0.4234
14	14	1.68	0.0491	0.05	0.15	0.1888	33	33	1.73	0.0471	0.05	0.15	0.3505
14	14	1.68	0.0491	0.05	0.20	0.3173	33	33	1.73	0.0471	0.05	0.20	0.5639
14	14	1.68	0.0491	0.05	0.25	0.4484	33	33	1.73	0.0471	0.05	0.25	0.7478
14	14	1.68	0.0491	0.05	0.30	0.5710	33	33	1.73	0.0471	0.05	0.30	0.8731
14	14	1.68	0.0491	0.05	0.35	0.6788	33	33	1.73	0.0471	0.05	0.35	0.9441
14	14	1.68	0.0491	0.05	0.40	0.7692	33	33	1.73	0.0471	0.05	0.40	0.9785
14	14	1.68	0.0491	0.05	0.45	0.8416	33	33	1.73	0.0471	0.05	0.45	0.9929
14	14	1.68	0.0491	0.10	0.25	0.2675	33	33	1.73	0.0471	0.10	0.25	0.4579
14	14	1.68	0.0491	0.10	0.30	0.3678	33	33	1.73	0.0471	0.10	0.30	0.6353
14	14	1.68	0.0491	0.10	0.35	0.4717	33	33	1.73	0.0471	0.10	0.35	0.7814
14	14	1.68	0.0491	0.10	0.40	0.5745	33	33	1.73	0.0471	0.10	0.40	0.8847
14	14	1.68	0.0491	0.10	0.45	0.6719	33	33	1.73	0.0471	0.10	0.45	0.9474
14	14	1.68	0.0491	0.10	0.50	0.7599	33	33	1.73	0.0471	0.10	0.50	0.9797
14	14	1.68	0.0491	0.10	0.55	0.8350	33	33	1.73	0.0471	0.10	0.55	0.9936
14	14	1.68	0.0491	0.10	0.60	0.8951	33	33	1.73	0.0471	0.10	0.60	0.9984
14	14	1.68	0.0491	0.15	0.30	0.2263	33	33	1.73	0.0471	0.15	0.30	0.3895
14	14	1.68	0.0491	0.15	0.35	0.3123	33	33	1.73	0.0471	0.15	0.35	0.5598
14	14	1.68	0.0491	0.15	0.40	0.4086	33	33	1.73	0.0471	0.15	0.40	0.7183
14	14	1.68	0.0491	0.15	0.45	0.5113	33	33	1.73	0.0471	0.15	0.45	0.8431
14	14	1.68	0.0491	0.15	0.50	0.6152	33	33	1.73	0.0471	0.15	0.50	0.9252
14	14	1.68	0.0491	0.15	0.55	0.7140	33	33	1.73	0.0471	0.15	0.55	0.9700
14	14	1.68	0.0491	0.15	0.60	0.8016	33	33	1.73	0.0471	0.15	0.60	0.9900
14	14	1.68	0.0491	0.15	0.65	0.8733	33	33	1.73	0.0471	0.15	0.65	0.9973
14	14	1.68	0.0491	0.20	0.35	0.1987	33	33	1.73	0.0471	0.20	0.35	0.3537
14	14	1.68	0.0491	0.20	0.40	0.2793	33	33	1.73	0.0471	0.20	0.40	0.5241
14	14	1.68	0.0491	0.20	0.45	0.3742	33	33	1.73	0.0471	0.20	0.45	0.6894
14	14	1.68	0.0491	0.20	0.50	0.4791	33	33	1.73	0.0471	0.20	0.50	0.8226
14	14	1.68	0.0491	0.20	0.55	0.5879	33	33	1.73	0.0471	0.20	0.55	0.9121
14	14	1.68	0.0491	0.20	0.60	0.6929	33	33	1.73	0.0471	0.20	0.60	0.9623
14	14	1.68	0.0491	0.20	0.65	0.7869	33	33	1.73	0.0471	0.20	0.65	0.9861
14	14	1.68	0.0491	0.20	0.70	0.8642	33	33	1.73	0.0471	0.20	0.70	0.9957
14	14	1.68	0.0491	0.25	0.40	0.1842	33	33	1.73	0.0471	0.25	0.40	0.3440
14	14	1.68	0.0491	0.25	0.45	0.2640	33	33	1.73	0.0471	0.25	0.45	0.5115
14	14	1.68	0.0491	0.25	0.50	0.3594	33	33	1.73	0.0471	0.25	0.50	0.6734
14	14	1.68	0.0491	0.25	0.55	0.4661	33	33	1.73	0.0471	0.25	0.55	0.8051
14	14	1.68	0.0491	0.25	0.60	0.5772	33	33	1.73	0.0471	0.25	0.60	0.8969
14	14	1.68	0.0491	0.25	0.65	0.6850	33	33	1.73	0.0471	0.25	0.65	0.9524
14	14	1.68	0.0491	0.25	0.70	0.7818	33	33	1.73	0.0471	0.25	0.70	0.9818
14	14	1.68	0.0491	0.25	0.75	0.8619	33	33	1.73	0.0471	0.25	0.75	0.9947
14	14	1.68	0.0491	0.30	0.45	0.1794	33	33	1.73	0.0471	0.30	0.45	0.3394

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
14	14	1.68	0.0491	0.30	0.50	0.2594	33	33	1.73	0.0471	0.30	0.50	0.4967
14	14	1.68	0.0491	0.30	0.55	0.3551	33	33	1.73	0.0471	0.30	0.55	0.6504
14	14	1.68	0.0491	0.30	0.60	0.4622	33	33	1.73	0.0471	0.30	0.60	0.7818
14	14	1.68	0.0491	0.30	0.65	0.5740	33	33	1.73	0.0471	0.30	0.65	0.8813
14	14	1.68	0.0491	0.30	0.70	0.6830	33	33	1.73	0.0471	0.30	0.70	0.9467
14	14	1.68	0.0491	0.35	0.50	0.1794	33	33	1.73	0.0471	0.35	0.50	0.3246
14	14	1.68	0.0491	0.35	0.55	0.2591	33	33	1.73	0.0471	0.35	0.55	0.4724
14	14	1.68	0.0491	0.35	0.60	0.3545	33	33	1.73	0.0471	0.35	0.60	0.6264
14	14	1.68	0.0491	0.35	0.65	0.4614	33	33	1.73	0.0471	0.35	0.65	0.7689
14	14	1.68	0.0491	0.40	0.55	0.1804	33	33	1.73	0.0471	0.40	0.55	0.3067
14	14	1.68	0.0491	0.40	0.60	0.2594	33	33	1.73	0.0471	0.40	0.60	0.4586
15	15	1.66	0.0495	0.05	0.15	0.2064	34	34	1.71	0.0488	0.05	0.15	0.4192
15	15	1.66	0.0495	0.05	0.20	0.3415	34	34	1.71	0.0488	0.05	0.20	0.6218
15	15	1.66	0.0495	0.05	0.25	0.4768	34	34	1.71	0.0488	0.05	0.25	0.7836
15	15	1.66	0.0495	0.05	0.30	0.6010	34	34	1.71	0.0488	0.05	0.30	0.8927
15	15	1.66	0.0495	0.05	0.35	0.7084	34	34	1.71	0.0488	0.05	0.35	0.9546
15	15	1.66	0.0495	0.05	0.40	0.7966	34	34	1.71	0.0488	0.05	0.40	0.9837
15	15	1.66	0.0495	0.05	0.45	0.8655	34	34	1.71	0.0488	0.05	0.45	0.9951
15	15	1.66	0.0495	0.10	0.25	0.2824	34	34	1.71	0.0488	0.10	0.25	0.4883
15	15	1.66	0.0495	0.10	0.30	0.3882	34	34	1.71	0.0488	0.10	0.30	0.6693
15	15	1.66	0.0495	0.10	0.35	0.4975	34	34	1.71	0.0488	0.10	0.35	0.8127
15	15	1.66	0.0495	0.10	0.40	0.6049	34	34	1.71	0.0488	0.10	0.40	0.9071
15	15	1.66	0.0495	0.10	0.45	0.7049	34	34	1.71	0.0488	0.10	0.45	0.9599
15	15	1.66	0.0495	0.10	0.50	0.7928	34	34	1.71	0.0488	0.10	0.50	0.9852
15	15	1.66	0.0495	0.10	0.55	0.8648	34	34	1.71	0.0488	0.10	0.55	0.9955
15	15	1.66	0.0495	0.10	0.60	0.9192	34	34	1.71	0.0488	0.10	0.60	0.9989
15	15	1.66	0.0495	0.15	0.30	0.2386	34	34	1.71	0.0488	0.15	0.30	0.4274
15	15	1.66	0.0495	0.15	0.35	0.3320	34	34	1.71	0.0488	0.15	0.35	0.6013
15	15	1.66	0.0495	0.15	0.40	0.4366	34	34	1.71	0.0488	0.15	0.40	0.7528
15	15	1.66	0.0495	0.15	0.45	0.5468	34	34	1.71	0.0488	0.15	0.45	0.8659
15	15	1.66	0.0495	0.15	0.50	0.6554	34	34	1.71	0.0488	0.15	0.50	0.9376
15	15	1.66	0.0495	0.15	0.55	0.7548	34	34	1.71	0.0488	0.15	0.55	0.9756
15	15	1.66	0.0495	0.15	0.60	0.8385	34	34	1.71	0.0488	0.15	0.60	0.9921
15	15	1.66	0.0495	0.15	0.65	0.9030	34	34	1.71	0.0488	0.15	0.65	0.9979
15	15	1.66	0.0495	0.20	0.35	0.2128	34	34	1.71	0.0488	0.20	0.35	0.3862
15	15	1.66	0.0495	0.20	0.40	0.3027	34	34	1.71	0.0488	0.20	0.40	0.5556
15	15	1.66	0.0495	0.20	0.45	0.4073	34	34	1.71	0.0488	0.20	0.45	0.7147
15	15	1.66	0.0495	0.20	0.50	0.5204	34	34	1.71	0.0488	0.20	0.50	0.8401
15	15	1.66	0.0495	0.20	0.55	0.6337	34	34	1.71	0.0488	0.20	0.55	0.9223
15	15	1.66	0.0495	0.20	0.60	0.7384	34	34	1.71	0.0488	0.20	0.60	0.9674
15	15	1.66	0.0495	0.20	0.65	0.8273	34	34	1.71	0.0488	0.20	0.65	0.9882
15	15	1.66	0.0495	0.20	0.70	0.8962	34	34	1.71	0.0488	0.20	0.70	0.9965
15	15	1.66	0.0495	0.25	0.40	0.2021	34	34	1.71	0.0488	0.25	0.40	0.3652
15	15	1.66	0.0495	0.25	0.45	0.2917	34	34	1.71	0.0488	0.25	0.45	0.5327
15	15	1.66	0.0495	0.25	0.50	0.3968	34	34	1.71	0.0488	0.25	0.50	0.6916
15	15	1.66	0.0495	0.25	0.55	0.5110	34	34	1.71	0.0488	0.25	0.55	0.8184
15	15	1.66	0.0495	0.25	0.60	0.6256	34	34	1.71	0.0488	0.25	0.60	0.9053
15	15	1.66	0.0495	0.25	0.65	0.7321	34	34	1.71	0.0488	0.25	0.65	0.9572
15	15	1.66	0.0495	0.25	0.70	0.8232	34	34	1.71	0.0488	0.25	0.70	0.9841
15	15	1.66	0.0495	0.25	0.75	0.8944	34	34	1.71	0.0488	0.25	0.75	0.9956

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
15	15	1.66	0.0495	0.30	0.45	0.2005	34	34	1.71	0.0488	0.30	0.45	0.3530
15	15	1.66	0.0495	0.30	0.50	0.2900	34	34	1.71	0.0488	0.30	0.50	0.5109
15	15	1.66	0.0495	0.30	0.55	0.3947	34	34	1.71	0.0488	0.30	0.55	0.6631
15	15	1.66	0.0495	0.30	0.60	0.5084	34	34	1.71	0.0488	0.30	0.60	0.7922
15	15	1.66	0.0495	0.30	0.65	0.6232	34	34	1.71	0.0488	0.30	0.65	0.8891
15	15	1.66	0.0495	0.30	0.70	0.7306	34	34	1.71	0.0488	0.30	0.70	0.9516
15	15	1.66	0.0495	0.35	0.50	0.2024	34	34	1.71	0.0488	0.35	0.50	0.3325
15	15	1.66	0.0495	0.35	0.55	0.2911	34	34	1.71	0.0488	0.35	0.55	0.4814
15	15	1.66	0.0495	0.35	0.60	0.3948	34	34	1.71	0.0488	0.35	0.60	0.6364
15	15	1.66	0.0495	0.35	0.65	0.5080	34	34	1.71	0.0488	0.35	0.65	0.7787
15	15	1.66	0.0495	0.40	0.55	0.2040	34	34	1.71	0.0488	0.40	0.55	0.3114
15	15	1.66	0.0495	0.40	0.60	0.2917	34	34	1.71	0.0488	0.40	0.60	0.4661
16	16	1.82	0.0361	0.05	0.15	0.1021	35	35	1.71	0.0470	0.05	0.15	0.3691
16	16	1.82	0.0361	0.05	0.20	0.2113	35	35	1.71	0.0470	0.05	0.20	0.5918
16	16	1.82	0.0361	0.05	0.25	0.3448	35	35	1.71	0.0470	0.05	0.25	0.7746
16	16	1.82	0.0361	0.05	0.30	0.4864	35	35	1.71	0.0470	0.05	0.30	0.8925
16	16	1.82	0.0361	0.05	0.35	0.6217	35	35	1.71	0.0470	0.05	0.35	0.9555
16	16	1.82	0.0361	0.05	0.40	0.7400	35	35	1.71	0.0470	0.05	0.40	0.9841
16	16	1.82	0.0361	0.05	0.45	0.8344	35	35	1.71	0.0470	0.05	0.45	0.9952
16	16	1.82	0.0361	0.10	0.25	0.1985	35	35	1.71	0.0470	0.10	0.25	0.4810
16	16	1.82	0.0361	0.10	0.30	0.3109	35	35	1.71	0.0470	0.10	0.30	0.6620
16	16	1.82	0.0361	0.10	0.35	0.4381	35	35	1.71	0.0470	0.10	0.35	0.8063
16	16	1.82	0.0361	0.10	0.40	0.5678	35	35	1.71	0.0470	0.10	0.40	0.9039
16	16	1.82	0.0361	0.10	0.45	0.6878	35	35	1.71	0.0470	0.10	0.45	0.9595
16	16	1.82	0.0361	0.10	0.50	0.7887	35	35	1.71	0.0470	0.10	0.50	0.9858
16	16	1.82	0.0361	0.10	0.55	0.8662	35	35	1.71	0.0470	0.10	0.55	0.9960
16	16	1.82	0.0361	0.10	0.60	0.9210	35	35	1.71	0.0470	0.10	0.60	0.9991
16	16	1.82	0.0361	0.15	0.30	0.1940	35	35	1.71	0.0470	0.15	0.30	0.4117
16	16	1.82	0.0361	0.15	0.35	0.2976	35	35	1.71	0.0470	0.15	0.35	0.5903
16	16	1.82	0.0361	0.15	0.40	0.4150	35	35	1.71	0.0470	0.15	0.40	0.7505
16	16	1.82	0.0361	0.15	0.45	0.5354	35	35	1.71	0.0470	0.15	0.45	0.8693
16	16	1.82	0.0361	0.15	0.50	0.6486	35	35	1.71	0.0470	0.15	0.50	0.9417
16	16	1.82	0.0361	0.15	0.55	0.7472	35	35	1.71	0.0470	0.15	0.55	0.9779
16	16	1.82	0.0361	0.15	0.60	0.8278	35	35	1.71	0.0470	0.15	0.60	0.9929
16	16	1.82	0.0361	0.15	0.65	0.8902	35	35	1.71	0.0470	0.15	0.65	0.9981
16	16	1.82	0.0361	0.20	0.35	0.1923	35	35	1.71	0.0470	0.20	0.35	0.3803
16	16	1.82	0.0361	0.20	0.40	0.2859	35	35	1.71	0.0470	0.20	0.40	0.5585
16	16	1.82	0.0361	0.20	0.45	0.3908	35	35	1.71	0.0470	0.20	0.45	0.7222
16	16	1.82	0.0361	0.20	0.50	0.4995	35	35	1.71	0.0470	0.20	0.50	0.8462
16	16	1.82	0.0361	0.20	0.55	0.6057	35	35	1.71	0.0470	0.20	0.55	0.9251
16	16	1.82	0.0361	0.20	0.60	0.7044	35	35	1.71	0.0470	0.20	0.60	0.9682
16	16	1.82	0.0361	0.20	0.65	0.7920	35	35	1.71	0.0470	0.20	0.65	0.9886
16	16	1.82	0.0361	0.20	0.70	0.8655	35	35	1.71	0.0470	0.20	0.70	0.9967
16	16	1.82	0.0361	0.25	0.40	0.1846	35	35	1.71	0.0470	0.25	0.40	0.3685
16	16	1.82	0.0361	0.25	0.45	0.2668	35	35	1.71	0.0470	0.25	0.45	0.5368
16	16	1.82	0.0361	0.25	0.50	0.3605	35	35	1.71	0.0470	0.25	0.50	0.6929
16	16	1.82	0.0361	0.25	0.55	0.4621	35	35	1.71	0.0470	0.25	0.55	0.8176
16	16	1.82	0.0361	0.25	0.60	0.5677	35	35	1.71	0.0470	0.25	0.60	0.9050
16	16	1.82	0.0361	0.25	0.65	0.6727	35	35	1.71	0.0470	0.25	0.65	0.9582
16	16	1.82	0.0361	0.25	0.70	0.7711	35	35	1.71	0.0470	0.25	0.70	0.9852

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
16	16	1.82	0.0361	0.25	0.75	0.8563	35	35	1.71	0.0470	0.25	0.75	0.9961
16	16	1.82	0.0361	0.30	0.45	0.1705	35	35	1.71	0.0470	0.30	0.45	0.3495
16	16	1.82	0.0361	0.30	0.50	0.2443	35	35	1.71	0.0470	0.30	0.50	0.5044
16	16	1.82	0.0361	0.30	0.55	0.3327	35	35	1.71	0.0470	0.30	0.55	0.6576
16	16	1.82	0.0361	0.30	0.60	0.4345	35	35	1.71	0.0470	0.30	0.60	0.7911
16	16	1.82	0.0361	0.30	0.65	0.5461	35	35	1.71	0.0470	0.30	0.65	0.8915
16	16	1.82	0.0361	0.30	0.70	0.6613	35	35	1.71	0.0470	0.30	0.70	0.9542
16	16	1.82	0.0361	0.35	0.50	0.1559	35	35	1.71	0.0470	0.35	0.50	0.3225
16	16	1.82	0.0361	0.35	0.55	0.2270	35	35	1.71	0.0470	0.35	0.55	0.4743
16	16	1.82	0.0361	0.35	0.60	0.3167	35	35	1.71	0.0470	0.35	0.60	0.6352
16	16	1.82	0.0361	0.35	0.65	0.4246	35	35	1.71	0.0470	0.35	0.65	0.7812
16	16	1.82	0.0361	0.40	0.55	0.1472	35	35	1.71	0.0470	0.40	0.55	0.3048
16	16	1.82	0.0361	0.40	0.60	0.2206	35	35	1.71	0.0470	0.40	0.60	0.4631
17	17	1.80	0.0420	0.05	0.15	0.2141	36	36	1.71	0.0435	0.05	0.15	0.3785
17	17	1.80	0.0420	0.05	0.20	0.3346	36	36	1.71	0.0435	0.05	0.20	0.6053
17	17	1.80	0.0420	0.05	0.25	0.4560	36	36	1.71	0.0435	0.05	0.25	0.7870
17	17	1.80	0.0420	0.05	0.30	0.5764	36	36	1.71	0.0435	0.05	0.30	0.9011
17	17	1.80	0.0420	0.05	0.35	0.6907	36	36	1.71	0.0435	0.05	0.35	0.9604
17	17	1.80	0.0420	0.05	0.40	0.7910	36	36	1.71	0.0435	0.05	0.40	0.9864
17	17	1.80	0.0420	0.05	0.45	0.8706	36	36	1.71	0.0435	0.05	0.45	0.9960
17	17	1.80	0.0420	0.10	0.25	0.2498	36	36	1.71	0.0435	0.10	0.25	0.4923
17	17	1.80	0.0420	0.10	0.30	0.3609	36	36	1.71	0.0435	0.10	0.30	0.6748
17	17	1.80	0.0420	0.10	0.35	0.4865	36	36	1.71	0.0435	0.10	0.35	0.8180
17	17	1.80	0.0420	0.10	0.40	0.6133	36	36	1.71	0.0435	0.10	0.40	0.9124
17	17	1.80	0.0420	0.10	0.45	0.7280	36	36	1.71	0.0435	0.10	0.45	0.9644
17	17	1.80	0.0420	0.10	0.50	0.8213	36	36	1.71	0.0435	0.10	0.50	0.9880
17	17	1.80	0.0420	0.10	0.55	0.8906	36	36	1.71	0.0435	0.10	0.55	0.9967
17	17	1.80	0.0420	0.10	0.60	0.9377	36	36	1.71	0.0435	0.10	0.60	0.9993
17	17	1.80	0.0420	0.15	0.30	0.2214	36	36	1.71	0.0435	0.15	0.30	0.4229
17	17	1.80	0.0420	0.15	0.35	0.3295	36	36	1.71	0.0435	0.15	0.35	0.6047
17	17	1.80	0.0420	0.15	0.40	0.4501	36	36	1.71	0.0435	0.15	0.40	0.7640
17	17	1.80	0.0420	0.15	0.45	0.5711	36	36	1.71	0.0435	0.15	0.45	0.8784
17	17	1.80	0.0420	0.15	0.50	0.6821	36	36	1.71	0.0435	0.15	0.50	0.9460
17	17	1.80	0.0420	0.15	0.55	0.7769	36	36	1.71	0.0435	0.15	0.55	0.9794
17	17	1.80	0.0420	0.15	0.60	0.8530	36	36	1.71	0.0435	0.15	0.60	0.9933
17	17	1.80	0.0420	0.15	0.65	0.9104	36	36	1.71	0.0435	0.15	0.65	0.9982
17	17	1.80	0.0420	0.20	0.35	0.2111	36	36	1.71	0.0435	0.20	0.35	0.3907
17	17	1.80	0.0420	0.20	0.40	0.3091	36	36	1.71	0.0435	0.20	0.40	0.5684
17	17	1.80	0.0420	0.20	0.45	0.4176	36	36	1.71	0.0435	0.20	0.45	0.7279
17	17	1.80	0.0420	0.20	0.50	0.5290	36	36	1.71	0.0435	0.20	0.50	0.8479
17	17	1.80	0.0420	0.20	0.55	0.6369	36	36	1.71	0.0435	0.20	0.55	0.9255
17	17	1.80	0.0420	0.20	0.60	0.7361	36	36	1.71	0.0435	0.20	0.60	0.9689
17	17	1.80	0.0420	0.20	0.65	0.8220	36	36	1.71	0.0435	0.20	0.65	0.9894
17	17	1.80	0.0420	0.20	0.70	0.8912	36	36	1.71	0.0435	0.20	0.70	0.9972
17	17	1.80	0.0420	0.25	0.40	0.1981	36	36	1.71	0.0435	0.25	0.40	0.3689
17	17	1.80	0.0420	0.25	0.45	0.2848	36	36	1.71	0.0435	0.25	0.45	0.5334
17	17	1.80	0.0420	0.25	0.50	0.3838	36	36	1.71	0.0435	0.25	0.50	0.6889
17	17	1.80	0.0420	0.25	0.55	0.4914	36	36	1.71	0.0435	0.25	0.55	0.8170
17	17	1.80	0.0420	0.25	0.60	0.6023	36	36	1.71	0.0435	0.25	0.60	0.9079
17	17	1.80	0.0420	0.25	0.65	0.7097	36	36	1.71	0.0435	0.25	0.65	0.9617

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
17	17	1.80	0.0420	0.25	0.70	0.8062	36	36	1.71	0.0435	0.25	0.70	0.9874
17	17	1.80	0.0420	0.25	0.75	0.8848	36	36	1.71	0.0435	0.25	0.75	0.9969
17	17	1.80	0.0420	0.30	0.45	0.1815	36	36	1.71	0.0435	0.30	0.45	0.3408
17	17	1.80	0.0420	0.30	0.50	0.2615	36	36	1.71	0.0435	0.30	0.50	0.4986
17	17	1.80	0.0420	0.30	0.55	0.3579	36	36	1.71	0.0435	0.30	0.55	0.6594
17	17	1.80	0.0420	0.30	0.60	0.4677	36	36	1.71	0.0435	0.30	0.60	0.7992
17	17	1.80	0.0420	0.30	0.65	0.5851	36	36	1.71	0.0435	0.30	0.65	0.9003
17	17	1.80	0.0420	0.30	0.70	0.7012	36	36	1.71	0.0435	0.30	0.70	0.9597
17	17	1.80	0.0420	0.35	0.50	0.1678	36	36	1.71	0.0435	0.35	0.50	0.3196
17	17	1.80	0.0420	0.35	0.55	0.2465	36	36	1.71	0.0435	0.35	0.55	0.4802
17	17	1.80	0.0420	0.35	0.60	0.3450	36	36	1.71	0.0435	0.35	0.60	0.6481
17	17	1.80	0.0420	0.35	0.65	0.4601	36	36	1.71	0.0435	0.35	0.65	0.7947
17	17	1.80	0.0420	0.40	0.55	0.1608	36	36	1.71	0.0435	0.40	0.55	0.3121
17	17	1.80	0.0420	0.40	0.60	0.2416	36	36	1.71	0.0435	0.40	0.60	0.4760
18	18	1.79	0.0424	0.05	0.15	0.2246	37	37	1.67	0.0492	0.05	0.15	0.4416
18	18	1.79	0.0424	0.05	0.20	0.3489	37	37	1.67	0.0492	0.05	0.20	0.6521
18	18	1.79	0.0424	0.05	0.25	0.4759	37	37	1.67	0.0492	0.05	0.25	0.8142
18	18	1.79	0.0424	0.05	0.30	0.6023	37	37	1.67	0.0492	0.05	0.30	0.9162
18	18	1.79	0.0424	0.05	0.35	0.7199	37	37	1.67	0.0492	0.05	0.35	0.9684
18	18	1.79	0.0424	0.05	0.40	0.8190	37	37	1.67	0.0492	0.05	0.40	0.9900
18	18	1.79	0.0424	0.05	0.45	0.8936	37	37	1.67	0.0492	0.05	0.45	0.9974
18	18	1.79	0.0424	0.10	0.25	0.2640	37	37	1.67	0.0492	0.10	0.25	0.5241
18	18	1.79	0.0424	0.10	0.30	0.3850	37	37	1.67	0.0492	0.10	0.30	0.7096
18	18	1.79	0.0424	0.10	0.35	0.5183	37	37	1.67	0.0492	0.10	0.35	0.8464
18	18	1.79	0.0424	0.10	0.40	0.6479	37	37	1.67	0.0492	0.10	0.40	0.9299
18	18	1.79	0.0424	0.10	0.45	0.7601	37	37	1.67	0.0492	0.10	0.45	0.9727
18	18	1.79	0.0424	0.10	0.50	0.8476	37	37	1.67	0.0492	0.10	0.50	0.9912
18	18	1.79	0.0424	0.10	0.55	0.9098	37	37	1.67	0.0492	0.10	0.55	0.9977
18	18	1.79	0.0424	0.10	0.60	0.9507	37	37	1.67	0.0492	0.10	0.60	0.9995
18	18	1.79	0.0424	0.15	0.30	0.2386	37	37	1.67	0.0492	0.15	0.30	0.4610
18	18	1.79	0.0424	0.15	0.35	0.3543	37	37	1.67	0.0492	0.15	0.35	0.6416
18	18	1.79	0.0424	0.15	0.40	0.4796	37	37	1.67	0.0492	0.15	0.40	0.7919
18	18	1.79	0.0424	0.15	0.45	0.6019	37	37	1.67	0.0492	0.15	0.45	0.8962
18	18	1.79	0.0424	0.15	0.50	0.7116	37	37	1.67	0.0492	0.15	0.50	0.9559
18	18	1.79	0.0424	0.15	0.55	0.8033	37	37	1.67	0.0492	0.15	0.55	0.9841
18	18	1.79	0.0424	0.15	0.60	0.8752	37	37	1.67	0.0492	0.15	0.60	0.9952
18	18	1.79	0.0424	0.15	0.65	0.9279	37	37	1.67	0.0492	0.15	0.65	0.9988
18	18	1.79	0.0424	0.20	0.35	0.2266	37	37	1.67	0.0492	0.20	0.35	0.4203
18	18	1.79	0.0424	0.20	0.40	0.3296	37	37	1.67	0.0492	0.20	0.40	0.5986
18	18	1.79	0.0424	0.20	0.45	0.4422	37	37	1.67	0.0492	0.20	0.45	0.7551
18	18	1.79	0.0424	0.20	0.50	0.5569	37	37	1.67	0.0492	0.20	0.50	0.8688
18	18	1.79	0.0424	0.20	0.55	0.6671	37	37	1.67	0.0492	0.20	0.55	0.9386
18	18	1.79	0.0424	0.20	0.60	0.7665	37	37	1.67	0.0492	0.20	0.60	0.9755
18	18	1.79	0.0424	0.20	0.65	0.8500	37	37	1.67	0.0492	0.20	0.65	0.9920
18	18	1.79	0.0424	0.20	0.70	0.9137	37	37	1.67	0.0492	0.20	0.70	0.9980
18	18	1.79	0.0424	0.25	0.40	0.2103	37	37	1.67	0.0492	0.25	0.40	0.3959
18	18	1.79	0.0424	0.25	0.45	0.3024	37	37	1.67	0.0492	0.25	0.45	0.5650
18	18	1.79	0.0424	0.25	0.50	0.4079	37	37	1.67	0.0492	0.25	0.50	0.7187
18	18	1.79	0.0424	0.25	0.55	0.5220	37	37	1.67	0.0492	0.25	0.55	0.8393
18	18	1.79	0.0424	0.25	0.60	0.6377	37	37	1.67	0.0492	0.25	0.60	0.9213

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
18	18	1.79	0.0424	0.25	0.65	0.7461	37	37	1.67	0.0492	0.25	0.65	0.9683
18	18	1.79	0.0424	0.25	0.70	0.8386	37	37	1.67	0.0492	0.25	0.70	0.9900
18	18	1.79	0.0424	0.25	0.75	0.9094	37	37	1.67	0.0492	0.25	0.75	0.9977
18	18	1.79	0.0424	0.30	0.45	0.1932	37	37	1.67	0.0492	0.30	0.45	0.3679
18	18	1.79	0.0424	0.30	0.50	0.2807	37	37	1.67	0.0492	0.30	0.50	0.5283
18	18	1.79	0.0424	0.30	0.55	0.3857	37	37	1.67	0.0492	0.30	0.55	0.6857
18	18	1.79	0.0424	0.30	0.60	0.5033	37	37	1.67	0.0492	0.30	0.60	0.8186
18	18	1.79	0.0424	0.30	0.65	0.6250	37	37	1.67	0.0492	0.30	0.65	0.9124
18	18	1.79	0.0424	0.30	0.70	0.7401	37	37	1.67	0.0492	0.30	0.70	0.9660
18	18	1.79	0.0424	0.35	0.50	0.1818	37	37	1.67	0.0492	0.35	0.50	0.3415
18	18	1.79	0.0424	0.35	0.55	0.2691	37	37	1.67	0.0492	0.35	0.55	0.5037
18	18	1.79	0.0424	0.35	0.60	0.3763	37	37	1.67	0.0492	0.35	0.60	0.6700
18	18	1.79	0.0424	0.35	0.65	0.4980	37	37	1.67	0.0492	0.35	0.65	0.8125
18	18	1.79	0.0424	0.40	0.55	0.1770	37	37	1.67	0.0492	0.40	0.55	0.3293
18	18	1.79	0.0424	0.40	0.60	0.2658	37	37	1.67	0.0492	0.40	0.60	0.4967
19	19	1.78	0.0415	0.05	0.15	0.2342	38	38	1.68	0.0497	0.05	0.15	0.4488
19	19	1.78	0.0415	0.05	0.20	0.3628	38	38	1.68	0.0497	0.05	0.20	0.6620
19	19	1.78	0.0415	0.05	0.25	0.4962	38	38	1.68	0.0497	0.05	0.25	0.8238
19	19	1.78	0.0415	0.05	0.30	0.6283	38	38	1.68	0.0497	0.05	0.30	0.9231
19	19	1.78	0.0415	0.05	0.35	0.7479	38	38	1.68	0.0497	0.05	0.35	0.9720
19	19	1.78	0.0415	0.05	0.40	0.8444	38	38	1.68	0.0497	0.05	0.40	0.9915
19	19	1.78	0.0415	0.05	0.45	0.9131	38	38	1.68	0.0497	0.05	0.45	0.9979
19	19	1.78	0.0415	0.10	0.25	0.2793	38	38	1.68	0.0497	0.10	0.25	0.5359
19	19	1.78	0.0415	0.10	0.30	0.4098	38	38	1.68	0.0497	0.10	0.30	0.7220
19	19	1.78	0.0415	0.10	0.35	0.5493	38	38	1.68	0.0497	0.10	0.35	0.8562
19	19	1.78	0.0415	0.10	0.40	0.6798	38	38	1.68	0.0497	0.10	0.40	0.9360
19	19	1.78	0.0415	0.10	0.45	0.7883	38	38	1.68	0.0497	0.10	0.45	0.9758
19	19	1.78	0.0415	0.10	0.50	0.8697	38	38	1.68	0.0497	0.10	0.50	0.9924
19	19	1.78	0.0415	0.10	0.55	0.9256	38	38	1.68	0.0497	0.10	0.55	0.9980
19	19	1.78	0.0415	0.10	0.60	0.9611	38	38	1.68	0.0497	0.10	0.60	0.9996
19	19	1.78	0.0415	0.15	0.30	0.2560	38	38	1.68	0.0497	0.15	0.30	0.4713
19	19	1.78	0.0415	0.15	0.35	0.3782	38	38	1.68	0.0497	0.15	0.35	0.6529
19	19	1.78	0.0415	0.15	0.40	0.5071	38	38	1.68	0.0497	0.15	0.40	0.8010
19	19	1.78	0.0415	0.15	0.45	0.6301	38	38	1.68	0.0497	0.15	0.45	0.9013
19	19	1.78	0.0415	0.15	0.50	0.7383	38	38	1.68	0.0497	0.15	0.50	0.9579
19	19	1.78	0.0415	0.15	0.55	0.8271	38	38	1.68	0.0497	0.15	0.55	0.9847
19	19	1.78	0.0415	0.15	0.60	0.8950	38	38	1.68	0.0497	0.15	0.60	0.9954
19	19	1.78	0.0415	0.15	0.65	0.9427	38	38	1.68	0.0497	0.15	0.65	0.9989
19	19	1.78	0.0415	0.20	0.35	0.2412	38	38	1.68	0.0497	0.20	0.35	0.4264
19	19	1.78	0.0415	0.20	0.40	0.3490	38	38	1.68	0.0497	0.20	0.40	0.6026
19	19	1.78	0.0415	0.20	0.45	0.4659	38	38	1.68	0.0497	0.20	0.45	0.7557
19	19	1.78	0.0415	0.20	0.50	0.5844	38	38	1.68	0.0497	0.20	0.50	0.8681
19	19	1.78	0.0415	0.20	0.55	0.6967	38	38	1.68	0.0497	0.20	0.55	0.9389
19	19	1.78	0.0415	0.20	0.60	0.7956	38	38	1.68	0.0497	0.20	0.60	0.9765
19	19	1.78	0.0415	0.20	0.65	0.8751	38	38	1.68	0.0497	0.20	0.65	0.9928
19	19	1.78	0.0415	0.20	0.70	0.9325	38	38	1.68	0.0497	0.20	0.70	0.9984
19	19	1.78	0.0415	0.25	0.40	0.2223	38	38	1.68	0.0497	0.25	0.40	0.3910
19	19	1.78	0.0415	0.25	0.45	0.3205	38	38	1.68	0.0497	0.25	0.45	0.5586
19	19	1.78	0.0415	0.25	0.50	0.4331	38	38	1.68	0.0497	0.25	0.50	0.7155
19	19	1.78	0.0415	0.25	0.55	0.5536	38	38	1.68	0.0497	0.25	0.55	0.8413

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
19	19	1.78	0.0415	0.25	0.60	0.6728	38	38	1.68	0.0497	0.25	0.60	0.9258
19	19	1.78	0.0415	0.25	0.65	0.7801	38	38	1.68	0.0497	0.25	0.65	0.9719
19	19	1.78	0.0415	0.25	0.70	0.8671	38	38	1.68	0.0497	0.25	0.70	0.9917
19	19	1.78	0.0415	0.25	0.75	0.9296	38	38	1.68	0.0497	0.25	0.75	0.9982
19	19	1.78	0.0415	0.30	0.45	0.2062	38	38	1.68	0.0497	0.30	0.45	0.3599
19	19	1.78	0.0415	0.30	0.50	0.3017	38	38	1.68	0.0497	0.30	0.50	0.5270
19	19	1.78	0.0415	0.30	0.55	0.4153	38	38	1.68	0.0497	0.30	0.55	0.6927
19	19	1.78	0.0415	0.30	0.60	0.5396	38	38	1.68	0.0497	0.30	0.60	0.8292
19	19	1.78	0.0415	0.30	0.65	0.6637	38	38	1.68	0.0497	0.30	0.65	0.9211
19	19	1.78	0.0415	0.30	0.70	0.7760	38	38	1.68	0.0497	0.30	0.70	0.9707
19	19	1.78	0.0415	0.35	0.50	0.1976	38	38	1.68	0.0497	0.35	0.50	0.3441
19	19	1.78	0.0415	0.35	0.55	0.2936	38	38	1.68	0.0497	0.35	0.55	0.5150
19	19	1.78	0.0415	0.35	0.60	0.4090	38	38	1.68	0.0497	0.35	0.60	0.6858
19	19	1.78	0.0415	0.35	0.65	0.5361	38	38	1.68	0.0497	0.35	0.65	0.8265
19	19	1.78	0.0415	0.40	0.55	0.1950	38	38	1.68	0.0497	0.40	0.55	0.3406
19	19	1.78	0.0415	0.40	0.60	0.2918	38	38	1.68	0.0497	0.40	0.60	0.5129
20	20	1.78	0.0404	0.05	0.15	0.2430	39	39	1.70	0.0445	0.05	0.15	0.4071
20	20	1.78	0.0404	0.05	0.20	0.3755	39	39	1.70	0.0445	0.05	0.20	0.6436
20	20	1.78	0.0404	0.05	0.25	0.5133	39	39	1.70	0.0445	0.05	0.25	0.8203
20	20	1.78	0.0404	0.05	0.30	0.6474	39	39	1.70	0.0445	0.05	0.30	0.9231
20	20	1.78	0.0404	0.05	0.35	0.7649	39	39	1.70	0.0445	0.05	0.35	0.9720
20	20	1.78	0.0404	0.05	0.40	0.8563	39	39	1.70	0.0445	0.05	0.40	0.9914
20	20	1.78	0.0404	0.05	0.45	0.9197	39	39	1.70	0.0445	0.05	0.45	0.9978
20	20	1.78	0.0404	0.10	0.25	0.2842	39	39	1.70	0.0445	0.10	0.25	0.5249
20	20	1.78	0.0404	0.10	0.30	0.4132	39	39	1.70	0.0445	0.10	0.30	0.7111
20	20	1.78	0.0404	0.10	0.35	0.5483	39	39	1.70	0.0445	0.10	0.35	0.8496
20	20	1.78	0.0404	0.10	0.40	0.6747	39	39	1.70	0.0445	0.10	0.40	0.9338
20	20	1.78	0.0404	0.10	0.45	0.7821	39	39	1.70	0.0445	0.10	0.45	0.9755
20	20	1.78	0.0404	0.10	0.50	0.8656	39	39	1.70	0.0445	0.10	0.50	0.9925
20	20	1.78	0.0404	0.10	0.55	0.9248	39	39	1.70	0.0445	0.10	0.55	0.9981
20	20	1.78	0.0404	0.10	0.60	0.9627	39	39	1.70	0.0445	0.10	0.60	0.9996
20	20	1.78	0.0404	0.15	0.30	0.2454	39	39	1.70	0.0445	0.15	0.30	0.4553
20	20	1.78	0.0404	0.15	0.35	0.3616	39	39	1.70	0.0445	0.15	0.35	0.6430
20	20	1.78	0.0404	0.15	0.40	0.4890	39	39	1.70	0.0445	0.15	0.40	0.7965
20	20	1.78	0.0404	0.15	0.45	0.6167	39	39	1.70	0.0445	0.15	0.45	0.8995
20	20	1.78	0.0404	0.15	0.50	0.7338	39	39	1.70	0.0445	0.15	0.50	0.9574
20	20	1.78	0.0404	0.15	0.55	0.8312	39	39	1.70	0.0445	0.15	0.55	0.9849
20	20	1.78	0.0404	0.15	0.60	0.9039	39	39	1.70	0.0445	0.15	0.60	0.9957
20	20	1.78	0.0404	0.15	0.65	0.9518	39	39	1.70	0.0445	0.15	0.65	0.9991
20	20	1.78	0.0404	0.20	0.35	0.2219	39	39	1.70	0.0445	0.20	0.35	0.4152
20	20	1.78	0.0404	0.20	0.40	0.3307	39	39	1.70	0.0445	0.20	0.40	0.5934
20	20	1.78	0.0404	0.20	0.45	0.4560	39	39	1.70	0.0445	0.20	0.45	0.7503
20	20	1.78	0.0404	0.20	0.50	0.5870	39	39	1.70	0.0445	0.20	0.50	0.8675
20	20	1.78	0.0404	0.20	0.55	0.7106	39	39	1.70	0.0445	0.20	0.55	0.9410
20	20	1.78	0.0404	0.20	0.60	0.8153	39	39	1.70	0.0445	0.20	0.60	0.9787
20	20	1.78	0.0404	0.20	0.65	0.8944	39	39	1.70	0.0445	0.20	0.65	0.9940
20	20	1.78	0.0404	0.20	0.70	0.9469	39	39	1.70	0.0445	0.20	0.70	0.9987
20	20	1.78	0.0404	0.25	0.40	0.2105	39	39	1.70	0.0445	0.25	0.40	0.3802
20	20	1.78	0.0404	0.25	0.45	0.3178	39	39	1.70	0.0445	0.25	0.45	0.5535
20	20	1.78	0.0404	0.25	0.50	0.4434	39	39	1.70	0.0445	0.25	0.50	0.7186

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
20	20	1.78	0.0404	0.25	0.55	0.5759	39	39	1.70	0.0445	0.25	0.55	0.8490
20	20	1.78	0.0404	0.25	0.60	0.7018	39	39	1.70	0.0445	0.25	0.60	0.9328
20	20	1.78	0.0404	0.25	0.65	0.8091	39	39	1.70	0.0445	0.25	0.65	0.9759
20	20	1.78	0.0404	0.25	0.70	0.8908	39	39	1.70	0.0445	0.25	0.70	0.9933
20	20	1.78	0.0404	0.25	0.75	0.9456	39	39	1.70	0.0445	0.25	0.75	0.9986
20	20	1.78	0.0404	0.30	0.45	0.2088	39	39	1.70	0.0445	0.30	0.45	0.3592
20	20	1.78	0.0404	0.30	0.50	0.3157	39	39	1.70	0.0445	0.30	0.50	0.5353
20	20	1.78	0.0404	0.30	0.55	0.4407	39	39	1.70	0.0445	0.30	0.55	0.7064
20	20	1.78	0.0404	0.30	0.60	0.5728	39	39	1.70	0.0445	0.30	0.60	0.8423
20	20	1.78	0.0404	0.30	0.65	0.6990	39	39	1.70	0.0445	0.30	0.65	0.9299
20	20	1.78	0.0404	0.30	0.70	0.8075	39	39	1.70	0.0445	0.30	0.70	0.9751
20	20	1.78	0.0404	0.35	0.50	0.2110	39	39	1.70	0.0445	0.35	0.50	0.3543
20	20	1.78	0.0404	0.35	0.55	0.3168	39	39	1.70	0.0445	0.35	0.55	0.5312
20	20	1.78	0.0404	0.35	0.60	0.4406	39	39	1.70	0.0445	0.35	0.60	0.7033
20	20	1.78	0.0404	0.35	0.65	0.5722	39	39	1.70	0.0445	0.35	0.65	0.8407
20	20	1.78	0.0404	0.40	0.55	0.2128	39	39	1.70	0.0445	0.40	0.55	0.3546
20	20	1.78	0.0404	0.40	0.60	0.3175	39	39	1.70	0.0445	0.40	0.60	0.5307
21	21	1.76	0.0442	0.05	0.15	0.2945	40	40	1.70	0.0448	0.05	0.15	0.4166
21	21	1.76	0.0442	0.05	0.20	0.4580	40	40	1.70	0.0448	0.05	0.20	0.6557
21	21	1.76	0.0442	0.05	0.25	0.6081	40	40	1.70	0.0448	0.05	0.25	0.8302
21	21	1.76	0.0442	0.05	0.30	0.7330	40	40	1.70	0.0448	0.05	0.30	0.9293
21	21	1.76	0.0442	0.05	0.35	0.8289	40	40	1.70	0.0448	0.05	0.35	0.9751
21	21	1.76	0.0442	0.05	0.40	0.8975	40	40	1.70	0.0448	0.05	0.40	0.9927
21	21	1.76	0.0442	0.05	0.45	0.9432	40	40	1.70	0.0448	0.05	0.45	0.9982
21	21	1.76	0.0442	0.10	0.25	0.3490	40	40	1.70	0.0448	0.10	0.25	0.5355
21	21	1.76	0.0442	0.10	0.30	0.4759	40	40	1.70	0.0448	0.10	0.30	0.7227
21	21	1.76	0.0442	0.10	0.35	0.6009	40	40	1.70	0.0448	0.10	0.35	0.8592
21	21	1.76	0.0442	0.10	0.40	0.7154	40	40	1.70	0.0448	0.10	0.40	0.9399
21	21	1.76	0.0442	0.10	0.45	0.8125	40	40	1.70	0.0448	0.10	0.45	0.9786
21	21	1.76	0.0442	0.10	0.50	0.8875	40	40	1.70	0.0448	0.10	0.50	0.9936
21	21	1.76	0.0442	0.10	0.55	0.9397	40	40	1.70	0.0448	0.10	0.55	0.9984
21	21	1.76	0.0442	0.10	0.60	0.9717	40	40	1.70	0.0448	0.10	0.60	0.9997
21	21	1.76	0.0442	0.15	0.30	0.2788	40	40	1.70	0.0448	0.15	0.30	0.4665
21	21	1.76	0.0442	0.15	0.35	0.3947	40	40	1.70	0.0448	0.15	0.35	0.6559
21	21	1.76	0.0442	0.15	0.40	0.5219	40	40	1.70	0.0448	0.15	0.40	0.8077
21	21	1.76	0.0442	0.15	0.45	0.6491	40	40	1.70	0.0448	0.15	0.45	0.9072
21	21	1.76	0.0442	0.15	0.50	0.7639	40	40	1.70	0.0448	0.15	0.50	0.9618
21	21	1.76	0.0442	0.15	0.55	0.8564	40	40	1.70	0.0448	0.15	0.55	0.9870
21	21	1.76	0.0442	0.15	0.60	0.9223	40	40	1.70	0.0448	0.15	0.60	0.9965
21	21	1.76	0.0442	0.15	0.65	0.9633	40	40	1.70	0.0448	0.15	0.65	0.9993
21	21	1.76	0.0442	0.20	0.35	0.2411	40	40	1.70	0.0448	0.20	0.35	0.4254
21	21	1.76	0.0442	0.20	0.40	0.3555	40	40	1.70	0.0448	0.20	0.40	0.6055
21	21	1.76	0.0442	0.20	0.45	0.4865	40	40	1.70	0.0448	0.20	0.45	0.7623
21	21	1.76	0.0442	0.20	0.50	0.6207	40	40	1.70	0.0448	0.20	0.50	0.8774
21	21	1.76	0.0442	0.20	0.55	0.7434	40	40	1.70	0.0448	0.20	0.55	0.9475
21	21	1.76	0.0442	0.20	0.60	0.8430	40	40	1.70	0.0448	0.20	0.60	0.9819
21	21	1.76	0.0442	0.20	0.65	0.9146	40	40	1.70	0.0448	0.20	0.65	0.9952
21	21	1.76	0.0442	0.20	0.70	0.9595	40	40	1.70	0.0448	0.20	0.70	0.9990
21	21	1.76	0.0442	0.25	0.40	0.2281	40	40	1.70	0.0448	0.25	0.40	0.3901
21	21	1.76	0.0442	0.25	0.45	0.3433	40	40	1.70	0.0448	0.25	0.45	0.5674

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
21	21	1.76	0.0442	0.25	0.50	0.4756	40	40	1.70	0.0448	0.25	0.50	0.7336
21	21	1.76	0.0442	0.25	0.55	0.6112	40	40	1.70	0.0448	0.25	0.55	0.8613
21	21	1.76	0.0442	0.25	0.60	0.7357	40	40	1.70	0.0448	0.25	0.60	0.9405
21	21	1.76	0.0442	0.25	0.65	0.8376	40	40	1.70	0.0448	0.25	0.65	0.9795
21	21	1.76	0.0442	0.25	0.70	0.9115	40	40	1.70	0.0448	0.25	0.70	0.9946
21	21	1.76	0.0442	0.25	0.75	0.9584	40	40	1.70	0.0448	0.25	0.75	0.9990
21	21	1.76	0.0442	0.30	0.45	0.2277	40	40	1.70	0.0448	0.30	0.45	0.3717
21	21	1.76	0.0442	0.30	0.50	0.3424	40	40	1.70	0.0448	0.30	0.50	0.5521
21	21	1.76	0.0442	0.30	0.55	0.4736	40	40	1.70	0.0448	0.30	0.55	0.7233
21	21	1.76	0.0442	0.30	0.60	0.6084	40	40	1.70	0.0448	0.30	0.60	0.8555
21	21	1.76	0.0442	0.30	0.65	0.7330	40	40	1.70	0.0448	0.30	0.65	0.9379
21	21	1.76	0.0442	0.30	0.70	0.8360	40	40	1.70	0.0448	0.30	0.70	0.9789
21	21	1.76	0.0442	0.35	0.50	0.2306	40	40	1.70	0.0448	0.35	0.50	0.3685
21	21	1.76	0.0442	0.35	0.55	0.3439	40	40	1.70	0.0448	0.35	0.55	0.5488
21	21	1.76	0.0442	0.35	0.60	0.4736	40	40	1.70	0.0448	0.35	0.60	0.7205
21	21	1.76	0.0442	0.35	0.65	0.6078	40	40	1.70	0.0448	0.35	0.65	0.8540
21	21	1.76	0.0442	0.40	0.55	0.2327	40	40	1.70	0.0448	0.40	0.55	0.3691
21	21	1.76	0.0442	0.40	0.60	0.3447	40	40	1.70	0.0448	0.40	0.60	0.5484
22	22	1.75	0.0481	0.05	0.15	0.3067	50	50	1.69	0.0476	0.05	0.15	0.5071
22	22	1.75	0.0481	0.05	0.20	0.4739	50	50	1.69	0.0476	0.05	0.20	0.7566
22	22	1.75	0.0481	0.05	0.25	0.6256	50	50	1.69	0.0476	0.05	0.25	0.9045
22	22	1.75	0.0481	0.05	0.30	0.7499	50	50	1.69	0.0476	0.05	0.30	0.9700
22	22	1.75	0.0481	0.05	0.35	0.8437	50	50	1.69	0.0476	0.05	0.35	0.9925
22	22	1.75	0.0481	0.05	0.40	0.9092	50	50	1.69	0.0476	0.05	0.40	0.9985
22	22	1.75	0.0481	0.05	0.45	0.9517	50	50	1.69	0.0476	0.05	0.45	0.9998
22	22	1.75	0.0481	0.10	0.25	0.3590	50	50	1.69	0.0476	0.10	0.25	0.6308
22	22	1.75	0.0481	0.10	0.30	0.4904	50	50	1.69	0.0476	0.10	0.30	0.8151
22	22	1.75	0.0481	0.10	0.35	0.6192	50	50	1.69	0.0476	0.10	0.35	0.9244
22	22	1.75	0.0481	0.10	0.40	0.7357	50	50	1.69	0.0476	0.10	0.40	0.9750
22	22	1.75	0.0481	0.10	0.45	0.8321	50	50	1.69	0.0476	0.10	0.45	0.9935
22	22	1.75	0.0481	0.10	0.50	0.9039	50	50	1.69	0.0476	0.10	0.50	0.9987
22	22	1.75	0.0481	0.10	0.55	0.9513	50	50	1.69	0.0476	0.10	0.55	0.9998
22	22	1.75	0.0481	0.10	0.60	0.9786	50	50	1.69	0.0476	0.10	0.60	1.0000
22	22	1.75	0.0481	0.15	0.30	0.2884	50	50	1.69	0.0476	0.15	0.30	0.5513
22	22	1.75	0.0481	0.15	0.35	0.4115	50	50	1.69	0.0476	0.15	0.35	0.7468
22	22	1.75	0.0481	0.15	0.40	0.5453	50	50	1.69	0.0476	0.15	0.40	0.8828
22	22	1.75	0.0481	0.15	0.45	0.6763	50	50	1.69	0.0476	0.15	0.45	0.9558
22	22	1.75	0.0481	0.15	0.50	0.7904	50	50	1.69	0.0476	0.15	0.50	0.9865
22	22	1.75	0.0481	0.15	0.55	0.8783	50	50	1.69	0.0476	0.15	0.55	0.9967
22	22	1.75	0.0481	0.15	0.60	0.9376	50	50	1.69	0.0476	0.15	0.60	0.9994
22	22	1.75	0.0481	0.15	0.65	0.9723	50	50	1.69	0.0476	0.15	0.65	0.9999
22	22	1.75	0.0481	0.20	0.35	0.2543	50	50	1.69	0.0476	0.20	0.35	0.5026
22	22	1.75	0.0481	0.20	0.40	0.3773	50	50	1.69	0.0476	0.20	0.40	0.6997
22	22	1.75	0.0481	0.20	0.45	0.5153	50	50	1.69	0.0476	0.20	0.45	0.8471
22	22	1.75	0.0481	0.20	0.50	0.6525	50	50	1.69	0.0476	0.20	0.50	0.9355
22	22	1.75	0.0481	0.20	0.55	0.7732	50	50	1.69	0.0476	0.20	0.55	0.9782
22	22	1.75	0.0481	0.20	0.60	0.8670	50	50	1.69	0.0476	0.20	0.60	0.9944
22	22	1.75	0.0481	0.20	0.65	0.9311	50	50	1.69	0.0476	0.20	0.65	0.9990
22	22	1.75	0.0481	0.20	0.70	0.9692	50	50	1.69	0.0476	0.20	0.70	0.9999
22	22	1.75	0.0481	0.25	0.40	0.2451	50	50	1.69	0.0476	0.25	0.40	0.4646

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
22	22	1.75	0.0481	0.25	0.45	0.3685	50	50	1.69	0.0476	0.25	0.45	0.6569
22	22	1.75	0.0481	0.25	0.50	0.5068	50	50	1.69	0.0476	0.25	0.50	0.8156
22	22	1.75	0.0481	0.25	0.55	0.6445	50	50	1.69	0.0476	0.25	0.55	0.9199
22	22	1.75	0.0481	0.25	0.60	0.7663	50	50	1.69	0.0476	0.25	0.60	0.9729
22	22	1.75	0.0481	0.25	0.65	0.8621	50	50	1.69	0.0476	0.25	0.65	0.9932
22	22	1.75	0.0481	0.25	0.70	0.9284	50	50	1.69	0.0476	0.25	0.70	0.9988
22	22	1.75	0.0481	0.25	0.75	0.9683	50	50	1.69	0.0476	0.25	0.75	0.9999
22	22	1.75	0.0481	0.30	0.45	0.2468	50	50	1.69	0.0476	0.30	0.45	0.4336
22	22	1.75	0.0481	0.30	0.50	0.3689	50	50	1.69	0.0476	0.30	0.50	0.6309
22	22	1.75	0.0481	0.30	0.55	0.5053	50	50	1.69	0.0476	0.30	0.55	0.8007
22	22	1.75	0.0481	0.30	0.60	0.6417	50	50	1.69	0.0476	0.30	0.60	0.9138
22	22	1.75	0.0481	0.30	0.65	0.7636	50	50	1.69	0.0476	0.30	0.65	0.9711
22	22	1.75	0.0481	0.30	0.70	0.8606	50	50	1.69	0.0476	0.30	0.70	0.9928
22	22	1.75	0.0481	0.35	0.50	0.2503	50	50	1.69	0.0476	0.35	0.50	0.4228
22	22	1.75	0.0481	0.35	0.55	0.3705	50	50	1.69	0.0476	0.35	0.55	0.6236
22	22	1.75	0.0481	0.35	0.60	0.5052	50	50	1.69	0.0476	0.35	0.60	0.7968
22	22	1.75	0.0481	0.35	0.65	0.6410	50	50	1.69	0.0476	0.35	0.65	0.9123
22	22	1.75	0.0481	0.40	0.55	0.2525	50	50	1.69	0.0476	0.40	0.55	0.4218
22	22	1.75	0.0481	0.40	0.60	0.3712	50	50	1.69	0.0476	0.40	0.60	0.6226
23	23	1.78	0.0438	0.05	0.15	0.2673	60	60	1.68	0.0500	0.05	0.15	0.5849
23	23	1.78	0.0438	0.05	0.20	0.4168	60	60	1.68	0.0500	0.05	0.20	0.8290
23	23	1.78	0.0438	0.05	0.25	0.5731	60	60	1.68	0.0500	0.05	0.25	0.9475
23	23	1.78	0.0438	0.05	0.30	0.7162	60	60	1.68	0.0500	0.05	0.30	0.9879
23	23	1.78	0.0438	0.05	0.35	0.8291	60	60	1.68	0.0500	0.05	0.35	0.9979
23	23	1.78	0.0438	0.05	0.40	0.9069	60	60	1.68	0.0500	0.05	0.40	0.9997
23	23	1.78	0.0438	0.05	0.45	0.9542	60	60	1.68	0.0500	0.05	0.45	1.0000
23	23	1.78	0.0438	0.10	0.25	0.3270	60	60	1.68	0.0500	0.10	0.25	0.7116
23	23	1.78	0.0438	0.10	0.30	0.4748	60	60	1.68	0.0500	0.10	0.30	0.8802
23	23	1.78	0.0438	0.10	0.35	0.6204	60	60	1.68	0.0500	0.10	0.35	0.9615
23	23	1.78	0.0438	0.10	0.40	0.7477	60	60	1.68	0.0500	0.10	0.40	0.9905
23	23	1.78	0.0438	0.10	0.45	0.8476	60	60	1.68	0.0500	0.10	0.45	0.9982
23	23	1.78	0.0438	0.10	0.50	0.9175	60	60	1.68	0.0500	0.10	0.50	0.9997
23	23	1.78	0.0438	0.10	0.55	0.9607	60	60	1.68	0.0500	0.10	0.55	1.0000
23	23	1.78	0.0438	0.10	0.60	0.9838	60	60	1.68	0.0500	0.10	0.60	1.0000
23	23	1.78	0.0438	0.15	0.30	0.2860	60	60	1.68	0.0500	0.15	0.30	0.6313
23	23	1.78	0.0438	0.15	0.35	0.4220	60	60	1.68	0.0500	0.15	0.35	0.8207
23	23	1.78	0.0438	0.15	0.40	0.5658	60	60	1.68	0.0500	0.15	0.40	0.9310
23	23	1.78	0.0438	0.15	0.45	0.7010	60	60	1.68	0.0500	0.15	0.45	0.9796
23	23	1.78	0.0438	0.15	0.50	0.8134	60	60	1.68	0.0500	0.15	0.50	0.9955
23	23	1.78	0.0438	0.15	0.55	0.8954	60	60	1.68	0.0500	0.15	0.55	0.9993
23	23	1.78	0.0438	0.15	0.60	0.9478	60	60	1.68	0.0500	0.15	0.60	0.9999
23	23	1.78	0.0438	0.15	0.65	0.9769	60	60	1.68	0.0500	0.15	0.65	1.0000
23	23	1.78	0.0438	0.20	0.35	0.2658	60	60	1.68	0.0500	0.20	0.35	0.5733
23	23	1.78	0.0438	0.20	0.40	0.3976	60	60	1.68	0.0500	0.20	0.40	0.7747
23	23	1.78	0.0438	0.20	0.45	0.5407	60	60	1.68	0.0500	0.20	0.45	0.9070
23	23	1.78	0.0438	0.20	0.50	0.6772	60	60	1.68	0.0500	0.20	0.50	0.9705
23	23	1.78	0.0438	0.20	0.55	0.7919	60	60	1.68	0.0500	0.20	0.55	0.9928
23	23	1.78	0.0438	0.20	0.60	0.8775	60	60	1.68	0.0500	0.20	0.60	0.9987
23	23	1.78	0.0438	0.20	0.65	0.9346	60	60	1.68	0.0500	0.20	0.65	0.9998
23	23	1.78	0.0438	0.20	0.70	0.9690	60	60	1.68	0.0500	0.20	0.70	1.0000

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
23	23	1.78	0.0438	0.25	0.40	0.2599	60	60	1.68	0.0500	0.25	0.40	0.5426
23	23	1.78	0.0438	0.25	0.45	0.3871	60	60	1.68	0.0500	0.25	0.45	0.7487
23	23	1.78	0.0438	0.25	0.50	0.5241	60	60	1.68	0.0500	0.25	0.50	0.8884
23	23	1.78	0.0438	0.25	0.55	0.6553	60	60	1.68	0.0500	0.25	0.55	0.9603
23	23	1.78	0.0438	0.25	0.60	0.7686	60	60	1.68	0.0500	0.25	0.60	0.9891
23	23	1.78	0.0438	0.25	0.65	0.8581	60	60	1.68	0.0500	0.25	0.65	0.9979
23	23	1.78	0.0438	0.25	0.70	0.9228	60	60	1.68	0.0500	0.25	0.70	0.9997
23	23	1.78	0.0438	0.25	0.75	0.9647	60	60	1.68	0.0500	0.25	0.75	1.0000
23	23	1.78	0.0438	0.30	0.45	0.2552	60	60	1.68	0.0500	0.30	0.45	0.5191
23	23	1.78	0.0438	0.30	0.50	0.3736	60	60	1.68	0.0500	0.30	0.50	0.7182
23	23	1.78	0.0438	0.30	0.55	0.5023	60	60	1.68	0.0500	0.30	0.55	0.8655
23	23	1.78	0.0438	0.30	0.60	0.6305	60	60	1.68	0.0500	0.30	0.60	0.9503
23	23	1.78	0.0438	0.30	0.65	0.7486	60	60	1.68	0.0500	0.30	0.65	0.9867
23	23	1.78	0.0438	0.30	0.70	0.8484	60	60	1.68	0.0500	0.30	0.70	0.9976
23	23	1.78	0.0438	0.35	0.50	0.2440	60	60	1.68	0.0500	0.35	0.50	0.4864
23	23	1.78	0.0438	0.35	0.55	0.3555	60	60	1.68	0.0500	0.35	0.55	0.6906
23	23	1.78	0.0438	0.35	0.60	0.4830	60	60	1.68	0.0500	0.35	0.60	0.8524
23	23	1.78	0.0438	0.35	0.65	0.6184	60	60	1.68	0.0500	0.35	0.65	0.9471
23	23	1.78	0.0438	0.40	0.55	0.2327	60	60	1.68	0.0500	0.40	0.55	0.4687
23	23	1.78	0.0438	0.40	0.60	0.3463	60	60	1.68	0.0500	0.40	0.60	0.6826
24	24	1.74	0.0455	0.05	0.15	0.3293	70	70	1.70	0.0486	0.05	0.15	0.6228
24	24	1.74	0.0455	0.05	0.20	0.5034	70	70	1.70	0.0486	0.05	0.20	0.8649
24	24	1.74	0.0455	0.05	0.25	0.6577	70	70	1.70	0.0486	0.05	0.25	0.9667
24	24	1.74	0.0455	0.05	0.30	0.7806	70	70	1.70	0.0486	0.05	0.30	0.9941
24	24	1.74	0.0455	0.05	0.35	0.8699	70	70	1.70	0.0486	0.05	0.35	0.9992
24	24	1.74	0.0455	0.05	0.40	0.9295	70	70	1.70	0.0486	0.05	0.40	0.9999
24	24	1.74	0.0455	0.05	0.45	0.9656	70	70	1.70	0.0486	0.05	0.45	1.0000
24	24	1.74	0.0455	0.10	0.25	0.3789	70	70	1.70	0.0486	0.10	0.25	0.7528
24	24	1.74	0.0455	0.10	0.30	0.5197	70	70	1.70	0.0486	0.10	0.30	0.9111
24	24	1.74	0.0455	0.10	0.35	0.6560	70	70	1.70	0.0486	0.10	0.35	0.9766
24	24	1.74	0.0455	0.10	0.40	0.7752	70	70	1.70	0.0486	0.10	0.40	0.9956
24	24	1.74	0.0455	0.10	0.45	0.8679	70	70	1.70	0.0486	0.10	0.45	0.9994
24	24	1.74	0.0455	0.10	0.50	0.9313	70	70	1.70	0.0486	0.10	0.50	0.9999
24	24	1.74	0.0455	0.10	0.55	0.9688	70	70	1.70	0.0486	0.10	0.55	1.0000
24	24	1.74	0.0455	0.10	0.60	0.9879	70	70	1.70	0.0486	0.10	0.60	1.0000
24	24	1.74	0.0455	0.15	0.30	0.3102	70	70	1.70	0.0486	0.15	0.30	0.6712
24	24	1.74	0.0455	0.15	0.35	0.4480	70	70	1.70	0.0486	0.15	0.35	0.8602
24	24	1.74	0.0455	0.15	0.40	0.5934	70	70	1.70	0.0486	0.15	0.40	0.9551
24	24	1.74	0.0455	0.15	0.45	0.7275	70	70	1.70	0.0486	0.15	0.45	0.9893
24	24	1.74	0.0455	0.15	0.50	0.8355	70	70	1.70	0.0486	0.15	0.50	0.9982
24	24	1.74	0.0455	0.15	0.55	0.9111	70	70	1.70	0.0486	0.15	0.55	0.9998
24	24	1.74	0.0455	0.15	0.60	0.9572	70	70	1.70	0.0486	0.15	0.60	1.0000
24	24	1.74	0.0455	0.15	0.65	0.9817	70	70	1.70	0.0486	0.15	0.65	1.0000
24	24	1.74	0.0455	0.20	0.35	0.2835	70	70	1.70	0.0486	0.20	0.35	0.6150
24	24	1.74	0.0455	0.20	0.40	0.4212	70	70	1.70	0.0486	0.20	0.40	0.8169
24	24	1.74	0.0455	0.20	0.45	0.5674	70	70	1.70	0.0486	0.20	0.45	0.9351
24	24	1.74	0.0455	0.20	0.50	0.7027	70	70	1.70	0.0486	0.20	0.50	0.9835
24	24	1.74	0.0455	0.20	0.55	0.8126	70	70	1.70	0.0486	0.20	0.55	0.9971
24	24	1.74	0.0455	0.20	0.60	0.8919	70	70	1.70	0.0486	0.20	0.60	0.9996
24	24	1.74	0.0455	0.20	0.65	0.9435	70	70	1.70	0.0486	0.20	0.65	1.0000

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
24	24	1.74	0.0455	0.20	0.70	0.9739	70	70	1.70	0.0486	0.20	0.70	1.0000
24	24	1.74	0.0455	0.25	0.40	0.2766	70	70	1.70	0.0486	0.25	0.40	0.5802
24	24	1.74	0.0455	0.25	0.45	0.4082	70	70	1.70	0.0486	0.25	0.45	0.7943
24	24	1.74	0.0455	0.25	0.50	0.5464	70	70	1.70	0.0486	0.25	0.50	0.9246
24	24	1.74	0.0455	0.25	0.55	0.6755	70	70	1.70	0.0486	0.25	0.55	0.9796
24	24	1.74	0.0455	0.25	0.60	0.7849	70	70	1.70	0.0486	0.25	0.60	0.9959
24	24	1.74	0.0455	0.25	0.65	0.8702	70	70	1.70	0.0486	0.25	0.65	0.9994
24	24	1.74	0.0455	0.25	0.70	0.9311	70	70	1.70	0.0486	0.25	0.70	0.9999
24	24	1.74	0.0455	0.25	0.75	0.9697	70	70	1.70	0.0486	0.25	0.75	1.0000
24	24	1.74	0.0455	0.30	0.45	0.2682	70	70	1.70	0.0486	0.30	0.45	0.5698
24	24	1.74	0.0455	0.30	0.50	0.3886	70	70	1.70	0.0486	0.30	0.50	0.7814
24	24	1.74	0.0455	0.30	0.55	0.5176	70	70	1.70	0.0486	0.30	0.55	0.9135
24	24	1.74	0.0455	0.30	0.60	0.6449	70	70	1.70	0.0486	0.30	0.60	0.9738
24	24	1.74	0.0455	0.30	0.65	0.7618	70	70	1.70	0.0486	0.30	0.65	0.9944
24	24	1.74	0.0455	0.30	0.70	0.8597	70	70	1.70	0.0486	0.30	0.70	0.9992
24	24	1.74	0.0455	0.35	0.50	0.2513	70	70	1.70	0.0486	0.35	0.50	0.5521
24	24	1.74	0.0455	0.35	0.55	0.3641	70	70	1.70	0.0486	0.35	0.55	0.7573
24	24	1.74	0.0455	0.35	0.60	0.4933	70	70	1.70	0.0486	0.35	0.60	0.8982
24	24	1.74	0.0455	0.35	0.65	0.6306	70	70	1.70	0.0486	0.35	0.65	0.9698
24	24	1.74	0.0455	0.40	0.55	0.2359	70	70	1.70	0.0486	0.40	0.55	0.5229
24	24	1.74	0.0455	0.40	0.60	0.3524	70	70	1.70	0.0486	0.40	0.60	0.7406
25	25	1.71	0.0472	0.05	0.15	0.3399	80	80	1.67	0.0494	0.05	0.15	0.7021
25	25	1.71	0.0472	0.05	0.20	0.5171	80	80	1.67	0.0494	0.05	0.20	0.9128
25	25	1.71	0.0472	0.05	0.25	0.6726	80	80	1.67	0.0494	0.05	0.25	0.9829
25	25	1.71	0.0472	0.05	0.30	0.7946	80	80	1.67	0.0494	0.05	0.30	0.9977
25	25	1.71	0.0472	0.05	0.35	0.8817	80	80	1.67	0.0494	0.05	0.35	0.9998
25	25	1.71	0.0472	0.05	0.40	0.9382	80	80	1.67	0.0494	0.05	0.40	1.0000
25	25	1.71	0.0472	0.05	0.45	0.9712	80	80	1.67	0.0494	0.05	0.45	1.0000
25	25	1.71	0.0472	0.10	0.25	0.3889	80	80	1.67	0.0494	0.10	0.25	0.8078
25	25	1.71	0.0472	0.10	0.30	0.5347	80	80	1.67	0.0494	0.10	0.30	0.9439
25	25	1.71	0.0472	0.10	0.35	0.6746	80	80	1.67	0.0494	0.10	0.35	0.9887
25	25	1.71	0.0472	0.10	0.40	0.7941	80	80	1.67	0.0494	0.10	0.40	0.9984
25	25	1.71	0.0472	0.10	0.45	0.8839	80	80	1.67	0.0494	0.10	0.45	0.9998
25	25	1.71	0.0472	0.10	0.50	0.9425	80	80	1.67	0.0494	0.10	0.50	1.0000
25	25	1.71	0.0472	0.10	0.55	0.9753	80	80	1.67	0.0494	0.10	0.55	1.0000
25	25	1.71	0.0472	0.10	0.60	0.9909	80	80	1.67	0.0494	0.10	0.60	1.0000
25	25	1.71	0.0472	0.15	0.30	0.3224	80	80	1.67	0.0494	0.15	0.30	0.7353
25	25	1.71	0.0472	0.15	0.35	0.4675	80	80	1.67	0.0494	0.15	0.35	0.9047
25	25	1.71	0.0472	0.15	0.40	0.6174	80	80	1.67	0.0494	0.15	0.40	0.9758
25	25	1.71	0.0472	0.15	0.45	0.7514	80	80	1.67	0.0494	0.15	0.45	0.9958
25	25	1.71	0.0472	0.15	0.50	0.8549	80	80	1.67	0.0494	0.15	0.50	0.9995
25	25	1.71	0.0472	0.15	0.55	0.9243	80	80	1.67	0.0494	0.15	0.55	1.0000
25	25	1.71	0.0472	0.15	0.60	0.9647	80	80	1.67	0.0494	0.15	0.60	1.0000
25	25	1.71	0.0472	0.15	0.65	0.9854	80	80	1.67	0.0494	0.15	0.65	1.0000
25	25	1.71	0.0472	0.20	0.35	0.2993	80	80	1.67	0.0494	0.20	0.35	0.6831
25	25	1.71	0.0472	0.20	0.40	0.4434	80	80	1.67	0.0494	0.20	0.40	0.8736
25	25	1.71	0.0472	0.20	0.45	0.5922	80	80	1.67	0.0494	0.20	0.45	0.9635
25	25	1.71	0.0472	0.20	0.50	0.7256	80	80	1.67	0.0494	0.20	0.50	0.9924
25	25	1.71	0.0472	0.20	0.55	0.8306	80	80	1.67	0.0494	0.20	0.55	0.9989
25	25	1.71	0.0472	0.20	0.60	0.9044	80	80	1.67	0.0494	0.20	0.60	0.9999

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
25	25	1.71	0.0472	0.20	0.65	0.9513	80	80	1.67	0.0494	0.20	0.65	1.0000
25	25	1.71	0.0472	0.20	0.70	0.9784	80	80	1.67	0.0494	0.20	0.70	1.0000
25	25	1.71	0.0472	0.25	0.40	0.2924	80	80	1.67	0.0494	0.25	0.40	0.6492
25	25	1.71	0.0472	0.25	0.45	0.4278	80	80	1.67	0.0494	0.25	0.45	0.8444
25	25	1.71	0.0472	0.25	0.50	0.5668	80	80	1.67	0.0494	0.25	0.50	0.9493
25	25	1.71	0.0472	0.25	0.55	0.6943	80	80	1.67	0.0494	0.25	0.55	0.9886
25	25	1.71	0.0472	0.25	0.60	0.8008	80	80	1.67	0.0494	0.25	0.60	0.9983
25	25	1.71	0.0472	0.25	0.65	0.8828	80	80	1.67	0.0494	0.25	0.65	0.9999
25	25	1.71	0.0472	0.25	0.70	0.9401	80	80	1.67	0.0494	0.25	0.70	1.0000
25	25	1.71	0.0472	0.25	0.75	0.9749	80	80	1.67	0.0494	0.25	0.75	1.0000
25	25	1.71	0.0472	0.30	0.45	0.2801	80	80	1.67	0.0494	0.30	0.45	0.6128
25	25	1.71	0.0472	0.30	0.50	0.4028	80	80	1.67	0.0494	0.30	0.50	0.8213
25	25	1.71	0.0472	0.30	0.55	0.5332	80	80	1.67	0.0494	0.30	0.55	0.9413
25	25	1.71	0.0472	0.30	0.60	0.6615	80	80	1.67	0.0494	0.30	0.60	0.9869
25	25	1.71	0.0472	0.30	0.65	0.7779	80	80	1.67	0.0494	0.30	0.65	0.9981
25	25	1.71	0.0472	0.30	0.70	0.8730	80	80	1.67	0.0494	0.30	0.70	0.9998
25	25	1.71	0.0472	0.35	0.50	0.2591	80	80	1.67	0.0494	0.35	0.50	0.5984
25	25	1.71	0.0472	0.35	0.55	0.3750	80	80	1.67	0.0494	0.35	0.55	0.8143
25	25	1.71	0.0472	0.35	0.60	0.5076	80	80	1.67	0.0494	0.35	0.60	0.9389
25	25	1.71	0.0472	0.35	0.65	0.6471	80	80	1.67	0.0494	0.35	0.65	0.9865
25	25	1.71	0.0472	0.40	0.55	0.2420	80	80	1.67	0.0494	0.40	0.55	0.5963
25	25	1.71	0.0472	0.40	0.60	0.3626	80	80	1.67	0.0494	0.40	0.60	0.8129
26	26	1.70	0.0489	0.05	0.15	0.3500	90	90	1.67	0.0494	0.05	0.15	0.7328
26	26	1.70	0.0489	0.05	0.20	0.5304	90	90	1.67	0.0494	0.05	0.20	0.9369
26	26	1.70	0.0489	0.05	0.25	0.6869	90	90	1.67	0.0494	0.05	0.25	0.9907
26	26	1.70	0.0489	0.05	0.30	0.8079	90	90	1.67	0.0494	0.05	0.30	0.9991
26	26	1.70	0.0489	0.05	0.35	0.8926	90	90	1.67	0.0494	0.05	0.35	0.9999
26	26	1.70	0.0489	0.05	0.40	0.9460	90	90	1.67	0.0494	0.05	0.40	1.0000
26	26	1.70	0.0489	0.05	0.45	0.9761	90	90	1.67	0.0494	0.05	0.45	1.0000
26	26	1.70	0.0489	0.10	0.25	0.3991	90	90	1.67	0.0494	0.10	0.25	0.8504
26	26	1.70	0.0489	0.10	0.30	0.5501	90	90	1.67	0.0494	0.10	0.30	0.9637
26	26	1.70	0.0489	0.10	0.35	0.6932	90	90	1.67	0.0494	0.10	0.35	0.9942
26	26	1.70	0.0489	0.10	0.40	0.8123	90	90	1.67	0.0494	0.10	0.40	0.9994
26	26	1.70	0.0489	0.10	0.45	0.8985	90	90	1.67	0.0494	0.10	0.45	1.0000
26	26	1.70	0.0489	0.10	0.50	0.9521	90	90	1.67	0.0494	0.10	0.50	1.0000
26	26	1.70	0.0489	0.10	0.55	0.9805	90	90	1.67	0.0494	0.10	0.55	1.0000
26	26	1.70	0.0489	0.10	0.60	0.9932	90	90	1.67	0.0494	0.10	0.60	1.0000
26	26	1.70	0.0489	0.15	0.30	0.3354	90	90	1.67	0.0494	0.15	0.30	0.7786
26	26	1.70	0.0489	0.15	0.35	0.4875	90	90	1.67	0.0494	0.15	0.35	0.9322
26	26	1.70	0.0489	0.15	0.40	0.6409	90	90	1.67	0.0494	0.15	0.40	0.9858
26	26	1.70	0.0489	0.15	0.45	0.7735	90	90	1.67	0.0494	0.15	0.45	0.9980
26	26	1.70	0.0489	0.15	0.50	0.8720	90	90	1.67	0.0494	0.15	0.50	0.9998
26	26	1.70	0.0489	0.15	0.55	0.9353	90	90	1.67	0.0494	0.15	0.55	1.0000
26	26	1.70	0.0489	0.15	0.60	0.9708	90	90	1.67	0.0494	0.15	0.60	1.0000
26	26	1.70	0.0489	0.15	0.65	0.9883	90	90	1.67	0.0494	0.15	0.65	1.0000
26	26	1.70	0.0489	0.20	0.35	0.3154	90	90	1.67	0.0494	0.20	0.35	0.7251
26	26	1.70	0.0489	0.20	0.40	0.4650	90	90	1.67	0.0494	0.20	0.40	0.9018
26	26	1.70	0.0489	0.20	0.45	0.6153	90	90	1.67	0.0494	0.20	0.45	0.9765
26	26	1.70	0.0489	0.20	0.50	0.7461	90	90	1.67	0.0494	0.20	0.50	0.9963
26	26	1.70	0.0489	0.20	0.55	0.8463	90	90	1.67	0.0494	0.20	0.55	0.9996

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
26	26	1.70	0.0489	0.20	0.60	0.9153	90	90	1.67	0.0494	0.20	0.60	1.0000
26	26	1.70	0.0489	0.20	0.65	0.9583	90	90	1.67	0.0494	0.20	0.65	1.0000
26	26	1.70	0.0489	0.20	0.70	0.9824	90	90	1.67	0.0494	0.20	0.70	1.0000
26	26	1.70	0.0489	0.25	0.40	0.3075	90	90	1.67	0.0494	0.25	0.40	0.6897
26	26	1.70	0.0489	0.25	0.45	0.4459	90	90	1.67	0.0494	0.25	0.45	0.8829
26	26	1.70	0.0489	0.25	0.50	0.5854	90	90	1.67	0.0494	0.25	0.50	0.9692
26	26	1.70	0.0489	0.25	0.55	0.7117	90	90	1.67	0.0494	0.25	0.55	0.9944
26	26	1.70	0.0489	0.25	0.60	0.8164	90	90	1.67	0.0494	0.25	0.60	0.9993
26	26	1.70	0.0489	0.25	0.65	0.8955	90	90	1.67	0.0494	0.25	0.65	1.0000
26	26	1.70	0.0489	0.25	0.70	0.9489	90	90	1.67	0.0494	0.25	0.70	1.0000
26	26	1.70	0.0489	0.25	0.75	0.9797	90	90	1.67	0.0494	0.25	0.75	1.0000
26	26	1.70	0.0489	0.30	0.45	0.2911	90	90	1.67	0.0494	0.30	0.45	0.6680
26	26	1.70	0.0489	0.30	0.50	0.4165	90	90	1.67	0.0494	0.30	0.50	0.8622
26	26	1.70	0.0489	0.30	0.55	0.5496	90	90	1.67	0.0494	0.30	0.55	0.9594
26	26	1.70	0.0489	0.30	0.60	0.6797	90	90	1.67	0.0494	0.30	0.60	0.9922
26	26	1.70	0.0489	0.30	0.65	0.7957	90	90	1.67	0.0494	0.30	0.65	0.9991
26	26	1.70	0.0489	0.30	0.70	0.8872	90	90	1.67	0.0494	0.30	0.70	0.9999
26	26	1.70	0.0489	0.35	0.50	0.2676	90	90	1.67	0.0494	0.35	0.50	0.6355
26	26	1.70	0.0489	0.35	0.55	0.3881	90	90	1.67	0.0494	0.35	0.55	0.8431
26	26	1.70	0.0489	0.35	0.60	0.5253	90	90	1.67	0.0494	0.35	0.60	0.9544
26	26	1.70	0.0489	0.35	0.65	0.6669	90	90	1.67	0.0494	0.35	0.65	0.9916
26	26	1.70	0.0489	0.40	0.55	0.2510	90	90	1.67	0.0494	0.40	0.55	0.6211
26	26	1.70	0.0489	0.40	0.60	0.3766	90	90	1.67	0.0494	0.40	0.60	0.8389
27	27	1.74	0.0413	0.05	0.15	0.2986	100	100	1.67	0.0495	0.05	0.15	0.7782
27	27	1.74	0.0413	0.05	0.20	0.4752	100	100	1.67	0.0495	0.05	0.20	0.9572
27	27	1.74	0.0413	0.05	0.25	0.6505	100	100	1.67	0.0495	0.05	0.25	0.9951
27	27	1.74	0.0413	0.05	0.30	0.7932	100	100	1.67	0.0495	0.05	0.30	0.9997
27	27	1.74	0.0413	0.05	0.35	0.8910	100	100	1.67	0.0495	0.05	0.35	1.0000
27	27	1.74	0.0413	0.05	0.40	0.9490	100	100	1.67	0.0495	0.05	0.40	1.0000
27	27	1.74	0.0413	0.05	0.45	0.9789	100	100	1.67	0.0495	0.05	0.45	1.0000
27	27	1.74	0.0413	0.10	0.25	0.3846	100	100	1.67	0.0495	0.10	0.25	0.8852
27	27	1.74	0.0413	0.10	0.30	0.5508	100	100	1.67	0.0495	0.10	0.30	0.9773
27	27	1.74	0.0413	0.10	0.35	0.7023	100	100	1.67	0.0495	0.10	0.35	0.9972
27	27	1.74	0.0413	0.10	0.40	0.8221	100	100	1.67	0.0495	0.10	0.40	0.9998
27	27	1.74	0.0413	0.10	0.45	0.9046	100	100	1.67	0.0495	0.10	0.45	1.0000
27	27	1.74	0.0413	0.10	0.50	0.9543	100	100	1.67	0.0495	0.10	0.50	1.0000
27	27	1.74	0.0413	0.10	0.55	0.9806	100	100	1.67	0.0495	0.10	0.55	1.0000
27	27	1.74	0.0413	0.10	0.60	0.9928	100	100	1.67	0.0495	0.10	0.60	1.0000
27	27	1.74	0.0413	0.15	0.30	0.3384	100	100	1.67	0.0495	0.15	0.30	0.8189
27	27	1.74	0.0413	0.15	0.35	0.4923	100	100	1.67	0.0495	0.15	0.35	0.9523
27	27	1.74	0.0413	0.15	0.40	0.6416	100	100	1.67	0.0495	0.15	0.40	0.9920
27	27	1.74	0.0413	0.15	0.45	0.7682	100	100	1.67	0.0495	0.15	0.45	0.9992
27	27	1.74	0.0413	0.15	0.50	0.8637	100	100	1.67	0.0495	0.15	0.50	0.9999
27	27	1.74	0.0413	0.15	0.55	0.9282	100	100	1.67	0.0495	0.15	0.55	1.0000
27	27	1.74	0.0413	0.15	0.60	0.9670	100	100	1.67	0.0495	0.15	0.60	1.0000
27	27	1.74	0.0413	0.15	0.65	0.9872	100	100	1.67	0.0495	0.15	0.65	1.0000
27	27	1.74	0.0413	0.20	0.35	0.3076	100	100	1.67	0.0495	0.20	0.35	0.7684
27	27	1.74	0.0413	0.20	0.40	0.4478	100	100	1.67	0.0495	0.20	0.40	0.9295
27	27	1.74	0.0413	0.20	0.45	0.5909	100	100	1.67	0.0495	0.20	0.45	0.9856
27	27	1.74	0.0413	0.20	0.50	0.7221	100	100	1.67	0.0495	0.20	0.50	0.9981

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
27	27	1.74	0.0413	0.20	0.55	0.8301	100	100	1.67	0.0495	0.20	0.55	0.9999
27	27	1.74	0.0413	0.20	0.60	0.9087	100	100	1.67	0.0495	0.20	0.60	1.0000
27	27	1.74	0.0413	0.20	0.65	0.9580	100	100	1.67	0.0495	0.20	0.65	1.0000
27	27	1.74	0.0413	0.20	0.70	0.9840	100	100	1.67	0.0495	0.20	0.70	1.0000
27	27	1.74	0.0413	0.25	0.40	0.2798	100	100	1.67	0.0495	0.25	0.40	0.7288
27	27	1.74	0.0413	0.25	0.45	0.4113	100	100	1.67	0.0495	0.25	0.45	0.9065
27	27	1.74	0.0413	0.25	0.50	0.5546	100	100	1.67	0.0495	0.25	0.50	0.9792
27	27	1.74	0.0413	0.25	0.55	0.6937	100	100	1.67	0.0495	0.25	0.55	0.9972
27	27	1.74	0.0413	0.25	0.60	0.8124	100	100	1.67	0.0495	0.25	0.60	0.9998
27	27	1.74	0.0413	0.25	0.65	0.8998	100	100	1.67	0.0495	0.25	0.65	1.0000
27	27	1.74	0.0413	0.25	0.70	0.9546	100	100	1.67	0.0495	0.25	0.70	1.0000
27	27	1.74	0.0413	0.25	0.75	0.9832	100	100	1.67	0.0495	0.25	0.75	1.0000
27	27	1.74	0.0413	0.30	0.45	0.2604	100	100	1.67	0.0495	0.30	0.45	0.7012
27	27	1.74	0.0413	0.30	0.50	0.3911	100	100	1.67	0.0495	0.30	0.50	0.8949
27	27	1.74	0.0413	0.30	0.55	0.5380	100	100	1.67	0.0495	0.30	0.55	0.9762
27	27	1.74	0.0413	0.30	0.60	0.6827	100	100	1.67	0.0495	0.30	0.60	0.9967
27	27	1.74	0.0413	0.30	0.65	0.8064	100	100	1.67	0.0495	0.30	0.65	0.9997
27	27	1.74	0.0413	0.30	0.70	0.8976	100	100	1.67	0.0495	0.30	0.70	1.0000
27	27	1.74	0.0413	0.35	0.50	0.2529	100	100	1.67	0.0495	0.35	0.50	0.6947
27	27	1.74	0.0413	0.35	0.55	0.3848	100	100	1.67	0.0495	0.35	0.55	0.8909
27	27	1.74	0.0413	0.35	0.60	0.5335	100	100	1.67	0.0495	0.35	0.60	0.9750
27	27	1.74	0.0413	0.35	0.65	0.6803	100	100	1.67	0.0495	0.35	0.65	0.9966
27	27	1.74	0.0413	0.40	0.55	0.2519	100	100	1.67	0.0495	0.40	0.55	0.6928
27	27	1.74	0.0413	0.40	0.60	0.3839	100	100	1.67	0.0495	0.40	0.60	0.8897
28	28	1.73	0.0423	0.05	0.15	0.3068	150	150	1.66	0.0498	0.05	0.15	0.9070
28	28	1.73	0.0423	0.05	0.20	0.4902	150	150	1.66	0.0498	0.05	0.20	0.9937
28	28	1.73	0.0423	0.05	0.25	0.6686	150	150	1.66	0.0498	0.05	0.25	0.9998
28	28	1.73	0.0423	0.05	0.30	0.8095	150	150	1.66	0.0498	0.05	0.30	1.0000
28	28	1.73	0.0423	0.05	0.35	0.9030	150	150	1.66	0.0498	0.05	0.35	1.0000
28	28	1.73	0.0423	0.05	0.40	0.9563	150	150	1.66	0.0498	0.05	0.40	1.0000
28	28	1.73	0.0423	0.05	0.45	0.9828	150	150	1.66	0.0498	0.05	0.45	1.0000
28	28	1.73	0.0423	0.10	0.25	0.3988	150	150	1.66	0.0498	0.10	0.25	0.9680
28	28	1.73	0.0423	0.10	0.30	0.5688	150	150	1.66	0.0498	0.10	0.30	0.9977
28	28	1.73	0.0423	0.10	0.35	0.7208	150	150	1.66	0.0498	0.10	0.35	0.9999
28	28	1.73	0.0423	0.10	0.40	0.8378	150	150	1.66	0.0498	0.10	0.40	1.0000
28	28	1.73	0.0423	0.10	0.45	0.9157	150	150	1.66	0.0498	0.10	0.45	1.0000
28	28	1.73	0.0423	0.10	0.50	0.9609	150	150	1.66	0.0498	0.10	0.50	1.0000
28	28	1.73	0.0423	0.10	0.55	0.9840	150	150	1.66	0.0498	0.10	0.55	1.0000
28	28	1.73	0.0423	0.10	0.60	0.9944	150	150	1.66	0.0498	0.10	0.60	1.0000
28	28	1.73	0.0423	0.15	0.30	0.3518	150	150	1.66	0.0498	0.15	0.30	0.9324
28	28	1.73	0.0423	0.15	0.35	0.5095	150	150	1.66	0.0498	0.15	0.35	0.9924
28	28	1.73	0.0423	0.15	0.40	0.6598	150	150	1.66	0.0498	0.15	0.40	0.9996
28	28	1.73	0.0423	0.15	0.45	0.7847	150	150	1.66	0.0498	0.15	0.45	1.0000
28	28	1.73	0.0423	0.15	0.50	0.8769	150	150	1.66	0.0498	0.15	0.50	1.0000
28	28	1.73	0.0423	0.15	0.55	0.9376	150	150	1.66	0.0498	0.15	0.55	1.0000
28	28	1.73	0.0423	0.15	0.60	0.9727	150	150	1.66	0.0498	0.15	0.60	1.0000
28	28	1.73	0.0423	0.15	0.65	0.9901	150	150	1.66	0.0498	0.15	0.65	1.0000
28	28	1.73	0.0423	0.20	0.35	0.3191	150	150	1.66	0.0498	0.20	0.35	0.8997
28	28	1.73	0.0423	0.20	0.40	0.4631	150	150	1.66	0.0498	0.20	0.40	0.9852
28	28	1.73	0.0423	0.20	0.45	0.6090	150	150	1.66	0.0498	0.20	0.45	0.9989

Table B.10: continue on next page

Table B.10: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
28	28	1.73	0.0423	0.20	0.50	0.7410	150	150	1.66	0.0498	0.20	0.50	1.0000
28	28	1.73	0.0423	0.20	0.55	0.8471	150	150	1.66	0.0498	0.20	0.55	1.0000
28	28	1.73	0.0423	0.20	0.60	0.9214	150	150	1.66	0.0498	0.20	0.60	1.0000
28	28	1.73	0.0423	0.20	0.65	0.9658	150	150	1.66	0.0498	0.20	0.65	1.0000
28	28	1.73	0.0423	0.20	0.70	0.9878	150	150	1.66	0.0498	0.20	0.70	1.0000
28	28	1.73	0.0423	0.25	0.40	0.2907	150	150	1.66	0.0498	0.25	0.40	0.8715
28	28	1.73	0.0423	0.25	0.45	0.4280	150	150	1.66	0.0498	0.25	0.45	0.9786
28	28	1.73	0.0423	0.25	0.50	0.5761	150	150	1.66	0.0498	0.25	0.50	0.9981
28	28	1.73	0.0423	0.25	0.55	0.7168	150	150	1.66	0.0498	0.25	0.55	0.9999
28	28	1.73	0.0423	0.25	0.60	0.8326	150	150	1.66	0.0498	0.25	0.60	1.0000
28	28	1.73	0.0423	0.25	0.65	0.9144	150	150	1.66	0.0498	0.25	0.65	1.0000
28	28	1.73	0.0423	0.25	0.70	0.9631	150	150	1.66	0.0498	0.25	0.70	1.0000
28	28	1.73	0.0423	0.25	0.75	0.9871	150	150	1.66	0.0498	0.25	0.75	1.0000
28	28	1.73	0.0423	0.30	0.45	0.2736	150	150	1.66	0.0498	0.30	0.45	0.8514
28	28	1.73	0.0423	0.30	0.50	0.4113	150	150	1.66	0.0498	0.30	0.50	0.9709
28	28	1.73	0.0423	0.30	0.55	0.5630	150	150	1.66	0.0498	0.30	0.55	0.9971
28	28	1.73	0.0423	0.30	0.60	0.7081	150	150	1.66	0.0498	0.30	0.60	0.9999
28	28	1.73	0.0423	0.30	0.65	0.8279	150	150	1.66	0.0498	0.30	0.65	1.0000
28	28	1.73	0.0423	0.30	0.70	0.9127	150	150	1.66	0.0498	0.30	0.70	1.0000
28	28	1.73	0.0423	0.35	0.50	0.2687	150	150	1.66	0.0498	0.35	0.50	0.8300
28	28	1.73	0.0423	0.35	0.55	0.4072	150	150	1.66	0.0498	0.35	0.55	0.9664
28	28	1.73	0.0423	0.35	0.60	0.5598	150	150	1.66	0.0498	0.35	0.60	0.9967
28	28	1.73	0.0423	0.35	0.65	0.7062	150	150	1.66	0.0498	0.35	0.65	0.9999
28	28	1.73	0.0423	0.40	0.55	0.2687	150	150	1.66	0.0498	0.40	0.55	0.8254
28	28	1.73	0.0423	0.40	0.60	0.4068	150	150	1.66	0.0498	0.40	0.60	0.9655

Table B.10: concluded from previous page

Table B.11: Achieved power and p-values calculated for the z-pooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
10	10	1.96	0.0211	0.05	0.15	0.0304	29	29	2.02	0.0240	0.05	0.15	0.2090
10	10	1.96	0.0211	0.05	0.20	0.0744	29	29	2.02	0.0240	0.05	0.20	0.3774
10	10	1.96	0.0211	0.05	0.25	0.1407	29	29	2.02	0.0240	0.05	0.25	0.5634
10	10	1.96	0.0211	0.05	0.30	0.2255	29	29	2.02	0.0240	0.05	0.30	0.7297
10	10	1.96	0.0211	0.05	0.35	0.3230	29	29	2.02	0.0240	0.05	0.35	0.8521
10	10	1.96	0.0211	0.05	0.40	0.4265	29	29	2.02	0.0240	0.05	0.40	0.9284
10	10	1.96	0.0211	0.05	0.45	0.5298	29	29	2.02	0.0240	0.05	0.45	0.9694
10	10	1.96	0.0211	0.10	0.25	0.0865	29	29	2.02	0.0240	0.10	0.25	0.2983
10	10	1.96	0.0211	0.10	0.30	0.1427	29	29	2.02	0.0240	0.10	0.30	0.4626
10	10	1.96	0.0211	0.10	0.35	0.2116	29	29	2.02	0.0240	0.10	0.35	0.6246
10	10	1.96	0.0211	0.10	0.40	0.2911	29	29	2.02	0.0240	0.10	0.40	0.7621
10	10	1.96	0.0211	0.10	0.45	0.3786	29	29	2.02	0.0240	0.10	0.45	0.8644
10	10	1.96	0.0211	0.10	0.50	0.4713	29	29	2.02	0.0240	0.10	0.50	0.9314
10	10	1.96	0.0211	0.10	0.55	0.5660	29	29	2.02	0.0240	0.10	0.55	0.9699
10	10	1.96	0.0211	0.10	0.60	0.6590	29	29	2.02	0.0240	0.10	0.60	0.9889
10	10	1.96	0.0211	0.15	0.30	0.0886	29	29	2.02	0.0240	0.15	0.30	0.2529
10	10	1.96	0.0211	0.15	0.35	0.1365	29	29	2.02	0.0240	0.15	0.35	0.3951
10	10	1.96	0.0211	0.15	0.40	0.1961	29	29	2.02	0.0240	0.15	0.40	0.5480
10	10	1.96	0.0211	0.15	0.45	0.2673	29	29	2.02	0.0240	0.15	0.45	0.6928
10	10	1.96	0.0211	0.15	0.50	0.3490	29	29	2.02	0.0240	0.15	0.50	0.8135
10	10	1.96	0.0211	0.15	0.55	0.4393	29	29	2.02	0.0240	0.15	0.55	0.9011
10	10	1.96	0.0211	0.15	0.60	0.5352	29	29	2.02	0.0240	0.15	0.60	0.9553
10	10	1.96	0.0211	0.15	0.65	0.6321	29	29	2.02	0.0240	0.15	0.65	0.9833
10	10	1.96	0.0211	0.20	0.35	0.0866	29	29	2.02	0.0240	0.20	0.35	0.2199
10	10	1.96	0.0211	0.20	0.40	0.1301	29	29	2.02	0.0240	0.20	0.40	0.3500
10	10	1.96	0.0211	0.20	0.45	0.1857	29	29	2.02	0.0240	0.20	0.45	0.5009
10	10	1.96	0.0211	0.20	0.50	0.2540	29	29	2.02	0.0240	0.20	0.50	0.6535
10	10	1.96	0.0211	0.20	0.55	0.3343	29	29	2.02	0.0240	0.20	0.55	0.7868
10	10	1.96	0.0211	0.20	0.60	0.4248	29	29	2.02	0.0240	0.20	0.60	0.8861
10	10	1.96	0.0211	0.20	0.65	0.5221	29	29	2.02	0.0240	0.20	0.65	0.9484
10	10	1.96	0.0211	0.20	0.70	0.6216	29	29	2.02	0.0240	0.20	0.70	0.9808
10	10	1.96	0.0211	0.25	0.40	0.0847	29	29	2.02	0.0240	0.25	0.40	0.2019
10	10	1.96	0.0211	0.25	0.45	0.1267	29	29	2.02	0.0240	0.25	0.45	0.3295
10	10	1.96	0.0211	0.25	0.50	0.1811	29	29	2.02	0.0240	0.25	0.50	0.4821
10	10	1.96	0.0211	0.25	0.55	0.2487	29	29	2.02	0.0240	0.25	0.55	0.6389
10	10	1.96	0.0211	0.25	0.60	0.3288	29	29	2.02	0.0240	0.25	0.60	0.7769
10	10	1.96	0.0211	0.25	0.65	0.4196	29	29	2.02	0.0240	0.25	0.65	0.8804
10	10	1.96	0.0211	0.25	0.70	0.5178	29	29	2.02	0.0240	0.25	0.70	0.9458
10	10	1.96	0.0211	0.25	0.75	0.6190	29	29	2.02	0.0240	0.25	0.75	0.9800
10	10	1.96	0.0211	0.30	0.45	0.0845	29	29	2.02	0.0240	0.30	0.45	0.1978
10	10	1.96	0.0211	0.30	0.50	0.1260	29	29	2.02	0.0240	0.30	0.50	0.3254
10	10	1.96	0.0211	0.30	0.55	0.1801	29	29	2.02	0.0240	0.30	0.55	0.4779
10	10	1.96	0.0211	0.30	0.60	0.2474	29	29	2.02	0.0240	0.30	0.60	0.6348
10	10	1.96	0.0211	0.30	0.65	0.3273	29	29	2.02	0.0240	0.30	0.65	0.7737

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
10	10	1.96	0.0211	0.30	0.70	0.4184	29	29	2.02	0.0240	0.30	0.70	0.8788
10	10	1.96	0.0211	0.35	0.50	0.0852	29	29	2.02	0.0240	0.35	0.50	0.1998
10	10	1.96	0.0211	0.35	0.55	0.1266	29	29	2.02	0.0240	0.35	0.55	0.3264
10	10	1.96	0.0211	0.35	0.60	0.1803	29	29	2.02	0.0240	0.35	0.60	0.4775
10	10	1.96	0.0211	0.35	0.65	0.2473	29	29	2.02	0.0240	0.35	0.65	0.6340
10	10	1.96	0.0211	0.40	0.55	0.0860	29	29	2.02	0.0240	0.40	0.55	0.2018
10	10	1.96	0.0211	0.40	0.60	0.1269	29	29	2.02	0.0240	0.40	0.60	0.3271
11	11	2.14	0.0207	0.05	0.15	0.0404	30	30	2.07	0.0235	0.05	0.15	0.2167
11	11	2.14	0.0207	0.05	0.20	0.0957	30	30	2.07	0.0235	0.05	0.20	0.3923
11	11	2.14	0.0207	0.05	0.25	0.1750	30	30	2.07	0.0235	0.05	0.25	0.5832
11	11	2.14	0.0207	0.05	0.30	0.2725	30	30	2.07	0.0235	0.05	0.30	0.7489
11	11	2.14	0.0207	0.05	0.35	0.3801	30	30	2.07	0.0235	0.05	0.35	0.8668
11	11	2.14	0.0207	0.05	0.40	0.4901	30	30	2.07	0.0235	0.05	0.40	0.9377
11	11	2.14	0.0207	0.05	0.45	0.5962	30	30	2.07	0.0235	0.05	0.45	0.9744
11	11	2.14	0.0207	0.10	0.25	0.1048	30	30	2.07	0.0235	0.10	0.25	0.3113
11	11	2.14	0.0207	0.10	0.30	0.1697	30	30	2.07	0.0235	0.10	0.30	0.4801
11	11	2.14	0.0207	0.10	0.35	0.2482	30	30	2.07	0.0235	0.10	0.35	0.6435
11	11	2.14	0.0207	0.10	0.40	0.3371	30	30	2.07	0.0235	0.10	0.40	0.7794
11	11	2.14	0.0207	0.10	0.45	0.4329	30	30	2.07	0.0235	0.10	0.45	0.8780
11	11	2.14	0.0207	0.10	0.50	0.5314	30	30	2.07	0.0235	0.10	0.50	0.9407
11	11	2.14	0.0207	0.10	0.55	0.6278	30	30	2.07	0.0235	0.10	0.55	0.9752
11	11	2.14	0.0207	0.10	0.60	0.7175	30	30	2.07	0.0235	0.10	0.60	0.9914
11	11	2.14	0.0207	0.15	0.30	0.1038	30	30	2.07	0.0235	0.15	0.30	0.2634
11	11	2.14	0.0207	0.15	0.35	0.1592	30	30	2.07	0.0235	0.15	0.35	0.4105
11	11	2.14	0.0207	0.15	0.40	0.2275	30	30	2.07	0.0235	0.15	0.40	0.5673
11	11	2.14	0.0207	0.15	0.45	0.3074	30	30	2.07	0.0235	0.15	0.45	0.7133
11	11	2.14	0.0207	0.15	0.50	0.3963	30	30	2.07	0.0235	0.15	0.50	0.8318
11	11	2.14	0.0207	0.15	0.55	0.4902	30	30	2.07	0.0235	0.15	0.55	0.9145
11	11	2.14	0.0207	0.15	0.60	0.5847	30	30	2.07	0.0235	0.15	0.60	0.9632
11	11	2.14	0.0207	0.15	0.65	0.6753	30	30	2.07	0.0235	0.15	0.65	0.9869
11	11	2.14	0.0207	0.20	0.35	0.1000	30	30	2.07	0.0235	0.20	0.35	0.2300
11	11	2.14	0.0207	0.20	0.40	0.1500	30	30	2.07	0.0235	0.20	0.40	0.3668
11	11	2.14	0.0207	0.20	0.45	0.2125	30	30	2.07	0.0235	0.20	0.45	0.5233
11	11	2.14	0.0207	0.20	0.50	0.2864	30	30	2.07	0.0235	0.20	0.50	0.6777
11	11	2.14	0.0207	0.20	0.55	0.3697	30	30	2.07	0.0235	0.20	0.55	0.8076
11	11	2.14	0.0207	0.20	0.60	0.4594	30	30	2.07	0.0235	0.20	0.60	0.9001
11	11	2.14	0.0207	0.20	0.65	0.5522	30	30	2.07	0.0235	0.20	0.65	0.9556
11	11	2.14	0.0207	0.20	0.70	0.6449	30	30	2.07	0.0235	0.20	0.70	0.9834
11	11	2.14	0.0207	0.25	0.40	0.0961	30	30	2.07	0.0235	0.25	0.40	0.2138
11	11	2.14	0.0207	0.25	0.45	0.1424	30	30	2.07	0.0235	0.25	0.45	0.3484
11	11	2.14	0.0207	0.25	0.50	0.2003	30	30	2.07	0.0235	0.25	0.50	0.5052
11	11	2.14	0.0207	0.25	0.55	0.2694	30	30	2.07	0.0235	0.25	0.55	0.6608
11	11	2.14	0.0207	0.25	0.60	0.3489	30	30	2.07	0.0235	0.25	0.60	0.7929
11	11	2.14	0.0207	0.25	0.65	0.4373	30	30	2.07	0.0235	0.25	0.65	0.8892
11	11	2.14	0.0207	0.25	0.70	0.5329	30	30	2.07	0.0235	0.25	0.70	0.9496
11	11	2.14	0.0207	0.25	0.75	0.6333	30	30	2.07	0.0235	0.25	0.75	0.9816
11	11	2.14	0.0207	0.30	0.45	0.0923	30	30	2.07	0.0235	0.30	0.45	0.2100
11	11	2.14	0.0207	0.30	0.50	0.1354	30	30	2.07	0.0235	0.30	0.50	0.3415
11	11	2.14	0.0207	0.30	0.55	0.1900	30	30	2.07	0.0235	0.30	0.55	0.4940
11	11	2.14	0.0207	0.30	0.60	0.2568	30	30	2.07	0.0235	0.30	0.60	0.6471

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
11	11	2.14	0.0207	0.30	0.65	0.3365	30	30	2.07	0.0235	0.30	0.65	0.7814
11	11	2.14	0.0207	0.30	0.70	0.4289	30	30	2.07	0.0235	0.30	0.70	0.8837
11	11	2.14	0.0207	0.35	0.50	0.0884	30	30	2.07	0.0235	0.35	0.50	0.2076
11	11	2.14	0.0207	0.35	0.55	0.1297	30	30	2.07	0.0235	0.35	0.55	0.3342
11	11	2.14	0.0207	0.35	0.60	0.1836	30	30	2.07	0.0235	0.35	0.60	0.4840
11	11	2.14	0.0207	0.35	0.65	0.2520	30	30	2.07	0.0235	0.35	0.65	0.6400
11	11	2.14	0.0207	0.40	0.55	0.0858	30	30	2.07	0.0235	0.40	0.55	0.2036
11	11	2.14	0.0207	0.40	0.60	0.1275	30	30	2.07	0.0235	0.40	0.60	0.3298
12	12	2.05	0.0225	0.05	0.15	0.0515	31	31	2.04	0.0240	0.05	0.15	0.2246
12	12	2.05	0.0225	0.05	0.20	0.1180	31	31	2.04	0.0240	0.05	0.20	0.4073
12	12	2.05	0.0225	0.05	0.25	0.2098	31	31	2.04	0.0240	0.05	0.25	0.6025
12	12	2.05	0.0225	0.05	0.30	0.3183	31	31	2.04	0.0240	0.05	0.30	0.7670
12	12	2.05	0.0225	0.05	0.35	0.4341	31	31	2.04	0.0240	0.05	0.35	0.8802
12	12	2.05	0.0225	0.05	0.40	0.5488	31	31	2.04	0.0240	0.05	0.40	0.9459
12	12	2.05	0.0225	0.05	0.45	0.6555	31	31	2.04	0.0240	0.05	0.45	0.9787
12	12	2.05	0.0225	0.10	0.25	0.1230	31	31	2.04	0.0240	0.10	0.25	0.3242
12	12	2.05	0.0225	0.10	0.30	0.1967	31	31	2.04	0.0240	0.10	0.30	0.4971
12	12	2.05	0.0225	0.10	0.35	0.2846	31	31	2.04	0.0240	0.10	0.35	0.6616
12	12	2.05	0.0225	0.10	0.40	0.3826	31	31	2.04	0.0240	0.10	0.40	0.7957
12	12	2.05	0.0225	0.10	0.45	0.4858	31	31	2.04	0.0240	0.10	0.45	0.8905
12	12	2.05	0.0225	0.10	0.50	0.5884	31	31	2.04	0.0240	0.10	0.50	0.9489
12	12	2.05	0.0225	0.10	0.55	0.6846	31	31	2.04	0.0240	0.10	0.55	0.9798
12	12	2.05	0.0225	0.10	0.60	0.7695	31	31	2.04	0.0240	0.10	0.60	0.9934
12	12	2.05	0.0225	0.15	0.30	0.1193	31	31	2.04	0.0240	0.15	0.30	0.2739
12	12	2.05	0.0225	0.15	0.35	0.1828	31	31	2.04	0.0240	0.15	0.35	0.4260
12	12	2.05	0.0225	0.15	0.40	0.2602	31	31	2.04	0.0240	0.15	0.40	0.5865
12	12	2.05	0.0225	0.15	0.45	0.3486	31	31	2.04	0.0240	0.15	0.45	0.7333
12	12	2.05	0.0225	0.15	0.50	0.4439	31	31	2.04	0.0240	0.15	0.50	0.8490
12	12	2.05	0.0225	0.15	0.55	0.5408	31	31	2.04	0.0240	0.15	0.55	0.9265
12	12	2.05	0.0225	0.15	0.60	0.6342	31	31	2.04	0.0240	0.15	0.60	0.9699
12	12	2.05	0.0225	0.15	0.65	0.7204	31	31	2.04	0.0240	0.15	0.65	0.9897
12	12	2.05	0.0225	0.20	0.35	0.1142	31	31	2.04	0.0240	0.20	0.35	0.2406
12	12	2.05	0.0225	0.20	0.40	0.1712	31	31	2.04	0.0240	0.20	0.40	0.3841
12	12	2.05	0.0225	0.20	0.45	0.2408	31	31	2.04	0.0240	0.20	0.45	0.5459
12	12	2.05	0.0225	0.20	0.50	0.3207	31	31	2.04	0.0240	0.20	0.50	0.7011
12	12	2.05	0.0225	0.20	0.55	0.4078	31	31	2.04	0.0240	0.20	0.55	0.8268
12	12	2.05	0.0225	0.20	0.60	0.4988	31	31	2.04	0.0240	0.20	0.60	0.9126
12	12	2.05	0.0225	0.20	0.65	0.5909	31	31	2.04	0.0240	0.20	0.65	0.9619
12	12	2.05	0.0225	0.20	0.70	0.6816	31	31	2.04	0.0240	0.20	0.70	0.9859
12	12	2.05	0.0225	0.25	0.40	0.1085	31	31	2.04	0.0240	0.25	0.40	0.2265
12	12	2.05	0.0225	0.25	0.45	0.1595	31	31	2.04	0.0240	0.25	0.45	0.3676
12	12	2.05	0.0225	0.25	0.50	0.2217	31	31	2.04	0.0240	0.25	0.50	0.5279
12	12	2.05	0.0225	0.25	0.55	0.2942	31	31	2.04	0.0240	0.25	0.55	0.6819
12	12	2.05	0.0225	0.25	0.60	0.3761	31	31	2.04	0.0240	0.25	0.60	0.8083
12	12	2.05	0.0225	0.25	0.65	0.4665	31	31	2.04	0.0240	0.25	0.65	0.8983
12	12	2.05	0.0225	0.25	0.70	0.5641	31	31	2.04	0.0240	0.25	0.70	0.9541
12	12	2.05	0.0225	0.25	0.75	0.6664	31	31	2.04	0.0240	0.25	0.75	0.9836
12	12	2.05	0.0225	0.30	0.45	0.1011	31	31	2.04	0.0240	0.30	0.45	0.2226
12	12	2.05	0.0225	0.30	0.50	0.1467	31	31	2.04	0.0240	0.30	0.50	0.3577
12	12	2.05	0.0225	0.30	0.55	0.2037	31	31	2.04	0.0240	0.30	0.55	0.5102

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
12	12	2.05	0.0225	0.30	0.60	0.2733	31	31	2.04	0.0240	0.30	0.60	0.6602
12	12	2.05	0.0225	0.30	0.65	0.3566	31	31	2.04	0.0240	0.30	0.65	0.7907
12	12	2.05	0.0225	0.30	0.70	0.4541	31	31	2.04	0.0240	0.30	0.70	0.8903
12	12	2.05	0.0225	0.35	0.50	0.0931	31	31	2.04	0.0240	0.35	0.50	0.2156
12	12	2.05	0.0225	0.35	0.55	0.1360	31	31	2.04	0.0240	0.35	0.55	0.3426
12	12	2.05	0.0225	0.35	0.60	0.1924	31	31	2.04	0.0240	0.35	0.60	0.4919
12	12	2.05	0.0225	0.35	0.65	0.2653	31	31	2.04	0.0240	0.35	0.65	0.6482
12	12	2.05	0.0225	0.40	0.55	0.0878	31	31	2.04	0.0240	0.40	0.55	0.2061
12	12	2.05	0.0225	0.40	0.60	0.1317	31	31	2.04	0.0240	0.40	0.60	0.3337
13	13	1.99	0.0243	0.05	0.15	0.0634	32	32	2.02	0.0233	0.05	0.15	0.2325
13	13	1.99	0.0243	0.05	0.20	0.1410	32	32	2.02	0.0233	0.05	0.20	0.4224
13	13	1.99	0.0243	0.05	0.25	0.2443	32	32	2.02	0.0233	0.05	0.25	0.6212
13	13	1.99	0.0243	0.05	0.30	0.3625	32	32	2.02	0.0233	0.05	0.30	0.7839
13	13	1.99	0.0243	0.05	0.35	0.4849	32	32	2.02	0.0233	0.05	0.35	0.8923
13	13	1.99	0.0243	0.05	0.40	0.6024	32	32	2.02	0.0233	0.05	0.40	0.9531
13	13	1.99	0.0243	0.05	0.45	0.7080	32	32	2.02	0.0233	0.05	0.45	0.9822
13	13	1.99	0.0243	0.10	0.25	0.1412	32	32	2.02	0.0233	0.10	0.25	0.3369
13	13	1.99	0.0243	0.10	0.30	0.2237	32	32	2.02	0.0233	0.10	0.30	0.5136
13	13	1.99	0.0243	0.10	0.35	0.3208	32	32	2.02	0.0233	0.10	0.35	0.6790
13	13	1.99	0.0243	0.10	0.40	0.4270	32	32	2.02	0.0233	0.10	0.40	0.8110
13	13	1.99	0.0243	0.10	0.45	0.5358	32	32	2.02	0.0233	0.10	0.45	0.9020
13	13	1.99	0.0243	0.10	0.50	0.6400	32	32	2.02	0.0233	0.10	0.50	0.9561
13	13	1.99	0.0243	0.10	0.55	0.7336	32	32	2.02	0.0233	0.10	0.55	0.9835
13	13	1.99	0.0243	0.10	0.60	0.8125	32	32	2.02	0.0233	0.10	0.60	0.9949
13	13	1.99	0.0243	0.15	0.30	0.1351	32	32	2.02	0.0233	0.15	0.30	0.2843
13	13	1.99	0.0243	0.15	0.35	0.2067	32	32	2.02	0.0233	0.15	0.35	0.4415
13	13	1.99	0.0243	0.15	0.40	0.2926	32	32	2.02	0.0233	0.15	0.40	0.6054
13	13	1.99	0.0243	0.15	0.45	0.3884	32	32	2.02	0.0233	0.15	0.45	0.7520
13	13	1.99	0.0243	0.15	0.50	0.4886	32	32	2.02	0.0233	0.15	0.50	0.8639
13	13	1.99	0.0243	0.15	0.55	0.5873	32	32	2.02	0.0233	0.15	0.55	0.9356
13	13	1.99	0.0243	0.15	0.60	0.6799	32	32	2.02	0.0233	0.15	0.60	0.9740
13	13	1.99	0.0243	0.15	0.65	0.7630	32	32	2.02	0.0233	0.15	0.65	0.9911
13	13	1.99	0.0243	0.20	0.35	0.1286	32	32	2.02	0.0233	0.20	0.35	0.2513
13	13	1.99	0.0243	0.20	0.40	0.1923	32	32	2.02	0.0233	0.20	0.40	0.4007
13	13	1.99	0.0243	0.20	0.45	0.2684	32	32	2.02	0.0233	0.20	0.45	0.5653
13	13	1.99	0.0243	0.20	0.50	0.3541	32	32	2.02	0.0233	0.20	0.50	0.7179
13	13	1.99	0.0243	0.20	0.55	0.4459	32	32	2.02	0.0233	0.20	0.55	0.8373
13	13	1.99	0.0243	0.20	0.60	0.5405	32	32	2.02	0.0233	0.20	0.60	0.9171
13	13	1.99	0.0243	0.20	0.65	0.6349	32	32	2.02	0.0233	0.20	0.65	0.9631
13	13	1.99	0.0243	0.20	0.70	0.7260	32	32	2.02	0.0233	0.20	0.70	0.9862
13	13	1.99	0.0243	0.25	0.40	0.1206	32	32	2.02	0.0233	0.25	0.40	0.2368
13	13	1.99	0.0243	0.25	0.45	0.1765	32	32	2.02	0.0233	0.25	0.45	0.3799
13	13	1.99	0.0243	0.25	0.50	0.2440	32	32	2.02	0.0233	0.25	0.50	0.5375
13	13	1.99	0.0243	0.25	0.55	0.3222	32	32	2.02	0.0233	0.25	0.55	0.6858
13	13	1.99	0.0243	0.25	0.60	0.4102	32	32	2.02	0.0233	0.25	0.60	0.8078
13	13	1.99	0.0243	0.25	0.65	0.5066	32	32	2.02	0.0233	0.25	0.65	0.8968
13	13	1.99	0.0243	0.25	0.70	0.6088	32	32	2.02	0.0233	0.25	0.70	0.9536
13	13	1.99	0.0243	0.25	0.75	0.7123	32	32	2.02	0.0233	0.25	0.75	0.9837
13	13	1.99	0.0243	0.30	0.45	0.1104	32	32	2.02	0.0233	0.30	0.45	0.2255
13	13	1.99	0.0243	0.30	0.50	0.1601	32	32	2.02	0.0233	0.30	0.50	0.3564

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
13	13	1.99	0.0243	0.30	0.55	0.2225	32	32	2.02	0.0233	0.30	0.55	0.5037
13	13	1.99	0.0243	0.30	0.60	0.2988	32	32	2.02	0.0233	0.30	0.60	0.6517
13	13	1.99	0.0243	0.30	0.65	0.3896	32	32	2.02	0.0233	0.30	0.65	0.7842
13	13	1.99	0.0243	0.30	0.70	0.4942	32	32	2.02	0.0233	0.30	0.70	0.8873
13	13	1.99	0.0243	0.35	0.50	0.1003	32	32	2.02	0.0233	0.35	0.50	0.2073
13	13	1.99	0.0243	0.35	0.55	0.1474	32	32	2.02	0.0233	0.35	0.55	0.3292
13	13	1.99	0.0243	0.35	0.60	0.2098	32	32	2.02	0.0233	0.35	0.60	0.4770
13	13	1.99	0.0243	0.35	0.65	0.2901	32	32	2.02	0.0233	0.35	0.65	0.6364
13	13	1.99	0.0243	0.40	0.55	0.0940	32	32	2.02	0.0233	0.40	0.55	0.1918
13	13	1.99	0.0243	0.40	0.60	0.1426	32	32	2.02	0.0233	0.40	0.60	0.3169
14	14	2.03	0.0208	0.05	0.15	0.0756	33	33	2.00	0.0243	0.05	0.15	0.2406
14	14	2.03	0.0208	0.05	0.20	0.1632	33	33	2.00	0.0243	0.05	0.20	0.4375
14	14	2.03	0.0208	0.05	0.25	0.2749	33	33	2.00	0.0243	0.05	0.25	0.6394
14	14	2.03	0.0208	0.05	0.30	0.3974	33	33	2.00	0.0243	0.05	0.30	0.7998
14	14	2.03	0.0208	0.05	0.35	0.5192	33	33	2.00	0.0243	0.05	0.35	0.9033
14	14	2.03	0.0208	0.05	0.40	0.6318	33	33	2.00	0.0243	0.05	0.40	0.9593
14	14	2.03	0.0208	0.05	0.45	0.7300	33	33	2.00	0.0243	0.05	0.45	0.9852
14	14	2.03	0.0208	0.10	0.25	0.1521	33	33	2.00	0.0243	0.10	0.25	0.3495
14	14	2.03	0.0208	0.10	0.30	0.2347	33	33	2.00	0.0243	0.10	0.30	0.5298
14	14	2.03	0.0208	0.10	0.35	0.3286	33	33	2.00	0.0243	0.10	0.35	0.6957
14	14	2.03	0.0208	0.10	0.40	0.4292	33	33	2.00	0.0243	0.10	0.40	0.8254
14	14	2.03	0.0208	0.10	0.45	0.5318	33	33	2.00	0.0243	0.10	0.45	0.9126
14	14	2.03	0.0208	0.10	0.50	0.6318	33	33	2.00	0.0243	0.10	0.50	0.9625
14	14	2.03	0.0208	0.10	0.55	0.7250	33	33	2.00	0.0243	0.10	0.55	0.9866
14	14	2.03	0.0208	0.10	0.60	0.8072	33	33	2.00	0.0243	0.10	0.60	0.9961
14	14	2.03	0.0208	0.15	0.30	0.1330	33	33	2.00	0.0243	0.15	0.30	0.2949
14	14	2.03	0.0208	0.15	0.35	0.1990	33	33	2.00	0.0243	0.15	0.35	0.4572
14	14	2.03	0.0208	0.15	0.40	0.2781	33	33	2.00	0.0243	0.15	0.40	0.6242
14	14	2.03	0.0208	0.15	0.45	0.3690	33	33	2.00	0.0243	0.15	0.45	0.7704
14	14	2.03	0.0208	0.15	0.50	0.4686	33	33	2.00	0.0243	0.15	0.50	0.8782
14	14	2.03	0.0208	0.15	0.55	0.5728	33	33	2.00	0.0243	0.15	0.55	0.9445
14	14	2.03	0.0208	0.15	0.60	0.6756	33	33	2.00	0.0243	0.15	0.60	0.9784
14	14	2.03	0.0208	0.15	0.65	0.7706	33	33	2.00	0.0243	0.15	0.65	0.9929
14	14	2.03	0.0208	0.20	0.35	0.1157	33	33	2.00	0.0243	0.20	0.35	0.2627
14	14	2.03	0.0208	0.20	0.40	0.1732	33	33	2.00	0.0243	0.20	0.40	0.4183
14	14	2.03	0.0208	0.20	0.45	0.2460	33	33	2.00	0.0243	0.20	0.45	0.5861
14	14	2.03	0.0208	0.20	0.50	0.3340	33	33	2.00	0.0243	0.20	0.50	0.7373
14	14	2.03	0.0208	0.20	0.55	0.4349	33	33	2.00	0.0243	0.20	0.55	0.8520
14	14	2.03	0.0208	0.20	0.60	0.5436	33	33	2.00	0.0243	0.20	0.60	0.9264
14	14	2.03	0.0208	0.20	0.65	0.6531	33	33	2.00	0.0243	0.20	0.65	0.9684
14	14	2.03	0.0208	0.20	0.70	0.7554	33	33	2.00	0.0243	0.20	0.70	0.9888
14	14	2.03	0.0208	0.25	0.40	0.1039	33	33	2.00	0.0243	0.25	0.40	0.2490
14	14	2.03	0.0208	0.25	0.45	0.1582	33	33	2.00	0.0243	0.25	0.45	0.3967
14	14	2.03	0.0208	0.25	0.50	0.2294	33	33	2.00	0.0243	0.25	0.50	0.5559
14	14	2.03	0.0208	0.25	0.55	0.3177	33	33	2.00	0.0243	0.25	0.55	0.7030
14	14	2.03	0.0208	0.25	0.60	0.4205	33	33	2.00	0.0243	0.25	0.60	0.8225
14	14	2.03	0.0208	0.25	0.65	0.5322	33	33	2.00	0.0243	0.25	0.65	0.9079
14	14	2.03	0.0208	0.25	0.70	0.6454	33	33	2.00	0.0243	0.25	0.70	0.9605
14	14	2.03	0.0208	0.25	0.75	0.7516	33	33	2.00	0.0243	0.25	0.75	0.9869
14	14	2.03	0.0208	0.30	0.45	0.0980	33	33	2.00	0.0243	0.30	0.45	0.2354

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
14	14	2.03	0.0208	0.30	0.50	0.1517	33	33	2.00	0.0243	0.30	0.50	0.3698
14	14	2.03	0.0208	0.30	0.55	0.2231	33	33	2.00	0.0243	0.30	0.55	0.5201
14	14	2.03	0.0208	0.30	0.60	0.3121	33	33	2.00	0.0243	0.30	0.60	0.6699
14	14	2.03	0.0208	0.30	0.65	0.4160	33	33	2.00	0.0243	0.30	0.65	0.8014
14	14	2.03	0.0208	0.30	0.70	0.5295	33	33	2.00	0.0243	0.30	0.70	0.9001
14	14	2.03	0.0208	0.35	0.50	0.0963	33	33	2.00	0.0243	0.35	0.50	0.2153
14	14	2.03	0.0208	0.35	0.55	0.1501	33	33	2.00	0.0243	0.35	0.55	0.3423
14	14	2.03	0.0208	0.35	0.60	0.2216	33	33	2.00	0.0243	0.35	0.60	0.4951
14	14	2.03	0.0208	0.35	0.65	0.3109	33	33	2.00	0.0243	0.35	0.65	0.6565
14	14	2.03	0.0208	0.40	0.55	0.0962	33	33	2.00	0.0243	0.40	0.55	0.2004
14	14	2.03	0.0208	0.40	0.60	0.1499	33	33	2.00	0.0243	0.40	0.60	0.3311
15	15	2.00	0.0216	0.05	0.15	0.0884	34	34	2.00	0.0233	0.05	0.15	0.2489
15	15	2.00	0.0216	0.05	0.20	0.1859	34	34	2.00	0.0233	0.05	0.20	0.4526
15	15	2.00	0.0216	0.05	0.25	0.3063	34	34	2.00	0.0233	0.05	0.25	0.6569
15	15	2.00	0.0216	0.05	0.30	0.4348	34	34	2.00	0.0233	0.05	0.30	0.8146
15	15	2.00	0.0216	0.05	0.35	0.5593	34	34	2.00	0.0233	0.05	0.35	0.9132
15	15	2.00	0.0216	0.05	0.40	0.6714	34	34	2.00	0.0233	0.05	0.40	0.9648
15	15	2.00	0.0216	0.05	0.45	0.7667	34	34	2.00	0.0233	0.05	0.45	0.9877
15	15	2.00	0.0216	0.10	0.25	0.1670	34	34	2.00	0.0233	0.10	0.25	0.3619
15	15	2.00	0.0216	0.10	0.30	0.2558	34	34	2.00	0.0233	0.10	0.30	0.5455
15	15	2.00	0.0216	0.10	0.35	0.3561	34	34	2.00	0.0233	0.10	0.35	0.7117
15	15	2.00	0.0216	0.10	0.40	0.4627	34	34	2.00	0.0233	0.10	0.40	0.8388
15	15	2.00	0.0216	0.10	0.45	0.5702	34	34	2.00	0.0233	0.10	0.45	0.9218
15	15	2.00	0.0216	0.10	0.50	0.6732	34	34	2.00	0.0233	0.10	0.50	0.9676
15	15	2.00	0.0216	0.10	0.55	0.7664	34	34	2.00	0.0233	0.10	0.55	0.9888
15	15	2.00	0.0216	0.10	0.60	0.8452	34	34	2.00	0.0233	0.10	0.60	0.9968
15	15	2.00	0.0216	0.15	0.30	0.1439	34	34	2.00	0.0233	0.15	0.30	0.3053
15	15	2.00	0.0216	0.15	0.35	0.2162	34	34	2.00	0.0233	0.15	0.35	0.4720
15	15	2.00	0.0216	0.15	0.40	0.3034	34	34	2.00	0.0233	0.15	0.40	0.6406
15	15	2.00	0.0216	0.15	0.45	0.4034	34	34	2.00	0.0233	0.15	0.45	0.7840
15	15	2.00	0.0216	0.15	0.50	0.5117	34	34	2.00	0.0233	0.15	0.50	0.8865
15	15	2.00	0.0216	0.15	0.55	0.6218	34	34	2.00	0.0233	0.15	0.55	0.9481
15	15	2.00	0.0216	0.15	0.60	0.7262	34	34	2.00	0.0233	0.15	0.60	0.9796
15	15	2.00	0.0216	0.15	0.65	0.8174	34	34	2.00	0.0233	0.15	0.65	0.9933
15	15	2.00	0.0216	0.20	0.35	0.1259	34	34	2.00	0.0233	0.20	0.35	0.2717
15	15	2.00	0.0216	0.20	0.40	0.1911	34	34	2.00	0.0233	0.20	0.40	0.4290
15	15	2.00	0.0216	0.20	0.45	0.2740	34	34	2.00	0.0233	0.20	0.45	0.5945
15	15	2.00	0.0216	0.20	0.50	0.3732	34	34	2.00	0.0233	0.20	0.50	0.7413
15	15	2.00	0.0216	0.20	0.55	0.4841	34	34	2.00	0.0233	0.20	0.55	0.8534
15	15	2.00	0.0216	0.20	0.60	0.5992	34	34	2.00	0.0233	0.20	0.60	0.9279
15	15	2.00	0.0216	0.20	0.65	0.7095	34	34	2.00	0.0233	0.20	0.65	0.9703
15	15	2.00	0.0216	0.20	0.70	0.8066	34	34	2.00	0.0233	0.20	0.70	0.9903
15	15	2.00	0.0216	0.25	0.40	0.1160	34	34	2.00	0.0233	0.25	0.40	0.2508
15	15	2.00	0.0216	0.25	0.45	0.1793	34	34	2.00	0.0233	0.25	0.45	0.3954
15	15	2.00	0.0216	0.25	0.50	0.2617	34	34	2.00	0.0233	0.25	0.50	0.5526
15	15	2.00	0.0216	0.25	0.55	0.3616	34	34	2.00	0.0233	0.25	0.55	0.7022
15	15	2.00	0.0216	0.25	0.60	0.4740	34	34	2.00	0.0233	0.25	0.60	0.8263
15	15	2.00	0.0216	0.25	0.65	0.5913	34	34	2.00	0.0233	0.25	0.65	0.9142
15	15	2.00	0.0216	0.25	0.70	0.7042	34	34	2.00	0.0233	0.25	0.70	0.9655
15	15	2.00	0.0216	0.25	0.75	0.8039	34	34	2.00	0.0233	0.25	0.75	0.9893

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
15	15	2.00	0.0216	0.30	0.45	0.1128	34	34	2.00	0.0233	0.30	0.45	0.2290
15	15	2.00	0.0216	0.30	0.50	0.1761	34	34	2.00	0.0233	0.30	0.50	0.3641
15	15	2.00	0.0216	0.30	0.55	0.2586	34	34	2.00	0.0233	0.30	0.55	0.5209
15	15	2.00	0.0216	0.30	0.60	0.3587	34	34	2.00	0.0233	0.30	0.60	0.6790
15	15	2.00	0.0216	0.30	0.65	0.4714	34	34	2.00	0.0233	0.30	0.65	0.8143
15	15	2.00	0.0216	0.30	0.70	0.5895	34	34	2.00	0.0233	0.30	0.70	0.9103
15	15	2.00	0.0216	0.35	0.50	0.1132	34	34	2.00	0.0233	0.35	0.50	0.2120
15	15	2.00	0.0216	0.35	0.55	0.1764	34	34	2.00	0.0233	0.35	0.55	0.3463
15	15	2.00	0.0216	0.35	0.60	0.2586	34	34	2.00	0.0233	0.35	0.60	0.5079
15	15	2.00	0.0216	0.35	0.65	0.3583	34	34	2.00	0.0233	0.35	0.65	0.6728
15	15	2.00	0.0216	0.40	0.55	0.1142	34	34	2.00	0.0233	0.40	0.55	0.2052
15	15	2.00	0.0216	0.40	0.60	0.1769	34	34	2.00	0.0233	0.40	0.60	0.3419
16	16	2.13	0.0224	0.05	0.15	0.1014	35	35	2.00	0.0240	0.05	0.15	0.2573
16	16	2.13	0.0224	0.05	0.20	0.2082	35	35	2.00	0.0240	0.05	0.20	0.4676
16	16	2.13	0.0224	0.05	0.25	0.3364	35	35	2.00	0.0240	0.05	0.25	0.6738
16	16	2.13	0.0224	0.05	0.30	0.4699	35	35	2.00	0.0240	0.05	0.30	0.8284
16	16	2.13	0.0224	0.05	0.35	0.5961	35	35	2.00	0.0240	0.05	0.35	0.9221
16	16	2.13	0.0224	0.05	0.40	0.7072	35	35	2.00	0.0240	0.05	0.40	0.9695
16	16	2.13	0.0224	0.05	0.45	0.7991	35	35	2.00	0.0240	0.05	0.45	0.9898
16	16	2.13	0.0224	0.10	0.25	0.1813	35	35	2.00	0.0240	0.10	0.25	0.3741
16	16	2.13	0.0224	0.10	0.30	0.2763	35	35	2.00	0.0240	0.10	0.30	0.5608
16	16	2.13	0.0224	0.10	0.35	0.3830	35	35	2.00	0.0240	0.10	0.35	0.7271
16	16	2.13	0.0224	0.10	0.40	0.4956	35	35	2.00	0.0240	0.10	0.40	0.8516
16	16	2.13	0.0224	0.10	0.45	0.6075	35	35	2.00	0.0240	0.10	0.45	0.9305
16	16	2.13	0.0224	0.10	0.50	0.7119	35	35	2.00	0.0240	0.10	0.50	0.9724
16	16	2.13	0.0224	0.10	0.55	0.8027	35	35	2.00	0.0240	0.10	0.55	0.9909
16	16	2.13	0.0224	0.10	0.60	0.8755	35	35	2.00	0.0240	0.10	0.60	0.9975
16	16	2.13	0.0224	0.15	0.30	0.1548	35	35	2.00	0.0240	0.15	0.30	0.3160
16	16	2.13	0.0224	0.15	0.35	0.2339	35	35	2.00	0.0240	0.15	0.35	0.4875
16	16	2.13	0.0224	0.15	0.40	0.3294	35	35	2.00	0.0240	0.15	0.40	0.6581
16	16	2.13	0.0224	0.15	0.45	0.4375	35	35	2.00	0.0240	0.15	0.45	0.7997
16	16	2.13	0.0224	0.15	0.50	0.5515	35	35	2.00	0.0240	0.15	0.50	0.8976
16	16	2.13	0.0224	0.15	0.55	0.6629	35	35	2.00	0.0240	0.15	0.55	0.9547
16	16	2.13	0.0224	0.15	0.60	0.7631	35	35	2.00	0.0240	0.15	0.60	0.9829
16	16	2.13	0.0224	0.15	0.65	0.8456	35	35	2.00	0.0240	0.15	0.65	0.9947
16	16	2.13	0.0224	0.20	0.35	0.1368	35	35	2.00	0.0240	0.20	0.35	0.2828
16	16	2.13	0.0224	0.20	0.40	0.2094	35	35	2.00	0.0240	0.20	0.40	0.4447
16	16	2.13	0.0224	0.20	0.45	0.3005	35	35	2.00	0.0240	0.20	0.45	0.6117
16	16	2.13	0.0224	0.20	0.50	0.4063	35	35	2.00	0.0240	0.20	0.50	0.7570
16	16	2.13	0.0224	0.20	0.55	0.5197	35	35	2.00	0.0240	0.20	0.55	0.8659
16	16	2.13	0.0224	0.20	0.60	0.6320	35	35	2.00	0.0240	0.20	0.60	0.9364
16	16	2.13	0.0224	0.20	0.65	0.7353	35	35	2.00	0.0240	0.20	0.65	0.9751
16	16	2.13	0.0224	0.20	0.70	0.8235	35	35	2.00	0.0240	0.20	0.70	0.9924
16	16	2.13	0.0224	0.25	0.40	0.1274	35	35	2.00	0.0240	0.25	0.40	0.2607
16	16	2.13	0.0224	0.25	0.45	0.1967	35	35	2.00	0.0240	0.25	0.45	0.4091
16	16	2.13	0.0224	0.25	0.50	0.2841	35	35	2.00	0.0240	0.25	0.50	0.5694
16	16	2.13	0.0224	0.25	0.55	0.3861	35	35	2.00	0.0240	0.25	0.55	0.7200
16	16	2.13	0.0224	0.25	0.60	0.4968	35	35	2.00	0.0240	0.25	0.60	0.8421
16	16	2.13	0.0224	0.25	0.65	0.6094	35	35	2.00	0.0240	0.25	0.65	0.9254
16	16	2.13	0.0224	0.25	0.70	0.7174	35	35	2.00	0.0240	0.25	0.70	0.9716

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
16	16	2.13	0.0224	0.25	0.75	0.8141	35	35	2.00	0.0240	0.25	0.75	0.9917
16	16	2.13	0.0224	0.30	0.45	0.1223	35	35	2.00	0.0240	0.30	0.45	0.2380
16	16	2.13	0.0224	0.30	0.50	0.1883	35	35	2.00	0.0240	0.30	0.50	0.3788
16	16	2.13	0.0224	0.30	0.55	0.2718	35	35	2.00	0.0240	0.30	0.55	0.5409
16	16	2.13	0.0224	0.30	0.60	0.3709	35	35	2.00	0.0240	0.30	0.60	0.7007
16	16	2.13	0.0224	0.30	0.65	0.4822	35	35	2.00	0.0240	0.30	0.65	0.8327
16	16	2.13	0.0224	0.30	0.70	0.6002	35	35	2.00	0.0240	0.30	0.70	0.9225
16	16	2.13	0.0224	0.35	0.50	0.1181	35	35	2.00	0.0240	0.35	0.50	0.2229
16	16	2.13	0.0224	0.35	0.55	0.1814	35	35	2.00	0.0240	0.35	0.55	0.3643
16	16	2.13	0.0224	0.35	0.60	0.2636	35	35	2.00	0.0240	0.35	0.60	0.5309
16	16	2.13	0.0224	0.35	0.65	0.3647	35	35	2.00	0.0240	0.35	0.65	0.6961
16	16	2.13	0.0224	0.40	0.55	0.1149	35	35	2.00	0.0240	0.40	0.55	0.2182
16	16	2.13	0.0224	0.40	0.60	0.1785	35	35	2.00	0.0240	0.40	0.60	0.3613
17	17	2.07	0.0231	0.05	0.15	0.1144	36	36	1.99	0.0247	0.05	0.15	0.2658
17	17	2.07	0.0231	0.05	0.20	0.2300	36	36	1.99	0.0247	0.05	0.20	0.4825
17	17	2.07	0.0231	0.05	0.25	0.3652	36	36	1.99	0.0247	0.05	0.25	0.6900
17	17	2.07	0.0231	0.05	0.30	0.5028	36	36	1.99	0.0247	0.05	0.30	0.8412
17	17	2.07	0.0231	0.05	0.35	0.6302	36	36	1.99	0.0247	0.05	0.35	0.9301
17	17	2.07	0.0231	0.05	0.40	0.7397	36	36	1.99	0.0247	0.05	0.40	0.9736
17	17	2.07	0.0231	0.05	0.45	0.8277	36	36	1.99	0.0247	0.05	0.45	0.9915
17	17	2.07	0.0231	0.10	0.25	0.1952	36	36	1.99	0.0247	0.10	0.25	0.3861
17	17	2.07	0.0231	0.10	0.30	0.2965	36	36	1.99	0.0247	0.10	0.30	0.5758
17	17	2.07	0.0231	0.10	0.35	0.4098	36	36	1.99	0.0247	0.10	0.35	0.7419
17	17	2.07	0.0231	0.10	0.40	0.5283	36	36	1.99	0.0247	0.10	0.40	0.8636
17	17	2.07	0.0231	0.10	0.45	0.6437	36	36	1.99	0.0247	0.10	0.45	0.9384
17	17	2.07	0.0231	0.10	0.50	0.7482	36	36	1.99	0.0247	0.10	0.50	0.9765
17	17	2.07	0.0231	0.10	0.55	0.8353	36	36	1.99	0.0247	0.10	0.55	0.9926
17	17	2.07	0.0231	0.10	0.60	0.9012	36	36	1.99	0.0247	0.10	0.60	0.9981
17	17	2.07	0.0231	0.15	0.30	0.1661	36	36	1.99	0.0247	0.15	0.30	0.3268
17	17	2.07	0.0231	0.15	0.35	0.2526	36	36	1.99	0.0247	0.15	0.35	0.5030
17	17	2.07	0.0231	0.15	0.40	0.3567	36	36	1.99	0.0247	0.15	0.40	0.6752
17	17	2.07	0.0231	0.15	0.45	0.4725	36	36	1.99	0.0247	0.15	0.45	0.8143
17	17	2.07	0.0231	0.15	0.50	0.5910	36	36	1.99	0.0247	0.15	0.50	0.9076
17	17	2.07	0.0231	0.15	0.55	0.7019	36	36	1.99	0.0247	0.15	0.55	0.9604
17	17	2.07	0.0231	0.15	0.60	0.7969	36	36	1.99	0.0247	0.15	0.60	0.9856
17	17	2.07	0.0231	0.15	0.65	0.8713	36	36	1.99	0.0247	0.15	0.65	0.9958
17	17	2.07	0.0231	0.20	0.35	0.1487	36	36	1.99	0.0247	0.20	0.35	0.2940
17	17	2.07	0.0231	0.20	0.40	0.2292	36	36	1.99	0.0247	0.20	0.40	0.4600
17	17	2.07	0.0231	0.20	0.45	0.3284	36	36	1.99	0.0247	0.20	0.45	0.6282
17	17	2.07	0.0231	0.20	0.50	0.4400	36	36	1.99	0.0247	0.20	0.50	0.7719
17	17	2.07	0.0231	0.20	0.55	0.5552	36	36	1.99	0.0247	0.20	0.55	0.8776
17	17	2.07	0.0231	0.20	0.60	0.6650	36	36	1.99	0.0247	0.20	0.60	0.9443
17	17	2.07	0.0231	0.20	0.65	0.7626	36	36	1.99	0.0247	0.20	0.65	0.9793
17	17	2.07	0.0231	0.20	0.70	0.8441	36	36	1.99	0.0247	0.20	0.70	0.9941
17	17	2.07	0.0231	0.25	0.40	0.1398	36	36	1.99	0.0247	0.25	0.40	0.2704
17	17	2.07	0.0231	0.25	0.45	0.2153	36	36	1.99	0.0247	0.25	0.45	0.4228
17	17	2.07	0.0231	0.25	0.50	0.3077	36	36	1.99	0.0247	0.25	0.50	0.5861
17	17	2.07	0.0231	0.25	0.55	0.4121	36	36	1.99	0.0247	0.25	0.55	0.7376
17	17	2.07	0.0231	0.25	0.60	0.5224	36	36	1.99	0.0247	0.25	0.60	0.8572
17	17	2.07	0.0231	0.25	0.65	0.6328	36	36	1.99	0.0247	0.25	0.65	0.9354

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
17	17	2.07	0.0231	0.25	0.70	0.7379	36	36	1.99	0.0247	0.25	0.70	0.9767
17	17	2.07	0.0231	0.25	0.75	0.8319	36	36	1.99	0.0247	0.25	0.75	0.9936
17	17	2.07	0.0231	0.30	0.45	0.1325	36	36	1.99	0.0247	0.30	0.45	0.2474
17	17	2.07	0.0231	0.30	0.50	0.2016	36	36	1.99	0.0247	0.30	0.50	0.3942
17	17	2.07	0.0231	0.30	0.55	0.2870	36	36	1.99	0.0247	0.30	0.55	0.5613
17	17	2.07	0.0231	0.30	0.60	0.3872	36	36	1.99	0.0247	0.30	0.60	0.7218
17	17	2.07	0.0231	0.30	0.65	0.4994	36	36	1.99	0.0247	0.30	0.65	0.8498
17	17	2.07	0.0231	0.30	0.70	0.6190	36	36	1.99	0.0247	0.30	0.70	0.9332
17	17	2.07	0.0231	0.35	0.50	0.1237	36	36	1.99	0.0247	0.35	0.50	0.2346
17	17	2.07	0.0231	0.35	0.55	0.1883	36	36	1.99	0.0247	0.35	0.55	0.3828
17	17	2.07	0.0231	0.35	0.60	0.2722	36	36	1.99	0.0247	0.35	0.60	0.5537
17	17	2.07	0.0231	0.35	0.65	0.3766	36	36	1.99	0.0247	0.35	0.65	0.7183
17	17	2.07	0.0231	0.40	0.55	0.1169	36	36	1.99	0.0247	0.40	0.55	0.2316
17	17	2.07	0.0231	0.40	0.60	0.1824	36	36	1.99	0.0247	0.40	0.60	0.3808
18	18	2.02	0.0239	0.05	0.15	0.1274	37	37	1.99	0.0244	0.05	0.15	0.2745
18	18	2.02	0.0239	0.05	0.20	0.2512	37	37	1.99	0.0244	0.05	0.20	0.4973
18	18	2.02	0.0239	0.05	0.25	0.3927	37	37	1.99	0.0244	0.05	0.25	0.7055
18	18	2.02	0.0239	0.05	0.30	0.5338	37	37	1.99	0.0244	0.05	0.30	0.8532
18	18	2.02	0.0239	0.05	0.35	0.6617	37	37	1.99	0.0244	0.05	0.35	0.9373
18	18	2.02	0.0239	0.05	0.40	0.7692	37	37	1.99	0.0244	0.05	0.40	0.9772
18	18	2.02	0.0239	0.05	0.45	0.8531	37	37	1.99	0.0244	0.05	0.45	0.9930
18	18	2.02	0.0239	0.10	0.25	0.2088	37	37	1.99	0.0244	0.10	0.25	0.3979
18	18	2.02	0.0239	0.10	0.30	0.3166	37	37	1.99	0.0244	0.10	0.30	0.5899
18	18	2.02	0.0239	0.10	0.35	0.4367	37	37	1.99	0.0244	0.10	0.35	0.7548
18	18	2.02	0.0239	0.10	0.40	0.5606	37	37	1.99	0.0244	0.10	0.40	0.8727
18	18	2.02	0.0239	0.10	0.45	0.6786	37	37	1.99	0.0244	0.10	0.45	0.9431
18	18	2.02	0.0239	0.10	0.50	0.7816	37	37	1.99	0.0244	0.10	0.50	0.9784
18	18	2.02	0.0239	0.10	0.55	0.8634	37	37	1.99	0.0244	0.10	0.55	0.9931
18	18	2.02	0.0239	0.10	0.60	0.9220	37	37	1.99	0.0244	0.10	0.60	0.9982
18	18	2.02	0.0239	0.15	0.30	0.1779	37	37	1.99	0.0244	0.15	0.30	0.3350
18	18	2.02	0.0239	0.15	0.35	0.2723	37	37	1.99	0.0244	0.15	0.35	0.5116
18	18	2.02	0.0239	0.15	0.40	0.3848	37	37	1.99	0.0244	0.15	0.40	0.6809
18	18	2.02	0.0239	0.15	0.45	0.5072	37	37	1.99	0.0244	0.15	0.45	0.8165
18	18	2.02	0.0239	0.15	0.50	0.6282	37	37	1.99	0.0244	0.15	0.50	0.9084
18	18	2.02	0.0239	0.15	0.55	0.7370	37	37	1.99	0.0244	0.15	0.55	0.9612
18	18	2.02	0.0239	0.15	0.60	0.8262	37	37	1.99	0.0244	0.15	0.60	0.9866
18	18	2.02	0.0239	0.15	0.65	0.8933	37	37	1.99	0.0244	0.15	0.65	0.9964
18	18	2.02	0.0239	0.20	0.35	0.1616	37	37	1.99	0.0244	0.20	0.35	0.2933
18	18	2.02	0.0239	0.20	0.40	0.2498	37	37	1.99	0.0244	0.20	0.40	0.4563
18	18	2.02	0.0239	0.20	0.45	0.3562	37	37	1.99	0.0244	0.20	0.45	0.6243
18	18	2.02	0.0239	0.20	0.50	0.4724	37	37	1.99	0.0244	0.20	0.50	0.7718
18	18	2.02	0.0239	0.20	0.55	0.5887	37	37	1.99	0.0244	0.20	0.55	0.8815
18	18	2.02	0.0239	0.20	0.60	0.6963	37	37	1.99	0.0244	0.20	0.60	0.9490
18	18	2.02	0.0239	0.20	0.65	0.7898	37	37	1.99	0.0244	0.20	0.65	0.9824
18	18	2.02	0.0239	0.20	0.70	0.8663	37	37	1.99	0.0244	0.20	0.70	0.9953
18	18	2.02	0.0239	0.25	0.40	0.1526	37	37	1.99	0.0244	0.25	0.40	0.2629
18	18	2.02	0.0239	0.25	0.45	0.2337	37	37	1.99	0.0244	0.25	0.45	0.4184
18	18	2.02	0.0239	0.25	0.50	0.3308	37	37	1.99	0.0244	0.25	0.50	0.5899
18	18	2.02	0.0239	0.25	0.55	0.4383	37	37	1.99	0.0244	0.25	0.55	0.7483
18	18	2.02	0.0239	0.25	0.60	0.5501	37	37	1.99	0.0244	0.25	0.60	0.8691

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
18	18	2.02	0.0239	0.25	0.65	0.6607	37	37	1.99	0.0244	0.25	0.65	0.9438
18	18	2.02	0.0239	0.25	0.70	0.7643	37	37	1.99	0.0244	0.25	0.70	0.9808
18	18	2.02	0.0239	0.25	0.75	0.8546	37	37	1.99	0.0244	0.25	0.75	0.9950
18	18	2.02	0.0239	0.30	0.45	0.1427	37	37	1.99	0.0244	0.30	0.45	0.2468
18	18	2.02	0.0239	0.30	0.50	0.2153	37	37	1.99	0.0244	0.30	0.50	0.4027
18	18	2.02	0.0239	0.30	0.55	0.3044	37	37	1.99	0.0244	0.30	0.55	0.5778
18	18	2.02	0.0239	0.30	0.60	0.4082	37	37	1.99	0.0244	0.30	0.60	0.7407
18	18	2.02	0.0239	0.30	0.65	0.5240	37	37	1.99	0.0244	0.30	0.65	0.8652
18	18	2.02	0.0239	0.30	0.70	0.6459	37	37	1.99	0.0244	0.30	0.70	0.9426
18	18	2.02	0.0239	0.35	0.50	0.1304	37	37	1.99	0.0244	0.35	0.50	0.2439
18	18	2.02	0.0239	0.35	0.55	0.1980	37	37	1.99	0.0244	0.35	0.55	0.4000
18	18	2.02	0.0239	0.35	0.60	0.2862	37	37	1.99	0.0244	0.35	0.60	0.5754
18	18	2.02	0.0239	0.35	0.65	0.3959	37	37	1.99	0.0244	0.35	0.65	0.7392
18	18	2.02	0.0239	0.40	0.55	0.1215	37	37	1.99	0.0244	0.40	0.55	0.2449
18	18	2.02	0.0239	0.40	0.60	0.1908	37	37	1.99	0.0244	0.40	0.60	0.4001
19	19	2.02	0.0243	0.05	0.15	0.1402	38	38	1.99	0.0247	0.05	0.15	0.2833
19	19	2.02	0.0243	0.05	0.20	0.2717	38	38	1.99	0.0247	0.05	0.20	0.5118
19	19	2.02	0.0243	0.05	0.25	0.4189	38	38	1.99	0.0247	0.05	0.25	0.7204
19	19	2.02	0.0243	0.05	0.30	0.5628	38	38	1.99	0.0247	0.05	0.30	0.8643
19	19	2.02	0.0243	0.05	0.35	0.6905	38	38	1.99	0.0247	0.05	0.35	0.9439
19	19	2.02	0.0243	0.05	0.40	0.7949	38	38	1.99	0.0247	0.05	0.40	0.9803
19	19	2.02	0.0243	0.05	0.45	0.8738	38	38	1.99	0.0247	0.05	0.45	0.9942
19	19	2.02	0.0243	0.10	0.25	0.2217	38	38	1.99	0.0247	0.10	0.25	0.4096
19	19	2.02	0.0243	0.10	0.30	0.3350	38	38	1.99	0.0247	0.10	0.30	0.6040
19	19	2.02	0.0243	0.10	0.35	0.4594	38	38	1.99	0.0247	0.10	0.35	0.7682
19	19	2.02	0.0243	0.10	0.40	0.5846	38	38	1.99	0.0247	0.10	0.40	0.8828
19	19	2.02	0.0243	0.10	0.45	0.7000	38	38	1.99	0.0247	0.10	0.45	0.9493
19	19	2.02	0.0243	0.10	0.50	0.7975	38	38	1.99	0.0247	0.10	0.50	0.9814
19	19	2.02	0.0243	0.10	0.55	0.8731	38	38	1.99	0.0247	0.10	0.55	0.9943
19	19	2.02	0.0243	0.10	0.60	0.9268	38	38	1.99	0.0247	0.10	0.60	0.9986
19	19	2.02	0.0243	0.15	0.30	0.1866	38	38	1.99	0.0247	0.15	0.30	0.3452
19	19	2.02	0.0243	0.15	0.35	0.2838	38	38	1.99	0.0247	0.15	0.35	0.5255
19	19	2.02	0.0243	0.15	0.40	0.3965	38	38	1.99	0.0247	0.15	0.40	0.6954
19	19	2.02	0.0243	0.15	0.45	0.5159	38	38	1.99	0.0247	0.15	0.45	0.8288
19	19	2.02	0.0243	0.15	0.50	0.6323	38	38	1.99	0.0247	0.15	0.50	0.9171
19	19	2.02	0.0243	0.15	0.55	0.7375	38	38	1.99	0.0247	0.15	0.55	0.9663
19	19	2.02	0.0243	0.15	0.60	0.8261	38	38	1.99	0.0247	0.15	0.60	0.9889
19	19	2.02	0.0243	0.15	0.65	0.8950	38	38	1.99	0.0247	0.15	0.65	0.9972
19	19	2.02	0.0243	0.20	0.35	0.1635	38	38	1.99	0.0247	0.20	0.35	0.3027
19	19	2.02	0.0243	0.20	0.40	0.2492	38	38	1.99	0.0247	0.20	0.40	0.4698
19	19	2.02	0.0243	0.20	0.45	0.3513	38	38	1.99	0.0247	0.20	0.45	0.6401
19	19	2.02	0.0243	0.20	0.50	0.4642	38	38	1.99	0.0247	0.20	0.50	0.7872
19	19	2.02	0.0243	0.20	0.55	0.5808	38	38	1.99	0.0247	0.20	0.55	0.8934
19	19	2.02	0.0243	0.20	0.60	0.6935	38	38	1.99	0.0247	0.20	0.60	0.9561
19	19	2.02	0.0243	0.20	0.65	0.7943	38	38	1.99	0.0247	0.20	0.65	0.9856
19	19	2.02	0.0243	0.20	0.70	0.8762	38	38	1.99	0.0247	0.20	0.70	0.9964
19	19	2.02	0.0243	0.25	0.40	0.1453	38	38	1.99	0.0247	0.25	0.40	0.2726
19	19	2.02	0.0243	0.25	0.45	0.2220	38	38	1.99	0.0247	0.25	0.45	0.4339
19	19	2.02	0.0243	0.25	0.50	0.3173	38	38	1.99	0.0247	0.25	0.50	0.6092
19	19	2.02	0.0243	0.25	0.55	0.4282	38	38	1.99	0.0247	0.25	0.55	0.7669

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
19	19	2.02	0.0243	0.25	0.60	0.5489	38	38	1.99	0.0247	0.25	0.60	0.8830
19	19	2.02	0.0243	0.25	0.65	0.6699	38	38	1.99	0.0247	0.25	0.65	0.9519
19	19	2.02	0.0243	0.25	0.70	0.7804	38	38	1.99	0.0247	0.25	0.70	0.9844
19	19	2.02	0.0243	0.25	0.75	0.8706	38	38	1.99	0.0247	0.25	0.75	0.9962
19	19	2.02	0.0243	0.30	0.45	0.1308	38	38	1.99	0.0247	0.30	0.45	0.2589
19	19	2.02	0.0243	0.30	0.50	0.2029	38	38	1.99	0.0247	0.30	0.50	0.4210
19	19	2.02	0.0243	0.30	0.55	0.2966	38	38	1.99	0.0247	0.30	0.55	0.5994
19	19	2.02	0.0243	0.30	0.60	0.4096	38	38	1.99	0.0247	0.30	0.60	0.7605
19	19	2.02	0.0243	0.30	0.65	0.5354	38	38	1.99	0.0247	0.30	0.65	0.8796
19	19	2.02	0.0243	0.30	0.70	0.6631	38	38	1.99	0.0247	0.30	0.70	0.9508
19	19	2.02	0.0243	0.35	0.50	0.1217	38	38	1.99	0.0247	0.35	0.50	0.2576
19	19	2.02	0.0243	0.35	0.55	0.1931	38	38	1.99	0.0247	0.35	0.55	0.4194
19	19	2.02	0.0243	0.35	0.60	0.2880	38	38	1.99	0.0247	0.35	0.60	0.5974
19	19	2.02	0.0243	0.35	0.65	0.4043	38	38	1.99	0.0247	0.35	0.65	0.7591
19	19	2.02	0.0243	0.40	0.55	0.1180	38	38	1.99	0.0247	0.40	0.55	0.2590
19	19	2.02	0.0243	0.40	0.60	0.1903	38	38	1.99	0.0247	0.40	0.60	0.4196
20	20	1.99	0.0249	0.05	0.15	0.1529	39	39	2.04	0.0248	0.05	0.15	0.2625
20	20	1.99	0.0249	0.05	0.20	0.2915	39	39	2.04	0.0248	0.05	0.20	0.4771
20	20	1.99	0.0249	0.05	0.25	0.4439	39	39	2.04	0.0248	0.05	0.25	0.6888
20	20	1.99	0.0249	0.05	0.30	0.5903	39	39	2.04	0.0248	0.05	0.30	0.8451
20	20	1.99	0.0249	0.05	0.35	0.7175	39	39	2.04	0.0248	0.05	0.35	0.9354
20	20	1.99	0.0249	0.05	0.40	0.8189	39	39	2.04	0.0248	0.05	0.40	0.9775
20	20	1.99	0.0249	0.05	0.45	0.8929	39	39	2.04	0.0248	0.05	0.45	0.9935
20	20	1.99	0.0249	0.10	0.25	0.2348	39	39	2.04	0.0248	0.10	0.25	0.3749
20	20	1.99	0.0249	0.10	0.30	0.3544	39	39	2.04	0.0248	0.10	0.30	0.5765
20	20	1.99	0.0249	0.10	0.35	0.4845	39	39	2.04	0.0248	0.10	0.35	0.7523
20	20	1.99	0.0249	0.10	0.40	0.6128	39	39	2.04	0.0248	0.10	0.40	0.8758
20	20	1.99	0.0249	0.10	0.45	0.7280	39	39	2.04	0.0248	0.10	0.45	0.9470
20	20	1.99	0.0249	0.10	0.50	0.8222	39	39	2.04	0.0248	0.10	0.50	0.9810
20	20	1.99	0.0249	0.10	0.55	0.8927	39	39	2.04	0.0248	0.10	0.55	0.9944
20	20	1.99	0.0249	0.10	0.60	0.9409	39	39	2.04	0.0248	0.10	0.60	0.9987
20	20	1.99	0.0249	0.15	0.30	0.1979	39	39	2.04	0.0248	0.15	0.30	0.3236
20	20	1.99	0.0249	0.15	0.35	0.3015	39	39	2.04	0.0248	0.15	0.35	0.5080
20	20	1.99	0.0249	0.15	0.40	0.4200	39	39	2.04	0.0248	0.15	0.40	0.6846
20	20	1.99	0.0249	0.15	0.45	0.5434	39	39	2.04	0.0248	0.15	0.45	0.8251
20	20	1.99	0.0249	0.15	0.50	0.6614	39	39	2.04	0.0248	0.15	0.50	0.9181
20	20	1.99	0.0249	0.15	0.55	0.7659	39	39	2.04	0.0248	0.15	0.55	0.9686
20	20	1.99	0.0249	0.15	0.60	0.8513	39	39	2.04	0.0248	0.15	0.60	0.9904
20	20	1.99	0.0249	0.15	0.65	0.9151	39	39	2.04	0.0248	0.15	0.65	0.9978
20	20	1.99	0.0249	0.20	0.35	0.1737	39	39	2.04	0.0248	0.20	0.35	0.2886
20	20	1.99	0.0249	0.20	0.40	0.2651	39	39	2.04	0.0248	0.20	0.40	0.4610
20	20	1.99	0.0249	0.20	0.45	0.3735	39	39	2.04	0.0248	0.20	0.45	0.6407
20	20	1.99	0.0249	0.20	0.50	0.4924	39	39	2.04	0.0248	0.20	0.50	0.7947
20	20	1.99	0.0249	0.20	0.55	0.6136	39	39	2.04	0.0248	0.20	0.55	0.9017
20	20	1.99	0.0249	0.20	0.60	0.7279	39	39	2.04	0.0248	0.20	0.60	0.9614
20	20	1.99	0.0249	0.20	0.65	0.8260	39	39	2.04	0.0248	0.20	0.65	0.9878
20	20	1.99	0.0249	0.20	0.70	0.9014	39	39	2.04	0.0248	0.20	0.70	0.9970
20	20	1.99	0.0249	0.25	0.40	0.1549	39	39	2.04	0.0248	0.25	0.40	0.2699
20	20	1.99	0.0249	0.25	0.45	0.2380	39	39	2.04	0.0248	0.25	0.45	0.4406
20	20	1.99	0.0249	0.25	0.50	0.3414	39	39	2.04	0.0248	0.25	0.50	0.6230

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
20	20	1.99	0.0249	0.25	0.55	0.4607	39	39	2.04	0.0248	0.25	0.55	0.7811
20	20	1.99	0.0249	0.25	0.60	0.5874	39	39	2.04	0.0248	0.25	0.60	0.8923
20	20	1.99	0.0249	0.25	0.65	0.7099	39	39	2.04	0.0248	0.25	0.65	0.9560
20	20	1.99	0.0249	0.25	0.70	0.8161	39	39	2.04	0.0248	0.25	0.70	0.9857
20	20	1.99	0.0249	0.25	0.75	0.8977	39	39	2.04	0.0248	0.25	0.75	0.9965
20	20	1.99	0.0249	0.30	0.45	0.1414	39	39	2.04	0.0248	0.30	0.45	0.2669
20	20	1.99	0.0249	0.30	0.50	0.2215	39	39	2.04	0.0248	0.30	0.50	0.4347
20	20	1.99	0.0249	0.30	0.55	0.3247	39	39	2.04	0.0248	0.30	0.55	0.6133
20	20	1.99	0.0249	0.30	0.60	0.4467	39	39	2.04	0.0248	0.30	0.60	0.7701
20	20	1.99	0.0249	0.30	0.65	0.5778	39	39	2.04	0.0248	0.30	0.65	0.8844
20	20	1.99	0.0249	0.30	0.70	0.7052	39	39	2.04	0.0248	0.30	0.70	0.9531
20	20	1.99	0.0249	0.35	0.50	0.1346	39	39	2.04	0.0248	0.35	0.50	0.2656
20	20	1.99	0.0249	0.35	0.55	0.2147	39	39	2.04	0.0248	0.35	0.55	0.4275
20	20	1.99	0.0249	0.35	0.60	0.3190	39	39	2.04	0.0248	0.35	0.60	0.6034
20	20	1.99	0.0249	0.35	0.65	0.4432	39	39	2.04	0.0248	0.35	0.65	0.7638
20	20	1.99	0.0249	0.40	0.55	0.1326	39	39	2.04	0.0248	0.40	0.55	0.2612
20	20	1.99	0.0249	0.40	0.60	0.2132	39	39	2.04	0.0248	0.40	0.60	0.4224
21	21	2.05	0.0248	0.05	0.15	0.1652	40	40	2.02	0.0238	0.05	0.15	0.2997
21	21	2.05	0.0248	0.05	0.20	0.3101	40	40	2.02	0.0238	0.05	0.20	0.5336
21	21	2.05	0.0248	0.05	0.25	0.4656	40	40	2.02	0.0238	0.05	0.25	0.7363
21	21	2.05	0.0248	0.05	0.30	0.6111	40	40	2.02	0.0238	0.05	0.30	0.8720
21	21	2.05	0.0248	0.05	0.35	0.7339	40	40	2.02	0.0238	0.05	0.35	0.9471
21	21	2.05	0.0248	0.05	0.40	0.8294	40	40	2.02	0.0238	0.05	0.40	0.9818
21	21	2.05	0.0248	0.05	0.45	0.8981	40	40	2.02	0.0238	0.05	0.45	0.9949
21	21	2.05	0.0248	0.10	0.25	0.2408	40	40	2.02	0.0238	0.10	0.25	0.4038
21	21	2.05	0.0248	0.10	0.30	0.3578	40	40	2.02	0.0238	0.10	0.30	0.5996
21	21	2.05	0.0248	0.10	0.35	0.4827	40	40	2.02	0.0238	0.10	0.35	0.7690
21	21	2.05	0.0248	0.10	0.40	0.6062	40	40	2.02	0.0238	0.10	0.40	0.8865
21	21	2.05	0.0248	0.10	0.45	0.7198	40	40	2.02	0.0238	0.10	0.45	0.9529
21	21	2.05	0.0248	0.10	0.50	0.8163	40	40	2.02	0.0238	0.10	0.50	0.9838
21	21	2.05	0.0248	0.10	0.55	0.8910	40	40	2.02	0.0238	0.10	0.55	0.9955
21	21	2.05	0.0248	0.10	0.60	0.9428	40	40	2.02	0.0238	0.10	0.60	0.9990
21	21	2.05	0.0248	0.15	0.30	0.1901	40	40	2.02	0.0238	0.15	0.30	0.3365
21	21	2.05	0.0248	0.15	0.35	0.2874	40	40	2.02	0.0238	0.15	0.35	0.5230
21	21	2.05	0.0248	0.15	0.40	0.4027	40	40	2.02	0.0238	0.15	0.40	0.6999
21	21	2.05	0.0248	0.15	0.45	0.5290	40	40	2.02	0.0238	0.15	0.45	0.8380
21	21	2.05	0.0248	0.15	0.50	0.6556	40	40	2.02	0.0238	0.15	0.50	0.9268
21	21	2.05	0.0248	0.15	0.55	0.7700	40	40	2.02	0.0238	0.15	0.55	0.9731
21	21	2.05	0.0248	0.15	0.60	0.8622	40	40	2.02	0.0238	0.15	0.60	0.9921
21	21	2.05	0.0248	0.15	0.65	0.9273	40	40	2.02	0.0238	0.15	0.65	0.9982
21	21	2.05	0.0248	0.20	0.35	0.1588	40	40	2.02	0.0238	0.20	0.35	0.2990
21	21	2.05	0.0248	0.20	0.40	0.2492	40	40	2.02	0.0238	0.20	0.40	0.4764
21	21	2.05	0.0248	0.20	0.45	0.3635	40	40	2.02	0.0238	0.20	0.45	0.6583
21	21	2.05	0.0248	0.20	0.50	0.4942	40	40	2.02	0.0238	0.20	0.50	0.8097
21	21	2.05	0.0248	0.20	0.55	0.6283	40	40	2.02	0.0238	0.20	0.55	0.9109
21	21	2.05	0.0248	0.20	0.60	0.7511	40	40	2.02	0.0238	0.20	0.60	0.9653
21	21	2.05	0.0248	0.20	0.65	0.8505	40	40	2.02	0.0238	0.20	0.65	0.9888
21	21	2.05	0.0248	0.20	0.70	0.9212	40	40	2.02	0.0238	0.20	0.70	0.9971
21	21	2.05	0.0248	0.25	0.40	0.1453	40	40	2.02	0.0238	0.25	0.40	0.2816
21	21	2.05	0.0248	0.25	0.45	0.2352	40	40	2.02	0.0238	0.25	0.45	0.4566

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
21	21	2.05	0.0248	0.25	0.50	0.3506	40	40	2.02	0.0238	0.25	0.50	0.6380
21	21	2.05	0.0248	0.25	0.55	0.4832	40	40	2.02	0.0238	0.25	0.55	0.7901
21	21	2.05	0.0248	0.25	0.60	0.6195	40	40	2.02	0.0238	0.25	0.60	0.8949
21	21	2.05	0.0248	0.25	0.65	0.7446	40	40	2.02	0.0238	0.25	0.65	0.9554
21	21	2.05	0.0248	0.25	0.70	0.8465	40	40	2.02	0.0238	0.25	0.70	0.9848
21	21	2.05	0.0248	0.25	0.75	0.9195	40	40	2.02	0.0238	0.25	0.75	0.9963
21	21	2.05	0.0248	0.30	0.45	0.1433	40	40	2.02	0.0238	0.30	0.45	0.2757
21	21	2.05	0.0248	0.30	0.50	0.2336	40	40	2.02	0.0238	0.30	0.50	0.4414
21	21	2.05	0.0248	0.30	0.55	0.3489	40	40	2.02	0.0238	0.30	0.55	0.6135
21	21	2.05	0.0248	0.30	0.60	0.4811	40	40	2.02	0.0238	0.30	0.60	0.7642
21	21	2.05	0.0248	0.30	0.65	0.6172	40	40	2.02	0.0238	0.30	0.65	0.8777
21	21	2.05	0.0248	0.30	0.70	0.7430	40	40	2.02	0.0238	0.30	0.70	0.9494
21	21	2.05	0.0248	0.35	0.50	0.1455	40	40	2.02	0.0238	0.35	0.50	0.2621
21	21	2.05	0.0248	0.35	0.55	0.2354	40	40	2.02	0.0238	0.35	0.55	0.4158
21	21	2.05	0.0248	0.35	0.60	0.3496	40	40	2.02	0.0238	0.35	0.60	0.5862
21	21	2.05	0.0248	0.35	0.65	0.4809	40	40	2.02	0.0238	0.35	0.65	0.7492
21	21	2.05	0.0248	0.40	0.55	0.1475	40	40	2.02	0.0238	0.40	0.55	0.2441
21	21	2.05	0.0248	0.40	0.60	0.2363	40	40	2.02	0.0238	0.40	0.60	0.4006
22	22	2.04	0.0244	0.05	0.15	0.1773	50	50	2.01	0.0244	0.05	0.15	0.3460
22	22	2.04	0.0244	0.05	0.20	0.3284	50	50	2.01	0.0244	0.05	0.20	0.6147
22	22	2.04	0.0244	0.05	0.25	0.4878	50	50	2.01	0.0244	0.05	0.25	0.8210
22	22	2.04	0.0244	0.05	0.30	0.6342	50	50	2.01	0.0244	0.05	0.30	0.9335
22	22	2.04	0.0244	0.05	0.35	0.7554	50	50	2.01	0.0244	0.05	0.35	0.9802
22	22	2.04	0.0244	0.05	0.40	0.8475	50	50	2.01	0.0244	0.05	0.40	0.9953
22	22	2.04	0.0244	0.05	0.45	0.9121	50	50	2.01	0.0244	0.05	0.45	0.9991
22	22	2.04	0.0244	0.10	0.25	0.2515	50	50	2.01	0.0244	0.10	0.25	0.4870
22	22	2.04	0.0244	0.10	0.30	0.3734	50	50	2.01	0.0244	0.10	0.30	0.7035
22	22	2.04	0.0244	0.10	0.35	0.5029	50	50	2.01	0.0244	0.10	0.35	0.8606
22	22	2.04	0.0244	0.10	0.40	0.6298	50	50	2.01	0.0244	0.10	0.40	0.9474
22	22	2.04	0.0244	0.10	0.45	0.7446	50	50	2.01	0.0244	0.10	0.45	0.9841
22	22	2.04	0.0244	0.10	0.50	0.8393	50	50	2.01	0.0244	0.10	0.50	0.9962
22	22	2.04	0.0244	0.10	0.55	0.9095	50	50	2.01	0.0244	0.10	0.55	0.9993
22	22	2.04	0.0244	0.10	0.60	0.9554	50	50	2.01	0.0244	0.10	0.60	0.9999
22	22	2.04	0.0244	0.15	0.30	0.1985	50	50	2.01	0.0244	0.15	0.30	0.4165
22	22	2.04	0.0244	0.15	0.35	0.3023	50	50	2.01	0.0244	0.15	0.35	0.6309
22	22	2.04	0.0244	0.15	0.40	0.4254	50	50	2.01	0.0244	0.15	0.40	0.8049
22	22	2.04	0.0244	0.15	0.45	0.5584	50	50	2.01	0.0244	0.15	0.45	0.9150
22	22	2.04	0.0244	0.15	0.50	0.6881	50	50	2.01	0.0244	0.15	0.50	0.9704
22	22	2.04	0.0244	0.15	0.55	0.8006	50	50	2.01	0.0244	0.15	0.55	0.9920
22	22	2.04	0.0244	0.15	0.60	0.8866	50	50	2.01	0.0244	0.15	0.60	0.9984
22	22	2.04	0.0244	0.15	0.65	0.9438	50	50	2.01	0.0244	0.15	0.65	0.9998
22	22	2.04	0.0244	0.20	0.35	0.1687	50	50	2.01	0.0244	0.20	0.35	0.3744
22	22	2.04	0.0244	0.20	0.40	0.2677	50	50	2.01	0.0244	0.20	0.40	0.5783
22	22	2.04	0.0244	0.20	0.45	0.3913	50	50	2.01	0.0244	0.20	0.45	0.7616
22	22	2.04	0.0244	0.20	0.50	0.5292	50	50	2.01	0.0244	0.20	0.50	0.8905
22	22	2.04	0.0244	0.20	0.55	0.6657	50	50	2.01	0.0244	0.20	0.55	0.9602
22	22	2.04	0.0244	0.20	0.60	0.7852	50	50	2.01	0.0244	0.20	0.60	0.9887
22	22	2.04	0.0244	0.20	0.65	0.8772	50	50	2.01	0.0244	0.20	0.65	0.9975
22	22	2.04	0.0244	0.20	0.70	0.9389	50	50	2.01	0.0244	0.20	0.70	0.9996
22	22	2.04	0.0244	0.25	0.40	0.1585	50	50	2.01	0.0244	0.25	0.40	0.3466

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
22	22	2.04	0.0244	0.25	0.45	0.2575	50	50	2.01	0.0244	0.25	0.45	0.5496
22	22	2.04	0.0244	0.25	0.50	0.3820	50	50	2.01	0.0244	0.25	0.50	0.7391
22	22	2.04	0.0244	0.25	0.55	0.5208	50	50	2.01	0.0244	0.25	0.55	0.8751
22	22	2.04	0.0244	0.25	0.60	0.6584	50	50	2.01	0.0244	0.25	0.60	0.9509
22	22	2.04	0.0244	0.25	0.65	0.7796	50	50	2.01	0.0244	0.25	0.65	0.9845
22	22	2.04	0.0244	0.25	0.70	0.8737	50	50	2.01	0.0244	0.25	0.70	0.9963
22	22	2.04	0.0244	0.25	0.75	0.9375	50	50	2.01	0.0244	0.25	0.75	0.9994
22	22	2.04	0.0244	0.30	0.45	0.1589	50	50	2.01	0.0244	0.30	0.45	0.3366
22	22	2.04	0.0244	0.30	0.50	0.2580	50	50	2.01	0.0244	0.30	0.50	0.5327
22	22	2.04	0.0244	0.30	0.55	0.3815	50	50	2.01	0.0244	0.30	0.55	0.7165
22	22	2.04	0.0244	0.30	0.60	0.5192	50	50	2.01	0.0244	0.30	0.60	0.8548
22	22	2.04	0.0244	0.30	0.65	0.6563	50	50	2.01	0.0244	0.30	0.65	0.9400
22	22	2.04	0.0244	0.30	0.70	0.7781	50	50	2.01	0.0244	0.30	0.70	0.9816
22	22	2.04	0.0244	0.35	0.50	0.1622	50	50	2.01	0.0244	0.35	0.50	0.3212
22	22	2.04	0.0244	0.35	0.55	0.2603	50	50	2.01	0.0244	0.35	0.55	0.5047
22	22	2.04	0.0244	0.35	0.60	0.3824	50	50	2.01	0.0244	0.35	0.60	0.6895
22	22	2.04	0.0244	0.35	0.65	0.5190	50	50	2.01	0.0244	0.35	0.65	0.8422
22	22	2.04	0.0244	0.40	0.55	0.1644	50	50	2.01	0.0244	0.40	0.55	0.2991
22	22	2.04	0.0244	0.40	0.60	0.2613	50	50	2.01	0.0244	0.40	0.60	0.4870
23	23	2.07	0.0237	0.05	0.15	0.1621	60	60	2.02	0.0238	0.05	0.15	0.4278
23	23	2.07	0.0237	0.05	0.20	0.2919	60	60	2.02	0.0238	0.05	0.20	0.7165
23	23	2.07	0.0237	0.05	0.25	0.4399	60	60	2.02	0.0238	0.05	0.25	0.8948
23	23	2.07	0.0237	0.05	0.30	0.5922	60	60	2.02	0.0238	0.05	0.30	0.9704
23	23	2.07	0.0237	0.05	0.35	0.7297	60	60	2.02	0.0238	0.05	0.35	0.9937
23	23	2.07	0.0237	0.05	0.40	0.8380	60	60	2.02	0.0238	0.05	0.40	0.9990
23	23	2.07	0.0237	0.05	0.45	0.9125	60	60	2.02	0.0238	0.05	0.45	0.9999
23	23	2.07	0.0237	0.10	0.25	0.2201	60	60	2.02	0.0238	0.10	0.25	0.5792
23	23	2.07	0.0237	0.10	0.30	0.3500	60	60	2.02	0.0238	0.10	0.30	0.7942
23	23	2.07	0.0237	0.10	0.35	0.4953	60	60	2.02	0.0238	0.10	0.35	0.9216
23	23	2.07	0.0237	0.10	0.40	0.6374	60	60	2.02	0.0238	0.10	0.40	0.9769
23	23	2.07	0.0237	0.10	0.45	0.7613	60	60	2.02	0.0238	0.10	0.45	0.9948
23	23	2.07	0.0237	0.10	0.50	0.8579	60	60	2.02	0.0238	0.10	0.50	0.9991
23	23	2.07	0.0237	0.10	0.55	0.9248	60	60	2.02	0.0238	0.10	0.55	0.9999
23	23	2.07	0.0237	0.10	0.60	0.9654	60	60	2.02	0.0238	0.10	0.60	1.0000
23	23	2.07	0.0237	0.15	0.30	0.1908	60	60	2.02	0.0238	0.15	0.30	0.4954
23	23	2.07	0.0237	0.15	0.35	0.3064	60	60	2.02	0.0238	0.15	0.35	0.7174
23	23	2.07	0.0237	0.15	0.40	0.4423	60	60	2.02	0.0238	0.15	0.40	0.8735
23	23	2.07	0.0237	0.15	0.45	0.5848	60	60	2.02	0.0238	0.15	0.45	0.9555
23	23	2.07	0.0237	0.15	0.50	0.7176	60	60	2.02	0.0238	0.15	0.50	0.9880
23	23	2.07	0.0237	0.15	0.55	0.8269	60	60	2.02	0.0238	0.15	0.55	0.9976
23	23	2.07	0.0237	0.15	0.60	0.9056	60	60	2.02	0.0238	0.15	0.60	0.9997
23	23	2.07	0.0237	0.15	0.65	0.9549	60	60	2.02	0.0238	0.15	0.65	1.0000
23	23	2.07	0.0237	0.20	0.35	0.1756	60	60	2.02	0.0238	0.20	0.35	0.4392
23	23	2.07	0.0237	0.20	0.40	0.2848	60	60	2.02	0.0238	0.20	0.40	0.6585
23	23	2.07	0.0237	0.20	0.45	0.4178	60	60	2.02	0.0238	0.20	0.45	0.8327
23	23	2.07	0.0237	0.20	0.50	0.5607	60	60	2.02	0.0238	0.20	0.50	0.9367
23	23	2.07	0.0237	0.20	0.55	0.6960	60	60	2.02	0.0238	0.20	0.55	0.9821
23	23	2.07	0.0237	0.20	0.60	0.8088	60	60	2.02	0.0238	0.20	0.60	0.9963
23	23	2.07	0.0237	0.20	0.65	0.8919	60	60	2.02	0.0238	0.20	0.65	0.9994
23	23	2.07	0.0237	0.20	0.70	0.9460	60	60	2.02	0.0238	0.20	0.70	0.9999

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
23	23	2.07	0.0237	0.25	0.40	0.1712	60	60	2.02	0.0238	0.25	0.40	0.4016
23	23	2.07	0.0237	0.25	0.45	0.2779	60	60	2.02	0.0238	0.25	0.45	0.6236
23	23	2.07	0.0237	0.25	0.50	0.4075	60	60	2.02	0.0238	0.25	0.50	0.8104
23	23	2.07	0.0237	0.25	0.55	0.5465	60	60	2.02	0.0238	0.25	0.55	0.9252
23	23	2.07	0.0237	0.25	0.60	0.6793	60	60	2.02	0.0238	0.25	0.60	0.9770
23	23	2.07	0.0237	0.25	0.65	0.7932	60	60	2.02	0.0238	0.25	0.65	0.9946
23	23	2.07	0.0237	0.25	0.70	0.8812	60	60	2.02	0.0238	0.25	0.70	0.9991
23	23	2.07	0.0237	0.25	0.75	0.9416	60	60	2.02	0.0238	0.25	0.75	0.9999
23	23	2.07	0.0237	0.30	0.45	0.1712	60	60	2.02	0.0238	0.30	0.45	0.3877
23	23	2.07	0.0237	0.30	0.50	0.2737	60	60	2.02	0.0238	0.30	0.50	0.6060
23	23	2.07	0.0237	0.30	0.55	0.3976	60	60	2.02	0.0238	0.30	0.55	0.7908
23	23	2.07	0.0237	0.30	0.60	0.5324	60	60	2.02	0.0238	0.30	0.60	0.9104
23	23	2.07	0.0237	0.30	0.65	0.6659	60	60	2.02	0.0238	0.30	0.65	0.9706
23	23	2.07	0.0237	0.30	0.70	0.7856	60	60	2.02	0.0238	0.30	0.70	0.9934
23	23	2.07	0.0237	0.35	0.50	0.1691	60	60	2.02	0.0238	0.35	0.50	0.3715
23	23	2.07	0.0237	0.35	0.55	0.2672	60	60	2.02	0.0238	0.35	0.55	0.5777
23	23	2.07	0.0237	0.35	0.60	0.3884	60	60	2.02	0.0238	0.35	0.60	0.7661
23	23	2.07	0.0237	0.35	0.65	0.5255	60	60	2.02	0.0238	0.35	0.65	0.9006
23	23	2.07	0.0237	0.40	0.55	0.1657	60	60	2.02	0.0238	0.40	0.55	0.3466
23	23	2.07	0.0237	0.40	0.60	0.2635	60	60	2.02	0.0238	0.40	0.60	0.5588
24	24	2.03	0.0245	0.05	0.15	0.2006	70	70	1.98	0.0249	0.05	0.15	0.5050
24	24	2.03	0.0245	0.05	0.20	0.3629	70	70	1.98	0.0249	0.05	0.20	0.7938
24	24	2.03	0.0245	0.05	0.25	0.5290	70	70	1.98	0.0249	0.05	0.25	0.9395
24	24	2.03	0.0245	0.05	0.30	0.6763	70	70	1.98	0.0249	0.05	0.30	0.9874
24	24	2.03	0.0245	0.05	0.35	0.7937	70	70	1.98	0.0249	0.05	0.35	0.9981
24	24	2.03	0.0245	0.05	0.40	0.8790	70	70	1.98	0.0249	0.05	0.40	0.9998
24	24	2.03	0.0245	0.05	0.45	0.9354	70	70	1.98	0.0249	0.05	0.45	1.0000
24	24	2.03	0.0245	0.10	0.25	0.2724	70	70	1.98	0.0249	0.10	0.25	0.6605
24	24	2.03	0.0245	0.10	0.30	0.4042	70	70	1.98	0.0249	0.10	0.30	0.8601
24	24	2.03	0.0245	0.10	0.35	0.5433	70	70	1.98	0.0249	0.10	0.35	0.9569
24	24	2.03	0.0245	0.10	0.40	0.6765	70	70	1.98	0.0249	0.10	0.40	0.9902
24	24	2.03	0.0245	0.10	0.45	0.7916	70	70	1.98	0.0249	0.10	0.45	0.9984
24	24	2.03	0.0245	0.10	0.50	0.8800	70	70	1.98	0.0249	0.10	0.50	0.9998
24	24	2.03	0.0245	0.10	0.55	0.9393	70	70	1.98	0.0249	0.10	0.55	1.0000
24	24	2.03	0.0245	0.10	0.60	0.9736	70	70	1.98	0.0249	0.10	0.60	1.0000
24	24	2.03	0.0245	0.15	0.30	0.2167	70	70	1.98	0.0249	0.15	0.30	0.5662
24	24	2.03	0.0245	0.15	0.35	0.3352	70	70	1.98	0.0249	0.15	0.35	0.7872
24	24	2.03	0.0245	0.15	0.40	0.4737	70	70	1.98	0.0249	0.15	0.40	0.9218
24	24	2.03	0.0245	0.15	0.45	0.6173	70	70	1.98	0.0249	0.15	0.45	0.9789
24	24	2.03	0.0245	0.15	0.50	0.7478	70	70	1.98	0.0249	0.15	0.50	0.9959
24	24	2.03	0.0245	0.15	0.55	0.8511	70	70	1.98	0.0249	0.15	0.55	0.9994
24	24	2.03	0.0245	0.15	0.60	0.9220	70	70	1.98	0.0249	0.15	0.60	0.9999
24	24	2.03	0.0245	0.15	0.65	0.9640	70	70	1.98	0.0249	0.15	0.65	1.0000
24	24	2.03	0.0245	0.20	0.35	0.1919	70	70	1.98	0.0249	0.20	0.35	0.5080
24	24	2.03	0.0245	0.20	0.40	0.3079	70	70	1.98	0.0249	0.20	0.40	0.7384
24	24	2.03	0.0245	0.20	0.45	0.4470	70	70	1.98	0.0249	0.20	0.45	0.8922
24	24	2.03	0.0245	0.20	0.50	0.5921	70	70	1.98	0.0249	0.20	0.50	0.9664
24	24	2.03	0.0245	0.20	0.55	0.7245	70	70	1.98	0.0249	0.20	0.55	0.9925
24	24	2.03	0.0245	0.20	0.60	0.8305	70	70	1.98	0.0249	0.20	0.60	0.9989
24	24	2.03	0.0245	0.20	0.65	0.9057	70	70	1.98	0.0249	0.20	0.65	0.9999

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
24	24	2.03	0.0245	0.20	0.70	0.9534	70	70	1.98	0.0249	0.20	0.70	1.0000
24	24	2.03	0.0245	0.25	0.40	0.1862	70	70	1.98	0.0249	0.25	0.40	0.4694
24	24	2.03	0.0245	0.25	0.45	0.2994	70	70	1.98	0.0249	0.25	0.45	0.6966
24	24	2.03	0.0245	0.25	0.50	0.4329	70	70	1.98	0.0249	0.25	0.50	0.8664
24	24	2.03	0.0245	0.25	0.55	0.5716	70	70	1.98	0.0249	0.25	0.55	0.9570
24	24	2.03	0.0245	0.25	0.60	0.7001	70	70	1.98	0.0249	0.25	0.60	0.9904
24	24	2.03	0.0245	0.25	0.65	0.8081	70	70	1.98	0.0249	0.25	0.65	0.9986
24	24	2.03	0.0245	0.25	0.70	0.8909	70	70	1.98	0.0249	0.25	0.70	0.9999
24	24	2.03	0.0245	0.25	0.75	0.9477	70	70	1.98	0.0249	0.25	0.75	1.0000
24	24	2.03	0.0245	0.30	0.45	0.1839	70	70	1.98	0.0249	0.30	0.45	0.4402
24	24	2.03	0.0245	0.30	0.50	0.2896	70	70	1.98	0.0249	0.30	0.50	0.6744
24	24	2.03	0.0245	0.30	0.55	0.4141	70	70	1.98	0.0249	0.30	0.55	0.8557
24	24	2.03	0.0245	0.30	0.60	0.5474	70	70	1.98	0.0249	0.30	0.60	0.9534
24	24	2.03	0.0245	0.30	0.65	0.6786	70	70	1.98	0.0249	0.30	0.65	0.9896
24	24	2.03	0.0245	0.30	0.70	0.7968	70	70	1.98	0.0249	0.30	0.70	0.9985
24	24	2.03	0.0245	0.35	0.50	0.1764	70	70	1.98	0.0249	0.35	0.50	0.4336
24	24	2.03	0.0245	0.35	0.55	0.2750	70	70	1.98	0.0249	0.35	0.55	0.6694
24	24	2.03	0.0245	0.35	0.60	0.3966	70	70	1.98	0.0249	0.35	0.60	0.8528
24	24	2.03	0.0245	0.35	0.65	0.5353	70	70	1.98	0.0249	0.35	0.65	0.9525
24	24	2.03	0.0245	0.40	0.55	0.1679	70	70	1.98	0.0249	0.40	0.55	0.4337
24	24	2.03	0.0245	0.40	0.60	0.2673	70	70	1.98	0.0249	0.40	0.60	0.6685
25	25	2.01	0.0232	0.05	0.15	0.2117	80	80	1.98	0.0245	0.05	0.15	0.5728
25	25	2.01	0.0232	0.05	0.20	0.3793	80	80	1.98	0.0245	0.05	0.20	0.8489
25	25	2.01	0.0232	0.05	0.25	0.5482	80	80	1.98	0.0245	0.05	0.25	0.9638
25	25	2.01	0.0232	0.05	0.30	0.6956	80	80	1.98	0.0245	0.05	0.30	0.9941
25	25	2.01	0.0232	0.05	0.35	0.8109	80	80	1.98	0.0245	0.05	0.35	0.9993
25	25	2.01	0.0232	0.05	0.40	0.8926	80	80	1.98	0.0245	0.05	0.40	0.9999
25	25	2.01	0.0232	0.05	0.45	0.9450	80	80	1.98	0.0245	0.05	0.45	1.0000
25	25	2.01	0.0232	0.10	0.25	0.2826	80	80	1.98	0.0245	0.10	0.25	0.7091
25	25	2.01	0.0232	0.10	0.30	0.4198	80	80	1.98	0.0245	0.10	0.30	0.8970
25	25	2.01	0.0232	0.10	0.35	0.5636	80	80	1.98	0.0245	0.10	0.35	0.9747
25	25	2.01	0.0232	0.10	0.40	0.6991	80	80	1.98	0.0245	0.10	0.40	0.9958
25	25	2.01	0.0232	0.10	0.45	0.8129	80	80	1.98	0.0245	0.10	0.45	0.9995
25	25	2.01	0.0232	0.10	0.50	0.8965	80	80	1.98	0.0245	0.10	0.50	1.0000
25	25	2.01	0.0232	0.10	0.55	0.9498	80	80	1.98	0.0245	0.10	0.55	1.0000
25	25	2.01	0.0232	0.10	0.60	0.9789	80	80	1.98	0.0245	0.10	0.60	1.0000
25	25	2.01	0.0232	0.15	0.30	0.2267	80	80	1.98	0.0245	0.15	0.30	0.6214
25	25	2.01	0.0232	0.15	0.35	0.3524	80	80	1.98	0.0245	0.15	0.35	0.8402
25	25	2.01	0.0232	0.15	0.40	0.4971	80	80	1.98	0.0245	0.15	0.40	0.9514
25	25	2.01	0.0232	0.15	0.45	0.6422	80	80	1.98	0.0245	0.15	0.45	0.9896
25	25	2.01	0.0232	0.15	0.50	0.7689	80	80	1.98	0.0245	0.15	0.50	0.9985
25	25	2.01	0.0232	0.15	0.55	0.8650	80	80	1.98	0.0245	0.15	0.55	0.9999
25	25	2.01	0.0232	0.15	0.60	0.9290	80	80	1.98	0.0245	0.15	0.60	1.0000
25	25	2.01	0.0232	0.15	0.65	0.9666	80	80	1.98	0.0245	0.15	0.65	1.0000
25	25	2.01	0.0232	0.20	0.35	0.2032	80	80	1.98	0.0245	0.20	0.35	0.5641
25	25	2.01	0.0232	0.20	0.40	0.3245	80	80	1.98	0.0245	0.20	0.40	0.7942
25	25	2.01	0.0232	0.20	0.45	0.4650	80	80	1.98	0.0245	0.20	0.45	0.9293
25	25	2.01	0.0232	0.20	0.50	0.6065	80	80	1.98	0.0245	0.20	0.50	0.9825
25	25	2.01	0.0232	0.20	0.55	0.7324	80	80	1.98	0.0245	0.20	0.55	0.9969
25	25	2.01	0.0232	0.20	0.60	0.8330	80	80	1.98	0.0245	0.20	0.60	0.9997

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
25	25	2.01	0.0232	0.20	0.65	0.9061	80	80	1.98	0.0245	0.20	0.65	1.0000
25	25	2.01	0.0232	0.20	0.70	0.9539	80	80	1.98	0.0245	0.20	0.70	1.0000
25	25	2.01	0.0232	0.25	0.40	0.1935	80	80	1.98	0.0245	0.25	0.40	0.5257
25	25	2.01	0.0232	0.25	0.45	0.3056	80	80	1.98	0.0245	0.25	0.45	0.7577
25	25	2.01	0.0232	0.25	0.50	0.4347	80	80	1.98	0.0245	0.25	0.50	0.9071
25	25	2.01	0.0232	0.25	0.55	0.5682	80	80	1.98	0.0245	0.25	0.55	0.9748
25	25	2.01	0.0232	0.25	0.60	0.6946	80	80	1.98	0.0245	0.25	0.60	0.9955
25	25	2.01	0.0232	0.25	0.65	0.8043	80	80	1.98	0.0245	0.25	0.65	0.9995
25	25	2.01	0.0232	0.25	0.70	0.8902	80	80	1.98	0.0245	0.25	0.70	1.0000
25	25	2.01	0.0232	0.25	0.75	0.9486	80	80	1.98	0.0245	0.25	0.75	1.0000
25	25	2.01	0.0232	0.30	0.45	0.1810	80	80	1.98	0.0245	0.30	0.45	0.4896
25	25	2.01	0.0232	0.30	0.50	0.2815	80	80	1.98	0.0245	0.30	0.50	0.7265
25	25	2.01	0.0232	0.30	0.55	0.4019	80	80	1.98	0.0245	0.30	0.55	0.8931
25	25	2.01	0.0232	0.30	0.60	0.5350	80	80	1.98	0.0245	0.30	0.60	0.9713
25	25	2.01	0.0232	0.30	0.65	0.6701	80	80	1.98	0.0245	0.30	0.65	0.9950
25	25	2.01	0.0232	0.30	0.70	0.7930	80	80	1.98	0.0245	0.30	0.70	0.9995
25	25	2.01	0.0232	0.35	0.50	0.1647	80	80	1.98	0.0245	0.35	0.50	0.4717
25	25	2.01	0.0232	0.35	0.55	0.2594	80	80	1.98	0.0245	0.35	0.55	0.7165
25	25	2.01	0.0232	0.35	0.60	0.3805	80	80	1.98	0.0245	0.35	0.60	0.8894
25	25	2.01	0.0232	0.35	0.65	0.5221	80	80	1.98	0.0245	0.35	0.65	0.9705
25	25	2.01	0.0232	0.40	0.55	0.1534	80	80	1.98	0.0245	0.40	0.55	0.4698
25	25	2.01	0.0232	0.40	0.60	0.2507	80	80	1.98	0.0245	0.40	0.60	0.7151
26	26	1.98	0.0243	0.05	0.15	0.2226	90	90	1.98	0.0250	0.05	0.15	0.6317
26	26	1.98	0.0243	0.05	0.20	0.3951	90	90	1.98	0.0250	0.05	0.20	0.8904
26	26	1.98	0.0243	0.05	0.25	0.5665	90	90	1.98	0.0250	0.05	0.25	0.9794
26	26	1.98	0.0243	0.05	0.30	0.7138	90	90	1.98	0.0250	0.05	0.30	0.9975
26	26	1.98	0.0243	0.05	0.35	0.8268	90	90	1.98	0.0250	0.05	0.35	0.9998
26	26	1.98	0.0243	0.05	0.40	0.9049	90	90	1.98	0.0250	0.05	0.40	1.0000
26	26	1.98	0.0243	0.05	0.45	0.9534	90	90	1.98	0.0250	0.05	0.45	1.0000
26	26	1.98	0.0243	0.10	0.25	0.2929	90	90	1.98	0.0250	0.10	0.25	0.7668
26	26	1.98	0.0243	0.10	0.30	0.4355	90	90	1.98	0.0250	0.10	0.30	0.9317
26	26	1.98	0.0243	0.10	0.35	0.5841	90	90	1.98	0.0250	0.10	0.35	0.9867
26	26	1.98	0.0243	0.10	0.40	0.7215	90	90	1.98	0.0250	0.10	0.40	0.9983
26	26	1.98	0.0243	0.10	0.45	0.8331	90	90	1.98	0.0250	0.10	0.45	0.9999
26	26	1.98	0.0243	0.10	0.50	0.9117	90	90	1.98	0.0250	0.10	0.50	1.0000
26	26	1.98	0.0243	0.10	0.55	0.9592	90	90	1.98	0.0250	0.10	0.55	1.0000
26	26	1.98	0.0243	0.10	0.60	0.9836	90	90	1.98	0.0250	0.10	0.60	1.0000
26	26	1.98	0.0243	0.15	0.30	0.2374	90	90	1.98	0.0250	0.15	0.30	0.6784
26	26	1.98	0.0243	0.15	0.35	0.3708	90	90	1.98	0.0250	0.15	0.35	0.8815
26	26	1.98	0.0243	0.15	0.40	0.5216	90	90	1.98	0.0250	0.15	0.40	0.9699
26	26	1.98	0.0243	0.15	0.45	0.6685	90	90	1.98	0.0250	0.15	0.45	0.9949
26	26	1.98	0.0243	0.15	0.50	0.7919	90	90	1.98	0.0250	0.15	0.50	0.9994
26	26	1.98	0.0243	0.15	0.55	0.8821	90	90	1.98	0.0250	0.15	0.55	1.0000
26	26	1.98	0.0243	0.15	0.60	0.9399	90	90	1.98	0.0250	0.15	0.60	1.0000
26	26	1.98	0.0243	0.15	0.65	0.9729	90	90	1.98	0.0250	0.15	0.65	1.0000
26	26	1.98	0.0243	0.20	0.35	0.2161	90	90	1.98	0.0250	0.20	0.35	0.6135
26	26	1.98	0.0243	0.20	0.40	0.3441	90	90	1.98	0.0250	0.20	0.40	0.8366
26	26	1.98	0.0243	0.20	0.45	0.4887	90	90	1.98	0.0250	0.20	0.45	0.9526
26	26	1.98	0.0243	0.20	0.50	0.6307	90	90	1.98	0.0250	0.20	0.50	0.9910
26	26	1.98	0.0243	0.20	0.55	0.7541	90	90	1.98	0.0250	0.20	0.55	0.9989

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
26	26	1.98	0.0243	0.20	0.60	0.8508	90	90	1.98	0.0250	0.20	0.60	0.9999
26	26	1.98	0.0243	0.20	0.65	0.9194	90	90	1.98	0.0250	0.20	0.65	1.0000
26	26	1.98	0.0243	0.20	0.70	0.9626	90	90	1.98	0.0250	0.20	0.70	1.0000
26	26	1.98	0.0243	0.25	0.40	0.2056	90	90	1.98	0.0250	0.25	0.40	0.5720
26	26	1.98	0.0243	0.25	0.45	0.3222	90	90	1.98	0.0250	0.25	0.45	0.8092
26	26	1.98	0.0243	0.25	0.50	0.4548	90	90	1.98	0.0250	0.25	0.50	0.9401
26	26	1.98	0.0243	0.25	0.55	0.5906	90	90	1.98	0.0250	0.25	0.55	0.9869
26	26	1.98	0.0243	0.25	0.60	0.7178	90	90	1.98	0.0250	0.25	0.60	0.9981
26	26	1.98	0.0243	0.25	0.65	0.8257	90	90	1.98	0.0250	0.25	0.65	0.9998
26	26	1.98	0.0243	0.25	0.70	0.9068	90	90	1.98	0.0250	0.25	0.70	1.0000
26	26	1.98	0.0243	0.25	0.75	0.9588	90	90	1.98	0.0250	0.25	0.75	1.0000
26	26	1.98	0.0243	0.30	0.45	0.1905	90	90	1.98	0.0250	0.30	0.45	0.5491
26	26	1.98	0.0243	0.30	0.50	0.2958	90	90	1.98	0.0250	0.30	0.50	0.7828
26	26	1.98	0.0243	0.30	0.55	0.4219	90	90	1.98	0.0250	0.30	0.55	0.9247
26	26	1.98	0.0243	0.30	0.60	0.5602	90	90	1.98	0.0250	0.30	0.60	0.9827
26	26	1.98	0.0243	0.30	0.65	0.6972	90	90	1.98	0.0250	0.30	0.65	0.9976
26	26	1.98	0.0243	0.30	0.70	0.8169	90	90	1.98	0.0250	0.30	0.70	0.9998
26	26	1.98	0.0243	0.35	0.50	0.1738	90	90	1.98	0.0250	0.35	0.50	0.5167
26	26	1.98	0.0243	0.35	0.55	0.2750	90	90	1.98	0.0250	0.35	0.55	0.7593
26	26	1.98	0.0243	0.35	0.60	0.4034	90	90	1.98	0.0250	0.35	0.60	0.9170
26	26	1.98	0.0243	0.35	0.65	0.5497	90	90	1.98	0.0250	0.35	0.65	0.9816
26	26	1.98	0.0243	0.40	0.55	0.1639	90	90	1.98	0.0250	0.40	0.55	0.5028
26	26	1.98	0.0243	0.40	0.60	0.2678	90	90	1.98	0.0250	0.40	0.60	0.7543
27	27	2.03	0.0223	0.05	0.15	0.1936	100	100	1.99	0.0248	0.05	0.15	0.6640
27	27	2.03	0.0223	0.05	0.20	0.3482	100	100	1.99	0.0248	0.05	0.20	0.9156
27	27	2.03	0.0223	0.05	0.25	0.5229	100	100	1.99	0.0248	0.05	0.25	0.9874
27	27	2.03	0.0223	0.05	0.30	0.6882	100	100	1.99	0.0248	0.05	0.30	0.9988
27	27	2.03	0.0223	0.05	0.35	0.8188	100	100	1.99	0.0248	0.05	0.35	0.9999
27	27	2.03	0.0223	0.05	0.40	0.9065	100	100	1.99	0.0248	0.05	0.40	1.0000
27	27	2.03	0.0223	0.05	0.45	0.9575	100	100	1.99	0.0248	0.05	0.45	1.0000
27	27	2.03	0.0223	0.10	0.25	0.2731	100	100	1.99	0.0248	0.10	0.25	0.8043
27	27	2.03	0.0223	0.10	0.30	0.4298	100	100	1.99	0.0248	0.10	0.30	0.9516
27	27	2.03	0.0223	0.10	0.35	0.5916	100	100	1.99	0.0248	0.10	0.35	0.9924
27	27	2.03	0.0223	0.10	0.40	0.7351	100	100	1.99	0.0248	0.10	0.40	0.9992
27	27	2.03	0.0223	0.10	0.45	0.8456	100	100	1.99	0.0248	0.10	0.45	1.0000
27	27	2.03	0.0223	0.10	0.50	0.9197	100	100	1.99	0.0248	0.10	0.50	1.0000
27	27	2.03	0.0223	0.10	0.55	0.9629	100	100	1.99	0.0248	0.10	0.55	1.0000
27	27	2.03	0.0223	0.10	0.60	0.9850	100	100	1.99	0.0248	0.10	0.60	1.0000
27	27	2.03	0.0223	0.15	0.30	0.2393	100	100	1.99	0.0248	0.15	0.30	0.7172
27	27	2.03	0.0223	0.15	0.35	0.3797	100	100	1.99	0.0248	0.15	0.35	0.9087
27	27	2.03	0.0223	0.15	0.40	0.5325	100	100	1.99	0.0248	0.15	0.40	0.9811
27	27	2.03	0.0223	0.15	0.45	0.6766	100	100	1.99	0.0248	0.15	0.45	0.9975
27	27	2.03	0.0223	0.15	0.50	0.7958	100	100	1.99	0.0248	0.15	0.50	0.9998
27	27	2.03	0.0223	0.15	0.55	0.8836	100	100	1.99	0.0248	0.15	0.55	1.0000
27	27	2.03	0.0223	0.15	0.60	0.9413	100	100	1.99	0.0248	0.15	0.60	1.0000
27	27	2.03	0.0223	0.15	0.65	0.9746	100	100	1.99	0.0248	0.15	0.65	1.0000
27	27	2.03	0.0223	0.20	0.35	0.2183	100	100	1.99	0.0248	0.20	0.35	0.6568
27	27	2.03	0.0223	0.20	0.40	0.3445	100	100	1.99	0.0248	0.20	0.40	0.8730
27	27	2.03	0.0223	0.20	0.45	0.4858	100	100	1.99	0.0248	0.20	0.45	0.9685
27	27	2.03	0.0223	0.20	0.50	0.6269	100	100	1.99	0.0248	0.20	0.50	0.9950

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
27	27	2.03	0.0223	0.20	0.55	0.7534	100	100	1.99	0.0248	0.20	0.55	0.9995
27	27	2.03	0.0223	0.20	0.60	0.8549	100	100	1.99	0.0248	0.20	0.60	1.0000
27	27	2.03	0.0223	0.20	0.65	0.9260	100	100	1.99	0.0248	0.20	0.65	1.0000
27	27	2.03	0.0223	0.20	0.70	0.9684	100	100	1.99	0.0248	0.20	0.70	1.0000
27	27	2.03	0.0223	0.25	0.40	0.1990	100	100	1.99	0.0248	0.25	0.40	0.6121
27	27	2.03	0.0223	0.25	0.45	0.3132	100	100	1.99	0.0248	0.25	0.45	0.8428
27	27	2.03	0.0223	0.25	0.50	0.4485	100	100	1.99	0.0248	0.25	0.50	0.9585
27	27	2.03	0.0223	0.25	0.55	0.5925	100	100	1.99	0.0248	0.25	0.55	0.9931
27	27	2.03	0.0223	0.25	0.60	0.7286	100	100	1.99	0.0248	0.25	0.60	0.9993
27	27	2.03	0.0223	0.25	0.65	0.8409	100	100	1.99	0.0248	0.25	0.65	1.0000
27	27	2.03	0.0223	0.25	0.70	0.9200	100	100	1.99	0.0248	0.25	0.70	1.0000
27	27	2.03	0.0223	0.25	0.75	0.9668	100	100	1.99	0.0248	0.25	0.75	1.0000
27	27	2.03	0.0223	0.30	0.45	0.1825	100	100	1.99	0.0248	0.30	0.45	0.5895
27	27	2.03	0.0223	0.30	0.50	0.2925	100	100	1.99	0.0248	0.30	0.50	0.8281
27	27	2.03	0.0223	0.30	0.55	0.4288	100	100	1.99	0.0248	0.30	0.55	0.9507
27	27	2.03	0.0223	0.30	0.60	0.5777	100	100	1.99	0.0248	0.30	0.60	0.9906
27	27	2.03	0.0223	0.30	0.65	0.7200	100	100	1.99	0.0248	0.30	0.65	0.9989
27	27	2.03	0.0223	0.30	0.70	0.8374	100	100	1.99	0.0248	0.30	0.70	0.9999
27	27	2.03	0.0223	0.35	0.50	0.1742	100	100	1.99	0.0248	0.35	0.50	0.5715
27	27	2.03	0.0223	0.35	0.55	0.2846	100	100	1.99	0.0248	0.35	0.55	0.8061
27	27	2.03	0.0223	0.35	0.60	0.4227	100	100	1.99	0.0248	0.35	0.60	0.9403
27	27	2.03	0.0223	0.35	0.65	0.5744	100	100	1.99	0.0248	0.35	0.65	0.9889
27	27	2.03	0.0223	0.40	0.55	0.1723	100	100	1.99	0.0248	0.40	0.55	0.5417
27	27	2.03	0.0223	0.40	0.60	0.2832	100	100	1.99	0.0248	0.40	0.60	0.7914
28	28	2.03	0.0231	0.05	0.15	0.2013	150	150	1.99	0.0244	0.05	0.15	0.8320
28	28	2.03	0.0231	0.05	0.20	0.3627	150	150	1.99	0.0244	0.05	0.20	0.9833
28	28	2.03	0.0231	0.05	0.25	0.5435	150	150	1.99	0.0244	0.05	0.25	0.9993
28	28	2.03	0.0231	0.05	0.30	0.7098	150	150	1.99	0.0244	0.05	0.30	1.0000
28	28	2.03	0.0231	0.05	0.35	0.8368	150	150	1.99	0.0244	0.05	0.35	1.0000
28	28	2.03	0.0231	0.05	0.40	0.9190	150	150	1.99	0.0244	0.05	0.40	1.0000
28	28	2.03	0.0231	0.05	0.45	0.9648	150	150	1.99	0.0244	0.05	0.45	1.0000
28	28	2.03	0.0231	0.10	0.25	0.2867	150	150	1.99	0.0244	0.10	0.25	0.9351
28	28	2.03	0.0231	0.10	0.30	0.4494	150	150	1.99	0.0244	0.10	0.30	0.9937
28	28	2.03	0.0231	0.10	0.35	0.6140	150	150	1.99	0.0244	0.10	0.35	0.9997
28	28	2.03	0.0231	0.10	0.40	0.7563	150	150	1.99	0.0244	0.10	0.40	1.0000
28	28	2.03	0.0231	0.10	0.45	0.8624	150	150	1.99	0.0244	0.10	0.45	1.0000
28	28	2.03	0.0231	0.10	0.50	0.9309	150	150	1.99	0.0244	0.10	0.50	1.0000
28	28	2.03	0.0231	0.10	0.55	0.9693	150	150	1.99	0.0244	0.10	0.55	1.0000
28	28	2.03	0.0231	0.10	0.60	0.9882	150	150	1.99	0.0244	0.10	0.60	1.0000
28	28	2.03	0.0231	0.15	0.30	0.2519	150	150	1.99	0.0244	0.15	0.30	0.8780
28	28	2.03	0.0231	0.15	0.35	0.3981	150	150	1.99	0.0244	0.15	0.35	0.9819
28	28	2.03	0.0231	0.15	0.40	0.5542	150	150	1.99	0.0244	0.15	0.40	0.9987
28	28	2.03	0.0231	0.15	0.45	0.6979	150	150	1.99	0.0244	0.15	0.45	1.0000
28	28	2.03	0.0231	0.15	0.50	0.8142	150	150	1.99	0.0244	0.15	0.50	1.0000
28	28	2.03	0.0231	0.15	0.55	0.8976	150	150	1.99	0.0244	0.15	0.55	1.0000
28	28	2.03	0.0231	0.15	0.60	0.9507	150	150	1.99	0.0244	0.15	0.60	1.0000
28	28	2.03	0.0231	0.15	0.65	0.9799	150	150	1.99	0.0244	0.15	0.65	1.0000
28	28	2.03	0.0231	0.20	0.35	0.2296	150	150	1.99	0.0244	0.20	0.35	0.8278
28	28	2.03	0.0231	0.20	0.40	0.3606	150	150	1.99	0.0244	0.20	0.40	0.9679
28	28	2.03	0.0231	0.20	0.45	0.5058	150	150	1.99	0.0244	0.20	0.45	0.9969

Table B.11: continue on next page

Table B.11: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
28	28	2.03	0.0231	0.20	0.50	0.6490	150	150	1.99	0.0244	0.20	0.50	0.9998
28	28	2.03	0.0231	0.20	0.55	0.7751	150	150	1.99	0.0244	0.20	0.55	1.0000
28	28	2.03	0.0231	0.20	0.60	0.8730	150	150	1.99	0.0244	0.20	0.60	1.0000
28	28	2.03	0.0231	0.20	0.65	0.9386	150	150	1.99	0.0244	0.20	0.65	1.0000
28	28	2.03	0.0231	0.20	0.70	0.9754	150	150	1.99	0.0244	0.20	0.70	1.0000
28	28	2.03	0.0231	0.25	0.40	0.2089	150	150	1.99	0.0244	0.25	0.40	0.7887
28	28	2.03	0.0231	0.25	0.45	0.3291	150	150	1.99	0.0244	0.25	0.45	0.9538
28	28	2.03	0.0231	0.25	0.50	0.4706	150	150	1.99	0.0244	0.25	0.50	0.9949
28	28	2.03	0.0231	0.25	0.55	0.6188	150	150	1.99	0.0244	0.25	0.55	0.9997
28	28	2.03	0.0231	0.25	0.60	0.7546	150	150	1.99	0.0244	0.25	0.60	1.0000
28	28	2.03	0.0231	0.25	0.65	0.8621	150	150	1.99	0.0244	0.25	0.65	1.0000
28	28	2.03	0.0231	0.25	0.70	0.9341	150	150	1.99	0.0244	0.25	0.70	1.0000
28	28	2.03	0.0231	0.25	0.75	0.9742	150	150	1.99	0.0244	0.25	0.75	1.0000
28	28	2.03	0.0231	0.30	0.45	0.1935	150	150	1.99	0.0244	0.30	0.45	0.7649
28	28	2.03	0.0231	0.30	0.50	0.3112	150	150	1.99	0.0244	0.30	0.50	0.9446
28	28	2.03	0.0231	0.30	0.55	0.4546	150	150	1.99	0.0244	0.30	0.55	0.9928
28	28	2.03	0.0231	0.30	0.60	0.6073	150	150	1.99	0.0244	0.30	0.60	0.9995
28	28	2.03	0.0231	0.30	0.65	0.7481	150	150	1.99	0.0244	0.30	0.65	1.0000
28	28	2.03	0.0231	0.30	0.70	0.8595	150	150	1.99	0.0244	0.30	0.70	1.0000
28	28	2.03	0.0231	0.35	0.50	0.1876	150	150	1.99	0.0244	0.35	0.50	0.7402
28	28	2.03	0.0231	0.35	0.55	0.3058	150	150	1.99	0.0244	0.35	0.55	0.9324
28	28	2.03	0.0231	0.35	0.60	0.4506	150	150	1.99	0.0244	0.35	0.60	0.9911
28	28	2.03	0.0231	0.35	0.65	0.6050	150	150	1.99	0.0244	0.35	0.65	0.9995
28	28	2.03	0.0231	0.40	0.55	0.1870	150	150	1.99	0.0244	0.40	0.55	0.7223
28	28	2.03	0.0231	0.40	0.60	0.3052	150	150	1.99	0.0244	0.40	0.60	0.9292

Table B.11: concluded from previous page

Table B.12: Achieved power and p-values calculated for the z-pooled statistic in cases of equal sample sizes, $\boldsymbol{\alpha} = \mathbf{0.025}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
10	10	2.35	0.0064	0.05	0.15	0.0060	29	29	2.37	0.0096	0.05	0.15	0.0816
10	10	2.35	0.0064	0.05	0.20	0.0199	29	29	2.37	0.0096	0.05	0.20	0.2085
10	10	2.35	0.0064	0.05	0.25	0.0479	29	29	2.37	0.0096	0.05	0.25	0.3797
10	10	2.35	0.0064	0.05	0.30	0.0934	29	29	2.37	0.0096	0.05	0.30	0.5620
10	10	2.35	0.0064	0.05	0.35	0.1574	29	29	2.37	0.0096	0.05	0.35	0.7238
10	10	2.35	0.0064	0.05	0.40	0.2379	29	29	2.37	0.0096	0.05	0.40	0.8458
10	10	2.35	0.0064	0.05	0.45	0.3310	29	29	2.37	0.0096	0.05	0.45	0.9244
10	10	2.35	0.0064	0.10	0.25	0.0287	29	29	2.37	0.0096	0.10	0.25	0.1662
10	10	2.35	0.0064	0.10	0.30	0.0568	29	29	2.37	0.0096	0.10	0.30	0.3002
10	10	2.35	0.0064	0.10	0.35	0.0977	29	29	2.37	0.0096	0.10	0.35	0.4601
10	10	2.35	0.0064	0.10	0.40	0.1516	29	29	2.37	0.0096	0.10	0.40	0.6214
10	10	2.35	0.0064	0.10	0.45	0.2179	29	29	2.37	0.0096	0.10	0.45	0.7616
10	10	2.35	0.0064	0.10	0.50	0.2951	29	29	2.37	0.0096	0.10	0.50	0.8673
10	10	2.35	0.0064	0.10	0.55	0.3812	29	29	2.37	0.0096	0.10	0.55	0.9361
10	10	2.35	0.0064	0.10	0.60	0.4740	29	29	2.37	0.0096	0.10	0.60	0.9740
10	10	2.35	0.0064	0.15	0.30	0.0337	29	29	2.37	0.0096	0.15	0.30	0.1426
10	10	2.35	0.0064	0.15	0.35	0.0594	29	29	2.37	0.0096	0.15	0.35	0.2569
10	10	2.35	0.0064	0.15	0.40	0.0949	29	29	2.37	0.0096	0.15	0.40	0.4017
10	10	2.35	0.0064	0.15	0.45	0.1412	29	29	2.37	0.0096	0.15	0.45	0.5602
10	10	2.35	0.0064	0.15	0.50	0.1989	29	29	2.37	0.0096	0.15	0.50	0.7102
10	10	2.35	0.0064	0.15	0.55	0.2684	29	29	2.37	0.0096	0.15	0.55	0.8318
10	10	2.35	0.0064	0.15	0.60	0.3494	29	29	2.37	0.0096	0.15	0.60	0.9152
10	10	2.35	0.0064	0.15	0.65	0.4407	29	29	2.37	0.0096	0.15	0.65	0.9632
10	10	2.35	0.0064	0.20	0.35	0.0352	29	29	2.37	0.0096	0.20	0.35	0.1287
10	10	2.35	0.0064	0.20	0.40	0.0582	29	29	2.37	0.0096	0.20	0.40	0.2337
10	10	2.35	0.0064	0.20	0.45	0.0898	29	29	2.37	0.0096	0.20	0.45	0.3727
10	10	2.35	0.0064	0.20	0.50	0.1318	29	29	2.37	0.0096	0.20	0.50	0.5300
10	10	2.35	0.0064	0.20	0.55	0.1857	29	29	2.37	0.0096	0.20	0.55	0.6817
10	10	2.35	0.0064	0.20	0.60	0.2527	29	29	2.37	0.0096	0.20	0.60	0.8068
10	10	2.35	0.0064	0.20	0.65	0.3330	29	29	2.37	0.0096	0.20	0.65	0.8957
10	10	2.35	0.0064	0.20	0.70	0.4256	29	29	2.37	0.0096	0.20	0.70	0.9510
10	10	2.35	0.0064	0.25	0.40	0.0348	29	29	2.37	0.0096	0.25	0.40	0.1236
10	10	2.35	0.0064	0.25	0.45	0.0560	29	29	2.37	0.0096	0.25	0.45	0.2244
10	10	2.35	0.0064	0.25	0.50	0.0856	29	29	2.37	0.0096	0.25	0.50	0.3571
10	10	2.35	0.0064	0.25	0.55	0.1259	29	29	2.37	0.0096	0.25	0.55	0.5063
10	10	2.35	0.0064	0.25	0.60	0.1787	29	29	2.37	0.0096	0.25	0.60	0.6522
10	10	2.35	0.0064	0.25	0.65	0.2453	29	29	2.37	0.0096	0.25	0.65	0.7789
10	10	2.35	0.0064	0.25	0.70	0.3265	29	29	2.37	0.0096	0.25	0.70	0.8773
10	10	2.35	0.0064	0.25	0.75	0.4214	29	29	2.37	0.0096	0.25	0.75	0.9441
10	10	2.35	0.0064	0.30	0.45	0.0340	29	29	2.37	0.0096	0.30	0.45	0.1213
10	10	2.35	0.0064	0.30	0.50	0.0543	29	29	2.37	0.0096	0.30	0.50	0.2148
10	10	2.35	0.0064	0.30	0.55	0.0833	29	29	2.37	0.0096	0.30	0.55	0.3366
10	10	2.35	0.0064	0.30	0.60	0.1231	29	29	2.37	0.0096	0.30	0.60	0.4775
10	10	2.35	0.0064	0.30	0.65	0.1759	29	29	2.37	0.0096	0.30	0.65	0.6252

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
10	10	2.35	0.0064	0.30	0.70	0.2433	29	29	2.37	0.0096	0.30	0.70	0.7643
10	10	2.35	0.0064	0.35	0.50	0.0335	29	29	2.37	0.0096	0.35	0.50	0.1144
10	10	2.35	0.0064	0.35	0.55	0.0536	29	29	2.37	0.0096	0.35	0.55	0.1996
10	10	2.35	0.0064	0.35	0.60	0.0824	29	29	2.37	0.0096	0.35	0.60	0.3166
10	10	2.35	0.0064	0.35	0.65	0.1223	29	29	2.37	0.0096	0.35	0.65	0.4627
10	10	2.35	0.0064	0.40	0.55	0.0334	29	29	2.37	0.0096	0.40	0.55	0.1063
10	10	2.35	0.0064	0.40	0.60	0.0534	29	29	2.37	0.0096	0.40	0.60	0.1915
11	11	2.29	0.0087	0.05	0.15	0.0091	30	30	2.36	0.0092	0.05	0.15	0.0887
11	11	2.29	0.0087	0.05	0.20	0.0293	30	30	2.36	0.0092	0.05	0.20	0.2232
11	11	2.29	0.0087	0.05	0.25	0.0678	30	30	2.36	0.0092	0.05	0.25	0.4011
11	11	2.29	0.0087	0.05	0.30	0.1271	30	30	2.36	0.0092	0.05	0.30	0.5867
11	11	2.29	0.0087	0.05	0.35	0.2063	30	30	2.36	0.0092	0.05	0.35	0.7470
11	11	2.29	0.0087	0.05	0.40	0.3011	30	30	2.36	0.0092	0.05	0.40	0.8637
11	11	2.29	0.0087	0.05	0.45	0.4056	30	30	2.36	0.0092	0.05	0.45	0.9359
11	11	2.29	0.0087	0.10	0.25	0.0391	30	30	2.36	0.0092	0.10	0.25	0.1770
11	11	2.29	0.0087	0.10	0.30	0.0752	30	30	2.36	0.0092	0.10	0.30	0.3179
11	11	2.29	0.0087	0.10	0.35	0.1261	30	30	2.36	0.0092	0.10	0.35	0.4832
11	11	2.29	0.0087	0.10	0.40	0.1914	30	30	2.36	0.0092	0.10	0.40	0.6461
11	11	2.29	0.0087	0.10	0.45	0.2699	30	30	2.36	0.0092	0.10	0.45	0.7838
11	11	2.29	0.0087	0.10	0.50	0.3595	30	30	2.36	0.0092	0.10	0.50	0.8840
11	11	2.29	0.0087	0.10	0.55	0.4572	30	30	2.36	0.0092	0.10	0.55	0.9464
11	11	2.29	0.0087	0.10	0.60	0.5590	30	30	2.36	0.0092	0.10	0.60	0.9790
11	11	2.29	0.0087	0.15	0.30	0.0435	30	30	2.36	0.0092	0.15	0.30	0.1519
11	11	2.29	0.0087	0.15	0.35	0.0756	30	30	2.36	0.0092	0.15	0.35	0.2728
11	11	2.29	0.0087	0.15	0.40	0.1198	30	30	2.36	0.0092	0.15	0.40	0.4237
11	11	2.29	0.0087	0.15	0.45	0.1772	30	30	2.36	0.0092	0.15	0.45	0.5850
11	11	2.29	0.0087	0.15	0.50	0.2483	30	30	2.36	0.0092	0.15	0.50	0.7323
11	11	2.29	0.0087	0.15	0.55	0.3327	30	30	2.36	0.0092	0.15	0.55	0.8470
11	11	2.29	0.0087	0.15	0.60	0.4284	30	30	2.36	0.0092	0.15	0.60	0.9231
11	11	2.29	0.0087	0.15	0.65	0.5318	30	30	2.36	0.0092	0.15	0.65	0.9664
11	11	2.29	0.0087	0.20	0.35	0.0444	30	30	2.36	0.0092	0.20	0.35	0.1375
11	11	2.29	0.0087	0.20	0.40	0.0736	30	30	2.36	0.0092	0.20	0.40	0.2480
11	11	2.29	0.0087	0.20	0.45	0.1144	30	30	2.36	0.0092	0.20	0.45	0.3903
11	11	2.29	0.0087	0.20	0.50	0.1685	30	30	2.36	0.0092	0.20	0.50	0.5460
11	11	2.29	0.0087	0.20	0.55	0.2373	30	30	2.36	0.0092	0.20	0.55	0.6922
11	11	2.29	0.0087	0.20	0.60	0.3206	30	30	2.36	0.0092	0.20	0.60	0.8120
11	11	2.29	0.0087	0.20	0.65	0.4166	30	30	2.36	0.0092	0.20	0.65	0.8987
11	11	2.29	0.0087	0.20	0.70	0.5215	30	30	2.36	0.0092	0.20	0.70	0.9536
11	11	2.29	0.0087	0.25	0.40	0.0443	30	30	2.36	0.0092	0.25	0.40	0.1298
11	11	2.29	0.0087	0.25	0.45	0.0723	30	30	2.36	0.0092	0.25	0.45	0.2314
11	11	2.29	0.0087	0.25	0.50	0.1119	30	30	2.36	0.0092	0.25	0.50	0.3617
11	11	2.29	0.0087	0.25	0.55	0.1651	30	30	2.36	0.0092	0.25	0.55	0.5074
11	11	2.29	0.0087	0.25	0.60	0.2333	30	30	2.36	0.0092	0.25	0.60	0.6525
11	11	2.29	0.0087	0.25	0.65	0.3165	30	30	2.36	0.0092	0.25	0.65	0.7816
11	11	2.29	0.0087	0.25	0.70	0.4129	30	30	2.36	0.0092	0.25	0.70	0.8823
11	11	2.29	0.0087	0.25	0.75	0.5191	30	30	2.36	0.0092	0.25	0.75	0.9484
11	11	2.29	0.0087	0.30	0.45	0.0446	30	30	2.36	0.0092	0.30	0.45	0.1209
11	11	2.29	0.0087	0.30	0.50	0.0723	30	30	2.36	0.0092	0.30	0.50	0.2115
11	11	2.29	0.0087	0.30	0.55	0.1116	30	30	2.36	0.0092	0.30	0.55	0.3316
11	11	2.29	0.0087	0.30	0.60	0.1645	30	30	2.36	0.0092	0.30	0.60	0.4748

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
11	11	2.29	0.0087	0.30	0.65	0.2325	30	30	2.36	0.0092	0.30	0.65	0.6276
11	11	2.29	0.0087	0.30	0.70	0.3157	30	30	2.36	0.0092	0.30	0.70	0.7701
11	11	2.29	0.0087	0.35	0.50	0.0453	30	30	2.36	0.0092	0.35	0.50	0.1092
11	11	2.29	0.0087	0.35	0.55	0.0730	30	30	2.36	0.0092	0.35	0.55	0.1935
11	11	2.29	0.0087	0.35	0.60	0.1120	30	30	2.36	0.0092	0.35	0.60	0.3126
11	11	2.29	0.0087	0.35	0.65	0.1646	30	30	2.36	0.0092	0.35	0.65	0.4627
11	11	2.29	0.0087	0.40	0.55	0.0459	30	30	2.36	0.0092	0.40	0.55	0.1013
11	11	2.29	0.0087	0.40	0.60	0.0733	30	30	2.36	0.0092	0.40	0.60	0.1867
12	12	2.45	0.0087	0.05	0.15	0.0132	31	31	2.34	0.0097	0.05	0.15	0.0958
12	12	2.45	0.0087	0.05	0.20	0.0406	31	31	2.34	0.0097	0.05	0.20	0.2378
12	12	2.45	0.0087	0.05	0.25	0.0903	31	31	2.34	0.0097	0.05	0.25	0.4223
12	12	2.45	0.0087	0.05	0.30	0.1634	31	31	2.34	0.0097	0.05	0.30	0.6106
12	12	2.45	0.0087	0.05	0.35	0.2566	31	31	2.34	0.0097	0.05	0.35	0.7687
12	12	2.45	0.0087	0.05	0.40	0.3633	31	31	2.34	0.0097	0.05	0.40	0.8798
12	12	2.45	0.0087	0.05	0.45	0.4760	31	31	2.34	0.0097	0.05	0.45	0.9458
12	12	2.45	0.0087	0.10	0.25	0.0505	31	31	2.34	0.0097	0.10	0.25	0.1879
12	12	2.45	0.0087	0.10	0.30	0.0948	31	31	2.34	0.0097	0.10	0.30	0.3357
12	12	2.45	0.0087	0.10	0.35	0.1555	31	31	2.34	0.0097	0.10	0.35	0.5059
12	12	2.45	0.0087	0.10	0.40	0.2317	31	31	2.34	0.0097	0.10	0.40	0.6700
12	12	2.45	0.0087	0.10	0.45	0.3212	31	31	2.34	0.0097	0.10	0.45	0.8048
12	12	2.45	0.0087	0.10	0.50	0.4202	31	31	2.34	0.0097	0.10	0.50	0.8994
12	12	2.45	0.0087	0.10	0.55	0.5239	31	31	2.34	0.0097	0.10	0.55	0.9556
12	12	2.45	0.0087	0.10	0.60	0.6265	31	31	2.34	0.0097	0.10	0.60	0.9835
12	12	2.45	0.0087	0.15	0.30	0.0538	31	31	2.34	0.0097	0.15	0.30	0.1615
12	12	2.45	0.0087	0.15	0.35	0.0924	31	31	2.34	0.0097	0.15	0.35	0.2892
12	12	2.45	0.0087	0.15	0.40	0.1450	31	31	2.34	0.0097	0.15	0.40	0.4465
12	12	2.45	0.0087	0.15	0.45	0.2120	31	31	2.34	0.0097	0.15	0.45	0.6108
12	12	2.45	0.0087	0.15	0.50	0.2927	31	31	2.34	0.0097	0.15	0.50	0.7560
12	12	2.45	0.0087	0.15	0.55	0.3844	31	31	2.34	0.0097	0.15	0.55	0.8649
12	12	2.45	0.0087	0.15	0.60	0.4830	31	31	2.34	0.0097	0.15	0.60	0.9344
12	12	2.45	0.0087	0.15	0.65	0.5835	31	31	2.34	0.0097	0.15	0.65	0.9725
12	12	2.45	0.0087	0.20	0.35	0.0536	31	31	2.34	0.0097	0.20	0.35	0.1471
12	12	2.45	0.0087	0.20	0.40	0.0885	31	31	2.34	0.0097	0.20	0.40	0.2645
12	12	2.45	0.0087	0.20	0.45	0.1362	31	31	2.34	0.0097	0.20	0.45	0.4126
12	12	2.45	0.0087	0.20	0.50	0.1975	31	31	2.34	0.0097	0.20	0.50	0.5705
12	12	2.45	0.0087	0.20	0.55	0.2720	31	31	2.34	0.0097	0.20	0.55	0.7151
12	12	2.45	0.0087	0.20	0.60	0.3580	31	31	2.34	0.0097	0.20	0.60	0.8309
12	12	2.45	0.0087	0.20	0.65	0.4528	31	31	2.34	0.0097	0.20	0.65	0.9125
12	12	2.45	0.0087	0.20	0.70	0.5532	31	31	2.34	0.0097	0.20	0.70	0.9621
12	12	2.45	0.0087	0.25	0.40	0.0525	31	31	2.34	0.0097	0.25	0.40	0.1390
12	12	2.45	0.0087	0.25	0.45	0.0847	31	31	2.34	0.0097	0.25	0.45	0.2459
12	12	2.45	0.0087	0.25	0.50	0.1287	31	31	2.34	0.0097	0.25	0.50	0.3809
12	12	2.45	0.0087	0.25	0.55	0.1855	31	31	2.34	0.0097	0.25	0.55	0.5302
12	12	2.45	0.0087	0.25	0.60	0.2558	31	31	2.34	0.0097	0.25	0.60	0.6769
12	12	2.45	0.0087	0.25	0.65	0.3391	31	31	2.34	0.0097	0.25	0.65	0.8043
12	12	2.45	0.0087	0.25	0.70	0.4349	31	31	2.34	0.0097	0.25	0.70	0.8995
12	12	2.45	0.0087	0.25	0.75	0.5415	31	31	2.34	0.0097	0.25	0.75	0.9584
12	12	2.45	0.0087	0.30	0.45	0.0508	31	31	2.34	0.0097	0.30	0.45	0.1285
12	12	2.45	0.0087	0.30	0.50	0.0809	31	31	2.34	0.0097	0.30	0.50	0.2242
12	12	2.45	0.0087	0.30	0.55	0.1221	31	31	2.34	0.0097	0.30	0.55	0.3508

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
12	12	2.45	0.0087	0.30	0.60	0.1766	31	31	2.34	0.0097	0.30	0.60	0.5004
12	12	2.45	0.0087	0.30	0.65	0.2460	31	31	2.34	0.0097	0.30	0.65	0.6561
12	12	2.45	0.0087	0.30	0.70	0.3319	31	31	2.34	0.0097	0.30	0.70	0.7953
12	12	2.45	0.0087	0.35	0.50	0.0489	31	31	2.34	0.0097	0.35	0.50	0.1166
12	12	2.45	0.0087	0.35	0.55	0.0776	31	31	2.34	0.0097	0.35	0.55	0.2074
12	12	2.45	0.0087	0.35	0.60	0.1180	31	31	2.34	0.0097	0.35	0.60	0.3346
12	12	2.45	0.0087	0.35	0.65	0.1731	31	31	2.34	0.0097	0.35	0.65	0.4906
12	12	2.45	0.0087	0.40	0.55	0.0476	31	31	2.34	0.0097	0.40	0.55	0.1098
12	12	2.45	0.0087	0.40	0.60	0.0763	31	31	2.34	0.0097	0.40	0.60	0.2019
13	13	2.37	0.0096	0.05	0.15	0.0180	32	32	2.35	0.0091	0.05	0.15	0.1031
13	13	2.37	0.0096	0.05	0.20	0.0535	32	32	2.35	0.0091	0.05	0.20	0.2524
13	13	2.37	0.0096	0.05	0.25	0.1149	32	32	2.35	0.0091	0.05	0.25	0.4431
13	13	2.37	0.0096	0.05	0.30	0.2014	32	32	2.35	0.0091	0.05	0.30	0.6335
13	13	2.37	0.0096	0.05	0.35	0.3071	32	32	2.35	0.0091	0.05	0.35	0.7889
13	13	2.37	0.0096	0.05	0.40	0.4235	32	32	2.35	0.0091	0.05	0.40	0.8942
13	13	2.37	0.0096	0.05	0.45	0.5417	32	32	2.35	0.0091	0.05	0.45	0.9543
13	13	2.37	0.0096	0.10	0.25	0.0627	32	32	2.35	0.0091	0.10	0.25	0.1990
13	13	2.37	0.0096	0.10	0.30	0.1153	32	32	2.35	0.0091	0.10	0.30	0.3533
13	13	2.37	0.0096	0.10	0.35	0.1861	32	32	2.35	0.0091	0.10	0.35	0.5275
13	13	2.37	0.0096	0.10	0.40	0.2732	32	32	2.35	0.0091	0.10	0.40	0.6911
13	13	2.37	0.0096	0.10	0.45	0.3730	32	32	2.35	0.0091	0.10	0.45	0.8214
13	13	2.37	0.0096	0.10	0.50	0.4799	32	32	2.35	0.0091	0.10	0.50	0.9097
13	13	2.37	0.0096	0.10	0.55	0.5874	32	32	2.35	0.0091	0.10	0.55	0.9605
13	13	2.37	0.0096	0.10	0.60	0.6885	32	32	2.35	0.0091	0.10	0.60	0.9853
13	13	2.37	0.0096	0.15	0.30	0.0646	32	32	2.35	0.0091	0.15	0.30	0.1705
13	13	2.37	0.0096	0.15	0.35	0.1104	32	32	2.35	0.0091	0.15	0.35	0.3029
13	13	2.37	0.0096	0.15	0.40	0.1720	32	32	2.35	0.0091	0.15	0.40	0.4621
13	13	2.37	0.0096	0.15	0.45	0.2490	32	32	2.35	0.0091	0.15	0.45	0.6238
13	13	2.37	0.0096	0.15	0.50	0.3388	32	32	2.35	0.0091	0.15	0.50	0.7641
13	13	2.37	0.0096	0.15	0.55	0.4370	32	32	2.35	0.0091	0.15	0.55	0.8689
13	13	2.37	0.0096	0.15	0.60	0.5381	32	32	2.35	0.0091	0.15	0.60	0.9368
13	13	2.37	0.0096	0.15	0.65	0.6367	32	32	2.35	0.0091	0.15	0.65	0.9745
13	13	2.37	0.0096	0.20	0.35	0.0637	32	32	2.35	0.0091	0.20	0.35	0.1520
13	13	2.37	0.0096	0.20	0.40	0.1048	32	32	2.35	0.0091	0.20	0.40	0.2692
13	13	2.37	0.0096	0.20	0.45	0.1599	32	32	2.35	0.0091	0.20	0.45	0.4148
13	13	2.37	0.0096	0.20	0.50	0.2287	32	32	2.35	0.0091	0.20	0.50	0.5708
13	13	2.37	0.0096	0.20	0.55	0.3095	32	32	2.35	0.0091	0.20	0.55	0.7170
13	13	2.37	0.0096	0.20	0.60	0.3995	32	32	2.35	0.0091	0.20	0.60	0.8365
13	13	2.37	0.0096	0.20	0.65	0.4960	32	32	2.35	0.0091	0.20	0.65	0.9199
13	13	2.37	0.0096	0.20	0.70	0.5959	32	32	2.35	0.0091	0.20	0.70	0.9680
13	13	2.37	0.0096	0.25	0.40	0.0614	32	32	2.35	0.0091	0.25	0.40	0.1370
13	13	2.37	0.0096	0.25	0.45	0.0984	32	32	2.35	0.0091	0.25	0.45	0.2417
13	13	2.37	0.0096	0.25	0.50	0.1474	32	32	2.35	0.0091	0.25	0.50	0.3783
13	13	2.37	0.0096	0.25	0.55	0.2089	32	32	2.35	0.0091	0.25	0.55	0.5345
13	13	2.37	0.0096	0.25	0.60	0.2832	32	32	2.35	0.0091	0.25	0.60	0.6897
13	13	2.37	0.0096	0.25	0.65	0.3702	32	32	2.35	0.0091	0.25	0.65	0.8210
13	13	2.37	0.0096	0.25	0.70	0.4696	32	32	2.35	0.0091	0.25	0.70	0.9135
13	13	2.37	0.0096	0.25	0.75	0.5798	32	32	2.35	0.0091	0.25	0.75	0.9663
13	13	2.37	0.0096	0.30	0.45	0.0577	32	32	2.35	0.0091	0.30	0.45	0.1244
13	13	2.37	0.0096	0.30	0.50	0.0906	32	32	2.35	0.0091	0.30	0.50	0.2236

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
13	13	2.37	0.0096	0.30	0.55	0.1349	32	32	2.35	0.0091	0.30	0.55	0.3593
13	13	2.37	0.0096	0.30	0.60	0.1929	32	32	2.35	0.0091	0.30	0.60	0.5195
13	13	2.37	0.0096	0.30	0.65	0.2668	32	32	2.35	0.0091	0.30	0.65	0.6808
13	13	2.37	0.0096	0.30	0.70	0.3588	32	32	2.35	0.0091	0.30	0.70	0.8175
13	13	2.37	0.0096	0.35	0.50	0.0532	32	32	2.35	0.0091	0.35	0.50	0.1183
13	13	2.37	0.0096	0.35	0.55	0.0837	32	32	2.35	0.0091	0.35	0.55	0.2171
13	13	2.37	0.0096	0.35	0.60	0.1268	32	32	2.35	0.0091	0.35	0.60	0.3541
13	13	2.37	0.0096	0.35	0.65	0.1865	32	32	2.35	0.0091	0.35	0.65	0.5166
13	13	2.37	0.0096	0.40	0.55	0.0501	32	32	2.35	0.0091	0.40	0.55	0.1172
13	13	2.37	0.0096	0.40	0.60	0.0809	32	32	2.35	0.0091	0.40	0.60	0.2162
14	14	2.37	0.0083	0.05	0.15	0.0236	33	33	2.33	0.0094	0.05	0.15	0.1105
14	14	2.37	0.0083	0.05	0.20	0.0675	33	33	2.33	0.0094	0.05	0.20	0.2670
14	14	2.37	0.0083	0.05	0.25	0.1401	33	33	2.33	0.0094	0.05	0.25	0.4637
14	14	2.37	0.0083	0.05	0.30	0.2374	33	33	2.33	0.0094	0.05	0.30	0.6556
14	14	2.37	0.0083	0.05	0.35	0.3506	33	33	2.33	0.0094	0.05	0.35	0.8076
14	14	2.37	0.0083	0.05	0.40	0.4696	33	33	2.33	0.0094	0.05	0.40	0.9071
14	14	2.37	0.0083	0.05	0.45	0.5850	33	33	2.33	0.0094	0.05	0.45	0.9615
14	14	2.37	0.0083	0.10	0.25	0.0733	33	33	2.33	0.0094	0.10	0.25	0.2102
14	14	2.37	0.0083	0.10	0.30	0.1306	33	33	2.33	0.0094	0.10	0.30	0.3709
14	14	2.37	0.0083	0.10	0.35	0.2044	33	33	2.33	0.0094	0.10	0.35	0.5490
14	14	2.37	0.0083	0.10	0.40	0.2915	33	33	2.33	0.0094	0.10	0.40	0.7124
14	14	2.37	0.0083	0.10	0.45	0.3879	33	33	2.33	0.0094	0.10	0.45	0.8387
14	14	2.37	0.0083	0.10	0.50	0.4892	33	33	2.33	0.0094	0.10	0.50	0.9214
14	14	2.37	0.0083	0.10	0.55	0.5910	33	33	2.33	0.0094	0.10	0.55	0.9670
14	14	2.37	0.0083	0.10	0.60	0.6886	33	33	2.33	0.0094	0.10	0.60	0.9883
14	14	2.37	0.0083	0.15	0.30	0.0692	33	33	2.33	0.0094	0.15	0.30	0.1802
14	14	2.37	0.0083	0.15	0.35	0.1144	33	33	2.33	0.0094	0.15	0.35	0.3188
14	14	2.37	0.0083	0.15	0.40	0.1732	33	33	2.33	0.0094	0.15	0.40	0.4828
14	14	2.37	0.0083	0.15	0.45	0.2454	33	33	2.33	0.0094	0.15	0.45	0.6457
14	14	2.37	0.0083	0.15	0.50	0.3304	33	33	2.33	0.0094	0.15	0.50	0.7834
14	14	2.37	0.0083	0.15	0.55	0.4262	33	33	2.33	0.0094	0.15	0.55	0.8836
14	14	2.37	0.0083	0.15	0.60	0.5296	33	33	2.33	0.0094	0.15	0.60	0.9463
14	14	2.37	0.0083	0.15	0.65	0.6355	33	33	2.33	0.0094	0.15	0.65	0.9796
14	14	2.37	0.0083	0.20	0.35	0.0615	33	33	2.33	0.0094	0.20	0.35	0.1608
14	14	2.37	0.0083	0.20	0.40	0.0987	33	33	2.33	0.0094	0.20	0.40	0.2835
14	14	2.37	0.0083	0.20	0.45	0.1490	33	33	2.33	0.0094	0.20	0.45	0.4341
14	14	2.37	0.0083	0.20	0.50	0.2141	33	33	2.33	0.0094	0.20	0.50	0.5931
14	14	2.37	0.0083	0.20	0.55	0.2949	33	33	2.33	0.0094	0.20	0.55	0.7394
14	14	2.37	0.0083	0.20	0.60	0.3906	33	33	2.33	0.0094	0.20	0.60	0.8553
14	14	2.37	0.0083	0.20	0.65	0.4980	33	33	2.33	0.0094	0.20	0.65	0.9326
14	14	2.37	0.0083	0.20	0.70	0.6113	33	33	2.33	0.0094	0.20	0.70	0.9747
14	14	2.37	0.0083	0.25	0.40	0.0541	33	33	2.33	0.0094	0.25	0.40	0.1448
14	14	2.37	0.0083	0.25	0.45	0.0871	33	33	2.33	0.0094	0.25	0.45	0.2554
14	14	2.37	0.0083	0.25	0.50	0.1336	33	33	2.33	0.0094	0.25	0.50	0.3989
14	14	2.37	0.0083	0.25	0.55	0.1963	33	33	2.33	0.0094	0.25	0.55	0.5604
14	14	2.37	0.0083	0.25	0.60	0.2768	33	33	2.33	0.0094	0.25	0.60	0.7164
14	14	2.37	0.0083	0.25	0.65	0.3745	33	33	2.33	0.0094	0.25	0.65	0.8430
14	14	2.37	0.0083	0.25	0.70	0.4860	33	33	2.33	0.0094	0.25	0.70	0.9278
14	14	2.37	0.0083	0.25	0.75	0.6047	33	33	2.33	0.0094	0.25	0.75	0.9735
14	14	2.37	0.0083	0.30	0.45	0.0490	33	33	2.33	0.0094	0.30	0.45	0.1328

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
14	14	2.37	0.0083	0.30	0.50	0.0803	33	33	2.33	0.0094	0.30	0.50	0.2393
14	14	2.37	0.0083	0.30	0.55	0.1258	33	33	2.33	0.0094	0.30	0.55	0.3831
14	14	2.37	0.0083	0.30	0.60	0.1884	33	33	2.33	0.0094	0.30	0.60	0.5487
14	14	2.37	0.0083	0.30	0.65	0.2700	33	33	2.33	0.0094	0.30	0.65	0.7095
14	14	2.37	0.0083	0.30	0.70	0.3702	33	33	2.33	0.0094	0.30	0.70	0.8403
14	14	2.37	0.0083	0.35	0.50	0.0463	33	33	2.33	0.0094	0.35	0.50	0.1284
14	14	2.37	0.0083	0.35	0.55	0.0773	33	33	2.33	0.0094	0.35	0.55	0.2350
14	14	2.37	0.0083	0.35	0.60	0.1229	33	33	2.33	0.0094	0.35	0.60	0.3797
14	14	2.37	0.0083	0.35	0.65	0.1863	33	33	2.33	0.0094	0.35	0.65	0.5466
14	14	2.37	0.0083	0.40	0.55	0.0454	33	33	2.33	0.0094	0.40	0.55	0.1283
14	14	2.37	0.0083	0.40	0.60	0.0765	33	33	2.33	0.0094	0.40	0.60	0.2348
15	15	2.33	0.0088	0.05	0.15	0.0299	34	34	2.43	0.0084	0.05	0.15	0.1170
15	15	2.33	0.0088	0.05	0.20	0.0828	34	34	2.43	0.0084	0.05	0.20	0.2764
15	15	2.33	0.0088	0.05	0.25	0.1665	34	34	2.43	0.0084	0.05	0.25	0.4699
15	15	2.33	0.0088	0.05	0.30	0.2746	34	34	2.43	0.0084	0.05	0.30	0.6555
15	15	2.33	0.0088	0.05	0.35	0.3960	34	34	2.43	0.0084	0.05	0.35	0.8037
15	15	2.33	0.0088	0.05	0.40	0.5192	34	34	2.43	0.0084	0.05	0.40	0.9035
15	15	2.33	0.0088	0.05	0.45	0.6349	34	34	2.43	0.0084	0.05	0.45	0.9599
15	15	2.33	0.0088	0.10	0.25	0.0852	34	34	2.43	0.0084	0.10	0.25	0.2002
15	15	2.33	0.0088	0.10	0.30	0.1493	34	34	2.43	0.0084	0.10	0.30	0.3547
15	15	2.33	0.0088	0.10	0.35	0.2305	34	34	2.43	0.0084	0.10	0.35	0.5333
15	15	2.33	0.0088	0.10	0.40	0.3252	34	34	2.43	0.0084	0.10	0.40	0.7025
15	15	2.33	0.0088	0.10	0.45	0.4287	34	34	2.43	0.0084	0.10	0.45	0.8344
15	15	2.33	0.0088	0.10	0.50	0.5358	34	34	2.43	0.0084	0.10	0.50	0.9202
15	15	2.33	0.0088	0.10	0.55	0.6412	34	34	2.43	0.0084	0.10	0.55	0.9672
15	15	2.33	0.0088	0.10	0.60	0.7394	34	34	2.43	0.0084	0.10	0.60	0.9888
15	15	2.33	0.0088	0.15	0.30	0.0779	34	34	2.43	0.0084	0.15	0.30	0.1670
15	15	2.33	0.0088	0.15	0.35	0.1284	34	34	2.43	0.0084	0.15	0.35	0.3046
15	15	2.33	0.0088	0.15	0.40	0.1943	34	34	2.43	0.0084	0.15	0.40	0.4710
15	15	2.33	0.0088	0.15	0.45	0.2755	34	34	2.43	0.0084	0.15	0.45	0.6383
15	15	2.33	0.0088	0.15	0.50	0.3706	34	34	2.43	0.0084	0.15	0.50	0.7814
15	15	2.33	0.0088	0.15	0.55	0.4764	34	34	2.43	0.0084	0.15	0.55	0.8857
15	15	2.33	0.0088	0.15	0.60	0.5876	34	34	2.43	0.0084	0.15	0.60	0.9496
15	15	2.33	0.0088	0.15	0.65	0.6968	34	34	2.43	0.0084	0.15	0.65	0.9816
15	15	2.33	0.0088	0.20	0.35	0.0686	34	34	2.43	0.0084	0.20	0.35	0.1506
15	15	2.33	0.0088	0.20	0.40	0.1114	34	34	2.43	0.0084	0.20	0.40	0.2729
15	15	2.33	0.0088	0.20	0.45	0.1699	34	34	2.43	0.0084	0.20	0.45	0.4275
15	15	2.33	0.0088	0.20	0.50	0.2459	34	34	2.43	0.0084	0.20	0.50	0.5939
15	15	2.33	0.0088	0.20	0.55	0.3393	34	34	2.43	0.0084	0.20	0.55	0.7455
15	15	2.33	0.0088	0.20	0.60	0.4473	34	34	2.43	0.0084	0.20	0.60	0.8612
15	15	2.33	0.0088	0.20	0.65	0.5636	34	34	2.43	0.0084	0.20	0.65	0.9348
15	15	2.33	0.0088	0.20	0.70	0.6796	34	34	2.43	0.0084	0.20	0.70	0.9742
15	15	2.33	0.0088	0.25	0.40	0.0614	34	34	2.43	0.0084	0.25	0.40	0.1384
15	15	2.33	0.0088	0.25	0.45	0.1009	34	34	2.43	0.0084	0.25	0.45	0.2524
15	15	2.33	0.0088	0.25	0.50	0.1570	34	34	2.43	0.0084	0.25	0.50	0.4013
15	15	2.33	0.0088	0.25	0.55	0.2321	34	34	2.43	0.0084	0.25	0.55	0.5648
15	15	2.33	0.0088	0.25	0.60	0.3262	34	34	2.43	0.0084	0.25	0.60	0.7166
15	15	2.33	0.0088	0.25	0.65	0.4363	34	34	2.43	0.0084	0.25	0.65	0.8376
15	15	2.33	0.0088	0.25	0.70	0.5557	34	34	2.43	0.0084	0.25	0.70	0.9211
15	15	2.33	0.0088	0.25	0.75	0.6755	34	34	2.43	0.0084	0.25	0.75	0.9698

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
15	15	2.33	0.0088	0.30	0.45	0.0577	34	34	2.43	0.0084	0.30	0.45	0.1313
15	15	2.33	0.0088	0.30	0.50	0.0963	34	34	2.43	0.0084	0.30	0.50	0.2386
15	15	2.33	0.0088	0.30	0.55	0.1522	34	34	2.43	0.0084	0.30	0.55	0.3784
15	15	2.33	0.0088	0.30	0.60	0.2275	34	34	2.43	0.0084	0.30	0.60	0.5354
15	15	2.33	0.0088	0.30	0.65	0.3223	34	34	2.43	0.0084	0.30	0.65	0.6906
15	15	2.33	0.0088	0.30	0.70	0.4338	34	34	2.43	0.0084	0.30	0.70	0.8246
15	15	2.33	0.0088	0.35	0.50	0.0566	34	34	2.43	0.0084	0.35	0.50	0.1235
15	15	2.33	0.0088	0.35	0.55	0.0953	34	34	2.43	0.0084	0.35	0.55	0.2222
15	15	2.33	0.0088	0.35	0.60	0.1511	34	34	2.43	0.0084	0.35	0.60	0.3568
15	15	2.33	0.0088	0.35	0.65	0.2266	34	34	2.43	0.0084	0.35	0.65	0.5197
15	15	2.33	0.0088	0.40	0.55	0.0566	34	34	2.43	0.0084	0.40	0.55	0.1148
15	15	2.33	0.0088	0.40	0.60	0.0952	34	34	2.43	0.0084	0.40	0.60	0.2131
16	16	2.29	0.0094	0.05	0.15	0.0369	35	35	2.40	0.0089	0.05	0.15	0.1243
16	16	2.29	0.0094	0.05	0.20	0.0989	35	35	2.40	0.0089	0.05	0.20	0.2899
16	16	2.29	0.0094	0.05	0.25	0.1934	35	35	2.40	0.0089	0.05	0.25	0.4879
16	16	2.29	0.0094	0.05	0.30	0.3111	35	35	2.40	0.0089	0.05	0.30	0.6745
16	16	2.29	0.0094	0.05	0.35	0.4391	35	35	2.40	0.0089	0.05	0.35	0.8200
16	16	2.29	0.0094	0.05	0.40	0.5651	35	35	2.40	0.0089	0.05	0.40	0.9149
16	16	2.29	0.0094	0.05	0.45	0.6798	35	35	2.40	0.0089	0.05	0.45	0.9662
16	16	2.29	0.0094	0.10	0.25	0.0970	35	35	2.40	0.0089	0.10	0.25	0.2099
16	16	2.29	0.0094	0.10	0.30	0.1678	35	35	2.40	0.0089	0.10	0.30	0.3713
16	16	2.29	0.0094	0.10	0.35	0.2564	35	35	2.40	0.0089	0.10	0.35	0.5546
16	16	2.29	0.0094	0.10	0.40	0.3586	35	35	2.40	0.0089	0.10	0.40	0.7234
16	16	2.29	0.0094	0.10	0.45	0.4690	35	35	2.40	0.0089	0.10	0.45	0.8508
16	16	2.29	0.0094	0.10	0.50	0.5814	35	35	2.40	0.0089	0.10	0.50	0.9307
16	16	2.29	0.0094	0.10	0.55	0.6891	35	35	2.40	0.0089	0.10	0.55	0.9727
16	16	2.29	0.0094	0.10	0.60	0.7856	35	35	2.40	0.0089	0.10	0.60	0.9912
16	16	2.29	0.0094	0.15	0.30	0.0866	35	35	2.40	0.0089	0.15	0.30	0.1767
16	16	2.29	0.0094	0.15	0.35	0.1429	35	35	2.40	0.0089	0.15	0.35	0.3206
16	16	2.29	0.0094	0.15	0.40	0.2166	35	35	2.40	0.0089	0.15	0.40	0.4915
16	16	2.29	0.0094	0.15	0.45	0.3075	35	35	2.40	0.0089	0.15	0.45	0.6600
16	16	2.29	0.0094	0.15	0.50	0.4129	35	35	2.40	0.0089	0.15	0.50	0.8006
16	16	2.29	0.0094	0.15	0.55	0.5278	35	35	2.40	0.0089	0.15	0.55	0.8997
16	16	2.29	0.0094	0.15	0.60	0.6441	35	35	2.40	0.0089	0.15	0.60	0.9576
16	16	2.29	0.0094	0.15	0.65	0.7524	35	35	2.40	0.0089	0.15	0.65	0.9852
16	16	2.29	0.0094	0.20	0.35	0.0763	35	35	2.40	0.0089	0.20	0.35	0.1594
16	16	2.29	0.0094	0.20	0.40	0.1256	35	35	2.40	0.0089	0.20	0.40	0.2878
16	16	2.29	0.0094	0.20	0.45	0.1934	35	35	2.40	0.0089	0.20	0.45	0.4483
16	16	2.29	0.0094	0.20	0.50	0.2811	35	35	2.40	0.0089	0.20	0.50	0.6175
16	16	2.29	0.0094	0.20	0.55	0.3868	35	35	2.40	0.0089	0.20	0.55	0.7667
16	16	2.29	0.0094	0.20	0.60	0.5048	35	35	2.40	0.0089	0.20	0.60	0.8763
16	16	2.29	0.0094	0.20	0.65	0.6262	35	35	2.40	0.0089	0.20	0.65	0.9436
16	16	2.29	0.0094	0.20	0.70	0.7402	35	35	2.40	0.0089	0.20	0.70	0.9784
16	16	2.29	0.0094	0.25	0.40	0.0701	35	35	2.40	0.0089	0.25	0.40	0.1472
16	16	2.29	0.0094	0.25	0.45	0.1171	35	35	2.40	0.0089	0.25	0.45	0.2678
16	16	2.29	0.0094	0.25	0.50	0.1837	35	35	2.40	0.0089	0.25	0.50	0.4220
16	16	2.29	0.0094	0.25	0.55	0.2713	35	35	2.40	0.0089	0.25	0.55	0.5868
16	16	2.29	0.0094	0.25	0.60	0.3779	35	35	2.40	0.0089	0.25	0.60	0.7358
16	16	2.29	0.0094	0.25	0.65	0.4974	35	35	2.40	0.0089	0.25	0.65	0.8518
16	16	2.29	0.0094	0.25	0.70	0.6208	35	35	2.40	0.0089	0.25	0.70	0.9302

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
16	16	2.29	0.0094	0.25	0.75	0.7373	35	35	2.40	0.0089	0.25	0.75	0.9744
16	16	2.29	0.0094	0.30	0.45	0.0681	35	35	2.40	0.0089	0.30	0.45	0.1400
16	16	2.29	0.0094	0.30	0.50	0.1150	35	35	2.40	0.0089	0.30	0.50	0.2520
16	16	2.29	0.0094	0.30	0.55	0.1817	35	35	2.40	0.0089	0.30	0.55	0.3952
16	16	2.29	0.0094	0.30	0.60	0.2693	35	35	2.40	0.0089	0.30	0.60	0.5535
16	16	2.29	0.0094	0.30	0.65	0.3759	35	35	2.40	0.0089	0.30	0.65	0.7079
16	16	2.29	0.0094	0.30	0.70	0.4960	35	35	2.40	0.0089	0.30	0.70	0.8388
16	16	2.29	0.0094	0.35	0.50	0.0686	35	35	2.40	0.0089	0.35	0.50	0.1300
16	16	2.29	0.0094	0.35	0.55	0.1156	35	35	2.40	0.0089	0.35	0.55	0.2320
16	16	2.29	0.0094	0.35	0.60	0.1820	35	35	2.40	0.0089	0.35	0.60	0.3702
16	16	2.29	0.0094	0.35	0.65	0.2693	35	35	2.40	0.0089	0.35	0.65	0.5364
16	16	2.29	0.0094	0.40	0.55	0.0695	35	35	2.40	0.0089	0.40	0.55	0.1192
16	16	2.29	0.0094	0.40	0.60	0.1161	35	35	2.40	0.0089	0.40	0.60	0.2213
17	17	2.42	0.0099	0.05	0.15	0.0444	36	36	2.38	0.0094	0.05	0.15	0.1330
17	17	2.42	0.0099	0.05	0.20	0.1156	36	36	2.38	0.0094	0.05	0.20	0.3109
17	17	2.42	0.0099	0.05	0.25	0.2203	36	36	2.38	0.0094	0.05	0.25	0.5232
17	17	2.42	0.0099	0.05	0.30	0.3466	36	36	2.38	0.0094	0.05	0.30	0.7162
17	17	2.42	0.0099	0.05	0.35	0.4798	36	36	2.38	0.0094	0.05	0.35	0.8553
17	17	2.42	0.0099	0.05	0.40	0.6072	36	36	2.38	0.0094	0.05	0.40	0.9369
17	17	2.42	0.0099	0.05	0.45	0.7197	36	36	2.38	0.0094	0.05	0.45	0.9766
17	17	2.42	0.0099	0.10	0.25	0.1088	36	36	2.38	0.0094	0.10	0.25	0.2436
17	17	2.42	0.0099	0.10	0.30	0.1861	36	36	2.38	0.0094	0.10	0.30	0.4196
17	17	2.42	0.0099	0.10	0.35	0.2817	36	36	2.38	0.0094	0.10	0.35	0.6025
17	17	2.42	0.0099	0.10	0.40	0.3904	36	36	2.38	0.0094	0.10	0.40	0.7591
17	17	2.42	0.0099	0.10	0.45	0.5054	36	36	2.38	0.0094	0.10	0.45	0.8722
17	17	2.42	0.0099	0.10	0.50	0.6191	36	36	2.38	0.0094	0.10	0.50	0.9418
17	17	2.42	0.0099	0.10	0.55	0.7237	36	36	2.38	0.0094	0.10	0.55	0.9778
17	17	2.42	0.0099	0.10	0.60	0.8127	36	36	2.38	0.0094	0.10	0.60	0.9932
17	17	2.42	0.0099	0.15	0.30	0.0950	36	36	2.38	0.0094	0.15	0.30	0.2026
17	17	2.42	0.0099	0.15	0.35	0.1566	36	36	2.38	0.0094	0.15	0.35	0.3504
17	17	2.42	0.0099	0.15	0.40	0.2363	36	36	2.38	0.0094	0.15	0.40	0.5197
17	17	2.42	0.0099	0.15	0.45	0.3322	36	36	2.38	0.0094	0.15	0.45	0.6843
17	17	2.42	0.0099	0.15	0.50	0.4396	36	36	2.38	0.0094	0.15	0.50	0.8196
17	17	2.42	0.0099	0.15	0.55	0.5512	36	36	2.38	0.0094	0.15	0.55	0.9124
17	17	2.42	0.0099	0.15	0.60	0.6592	36	36	2.38	0.0094	0.15	0.60	0.9645
17	17	2.42	0.0099	0.15	0.65	0.7565	36	36	2.38	0.0094	0.15	0.65	0.9881
17	17	2.42	0.0099	0.20	0.35	0.0826	36	36	2.38	0.0094	0.20	0.35	0.1728
17	17	2.42	0.0099	0.20	0.40	0.1352	36	36	2.38	0.0094	0.20	0.40	0.3056
17	17	2.42	0.0099	0.20	0.45	0.2052	36	36	2.38	0.0094	0.20	0.45	0.4702
17	17	2.42	0.0099	0.20	0.50	0.2917	36	36	2.38	0.0094	0.20	0.50	0.6405
17	17	2.42	0.0099	0.20	0.55	0.3911	36	36	2.38	0.0094	0.20	0.55	0.7863
17	17	2.42	0.0099	0.20	0.60	0.4983	36	36	2.38	0.0094	0.20	0.60	0.8898
17	17	2.42	0.0099	0.20	0.65	0.6076	36	36	2.38	0.0094	0.20	0.65	0.9512
17	17	2.42	0.0099	0.20	0.70	0.7135	36	36	2.38	0.0094	0.20	0.70	0.9821
17	17	2.42	0.0099	0.25	0.40	0.0730	36	36	2.38	0.0094	0.25	0.40	0.1571
17	17	2.42	0.0099	0.25	0.45	0.1190	36	36	2.38	0.0094	0.25	0.45	0.2835
17	17	2.42	0.0099	0.25	0.50	0.1810	36	36	2.38	0.0094	0.25	0.50	0.4422
17	17	2.42	0.0099	0.25	0.55	0.2592	36	36	2.38	0.0094	0.25	0.55	0.6077
17	17	2.42	0.0099	0.25	0.60	0.3527	36	36	2.38	0.0094	0.25	0.60	0.7539
17	17	2.42	0.0099	0.25	0.65	0.4596	36	36	2.38	0.0094	0.25	0.65	0.8656

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
17	17	2.42	0.0099	0.25	0.70	0.5764	36	36	2.38	0.0094	0.25	0.70	0.9391
17	17	2.42	0.0099	0.25	0.75	0.6967	36	36	2.38	0.0094	0.25	0.75	0.9788
17	17	2.42	0.0099	0.30	0.45	0.0647	36	36	2.38	0.0094	0.30	0.45	0.1487
17	17	2.42	0.0099	0.30	0.50	0.1051	36	36	2.38	0.0094	0.30	0.50	0.2652
17	17	2.42	0.0099	0.30	0.55	0.1611	36	36	2.38	0.0094	0.30	0.55	0.4118
17	17	2.42	0.0099	0.30	0.60	0.2352	36	36	2.38	0.0094	0.30	0.60	0.5723
17	17	2.42	0.0099	0.30	0.65	0.3297	36	36	2.38	0.0094	0.30	0.65	0.7265
17	17	2.42	0.0099	0.30	0.70	0.4448	36	36	2.38	0.0094	0.30	0.70	0.8537
17	17	2.42	0.0099	0.35	0.50	0.0572	36	36	2.38	0.0094	0.35	0.50	0.1365
17	17	2.42	0.0099	0.35	0.55	0.0944	36	36	2.38	0.0094	0.35	0.55	0.2427
17	17	2.42	0.0099	0.35	0.60	0.1490	36	36	2.38	0.0094	0.35	0.60	0.3857
17	17	2.42	0.0099	0.35	0.65	0.2261	36	36	2.38	0.0094	0.35	0.65	0.5554
17	17	2.42	0.0099	0.40	0.55	0.0525	36	36	2.38	0.0094	0.40	0.55	0.1248
17	17	2.42	0.0099	0.40	0.60	0.0902	36	36	2.38	0.0094	0.40	0.60	0.2316
18	18	2.41	0.0083	0.05	0.15	0.0178	37	37	2.35	0.0098	0.05	0.15	0.1405
18	18	2.41	0.0083	0.05	0.20	0.0597	37	37	2.35	0.0098	0.05	0.20	0.3254
18	18	2.41	0.0083	0.05	0.25	0.1372	37	37	2.35	0.0098	0.05	0.25	0.5423
18	18	2.41	0.0083	0.05	0.30	0.2489	37	37	2.35	0.0098	0.05	0.30	0.7345
18	18	2.41	0.0083	0.05	0.35	0.3847	37	37	2.35	0.0098	0.05	0.35	0.8688
18	18	2.41	0.0083	0.05	0.40	0.5294	37	37	2.35	0.0098	0.05	0.40	0.9448
18	18	2.41	0.0083	0.05	0.45	0.6670	37	37	2.35	0.0098	0.05	0.45	0.9803
18	18	2.41	0.0083	0.10	0.25	0.0659	37	37	2.35	0.0098	0.10	0.25	0.2549
18	18	2.41	0.0083	0.10	0.30	0.1326	37	37	2.35	0.0098	0.10	0.30	0.4358
18	18	2.41	0.0083	0.10	0.35	0.2283	37	37	2.35	0.0098	0.10	0.35	0.6204
18	18	2.41	0.0083	0.10	0.40	0.3486	37	37	2.35	0.0098	0.10	0.40	0.7752
18	18	2.41	0.0083	0.10	0.45	0.4829	37	37	2.35	0.0098	0.10	0.45	0.8843
18	18	2.41	0.0083	0.10	0.50	0.6168	37	37	2.35	0.0098	0.10	0.50	0.9493
18	18	2.41	0.0083	0.10	0.55	0.7365	37	37	2.35	0.0098	0.10	0.55	0.9816
18	18	2.41	0.0083	0.10	0.60	0.8325	37	37	2.35	0.0098	0.10	0.60	0.9947
18	18	2.41	0.0083	0.15	0.30	0.0695	37	37	2.35	0.0098	0.15	0.30	0.2114
18	18	2.41	0.0083	0.15	0.35	0.1319	37	37	2.35	0.0098	0.15	0.35	0.3643
18	18	2.41	0.0083	0.15	0.40	0.2202	37	37	2.35	0.0098	0.15	0.40	0.5379
18	18	2.41	0.0083	0.15	0.45	0.3304	37	37	2.35	0.0098	0.15	0.45	0.7036
18	18	2.41	0.0083	0.15	0.50	0.4532	37	37	2.35	0.0098	0.15	0.50	0.8360
18	18	2.41	0.0083	0.15	0.55	0.5771	37	37	2.35	0.0098	0.15	0.55	0.9234
18	18	2.41	0.0083	0.15	0.60	0.6916	37	37	2.35	0.0098	0.15	0.60	0.9702
18	18	2.41	0.0083	0.15	0.65	0.7897	37	37	2.35	0.0098	0.15	0.65	0.9905
18	18	2.41	0.0083	0.20	0.35	0.0729	37	37	2.35	0.0098	0.20	0.35	0.1810
18	18	2.41	0.0083	0.20	0.40	0.1313	37	37	2.35	0.0098	0.20	0.40	0.3204
18	18	2.41	0.0083	0.20	0.45	0.2109	37	37	2.35	0.0098	0.20	0.45	0.4906
18	18	2.41	0.0083	0.20	0.50	0.3087	37	37	2.35	0.0098	0.20	0.50	0.6621
18	18	2.41	0.0083	0.20	0.55	0.4186	37	37	2.35	0.0098	0.20	0.55	0.8042
18	18	2.41	0.0083	0.20	0.60	0.5339	37	37	2.35	0.0098	0.20	0.60	0.9017
18	18	2.41	0.0083	0.20	0.65	0.6480	37	37	2.35	0.0098	0.20	0.65	0.9579
18	18	2.41	0.0083	0.20	0.70	0.7543	37	37	2.35	0.0098	0.20	0.70	0.9853
18	18	2.41	0.0083	0.25	0.40	0.0731	37	37	2.35	0.0098	0.25	0.40	0.1663
18	18	2.41	0.0083	0.25	0.45	0.1250	37	37	2.35	0.0098	0.25	0.45	0.2989
18	18	2.41	0.0083	0.25	0.50	0.1948	37	37	2.35	0.0098	0.25	0.50	0.4615
18	18	2.41	0.0083	0.25	0.55	0.2820	37	37	2.35	0.0098	0.25	0.55	0.6273
18	18	2.41	0.0083	0.25	0.60	0.3847	37	37	2.35	0.0098	0.25	0.60	0.7712

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
18	18	2.41	0.0083	0.25	0.65	0.4999	37	37	2.35	0.0098	0.25	0.65	0.8789
18	18	2.41	0.0083	0.25	0.70	0.6216	37	37	2.35	0.0098	0.25	0.70	0.9475
18	18	2.41	0.0083	0.25	0.75	0.7409	37	37	2.35	0.0098	0.25	0.75	0.9827
18	18	2.41	0.0083	0.30	0.45	0.0687	37	37	2.35	0.0098	0.30	0.45	0.1571
18	18	2.41	0.0083	0.30	0.50	0.1143	37	37	2.35	0.0098	0.30	0.50	0.2779
18	18	2.41	0.0083	0.30	0.55	0.1773	37	37	2.35	0.0098	0.30	0.55	0.4285
18	18	2.41	0.0083	0.30	0.60	0.2603	37	37	2.35	0.0098	0.30	0.60	0.5918
18	18	2.41	0.0083	0.30	0.65	0.3644	37	37	2.35	0.0098	0.30	0.65	0.7458
18	18	2.41	0.0083	0.30	0.70	0.4872	37	37	2.35	0.0098	0.30	0.70	0.8687
18	18	2.41	0.0083	0.35	0.50	0.0625	37	37	2.35	0.0098	0.35	0.50	0.1432
18	18	2.41	0.0083	0.35	0.55	0.1046	37	37	2.35	0.0098	0.35	0.55	0.2543
18	18	2.41	0.0083	0.35	0.60	0.1663	37	37	2.35	0.0098	0.35	0.60	0.4032
18	18	2.41	0.0083	0.35	0.65	0.2522	37	37	2.35	0.0098	0.35	0.65	0.5764
18	18	2.41	0.0083	0.40	0.55	0.0582	37	37	2.35	0.0098	0.40	0.55	0.1315
18	18	2.41	0.0083	0.40	0.60	0.1009	37	37	2.35	0.0098	0.40	0.60	0.2438
19	19	2.39	0.0091	0.05	0.15	0.0562	38	38	2.35	0.0098	0.05	0.15	0.1482
19	19	2.39	0.0091	0.05	0.20	0.1333	38	38	2.35	0.0098	0.05	0.20	0.3400
19	19	2.39	0.0091	0.05	0.25	0.2366	38	38	2.35	0.0098	0.05	0.25	0.5609
19	19	2.39	0.0091	0.05	0.30	0.3563	38	38	2.35	0.0098	0.05	0.30	0.7519
19	19	2.39	0.0091	0.05	0.35	0.4849	38	38	2.35	0.0098	0.05	0.35	0.8811
19	19	2.39	0.0091	0.05	0.40	0.6141	38	38	2.35	0.0098	0.05	0.40	0.9517
19	19	2.39	0.0091	0.05	0.45	0.7336	38	38	2.35	0.0098	0.05	0.45	0.9834
19	19	2.39	0.0091	0.10	0.25	0.1041	38	38	2.35	0.0098	0.10	0.25	0.2661
19	19	2.39	0.0091	0.10	0.30	0.1789	38	38	2.35	0.0098	0.10	0.30	0.4517
19	19	2.39	0.0091	0.10	0.35	0.2798	38	38	2.35	0.0098	0.10	0.35	0.6376
19	19	2.39	0.0091	0.10	0.40	0.4031	38	38	2.35	0.0098	0.10	0.40	0.7903
19	19	2.39	0.0091	0.10	0.45	0.5374	38	38	2.35	0.0098	0.10	0.45	0.8953
19	19	2.39	0.0091	0.10	0.50	0.6671	38	38	2.35	0.0098	0.10	0.50	0.9557
19	19	2.39	0.0091	0.10	0.55	0.7787	38	38	2.35	0.0098	0.10	0.55	0.9846
19	19	2.39	0.0091	0.10	0.60	0.8646	38	38	2.35	0.0098	0.10	0.60	0.9957
19	19	2.39	0.0091	0.15	0.30	0.0894	38	38	2.35	0.0098	0.15	0.30	0.2201
19	19	2.39	0.0091	0.15	0.35	0.1584	38	38	2.35	0.0098	0.15	0.35	0.3780
19	19	2.39	0.0091	0.15	0.40	0.2539	38	38	2.35	0.0098	0.15	0.40	0.5549
19	19	2.39	0.0091	0.15	0.45	0.3700	38	38	2.35	0.0098	0.15	0.45	0.7200
19	19	2.39	0.0091	0.15	0.50	0.4959	38	38	2.35	0.0098	0.15	0.50	0.8479
19	19	2.39	0.0091	0.15	0.55	0.6194	38	38	2.35	0.0098	0.15	0.55	0.9296
19	19	2.39	0.0091	0.15	0.60	0.7307	38	38	2.35	0.0098	0.15	0.60	0.9726
19	19	2.39	0.0091	0.15	0.65	0.8236	38	38	2.35	0.0098	0.15	0.65	0.9912
19	19	2.39	0.0091	0.20	0.35	0.0859	38	38	2.35	0.0098	0.20	0.35	0.1887
19	19	2.39	0.0091	0.20	0.40	0.1502	38	38	2.35	0.0098	0.20	0.40	0.3321
19	19	2.39	0.0091	0.20	0.45	0.2363	38	38	2.35	0.0098	0.20	0.45	0.5031
19	19	2.39	0.0091	0.20	0.50	0.3401	38	38	2.35	0.0098	0.20	0.50	0.6711
19	19	2.39	0.0091	0.20	0.55	0.4552	38	38	2.35	0.0098	0.20	0.55	0.8088
19	19	2.39	0.0091	0.20	0.60	0.5744	38	38	2.35	0.0098	0.20	0.60	0.9043
19	19	2.39	0.0091	0.20	0.65	0.6901	38	38	2.35	0.0098	0.20	0.65	0.9602
19	19	2.39	0.0091	0.20	0.70	0.7943	38	38	2.35	0.0098	0.20	0.70	0.9870
19	19	2.39	0.0091	0.25	0.40	0.0826	38	38	2.35	0.0098	0.25	0.40	0.1705
19	19	2.39	0.0091	0.25	0.45	0.1396	38	38	2.35	0.0098	0.25	0.45	0.3022
19	19	2.39	0.0091	0.25	0.50	0.2157	38	38	2.35	0.0098	0.25	0.50	0.4625
19	19	2.39	0.0091	0.25	0.55	0.3106	38	38	2.35	0.0098	0.25	0.55	0.6283

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
19	19	2.39	0.0091	0.25	0.60	0.4219	38	38	2.35	0.0098	0.25	0.60	0.7756
19	19	2.39	0.0091	0.25	0.65	0.5442	38	38	2.35	0.0098	0.25	0.65	0.8860
19	19	2.39	0.0091	0.25	0.70	0.6689	38	38	2.35	0.0098	0.25	0.70	0.9535
19	19	2.39	0.0091	0.25	0.75	0.7844	38	38	2.35	0.0098	0.25	0.75	0.9856
19	19	2.39	0.0091	0.30	0.45	0.0763	38	38	2.35	0.0098	0.30	0.45	0.1548
19	19	2.39	0.0091	0.30	0.50	0.1271	38	38	2.35	0.0098	0.30	0.50	0.2748
19	19	2.39	0.0091	0.30	0.55	0.1978	38	38	2.35	0.0098	0.30	0.55	0.4295
19	19	2.39	0.0091	0.30	0.60	0.2906	38	38	2.35	0.0098	0.30	0.60	0.6006
19	19	2.39	0.0091	0.30	0.65	0.4046	38	38	2.35	0.0098	0.30	0.65	0.7597
19	19	2.39	0.0091	0.30	0.70	0.5343	38	38	2.35	0.0098	0.30	0.70	0.8806
19	19	2.39	0.0091	0.35	0.50	0.0698	38	38	2.35	0.0098	0.35	0.50	0.1409
19	19	2.39	0.0091	0.35	0.55	0.1181	38	38	2.35	0.0098	0.35	0.55	0.2573
19	19	2.39	0.0091	0.35	0.60	0.1884	38	38	2.35	0.0098	0.35	0.60	0.4146
19	19	2.39	0.0091	0.35	0.65	0.2840	38	38	2.35	0.0098	0.35	0.65	0.5929
19	19	2.39	0.0091	0.40	0.55	0.0662	38	38	2.35	0.0098	0.40	0.55	0.1347
19	19	2.39	0.0091	0.40	0.60	0.1150	38	38	2.35	0.0098	0.40	0.60	0.2526
20	20	2.38	0.0084	0.05	0.15	0.0635	39	39	2.37	0.0093	0.05	0.15	0.1531
20	20	2.38	0.0084	0.05	0.20	0.1468	39	39	2.37	0.0093	0.05	0.20	0.3425
20	20	2.38	0.0084	0.05	0.25	0.2562	39	39	2.37	0.0093	0.05	0.25	0.5563
20	20	2.38	0.0084	0.05	0.30	0.3818	39	39	2.37	0.0093	0.05	0.30	0.7437
20	20	2.38	0.0084	0.05	0.35	0.5149	39	39	2.37	0.0093	0.05	0.35	0.8755
20	20	2.38	0.0084	0.05	0.40	0.6453	39	39	2.37	0.0093	0.05	0.40	0.9500
20	20	2.38	0.0084	0.05	0.45	0.7612	39	39	2.37	0.0093	0.05	0.45	0.9836
20	20	2.38	0.0084	0.10	0.25	0.1112	39	39	2.37	0.0093	0.10	0.25	0.2512
20	20	2.38	0.0084	0.10	0.30	0.1903	39	39	2.37	0.0093	0.10	0.30	0.4391
20	20	2.38	0.0084	0.10	0.35	0.2948	39	39	2.37	0.0093	0.10	0.35	0.6348
20	20	2.38	0.0084	0.10	0.40	0.4186	39	39	2.37	0.0093	0.10	0.40	0.7953
20	20	2.38	0.0084	0.10	0.45	0.5496	39	39	2.37	0.0093	0.10	0.45	0.9017
20	20	2.38	0.0084	0.10	0.50	0.6745	39	39	2.37	0.0093	0.10	0.50	0.9599
20	20	2.38	0.0084	0.10	0.55	0.7827	39	39	2.37	0.0093	0.10	0.55	0.9863
20	20	2.38	0.0084	0.10	0.60	0.8679	39	39	2.37	0.0093	0.10	0.60	0.9962
20	20	2.38	0.0084	0.15	0.30	0.0919	39	39	2.37	0.0093	0.15	0.30	0.2164
20	20	2.38	0.0084	0.15	0.35	0.1604	39	39	2.37	0.0093	0.15	0.35	0.3820
20	20	2.38	0.0084	0.15	0.40	0.2532	39	39	2.37	0.0093	0.15	0.40	0.5643
20	20	2.38	0.0084	0.15	0.45	0.3661	39	39	2.37	0.0093	0.15	0.45	0.7291
20	20	2.38	0.0084	0.15	0.50	0.4913	39	39	2.37	0.0093	0.15	0.50	0.8534
20	20	2.38	0.0084	0.15	0.55	0.6188	39	39	2.37	0.0093	0.15	0.55	0.9321
20	20	2.38	0.0084	0.15	0.60	0.7373	39	39	2.37	0.0093	0.15	0.60	0.9739
20	20	2.38	0.0084	0.15	0.65	0.8369	39	39	2.37	0.0093	0.15	0.65	0.9920
20	20	2.38	0.0084	0.20	0.35	0.0821	39	39	2.37	0.0093	0.20	0.35	0.1914
20	20	2.38	0.0084	0.20	0.40	0.1430	39	39	2.37	0.0093	0.20	0.40	0.3362
20	20	2.38	0.0084	0.20	0.45	0.2272	39	39	2.37	0.0093	0.20	0.45	0.5056
20	20	2.38	0.0084	0.20	0.50	0.3340	39	39	2.37	0.0093	0.20	0.50	0.6723
20	20	2.38	0.0084	0.20	0.55	0.4583	39	39	2.37	0.0093	0.20	0.55	0.8112
20	20	2.38	0.0084	0.20	0.60	0.5902	39	39	2.37	0.0093	0.20	0.60	0.9085
20	20	2.38	0.0084	0.20	0.65	0.7165	39	39	2.37	0.0093	0.20	0.65	0.9643
20	20	2.38	0.0084	0.20	0.70	0.8243	39	39	2.37	0.0093	0.20	0.70	0.9893
20	20	2.38	0.0084	0.25	0.40	0.0758	39	39	2.37	0.0093	0.25	0.40	0.1687
20	20	2.38	0.0084	0.25	0.45	0.1325	39	39	2.37	0.0093	0.25	0.45	0.2988
20	20	2.38	0.0084	0.25	0.50	0.2136	39	39	2.37	0.0093	0.25	0.50	0.4614

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
20	20	2.38	0.0084	0.25	0.55	0.3195	39	39	2.37	0.0093	0.25	0.55	0.6340
20	20	2.38	0.0084	0.25	0.60	0.4451	39	39	2.37	0.0093	0.25	0.60	0.7869
20	20	2.38	0.0084	0.25	0.65	0.5800	39	39	2.37	0.0093	0.25	0.65	0.8974
20	20	2.38	0.0084	0.25	0.70	0.7099	39	39	2.37	0.0093	0.25	0.70	0.9607
20	20	2.38	0.0084	0.25	0.75	0.8213	39	39	2.37	0.0093	0.25	0.75	0.9886
20	20	2.38	0.0084	0.30	0.45	0.0728	39	39	2.37	0.0093	0.30	0.45	0.1514
20	20	2.38	0.0084	0.30	0.50	0.1286	39	39	2.37	0.0093	0.30	0.50	0.2760
20	20	2.38	0.0084	0.30	0.55	0.2094	39	39	2.37	0.0093	0.30	0.55	0.4400
20	20	2.38	0.0084	0.30	0.60	0.3155	39	39	2.37	0.0093	0.30	0.60	0.6193
20	20	2.38	0.0084	0.30	0.65	0.4418	39	39	2.37	0.0093	0.30	0.65	0.7795
20	20	2.38	0.0084	0.30	0.70	0.5779	39	39	2.37	0.0093	0.30	0.70	0.8949
20	20	2.38	0.0084	0.35	0.50	0.0728	39	39	2.37	0.0093	0.35	0.50	0.1442
20	20	2.38	0.0084	0.35	0.55	0.1286	39	39	2.37	0.0093	0.35	0.55	0.2690
20	20	2.38	0.0084	0.35	0.60	0.2092	39	39	2.37	0.0093	0.35	0.60	0.4349
20	20	2.38	0.0084	0.35	0.65	0.3150	39	39	2.37	0.0093	0.35	0.65	0.6166
20	20	2.38	0.0084	0.40	0.55	0.0735	39	39	2.37	0.0093	0.40	0.55	0.1434
20	20	2.38	0.0084	0.40	0.60	0.1290	39	39	2.37	0.0093	0.40	0.60	0.2684
21	21	2.36	0.0098	0.05	0.15	0.0708	40	40	2.36	0.0096	0.05	0.15	0.1603
21	21	2.36	0.0098	0.05	0.20	0.1601	40	40	2.36	0.0096	0.05	0.20	0.3553
21	21	2.36	0.0098	0.05	0.25	0.2759	40	40	2.36	0.0096	0.05	0.25	0.5726
21	21	2.36	0.0098	0.05	0.30	0.4084	40	40	2.36	0.0096	0.05	0.30	0.7595
21	21	2.36	0.0098	0.05	0.35	0.5475	40	40	2.36	0.0096	0.05	0.35	0.8872
21	21	2.36	0.0098	0.05	0.40	0.6801	40	40	2.36	0.0096	0.05	0.40	0.9565
21	21	2.36	0.0098	0.05	0.45	0.7933	40	40	2.36	0.0096	0.05	0.45	0.9864
21	21	2.36	0.0098	0.10	0.25	0.1198	40	40	2.36	0.0096	0.10	0.25	0.2622
21	21	2.36	0.0098	0.10	0.30	0.2066	40	40	2.36	0.0096	0.10	0.30	0.4560
21	21	2.36	0.0098	0.10	0.35	0.3201	40	40	2.36	0.0096	0.10	0.35	0.6533
21	21	2.36	0.0098	0.10	0.40	0.4513	40	40	2.36	0.0096	0.10	0.40	0.8105
21	21	2.36	0.0098	0.10	0.45	0.5862	40	40	2.36	0.0096	0.10	0.45	0.9116
21	21	2.36	0.0098	0.10	0.50	0.7108	40	40	2.36	0.0096	0.10	0.50	0.9652
21	21	2.36	0.0098	0.10	0.55	0.8149	40	40	2.36	0.0096	0.10	0.55	0.9886
21	21	2.36	0.0098	0.10	0.60	0.8933	40	40	2.36	0.0096	0.10	0.60	0.9970
21	21	2.36	0.0098	0.15	0.30	0.1004	40	40	2.36	0.0096	0.15	0.30	0.2265
21	21	2.36	0.0098	0.15	0.35	0.1759	40	40	2.36	0.0096	0.15	0.35	0.3970
21	21	2.36	0.0098	0.15	0.40	0.2768	40	40	2.36	0.0096	0.15	0.40	0.5816
21	21	2.36	0.0098	0.15	0.45	0.3977	40	40	2.36	0.0096	0.15	0.45	0.7452
21	21	2.36	0.0098	0.15	0.50	0.5294	40	40	2.36	0.0096	0.15	0.50	0.8657
21	21	2.36	0.0098	0.15	0.55	0.6597	40	40	2.36	0.0096	0.15	0.55	0.9399
21	21	2.36	0.0098	0.15	0.60	0.7762	40	40	2.36	0.0096	0.15	0.60	0.9779
21	21	2.36	0.0098	0.15	0.65	0.8689	40	40	2.36	0.0096	0.15	0.65	0.9936
21	21	2.36	0.0098	0.20	0.35	0.0904	40	40	2.36	0.0096	0.20	0.35	0.1997
21	21	2.36	0.0098	0.20	0.40	0.1580	40	40	2.36	0.0096	0.20	0.40	0.3492
21	21	2.36	0.0098	0.20	0.45	0.2512	40	40	2.36	0.0096	0.20	0.45	0.5222
21	21	2.36	0.0098	0.20	0.50	0.3679	40	40	2.36	0.0096	0.20	0.50	0.6898
21	21	2.36	0.0098	0.20	0.55	0.5006	40	40	2.36	0.0096	0.20	0.55	0.8266
21	21	2.36	0.0098	0.20	0.60	0.6362	40	40	2.36	0.0096	0.20	0.60	0.9194
21	21	2.36	0.0098	0.20	0.65	0.7599	40	40	2.36	0.0096	0.20	0.65	0.9702
21	21	2.36	0.0098	0.20	0.70	0.8594	40	40	2.36	0.0096	0.20	0.70	0.9916
21	21	2.36	0.0098	0.25	0.40	0.0846	40	40	2.36	0.0096	0.25	0.40	0.1760
21	21	2.36	0.0098	0.25	0.45	0.1490	40	40	2.36	0.0096	0.25	0.45	0.3116

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
21	21	2.36	0.0098	0.25	0.50	0.2402	40	40	2.36	0.0096	0.25	0.50	0.4799
21	21	2.36	0.0098	0.25	0.55	0.3567	40	40	2.36	0.0096	0.25	0.55	0.6553
21	21	2.36	0.0098	0.25	0.60	0.4907	40	40	2.36	0.0096	0.25	0.60	0.8061
21	21	2.36	0.0098	0.25	0.65	0.6285	40	40	2.36	0.0096	0.25	0.65	0.9105
21	21	2.36	0.0098	0.25	0.70	0.7549	40	40	2.36	0.0096	0.25	0.70	0.9674
21	21	2.36	0.0098	0.25	0.75	0.8571	40	40	2.36	0.0096	0.25	0.75	0.9911
21	21	2.36	0.0098	0.30	0.45	0.0832	40	40	2.36	0.0096	0.30	0.45	0.1596
21	21	2.36	0.0098	0.30	0.50	0.1472	40	40	2.36	0.0096	0.30	0.50	0.2913
21	21	2.36	0.0098	0.30	0.55	0.2383	40	40	2.36	0.0096	0.30	0.55	0.4619
21	21	2.36	0.0098	0.30	0.60	0.3547	40	40	2.36	0.0096	0.30	0.60	0.6434
21	21	2.36	0.0098	0.30	0.65	0.4885	40	40	2.36	0.0096	0.30	0.65	0.8001
21	21	2.36	0.0098	0.30	0.70	0.6270	40	40	2.36	0.0096	0.30	0.70	0.9085
21	21	2.36	0.0098	0.35	0.50	0.0844	40	40	2.36	0.0096	0.35	0.50	0.1542
21	21	2.36	0.0098	0.35	0.55	0.1485	40	40	2.36	0.0096	0.35	0.55	0.2864
21	21	2.36	0.0098	0.35	0.60	0.2390	40	40	2.36	0.0096	0.35	0.60	0.4583
21	21	2.36	0.0098	0.35	0.65	0.3547	40	40	2.36	0.0096	0.35	0.65	0.6414
21	21	2.36	0.0098	0.40	0.55	0.0858	40	40	2.36	0.0096	0.40	0.55	0.1543
21	21	2.36	0.0098	0.40	0.60	0.1493	40	40	2.36	0.0096	0.40	0.60	0.2863
22	22	2.42	0.0097	0.05	0.15	0.0372	50	50	2.41	0.0086	0.05	0.15	0.2281
22	22	2.42	0.0097	0.05	0.20	0.1118	50	50	2.41	0.0086	0.05	0.20	0.4659
22	22	2.42	0.0097	0.05	0.25	0.2331	50	50	2.41	0.0086	0.05	0.25	0.6948
22	22	2.42	0.0097	0.05	0.30	0.3870	50	50	2.41	0.0086	0.05	0.30	0.8591
22	22	2.42	0.0097	0.05	0.35	0.5499	50	50	2.41	0.0086	0.05	0.35	0.9487
22	22	2.42	0.0097	0.05	0.40	0.6982	50	50	2.41	0.0086	0.05	0.40	0.9855
22	22	2.42	0.0097	0.05	0.45	0.8161	50	50	2.41	0.0086	0.05	0.45	0.9968
22	22	2.42	0.0097	0.10	0.25	0.1098	50	50	2.41	0.0086	0.10	0.25	0.3290
22	22	2.42	0.0097	0.10	0.30	0.2089	50	50	2.41	0.0086	0.10	0.30	0.5537
22	22	2.42	0.0097	0.10	0.35	0.3367	50	50	2.41	0.0086	0.10	0.35	0.7550
22	22	2.42	0.0097	0.10	0.40	0.4791	50	50	2.41	0.0086	0.10	0.40	0.8898
22	22	2.42	0.0097	0.10	0.45	0.6194	50	50	2.41	0.0086	0.10	0.45	0.9597
22	22	2.42	0.0097	0.10	0.50	0.7437	50	50	2.41	0.0086	0.10	0.50	0.9882
22	22	2.42	0.0097	0.10	0.55	0.8431	50	50	2.41	0.0086	0.10	0.55	0.9973
22	22	2.42	0.0097	0.10	0.60	0.9143	50	50	2.41	0.0086	0.10	0.60	0.9995
22	22	2.42	0.0097	0.15	0.30	0.1051	50	50	2.41	0.0086	0.15	0.30	0.2749
22	22	2.42	0.0097	0.15	0.35	0.1893	50	50	2.41	0.0086	0.15	0.35	0.4769
22	22	2.42	0.0097	0.15	0.40	0.2996	50	50	2.41	0.0086	0.15	0.40	0.6774
22	22	2.42	0.0097	0.15	0.45	0.4289	50	50	2.41	0.0086	0.15	0.45	0.8335
22	22	2.42	0.0097	0.15	0.50	0.5659	50	50	2.41	0.0086	0.15	0.50	0.9299
22	22	2.42	0.0097	0.15	0.55	0.6966	50	50	2.41	0.0086	0.15	0.55	0.9768
22	22	2.42	0.0097	0.15	0.60	0.8078	50	50	2.41	0.0086	0.15	0.60	0.9942
22	22	2.42	0.0097	0.15	0.65	0.8914	50	50	2.41	0.0086	0.15	0.65	0.9990
22	22	2.42	0.0097	0.20	0.35	0.0984	50	50	2.41	0.0086	0.20	0.35	0.2372
22	22	2.42	0.0097	0.20	0.40	0.1733	50	50	2.41	0.0086	0.20	0.40	0.4192
22	22	2.42	0.0097	0.20	0.45	0.2753	50	50	2.41	0.0086	0.20	0.45	0.6188
22	22	2.42	0.0097	0.20	0.50	0.3999	50	50	2.41	0.0086	0.20	0.50	0.7919
22	22	2.42	0.0097	0.20	0.55	0.5362	50	50	2.41	0.0086	0.20	0.55	0.9084
22	22	2.42	0.0097	0.20	0.60	0.6693	50	50	2.41	0.0086	0.20	0.60	0.9682
22	22	2.42	0.0097	0.20	0.65	0.7851	50	50	2.41	0.0086	0.20	0.65	0.9914
22	22	2.42	0.0097	0.20	0.70	0.8748	50	50	2.41	0.0086	0.20	0.70	0.9982
22	22	2.42	0.0097	0.25	0.40	0.0936	50	50	2.41	0.0086	0.25	0.40	0.2117

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
22	22	2.42	0.0097	0.25	0.45	0.1647	50	50	2.41	0.0086	0.25	0.45	0.3863
22	22	2.42	0.0097	0.25	0.50	0.2627	50	50	2.41	0.0086	0.25	0.50	0.5881
22	22	2.42	0.0097	0.25	0.55	0.3834	50	50	2.41	0.0086	0.25	0.55	0.7677
22	22	2.42	0.0097	0.25	0.60	0.5166	50	50	2.41	0.0086	0.25	0.60	0.8914
22	22	2.42	0.0097	0.25	0.65	0.6494	50	50	2.41	0.0086	0.25	0.65	0.9588
22	22	2.42	0.0097	0.25	0.70	0.7695	50	50	2.41	0.0086	0.25	0.70	0.9881
22	22	2.42	0.0097	0.25	0.75	0.8672	50	50	2.41	0.0086	0.25	0.75	0.9977
22	22	2.42	0.0097	0.30	0.45	0.0917	50	50	2.41	0.0086	0.30	0.45	0.2015
22	22	2.42	0.0097	0.30	0.50	0.1600	50	50	2.41	0.0086	0.30	0.50	0.3694
22	22	2.42	0.0097	0.30	0.55	0.2539	50	50	2.41	0.0086	0.30	0.55	0.5626
22	22	2.42	0.0097	0.30	0.60	0.3705	50	50	2.41	0.0086	0.30	0.60	0.7399
22	22	2.42	0.0097	0.30	0.65	0.5030	50	50	2.41	0.0086	0.30	0.65	0.8729
22	22	2.42	0.0097	0.30	0.70	0.6406	50	50	2.41	0.0086	0.30	0.70	0.9527
22	22	2.42	0.0097	0.35	0.50	0.0900	50	50	2.41	0.0086	0.35	0.50	0.1906
22	22	2.42	0.0097	0.35	0.55	0.1555	50	50	2.41	0.0086	0.35	0.55	0.3451
22	22	2.42	0.0097	0.35	0.60	0.2470	50	50	2.41	0.0086	0.35	0.60	0.5334
22	22	2.42	0.0097	0.35	0.65	0.3647	50	50	2.41	0.0086	0.35	0.65	0.7229
22	22	2.42	0.0097	0.40	0.55	0.0881	50	50	2.41	0.0086	0.40	0.55	0.1751
22	22	2.42	0.0097	0.40	0.60	0.1532	50	50	2.41	0.0086	0.40	0.60	0.3296
23	23	2.38	0.0091	0.05	0.15	0.0431	60	60	2.38	0.0096	0.05	0.15	0.2907
23	23	2.38	0.0091	0.05	0.20	0.1265	60	60	2.38	0.0096	0.05	0.20	0.5642
23	23	2.38	0.0091	0.05	0.25	0.2584	60	60	2.38	0.0096	0.05	0.25	0.7937
23	23	2.38	0.0091	0.05	0.30	0.4210	60	60	2.38	0.0096	0.05	0.30	0.9262
23	23	2.38	0.0091	0.05	0.35	0.5873	60	60	2.38	0.0096	0.05	0.35	0.9802
23	23	2.38	0.0091	0.05	0.40	0.7329	60	60	2.38	0.0096	0.05	0.40	0.9961
23	23	2.38	0.0091	0.05	0.45	0.8436	60	60	2.38	0.0096	0.05	0.45	0.9994
23	23	2.38	0.0091	0.10	0.25	0.1221	60	60	2.38	0.0096	0.10	0.25	0.4112
23	23	2.38	0.0091	0.10	0.30	0.2294	60	60	2.38	0.0096	0.10	0.30	0.6570
23	23	2.38	0.0091	0.10	0.35	0.3648	60	60	2.38	0.0096	0.10	0.35	0.8432
23	23	2.38	0.0091	0.10	0.40	0.5117	60	60	2.38	0.0096	0.10	0.40	0.9444
23	23	2.38	0.0091	0.10	0.45	0.6524	60	60	2.38	0.0096	0.10	0.45	0.9849
23	23	2.38	0.0091	0.10	0.50	0.7731	60	60	2.38	0.0096	0.10	0.50	0.9969
23	23	2.38	0.0091	0.10	0.55	0.8658	60	60	2.38	0.0096	0.10	0.55	0.9995
23	23	2.38	0.0091	0.10	0.60	0.9291	60	60	2.38	0.0096	0.10	0.60	1.0000
23	23	2.38	0.0091	0.15	0.30	0.1153	60	60	2.38	0.0096	0.15	0.30	0.3413
23	23	2.38	0.0091	0.15	0.35	0.2061	60	60	2.38	0.0096	0.15	0.35	0.5734
23	23	2.38	0.0091	0.15	0.40	0.3231	60	60	2.38	0.0096	0.15	0.40	0.7763
23	23	2.38	0.0091	0.15	0.45	0.4572	60	60	2.38	0.0096	0.15	0.45	0.9070
23	23	2.38	0.0091	0.15	0.50	0.5947	60	60	2.38	0.0096	0.15	0.50	0.9700
23	23	2.38	0.0091	0.15	0.55	0.7208	60	60	2.38	0.0096	0.15	0.55	0.9928
23	23	2.38	0.0091	0.15	0.60	0.8238	60	60	2.38	0.0096	0.15	0.60	0.9988
23	23	2.38	0.0091	0.15	0.65	0.8992	60	60	2.38	0.0096	0.15	0.65	0.9999
23	23	2.38	0.0091	0.20	0.35	0.1069	60	60	2.38	0.0096	0.20	0.35	0.2982
23	23	2.38	0.0091	0.20	0.40	0.1869	60	60	2.38	0.0096	0.20	0.40	0.5144
23	23	2.38	0.0091	0.20	0.45	0.2929	60	60	2.38	0.0096	0.20	0.45	0.7230
23	23	2.38	0.0091	0.20	0.50	0.4179	60	60	2.38	0.0096	0.20	0.50	0.8749
23	23	2.38	0.0091	0.20	0.55	0.5497	60	60	2.38	0.0096	0.20	0.55	0.9572
23	23	2.38	0.0091	0.20	0.60	0.6753	60	60	2.38	0.0096	0.20	0.60	0.9893
23	23	2.38	0.0091	0.20	0.65	0.7845	60	60	2.38	0.0096	0.20	0.65	0.9981
23	23	2.38	0.0091	0.20	0.70	0.8716	60	60	2.38	0.0096	0.20	0.70	0.9998

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
23	23	2.38	0.0091	0.25	0.40	0.0994	60	60	2.38	0.0096	0.25	0.40	0.2678
23	23	2.38	0.0091	0.25	0.45	0.1715	60	60	2.38	0.0096	0.25	0.45	0.4762
23	23	2.38	0.0091	0.25	0.50	0.2673	60	60	2.38	0.0096	0.25	0.50	0.6927
23	23	2.38	0.0091	0.25	0.55	0.3821	60	60	2.38	0.0096	0.25	0.55	0.8576
23	23	2.38	0.0091	0.25	0.60	0.5082	60	60	2.38	0.0096	0.25	0.60	0.9489
23	23	2.38	0.0091	0.25	0.65	0.6367	60	60	2.38	0.0096	0.25	0.65	0.9860
23	23	2.38	0.0091	0.25	0.70	0.7575	60	60	2.38	0.0096	0.25	0.70	0.9972
23	23	2.38	0.0091	0.25	0.75	0.8598	60	60	2.38	0.0096	0.25	0.75	0.9997
23	23	2.38	0.0091	0.30	0.45	0.0914	60	60	2.38	0.0096	0.30	0.45	0.2553
23	23	2.38	0.0091	0.30	0.50	0.1553	60	60	2.38	0.0096	0.30	0.50	0.4611
23	23	2.38	0.0091	0.30	0.55	0.2422	60	60	2.38	0.0096	0.30	0.55	0.6749
23	23	2.38	0.0091	0.30	0.60	0.3517	60	60	2.38	0.0096	0.30	0.60	0.8406
23	23	2.38	0.0091	0.30	0.65	0.4808	60	60	2.38	0.0096	0.30	0.65	0.9391
23	23	2.38	0.0091	0.30	0.70	0.6210	60	60	2.38	0.0096	0.30	0.70	0.9835
23	23	2.38	0.0091	0.35	0.50	0.0821	60	60	2.38	0.0096	0.35	0.50	0.2480
23	23	2.38	0.0091	0.35	0.55	0.1406	60	60	2.38	0.0096	0.35	0.55	0.4415
23	23	2.38	0.0091	0.35	0.60	0.2252	60	60	2.38	0.0096	0.35	0.60	0.6506
23	23	2.38	0.0091	0.35	0.65	0.3394	60	60	2.38	0.0096	0.35	0.65	0.8277
23	23	2.38	0.0091	0.40	0.55	0.0753	60	60	2.38	0.0096	0.40	0.55	0.2325
23	23	2.38	0.0091	0.40	0.60	0.1345	60	60	2.38	0.0096	0.40	0.60	0.4255
24	24	2.35	0.0097	0.05	0.15	0.0924	70	70	2.37	0.0100	0.05	0.15	0.3504
24	24	2.35	0.0097	0.05	0.20	0.1990	70	70	2.37	0.0100	0.05	0.20	0.6530
24	24	2.35	0.0097	0.05	0.25	0.3353	70	70	2.37	0.0100	0.05	0.25	0.8675
24	24	2.35	0.0097	0.05	0.30	0.4887	70	70	2.37	0.0100	0.05	0.30	0.9638
24	24	2.35	0.0097	0.05	0.35	0.6408	70	70	2.37	0.0100	0.05	0.35	0.9928
24	24	2.35	0.0097	0.05	0.40	0.7719	70	70	2.37	0.0100	0.05	0.40	0.9990
24	24	2.35	0.0097	0.05	0.45	0.8701	70	70	2.37	0.0100	0.05	0.45	0.9999
24	24	2.35	0.0097	0.10	0.25	0.1486	70	70	2.37	0.0100	0.10	0.25	0.4900
24	24	2.35	0.0097	0.10	0.30	0.2594	70	70	2.37	0.0100	0.10	0.30	0.7394
24	24	2.35	0.0097	0.10	0.35	0.3973	70	70	2.37	0.0100	0.10	0.35	0.9002
24	24	2.35	0.0097	0.10	0.40	0.5453	70	70	2.37	0.0100	0.10	0.40	0.9719
24	24	2.35	0.0097	0.10	0.45	0.6846	70	70	2.37	0.0100	0.10	0.45	0.9943
24	24	2.35	0.0097	0.10	0.50	0.8010	70	70	2.37	0.0100	0.10	0.50	0.9992
24	24	2.35	0.0097	0.10	0.55	0.8871	70	70	2.37	0.0100	0.10	0.55	0.9999
24	24	2.35	0.0097	0.10	0.60	0.9431	70	70	2.37	0.0100	0.10	0.60	1.0000
24	24	2.35	0.0097	0.15	0.30	0.1281	70	70	2.37	0.0100	0.15	0.30	0.3998
24	24	2.35	0.0097	0.15	0.35	0.2246	70	70	2.37	0.0100	0.15	0.35	0.6501
24	24	2.35	0.0097	0.15	0.40	0.3481	70	70	2.37	0.0100	0.15	0.40	0.8439
24	24	2.35	0.0097	0.15	0.45	0.4875	70	70	2.37	0.0100	0.15	0.45	0.9479
24	24	2.35	0.0097	0.15	0.50	0.6268	70	70	2.37	0.0100	0.15	0.50	0.9872
24	24	2.35	0.0097	0.15	0.55	0.7502	70	70	2.37	0.0100	0.15	0.55	0.9978
24	24	2.35	0.0097	0.15	0.60	0.8475	70	70	2.37	0.0100	0.15	0.60	0.9997
24	24	2.35	0.0097	0.15	0.65	0.9161	70	70	2.37	0.0100	0.15	0.65	1.0000
24	24	2.35	0.0097	0.20	0.35	0.1165	70	70	2.37	0.0100	0.20	0.35	0.3512
24	24	2.35	0.0097	0.20	0.40	0.2029	70	70	2.37	0.0100	0.20	0.40	0.5930
24	24	2.35	0.0097	0.20	0.45	0.3157	70	70	2.37	0.0100	0.20	0.45	0.7989
24	24	2.35	0.0097	0.20	0.50	0.4458	70	70	2.37	0.0100	0.20	0.50	0.9250
24	24	2.35	0.0097	0.20	0.55	0.5798	70	70	2.37	0.0100	0.20	0.55	0.9800
24	24	2.35	0.0097	0.20	0.60	0.7046	70	70	2.37	0.0100	0.20	0.60	0.9964
24	24	2.35	0.0097	0.20	0.65	0.8107	70	70	2.37	0.0100	0.20	0.65	0.9996

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
24	24	2.35	0.0097	0.20	0.70	0.8926	70	70	2.37	0.0100	0.20	0.70	1.0000
24	24	2.35	0.0097	0.25	0.40	0.1081	70	70	2.37	0.0100	0.25	0.40	0.3183
24	24	2.35	0.0097	0.25	0.45	0.1856	70	70	2.37	0.0100	0.25	0.45	0.5519
24	24	2.35	0.0097	0.25	0.50	0.2871	70	70	2.37	0.0100	0.25	0.50	0.7699
24	24	2.35	0.0097	0.25	0.55	0.4074	70	70	2.37	0.0100	0.25	0.55	0.9121
24	24	2.35	0.0097	0.25	0.60	0.5381	70	70	2.37	0.0100	0.25	0.60	0.9758
24	24	2.35	0.0097	0.25	0.65	0.6689	70	70	2.37	0.0100	0.25	0.65	0.9953
24	24	2.35	0.0097	0.25	0.70	0.7878	70	70	2.37	0.0100	0.25	0.70	0.9994
24	24	2.35	0.0097	0.25	0.75	0.8834	70	70	2.37	0.0100	0.25	0.75	1.0000
24	24	2.35	0.0097	0.30	0.45	0.0987	70	70	2.37	0.0100	0.30	0.45	0.3025
24	24	2.35	0.0097	0.30	0.50	0.1674	70	70	2.37	0.0100	0.30	0.50	0.5367
24	24	2.35	0.0097	0.30	0.55	0.2607	70	70	2.37	0.0100	0.30	0.55	0.7569
24	24	2.35	0.0097	0.30	0.60	0.3777	70	70	2.37	0.0100	0.30	0.60	0.9024
24	24	2.35	0.0097	0.30	0.65	0.5133	70	70	2.37	0.0100	0.30	0.65	0.9712
24	24	2.35	0.0097	0.30	0.70	0.6556	70	70	2.37	0.0100	0.30	0.70	0.9944
24	24	2.35	0.0097	0.35	0.50	0.0886	70	70	2.37	0.0100	0.35	0.50	0.2981
24	24	2.35	0.0097	0.35	0.55	0.1526	70	70	2.37	0.0100	0.35	0.55	0.5230
24	24	2.35	0.0097	0.35	0.60	0.2447	70	70	2.37	0.0100	0.35	0.60	0.7400
24	24	2.35	0.0097	0.35	0.65	0.3668	70	70	2.37	0.0100	0.35	0.65	0.8943
24	24	2.35	0.0097	0.40	0.55	0.0821	70	70	2.37	0.0100	0.40	0.55	0.2857
24	24	2.35	0.0097	0.40	0.60	0.1469	70	70	2.37	0.0100	0.40	0.60	0.5095
25	25	2.36	0.0093	0.05	0.15	0.0560	80	80	2.35	0.0097	0.05	0.15	0.4099
25	25	2.36	0.0093	0.05	0.20	0.1575	80	80	2.35	0.0097	0.05	0.20	0.7310
25	25	2.36	0.0093	0.05	0.25	0.3098	80	80	2.35	0.0097	0.05	0.25	0.9182
25	25	2.36	0.0093	0.05	0.30	0.4867	80	80	2.35	0.0097	0.05	0.30	0.9832
25	25	2.36	0.0093	0.05	0.35	0.6555	80	80	2.35	0.0097	0.05	0.35	0.9976
25	25	2.36	0.0093	0.05	0.40	0.7919	80	80	2.35	0.0097	0.05	0.40	0.9998
25	25	2.36	0.0093	0.05	0.45	0.8871	80	80	2.35	0.0097	0.05	0.45	1.0000
25	25	2.36	0.0093	0.10	0.25	0.1472	80	80	2.35	0.0097	0.10	0.25	0.5704
25	25	2.36	0.0093	0.10	0.30	0.2699	80	80	2.35	0.0097	0.10	0.30	0.8152
25	25	2.36	0.0093	0.10	0.35	0.4171	80	80	2.35	0.0097	0.10	0.35	0.9439
25	25	2.36	0.0093	0.10	0.40	0.5685	80	80	2.35	0.0097	0.10	0.40	0.9881
25	25	2.36	0.0093	0.10	0.45	0.7053	80	80	2.35	0.0097	0.10	0.45	0.9983
25	25	2.36	0.0093	0.10	0.50	0.8157	80	80	2.35	0.0097	0.10	0.50	0.9998
25	25	2.36	0.0093	0.10	0.55	0.8954	80	80	2.35	0.0097	0.10	0.55	1.0000
25	25	2.36	0.0093	0.10	0.60	0.9470	80	80	2.35	0.0097	0.10	0.60	1.0000
25	25	2.36	0.0093	0.15	0.30	0.1345	80	80	2.35	0.0097	0.15	0.30	0.4779
25	25	2.36	0.0093	0.15	0.35	0.2353	80	80	2.35	0.0097	0.15	0.35	0.7347
25	25	2.36	0.0093	0.15	0.40	0.3602	80	80	2.35	0.0097	0.15	0.40	0.9011
25	25	2.36	0.0093	0.15	0.45	0.4973	80	80	2.35	0.0097	0.15	0.45	0.9736
25	25	2.36	0.0093	0.15	0.50	0.6325	80	80	2.35	0.0097	0.15	0.50	0.9951
25	25	2.36	0.0093	0.15	0.55	0.7531	80	80	2.35	0.0097	0.15	0.55	0.9994
25	25	2.36	0.0093	0.15	0.60	0.8503	80	80	2.35	0.0097	0.15	0.60	0.9999
25	25	2.36	0.0093	0.15	0.65	0.9203	80	80	2.35	0.0097	0.15	0.65	1.0000
25	25	2.36	0.0093	0.20	0.35	0.1190	80	80	2.35	0.0097	0.20	0.35	0.4182
25	25	2.36	0.0093	0.20	0.40	0.2040	80	80	2.35	0.0097	0.20	0.40	0.6722
25	25	2.36	0.0093	0.20	0.45	0.3138	80	80	2.35	0.0097	0.20	0.45	0.8609
25	25	2.36	0.0093	0.20	0.50	0.4422	80	80	2.35	0.0097	0.20	0.50	0.9572
25	25	2.36	0.0093	0.20	0.55	0.5787	80	80	2.35	0.0097	0.20	0.55	0.9910
25	25	2.36	0.0093	0.20	0.60	0.7100	80	80	2.35	0.0097	0.20	0.60	0.9988

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
25	25	2.36	0.0093	0.20	0.65	0.8224	80	80	2.35	0.0097	0.20	0.65	0.9999
25	25	2.36	0.0093	0.20	0.70	0.9061	80	80	2.35	0.0097	0.20	0.70	1.0000
25	25	2.36	0.0093	0.25	0.40	0.1042	80	80	2.35	0.0097	0.25	0.40	0.3747
25	25	2.36	0.0093	0.25	0.45	0.1791	80	80	2.35	0.0097	0.25	0.45	0.6237
25	25	2.36	0.0093	0.25	0.50	0.2814	80	80	2.35	0.0097	0.25	0.50	0.8301
25	25	2.36	0.0093	0.25	0.55	0.4081	80	80	2.35	0.0097	0.25	0.55	0.9460
25	25	2.36	0.0093	0.25	0.60	0.5497	80	80	2.35	0.0097	0.25	0.60	0.9886
25	25	2.36	0.0093	0.25	0.65	0.6902	80	80	2.35	0.0097	0.25	0.65	0.9985
25	25	2.36	0.0093	0.25	0.70	0.8119	80	80	2.35	0.0097	0.25	0.70	0.9999
25	25	2.36	0.0093	0.25	0.75	0.9024	80	80	2.35	0.0097	0.25	0.75	1.0000
25	25	2.36	0.0093	0.30	0.45	0.0933	80	80	2.35	0.0097	0.30	0.45	0.3484
25	25	2.36	0.0093	0.30	0.50	0.1641	80	80	2.35	0.0097	0.30	0.50	0.6018
25	25	2.36	0.0093	0.30	0.55	0.2650	80	80	2.35	0.0097	0.30	0.55	0.8190
25	25	2.36	0.0093	0.30	0.60	0.3938	80	80	2.35	0.0097	0.30	0.60	0.9421
25	25	2.36	0.0093	0.30	0.65	0.5398	80	80	2.35	0.0097	0.30	0.65	0.9877
25	25	2.36	0.0093	0.30	0.70	0.6854	80	80	2.35	0.0097	0.30	0.70	0.9984
25	25	2.36	0.0093	0.35	0.50	0.0880	80	80	2.35	0.0097	0.35	0.50	0.3446
25	25	2.36	0.0093	0.35	0.55	0.1584	80	80	2.35	0.0097	0.35	0.55	0.5981
25	25	2.36	0.0093	0.35	0.60	0.2600	80	80	2.35	0.0097	0.35	0.60	0.8161
25	25	2.36	0.0093	0.35	0.65	0.3907	80	80	2.35	0.0097	0.35	0.65	0.9411
25	25	2.36	0.0093	0.40	0.55	0.0867	80	80	2.35	0.0097	0.40	0.55	0.3458
25	25	2.36	0.0093	0.40	0.60	0.1574	80	80	2.35	0.0097	0.40	0.60	0.5976
26	26	2.34	0.0098	0.05	0.15	0.1063	90	90	2.34	0.0097	0.05	0.15	0.4697
26	26	2.34	0.0098	0.05	0.20	0.2248	90	90	2.34	0.0097	0.05	0.20	0.7954
26	26	2.34	0.0098	0.05	0.25	0.3758	90	90	2.34	0.0097	0.05	0.25	0.9500
26	26	2.34	0.0098	0.05	0.30	0.5416	90	90	2.34	0.0097	0.05	0.30	0.9920
26	26	2.34	0.0098	0.05	0.35	0.6969	90	90	2.34	0.0097	0.05	0.35	0.9992
26	26	2.34	0.0098	0.05	0.40	0.8208	90	90	2.34	0.0097	0.05	0.40	0.9999
26	26	2.34	0.0098	0.05	0.45	0.9056	90	90	2.34	0.0097	0.05	0.45	1.0000
26	26	2.34	0.0098	0.10	0.25	0.1699	90	90	2.34	0.0097	0.10	0.25	0.6310
26	26	2.34	0.0098	0.10	0.30	0.2957	90	90	2.34	0.0097	0.10	0.30	0.8640
26	26	2.34	0.0098	0.10	0.35	0.4451	90	90	2.34	0.0097	0.10	0.35	0.9667
26	26	2.34	0.0098	0.10	0.40	0.5967	90	90	2.34	0.0097	0.10	0.40	0.9946
26	26	2.34	0.0098	0.10	0.45	0.7312	90	90	2.34	0.0097	0.10	0.45	0.9994
26	26	2.34	0.0098	0.10	0.50	0.8369	90	90	2.34	0.0097	0.10	0.50	1.0000
26	26	2.34	0.0098	0.10	0.55	0.9108	90	90	2.34	0.0097	0.10	0.55	1.0000
26	26	2.34	0.0098	0.10	0.60	0.9569	90	90	2.34	0.0097	0.10	0.60	1.0000
26	26	2.34	0.0098	0.15	0.30	0.1457	90	90	2.34	0.0097	0.15	0.30	0.5355
26	26	2.34	0.0098	0.15	0.35	0.2515	90	90	2.34	0.0097	0.15	0.35	0.7912
26	26	2.34	0.0098	0.15	0.40	0.3815	90	90	2.34	0.0097	0.15	0.40	0.9343
26	26	2.34	0.0098	0.15	0.45	0.5224	90	90	2.34	0.0097	0.15	0.45	0.9861
26	26	2.34	0.0098	0.15	0.50	0.6591	90	90	2.34	0.0097	0.15	0.50	0.9981
26	26	2.34	0.0098	0.15	0.55	0.7783	90	90	2.34	0.0097	0.15	0.55	0.9998
26	26	2.34	0.0098	0.15	0.60	0.8714	90	90	2.34	0.0097	0.15	0.60	1.0000
26	26	2.34	0.0098	0.15	0.65	0.9353	90	90	2.34	0.0097	0.15	0.65	1.0000
26	26	2.34	0.0098	0.20	0.35	0.1270	90	90	2.34	0.0097	0.20	0.35	0.4690
26	26	2.34	0.0098	0.20	0.40	0.2173	90	90	2.34	0.0097	0.20	0.40	0.7326
26	26	2.34	0.0098	0.20	0.45	0.3335	90	90	2.34	0.0097	0.20	0.45	0.9050
26	26	2.34	0.0098	0.20	0.50	0.4684	90	90	2.34	0.0097	0.20	0.50	0.9767
26	26	2.34	0.0098	0.20	0.55	0.6094	90	90	2.34	0.0097	0.20	0.55	0.9962

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
26	26	2.34	0.0098	0.20	0.60	0.7411	90	90	2.34	0.0097	0.20	0.60	0.9996
26	26	2.34	0.0098	0.20	0.65	0.8490	90	90	2.34	0.0097	0.20	0.65	1.0000
26	26	2.34	0.0098	0.20	0.70	0.9248	90	90	2.34	0.0097	0.20	0.70	1.0000
26	26	2.34	0.0098	0.25	0.40	0.1114	90	90	2.34	0.0097	0.25	0.40	0.4295
26	26	2.34	0.0098	0.25	0.45	0.1926	90	90	2.34	0.0097	0.25	0.45	0.6912
26	26	2.34	0.0098	0.25	0.50	0.3032	90	90	2.34	0.0097	0.25	0.50	0.8784
26	26	2.34	0.0098	0.25	0.55	0.4385	90	90	2.34	0.0097	0.25	0.55	0.9674
26	26	2.34	0.0098	0.25	0.60	0.5856	90	90	2.34	0.0097	0.25	0.60	0.9945
26	26	2.34	0.0098	0.25	0.65	0.7258	90	90	2.34	0.0097	0.25	0.65	0.9995
26	26	2.34	0.0098	0.25	0.70	0.8413	90	90	2.34	0.0097	0.25	0.70	1.0000
26	26	2.34	0.0098	0.25	0.75	0.9222	90	90	2.34	0.0097	0.25	0.75	1.0000
26	26	2.34	0.0098	0.30	0.45	0.1015	90	90	2.34	0.0097	0.30	0.45	0.3967
26	26	2.34	0.0098	0.30	0.50	0.1799	90	90	2.34	0.0097	0.30	0.50	0.6591
26	26	2.34	0.0098	0.30	0.55	0.2903	90	90	2.34	0.0097	0.30	0.55	0.8632
26	26	2.34	0.0098	0.30	0.60	0.4279	90	90	2.34	0.0097	0.30	0.60	0.9635
26	26	2.34	0.0098	0.30	0.65	0.5785	90	90	2.34	0.0097	0.30	0.65	0.9939
26	26	2.34	0.0098	0.30	0.70	0.7224	90	90	2.34	0.0097	0.30	0.70	0.9994
26	26	2.34	0.0098	0.35	0.50	0.0980	90	90	2.34	0.0097	0.35	0.50	0.3830
26	26	2.34	0.0098	0.35	0.55	0.1764	90	90	2.34	0.0097	0.35	0.55	0.6507
26	26	2.34	0.0098	0.35	0.60	0.2874	90	90	2.34	0.0097	0.35	0.60	0.8596
26	26	2.34	0.0098	0.35	0.65	0.4259	90	90	2.34	0.0097	0.35	0.65	0.9626
26	26	2.34	0.0098	0.40	0.55	0.0978	90	90	2.34	0.0097	0.40	0.55	0.3827
26	26	2.34	0.0098	0.40	0.60	0.1761	90	90	2.34	0.0097	0.40	0.60	0.6497
27	27	2.37	0.0100	0.05	0.15	0.0678	100	100	2.34	0.0099	0.05	0.15	0.5281
27	27	2.37	0.0100	0.05	0.20	0.1795	100	100	2.34	0.0099	0.05	0.20	0.8462
27	27	2.37	0.0100	0.05	0.25	0.3366	100	100	2.34	0.0099	0.05	0.25	0.9700
27	27	2.37	0.0100	0.05	0.30	0.5116	100	100	2.34	0.0099	0.05	0.30	0.9964
27	27	2.37	0.0100	0.05	0.35	0.6760	100	100	2.34	0.0099	0.05	0.35	0.9997
27	27	2.37	0.0100	0.05	0.40	0.8088	100	100	2.34	0.0099	0.05	0.40	1.0000
27	27	2.37	0.0100	0.05	0.45	0.9009	100	100	2.34	0.0099	0.05	0.45	1.0000
27	27	2.37	0.0100	0.10	0.25	0.1475	100	100	2.34	0.0099	0.10	0.25	0.6899
27	27	2.37	0.0100	0.10	0.30	0.2719	100	100	2.34	0.0099	0.10	0.30	0.9026
27	27	2.37	0.0100	0.10	0.35	0.4271	100	100	2.34	0.0099	0.10	0.35	0.9806
27	27	2.37	0.0100	0.10	0.40	0.5902	100	100	2.34	0.0099	0.10	0.40	0.9976
27	27	2.37	0.0100	0.10	0.45	0.7356	100	100	2.34	0.0099	0.10	0.45	0.9998
27	27	2.37	0.0100	0.10	0.50	0.8470	100	100	2.34	0.0099	0.10	0.50	1.0000
27	27	2.37	0.0100	0.10	0.55	0.9211	100	100	2.34	0.0099	0.10	0.55	1.0000
27	27	2.37	0.0100	0.10	0.60	0.9644	100	100	2.34	0.0099	0.10	0.60	1.0000
27	27	2.37	0.0100	0.15	0.30	0.1338	100	100	2.34	0.0099	0.15	0.30	0.5886
27	27	2.37	0.0100	0.15	0.35	0.2449	100	100	2.34	0.0099	0.15	0.35	0.8379
27	27	2.37	0.0100	0.15	0.40	0.3852	100	100	2.34	0.0099	0.15	0.40	0.9577
27	27	2.37	0.0100	0.15	0.45	0.5367	100	100	2.34	0.0099	0.15	0.45	0.9929
27	27	2.37	0.0100	0.15	0.50	0.6800	100	100	2.34	0.0099	0.15	0.50	0.9993
27	27	2.37	0.0100	0.15	0.55	0.8003	100	100	2.34	0.0099	0.15	0.55	1.0000
27	27	2.37	0.0100	0.15	0.60	0.8899	100	100	2.34	0.0099	0.15	0.60	1.0000
27	27	2.37	0.0100	0.15	0.65	0.9480	100	100	2.34	0.0099	0.15	0.65	1.0000
27	27	2.37	0.0100	0.20	0.35	0.1264	100	100	2.34	0.0099	0.20	0.35	0.5206
27	27	2.37	0.0100	0.20	0.40	0.2241	100	100	2.34	0.0099	0.20	0.40	0.7835
27	27	2.37	0.0100	0.20	0.45	0.3498	100	100	2.34	0.0099	0.20	0.45	0.9343
27	27	2.37	0.0100	0.20	0.50	0.4932	100	100	2.34	0.0099	0.20	0.50	0.9872

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
27	27	2.37	0.0100	0.20	0.55	0.6392	100	100	2.34	0.0099	0.20	0.55	0.9984
27	27	2.37	0.0100	0.20	0.60	0.7704	100	100	2.34	0.0099	0.20	0.60	0.9999
27	27	2.37	0.0100	0.20	0.65	0.8727	100	100	2.34	0.0099	0.20	0.65	1.0000
27	27	2.37	0.0100	0.20	0.70	0.9403	100	100	2.34	0.0099	0.20	0.70	1.0000
27	27	2.37	0.0100	0.25	0.40	0.1170	100	100	2.34	0.0099	0.25	0.40	0.4759
27	27	2.37	0.0100	0.25	0.45	0.2058	100	100	2.34	0.0099	0.25	0.45	0.7453
27	27	2.37	0.0100	0.25	0.50	0.3257	100	100	2.34	0.0099	0.25	0.50	0.9139
27	27	2.37	0.0100	0.25	0.55	0.4694	100	100	2.34	0.0099	0.25	0.55	0.9808
27	27	2.37	0.0100	0.25	0.60	0.6206	100	100	2.34	0.0099	0.25	0.60	0.9974
27	27	2.37	0.0100	0.25	0.65	0.7587	100	100	2.34	0.0099	0.25	0.65	0.9998
27	27	2.37	0.0100	0.25	0.70	0.8669	100	100	2.34	0.0099	0.25	0.70	1.0000
27	27	2.37	0.0100	0.25	0.75	0.9384	100	100	2.34	0.0099	0.25	0.75	1.0000
27	27	2.37	0.0100	0.30	0.45	0.1103	100	100	2.34	0.0099	0.30	0.45	0.4432
27	27	2.37	0.0100	0.30	0.50	0.1969	100	100	2.34	0.0099	0.30	0.50	0.7106
27	27	2.37	0.0100	0.30	0.55	0.3166	100	100	2.34	0.0099	0.30	0.55	0.8971
27	27	2.37	0.0100	0.30	0.60	0.4619	100	100	2.34	0.0099	0.30	0.60	0.9770
27	27	2.37	0.0100	0.30	0.65	0.6154	100	100	2.34	0.0099	0.30	0.65	0.9970
27	27	2.37	0.0100	0.30	0.70	0.7562	100	100	2.34	0.0099	0.30	0.70	0.9998
27	27	2.37	0.0100	0.35	0.50	0.1088	100	100	2.34	0.0099	0.35	0.50	0.4196
27	27	2.37	0.0100	0.35	0.55	0.1954	100	100	2.34	0.0099	0.35	0.55	0.6962
27	27	2.37	0.0100	0.35	0.60	0.3152	100	100	2.34	0.0099	0.35	0.60	0.8926
27	27	2.37	0.0100	0.35	0.65	0.4607	100	100	2.34	0.0099	0.35	0.65	0.9763
27	27	2.37	0.0100	0.40	0.55	0.1095	100	100	2.34	0.0099	0.40	0.55	0.4164
27	27	2.37	0.0100	0.40	0.60	0.1957	100	100	2.34	0.0099	0.40	0.60	0.6945
28	28	2.41	0.0091	0.05	0.15	0.0746	150	150	2.34	0.0099	0.05	0.15	0.7258
28	28	2.41	0.0091	0.05	0.20	0.1940	150	150	2.34	0.0099	0.05	0.20	0.9603
28	28	2.41	0.0091	0.05	0.25	0.3580	150	150	2.34	0.0099	0.05	0.25	0.9976
28	28	2.41	0.0091	0.05	0.30	0.5365	150	150	2.34	0.0099	0.05	0.30	0.9999
28	28	2.41	0.0091	0.05	0.35	0.6991	150	150	2.34	0.0099	0.05	0.35	1.0000
28	28	2.41	0.0091	0.05	0.40	0.8260	150	150	2.34	0.0099	0.05	0.40	1.0000
28	28	2.41	0.0091	0.05	0.45	0.9111	150	150	2.34	0.0099	0.05	0.45	1.0000
28	28	2.41	0.0091	0.10	0.25	0.1557	150	150	2.34	0.0099	0.10	0.25	0.8744
28	28	2.41	0.0091	0.10	0.30	0.2825	150	150	2.34	0.0099	0.10	0.30	0.9831
28	28	2.41	0.0091	0.10	0.35	0.4366	150	150	2.34	0.0099	0.10	0.35	0.9989
28	28	2.41	0.0091	0.10	0.40	0.5956	150	150	2.34	0.0099	0.10	0.40	1.0000
28	28	2.41	0.0091	0.10	0.45	0.7375	150	150	2.34	0.0099	0.10	0.45	1.0000
28	28	2.41	0.0091	0.10	0.50	0.8480	150	150	2.34	0.0099	0.10	0.50	1.0000
28	28	2.41	0.0091	0.10	0.55	0.9231	150	150	2.34	0.0099	0.10	0.55	1.0000
28	28	2.41	0.0091	0.10	0.60	0.9668	150	150	2.34	0.0099	0.10	0.60	1.0000
28	28	2.41	0.0091	0.15	0.30	0.1335	150	150	2.34	0.0099	0.15	0.30	0.7879
28	28	2.41	0.0091	0.15	0.35	0.2410	150	150	2.34	0.0099	0.15	0.35	0.9585
28	28	2.41	0.0091	0.15	0.40	0.3788	150	150	2.34	0.0099	0.15	0.40	0.9959
28	28	2.41	0.0091	0.15	0.45	0.5324	150	150	2.34	0.0099	0.15	0.45	0.9998
28	28	2.41	0.0091	0.15	0.50	0.6819	150	150	2.34	0.0099	0.15	0.50	1.0000
28	28	2.41	0.0091	0.15	0.55	0.8080	150	150	2.34	0.0099	0.15	0.55	1.0000
28	28	2.41	0.0091	0.15	0.60	0.8990	150	150	2.34	0.0099	0.15	0.60	1.0000
28	28	2.41	0.0091	0.15	0.65	0.9544	150	150	2.34	0.0099	0.15	0.65	1.0000
28	28	2.41	0.0091	0.20	0.35	0.1197	150	150	2.34	0.0099	0.20	0.35	0.7220
28	28	2.41	0.0091	0.20	0.40	0.2171	150	150	2.34	0.0099	0.20	0.40	0.9320
28	28	2.41	0.0091	0.20	0.45	0.3481	150	150	2.34	0.0099	0.20	0.45	0.9912

Table B.12: continue on next page

Table B.12: –continued from previous page

n_1	n_2	z_p	pvalue	p_1	p_2	power	n_1	n_2	z_p	pvalue	p_1	p_2	power
28	28	2.41	0.0091	0.20	0.50	0.5004	150	150	2.34	0.0099	0.20	0.50	0.9994
28	28	2.41	0.0091	0.20	0.55	0.6529	150	150	2.34	0.0099	0.20	0.55	1.0000
28	28	2.41	0.0091	0.20	0.60	0.7838	150	150	2.34	0.0099	0.20	0.60	1.0000
28	28	2.41	0.0091	0.20	0.65	0.8805	150	150	2.34	0.0099	0.20	0.65	1.0000
28	28	2.41	0.0091	0.20	0.70	0.9425	150	150	2.34	0.0099	0.20	0.70	1.0000
28	28	2.41	0.0091	0.25	0.40	0.1136	150	150	2.34	0.0099	0.25	0.40	0.6728
28	28	2.41	0.0091	0.25	0.45	0.2073	150	150	2.34	0.0099	0.25	0.45	0.9076
28	28	2.41	0.0091	0.25	0.50	0.3339	150	150	2.34	0.0099	0.25	0.50	0.9864
28	28	2.41	0.0091	0.25	0.55	0.4807	150	150	2.34	0.0099	0.25	0.55	0.9990
28	28	2.41	0.0091	0.25	0.60	0.6287	150	150	2.34	0.0099	0.25	0.60	1.0000
28	28	2.41	0.0091	0.25	0.65	0.7600	150	150	2.34	0.0099	0.25	0.65	1.0000
28	28	2.41	0.0091	0.25	0.70	0.8638	150	150	2.34	0.0099	0.25	0.70	1.0000
28	28	2.41	0.0091	0.25	0.75	0.9357	150	150	2.34	0.0099	0.25	0.75	1.0000
28	28	2.41	0.0091	0.30	0.45	0.1119	150	150	2.34	0.0099	0.30	0.45	0.6413
28	28	2.41	0.0091	0.30	0.50	0.2007	150	150	2.34	0.0099	0.30	0.50	0.8911
28	28	2.41	0.0091	0.30	0.55	0.3193	150	150	2.34	0.0099	0.30	0.55	0.9816
28	28	2.41	0.0091	0.30	0.60	0.4589	150	150	2.34	0.0099	0.30	0.60	0.9985
28	28	2.41	0.0091	0.30	0.65	0.6068	150	150	2.34	0.0099	0.30	0.65	0.9999
28	28	2.41	0.0091	0.30	0.70	0.7475	150	150	2.34	0.0099	0.30	0.70	1.0000
28	28	2.41	0.0091	0.35	0.50	0.1080	150	150	2.34	0.0099	0.35	0.50	0.6121
28	28	2.41	0.0091	0.35	0.55	0.1906	150	150	2.34	0.0099	0.35	0.55	0.8726
28	28	2.41	0.0091	0.35	0.60	0.3046	150	150	2.34	0.0099	0.35	0.60	0.9783
28	28	2.41	0.0091	0.35	0.65	0.4474	150	150	2.34	0.0099	0.35	0.65	0.9983
28	28	2.41	0.0091	0.40	0.55	0.1027	150	150	2.34	0.0099	0.40	0.55	0.5944
28	28	2.41	0.0091	0.40	0.60	0.1848	150	150	2.34	0.0099	0.40	0.60	0.8684

Table B.12: concluded from previous page

Table B.13: P-values calculated for the z-unpooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}= \mathbf{0.05}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
10	20	2.24	0.2119	0.0427
10	30	2.74	0.2087	0.0427
10	40	3.17	0.2132	0.0445
10	50	3.54	0.2171	0.0463
10	60	3.88	0.2197	0.0479
10	70	4.19	0.2214	0.0494
10	80	4.65	0.2338	0.0430
10	90	4.91	0.2335	0.0448
10	100	5.16	0.2332	0.0464
20	30	1.87	0.4135	0.0412
20	40	2.14	0.1048	0.0467
20	50	2.36	0.1069	0.0480
20	60	2.59	0.1067	0.0486
20	70	2.79	0.1079	0.0498
20	80	3.19	0.1194	0.0385
20	90	3.36	0.1194	0.0405
20	100	3.52	0.1194	0.0423
30	40	1.79	0.2770	0.0459
30	50	1.84	0.2094	0.0468
30	60	2.08	0.0714	0.0489
30	70	2.33	0.0750	0.0427
30	80	2.55	0.0782	0.0387
30	90	2.76	0.0810	0.0359
30	100	2.75	0.0748	0.0462
40	50	1.78	0.2003	0.0442
40	60	1.86	0.3169	0.0381
40	70	1.79	0.3262	0.0473
40	80	2.1	0.0540	0.0500
40	90	2.31	0.0577	0.0402
40	100	2.52	0.0526	0.0498

Table B.13: concluded from previous page

Table B.14: P-values calculated for the z-unpooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
10	20	2.59	0.2478	0.0242
10	30	3.31	0.2569	0.0185
10	40	3.66	0.2529	0.0235
10	50	4.20	0.2668	0.0211
10	60	4.48	0.2624	0.0247
10	70	4.93	0.2713	0.0230
10	80	5.34	0.2781	0.0218
10	90	5.56	0.2735	0.0245
10	100	5.93	0.2787	0.0234
20	30	2.30	0.3053	0.0209
20	40	2.66	0.1430	0.0171
20	50	2.86	0.1388	0.0208
20	60	3.04	0.1331	0.0236
20	70	3.42	0.1419	0.0191
20	80	3.58	0.1397	0.0219
20	90	3.73	0.1380	0.0244
20	100	4.04	0.1450	0.0212
30	40	2.21	0.1329	0.0236
30	50	2.36	0.1012	0.0200
30	60	2.59	0.0980	0.0188
30	70	2.79	0.0977	0.0183
30	80	2.99	0.0982	0.0180
30	90	3.17	0.0977	0.0177
30	100	3.15	0.0909	0.0245
40	50	2.05	0.3855	0.0245
40	60	2.06	0.3861	0.0249
40	70	2.33	0.0802	0.0246
40	80	2.55	0.0749	0.0198
40	90	2.76	0.0754	0.0171
40	100	2.75	0.0690	0.0227

Table B.14: concluded from previous page

Table B.15: P-values calculated for the z-unpooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}= \mathbf{0.01}$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_u}$	p	pvalue
10	20	3.29	0.3138	0.0071
10	30	3.88	0.3056	0.0077
10	40	4.39	0.3116	0.0085
10	50	4.86	0.3159	0.0092
10	60	5.28	0.3187	0.0097
10	70	5.86	0.3328	0.0083
10	80	6.21	0.3328	0.0089
10	90	6.55	0.3327	0.0094
10	100	6.86	0.3326	0.0098
20	30	2.74	0.2031	0.0085
20	40	3.11	0.1540	0.0097
20	50	3.32	0.1644	0.0085
20	60	3.68	0.1703	0.0077
20	70	3.92	0.1642	0.0100
20	80	4.12	0.1701	0.0092
20	90	4.42	0.1747	0.0087
20	100	4.69	0.1786	0.0083
30	40	2.50	0.4129	0.0097
30	50	2.86	0.1391	0.0068
30	60	3.04	0.1253	0.0072
30	70	3.22	0.1207	0.0078
30	80	3.39	0.1154	0.0081
30	90	3.55	0.1151	0.0088
30	100	3.70	0.1144	0.0093
40	50	2.50	0.2674	0.0091
40	60	2.62	0.1579	0.0096
40	70	2.79	0.1016	0.0090
40	80	2.99	0.0969	0.0079
40	90	3.17	0.0934	0.0073
40	100	3.34	0.0928	0.0070

Table B.15: concluded from previous page

Table B.16: Achieved power and p-values calculated for the z-unpooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.05**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.24	0.0427	0.05	0.15	0.1023	20	90	3.36	0.0405	0.05	0.15	0.2907
10	20	2.24	0.0427	0.05	0.20	0.2249	20	90	3.36	0.0405	0.05	0.20	0.3622
10	20	2.24	0.0427	0.05	0.25	0.3633	20	90	3.36	0.0405	0.05	0.25	0.4454
10	20	2.24	0.0427	0.05	0.30	0.4926	20	90	3.36	0.0405	0.05	0.30	0.6045
10	20	2.24	0.0427	0.05	0.35	0.6043	20	90	3.36	0.0405	0.05	0.35	0.7496
10	20	2.24	0.0427	0.05	0.40	0.7000	20	90	3.36	0.0405	0.05	0.40	0.8544
10	20	2.24	0.0427	0.05	0.45	0.7820	20	90	3.36	0.0405	0.05	0.45	0.9255
10	20	2.24	0.0427	0.10	0.25	0.2201	20	90	3.36	0.0405	0.10	0.25	0.1843
10	20	2.24	0.0427	0.10	0.30	0.3108	20	90	3.36	0.0405	0.10	0.30	0.3045
10	20	2.24	0.0427	0.10	0.35	0.4034	20	90	3.36	0.0405	0.10	0.35	0.4406
10	20	2.24	0.0427	0.10	0.40	0.4989	20	90	3.36	0.0405	0.10	0.40	0.5825
10	20	2.24	0.0427	0.10	0.45	0.5956	20	90	3.36	0.0405	0.10	0.45	0.7141
10	20	2.24	0.0427	0.10	0.50	0.6886	20	90	3.36	0.0405	0.10	0.50	0.8222
10	20	2.24	0.0427	0.10	0.55	0.7727	20	90	3.36	0.0405	0.10	0.55	0.9019
10	20	2.24	0.0427	0.10	0.60	0.8440	20	90	3.36	0.0405	0.10	0.60	0.9530
10	20	2.24	0.0427	0.15	0.30	0.1909	20	90	3.36	0.0405	0.15	0.30	0.1352
10	20	2.24	0.0427	0.15	0.35	0.2618	20	90	3.36	0.0405	0.15	0.35	0.2229
10	20	2.24	0.0427	0.15	0.40	0.3438	20	90	3.36	0.0405	0.15	0.40	0.3374
10	20	2.24	0.0427	0.15	0.45	0.4355	20	90	3.36	0.0405	0.15	0.45	0.4682
10	20	2.24	0.0427	0.15	0.50	0.5327	20	90	3.36	0.0405	0.15	0.50	0.6046
10	20	2.24	0.0427	0.15	0.55	0.6299	20	90	3.36	0.0405	0.15	0.55	0.7327
10	20	2.24	0.0427	0.15	0.60	0.7221	20	90	3.36	0.0405	0.15	0.60	0.8389
10	20	2.24	0.0427	0.15	0.65	0.8038	20	90	3.36	0.0405	0.15	0.65	0.9144
10	20	2.24	0.0427	0.20	0.35	0.1647	20	90	3.36	0.0405	0.20	0.35	0.1002
10	20	2.24	0.0427	0.20	0.40	0.2288	20	90	3.36	0.0405	0.20	0.40	0.1712
10	20	2.24	0.0427	0.20	0.45	0.3064	20	90	3.36	0.0405	0.20	0.45	0.2673
10	20	2.24	0.0427	0.20	0.50	0.3953	20	90	3.36	0.0405	0.20	0.50	0.3879
10	20	2.24	0.0427	0.20	0.55	0.4923	20	90	3.36	0.0405	0.20	0.55	0.5247
10	20	2.24	0.0427	0.20	0.60	0.5923	20	90	3.36	0.0405	0.20	0.60	0.6633
10	20	2.24	0.0427	0.20	0.65	0.6889	20	90	3.36	0.0405	0.20	0.65	0.7847
10	20	2.24	0.0427	0.20	0.70	0.7750	20	90	3.36	0.0405	0.20	0.70	0.8780
10	20	2.24	0.0427	0.25	0.40	0.1469	20	90	3.36	0.0405	0.25	0.40	0.0772
10	20	2.24	0.0427	0.25	0.45	0.2074	20	90	3.36	0.0405	0.25	0.45	0.1349
10	20	2.24	0.0427	0.25	0.50	0.2819	20	90	3.36	0.0405	0.25	0.50	0.2194
10	20	2.24	0.0427	0.25	0.55	0.3693	20	90	3.36	0.0405	0.25	0.55	0.3323
10	20	2.24	0.0427	0.25	0.60	0.4662	20	90	3.36	0.0405	0.25	0.60	0.4675
10	20	2.24	0.0427	0.25	0.65	0.5665	20	90	3.36	0.0405	0.25	0.65	0.6088
10	20	2.24	0.0427	0.25	0.70	0.6626	20	90	3.36	0.0405	0.25	0.70	0.7410
10	20	2.24	0.0427	0.25	0.75	0.7488	20	90	3.36	0.0405	0.25	0.75	0.8509
10	20	2.24	0.0427	0.30	0.45	0.1349	20	90	3.36	0.0405	0.30	0.45	0.0605
10	20	2.24	0.0427	0.30	0.50	0.1931	20	90	3.36	0.0405	0.30	0.50	0.1100
10	20	2.24	0.0427	0.30	0.55	0.2659	20	90	3.36	0.0405	0.30	0.55	0.1866
10	20	2.24	0.0427	0.30	0.60	0.3518	20	90	3.36	0.0405	0.30	0.60	0.2930
10	20	2.24	0.0427	0.30	0.65	0.4462	20	90	3.36	0.0405	0.30	0.65	0.4232

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.24	0.0427	0.30	0.70	0.5430	20	90	3.36	0.0405	0.30	0.70	0.5683
10	20	2.24	0.0427	0.35	0.50	0.1267	20	90	3.36	0.0405	0.35	0.50	0.0490
10	20	2.24	0.0427	0.35	0.55	0.1833	20	90	3.36	0.0405	0.35	0.55	0.0929
10	20	2.24	0.0427	0.35	0.60	0.2539	20	90	3.36	0.0405	0.35	0.60	0.1629
10	20	2.24	0.0427	0.35	0.65	0.3359	20	90	3.36	0.0405	0.35	0.65	0.2622
10	20	2.24	0.0427	0.40	0.55	0.1205	20	90	3.36	0.0405	0.40	0.55	0.0408
10	20	2.24	0.0427	0.40	0.60	0.1746	20	90	3.36	0.0405	0.40	0.60	0.0800
10	30	2.74	0.0427	0.05	0.15	0.0914	20	100	3.52	0.0423	0.05	0.15	0.3000
10	30	2.74	0.0427	0.05	0.20	0.2356	20	100	3.52	0.0423	0.05	0.20	0.3615
10	30	2.74	0.0427	0.05	0.25	0.3929	20	100	3.52	0.0423	0.05	0.25	0.4368
10	30	2.74	0.0427	0.05	0.30	0.5159	20	100	3.52	0.0423	0.05	0.30	0.5976
10	30	2.74	0.0427	0.05	0.35	0.6036	20	100	3.52	0.0423	0.05	0.35	0.7365
10	30	2.74	0.0427	0.05	0.40	0.6790	20	100	3.52	0.0423	0.05	0.40	0.8367
10	30	2.74	0.0427	0.05	0.45	0.7556	20	100	3.52	0.0423	0.05	0.45	0.9135
10	30	2.74	0.0427	0.10	0.25	0.2305	20	100	3.52	0.0423	0.10	0.25	0.1778
10	30	2.74	0.0427	0.10	0.30	0.3086	20	100	3.52	0.0423	0.10	0.30	0.2959
10	30	2.74	0.0427	0.10	0.35	0.3775	20	100	3.52	0.0423	0.10	0.35	0.4185
10	30	2.74	0.0427	0.10	0.40	0.4549	20	100	3.52	0.0423	0.10	0.40	0.5510
10	30	2.74	0.0427	0.10	0.45	0.5465	20	100	3.52	0.0423	0.10	0.45	0.6852
10	30	2.74	0.0427	0.10	0.50	0.6422	20	100	3.52	0.0423	0.10	0.50	0.7982
10	30	2.74	0.0427	0.10	0.55	0.7293	20	100	3.52	0.0423	0.10	0.55	0.8843
10	30	2.74	0.0427	0.10	0.60	0.8035	20	100	3.52	0.0423	0.10	0.60	0.9415
10	30	2.74	0.0427	0.15	0.30	0.1794	20	100	3.52	0.0423	0.15	0.30	0.1288
10	30	2.74	0.0427	0.15	0.35	0.2296	20	100	3.52	0.0423	0.15	0.35	0.2042
10	30	2.74	0.0427	0.15	0.40	0.2950	20	100	3.52	0.0423	0.15	0.40	0.3081
10	30	2.74	0.0427	0.15	0.45	0.3782	20	100	3.52	0.0423	0.15	0.45	0.4344
10	30	2.74	0.0427	0.15	0.50	0.4706	20	100	3.52	0.0423	0.15	0.50	0.5688
10	30	2.74	0.0427	0.15	0.55	0.5629	20	100	3.52	0.0423	0.15	0.55	0.6984
10	30	2.74	0.0427	0.15	0.60	0.6522	20	100	3.52	0.0423	0.15	0.60	0.8100
10	30	2.74	0.0427	0.15	0.65	0.7370	20	100	3.52	0.0423	0.15	0.65	0.8952
10	30	2.74	0.0427	0.20	0.35	0.1354	20	100	3.52	0.0423	0.20	0.35	0.0885
10	30	2.74	0.0427	0.20	0.40	0.1847	20	100	3.52	0.0423	0.20	0.40	0.1511
10	30	2.74	0.0427	0.20	0.45	0.2507	20	100	3.52	0.0423	0.20	0.45	0.2394
10	30	2.74	0.0427	0.20	0.50	0.3281	20	100	3.52	0.0423	0.20	0.50	0.3522
10	30	2.74	0.0427	0.20	0.55	0.4121	20	100	3.52	0.0423	0.20	0.55	0.4828
10	30	2.74	0.0427	0.20	0.60	0.5020	20	100	3.52	0.0423	0.20	0.60	0.6204
10	30	2.74	0.0427	0.20	0.65	0.5958	20	100	3.52	0.0423	0.20	0.65	0.7501
10	30	2.74	0.0427	0.20	0.70	0.6884	20	100	3.52	0.0423	0.20	0.70	0.8561
10	30	2.74	0.0427	0.25	0.40	0.1113	20	100	3.52	0.0423	0.25	0.40	0.0659
10	30	2.74	0.0427	0.25	0.45	0.1590	20	100	3.52	0.0423	0.25	0.45	0.1165
10	30	2.74	0.0427	0.25	0.50	0.2180	20	100	3.52	0.0423	0.25	0.50	0.1918
10	30	2.74	0.0427	0.25	0.55	0.2871	20	100	3.52	0.0423	0.25	0.55	0.2938
10	30	2.74	0.0427	0.25	0.60	0.3675	20	100	3.52	0.0423	0.25	0.60	0.4212
10	30	2.74	0.0427	0.25	0.65	0.4582	20	100	3.52	0.0423	0.25	0.65	0.5648
10	30	2.74	0.0427	0.25	0.70	0.5552	20	100	3.52	0.0423	0.25	0.70	0.7065
10	30	2.74	0.0427	0.25	0.75	0.6544	20	100	3.52	0.0423	0.25	0.75	0.8253
10	30	2.74	0.0427	0.30	0.45	0.0963	20	100	3.52	0.0423	0.30	0.45	0.0504
10	30	2.74	0.0427	0.30	0.50	0.1380	20	100	3.52	0.0423	0.30	0.50	0.0924
10	30	2.74	0.0427	0.30	0.55	0.1905	20	100	3.52	0.0423	0.30	0.55	0.1581
10	30	2.74	0.0427	0.30	0.60	0.2560	20	100	3.52	0.0423	0.30	0.60	0.2535

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	30	2.74	0.0427	0.30	0.65	0.3352	20	100	3.52	0.0423	0.30	0.65	0.3797
10	30	2.74	0.0427	0.30	0.70	0.4265	20	100	3.52	0.0423	0.30	0.70	0.5267
10	30	2.74	0.0427	0.35	0.50	0.0830	20	100	3.52	0.0423	0.35	0.50	0.0394
10	30	2.74	0.0427	0.35	0.55	0.1201	20	100	3.52	0.0423	0.35	0.55	0.0752
10	30	2.74	0.0427	0.35	0.60	0.1695	20	100	3.52	0.0423	0.35	0.60	0.1351
10	30	2.74	0.0427	0.35	0.65	0.2331	20	100	3.52	0.0423	0.35	0.65	0.2270
10	30	2.74	0.0427	0.40	0.55	0.0717	20	100	3.52	0.0423	0.40	0.55	0.0316
10	30	2.74	0.0427	0.40	0.60	0.1063	20	100	3.52	0.0423	0.40	0.60	0.0635
10	40	3.17	0.0445	0.05	0.15	0.0811	30	40	1.79	0.0459	0.05	0.15	0.3765
10	40	3.17	0.0445	0.05	0.20	0.2436	30	40	1.79	0.0459	0.05	0.20	0.5828
10	40	3.17	0.0445	0.05	0.25	0.4194	30	40	1.79	0.0459	0.05	0.25	0.7641
10	40	3.17	0.0445	0.05	0.30	0.5342	30	40	1.79	0.0459	0.05	0.30	0.8863
10	40	3.17	0.0445	0.05	0.35	0.5921	30	40	1.79	0.0459	0.05	0.35	0.9532
10	40	3.17	0.0445	0.05	0.40	0.6360	30	40	1.79	0.0459	0.05	0.40	0.9837
10	40	3.17	0.0445	0.05	0.45	0.6979	30	40	1.79	0.0459	0.05	0.45	0.9953
10	40	3.17	0.0445	0.10	0.25	0.2444	30	40	1.79	0.0459	0.10	0.25	0.4713
10	40	3.17	0.0445	0.10	0.30	0.3124	30	40	1.79	0.0459	0.10	0.30	0.6573
10	40	3.17	0.0445	0.10	0.35	0.3522	30	40	1.79	0.0459	0.10	0.35	0.8070
10	40	3.17	0.0445	0.10	0.40	0.3969	30	40	1.79	0.0459	0.10	0.40	0.9061
10	40	3.17	0.0445	0.10	0.45	0.4713	30	40	1.79	0.0459	0.10	0.45	0.9606
10	40	3.17	0.0445	0.10	0.50	0.5704	30	40	1.79	0.0459	0.10	0.50	0.9857
10	40	3.17	0.0445	0.10	0.55	0.6681	30	40	1.79	0.0459	0.10	0.55	0.9956
10	40	3.17	0.0445	0.10	0.60	0.7483	30	40	1.79	0.0459	0.10	0.60	0.9989
10	40	3.17	0.0445	0.15	0.30	0.1772	30	40	1.79	0.0459	0.15	0.30	0.4167
10	40	3.17	0.0445	0.15	0.35	0.2035	30	40	1.79	0.0459	0.15	0.35	0.5962
10	40	3.17	0.0445	0.15	0.40	0.2409	30	40	1.79	0.0459	0.15	0.40	0.7514
10	40	3.17	0.0445	0.15	0.45	0.3073	30	40	1.79	0.0459	0.15	0.45	0.8645
10	40	3.17	0.0445	0.15	0.50	0.3977	30	40	1.79	0.0459	0.15	0.50	0.9355
10	40	3.17	0.0445	0.15	0.55	0.4910	30	40	1.79	0.0459	0.15	0.55	0.9737
10	40	3.17	0.0445	0.15	0.60	0.5770	30	40	1.79	0.0459	0.15	0.60	0.9911
10	40	3.17	0.0445	0.15	0.65	0.6615	30	40	1.79	0.0459	0.15	0.65	0.9975
10	40	3.17	0.0445	0.20	0.35	0.1139	30	40	1.79	0.0459	0.20	0.35	0.3824
10	40	3.17	0.0445	0.20	0.40	0.1417	30	40	1.79	0.0459	0.20	0.40	0.5492
10	40	3.17	0.0445	0.20	0.45	0.1930	30	40	1.79	0.0459	0.20	0.45	0.7042
10	40	3.17	0.0445	0.20	0.50	0.2642	30	40	1.79	0.0459	0.20	0.50	0.8284
10	40	3.17	0.0445	0.20	0.55	0.3413	30	40	1.79	0.0459	0.20	0.55	0.9137
10	40	3.17	0.0445	0.20	0.60	0.4200	30	40	1.79	0.0459	0.20	0.60	0.9631
10	40	3.17	0.0445	0.20	0.65	0.5068	30	40	1.79	0.0459	0.20	0.65	0.9869
10	40	3.17	0.0445	0.20	0.70	0.5987	30	40	1.79	0.0459	0.20	0.70	0.9963
10	40	3.17	0.0445	0.25	0.40	0.0804	30	40	1.79	0.0459	0.25	0.40	0.3520
10	40	3.17	0.0445	0.25	0.45	0.1165	30	40	1.79	0.0459	0.25	0.45	0.5117
10	40	3.17	0.0445	0.25	0.50	0.1674	30	40	1.79	0.0459	0.25	0.50	0.6694
10	40	3.17	0.0445	0.25	0.55	0.2252	30	40	1.79	0.0459	0.25	0.55	0.8023
10	40	3.17	0.0445	0.25	0.60	0.2900	30	40	1.79	0.0459	0.25	0.60	0.8977
10	40	3.17	0.0445	0.25	0.65	0.3680	30	40	1.79	0.0459	0.25	0.65	0.9554
10	40	3.17	0.0445	0.25	0.70	0.4555	30	40	1.79	0.0459	0.25	0.70	0.9843
10	40	3.17	0.0445	0.25	0.75	0.5427	30	40	1.79	0.0459	0.25	0.75	0.9957
10	40	3.17	0.0445	0.30	0.45	0.0672	30	40	1.79	0.0459	0.30	0.45	0.3298
10	40	3.17	0.0445	0.30	0.50	0.1009	30	40	1.79	0.0459	0.30	0.50	0.4865
10	40	3.17	0.0445	0.30	0.55	0.1411	30	40	1.79	0.0459	0.30	0.55	0.6462

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	40	3.17	0.0445	0.30	0.60	0.1902	30	40	1.79	0.0459	0.30	0.60	0.7855
10	40	3.17	0.0445	0.30	0.65	0.2534	30	40	1.79	0.0459	0.30	0.65	0.8887
10	40	3.17	0.0445	0.30	0.70	0.3281	30	40	1.79	0.0459	0.30	0.70	0.9522
10	40	3.17	0.0445	0.35	0.50	0.0576	30	40	1.79	0.0459	0.35	0.50	0.3152
10	40	3.17	0.0445	0.35	0.55	0.0838	30	40	1.79	0.0459	0.35	0.55	0.4706
10	40	3.17	0.0445	0.35	0.60	0.1182	30	40	1.79	0.0459	0.35	0.60	0.6334
10	40	3.17	0.0445	0.35	0.65	0.1653	30	40	1.79	0.0459	0.35	0.65	0.7785
10	40	3.17	0.0445	0.40	0.55	0.0469	30	40	1.79	0.0459	0.40	0.55	0.3066
10	40	3.17	0.0445	0.40	0.60	0.0693	30	40	1.79	0.0459	0.40	0.60	0.4635
10	50	3.54	0.0463	0.05	0.15	0.0718	30	50	1.84	0.0468	0.05	0.15	0.4029
10	50	3.54	0.0463	0.05	0.20	0.2493	30	50	1.84	0.0468	0.05	0.20	0.6220
10	50	3.54	0.0463	0.05	0.25	0.4418	30	50	1.84	0.0468	0.05	0.25	0.8031
10	50	3.54	0.0463	0.05	0.30	0.5518	30	50	1.84	0.0468	0.05	0.30	0.9160
10	50	3.54	0.0463	0.05	0.35	0.5923	30	50	1.84	0.0468	0.05	0.35	0.9700
10	50	3.54	0.0463	0.05	0.40	0.6155	30	50	1.84	0.0468	0.05	0.40	0.9908
10	50	3.54	0.0463	0.05	0.45	0.6606	30	50	1.84	0.0468	0.05	0.45	0.9975
10	50	3.54	0.0463	0.10	0.25	0.2573	30	50	1.84	0.0468	0.10	0.25	0.5116
10	50	3.54	0.0463	0.10	0.30	0.3215	30	50	1.84	0.0468	0.10	0.30	0.7006
10	50	3.54	0.0463	0.10	0.35	0.3470	30	50	1.84	0.0468	0.10	0.35	0.8378
10	50	3.54	0.0463	0.10	0.40	0.3701	30	50	1.84	0.0468	0.10	0.40	0.9226
10	50	3.54	0.0463	0.10	0.45	0.4248	30	50	1.84	0.0468	0.10	0.45	0.9683
10	50	3.54	0.0463	0.10	0.50	0.5209	30	50	1.84	0.0468	0.10	0.50	0.9892
10	50	3.54	0.0463	0.10	0.55	0.6281	30	50	1.84	0.0468	0.10	0.55	0.9970
10	50	3.54	0.0463	0.10	0.60	0.7087	30	50	1.84	0.0468	0.10	0.60	0.9994
10	50	3.54	0.0463	0.15	0.30	0.1817	30	50	1.84	0.0468	0.15	0.30	0.4419
10	50	3.54	0.0463	0.15	0.35	0.1972	30	50	1.84	0.0468	0.15	0.35	0.6145
10	50	3.54	0.0463	0.15	0.40	0.2164	30	50	1.84	0.0468	0.15	0.40	0.7639
10	50	3.54	0.0463	0.15	0.45	0.2652	30	50	1.84	0.0468	0.15	0.45	0.8750
10	50	3.54	0.0463	0.15	0.50	0.3514	30	50	1.84	0.0468	0.15	0.50	0.9440
10	50	3.54	0.0463	0.15	0.55	0.4485	30	50	1.84	0.0468	0.15	0.55	0.9792
10	50	3.54	0.0463	0.15	0.60	0.5252	30	50	1.84	0.0468	0.15	0.60	0.9938
10	50	3.54	0.0463	0.15	0.65	0.5890	30	50	1.84	0.0468	0.15	0.65	0.9986
10	50	3.54	0.0463	0.20	0.35	0.1084	30	50	1.84	0.0468	0.20	0.35	0.3823
10	50	3.54	0.0463	0.20	0.40	0.1225	30	50	1.84	0.0468	0.20	0.40	0.5509
10	50	3.54	0.0463	0.20	0.45	0.1602	30	50	1.84	0.0468	0.20	0.45	0.7120
10	50	3.54	0.0463	0.20	0.50	0.2269	30	50	1.84	0.0468	0.20	0.50	0.8407
10	50	3.54	0.0463	0.20	0.55	0.3027	30	50	1.84	0.0468	0.20	0.55	0.9258
10	50	3.54	0.0463	0.20	0.60	0.3659	30	50	1.84	0.0468	0.20	0.60	0.9716
10	50	3.54	0.0463	0.20	0.65	0.4271	30	50	1.84	0.0468	0.20	0.65	0.9912
10	50	3.54	0.0463	0.20	0.70	0.5116	30	50	1.84	0.0468	0.20	0.70	0.9978
10	50	3.54	0.0463	0.25	0.40	0.0670	30	50	1.84	0.0468	0.25	0.40	0.3451
10	50	3.54	0.0463	0.25	0.45	0.0932	30	50	1.84	0.0468	0.25	0.45	0.5136
10	50	3.54	0.0463	0.25	0.50	0.1400	30	50	1.84	0.0468	0.25	0.50	0.6819
10	50	3.54	0.0463	0.25	0.55	0.1936	30	50	1.84	0.0468	0.25	0.55	0.8211
10	50	3.54	0.0463	0.25	0.60	0.2409	30	50	1.84	0.0468	0.25	0.60	0.9149
10	50	3.54	0.0463	0.25	0.65	0.2932	30	50	1.84	0.0468	0.25	0.65	0.9661
10	50	3.54	0.0463	0.25	0.70	0.3712	30	50	1.84	0.0468	0.25	0.70	0.9890
10	50	3.54	0.0463	0.25	0.75	0.4660	30	50	1.84	0.0468	0.25	0.75	0.9973
10	50	3.54	0.0463	0.30	0.45	0.0521	30	50	1.84	0.0468	0.30	0.45	0.3267
10	50	3.54	0.0463	0.30	0.50	0.0823	30	50	1.84	0.0468	0.30	0.50	0.4962

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	50	3.54	0.0463	0.30	0.55	0.1174	30	50	1.84	0.0468	0.30	0.55	0.6676
10	50	3.54	0.0463	0.30	0.60	0.1501	30	50	1.84	0.0468	0.30	0.60	0.8093
10	50	3.54	0.0463	0.30	0.65	0.1909	30	50	1.84	0.0468	0.30	0.65	0.9063
10	50	3.54	0.0463	0.30	0.70	0.2553	30	50	1.84	0.0468	0.30	0.70	0.9621
10	50	3.54	0.0463	0.35	0.50	0.0459	30	50	1.84	0.0468	0.35	0.50	0.3206
10	50	3.54	0.0463	0.35	0.55	0.0672	30	50	1.84	0.0468	0.35	0.55	0.4880
10	50	3.54	0.0463	0.35	0.60	0.0884	30	50	1.84	0.0468	0.35	0.60	0.6562
10	50	3.54	0.0463	0.35	0.65	0.1176	30	50	1.84	0.0468	0.35	0.65	0.7993
10	50	3.54	0.0463	0.40	0.55	0.0362	30	50	1.84	0.0468	0.40	0.55	0.3155
10	50	3.54	0.0463	0.40	0.60	0.0490	30	50	1.84	0.0468	0.40	0.60	0.4782
10	60	3.88	0.0479	0.05	0.15	0.0636	30	60	2.08	0.0489	0.05	0.15	0.3745
10	60	3.88	0.0479	0.05	0.20	0.2536	30	60	2.08	0.0489	0.05	0.20	0.6076
10	60	3.88	0.0479	0.05	0.25	0.4601	30	60	2.08	0.0489	0.05	0.25	0.7988
10	60	3.88	0.0479	0.05	0.30	0.5648	30	60	2.08	0.0489	0.05	0.30	0.9134
10	60	3.88	0.0479	0.05	0.35	0.5940	30	60	2.08	0.0489	0.05	0.35	0.9682
10	60	3.88	0.0479	0.05	0.40	0.6024	30	60	2.08	0.0489	0.05	0.40	0.9900
10	60	3.88	0.0479	0.05	0.45	0.6230	30	60	2.08	0.0489	0.05	0.45	0.9974
10	60	3.88	0.0479	0.10	0.25	0.2679	30	60	2.08	0.0489	0.10	0.25	0.4836
10	60	3.88	0.0479	0.10	0.30	0.3289	30	60	2.08	0.0489	0.10	0.30	0.6719
10	60	3.88	0.0479	0.10	0.35	0.3461	30	60	2.08	0.0489	0.10	0.35	0.8170
10	60	3.88	0.0479	0.10	0.40	0.3535	30	60	2.08	0.0489	0.10	0.40	0.9114
10	60	3.88	0.0479	0.10	0.45	0.3785	30	60	2.08	0.0489	0.10	0.45	0.9638
10	60	3.88	0.0479	0.10	0.50	0.4492	30	60	2.08	0.0489	0.10	0.50	0.9880
10	60	3.88	0.0479	0.10	0.55	0.5632	30	60	2.08	0.0489	0.10	0.55	0.9968
10	60	3.88	0.0479	0.10	0.60	0.6693	30	60	2.08	0.0489	0.10	0.60	0.9993
10	60	3.88	0.0479	0.15	0.30	0.1857	30	60	2.08	0.0489	0.15	0.30	0.3986
10	60	3.88	0.0479	0.15	0.35	0.1956	30	60	2.08	0.0489	0.15	0.35	0.5736
10	60	3.88	0.0479	0.15	0.40	0.2013	30	60	2.08	0.0489	0.15	0.40	0.7335
10	60	3.88	0.0479	0.15	0.45	0.2237	30	60	2.08	0.0489	0.15	0.45	0.8577
10	60	3.88	0.0479	0.15	0.50	0.2870	30	60	2.08	0.0489	0.15	0.50	0.9367
10	60	3.88	0.0479	0.15	0.55	0.3894	30	60	2.08	0.0489	0.15	0.55	0.9766
10	60	3.88	0.0479	0.15	0.60	0.4855	30	60	2.08	0.0489	0.15	0.60	0.9928
10	60	3.88	0.0479	0.15	0.65	0.5481	30	60	2.08	0.0489	0.15	0.65	0.9983
10	60	3.88	0.0479	0.20	0.35	0.1068	30	60	2.08	0.0489	0.20	0.35	0.3366
10	60	3.88	0.0479	0.20	0.40	0.1109	30	60	2.08	0.0489	0.20	0.40	0.5066
10	60	3.88	0.0479	0.20	0.45	0.1281	30	60	2.08	0.0489	0.20	0.45	0.6787
10	60	3.88	0.0479	0.20	0.50	0.1770	30	60	2.08	0.0489	0.20	0.50	0.8196
10	60	3.88	0.0479	0.20	0.55	0.2562	30	60	2.08	0.0489	0.20	0.55	0.9132
10	60	3.88	0.0479	0.20	0.60	0.3314	30	60	2.08	0.0489	0.20	0.60	0.9650
10	60	3.88	0.0479	0.20	0.65	0.3846	30	60	2.08	0.0489	0.20	0.65	0.9887
10	60	3.88	0.0479	0.20	0.70	0.4482	30	60	2.08	0.0489	0.20	0.70	0.9973
10	60	3.88	0.0479	0.25	0.40	0.0588	30	60	2.08	0.0489	0.25	0.40	0.3006
10	60	3.88	0.0479	0.25	0.45	0.0708	30	60	2.08	0.0489	0.25	0.45	0.4692
10	60	3.88	0.0479	0.25	0.50	0.1050	30	60	2.08	0.0489	0.25	0.50	0.6418
10	60	3.88	0.0479	0.25	0.55	0.1605	30	60	2.08	0.0489	0.25	0.55	0.7885
10	60	3.88	0.0479	0.25	0.60	0.2137	30	60	2.08	0.0489	0.25	0.60	0.8942
10	60	3.88	0.0479	0.25	0.65	0.2548	30	60	2.08	0.0489	0.25	0.65	0.9569
10	60	3.88	0.0479	0.25	0.70	0.3118	30	60	2.08	0.0489	0.25	0.70	0.9862
10	60	3.88	0.0479	0.25	0.75	0.4049	30	60	2.08	0.0489	0.25	0.75	0.9966
10	60	3.88	0.0479	0.30	0.45	0.0376	30	60	2.08	0.0489	0.30	0.45	0.2809

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	60	3.88	0.0479	0.30	0.50	0.0597	30	60	2.08	0.0489	0.30	0.50	0.4414
10	60	3.88	0.0479	0.30	0.55	0.0955	30	60	2.08	0.0489	0.30	0.55	0.6127
10	60	3.88	0.0479	0.30	0.60	0.1303	30	60	2.08	0.0489	0.30	0.60	0.7685
10	60	3.88	0.0479	0.30	0.65	0.1596	30	60	2.08	0.0489	0.30	0.65	0.8845
10	60	3.88	0.0479	0.30	0.70	0.2057	30	60	2.08	0.0489	0.30	0.70	0.9532
10	60	3.88	0.0479	0.35	0.50	0.0323	30	60	2.08	0.0489	0.35	0.50	0.2638
10	60	3.88	0.0479	0.35	0.55	0.0538	30	60	2.08	0.0489	0.35	0.55	0.4216
10	60	3.88	0.0479	0.35	0.60	0.0750	30	60	2.08	0.0489	0.35	0.60	0.5984
10	60	3.88	0.0479	0.35	0.65	0.0945	30	60	2.08	0.0489	0.35	0.65	0.7609
10	60	3.88	0.0479	0.40	0.55	0.0285	30	60	2.08	0.0489	0.40	0.55	0.2538
10	60	3.88	0.0479	0.40	0.60	0.0405	30	60	2.08	0.0489	0.40	0.60	0.4143
10	70	4.19	0.0494	0.05	0.15	0.0564	30	70	2.33	0.0427	0.05	0.15	0.3410
10	70	4.19	0.0494	0.05	0.20	0.2569	30	70	2.33	0.0427	0.05	0.20	0.5641
10	70	4.19	0.0494	0.05	0.25	0.4754	30	70	2.33	0.0427	0.05	0.25	0.7609
10	70	4.19	0.0494	0.05	0.30	0.5740	30	70	2.33	0.0427	0.05	0.30	0.8904
10	70	4.19	0.0494	0.05	0.35	0.5960	30	70	2.33	0.0427	0.05	0.35	0.9585
10	70	4.19	0.0494	0.05	0.40	0.5994	30	70	2.33	0.0427	0.05	0.40	0.9869
10	70	4.19	0.0494	0.05	0.45	0.6074	30	70	2.33	0.0427	0.05	0.45	0.9965
10	70	4.19	0.0494	0.10	0.25	0.2769	30	70	2.33	0.0427	0.10	0.25	0.4212
10	70	4.19	0.0494	0.10	0.30	0.3343	30	70	2.33	0.0427	0.10	0.30	0.6162
10	70	4.19	0.0494	0.10	0.35	0.3471	30	70	2.33	0.0427	0.10	0.35	0.7792
10	70	4.19	0.0494	0.10	0.40	0.3496	30	70	2.33	0.0427	0.10	0.40	0.8895
10	70	4.19	0.0494	0.10	0.45	0.3594	30	70	2.33	0.0427	0.10	0.45	0.9529
10	70	4.19	0.0494	0.10	0.50	0.4033	30	70	2.33	0.0427	0.10	0.50	0.9835
10	70	4.19	0.0494	0.10	0.55	0.5062	30	70	2.33	0.0427	0.10	0.55	0.9954
10	70	4.19	0.0494	0.10	0.60	0.6321	30	70	2.33	0.0427	0.10	0.60	0.9990
10	70	4.19	0.0494	0.15	0.30	0.1888	30	70	2.33	0.0427	0.15	0.30	0.3400
10	70	4.19	0.0494	0.15	0.35	0.1960	30	70	2.33	0.0427	0.15	0.35	0.5160
10	70	4.19	0.0494	0.15	0.40	0.1978	30	70	2.33	0.0427	0.15	0.40	0.6841
10	70	4.19	0.0494	0.15	0.45	0.2065	30	70	2.33	0.0427	0.15	0.45	0.8216
10	70	4.19	0.0494	0.15	0.50	0.2459	30	70	2.33	0.0427	0.15	0.50	0.9151
10	70	4.19	0.0494	0.15	0.55	0.3382	30	70	2.33	0.0427	0.15	0.55	0.9670
10	70	4.19	0.0494	0.15	0.60	0.4512	30	70	2.33	0.0427	0.15	0.60	0.9898
10	70	4.19	0.0494	0.15	0.65	0.5262	30	70	2.33	0.0427	0.15	0.65	0.9976
10	70	4.19	0.0494	0.20	0.35	0.1069	30	70	2.33	0.0427	0.20	0.35	0.2812
10	70	4.19	0.0494	0.20	0.40	0.1081	30	70	2.33	0.0427	0.20	0.40	0.4416
10	70	4.19	0.0494	0.20	0.45	0.1148	30	70	2.33	0.0427	0.20	0.45	0.6148
10	70	4.19	0.0494	0.20	0.50	0.1452	30	70	2.33	0.0427	0.20	0.50	0.7704
10	70	4.19	0.0494	0.20	0.55	0.2166	30	70	2.33	0.0427	0.20	0.55	0.8852
10	70	4.19	0.0494	0.20	0.60	0.3041	30	70	2.33	0.0427	0.20	0.60	0.9531
10	70	4.19	0.0494	0.20	0.65	0.3636	30	70	2.33	0.0427	0.20	0.65	0.9846
10	70	4.19	0.0494	0.20	0.70	0.4095	30	70	2.33	0.0427	0.20	0.70	0.9961
10	70	4.19	0.0494	0.25	0.40	0.0568	30	70	2.33	0.0427	0.25	0.40	0.2404
10	70	4.19	0.0494	0.25	0.45	0.0615	30	70	2.33	0.0427	0.25	0.45	0.3944
10	70	4.19	0.0494	0.25	0.50	0.0828	30	70	2.33	0.0427	0.25	0.50	0.5711
10	70	4.19	0.0494	0.25	0.55	0.1327	30	70	2.33	0.0427	0.25	0.55	0.7382
10	70	4.19	0.0494	0.25	0.60	0.1940	30	70	2.33	0.0427	0.25	0.60	0.8653
10	70	4.19	0.0494	0.25	0.65	0.2369	30	70	2.33	0.0427	0.25	0.65	0.9428
10	70	4.19	0.0494	0.25	0.70	0.2759	30	70	2.33	0.0427	0.25	0.70	0.9806
10	70	4.19	0.0494	0.25	0.75	0.3565	30	70	2.33	0.0427	0.25	0.75	0.9950

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	70	4.19	0.0494	0.30	0.45	0.0316	30	70	2.33	0.0427	0.30	0.45	0.2166
10	70	4.19	0.0494	0.30	0.50	0.0453	30	70	2.33	0.0427	0.30	0.50	0.3681
10	70	4.19	0.0494	0.30	0.55	0.0775	30	70	2.33	0.0427	0.30	0.55	0.5470
10	70	4.19	0.0494	0.30	0.60	0.1171	30	70	2.33	0.0427	0.30	0.60	0.7183
10	70	4.19	0.0494	0.30	0.65	0.1457	30	70	2.33	0.0427	0.30	0.65	0.8517
10	70	4.19	0.0494	0.30	0.70	0.1760	30	70	2.33	0.0427	0.30	0.70	0.9363
10	70	4.19	0.0494	0.35	0.50	0.0237	30	70	2.33	0.0427	0.35	0.50	0.2047
10	70	4.19	0.0494	0.35	0.55	0.0430	30	70	2.33	0.0427	0.35	0.55	0.3543
10	70	4.19	0.0494	0.35	0.60	0.0668	30	70	2.33	0.0427	0.35	0.60	0.5318
10	70	4.19	0.0494	0.35	0.65	0.0845	30	70	2.33	0.0427	0.35	0.65	0.7055
10	70	4.19	0.0494	0.40	0.55	0.0225	30	70	2.33	0.0427	0.40	0.55	0.1981
10	70	4.19	0.0494	0.40	0.60	0.0357	30	70	2.33	0.0427	0.40	0.60	0.3447
10	80	4.65	0.0430	0.05	0.15	0.0287	30	80	2.55	0.0387	0.05	0.15	0.3188
10	80	4.65	0.0430	0.05	0.20	0.1971	30	80	2.55	0.0387	0.05	0.20	0.5338
10	80	4.65	0.0430	0.05	0.25	0.4409	30	80	2.55	0.0387	0.05	0.25	0.7302
10	80	4.65	0.0430	0.05	0.30	0.5670	30	80	2.55	0.0387	0.05	0.30	0.8665
10	80	4.65	0.0430	0.05	0.35	0.5954	30	80	2.55	0.0387	0.05	0.35	0.9450
10	80	4.65	0.0430	0.05	0.40	0.5986	30	80	2.55	0.0387	0.05	0.40	0.9817
10	80	4.65	0.0430	0.05	0.45	0.5995	30	80	2.55	0.0387	0.05	0.45	0.9952
10	80	4.65	0.0430	0.10	0.25	0.2568	30	80	2.55	0.0387	0.10	0.25	0.3727
10	80	4.65	0.0430	0.10	0.30	0.3302	30	80	2.55	0.0387	0.10	0.30	0.5575
10	80	4.65	0.0430	0.10	0.35	0.3468	30	80	2.55	0.0387	0.10	0.35	0.7308
10	80	4.65	0.0430	0.10	0.40	0.3486	30	80	2.55	0.0387	0.10	0.40	0.8618
10	80	4.65	0.0430	0.10	0.45	0.3497	30	80	2.55	0.0387	0.10	0.45	0.9413
10	80	4.65	0.0430	0.10	0.50	0.3597	30	80	2.55	0.0387	0.10	0.50	0.9794
10	80	4.65	0.0430	0.10	0.55	0.4091	30	80	2.55	0.0387	0.10	0.55	0.9941
10	80	4.65	0.0430	0.10	0.60	0.5260	30	80	2.55	0.0387	0.10	0.60	0.9987
10	80	4.65	0.0430	0.15	0.30	0.1864	30	80	2.55	0.0387	0.15	0.30	0.2817
10	80	4.65	0.0430	0.15	0.35	0.1958	30	80	2.55	0.0387	0.15	0.35	0.4535
10	80	4.65	0.0430	0.15	0.40	0.1969	30	80	2.55	0.0387	0.15	0.40	0.6355
10	80	4.65	0.0430	0.15	0.45	0.1978	30	80	2.55	0.0387	0.15	0.45	0.7908
10	80	4.65	0.0430	0.15	0.50	0.2067	30	80	2.55	0.0387	0.15	0.50	0.8976
10	80	4.65	0.0430	0.15	0.55	0.2510	30	80	2.55	0.0387	0.15	0.55	0.9583
10	80	4.65	0.0430	0.15	0.60	0.3559	30	80	2.55	0.0387	0.15	0.60	0.9865
10	80	4.65	0.0430	0.15	0.65	0.4732	30	80	2.55	0.0387	0.15	0.65	0.9966
10	80	4.65	0.0430	0.20	0.35	0.1068	30	80	2.55	0.0387	0.20	0.35	0.2311
10	80	4.65	0.0430	0.20	0.40	0.1074	30	80	2.55	0.0387	0.20	0.40	0.3899
10	80	4.65	0.0430	0.20	0.45	0.1081	30	80	2.55	0.0387	0.20	0.45	0.5682
10	80	4.65	0.0430	0.20	0.50	0.1150	30	80	2.55	0.0387	0.20	0.50	0.7324
10	80	4.65	0.0430	0.20	0.55	0.1492	30	80	2.55	0.0387	0.20	0.55	0.8594
10	80	4.65	0.0430	0.20	0.60	0.2302	30	80	2.55	0.0387	0.20	0.60	0.9391
10	80	4.65	0.0430	0.20	0.65	0.3209	30	80	2.55	0.0387	0.20	0.65	0.9786
10	80	4.65	0.0430	0.20	0.70	0.3685	30	80	2.55	0.0387	0.20	0.70	0.9941
10	80	4.65	0.0430	0.25	0.40	0.0563	30	80	2.55	0.0387	0.25	0.40	0.2004
10	80	4.65	0.0430	0.25	0.45	0.0568	30	80	2.55	0.0387	0.25	0.45	0.3454
10	80	4.65	0.0430	0.25	0.50	0.0616	30	80	2.55	0.0387	0.25	0.50	0.5179
10	80	4.65	0.0430	0.25	0.55	0.0856	30	80	2.55	0.0387	0.25	0.55	0.6906
10	80	4.65	0.0430	0.25	0.60	0.1422	30	80	2.55	0.0387	0.25	0.60	0.8312
10	80	4.65	0.0430	0.25	0.65	0.2057	30	80	2.55	0.0387	0.25	0.65	0.9234
10	80	4.65	0.0430	0.25	0.70	0.2395	30	80	2.55	0.0387	0.25	0.70	0.9723

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	80	4.65	0.0430	0.25	0.75	0.2644	30	80	2.55	0.0387	0.25	0.75	0.9925
10	80	4.65	0.0430	0.30	0.45	0.0286	30	80	2.55	0.0387	0.30	0.45	0.1775
10	80	4.65	0.0430	0.30	0.50	0.0317	30	80	2.55	0.0387	0.30	0.50	0.3138
10	80	4.65	0.0430	0.30	0.55	0.0471	30	80	2.55	0.0387	0.30	0.55	0.4855
10	80	4.65	0.0430	0.30	0.60	0.0837	30	80	2.55	0.0387	0.30	0.60	0.6620
10	80	4.65	0.0430	0.30	0.65	0.1246	30	80	2.55	0.0387	0.30	0.65	0.8109
10	80	4.65	0.0430	0.30	0.70	0.1468	30	80	2.55	0.0387	0.30	0.70	0.9139
10	80	4.65	0.0430	0.35	0.50	0.0155	30	80	2.55	0.0387	0.35	0.50	0.1620
10	80	4.65	0.0430	0.35	0.55	0.0248	30	80	2.55	0.0387	0.35	0.55	0.2941
10	80	4.65	0.0430	0.35	0.60	0.0466	30	80	2.55	0.0387	0.35	0.60	0.4631
10	80	4.65	0.0430	0.35	0.65	0.0712	30	80	2.55	0.0387	0.35	0.65	0.6433
10	80	4.65	0.0430	0.40	0.55	0.0123	30	80	2.55	0.0387	0.40	0.55	0.1519
10	80	4.65	0.0430	0.40	0.60	0.0245	30	80	2.55	0.0387	0.40	0.60	0.2798
10	90	4.91	0.0448	0.05	0.15	0.0260	30	90	2.76	0.0359	0.05	0.15	0.3028
10	90	4.91	0.0448	0.05	0.20	0.2025	30	90	2.76	0.0359	0.05	0.20	0.5120
10	90	4.91	0.0448	0.05	0.25	0.4577	30	90	2.76	0.0359	0.05	0.25	0.7074
10	90	4.91	0.0448	0.05	0.30	0.5754	30	90	2.76	0.0359	0.05	0.30	0.8491
10	90	4.91	0.0448	0.05	0.35	0.5969	30	90	2.76	0.0359	0.05	0.35	0.9362
10	90	4.91	0.0448	0.05	0.40	0.5987	30	90	2.76	0.0359	0.05	0.40	0.9787
10	90	4.91	0.0448	0.05	0.45	0.5988	30	90	2.76	0.0359	0.05	0.45	0.9941
10	90	4.91	0.0448	0.10	0.25	0.2665	30	90	2.76	0.0359	0.10	0.25	0.3418
10	90	4.91	0.0448	0.10	0.30	0.3351	30	90	2.76	0.0359	0.10	0.30	0.5222
10	90	4.91	0.0448	0.10	0.35	0.3476	30	90	2.76	0.0359	0.10	0.35	0.7029
10	90	4.91	0.0448	0.10	0.40	0.3486	30	90	2.76	0.0359	0.10	0.40	0.8423
10	90	4.91	0.0448	0.10	0.45	0.3488	30	90	2.76	0.0359	0.10	0.45	0.9286
10	90	4.91	0.0448	0.10	0.50	0.3516	30	90	2.76	0.0359	0.10	0.50	0.9736
10	90	4.91	0.0448	0.10	0.55	0.3751	30	90	2.76	0.0359	0.10	0.55	0.9923
10	90	4.91	0.0448	0.10	0.60	0.4638	30	90	2.76	0.0359	0.10	0.60	0.9983
10	90	4.91	0.0448	0.15	0.30	0.1892	30	90	2.76	0.0359	0.15	0.30	0.2509
10	90	4.91	0.0448	0.15	0.35	0.1963	30	90	2.76	0.0359	0.15	0.35	0.4175
10	90	4.91	0.0448	0.15	0.40	0.1969	30	90	2.76	0.0359	0.15	0.40	0.5957
10	90	4.91	0.0448	0.15	0.45	0.1970	30	90	2.76	0.0359	0.15	0.45	0.7553
10	90	4.91	0.0448	0.15	0.50	0.1995	30	90	2.76	0.0359	0.15	0.50	0.8759
10	90	4.91	0.0448	0.15	0.55	0.2206	30	90	2.76	0.0359	0.15	0.55	0.9488
10	90	4.91	0.0448	0.15	0.60	0.3001	30	90	2.76	0.0359	0.15	0.60	0.9830
10	90	4.91	0.0448	0.15	0.65	0.4310	30	90	2.76	0.0359	0.15	0.65	0.9955
10	90	4.91	0.0448	0.20	0.35	0.1070	30	90	2.76	0.0359	0.20	0.35	0.2013
10	90	4.91	0.0448	0.20	0.40	0.1074	30	90	2.76	0.0359	0.20	0.40	0.3449
10	90	4.91	0.0448	0.20	0.45	0.1075	30	90	2.76	0.0359	0.20	0.45	0.5178
10	90	4.91	0.0448	0.20	0.50	0.1094	30	90	2.76	0.0359	0.20	0.50	0.6927
10	90	4.91	0.0448	0.20	0.55	0.1257	30	90	2.76	0.0359	0.20	0.55	0.8348
10	90	4.91	0.0448	0.20	0.60	0.1872	30	90	2.76	0.0359	0.20	0.60	0.9257
10	90	4.91	0.0448	0.20	0.65	0.2883	30	90	2.76	0.0359	0.20	0.65	0.9724
10	90	4.91	0.0448	0.20	0.70	0.3573	30	90	2.76	0.0359	0.20	0.70	0.9917
10	90	4.91	0.0448	0.25	0.40	0.0563	30	90	2.76	0.0359	0.25	0.40	0.1657
10	90	4.91	0.0448	0.25	0.45	0.0564	30	90	2.76	0.0359	0.25	0.45	0.2980
10	90	4.91	0.0448	0.25	0.50	0.0577	30	90	2.76	0.0359	0.25	0.50	0.4701
10	90	4.91	0.0448	0.25	0.55	0.0691	30	90	2.76	0.0359	0.25	0.55	0.6503
10	90	4.91	0.0448	0.25	0.60	0.1121	30	90	2.76	0.0359	0.25	0.60	0.8010
10	90	4.91	0.0448	0.25	0.65	0.1828	30	90	2.76	0.0359	0.25	0.65	0.9041

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	90	4.91	0.0448	0.25	0.70	0.2311	30	90	2.76	0.0359	0.25	0.70	0.9623
10	90	4.91	0.0448	0.25	0.75	0.2462	30	90	2.76	0.0359	0.25	0.75	0.9888
10	90	4.91	0.0448	0.30	0.45	0.0283	30	90	2.76	0.0359	0.30	0.45	0.1445
10	90	4.91	0.0448	0.30	0.50	0.0291	30	90	2.76	0.0359	0.30	0.50	0.2713
10	90	4.91	0.0448	0.30	0.55	0.0365	30	90	2.76	0.0359	0.30	0.55	0.4380
10	90	4.91	0.0448	0.30	0.60	0.0642	30	90	2.76	0.0359	0.30	0.60	0.6154
10	90	4.91	0.0448	0.30	0.65	0.1098	30	90	2.76	0.0359	0.30	0.65	0.7719
10	90	4.91	0.0448	0.30	0.70	0.1410	30	90	2.76	0.0359	0.30	0.70	0.8876
10	90	4.91	0.0448	0.35	0.50	0.0140	30	90	2.76	0.0359	0.35	0.50	0.1325
10	90	4.91	0.0448	0.35	0.55	0.0184	30	90	2.76	0.0359	0.35	0.55	0.2516
10	90	4.91	0.0448	0.35	0.60	0.0350	30	90	2.76	0.0359	0.35	0.60	0.4100
10	90	4.91	0.0448	0.35	0.65	0.0623	30	90	2.76	0.0359	0.35	0.65	0.5865
10	90	4.91	0.0448	0.40	0.55	0.0088	30	90	2.76	0.0359	0.40	0.55	0.1220
10	90	4.91	0.0448	0.40	0.60	0.0180	30	90	2.76	0.0359	0.40	0.60	0.2329
10	100	5.16	0.0464	0.05	0.15	0.0235	30	100	2.75	0.0462	0.05	0.15	0.2953
10	100	5.16	0.0464	0.05	0.20	0.2071	30	100	2.75	0.0462	0.05	0.20	0.5119
10	100	5.16	0.0464	0.05	0.25	0.4721	30	100	2.75	0.0462	0.05	0.25	0.7232
10	100	5.16	0.0464	0.05	0.30	0.5815	30	100	2.75	0.0462	0.05	0.30	0.8678
10	100	5.16	0.0464	0.05	0.35	0.5977	30	100	2.75	0.0462	0.05	0.35	0.9483
10	100	5.16	0.0464	0.05	0.40	0.5987	30	100	2.75	0.0462	0.05	0.40	0.9837
10	100	5.16	0.0464	0.05	0.45	0.5988	30	100	2.75	0.0462	0.05	0.45	0.9958
10	100	5.16	0.0464	0.10	0.25	0.2750	30	100	2.75	0.0462	0.10	0.25	0.3598
10	100	5.16	0.0464	0.10	0.30	0.3386	30	100	2.75	0.0462	0.10	0.30	0.5518
10	100	5.16	0.0464	0.10	0.35	0.3481	30	100	2.75	0.0462	0.10	0.35	0.7308
10	100	5.16	0.0464	0.10	0.40	0.3487	30	100	2.75	0.0462	0.10	0.40	0.8622
10	100	5.16	0.0464	0.10	0.45	0.3487	30	100	2.75	0.0462	0.10	0.45	0.9402
10	100	5.16	0.0464	0.10	0.50	0.3494	30	100	2.75	0.0462	0.10	0.50	0.9789
10	100	5.16	0.0464	0.10	0.55	0.3592	30	100	2.75	0.0462	0.10	0.55	0.9942
10	100	5.16	0.0464	0.10	0.60	0.4182	30	100	2.75	0.0462	0.10	0.60	0.9988
10	100	5.16	0.0464	0.15	0.30	0.1912	30	100	2.75	0.0462	0.15	0.30	0.2721
10	100	5.16	0.0464	0.15	0.35	0.1965	30	100	2.75	0.0462	0.15	0.35	0.4446
10	100	5.16	0.0464	0.15	0.40	0.1969	30	100	2.75	0.0462	0.15	0.40	0.6238
10	100	5.16	0.0464	0.15	0.45	0.1969	30	100	2.75	0.0462	0.15	0.45	0.7787
10	100	5.16	0.0464	0.15	0.50	0.1975	30	100	2.75	0.0462	0.15	0.50	0.8914
10	100	5.16	0.0464	0.15	0.55	0.2063	30	100	2.75	0.0462	0.15	0.55	0.9567
10	100	5.16	0.0464	0.15	0.60	0.2592	30	100	2.75	0.0462	0.15	0.60	0.9860
10	100	5.16	0.0464	0.15	0.65	0.3865	30	100	2.75	0.0462	0.15	0.65	0.9963
10	100	5.16	0.0464	0.20	0.35	0.1072	30	100	2.75	0.0462	0.20	0.35	0.2186
10	100	5.16	0.0464	0.20	0.40	0.1074	30	100	2.75	0.0462	0.20	0.40	0.3687
10	100	5.16	0.0464	0.20	0.45	0.1074	30	100	2.75	0.0462	0.20	0.45	0.5438
10	100	5.16	0.0464	0.20	0.50	0.1078	30	100	2.75	0.0462	0.20	0.50	0.7158
10	100	5.16	0.0464	0.20	0.55	0.1147	30	100	2.75	0.0462	0.20	0.55	0.8504
10	100	5.16	0.0464	0.20	0.60	0.1556	30	100	2.75	0.0462	0.20	0.60	0.9339
10	100	5.16	0.0464	0.20	0.65	0.2539	30	100	2.75	0.0462	0.20	0.65	0.9760
10	100	5.16	0.0464	0.20	0.70	0.3447	30	100	2.75	0.0462	0.20	0.70	0.9932
10	100	5.16	0.0464	0.25	0.40	0.0563	30	100	2.75	0.0462	0.25	0.40	0.1800
10	100	5.16	0.0464	0.25	0.45	0.0563	30	100	2.75	0.0462	0.25	0.45	0.3178
10	100	5.16	0.0464	0.25	0.50	0.0566	30	100	2.75	0.0462	0.25	0.50	0.4926
10	100	5.16	0.0464	0.25	0.55	0.0614	30	100	2.75	0.0462	0.25	0.55	0.6696
10	100	5.16	0.0464	0.25	0.60	0.0900	30	100	2.75	0.0462	0.25	0.60	0.8145

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	100	5.16	0.0464	0.25	0.65	0.1588	30	100	2.75	0.0462	0.25	0.65	0.9128
10	100	5.16	0.0464	0.25	0.70	0.2222	30	100	2.75	0.0462	0.25	0.70	0.9674
10	100	5.16	0.0464	0.25	0.75	0.2425	30	100	2.75	0.0462	0.25	0.75	0.9908
10	100	5.16	0.0464	0.30	0.45	0.0283	30	100	2.75	0.0462	0.30	0.45	0.1557
10	100	5.16	0.0464	0.30	0.50	0.0285	30	100	2.75	0.0462	0.30	0.50	0.2870
10	100	5.16	0.0464	0.30	0.55	0.0315	30	100	2.75	0.0462	0.30	0.55	0.4549
10	100	5.16	0.0464	0.30	0.60	0.0500	30	100	2.75	0.0462	0.30	0.60	0.6309
10	100	5.16	0.0464	0.30	0.65	0.0943	30	100	2.75	0.0462	0.30	0.65	0.7862
10	100	5.16	0.0464	0.30	0.70	0.1353	30	100	2.75	0.0462	0.30	0.70	0.8988
10	100	5.16	0.0464	0.35	0.50	0.0136	30	100	2.75	0.0462	0.35	0.50	0.1407
10	100	5.16	0.0464	0.35	0.55	0.0154	30	100	2.75	0.0462	0.35	0.55	0.2626
10	100	5.16	0.0464	0.35	0.60	0.0265	30	100	2.75	0.0462	0.35	0.60	0.4234
10	100	5.16	0.0464	0.35	0.65	0.0530	30	100	2.75	0.0462	0.35	0.65	0.6038
10	100	5.16	0.0464	0.40	0.55	0.0071	30	100	2.75	0.0462	0.40	0.55	0.1274
10	100	5.16	0.0464	0.40	0.60	0.0133	30	100	2.75	0.0462	0.40	0.60	0.2420
20	30	1.87	0.0412	0.05	0.15	0.3026	40	50	1.78	0.0442	0.05	0.15	0.4584
20	30	1.87	0.0412	0.05	0.20	0.4749	40	50	1.78	0.0442	0.05	0.20	0.6855
20	30	1.87	0.0412	0.05	0.25	0.6313	40	50	1.78	0.0442	0.05	0.25	0.8561
20	30	1.87	0.0412	0.05	0.30	0.7600	40	50	1.78	0.0442	0.05	0.30	0.9480
20	30	1.87	0.0412	0.05	0.35	0.8567	40	50	1.78	0.0442	0.05	0.35	0.9848
20	30	1.87	0.0412	0.05	0.40	0.9228	40	50	1.78	0.0442	0.05	0.40	0.9964
20	30	1.87	0.0412	0.05	0.45	0.9631	40	50	1.78	0.0442	0.05	0.45	0.9993
20	30	1.87	0.0412	0.10	0.25	0.3597	40	50	1.78	0.0442	0.10	0.25	0.5682
20	30	1.87	0.0412	0.10	0.30	0.4992	40	50	1.78	0.0442	0.10	0.30	0.7616
20	30	1.87	0.0412	0.10	0.35	0.6381	40	50	1.78	0.0442	0.10	0.35	0.8894
20	30	1.87	0.0412	0.10	0.40	0.7618	40	50	1.78	0.0442	0.10	0.40	0.9574
20	30	1.87	0.0412	0.10	0.45	0.8592	40	50	1.78	0.0442	0.10	0.45	0.9866
20	30	1.87	0.0412	0.10	0.50	0.9263	40	50	1.78	0.0442	0.10	0.50	0.9966
20	30	1.87	0.0412	0.10	0.55	0.9664	40	50	1.78	0.0442	0.10	0.55	0.9993
20	30	1.87	0.0412	0.10	0.60	0.9868	40	50	1.78	0.0442	0.10	0.60	0.9999
20	30	1.87	0.0412	0.15	0.30	0.2955	40	50	1.78	0.0442	0.15	0.30	0.4959
20	30	1.87	0.0412	0.15	0.35	0.4289	40	50	1.78	0.0442	0.15	0.35	0.6891
20	30	1.87	0.0412	0.15	0.40	0.5726	40	50	1.78	0.0442	0.15	0.40	0.8377
20	30	1.87	0.0412	0.15	0.45	0.7086	40	50	1.78	0.0442	0.15	0.45	0.9290
20	30	1.87	0.0412	0.15	0.50	0.8212	40	50	1.78	0.0442	0.15	0.50	0.9743
20	30	1.87	0.0412	0.15	0.55	0.9021	40	50	1.78	0.0442	0.15	0.55	0.9924
20	30	1.87	0.0412	0.15	0.60	0.9525	40	50	1.78	0.0442	0.15	0.60	0.9983
20	30	1.87	0.0412	0.15	0.65	0.9797	40	50	1.78	0.0442	0.15	0.65	0.9997
20	30	1.87	0.0412	0.20	0.35	0.2650	40	50	1.78	0.0442	0.20	0.35	0.4477
20	30	1.87	0.0412	0.20	0.40	0.3965	40	50	1.78	0.0442	0.20	0.40	0.6380
20	30	1.87	0.0412	0.20	0.45	0.5414	40	50	1.78	0.0442	0.20	0.45	0.7962
20	30	1.87	0.0412	0.20	0.50	0.6807	40	50	1.78	0.0442	0.20	0.50	0.9032
20	30	1.87	0.0412	0.20	0.55	0.7975	40	50	1.78	0.0442	0.20	0.55	0.9623
20	30	1.87	0.0412	0.20	0.60	0.8837	40	50	1.78	0.0442	0.20	0.60	0.9884
20	30	1.87	0.0412	0.20	0.65	0.9402	40	50	1.78	0.0442	0.20	0.65	0.9973
20	30	1.87	0.0412	0.20	0.70	0.9732	40	50	1.78	0.0442	0.20	0.70	0.9996
20	30	1.87	0.0412	0.25	0.40	0.2541	40	50	1.78	0.0442	0.25	0.40	0.4134
20	30	1.87	0.0412	0.25	0.45	0.3830	40	50	1.78	0.0442	0.25	0.45	0.5993
20	30	1.87	0.0412	0.25	0.50	0.5241	40	50	1.78	0.0442	0.25	0.50	0.7651
20	30	1.87	0.0412	0.25	0.55	0.6600	40	50	1.78	0.0442	0.25	0.55	0.8856

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	30	1.87	0.0412	0.25	0.60	0.7769	40	50	1.78	0.0442	0.25	0.60	0.9552
20	30	1.87	0.0412	0.25	0.65	0.8679	40	50	1.78	0.0442	0.25	0.65	0.9863
20	30	1.87	0.0412	0.25	0.70	0.9313	40	50	1.78	0.0442	0.25	0.70	0.9969
20	30	1.87	0.0412	0.25	0.75	0.9698	40	50	1.78	0.0442	0.25	0.75	0.9995
20	30	1.87	0.0412	0.30	0.45	0.2501	40	50	1.78	0.0442	0.30	0.45	0.3895
20	30	1.87	0.0412	0.30	0.50	0.3727	40	50	1.78	0.0442	0.30	0.50	0.5770
20	30	1.87	0.0412	0.30	0.55	0.5073	40	50	1.78	0.0442	0.30	0.55	0.7507
20	30	1.87	0.0412	0.30	0.60	0.6409	40	50	1.78	0.0442	0.30	0.60	0.8785
20	30	1.87	0.0412	0.30	0.65	0.7616	40	50	1.78	0.0442	0.30	0.65	0.9523
20	30	1.87	0.0412	0.30	0.70	0.8595	40	50	1.78	0.0442	0.30	0.70	0.9855
20	30	1.87	0.0412	0.35	0.50	0.2436	40	50	1.78	0.0442	0.35	0.50	0.3811
20	30	1.87	0.0412	0.35	0.55	0.3602	40	50	1.78	0.0442	0.35	0.55	0.5709
20	30	1.87	0.0412	0.35	0.60	0.4926	40	50	1.78	0.0442	0.35	0.60	0.7464
20	30	1.87	0.0412	0.35	0.65	0.6295	40	50	1.78	0.0442	0.35	0.65	0.8761
20	30	1.87	0.0412	0.40	0.55	0.2353	40	50	1.78	0.0442	0.40	0.55	0.3806
20	30	1.87	0.0412	0.40	0.60	0.3507	40	50	1.78	0.0442	0.40	0.60	0.5694
20	40	2.14	0.0467	0.05	0.15	0.2903	40	60	1.86	0.0381	0.05	0.15	0.4979
20	40	2.14	0.0467	0.05	0.20	0.4408	40	60	1.86	0.0381	0.05	0.20	0.7326
20	40	2.14	0.0467	0.05	0.25	0.5996	40	60	1.86	0.0381	0.05	0.25	0.8833
20	40	2.14	0.0467	0.05	0.30	0.7478	40	60	1.86	0.0381	0.05	0.30	0.9580
20	40	2.14	0.0467	0.05	0.35	0.8600	40	60	1.86	0.0381	0.05	0.35	0.9879
20	40	2.14	0.0467	0.05	0.40	0.9307	40	60	1.86	0.0381	0.05	0.40	0.9973
20	40	2.14	0.0467	0.05	0.45	0.9693	40	60	1.86	0.0381	0.05	0.45	0.9995
20	40	2.14	0.0467	0.10	0.25	0.3273	40	60	1.86	0.0381	0.10	0.25	0.5727
20	40	2.14	0.0467	0.10	0.30	0.4824	40	60	1.86	0.0381	0.10	0.30	0.7626
20	40	2.14	0.0467	0.10	0.35	0.6347	40	60	1.86	0.0381	0.10	0.35	0.8935
20	40	2.14	0.0467	0.10	0.40	0.7637	40	60	1.86	0.0381	0.10	0.40	0.9622
20	40	2.14	0.0467	0.10	0.45	0.8608	40	60	1.86	0.0381	0.10	0.45	0.9895
20	40	2.14	0.0467	0.10	0.50	0.9264	40	60	1.86	0.0381	0.10	0.50	0.9977
20	40	2.14	0.0467	0.10	0.55	0.9657	40	60	1.86	0.0381	0.10	0.55	0.9996
20	40	2.14	0.0467	0.10	0.60	0.9861	40	60	1.86	0.0381	0.10	0.60	0.9999
20	40	2.14	0.0467	0.15	0.30	0.2765	40	60	1.86	0.0381	0.15	0.30	0.4847
20	40	2.14	0.0467	0.15	0.35	0.4127	40	60	1.86	0.0381	0.15	0.35	0.6908
20	40	2.14	0.0467	0.15	0.40	0.5553	40	60	1.86	0.0381	0.15	0.40	0.8476
20	40	2.14	0.0467	0.15	0.45	0.6896	40	60	1.86	0.0381	0.15	0.45	0.9383
20	40	2.14	0.0467	0.15	0.50	0.8031	40	60	1.86	0.0381	0.15	0.50	0.9795
20	40	2.14	0.0467	0.15	0.55	0.8877	40	60	1.86	0.0381	0.15	0.55	0.9945
20	40	2.14	0.0467	0.15	0.60	0.9429	40	60	1.86	0.0381	0.15	0.60	0.9989
20	40	2.14	0.0467	0.15	0.65	0.9744	40	60	1.86	0.0381	0.15	0.65	0.9998
20	40	2.14	0.0467	0.20	0.35	0.2404	40	60	1.86	0.0381	0.20	0.35	0.4456
20	40	2.14	0.0467	0.20	0.40	0.3621	40	60	1.86	0.0381	0.20	0.40	0.6475
20	40	2.14	0.0467	0.20	0.45	0.4990	40	60	1.86	0.0381	0.20	0.45	0.8095
20	40	2.14	0.0467	0.20	0.50	0.6367	40	60	1.86	0.0381	0.20	0.50	0.9141
20	40	2.14	0.0467	0.20	0.55	0.7588	40	60	1.86	0.0381	0.20	0.55	0.9686
20	40	2.14	0.0467	0.20	0.60	0.8547	40	60	1.86	0.0381	0.20	0.60	0.9909
20	40	2.14	0.0467	0.20	0.65	0.9223	40	60	1.86	0.0381	0.20	0.65	0.9980
20	40	2.14	0.0467	0.20	0.70	0.9645	40	60	1.86	0.0381	0.20	0.70	0.9997
20	40	2.14	0.0467	0.25	0.40	0.2135	40	60	1.86	0.0381	0.25	0.40	0.4162
20	40	2.14	0.0467	0.25	0.45	0.3273	40	60	1.86	0.0381	0.25	0.45	0.6089
20	40	2.14	0.0467	0.25	0.50	0.4598	40	60	1.86	0.0381	0.25	0.50	0.7768

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	40	2.14	0.0467	0.25	0.55	0.5965	40	60	1.86	0.0381	0.25	0.55	0.8943
20	40	2.14	0.0467	0.25	0.60	0.7233	40	60	1.86	0.0381	0.25	0.60	0.9596
20	40	2.14	0.0467	0.25	0.65	0.8299	40	60	1.86	0.0381	0.25	0.65	0.9880
20	40	2.14	0.0467	0.25	0.70	0.9092	40	60	1.86	0.0381	0.25	0.70	0.9974
20	40	2.14	0.0467	0.25	0.75	0.9593	40	60	1.86	0.0381	0.25	0.75	0.9996
20	40	2.14	0.0467	0.30	0.45	0.1948	40	60	1.86	0.0381	0.30	0.45	0.3898
20	40	2.14	0.0467	0.30	0.50	0.3019	40	60	1.86	0.0381	0.30	0.50	0.5800
20	40	2.14	0.0467	0.30	0.55	0.4289	40	60	1.86	0.0381	0.30	0.55	0.7537
20	40	2.14	0.0467	0.30	0.60	0.5660	40	60	1.86	0.0381	0.30	0.60	0.8810
20	40	2.14	0.0467	0.30	0.65	0.7007	40	60	1.86	0.0381	0.30	0.65	0.9544
20	40	2.14	0.0467	0.30	0.70	0.8176	40	60	1.86	0.0381	0.30	0.70	0.9868
20	40	2.14	0.0467	0.35	0.50	0.1797	40	60	1.86	0.0381	0.35	0.50	0.3715
20	40	2.14	0.0467	0.35	0.55	0.2809	40	60	1.86	0.0381	0.35	0.55	0.5614
20	40	2.14	0.0467	0.35	0.60	0.4070	40	60	1.86	0.0381	0.35	0.60	0.7411
20	40	2.14	0.0467	0.35	0.65	0.5496	40	60	1.86	0.0381	0.35	0.65	0.8756
20	40	2.14	0.0467	0.40	0.55	0.1670	40	60	1.86	0.0381	0.40	0.55	0.3610
20	40	2.14	0.0467	0.40	0.60	0.2674	40	60	1.86	0.0381	0.40	0.60	0.5539
20	50	2.36	0.0480	0.05	0.15	0.3037	40	70	1.79	0.0473	0.05	0.15	0.5245
20	50	2.36	0.0480	0.05	0.20	0.4532	40	70	1.79	0.0473	0.05	0.20	0.7641
20	50	2.36	0.0480	0.05	0.25	0.6087	40	70	1.79	0.0473	0.05	0.25	0.9095
20	50	2.36	0.0480	0.05	0.30	0.7479	40	70	1.79	0.0473	0.05	0.30	0.9729
20	50	2.36	0.0480	0.05	0.35	0.8550	40	70	1.79	0.0473	0.05	0.35	0.9936
20	50	2.36	0.0480	0.05	0.40	0.9281	40	70	1.79	0.0473	0.05	0.40	0.9989
20	50	2.36	0.0480	0.05	0.45	0.9695	40	70	1.79	0.0473	0.05	0.45	0.9999
20	50	2.36	0.0480	0.10	0.25	0.3185	40	70	1.79	0.0473	0.10	0.25	0.6286
20	50	2.36	0.0480	0.10	0.30	0.4609	40	70	1.79	0.0473	0.10	0.30	0.8148
20	50	2.36	0.0480	0.10	0.35	0.6125	40	70	1.79	0.0473	0.10	0.35	0.9272
20	50	2.36	0.0480	0.10	0.40	0.7512	40	70	1.79	0.0473	0.10	0.40	0.9778
20	50	2.36	0.0480	0.10	0.45	0.8562	40	70	1.79	0.0473	0.10	0.45	0.9947
20	50	2.36	0.0480	0.10	0.50	0.9248	40	70	1.79	0.0473	0.10	0.50	0.9990
20	50	2.36	0.0480	0.10	0.55	0.9652	40	70	1.79	0.0473	0.10	0.55	0.9999
20	50	2.36	0.0480	0.10	0.60	0.9861	40	70	1.79	0.0473	0.10	0.60	1.0000
20	50	2.36	0.0480	0.15	0.30	0.2507	40	70	1.79	0.0473	0.15	0.30	0.5490
20	50	2.36	0.0480	0.15	0.35	0.3852	40	70	1.79	0.0473	0.15	0.35	0.7515
20	50	2.36	0.0480	0.15	0.40	0.5346	40	70	1.79	0.0473	0.15	0.40	0.8892
20	50	2.36	0.0480	0.15	0.45	0.6746	40	70	1.79	0.0473	0.15	0.45	0.9602
20	50	2.36	0.0480	0.15	0.50	0.7919	40	70	1.79	0.0473	0.15	0.50	0.9886
20	50	2.36	0.0480	0.15	0.55	0.8809	40	70	1.79	0.0473	0.15	0.55	0.9974
20	50	2.36	0.0480	0.15	0.60	0.9401	40	70	1.79	0.0473	0.15	0.60	0.9995
20	50	2.36	0.0480	0.15	0.65	0.9737	40	70	1.79	0.0473	0.15	0.65	0.9999
20	50	2.36	0.0480	0.20	0.35	0.2165	40	70	1.79	0.0473	0.20	0.35	0.5071
20	50	2.36	0.0480	0.20	0.40	0.3380	40	70	1.79	0.0473	0.20	0.40	0.7085
20	50	2.36	0.0480	0.20	0.45	0.4744	40	70	1.79	0.0473	0.20	0.45	0.8568
20	50	2.36	0.0480	0.20	0.50	0.6137	40	70	1.79	0.0473	0.20	0.50	0.9423
20	50	2.36	0.0480	0.20	0.55	0.7419	40	70	1.79	0.0473	0.20	0.55	0.9812
20	50	2.36	0.0480	0.20	0.60	0.8452	40	70	1.79	0.0473	0.20	0.60	0.9952
20	50	2.36	0.0480	0.20	0.65	0.9174	40	70	1.79	0.0473	0.20	0.65	0.9991
20	50	2.36	0.0480	0.20	0.70	0.9614	40	70	1.79	0.0473	0.20	0.70	0.9999
20	50	2.36	0.0480	0.25	0.40	0.1914	40	70	1.79	0.0473	0.25	0.40	0.4765
20	50	2.36	0.0480	0.25	0.45	0.2993	40	70	1.79	0.0473	0.25	0.45	0.6727

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	50	2.36	0.0480	0.25	0.50	0.4296	40	70	1.79	0.0473	0.25	0.50	0.8276
20	50	2.36	0.0480	0.25	0.55	0.5706	40	70	1.79	0.0473	0.25	0.55	0.9252
20	50	2.36	0.0480	0.25	0.60	0.7043	40	70	1.79	0.0473	0.25	0.60	0.9742
20	50	2.36	0.0480	0.25	0.65	0.8158	40	70	1.79	0.0473	0.25	0.65	0.9933
20	50	2.36	0.0480	0.25	0.70	0.8985	40	70	1.79	0.0473	0.25	0.70	0.9988
20	50	2.36	0.0480	0.25	0.75	0.9531	40	70	1.79	0.0473	0.25	0.75	0.9998
20	50	2.36	0.0480	0.30	0.45	0.1700	40	70	1.79	0.0473	0.30	0.45	0.4491
20	50	2.36	0.0480	0.30	0.50	0.2716	40	70	1.79	0.0473	0.30	0.50	0.6414
20	50	2.36	0.0480	0.30	0.55	0.3984	40	70	1.79	0.0473	0.30	0.55	0.8035
20	50	2.36	0.0480	0.30	0.60	0.5378	40	70	1.79	0.0473	0.30	0.60	0.9130
20	50	2.36	0.0480	0.30	0.65	0.6741	40	70	1.79	0.0473	0.30	0.65	0.9703
20	50	2.36	0.0480	0.30	0.70	0.7946	40	70	1.79	0.0473	0.30	0.70	0.9924
20	50	2.36	0.0480	0.35	0.50	0.1547	40	70	1.79	0.0473	0.35	0.50	0.4252
20	50	2.36	0.0480	0.35	0.55	0.2514	40	70	1.79	0.0473	0.35	0.55	0.6192
20	50	2.36	0.0480	0.35	0.60	0.3733	40	70	1.79	0.0473	0.35	0.60	0.7910
20	50	2.36	0.0480	0.35	0.65	0.5118	40	70	1.79	0.0473	0.35	0.65	0.9086
20	50	2.36	0.0480	0.40	0.55	0.1426	40	70	1.79	0.0473	0.40	0.55	0.4116
20	50	2.36	0.0480	0.40	0.60	0.2340	40	70	1.79	0.0473	0.40	0.60	0.6116
20	60	2.59	0.0486	0.05	0.15	0.3032	40	80	2.1	0.0500	0.05	0.15	0.4412
20	60	2.59	0.0486	0.05	0.20	0.4263	40	80	2.1	0.0500	0.05	0.20	0.6968
20	60	2.59	0.0486	0.05	0.25	0.5751	40	80	2.1	0.0500	0.05	0.25	0.8746
20	60	2.59	0.0486	0.05	0.30	0.7216	40	80	2.1	0.0500	0.05	0.30	0.9602
20	60	2.59	0.0486	0.05	0.35	0.8360	40	80	2.1	0.0500	0.05	0.35	0.9904
20	60	2.59	0.0486	0.05	0.40	0.9164	40	80	2.1	0.0500	0.05	0.40	0.9983
20	60	2.59	0.0486	0.05	0.45	0.9636	40	80	2.1	0.0500	0.05	0.45	0.9998
20	60	2.59	0.0486	0.10	0.25	0.2857	40	80	2.1	0.0500	0.10	0.25	0.5491
20	60	2.59	0.0486	0.10	0.30	0.4227	40	80	2.1	0.0500	0.10	0.30	0.7610
20	60	2.59	0.0486	0.10	0.35	0.5720	40	80	2.1	0.0500	0.10	0.35	0.9000
20	60	2.59	0.0486	0.10	0.40	0.7160	40	80	2.1	0.0500	0.10	0.40	0.9670
20	60	2.59	0.0486	0.10	0.45	0.8296	40	80	2.1	0.0500	0.10	0.45	0.9913
20	60	2.59	0.0486	0.10	0.50	0.9061	40	80	2.1	0.0500	0.10	0.50	0.9982
20	60	2.59	0.0486	0.10	0.55	0.9537	40	80	2.1	0.0500	0.10	0.55	0.9997
20	60	2.59	0.0486	0.10	0.60	0.9806	40	80	2.1	0.0500	0.10	0.60	1.0000
20	60	2.59	0.0486	0.15	0.30	0.2169	40	80	2.1	0.0500	0.15	0.30	0.4689
20	60	2.59	0.0486	0.15	0.35	0.3402	40	80	2.1	0.0500	0.15	0.35	0.6838
20	60	2.59	0.0486	0.15	0.40	0.4854	40	80	2.1	0.0500	0.15	0.40	0.8446
20	60	2.59	0.0486	0.15	0.45	0.6265	40	80	2.1	0.0500	0.15	0.45	0.9374
20	60	2.59	0.0486	0.15	0.50	0.7487	40	80	2.1	0.0500	0.15	0.50	0.9797
20	60	2.59	0.0486	0.15	0.55	0.8482	40	80	2.1	0.0500	0.15	0.55	0.9949
20	60	2.59	0.0486	0.15	0.60	0.9206	40	80	2.1	0.0500	0.15	0.60	0.9991
20	60	2.59	0.0486	0.15	0.65	0.9646	40	80	2.1	0.0500	0.15	0.65	0.9999
20	60	2.59	0.0486	0.20	0.35	0.1801	40	80	2.1	0.0500	0.20	0.35	0.4172
20	60	2.59	0.0486	0.20	0.40	0.2901	40	80	2.1	0.0500	0.20	0.40	0.6222
20	60	2.59	0.0486	0.20	0.45	0.4171	40	80	2.1	0.0500	0.20	0.45	0.7933
20	60	2.59	0.0486	0.20	0.50	0.5521	40	80	2.1	0.0500	0.20	0.50	0.9074
20	60	2.59	0.0486	0.20	0.55	0.6869	40	80	2.1	0.0500	0.20	0.55	0.9676
20	60	2.59	0.0486	0.20	0.60	0.8061	40	80	2.1	0.0500	0.20	0.60	0.9916
20	60	2.59	0.0486	0.20	0.65	0.8943	40	80	2.1	0.0500	0.20	0.65	0.9984
20	60	2.59	0.0486	0.20	0.70	0.9494	40	80	2.1	0.0500	0.20	0.70	0.9998
20	60	2.59	0.0486	0.25	0.40	0.1543	40	80	2.1	0.0500	0.25	0.40	0.3744

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	60	2.59	0.0486	0.25	0.45	0.2469	40	80	2.1	0.0500	0.25	0.45	0.5714
20	60	2.59	0.0486	0.25	0.50	0.3641	40	80	2.1	0.0500	0.25	0.50	0.7538
20	60	2.59	0.0486	0.25	0.55	0.5032	40	80	2.1	0.0500	0.25	0.55	0.8870
20	60	2.59	0.0486	0.25	0.60	0.6479	40	80	2.1	0.0500	0.25	0.60	0.9602
20	60	2.59	0.0486	0.25	0.65	0.7750	40	80	2.1	0.0500	0.25	0.65	0.9895
20	60	2.59	0.0486	0.25	0.70	0.8719	40	80	2.1	0.0500	0.25	0.70	0.9980
20	60	2.59	0.0486	0.25	0.75	0.9378	40	80	2.1	0.0500	0.25	0.75	0.9997
20	60	2.59	0.0486	0.30	0.45	0.1305	40	80	2.1	0.0500	0.30	0.45	0.3417
20	60	2.59	0.0486	0.30	0.50	0.2154	40	80	2.1	0.0500	0.30	0.50	0.5407
20	60	2.59	0.0486	0.30	0.55	0.3326	40	80	2.1	0.0500	0.30	0.55	0.7350
20	60	2.59	0.0486	0.30	0.60	0.4734	40	80	2.1	0.0500	0.30	0.60	0.8780
20	60	2.59	0.0486	0.30	0.65	0.6182	40	80	2.1	0.0500	0.30	0.65	0.9564
20	60	2.59	0.0486	0.30	0.70	0.7501	40	80	2.1	0.0500	0.30	0.70	0.9883
20	60	2.59	0.0486	0.35	0.50	0.1143	40	80	2.1	0.0500	0.35	0.50	0.3274
20	60	2.59	0.0486	0.35	0.55	0.1978	40	80	2.1	0.0500	0.35	0.55	0.5311
20	60	2.59	0.0486	0.35	0.60	0.3124	40	80	2.1	0.0500	0.35	0.60	0.7288
20	60	2.59	0.0486	0.35	0.65	0.4489	40	80	2.1	0.0500	0.35	0.65	0.8740
20	60	2.59	0.0486	0.40	0.55	0.1053	40	80	2.1	0.0500	0.40	0.55	0.3257
20	60	2.59	0.0486	0.40	0.60	0.1849	40	80	2.1	0.0500	0.40	0.60	0.5291
20	70	2.79	0.0498	0.05	0.15	0.3073	40	90	2.31	0.0402	0.05	0.15	0.4049
20	70	2.79	0.0498	0.05	0.20	0.4075	40	90	2.31	0.0402	0.05	0.20	0.6687
20	70	2.79	0.0498	0.05	0.25	0.5489	40	90	2.31	0.0402	0.05	0.25	0.8592
20	70	2.79	0.0498	0.05	0.30	0.7022	40	90	2.31	0.0402	0.05	0.30	0.9552
20	70	2.79	0.0498	0.05	0.35	0.8217	40	90	2.31	0.0402	0.05	0.35	0.9888
20	70	2.79	0.0498	0.05	0.40	0.9073	40	90	2.31	0.0402	0.05	0.40	0.9977
20	70	2.79	0.0498	0.05	0.45	0.9589	40	90	2.31	0.0402	0.05	0.45	0.9997
20	70	2.79	0.0498	0.10	0.25	0.2627	40	90	2.31	0.0402	0.10	0.25	0.5149
20	70	2.79	0.0498	0.10	0.30	0.3969	40	90	2.31	0.0402	0.10	0.30	0.7307
20	70	2.79	0.0498	0.10	0.35	0.5434	40	90	2.31	0.0402	0.10	0.35	0.8763
20	70	2.79	0.0498	0.10	0.40	0.6902	40	90	2.31	0.0402	0.10	0.40	0.9555
20	70	2.79	0.0498	0.10	0.45	0.8099	40	90	2.31	0.0402	0.10	0.45	0.9880
20	70	2.79	0.0498	0.10	0.50	0.8928	40	90	2.31	0.0402	0.10	0.50	0.9975
20	70	2.79	0.0498	0.10	0.55	0.9467	40	90	2.31	0.0402	0.10	0.55	0.9996
20	70	2.79	0.0498	0.10	0.60	0.9781	40	90	2.31	0.0402	0.10	0.60	1.0000
20	70	2.79	0.0498	0.15	0.30	0.1957	40	90	2.31	0.0402	0.15	0.30	0.4163
20	70	2.79	0.0498	0.15	0.35	0.3104	40	90	2.31	0.0402	0.15	0.35	0.6260
20	70	2.79	0.0498	0.15	0.40	0.4518	40	90	2.31	0.0402	0.15	0.40	0.8067
20	70	2.79	0.0498	0.15	0.45	0.5940	40	90	2.31	0.0402	0.15	0.45	0.9201
20	70	2.79	0.0498	0.15	0.50	0.7214	40	90	2.31	0.0402	0.15	0.50	0.9732
20	70	2.79	0.0498	0.15	0.55	0.8304	40	90	2.31	0.0402	0.15	0.55	0.9930
20	70	2.79	0.0498	0.15	0.60	0.9120	40	90	2.31	0.0402	0.15	0.60	0.9987
20	70	2.79	0.0498	0.15	0.65	0.9612	40	90	2.31	0.0402	0.15	0.65	0.9998
20	70	2.79	0.0498	0.20	0.35	0.1574	40	90	2.31	0.0402	0.20	0.35	0.3527
20	70	2.79	0.0498	0.20	0.40	0.2597	40	90	2.31	0.0402	0.20	0.40	0.5636
20	70	2.79	0.0498	0.20	0.45	0.3819	40	90	2.31	0.0402	0.20	0.45	0.7521
20	70	2.79	0.0498	0.20	0.50	0.5170	40	90	2.31	0.0402	0.20	0.50	0.8834
20	70	2.79	0.0498	0.20	0.55	0.6594	40	90	2.31	0.0402	0.20	0.55	0.9568
20	70	2.79	0.0498	0.20	0.60	0.7887	40	90	2.31	0.0402	0.20	0.60	0.9880
20	70	2.79	0.0498	0.20	0.65	0.8851	40	90	2.31	0.0402	0.20	0.65	0.9976
20	70	2.79	0.0498	0.20	0.70	0.9453	40	90	2.31	0.0402	0.20	0.70	0.9997

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	70	2.79	0.0498	0.25	0.40	0.1326	40	90	2.31	0.0402	0.25	0.40	0.3171
20	70	2.79	0.0498	0.25	0.45	0.2176	40	90	2.31	0.0402	0.25	0.45	0.5126
20	70	2.79	0.0498	0.25	0.50	0.3302	40	90	2.31	0.0402	0.25	0.50	0.7050
20	70	2.79	0.0498	0.25	0.55	0.4714	40	90	2.31	0.0402	0.25	0.55	0.8556
20	70	2.79	0.0498	0.25	0.60	0.6228	40	90	2.31	0.0402	0.25	0.60	0.9451
20	70	2.79	0.0498	0.25	0.65	0.7583	40	90	2.31	0.0402	0.25	0.65	0.9842
20	70	2.79	0.0498	0.25	0.70	0.8619	40	90	2.31	0.0402	0.25	0.70	0.9967
20	70	2.79	0.0498	0.25	0.75	0.9306	40	90	2.31	0.0402	0.25	0.75	0.9995
20	70	2.79	0.0498	0.30	0.45	0.1104	40	90	2.31	0.0402	0.30	0.45	0.2849
20	70	2.79	0.0498	0.30	0.50	0.1886	40	90	2.31	0.0402	0.30	0.50	0.4756
20	70	2.79	0.0498	0.30	0.55	0.3028	40	90	2.31	0.0402	0.30	0.55	0.6775
20	70	2.79	0.0498	0.30	0.60	0.4452	40	90	2.31	0.0402	0.30	0.60	0.8400
20	70	2.79	0.0498	0.30	0.65	0.5953	40	90	2.31	0.0402	0.30	0.65	0.9377
20	70	2.79	0.0498	0.30	0.70	0.7323	40	90	2.31	0.0402	0.30	0.70	0.9815
20	70	2.79	0.0498	0.35	0.50	0.0964	40	90	2.31	0.0402	0.35	0.50	0.2657
20	70	2.79	0.0498	0.35	0.55	0.1744	40	90	2.31	0.0402	0.35	0.55	0.4583
20	70	2.79	0.0498	0.35	0.60	0.2863	40	90	2.31	0.0402	0.35	0.60	0.6639
20	70	2.79	0.0498	0.35	0.65	0.4236	40	90	2.31	0.0402	0.35	0.65	0.8302
20	70	2.79	0.0498	0.40	0.55	0.0896	40	90	2.31	0.0402	0.40	0.55	0.2581
20	70	2.79	0.0498	0.40	0.60	0.1646	40	90	2.31	0.0402	0.40	0.60	0.4492
20	80	3.19	0.0385	0.05	0.15	0.2803	40	100	2.52	0.0498	0.05	0.15	0.3543
20	80	3.19	0.0385	0.05	0.20	0.3731	40	100	2.52	0.0498	0.05	0.20	0.6171
20	80	3.19	0.0385	0.05	0.25	0.4888	40	100	2.52	0.0498	0.05	0.25	0.8268
20	80	3.19	0.0385	0.05	0.30	0.6496	40	100	2.52	0.0498	0.05	0.30	0.9396
20	80	3.19	0.0385	0.05	0.35	0.7818	40	100	2.52	0.0498	0.05	0.35	0.9839
20	80	3.19	0.0385	0.05	0.40	0.8770	40	100	2.52	0.0498	0.05	0.40	0.9969
20	80	3.19	0.0385	0.05	0.45	0.9389	40	100	2.52	0.0498	0.05	0.45	0.9996
20	80	3.19	0.0385	0.10	0.25	0.2165	40	100	2.52	0.0498	0.10	0.25	0.4507
20	80	3.19	0.0385	0.10	0.30	0.3440	40	100	2.52	0.0498	0.10	0.30	0.6754
20	80	3.19	0.0385	0.10	0.35	0.4822	40	100	2.52	0.0498	0.10	0.35	0.8487
20	80	3.19	0.0385	0.10	0.40	0.6232	40	100	2.52	0.0498	0.10	0.40	0.9449
20	80	3.19	0.0385	0.10	0.45	0.7494	40	100	2.52	0.0498	0.10	0.45	0.9839
20	80	3.19	0.0385	0.10	0.50	0.8500	40	100	2.52	0.0498	0.10	0.50	0.9963
20	80	3.19	0.0385	0.10	0.55	0.9200	40	100	2.52	0.0498	0.10	0.55	0.9994
20	80	3.19	0.0385	0.10	0.60	0.9620	40	100	2.52	0.0498	0.10	0.60	0.9999
20	80	3.19	0.0385	0.15	0.30	0.1594	40	100	2.52	0.0498	0.15	0.30	0.3575
20	80	3.19	0.0385	0.15	0.35	0.2555	40	100	2.52	0.0498	0.15	0.35	0.5785
20	80	3.19	0.0385	0.15	0.40	0.3769	40	100	2.52	0.0498	0.15	0.40	0.7697
20	80	3.19	0.0385	0.15	0.45	0.5122	40	100	2.52	0.0498	0.15	0.45	0.8965
20	80	3.19	0.0385	0.15	0.50	0.6484	40	100	2.52	0.0498	0.15	0.50	0.9635
20	80	3.19	0.0385	0.15	0.55	0.7684	40	100	2.52	0.0498	0.15	0.55	0.9903
20	80	3.19	0.0385	0.15	0.60	0.8614	40	100	2.52	0.0498	0.15	0.60	0.9981
20	80	3.19	0.0385	0.15	0.65	0.9266	40	100	2.52	0.0498	0.15	0.65	0.9997
20	80	3.19	0.0385	0.20	0.35	0.1199	40	100	2.52	0.0498	0.20	0.35	0.3044
20	80	3.19	0.0385	0.20	0.40	0.1997	40	100	2.52	0.0498	0.20	0.40	0.5038
20	80	3.19	0.0385	0.20	0.45	0.3058	40	100	2.52	0.0498	0.20	0.45	0.7003
20	80	3.19	0.0385	0.20	0.50	0.4336	40	100	2.52	0.0498	0.20	0.50	0.8533
20	80	3.19	0.0385	0.20	0.55	0.5689	40	100	2.52	0.0498	0.20	0.55	0.9440
20	80	3.19	0.0385	0.20	0.60	0.6973	40	100	2.52	0.0498	0.20	0.60	0.9839
20	80	3.19	0.0385	0.20	0.65	0.8088	40	100	2.52	0.0498	0.20	0.65	0.9965

Table B.16: continue on next page

Table B.16: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	80	3.19	0.0385	0.20	0.70	0.8938	40	100	2.52	0.0498	0.20	0.70	0.9994
20	80	3.19	0.0385	0.25	0.40	0.0940	40	100	2.52	0.0498	0.25	0.40	0.2606
20	80	3.19	0.0385	0.25	0.45	0.1615	40	100	2.52	0.0498	0.25	0.45	0.4486
20	80	3.19	0.0385	0.25	0.50	0.2561	40	100	2.52	0.0498	0.25	0.50	0.6530
20	80	3.19	0.0385	0.25	0.55	0.3732	40	100	2.52	0.0498	0.25	0.55	0.8234
20	80	3.19	0.0385	0.25	0.60	0.5051	40	100	2.52	0.0498	0.25	0.60	0.9289
20	80	3.19	0.0385	0.25	0.65	0.6420	40	100	2.52	0.0498	0.25	0.65	0.9775
20	80	3.19	0.0385	0.25	0.70	0.7674	40	100	2.52	0.0498	0.25	0.70	0.9947
20	80	3.19	0.0385	0.25	0.75	0.8680	40	100	2.52	0.0498	0.25	0.75	0.9992
20	80	3.19	0.0385	0.30	0.45	0.0759	40	100	2.52	0.0498	0.30	0.45	0.2321
20	80	3.19	0.0385	0.30	0.50	0.1342	40	100	2.52	0.0498	0.30	0.50	0.4166
20	80	3.19	0.0385	0.30	0.55	0.2173	40	100	2.52	0.0498	0.30	0.55	0.6251
20	80	3.19	0.0385	0.30	0.60	0.3264	40	100	2.52	0.0498	0.30	0.60	0.8011
20	80	3.19	0.0385	0.30	0.65	0.4588	40	100	2.52	0.0498	0.30	0.65	0.9149
20	80	3.19	0.0385	0.30	0.70	0.6016	40	100	2.52	0.0498	0.30	0.70	0.9728
20	80	3.19	0.0385	0.35	0.50	0.0624	40	100	2.52	0.0498	0.35	0.50	0.2173
20	80	3.19	0.0385	0.35	0.55	0.1122	40	100	2.52	0.0498	0.35	0.55	0.3980
20	80	3.19	0.0385	0.35	0.60	0.1876	40	100	2.52	0.0498	0.35	0.60	0.6013
20	80	3.19	0.0385	0.35	0.65	0.2933	40	100	2.52	0.0498	0.35	0.65	0.7820
20	80	3.19	0.0385	0.40	0.55	0.0512	40	100	2.52	0.0498	0.40	0.55	0.2070
20	80	3.19	0.0385	0.40	0.60	0.0955	40	100	2.52	0.0498	0.40	0.60	0.3785

Table B.16: concluded from previous page

Table B.17: Achieved power and p-values calculated for the z-unpooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.59	0.0242	0.05	0.15	0.0404	20	90	3.73	0.0244	0.05	0.15	0.2164
10	20	2.59	0.0242	0.05	0.20	0.1180	20	90	3.73	0.0244	0.05	0.20	0.3370
10	20	2.59	0.0242	0.05	0.25	0.2336	20	90	3.73	0.0244	0.05	0.25	0.3995
10	20	2.59	0.0242	0.05	0.30	0.3646	20	90	3.73	0.0244	0.05	0.30	0.5293
10	20	2.59	0.0242	0.05	0.35	0.4906	20	90	3.73	0.0244	0.05	0.35	0.6822
10	20	2.59	0.0242	0.05	0.40	0.6022	20	90	3.73	0.0244	0.05	0.40	0.7950
10	20	2.59	0.0242	0.05	0.45	0.6987	20	90	3.73	0.0244	0.05	0.45	0.8826
10	20	2.59	0.0242	0.10	0.25	0.1389	20	90	3.73	0.0244	0.10	0.25	0.1516
10	20	2.59	0.0242	0.10	0.30	0.2223	20	90	3.73	0.0244	0.10	0.30	0.2453
10	20	2.59	0.0242	0.10	0.35	0.3115	20	90	3.73	0.0244	0.10	0.35	0.3676
10	20	2.59	0.0242	0.10	0.40	0.4038	20	90	3.73	0.0244	0.10	0.40	0.4930
10	20	2.59	0.0242	0.10	0.45	0.4990	20	90	3.73	0.0244	0.10	0.45	0.6292
10	20	2.59	0.0242	0.10	0.50	0.5951	20	90	3.73	0.0244	0.10	0.50	0.7529
10	20	2.59	0.0242	0.10	0.55	0.6872	20	90	3.73	0.0244	0.10	0.55	0.8519
10	20	2.59	0.0242	0.10	0.60	0.7697	20	90	3.73	0.0244	0.10	0.60	0.9207
10	20	2.59	0.0242	0.15	0.30	0.1319	20	90	3.73	0.0244	0.15	0.30	0.1022
10	20	2.59	0.0242	0.15	0.35	0.1925	20	90	3.73	0.0244	0.15	0.35	0.1715
10	20	2.59	0.0242	0.15	0.40	0.2630	20	90	3.73	0.0244	0.15	0.40	0.2615
10	20	2.59	0.0242	0.15	0.45	0.3442	20	90	3.73	0.0244	0.15	0.45	0.3803
10	20	2.59	0.0242	0.15	0.50	0.4342	20	90	3.73	0.0244	0.15	0.50	0.5135
10	20	2.59	0.0242	0.15	0.55	0.5284	20	90	3.73	0.0244	0.15	0.55	0.6480
10	20	2.59	0.0242	0.15	0.60	0.6212	20	90	3.73	0.0244	0.15	0.60	0.7664
10	20	2.59	0.0242	0.15	0.65	0.7074	20	90	3.73	0.0244	0.15	0.65	0.8592
10	20	2.59	0.0242	0.20	0.35	0.1155	20	90	3.73	0.0244	0.20	0.35	0.0713
10	20	2.59	0.0242	0.20	0.40	0.1660	20	90	3.73	0.0244	0.20	0.40	0.1226
10	20	2.59	0.0242	0.20	0.45	0.2290	20	90	3.73	0.0244	0.20	0.45	0.2008
10	20	2.59	0.0242	0.20	0.50	0.3040	20	90	3.73	0.0244	0.20	0.50	0.3049
10	20	2.59	0.0242	0.20	0.55	0.3882	20	90	3.73	0.0244	0.20	0.55	0.4303
10	20	2.59	0.0242	0.20	0.60	0.4776	20	90	3.73	0.0244	0.20	0.60	0.5632
10	20	2.59	0.0242	0.20	0.65	0.5679	20	90	3.73	0.0244	0.20	0.65	0.6915
10	20	2.59	0.0242	0.20	0.70	0.6556	20	90	3.73	0.0244	0.20	0.70	0.8083
10	20	2.59	0.0242	0.25	0.40	0.1012	20	90	3.73	0.0244	0.25	0.40	0.0514
10	20	2.59	0.0242	0.25	0.45	0.1466	20	90	3.73	0.0244	0.25	0.45	0.0940
10	20	2.59	0.0242	0.25	0.50	0.2041	20	90	3.73	0.0244	0.25	0.50	0.1598
10	20	2.59	0.0242	0.25	0.55	0.2727	20	90	3.73	0.0244	0.25	0.55	0.2516
10	20	2.59	0.0242	0.25	0.60	0.3504	20	90	3.73	0.0244	0.25	0.60	0.3654
10	20	2.59	0.0242	0.25	0.65	0.4347	20	90	3.73	0.0244	0.25	0.65	0.4967
10	20	2.59	0.0242	0.25	0.70	0.5233	20	90	3.73	0.0244	0.25	0.70	0.6401
10	20	2.59	0.0242	0.25	0.75	0.6148	20	90	3.73	0.0244	0.25	0.75	0.7690
10	20	2.59	0.0242	0.30	0.45	0.0901	20	90	3.73	0.0244	0.30	0.45	0.0392
10	20	2.59	0.0242	0.30	0.50	0.1312	20	90	3.73	0.0244	0.30	0.50	0.0743
10	20	2.59	0.0242	0.30	0.55	0.1830	20	90	3.73	0.0244	0.30	0.55	0.1301
10	20	2.59	0.0242	0.30	0.60	0.2453	20	90	3.73	0.0244	0.30	0.60	0.2097
10	20	2.59	0.0242	0.30	0.65	0.3174	20	90	3.73	0.0244	0.30	0.65	0.3176

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.59	0.0242	0.30	0.70	0.3988	20	90	3.73	0.0244	0.30	0.70	0.4553
10	20	2.59	0.0242	0.35	0.50	0.0805	20	90	3.73	0.0244	0.35	0.50	0.0306
10	20	2.59	0.0242	0.35	0.55	0.1171	20	90	3.73	0.0244	0.35	0.55	0.0595
10	20	2.59	0.0242	0.35	0.60	0.1635	20	90	3.73	0.0244	0.35	0.60	0.1065
10	20	2.59	0.0242	0.35	0.65	0.2207	20	90	3.73	0.0244	0.35	0.65	0.1803
10	20	2.59	0.0242	0.40	0.55	0.0711	20	90	3.73	0.0244	0.40	0.55	0.0240
10	20	2.59	0.0242	0.40	0.60	0.1035	20	90	3.73	0.0244	0.40	0.60	0.0477
10	30	3.31	0.0185	0.05	0.15	0.0166	20	100	4.04	0.0212	0.05	0.15	0.1946
10	30	3.31	0.0185	0.05	0.20	0.0770	20	100	4.04	0.0212	0.05	0.20	0.3302
10	30	3.31	0.0185	0.05	0.25	0.1955	20	100	4.04	0.0212	0.05	0.25	0.3734
10	30	3.31	0.0185	0.05	0.30	0.3410	20	100	4.04	0.0212	0.05	0.30	0.4680
10	30	3.31	0.0185	0.05	0.35	0.4681	20	100	4.04	0.0212	0.05	0.35	0.6289
10	30	3.31	0.0185	0.05	0.40	0.5576	20	100	4.04	0.0212	0.05	0.40	0.7574
10	30	3.31	0.0185	0.05	0.45	0.6229	20	100	4.04	0.0212	0.05	0.45	0.8529
10	30	3.31	0.0185	0.10	0.25	0.1139	20	100	4.04	0.0212	0.10	0.25	0.1330
10	30	3.31	0.0185	0.10	0.30	0.1990	20	100	4.04	0.0212	0.10	0.30	0.2003
10	30	3.31	0.0185	0.10	0.35	0.2751	20	100	4.04	0.0212	0.10	0.35	0.3210
10	30	3.31	0.0185	0.10	0.40	0.3346	20	100	4.04	0.0212	0.10	0.40	0.4432
10	30	3.31	0.0185	0.10	0.45	0.3906	20	100	4.04	0.0212	0.10	0.45	0.5747
10	30	3.31	0.0185	0.10	0.50	0.4607	20	100	4.04	0.0212	0.10	0.50	0.6963
10	30	3.31	0.0185	0.10	0.55	0.5489	20	100	4.04	0.0212	0.10	0.55	0.8003
10	30	3.31	0.0185	0.10	0.60	0.6440	20	100	4.04	0.0212	0.10	0.60	0.8848
10	30	3.31	0.0185	0.15	0.30	0.1127	20	100	4.04	0.0212	0.15	0.30	0.0788
10	30	3.31	0.0185	0.15	0.35	0.1569	20	100	4.04	0.0212	0.15	0.35	0.1431
10	30	3.31	0.0185	0.15	0.40	0.1951	20	100	4.04	0.0212	0.15	0.40	0.2222
10	30	3.31	0.0185	0.15	0.45	0.2383	20	100	4.04	0.0212	0.15	0.45	0.3272
10	30	3.31	0.0185	0.15	0.50	0.2991	20	100	4.04	0.0212	0.15	0.50	0.4434
10	30	3.31	0.0185	0.15	0.55	0.3799	20	100	4.04	0.0212	0.15	0.55	0.5706
10	30	3.31	0.0185	0.15	0.60	0.4717	20	100	4.04	0.0212	0.15	0.60	0.6988
10	30	3.31	0.0185	0.15	0.65	0.5654	20	100	4.04	0.0212	0.15	0.65	0.8107
10	30	3.31	0.0185	0.20	0.35	0.0866	20	100	4.04	0.0212	0.20	0.35	0.0571
10	30	3.31	0.0185	0.20	0.40	0.1103	20	100	4.04	0.0212	0.20	0.40	0.0987
10	30	3.31	0.0185	0.20	0.45	0.1409	20	100	4.04	0.0212	0.20	0.45	0.1625
10	30	3.31	0.0185	0.20	0.50	0.1874	20	100	4.04	0.0212	0.20	0.50	0.2449
10	30	3.31	0.0185	0.20	0.55	0.2517	20	100	4.04	0.0212	0.20	0.55	0.3532
10	30	3.31	0.0185	0.20	0.60	0.3287	20	100	4.04	0.0212	0.20	0.60	0.4828
10	30	3.31	0.0185	0.20	0.65	0.4144	20	100	4.04	0.0212	0.20	0.65	0.6206
10	30	3.31	0.0185	0.20	0.70	0.5108	20	100	4.04	0.0212	0.20	0.70	0.7510
10	30	3.31	0.0185	0.25	0.40	0.0601	20	100	4.04	0.0212	0.25	0.40	0.0393
10	30	3.31	0.0185	0.25	0.45	0.0805	20	100	4.04	0.0212	0.25	0.45	0.0715
10	30	3.31	0.0185	0.25	0.50	0.1130	20	100	4.04	0.0212	0.25	0.50	0.1192
10	30	3.31	0.0185	0.25	0.55	0.1596	20	100	4.04	0.0212	0.25	0.55	0.1922
10	30	3.31	0.0185	0.25	0.60	0.2183	20	100	4.04	0.0212	0.25	0.60	0.2934
10	30	3.31	0.0185	0.25	0.65	0.2894	20	100	4.04	0.0212	0.25	0.65	0.4208
10	30	3.31	0.0185	0.25	0.70	0.3772	20	100	4.04	0.0212	0.25	0.70	0.5650
10	30	3.31	0.0185	0.25	0.75	0.4831	20	100	4.04	0.0212	0.25	0.75	0.7075
10	30	3.31	0.0185	0.30	0.45	0.0442	20	100	4.04	0.0212	0.30	0.45	0.0280
10	30	3.31	0.0185	0.30	0.50	0.0653	20	100	4.04	0.0212	0.30	0.50	0.0515
10	30	3.31	0.0185	0.30	0.55	0.0966	20	100	4.04	0.0212	0.30	0.55	0.0925
10	30	3.31	0.0185	0.30	0.60	0.1382	20	100	4.04	0.0212	0.30	0.60	0.1576

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	30	3.31	0.0185	0.30	0.65	0.1927	20	100	4.04	0.0212	0.30	0.65	0.2527
10	30	3.31	0.0185	0.30	0.70	0.2657	20	100	4.04	0.0212	0.30	0.70	0.3790
10	30	3.31	0.0185	0.35	0.50	0.0360	20	100	4.04	0.0212	0.35	0.50	0.0197
10	30	3.31	0.0185	0.35	0.55	0.0556	20	100	4.04	0.0212	0.35	0.55	0.0394
10	30	3.31	0.0185	0.35	0.60	0.0832	20	100	4.04	0.0212	0.35	0.60	0.0749
10	30	3.31	0.0185	0.35	0.65	0.1221	20	100	4.04	0.0212	0.35	0.65	0.1343
10	30	3.31	0.0185	0.40	0.55	0.0303	20	100	4.04	0.0212	0.40	0.55	0.0148
10	30	3.31	0.0185	0.40	0.60	0.0474	20	100	4.04	0.0212	0.40	0.60	0.0313
10	40	3.66	0.0235	0.05	0.15	0.0179	30	40	2.21	0.0236	0.05	0.15	0.2588
10	40	3.66	0.0235	0.05	0.20	0.0963	30	40	2.21	0.0236	0.05	0.20	0.4649
10	40	3.66	0.0235	0.05	0.25	0.2491	30	40	2.21	0.0236	0.05	0.25	0.6611
10	40	3.66	0.0235	0.05	0.30	0.4140	30	40	2.21	0.0236	0.05	0.30	0.8108
10	40	3.66	0.0235	0.05	0.35	0.5269	30	40	2.21	0.0236	0.05	0.35	0.9077
10	40	3.66	0.0235	0.05	0.40	0.5836	30	40	2.21	0.0236	0.05	0.40	0.9616
10	40	3.66	0.0235	0.05	0.45	0.6185	30	40	2.21	0.0236	0.05	0.45	0.9867
10	40	3.66	0.0235	0.10	0.25	0.1451	30	40	2.21	0.0236	0.10	0.25	0.3484
10	40	3.66	0.0235	0.10	0.30	0.2411	30	40	2.21	0.0236	0.10	0.30	0.5246
10	40	3.66	0.0235	0.10	0.35	0.3075	30	40	2.21	0.0236	0.10	0.35	0.6937
10	40	3.66	0.0235	0.10	0.40	0.3437	30	40	2.21	0.0236	0.10	0.40	0.8278
10	40	3.66	0.0235	0.10	0.45	0.3758	30	40	2.21	0.0236	0.10	0.45	0.9155
10	40	3.66	0.0235	0.10	0.50	0.4317	30	40	2.21	0.0236	0.10	0.50	0.9637
10	40	3.66	0.0235	0.10	0.55	0.5202	30	40	2.21	0.0236	0.10	0.55	0.9866
10	40	3.66	0.0235	0.10	0.60	0.6223	30	40	2.21	0.0236	0.10	0.60	0.9959
10	40	3.66	0.0235	0.15	0.30	0.1362	30	40	2.21	0.0236	0.15	0.30	0.2875
10	40	3.66	0.0235	0.15	0.35	0.1740	30	40	2.21	0.0236	0.15	0.35	0.4520
10	40	3.66	0.0235	0.15	0.40	0.1965	30	40	2.21	0.0236	0.15	0.40	0.6191
10	40	3.66	0.0235	0.15	0.45	0.2221	30	40	2.21	0.0236	0.15	0.45	0.7622
10	40	3.66	0.0235	0.15	0.50	0.2716	30	40	2.21	0.0236	0.15	0.50	0.8683
10	40	3.66	0.0235	0.15	0.55	0.3514	30	40	2.21	0.0236	0.15	0.55	0.9369
10	40	3.66	0.0235	0.15	0.60	0.4458	30	40	2.21	0.0236	0.15	0.60	0.9747
10	40	3.66	0.0235	0.15	0.65	0.5350	30	40	2.21	0.0236	0.15	0.65	0.9918
10	40	3.66	0.0235	0.20	0.35	0.0951	30	40	2.21	0.0236	0.20	0.35	0.2524
10	40	3.66	0.0235	0.20	0.40	0.1087	30	40	2.21	0.0236	0.20	0.40	0.3988
10	40	3.66	0.0235	0.20	0.45	0.1272	30	40	2.21	0.0236	0.20	0.45	0.5573
10	40	3.66	0.0235	0.20	0.50	0.1652	30	40	2.21	0.0236	0.20	0.50	0.7075
10	40	3.66	0.0235	0.20	0.55	0.2275	30	40	2.21	0.0236	0.20	0.55	0.8310
10	40	3.66	0.0235	0.20	0.60	0.3029	30	40	2.21	0.0236	0.20	0.60	0.9170
10	40	3.66	0.0235	0.20	0.65	0.3795	30	40	2.21	0.0236	0.20	0.65	0.9664
10	40	3.66	0.0235	0.20	0.70	0.4622	30	40	2.21	0.0236	0.20	0.70	0.9892
10	40	3.66	0.0235	0.25	0.40	0.0579	30	40	2.21	0.0236	0.25	0.40	0.2223
10	40	3.66	0.0235	0.25	0.45	0.0703	30	40	2.21	0.0236	0.25	0.45	0.3574
10	40	3.66	0.0235	0.25	0.50	0.0969	30	40	2.21	0.0236	0.25	0.50	0.5156
10	40	3.66	0.0235	0.25	0.55	0.1408	30	40	2.21	0.0236	0.25	0.55	0.6750
10	40	3.66	0.0235	0.25	0.60	0.1955	30	40	2.21	0.0236	0.25	0.60	0.8110
10	40	3.66	0.0235	0.25	0.65	0.2553	30	40	2.21	0.0236	0.25	0.65	0.9072
10	40	3.66	0.0235	0.25	0.70	0.3271	30	40	2.21	0.0236	0.25	0.70	0.9627
10	40	3.66	0.0235	0.25	0.75	0.4184	30	40	2.21	0.0236	0.25	0.75	0.9881
10	40	3.66	0.0235	0.30	0.45	0.0373	30	40	2.21	0.0236	0.30	0.45	0.2020
10	40	3.66	0.0235	0.30	0.50	0.0545	30	40	2.21	0.0236	0.30	0.50	0.3350
10	40	3.66	0.0235	0.30	0.55	0.0831	30	40	2.21	0.0236	0.30	0.55	0.4964

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	40	3.66	0.0235	0.30	0.60	0.1199	30	40	2.21	0.0236	0.30	0.60	0.6619
10	40	3.66	0.0235	0.30	0.65	0.1630	30	40	2.21	0.0236	0.30	0.65	0.8036
10	40	3.66	0.0235	0.30	0.70	0.2198	30	40	2.21	0.0236	0.30	0.70	0.9038
10	40	3.66	0.0235	0.35	0.50	0.0292	30	40	2.21	0.0236	0.35	0.50	0.1939
10	40	3.66	0.0235	0.35	0.55	0.0466	30	40	2.21	0.0236	0.35	0.55	0.3278
10	40	3.66	0.0235	0.35	0.60	0.0696	30	40	2.21	0.0236	0.35	0.60	0.4911
10	40	3.66	0.0235	0.35	0.65	0.0986	30	40	2.21	0.0236	0.35	0.65	0.6583
10	40	3.66	0.0235	0.40	0.55	0.0246	30	40	2.21	0.0236	0.40	0.55	0.1928
10	40	3.66	0.0235	0.40	0.60	0.0381	30	40	2.21	0.0236	0.40	0.60	0.3268
10	50	4.20	0.0211	0.05	0.15	0.0079	30	50	2.36	0.0200	0.05	0.15	0.2464
10	50	4.20	0.0211	0.05	0.20	0.0662	30	50	2.36	0.0200	0.05	0.20	0.4452
10	50	4.20	0.0211	0.05	0.25	0.2173	30	50	2.36	0.0200	0.05	0.25	0.6464
10	50	4.20	0.0211	0.05	0.30	0.4024	30	50	2.36	0.0200	0.05	0.30	0.8064
10	50	4.20	0.0211	0.05	0.35	0.5292	30	50	2.36	0.0200	0.05	0.35	0.9103
10	50	4.20	0.0211	0.05	0.40	0.5830	30	50	2.36	0.0200	0.05	0.40	0.9656
10	50	4.20	0.0211	0.05	0.45	0.6035	30	50	2.36	0.0200	0.05	0.45	0.9894
10	50	4.20	0.0211	0.10	0.25	0.1266	30	50	2.36	0.0200	0.10	0.25	0.3214
10	50	4.20	0.0211	0.10	0.30	0.2344	30	50	2.36	0.0200	0.10	0.30	0.5051
10	50	4.20	0.0211	0.10	0.35	0.3082	30	50	2.36	0.0200	0.10	0.35	0.6868
10	50	4.20	0.0211	0.10	0.40	0.3402	30	50	2.36	0.0200	0.10	0.40	0.8313
10	50	4.20	0.0211	0.10	0.45	0.3562	30	50	2.36	0.0200	0.10	0.45	0.9228
10	50	4.20	0.0211	0.10	0.50	0.3878	30	50	2.36	0.0200	0.10	0.50	0.9697
10	50	4.20	0.0211	0.10	0.55	0.4596	30	50	2.36	0.0200	0.10	0.55	0.9899
10	50	4.20	0.0211	0.10	0.60	0.5665	30	50	2.36	0.0200	0.10	0.60	0.9973
10	50	4.20	0.0211	0.15	0.30	0.1323	30	50	2.36	0.0200	0.15	0.30	0.2637
10	50	4.20	0.0211	0.15	0.35	0.1741	30	50	2.36	0.0200	0.15	0.35	0.4364
10	50	4.20	0.0211	0.15	0.40	0.1925	30	50	2.36	0.0200	0.15	0.40	0.6177
10	50	4.20	0.0211	0.15	0.45	0.2042	30	50	2.36	0.0200	0.15	0.45	0.7712
10	50	4.20	0.0211	0.15	0.50	0.2320	30	50	2.36	0.0200	0.15	0.50	0.8802
10	50	4.20	0.0211	0.15	0.55	0.2963	30	50	2.36	0.0200	0.15	0.55	0.9466
10	50	4.20	0.0211	0.15	0.60	0.3924	30	50	2.36	0.0200	0.15	0.60	0.9805
10	50	4.20	0.0211	0.15	0.65	0.4841	30	50	2.36	0.0200	0.15	0.65	0.9943
10	50	4.20	0.0211	0.20	0.35	0.0950	30	50	2.36	0.0200	0.20	0.35	0.2368
10	50	4.20	0.0211	0.20	0.40	0.1053	30	50	2.36	0.0200	0.20	0.40	0.3930
10	50	4.20	0.0211	0.20	0.45	0.1132	30	50	2.36	0.0200	0.20	0.45	0.5627
10	50	4.20	0.0211	0.20	0.50	0.1345	30	50	2.36	0.0200	0.20	0.50	0.7204
10	50	4.20	0.0211	0.20	0.55	0.1842	30	50	2.36	0.0200	0.20	0.55	0.8459
10	50	4.20	0.0211	0.20	0.60	0.2586	30	50	2.36	0.0200	0.20	0.60	0.9284
10	50	4.20	0.0211	0.20	0.65	0.3307	30	50	2.36	0.0200	0.20	0.65	0.9722
10	50	4.20	0.0211	0.20	0.70	0.3868	30	50	2.36	0.0200	0.20	0.70	0.9912
10	50	4.20	0.0211	0.25	0.40	0.0554	30	50	2.36	0.0200	0.25	0.40	0.2146
10	50	4.20	0.0211	0.25	0.45	0.0605	30	50	2.36	0.0200	0.25	0.45	0.3565
10	50	4.20	0.0211	0.25	0.50	0.0753	30	50	2.36	0.0200	0.25	0.50	0.5229
10	50	4.20	0.0211	0.25	0.55	0.1101	30	50	2.36	0.0200	0.25	0.55	0.6876
10	50	4.20	0.0211	0.25	0.60	0.1622	30	50	2.36	0.0200	0.25	0.60	0.8221
10	50	4.20	0.0211	0.25	0.65	0.2136	30	50	2.36	0.0200	0.25	0.65	0.9131
10	50	4.20	0.0211	0.25	0.70	0.2573	30	50	2.36	0.0200	0.25	0.70	0.9649
10	50	4.20	0.0211	0.25	0.75	0.3168	30	50	2.36	0.0200	0.25	0.75	0.9891
10	50	4.20	0.0211	0.30	0.45	0.0310	30	50	2.36	0.0200	0.30	0.45	0.1966
10	50	4.20	0.0211	0.30	0.50	0.0405	30	50	2.36	0.0200	0.30	0.50	0.3338

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	50	4.20	0.0211	0.30	0.55	0.0629	30	50	2.36	0.0200	0.30	0.55	0.4985
10	50	4.20	0.0211	0.30	0.60	0.0967	30	50	2.36	0.0200	0.30	0.60	0.6628
10	50	4.20	0.0211	0.30	0.65	0.1305	30	50	2.36	0.0200	0.30	0.65	0.8021
10	50	4.20	0.0211	0.30	0.70	0.1619	30	50	2.36	0.0200	0.30	0.70	0.9028
10	50	4.20	0.0211	0.35	0.50	0.0208	30	50	2.36	0.0200	0.35	0.50	0.1861
10	50	4.20	0.0211	0.35	0.55	0.0342	30	50	2.36	0.0200	0.35	0.55	0.3176
10	50	4.20	0.0211	0.35	0.60	0.0545	30	50	2.36	0.0200	0.35	0.60	0.4769
10	50	4.20	0.0211	0.35	0.65	0.0753	30	50	2.36	0.0200	0.35	0.65	0.6437
10	50	4.20	0.0211	0.40	0.55	0.0176	30	50	2.36	0.0200	0.40	0.55	0.1759
10	50	4.20	0.0211	0.40	0.60	0.0289	30	50	2.36	0.0200	0.40	0.60	0.3022
10	60	4.48	0.0247	0.05	0.15	0.0081	30	60	2.59	0.0188	0.05	0.15	0.2398
10	60	4.48	0.0247	0.05	0.20	0.0782	30	60	2.59	0.0188	0.05	0.20	0.4316
10	60	4.48	0.0247	0.05	0.25	0.2582	30	60	2.59	0.0188	0.05	0.25	0.6346
10	60	4.48	0.0247	0.05	0.30	0.4528	30	60	2.59	0.0188	0.05	0.30	0.8023
10	60	4.48	0.0247	0.05	0.35	0.5595	30	60	2.59	0.0188	0.05	0.35	0.9112
10	60	4.48	0.0247	0.05	0.40	0.5924	30	60	2.59	0.0188	0.05	0.40	0.9667
10	60	4.48	0.0247	0.05	0.45	0.6003	30	60	2.59	0.0188	0.05	0.45	0.9895
10	60	4.48	0.0247	0.10	0.25	0.1504	30	60	2.59	0.0188	0.10	0.25	0.3016
10	60	4.48	0.0247	0.10	0.30	0.2637	30	60	2.59	0.0188	0.10	0.30	0.4874
10	60	4.48	0.0247	0.10	0.35	0.3258	30	60	2.59	0.0188	0.10	0.35	0.6703
10	60	4.48	0.0247	0.10	0.40	0.3451	30	60	2.59	0.0188	0.10	0.40	0.8148
10	60	4.48	0.0247	0.10	0.45	0.3510	30	60	2.59	0.0188	0.10	0.45	0.9099
10	60	4.48	0.0247	0.10	0.50	0.3666	30	60	2.59	0.0188	0.10	0.50	0.9629
10	60	4.48	0.0247	0.10	0.55	0.4192	30	60	2.59	0.0188	0.10	0.55	0.9874
10	60	4.48	0.0247	0.10	0.60	0.5235	30	60	2.59	0.0188	0.10	0.60	0.9966
10	60	4.48	0.0247	0.15	0.30	0.1489	30	60	2.59	0.0188	0.15	0.30	0.2397
10	60	4.48	0.0247	0.15	0.35	0.1840	30	60	2.59	0.0188	0.15	0.35	0.3998
10	60	4.48	0.0247	0.15	0.40	0.1949	30	60	2.59	0.0188	0.15	0.40	0.5728
10	60	4.48	0.0247	0.15	0.45	0.1991	30	60	2.59	0.0188	0.15	0.45	0.7309
10	60	4.48	0.0247	0.15	0.50	0.2129	30	60	2.59	0.0188	0.15	0.50	0.8536
10	60	4.48	0.0247	0.15	0.55	0.2602	30	60	2.59	0.0188	0.15	0.55	0.9327
10	60	4.48	0.0247	0.15	0.60	0.3537	30	60	2.59	0.0188	0.15	0.60	0.9745
10	60	4.48	0.0247	0.15	0.65	0.4595	30	60	2.59	0.0188	0.15	0.65	0.9924
10	60	4.48	0.0247	0.20	0.35	0.1003	30	60	2.59	0.0188	0.20	0.35	0.1980
10	60	4.48	0.0247	0.20	0.40	0.1064	30	60	2.59	0.0188	0.20	0.40	0.3368
10	60	4.48	0.0247	0.20	0.45	0.1091	30	60	2.59	0.0188	0.20	0.45	0.5021
10	60	4.48	0.0247	0.20	0.50	0.1198	30	60	2.59	0.0188	0.20	0.50	0.6688
10	60	4.48	0.0247	0.20	0.55	0.1563	30	60	2.59	0.0188	0.20	0.55	0.8091
10	60	4.48	0.0247	0.20	0.60	0.2286	30	60	2.59	0.0188	0.20	0.60	0.9075
10	60	4.48	0.0247	0.20	0.65	0.3106	30	60	2.59	0.0188	0.20	0.65	0.9640
10	60	4.48	0.0247	0.20	0.70	0.3677	30	60	2.59	0.0188	0.20	0.70	0.9892
10	60	4.48	0.0247	0.25	0.40	0.0558	30	60	2.59	0.0188	0.25	0.40	0.1677
10	60	4.48	0.0247	0.25	0.45	0.0576	30	60	2.59	0.0188	0.25	0.45	0.2947
10	60	4.48	0.0247	0.25	0.50	0.0650	30	60	2.59	0.0188	0.25	0.50	0.4553
10	60	4.48	0.0247	0.25	0.55	0.0905	30	60	2.59	0.0188	0.25	0.55	0.6264
10	60	4.48	0.0247	0.25	0.60	0.1411	30	60	2.59	0.0188	0.25	0.60	0.7801
10	60	4.48	0.0247	0.25	0.65	0.1987	30	60	2.59	0.0188	0.25	0.65	0.8931
10	60	4.48	0.0247	0.25	0.70	0.2405	30	60	2.59	0.0188	0.25	0.70	0.9584
10	60	4.48	0.0247	0.25	0.75	0.2842	30	60	2.59	0.0188	0.25	0.75	0.9874
10	60	4.48	0.0247	0.30	0.45	0.0291	30	60	2.59	0.0188	0.30	0.45	0.1482

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	60	4.48	0.0247	0.30	0.50	0.0338	30	60	2.59	0.0188	0.30	0.50	0.2678
10	60	4.48	0.0247	0.30	0.55	0.0503	30	60	2.59	0.0188	0.30	0.55	0.4266
10	60	4.48	0.0247	0.30	0.60	0.0829	30	60	2.59	0.0188	0.30	0.60	0.6045
10	60	4.48	0.0247	0.30	0.65	0.1202	30	60	2.59	0.0188	0.30	0.65	0.7677
10	60	4.48	0.0247	0.30	0.70	0.1485	30	60	2.59	0.0188	0.30	0.70	0.8870
10	60	4.48	0.0247	0.35	0.50	0.0168	30	60	2.59	0.0188	0.35	0.50	0.1359
10	60	4.48	0.0247	0.35	0.55	0.0267	30	60	2.59	0.0188	0.35	0.55	0.2536
10	60	4.48	0.0247	0.35	0.60	0.0462	30	60	2.59	0.0188	0.35	0.60	0.4153
10	60	4.48	0.0247	0.35	0.65	0.0687	30	60	2.59	0.0188	0.35	0.65	0.5976
10	60	4.48	0.0247	0.40	0.55	0.0134	30	60	2.59	0.0188	0.40	0.55	0.1307
10	60	4.48	0.0247	0.40	0.60	0.0243	30	60	2.59	0.0188	0.40	0.60	0.2498
10	70	4.93	0.0230	0.05	0.15	0.0037	30	70	2.79	0.0183	0.05	0.15	0.2358
10	70	4.93	0.0230	0.05	0.20	0.0554	30	70	2.79	0.0183	0.05	0.20	0.4209
10	70	4.93	0.0230	0.05	0.25	0.2294	30	70	2.79	0.0183	0.05	0.25	0.6189
10	70	4.93	0.0230	0.05	0.30	0.4427	30	70	2.79	0.0183	0.05	0.30	0.7866
10	70	4.93	0.0230	0.05	0.35	0.5605	30	70	2.79	0.0183	0.05	0.35	0.9017
10	70	4.93	0.0230	0.05	0.40	0.5934	30	70	2.79	0.0183	0.05	0.40	0.9632
10	70	4.93	0.0230	0.05	0.45	0.5984	30	70	2.79	0.0183	0.05	0.45	0.9886
10	70	4.93	0.0230	0.10	0.25	0.1336	30	70	2.79	0.0183	0.10	0.25	0.2754
10	70	4.93	0.0230	0.10	0.30	0.2578	30	70	2.79	0.0183	0.10	0.30	0.4529
10	70	4.93	0.0230	0.10	0.35	0.3264	30	70	2.79	0.0183	0.10	0.35	0.6413
10	70	4.93	0.0230	0.10	0.40	0.3456	30	70	2.79	0.0183	0.10	0.40	0.7967
10	70	4.93	0.0230	0.10	0.45	0.3486	30	70	2.79	0.0183	0.10	0.45	0.9002
10	70	4.93	0.0230	0.10	0.50	0.3509	30	70	2.79	0.0183	0.10	0.50	0.9587
10	70	4.93	0.0230	0.10	0.55	0.3662	30	70	2.79	0.0183	0.10	0.55	0.9861
10	70	4.93	0.0230	0.10	0.60	0.4251	30	70	2.79	0.0183	0.10	0.60	0.9963
10	70	4.93	0.0230	0.15	0.30	0.1456	30	70	2.79	0.0183	0.15	0.30	0.2096
10	70	4.93	0.0230	0.15	0.35	0.1843	30	70	2.79	0.0183	0.15	0.35	0.3657
10	70	4.93	0.0230	0.15	0.40	0.1951	30	70	2.79	0.0183	0.15	0.40	0.5410
10	70	4.93	0.0230	0.15	0.45	0.1969	30	70	2.79	0.0183	0.15	0.45	0.7056
10	70	4.93	0.0230	0.15	0.50	0.1989	30	70	2.79	0.0183	0.15	0.50	0.8375
10	70	4.93	0.0230	0.15	0.55	0.2126	30	70	2.79	0.0183	0.15	0.55	0.9250
10	70	4.93	0.0230	0.15	0.60	0.2654	30	70	2.79	0.0183	0.15	0.60	0.9719
10	70	4.93	0.0230	0.15	0.65	0.3724	30	70	2.79	0.0183	0.15	0.65	0.9917
10	70	4.93	0.0230	0.20	0.35	0.1005	30	70	2.79	0.0183	0.20	0.35	0.1718
10	70	4.93	0.0230	0.20	0.40	0.1064	30	70	2.79	0.0183	0.20	0.40	0.3035
10	70	4.93	0.0230	0.20	0.45	0.1074	30	70	2.79	0.0183	0.20	0.45	0.4666
10	70	4.93	0.0230	0.20	0.50	0.1089	30	70	2.79	0.0183	0.20	0.50	0.6388
10	70	4.93	0.0230	0.20	0.55	0.1195	30	70	2.79	0.0183	0.20	0.55	0.7898
10	70	4.93	0.0230	0.20	0.60	0.1603	30	70	2.79	0.0183	0.20	0.60	0.8976
10	70	4.93	0.0230	0.20	0.65	0.2430	30	70	2.79	0.0183	0.20	0.65	0.9588
10	70	4.93	0.0230	0.20	0.70	0.3281	30	70	2.79	0.0183	0.20	0.70	0.9866
10	70	4.93	0.0230	0.25	0.40	0.0558	30	70	2.79	0.0183	0.25	0.40	0.1428
10	70	4.93	0.0230	0.25	0.45	0.0563	30	70	2.79	0.0183	0.25	0.45	0.2609
10	70	4.93	0.0230	0.25	0.50	0.0574	30	70	2.79	0.0183	0.25	0.50	0.4190
10	70	4.93	0.0230	0.25	0.55	0.0648	30	70	2.79	0.0183	0.25	0.55	0.5957
10	70	4.93	0.0230	0.25	0.60	0.0933	30	70	2.79	0.0183	0.25	0.60	0.7569
10	70	4.93	0.0230	0.25	0.65	0.1511	30	70	2.79	0.0183	0.25	0.65	0.8754
10	70	4.93	0.0230	0.25	0.70	0.2108	30	70	2.79	0.0183	0.25	0.70	0.9473
10	70	4.93	0.0230	0.25	0.75	0.2446	30	70	2.79	0.0183	0.25	0.75	0.9829

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	70	4.93	0.0230	0.30	0.45	0.0283	30	70	2.79	0.0183	0.30	0.45	0.1240
10	70	4.93	0.0230	0.30	0.50	0.0289	30	70	2.79	0.0183	0.30	0.50	0.2356
10	70	4.93	0.0230	0.30	0.55	0.0337	30	70	2.79	0.0183	0.30	0.55	0.3906
10	70	4.93	0.0230	0.30	0.60	0.0521	30	70	2.79	0.0183	0.30	0.60	0.5665
10	70	4.93	0.0230	0.30	0.65	0.0894	30	70	2.79	0.0183	0.30	0.65	0.7303
10	70	4.93	0.0230	0.30	0.70	0.1280	30	70	2.79	0.0183	0.30	0.70	0.8593
10	70	4.93	0.0230	0.35	0.50	0.0139	30	70	2.79	0.0183	0.35	0.50	0.1132
10	70	4.93	0.0230	0.35	0.55	0.0167	30	70	2.79	0.0183	0.35	0.55	0.2204
10	70	4.93	0.0230	0.35	0.60	0.0278	30	70	2.79	0.0183	0.35	0.60	0.3691
10	70	4.93	0.0230	0.35	0.65	0.0501	30	70	2.79	0.0183	0.35	0.65	0.5425
10	70	4.93	0.0230	0.40	0.55	0.0079	30	70	2.79	0.0183	0.40	0.55	0.1059
10	70	4.93	0.0230	0.40	0.60	0.0140	30	70	2.79	0.0183	0.40	0.60	0.2066
10	80	5.34	0.0218	0.05	0.15	0.0017	30	80	2.99	0.0180	0.05	0.15	0.2332
10	80	5.34	0.0218	0.05	0.20	0.0395	30	80	2.99	0.0180	0.05	0.20	0.4138
10	80	5.34	0.0218	0.05	0.25	0.2051	30	80	2.99	0.0180	0.05	0.25	0.6076
10	80	5.34	0.0218	0.05	0.30	0.4344	30	80	2.99	0.0180	0.05	0.30	0.7725
10	80	5.34	0.0218	0.05	0.35	0.5619	30	80	2.99	0.0180	0.05	0.35	0.8897
10	80	5.34	0.0218	0.05	0.40	0.5944	30	80	2.99	0.0180	0.05	0.40	0.9565
10	80	5.34	0.0218	0.05	0.45	0.5985	30	80	2.99	0.0180	0.05	0.45	0.9863
10	80	5.34	0.0218	0.10	0.25	0.1195	30	80	2.99	0.0180	0.10	0.25	0.2572
10	80	5.34	0.0218	0.10	0.30	0.2530	30	80	2.99	0.0180	0.10	0.30	0.4209
10	80	5.34	0.0218	0.10	0.35	0.3272	30	80	2.99	0.0180	0.10	0.35	0.6031
10	80	5.34	0.0218	0.10	0.40	0.3462	30	80	2.99	0.0180	0.10	0.40	0.7673
10	80	5.34	0.0218	0.10	0.45	0.3485	30	80	2.99	0.0180	0.10	0.45	0.8857
10	80	5.34	0.0218	0.10	0.50	0.3489	30	80	2.99	0.0180	0.10	0.50	0.9538
10	80	5.34	0.0218	0.10	0.55	0.3519	30	80	2.99	0.0180	0.10	0.55	0.9847
10	80	5.34	0.0218	0.10	0.60	0.3748	30	80	2.99	0.0180	0.10	0.60	0.9959
10	80	5.34	0.0218	0.15	0.30	0.1428	30	80	2.99	0.0180	0.15	0.30	0.1811
10	80	5.34	0.0218	0.15	0.35	0.1848	30	80	2.99	0.0180	0.15	0.35	0.3231
10	80	5.34	0.0218	0.15	0.40	0.1955	30	80	2.99	0.0180	0.15	0.40	0.4997
10	80	5.34	0.0218	0.15	0.45	0.1968	30	80	2.99	0.0180	0.15	0.45	0.6778
10	80	5.34	0.0218	0.15	0.50	0.1971	30	80	2.99	0.0180	0.15	0.50	0.8221
10	80	5.34	0.0218	0.15	0.55	0.1998	30	80	2.99	0.0180	0.15	0.55	0.9169
10	80	5.34	0.0218	0.15	0.60	0.2203	30	80	2.99	0.0180	0.15	0.60	0.9682
10	80	5.34	0.0218	0.15	0.65	0.2947	30	80	2.99	0.0180	0.15	0.65	0.9904
10	80	5.34	0.0218	0.20	0.35	0.1008	30	80	2.99	0.0180	0.20	0.35	0.1425
10	80	5.34	0.0218	0.20	0.40	0.1066	30	80	2.99	0.0180	0.20	0.40	0.2683
10	80	5.34	0.0218	0.20	0.45	0.1073	30	80	2.99	0.0180	0.20	0.45	0.4344
10	80	5.34	0.0218	0.20	0.50	0.1075	30	80	2.99	0.0180	0.20	0.50	0.6117
10	80	5.34	0.0218	0.20	0.55	0.1096	30	80	2.99	0.0180	0.20	0.55	0.7686
10	80	5.34	0.0218	0.20	0.60	0.1255	30	80	2.99	0.0180	0.20	0.60	0.8845
10	80	5.34	0.0218	0.20	0.65	0.1830	30	80	2.99	0.0180	0.20	0.65	0.9529
10	80	5.34	0.0218	0.20	0.70	0.2813	30	80	2.99	0.0180	0.20	0.70	0.9845
10	80	5.34	0.0218	0.25	0.40	0.0559	30	80	2.99	0.0180	0.25	0.40	0.1207
10	80	5.34	0.0218	0.25	0.45	0.0563	30	80	2.99	0.0180	0.25	0.45	0.2336
10	80	5.34	0.0218	0.25	0.50	0.0564	30	80	2.99	0.0180	0.25	0.50	0.3869
10	80	5.34	0.0218	0.25	0.55	0.0579	30	80	2.99	0.0180	0.25	0.55	0.5626
10	80	5.34	0.0218	0.25	0.60	0.0690	30	80	2.99	0.0180	0.25	0.60	0.7305
10	80	5.34	0.0218	0.25	0.65	0.1092	30	80	2.99	0.0180	0.25	0.65	0.8598
10	80	5.34	0.0218	0.25	0.70	0.1779	30	80	2.99	0.0180	0.25	0.70	0.9394

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	80	5.34	0.0218	0.25	0.75	0.2291	30	80	2.99	0.0180	0.25	0.75	0.9791
10	80	5.34	0.0218	0.30	0.45	0.0282	30	80	2.99	0.0180	0.30	0.45	0.1058
10	80	5.34	0.0218	0.30	0.50	0.0283	30	80	2.99	0.0180	0.30	0.50	0.2075
10	80	5.34	0.0218	0.30	0.55	0.0293	30	80	2.99	0.0180	0.30	0.55	0.3542
10	80	5.34	0.0218	0.30	0.60	0.0364	30	80	2.99	0.0180	0.30	0.60	0.5307
10	80	5.34	0.0218	0.30	0.65	0.0624	30	80	2.99	0.0180	0.30	0.65	0.7027
10	80	5.34	0.0218	0.30	0.70	0.1067	30	80	2.99	0.0180	0.30	0.70	0.8396
10	80	5.34	0.0218	0.35	0.50	0.0135	30	80	2.99	0.0180	0.35	0.50	0.0942
10	80	5.34	0.0218	0.35	0.55	0.0141	30	80	2.99	0.0180	0.35	0.55	0.1904
10	80	5.34	0.0218	0.35	0.60	0.0184	30	80	2.99	0.0180	0.35	0.60	0.3330
10	80	5.34	0.0218	0.35	0.65	0.0339	30	80	2.99	0.0180	0.35	0.65	0.5061
10	80	5.34	0.0218	0.40	0.55	0.0064	30	80	2.99	0.0180	0.40	0.55	0.0866
10	80	5.34	0.0218	0.40	0.60	0.0088	30	80	2.99	0.0180	0.40	0.60	0.1781
10	90	5.56	0.0245	0.05	0.15	0.0018	30	90	3.17	0.0177	0.05	0.15	0.2155
10	90	5.56	0.0245	0.05	0.20	0.0461	30	90	3.17	0.0177	0.05	0.20	0.3734
10	90	5.56	0.0245	0.05	0.25	0.2374	30	90	3.17	0.0177	0.05	0.25	0.5808
10	90	5.56	0.0245	0.05	0.30	0.4718	30	90	3.17	0.0177	0.05	0.30	0.7592
10	90	5.56	0.0245	0.05	0.35	0.5771	30	90	3.17	0.0177	0.05	0.35	0.8825
10	90	5.56	0.0245	0.05	0.40	0.5970	30	90	3.17	0.0177	0.05	0.40	0.9539
10	90	5.56	0.0245	0.05	0.45	0.5987	30	90	3.17	0.0177	0.05	0.45	0.9856
10	90	5.56	0.0245	0.10	0.25	0.1383	30	90	3.17	0.0177	0.10	0.25	0.2376
10	90	5.56	0.0245	0.10	0.30	0.2748	30	90	3.17	0.0177	0.10	0.30	0.4005
10	90	5.56	0.0245	0.10	0.35	0.3361	30	90	3.17	0.0177	0.10	0.35	0.5844
10	90	5.56	0.0245	0.10	0.40	0.3477	30	90	3.17	0.0177	0.10	0.40	0.7545
10	90	5.56	0.0245	0.10	0.45	0.3486	30	90	3.17	0.0177	0.10	0.45	0.8760
10	90	5.56	0.0245	0.10	0.50	0.3487	30	90	3.17	0.0177	0.10	0.50	0.9471
10	90	5.56	0.0245	0.10	0.55	0.3497	30	90	3.17	0.0177	0.10	0.55	0.9815
10	90	5.56	0.0245	0.10	0.60	0.3611	30	90	3.17	0.0177	0.10	0.60	0.9948
10	90	5.56	0.0245	0.15	0.30	0.1551	30	90	3.17	0.0177	0.15	0.30	0.1660
10	90	5.56	0.0245	0.15	0.35	0.1898	30	90	3.17	0.0177	0.15	0.35	0.3038
10	90	5.56	0.0245	0.15	0.40	0.1963	30	90	3.17	0.0177	0.15	0.40	0.4775
10	90	5.56	0.0245	0.15	0.45	0.1969	30	90	3.17	0.0177	0.15	0.45	0.6516
10	90	5.56	0.0245	0.15	0.50	0.1969	30	90	3.17	0.0177	0.15	0.50	0.7988
10	90	5.56	0.0245	0.15	0.55	0.1978	30	90	3.17	0.0177	0.15	0.55	0.9013
10	90	5.56	0.0245	0.15	0.60	0.2080	30	90	3.17	0.0177	0.15	0.60	0.9592
10	90	5.56	0.0245	0.15	0.65	0.2626	30	90	3.17	0.0177	0.15	0.65	0.9864
10	90	5.56	0.0245	0.20	0.35	0.1035	30	90	3.17	0.0177	0.20	0.35	0.1291
10	90	5.56	0.0245	0.20	0.40	0.1071	30	90	3.17	0.0177	0.20	0.40	0.2456
10	90	5.56	0.0245	0.20	0.45	0.1074	30	90	3.17	0.0177	0.20	0.45	0.3997
10	90	5.56	0.0245	0.20	0.50	0.1074	30	90	3.17	0.0177	0.20	0.50	0.5729
10	90	5.56	0.0245	0.20	0.55	0.1081	30	90	3.17	0.0177	0.20	0.55	0.7330
10	90	5.56	0.0245	0.20	0.60	0.1160	30	90	3.17	0.0177	0.20	0.60	0.8561
10	90	5.56	0.0245	0.20	0.65	0.1581	30	90	3.17	0.0177	0.20	0.65	0.9362
10	90	5.56	0.0245	0.20	0.70	0.2555	30	90	3.17	0.0177	0.20	0.70	0.9785
10	90	5.56	0.0245	0.25	0.40	0.0561	30	90	3.17	0.0177	0.25	0.40	0.1047
10	90	5.56	0.0245	0.25	0.45	0.0563	30	90	3.17	0.0177	0.25	0.45	0.2036
10	90	5.56	0.0245	0.25	0.50	0.0563	30	90	3.17	0.0177	0.25	0.50	0.3449
10	90	5.56	0.0245	0.25	0.55	0.0568	30	90	3.17	0.0177	0.25	0.55	0.5115
10	90	5.56	0.0245	0.25	0.60	0.0623	30	90	3.17	0.0177	0.25	0.60	0.6784
10	90	5.56	0.0245	0.25	0.65	0.0918	30	90	3.17	0.0177	0.25	0.65	0.8221

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	90	5.56	0.0245	0.25	0.70	0.1599	30	90	3.17	0.0177	0.25	0.70	0.9222
10	90	5.56	0.0245	0.25	0.75	0.2228	30	90	3.17	0.0177	0.25	0.75	0.9740
10	90	5.56	0.0245	0.30	0.45	0.0282	30	90	3.17	0.0177	0.30	0.45	0.0868
10	90	5.56	0.0245	0.30	0.50	0.0283	30	90	3.17	0.0177	0.30	0.50	0.1740
10	90	5.56	0.0245	0.30	0.55	0.0286	30	90	3.17	0.0177	0.30	0.55	0.3023
10	90	5.56	0.0245	0.30	0.60	0.0321	30	90	3.17	0.0177	0.30	0.60	0.4657
10	90	5.56	0.0245	0.30	0.65	0.0511	30	90	3.17	0.0177	0.30	0.65	0.6462
10	90	5.56	0.0245	0.30	0.70	0.0950	30	90	3.17	0.0177	0.30	0.70	0.8072
10	90	5.56	0.0245	0.35	0.50	0.0135	30	90	3.17	0.0177	0.35	0.50	0.0735
10	90	5.56	0.0245	0.35	0.55	0.0136	30	90	3.17	0.0177	0.35	0.55	0.1504
10	90	5.56	0.0245	0.35	0.60	0.0158	30	90	3.17	0.0177	0.35	0.60	0.2733
10	90	5.56	0.0245	0.35	0.65	0.0272	30	90	3.17	0.0177	0.35	0.65	0.4442
10	90	5.56	0.0245	0.40	0.55	0.0062	30	90	3.17	0.0177	0.40	0.55	0.0627
10	90	5.56	0.0245	0.40	0.60	0.0073	30	90	3.17	0.0177	0.40	0.60	0.1360
10	100	5.93	0.0234	0.05	0.15	0.0008	30	100	3.15	0.0245	0.05	0.15	0.2393
10	100	5.93	0.0234	0.05	0.20	0.0334	30	100	3.15	0.0245	0.05	0.20	0.4117
10	100	5.93	0.0234	0.05	0.25	0.2145	30	100	3.15	0.0245	0.05	0.25	0.6182
10	100	5.93	0.0234	0.05	0.30	0.4644	30	100	3.15	0.0245	0.05	0.30	0.7894
10	100	5.93	0.0234	0.05	0.35	0.5777	30	100	3.15	0.0245	0.05	0.35	0.9024
10	100	5.93	0.0234	0.05	0.40	0.5973	30	100	3.15	0.0245	0.05	0.40	0.9618
10	100	5.93	0.0234	0.05	0.45	0.5987	30	100	3.15	0.0245	0.05	0.45	0.9878
10	100	5.93	0.0234	0.10	0.25	0.1249	30	100	3.15	0.0245	0.10	0.25	0.2620
10	100	5.93	0.0234	0.10	0.30	0.2704	30	100	3.15	0.0245	0.10	0.30	0.4335
10	100	5.93	0.0234	0.10	0.35	0.3364	30	100	3.15	0.0245	0.10	0.35	0.6129
10	100	5.93	0.0234	0.10	0.40	0.3478	30	100	3.15	0.0245	0.10	0.40	0.7691
10	100	5.93	0.0234	0.10	0.45	0.3487	30	100	3.15	0.0245	0.10	0.45	0.8853
10	100	5.93	0.0234	0.10	0.50	0.3487	30	100	3.15	0.0245	0.10	0.50	0.9539
10	100	5.93	0.0234	0.10	0.55	0.3487	30	100	3.15	0.0245	0.10	0.55	0.9848
10	100	5.93	0.0234	0.10	0.60	0.3505	30	100	3.15	0.0245	0.10	0.60	0.9959
10	100	5.93	0.0234	0.15	0.30	0.1527	30	100	3.15	0.0245	0.15	0.30	0.1844
10	100	5.93	0.0234	0.15	0.35	0.1900	30	100	3.15	0.0245	0.15	0.35	0.3211
10	100	5.93	0.0234	0.15	0.40	0.1964	30	100	3.15	0.0245	0.15	0.40	0.4895
10	100	5.93	0.0234	0.15	0.45	0.1969	30	100	3.15	0.0245	0.15	0.45	0.6670
10	100	5.93	0.0234	0.15	0.50	0.1969	30	100	3.15	0.0245	0.15	0.50	0.8150
10	100	5.93	0.0234	0.15	0.55	0.1969	30	100	3.15	0.0245	0.15	0.55	0.9124
10	100	5.93	0.0234	0.15	0.60	0.1985	30	100	3.15	0.0245	0.15	0.60	0.9658
10	100	5.93	0.0234	0.15	0.65	0.2163	30	100	3.15	0.0245	0.15	0.65	0.9894
10	100	5.93	0.0234	0.20	0.35	0.1036	30	100	3.15	0.0245	0.20	0.35	0.1359
10	100	5.93	0.0234	0.20	0.40	0.1071	30	100	3.15	0.0245	0.20	0.40	0.2528
10	100	5.93	0.0234	0.20	0.45	0.1074	30	100	3.15	0.0245	0.20	0.45	0.4150
10	100	5.93	0.0234	0.20	0.50	0.1074	30	100	3.15	0.0245	0.20	0.50	0.5929
10	100	5.93	0.0234	0.20	0.55	0.1074	30	100	3.15	0.0245	0.20	0.55	0.7522
10	100	5.93	0.0234	0.20	0.60	0.1086	30	100	3.15	0.0245	0.20	0.60	0.8726
10	100	5.93	0.0234	0.20	0.65	0.1224	30	100	3.15	0.0245	0.20	0.65	0.9459
10	100	5.93	0.0234	0.20	0.70	0.1869	30	100	3.15	0.0245	0.20	0.70	0.9816
10	100	5.93	0.0234	0.25	0.40	0.0562	30	100	3.15	0.0245	0.25	0.40	0.1082
10	100	5.93	0.0234	0.25	0.45	0.0563	30	100	3.15	0.0245	0.25	0.45	0.2141
10	100	5.93	0.0234	0.25	0.50	0.0563	30	100	3.15	0.0245	0.25	0.50	0.3616
10	100	5.93	0.0234	0.25	0.55	0.0563	30	100	3.15	0.0245	0.25	0.55	0.5336
10	100	5.93	0.0234	0.25	0.60	0.0572	30	100	3.15	0.0245	0.25	0.60	0.7032

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	100	5.93	0.0234	0.25	0.65	0.0668	30	100	3.15	0.0245	0.25	0.65	0.8392
10	100	5.93	0.0234	0.25	0.70	0.1119	30	100	3.15	0.0245	0.25	0.70	0.9288
10	100	5.93	0.0234	0.25	0.75	0.1919	30	100	3.15	0.0245	0.25	0.75	0.9763
10	100	5.93	0.0234	0.30	0.45	0.0282	30	100	3.15	0.0245	0.30	0.45	0.0921
10	100	5.93	0.0234	0.30	0.50	0.0282	30	100	3.15	0.0245	0.30	0.50	0.1844
10	100	5.93	0.0234	0.30	0.55	0.0283	30	100	3.15	0.0245	0.30	0.55	0.3208
10	100	5.93	0.0234	0.30	0.60	0.0288	30	100	3.15	0.0245	0.30	0.60	0.4909
10	100	5.93	0.0234	0.30	0.65	0.0350	30	100	3.15	0.0245	0.30	0.65	0.6655
10	100	5.93	0.0234	0.30	0.70	0.0641	30	100	3.15	0.0245	0.30	0.70	0.8163
10	100	5.93	0.0234	0.35	0.50	0.0135	30	100	3.15	0.0245	0.35	0.50	0.0786
10	100	5.93	0.0234	0.35	0.55	0.0135	30	100	3.15	0.0245	0.35	0.55	0.1623
10	100	5.93	0.0234	0.35	0.60	0.0138	30	100	3.15	0.0245	0.35	0.60	0.2918
10	100	5.93	0.0234	0.35	0.65	0.0175	30	100	3.15	0.0245	0.35	0.65	0.4594
10	100	5.93	0.0234	0.40	0.55	0.0061	30	100	3.15	0.0245	0.40	0.55	0.0686
10	100	5.93	0.0234	0.40	0.60	0.0062	30	100	3.15	0.0245	0.40	0.60	0.1460
20	30	2.30	0.0209	0.05	0.15	0.1815	40	50	2.05	0.0245	0.05	0.15	0.3664
20	30	2.30	0.0209	0.05	0.20	0.3206	40	50	2.05	0.0245	0.05	0.20	0.5906
20	30	2.30	0.0209	0.05	0.25	0.4678	40	50	2.05	0.0245	0.05	0.25	0.7829
20	30	2.30	0.0209	0.05	0.30	0.6183	40	50	2.05	0.0245	0.05	0.30	0.9075
20	30	2.30	0.0209	0.05	0.35	0.7552	40	50	2.05	0.0245	0.05	0.35	0.9686
20	30	2.30	0.0209	0.05	0.40	0.8611	40	50	2.05	0.0245	0.05	0.40	0.9915
20	30	2.30	0.0209	0.05	0.45	0.9304	40	50	2.05	0.0245	0.05	0.45	0.9982
20	30	2.30	0.0209	0.10	0.25	0.2324	40	50	2.05	0.0245	0.10	0.25	0.4509
20	30	2.30	0.0209	0.10	0.30	0.3660	40	50	2.05	0.0245	0.10	0.30	0.6633
20	30	2.30	0.0209	0.10	0.35	0.5186	40	50	2.05	0.0245	0.10	0.35	0.8268
20	30	2.30	0.0209	0.10	0.40	0.6657	40	50	2.05	0.0245	0.10	0.40	0.9253
20	30	2.30	0.0209	0.10	0.45	0.7883	40	50	2.05	0.0245	0.10	0.45	0.9733
20	30	2.30	0.0209	0.10	0.50	0.8781	40	50	2.05	0.0245	0.10	0.50	0.9923
20	30	2.30	0.0209	0.10	0.55	0.9365	40	50	2.05	0.0245	0.10	0.55	0.9983
20	30	2.30	0.0209	0.10	0.60	0.9704	40	50	2.05	0.0245	0.10	0.60	0.9997
20	30	2.30	0.0209	0.15	0.30	0.2010	40	50	2.05	0.0245	0.15	0.30	0.3879
20	30	2.30	0.0209	0.15	0.35	0.3240	40	50	2.05	0.0245	0.15	0.35	0.5864
20	30	2.30	0.0209	0.15	0.40	0.4648	40	50	2.05	0.0245	0.15	0.40	0.7600
20	30	2.30	0.0209	0.15	0.45	0.6056	40	50	2.05	0.0245	0.15	0.45	0.8833
20	30	2.30	0.0209	0.15	0.50	0.7311	40	50	2.05	0.0245	0.15	0.50	0.9537
20	30	2.30	0.0209	0.15	0.55	0.8316	40	50	2.05	0.0245	0.15	0.55	0.9853
20	30	2.30	0.0209	0.15	0.60	0.9045	40	50	2.05	0.0245	0.15	0.60	0.9964
20	30	2.30	0.0209	0.15	0.65	0.9520	40	50	2.05	0.0245	0.15	0.65	0.9993
20	30	2.30	0.0209	0.20	0.35	0.1852	40	50	2.05	0.0245	0.20	0.35	0.3426
20	30	2.30	0.0209	0.20	0.40	0.2950	40	50	2.05	0.0245	0.20	0.40	0.5329
20	30	2.30	0.0209	0.20	0.45	0.4230	40	50	2.05	0.0245	0.20	0.45	0.7155
20	30	2.30	0.0209	0.20	0.50	0.5568	40	50	2.05	0.0245	0.20	0.50	0.8546
20	30	2.30	0.0209	0.20	0.55	0.6839	40	50	2.05	0.0245	0.20	0.55	0.9386
20	30	2.30	0.0209	0.20	0.60	0.7938	40	50	2.05	0.0245	0.20	0.60	0.9788
20	30	2.30	0.0209	0.20	0.65	0.8797	40	50	2.05	0.0245	0.20	0.65	0.9942
20	30	2.30	0.0209	0.20	0.70	0.9391	40	50	2.05	0.0245	0.20	0.70	0.9988
20	30	2.30	0.0209	0.25	0.40	0.1709	40	50	2.05	0.0245	0.25	0.40	0.3177
20	30	2.30	0.0209	0.25	0.45	0.2695	40	50	2.05	0.0245	0.25	0.45	0.5045
20	30	2.30	0.0209	0.25	0.50	0.3882	40	50	2.05	0.0245	0.25	0.50	0.6879
20	30	2.30	0.0209	0.25	0.55	0.5188	40	50	2.05	0.0245	0.25	0.55	0.8323

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	30	2.30	0.0209	0.25	0.60	0.6504	40	50	2.05	0.0245	0.25	0.60	0.9248
20	30	2.30	0.0209	0.25	0.65	0.7700	40	50	2.05	0.0245	0.25	0.65	0.9730
20	30	2.30	0.0209	0.25	0.70	0.8664	40	50	2.05	0.0245	0.25	0.70	0.9927
20	30	2.30	0.0209	0.25	0.75	0.9332	40	50	2.05	0.0245	0.25	0.75	0.9986
20	30	2.30	0.0209	0.30	0.45	0.1569	40	50	2.05	0.0245	0.30	0.45	0.3045
20	30	2.30	0.0209	0.30	0.50	0.2480	40	50	2.05	0.0245	0.30	0.50	0.4830
20	30	2.30	0.0209	0.30	0.55	0.3629	40	50	2.05	0.0245	0.30	0.55	0.6634
20	30	2.30	0.0209	0.30	0.60	0.4953	40	50	2.05	0.0245	0.30	0.60	0.8142
20	30	2.30	0.0209	0.30	0.65	0.6330	40	50	2.05	0.0245	0.30	0.65	0.9165
20	30	2.30	0.0209	0.30	0.70	0.7599	40	50	2.05	0.0245	0.30	0.70	0.9708
20	30	2.30	0.0209	0.35	0.50	0.1453	40	50	2.05	0.0245	0.35	0.50	0.2903
20	30	2.30	0.0209	0.35	0.55	0.2339	40	50	2.05	0.0245	0.35	0.55	0.4639
20	30	2.30	0.0209	0.35	0.60	0.3494	40	50	2.05	0.0245	0.35	0.60	0.6486
20	30	2.30	0.0209	0.35	0.65	0.4852	40	50	2.05	0.0245	0.35	0.65	0.8076
20	30	2.30	0.0209	0.40	0.55	0.1385	40	50	2.05	0.0245	0.40	0.55	0.2803
20	30	2.30	0.0209	0.40	0.60	0.2272	40	50	2.05	0.0245	0.40	0.60	0.4566
20	40	2.66	0.0171	0.05	0.15	0.1456	40	60	2.06	0.0249	0.05	0.15	0.4145
20	40	2.66	0.0171	0.05	0.20	0.2905	40	60	2.06	0.0249	0.05	0.20	0.6604
20	40	2.66	0.0171	0.05	0.25	0.4420	40	60	2.06	0.0249	0.05	0.25	0.8403
20	40	2.66	0.0171	0.05	0.30	0.5993	40	60	2.06	0.0249	0.05	0.30	0.9381
20	40	2.66	0.0171	0.05	0.35	0.7452	40	60	2.06	0.0249	0.05	0.35	0.9805
20	40	2.66	0.0171	0.05	0.40	0.8572	40	60	2.06	0.0249	0.05	0.40	0.9952
20	40	2.66	0.0171	0.05	0.45	0.9291	40	60	2.06	0.0249	0.05	0.45	0.9991
20	40	2.66	0.0171	0.10	0.25	0.2033	40	60	2.06	0.0249	0.10	0.25	0.5016
20	40	2.66	0.0171	0.10	0.30	0.3310	40	60	2.06	0.0249	0.10	0.30	0.7025
20	40	2.66	0.0171	0.10	0.35	0.4829	40	60	2.06	0.0249	0.10	0.35	0.8537
20	40	2.66	0.0171	0.10	0.40	0.6333	40	60	2.06	0.0249	0.10	0.40	0.9418
20	40	2.66	0.0171	0.10	0.45	0.7614	40	60	2.06	0.0249	0.10	0.45	0.9816
20	40	2.66	0.0171	0.10	0.50	0.8578	40	60	2.06	0.0249	0.10	0.50	0.9955
20	40	2.66	0.0171	0.10	0.55	0.9228	40	60	2.06	0.0249	0.10	0.55	0.9992
20	40	2.66	0.0171	0.10	0.60	0.9624	40	60	2.06	0.0249	0.10	0.60	0.9999
20	40	2.66	0.0171	0.15	0.30	0.1667	40	60	2.06	0.0249	0.15	0.30	0.4101
20	40	2.66	0.0171	0.15	0.35	0.2788	40	60	2.06	0.0249	0.15	0.35	0.6151
20	40	2.66	0.0171	0.15	0.40	0.4125	40	60	2.06	0.0249	0.15	0.40	0.7909
20	40	2.66	0.0171	0.15	0.45	0.5516	40	60	2.06	0.0249	0.15	0.45	0.9077
20	40	2.66	0.0171	0.15	0.50	0.6813	40	60	2.06	0.0249	0.15	0.50	0.9674
20	40	2.66	0.0171	0.15	0.55	0.7912	40	60	2.06	0.0249	0.15	0.55	0.9909
20	40	2.66	0.0171	0.15	0.60	0.8764	40	60	2.06	0.0249	0.15	0.60	0.9980
20	40	2.66	0.0171	0.15	0.65	0.9361	40	60	2.06	0.0249	0.15	0.65	0.9997
20	40	2.66	0.0171	0.20	0.35	0.1453	40	60	2.06	0.0249	0.20	0.35	0.3635
20	40	2.66	0.0171	0.20	0.40	0.2403	40	60	2.06	0.0249	0.20	0.40	0.5668
20	40	2.66	0.0171	0.20	0.45	0.3567	40	60	2.06	0.0249	0.20	0.45	0.7518
20	40	2.66	0.0171	0.20	0.50	0.4853	40	60	2.06	0.0249	0.20	0.50	0.8823
20	40	2.66	0.0171	0.20	0.55	0.6162	40	60	2.06	0.0249	0.20	0.55	0.9545
20	40	2.66	0.0171	0.20	0.60	0.7389	40	60	2.06	0.0249	0.20	0.60	0.9860
20	40	2.66	0.0171	0.20	0.65	0.8428	40	60	2.06	0.0249	0.20	0.65	0.9967
20	40	2.66	0.0171	0.20	0.70	0.9190	40	60	2.06	0.0249	0.20	0.70	0.9994
20	40	2.66	0.0171	0.25	0.40	0.1262	40	60	2.06	0.0249	0.25	0.40	0.3416
20	40	2.66	0.0171	0.25	0.45	0.2073	40	60	2.06	0.0249	0.25	0.45	0.5384
20	40	2.66	0.0171	0.25	0.50	0.3115	40	60	2.06	0.0249	0.25	0.50	0.7233

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	40	2.66	0.0171	0.25	0.55	0.4358	40	60	2.06	0.0249	0.25	0.55	0.8612
20	40	2.66	0.0171	0.25	0.60	0.5728	40	60	2.06	0.0249	0.25	0.60	0.9432
20	40	2.66	0.0171	0.25	0.65	0.7090	40	60	2.06	0.0249	0.25	0.65	0.9818
20	40	2.66	0.0171	0.25	0.70	0.8262	40	60	2.06	0.0249	0.25	0.70	0.9957
20	40	2.66	0.0171	0.25	0.75	0.9111	40	60	2.06	0.0249	0.25	0.75	0.9993
20	40	2.66	0.0171	0.30	0.45	0.1087	40	60	2.06	0.0249	0.30	0.45	0.3266
20	40	2.66	0.0171	0.30	0.50	0.1808	40	60	2.06	0.0249	0.30	0.50	0.5155
20	40	2.66	0.0171	0.30	0.55	0.2803	40	60	2.06	0.0249	0.30	0.55	0.7000
20	40	2.66	0.0171	0.30	0.60	0.4072	40	60	2.06	0.0249	0.30	0.60	0.8452
20	40	2.66	0.0171	0.30	0.65	0.5525	40	60	2.06	0.0249	0.30	0.65	0.9361
20	40	2.66	0.0171	0.30	0.70	0.6971	40	60	2.06	0.0249	0.30	0.70	0.9798
20	40	2.66	0.0171	0.35	0.50	0.0950	40	60	2.06	0.0249	0.35	0.50	0.3126
20	40	2.66	0.0171	0.35	0.55	0.1640	40	60	2.06	0.0249	0.35	0.55	0.4973
20	40	2.66	0.0171	0.35	0.60	0.2647	40	60	2.06	0.0249	0.35	0.60	0.6854
20	40	2.66	0.0171	0.35	0.65	0.3962	40	60	2.06	0.0249	0.35	0.65	0.8381
20	40	2.66	0.0171	0.40	0.55	0.0871	40	60	2.06	0.0249	0.40	0.55	0.3022
20	40	2.66	0.0171	0.40	0.60	0.1568	40	60	2.06	0.0249	0.40	0.60	0.4883
20	50	2.86	0.0208	0.05	0.15	0.1775	40	70	2.33	0.0246	0.05	0.15	0.3689
20	50	2.86	0.0208	0.05	0.20	0.3324	40	70	2.33	0.0246	0.05	0.20	0.6281
20	50	2.86	0.0208	0.05	0.25	0.4847	40	70	2.33	0.0246	0.05	0.25	0.8219
20	50	2.86	0.0208	0.05	0.30	0.6368	40	70	2.33	0.0246	0.05	0.30	0.9300
20	50	2.86	0.0208	0.05	0.35	0.7673	40	70	2.33	0.0246	0.05	0.35	0.9779
20	50	2.86	0.0208	0.05	0.40	0.8650	40	70	2.33	0.0246	0.05	0.40	0.9946
20	50	2.86	0.0208	0.05	0.45	0.9302	40	70	2.33	0.0246	0.05	0.45	0.9990
20	50	2.86	0.0208	0.10	0.25	0.2225	40	70	2.33	0.0246	0.10	0.25	0.4596
20	50	2.86	0.0208	0.10	0.30	0.3447	40	70	2.33	0.0246	0.10	0.30	0.6669
20	50	2.86	0.0208	0.10	0.35	0.4820	40	70	2.33	0.0246	0.10	0.35	0.8322
20	50	2.86	0.0208	0.10	0.40	0.6211	40	70	2.33	0.0246	0.10	0.40	0.9321
20	50	2.86	0.0208	0.10	0.45	0.7464	40	70	2.33	0.0246	0.10	0.45	0.9778
20	50	2.86	0.0208	0.10	0.50	0.8456	40	70	2.33	0.0246	0.10	0.50	0.9942
20	50	2.86	0.0208	0.10	0.55	0.9156	40	70	2.33	0.0246	0.10	0.55	0.9988
20	50	2.86	0.0208	0.10	0.60	0.9597	40	70	2.33	0.0246	0.10	0.60	0.9998
20	50	2.86	0.0208	0.15	0.30	0.1657	40	70	2.33	0.0246	0.15	0.30	0.3630
20	50	2.86	0.0208	0.15	0.35	0.2645	40	70	2.33	0.0246	0.15	0.35	0.5701
20	50	2.86	0.0208	0.15	0.40	0.3870	40	70	2.33	0.0246	0.15	0.40	0.7545
20	50	2.86	0.0208	0.15	0.45	0.5218	40	70	2.33	0.0246	0.15	0.45	0.8828
20	50	2.86	0.0208	0.15	0.50	0.6543	40	70	2.33	0.0246	0.15	0.50	0.9547
20	50	2.86	0.0208	0.15	0.55	0.7724	40	70	2.33	0.0246	0.15	0.55	0.9864
20	50	2.86	0.0208	0.15	0.60	0.8668	40	70	2.33	0.0246	0.15	0.60	0.9969
20	50	2.86	0.0208	0.15	0.65	0.9321	40	70	2.33	0.0246	0.15	0.65	0.9995
20	50	2.86	0.0208	0.20	0.35	0.1299	40	70	2.33	0.0246	0.20	0.35	0.3099
20	50	2.86	0.0208	0.20	0.40	0.2140	40	70	2.33	0.0246	0.20	0.40	0.5011
20	50	2.86	0.0208	0.20	0.45	0.3230	40	70	2.33	0.0246	0.20	0.45	0.6905
20	50	2.86	0.0208	0.20	0.50	0.4505	40	70	2.33	0.0246	0.20	0.50	0.8410
20	50	2.86	0.0208	0.20	0.55	0.5875	40	70	2.33	0.0246	0.20	0.55	0.9342
20	50	2.86	0.0208	0.20	0.60	0.7192	40	70	2.33	0.0246	0.20	0.60	0.9787
20	50	2.86	0.0208	0.20	0.65	0.8296	40	70	2.33	0.0246	0.20	0.65	0.9949
20	50	2.86	0.0208	0.20	0.70	0.9096	40	70	2.33	0.0246	0.20	0.70	0.9991
20	50	2.86	0.0208	0.25	0.40	0.1062	40	70	2.33	0.0246	0.25	0.40	0.2701
20	50	2.86	0.0208	0.25	0.45	0.1787	40	70	2.33	0.0246	0.25	0.45	0.4528

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	50	2.86	0.0208	0.25	0.50	0.2780	40	70	2.33	0.0246	0.25	0.50	0.6481
20	50	2.86	0.0208	0.25	0.55	0.4028	40	70	2.33	0.0246	0.25	0.55	0.8120
20	50	2.86	0.0208	0.25	0.60	0.5434	40	70	2.33	0.0246	0.25	0.60	0.9198
20	50	2.86	0.0208	0.25	0.65	0.6824	40	70	2.33	0.0246	0.25	0.65	0.9739
20	50	2.86	0.0208	0.25	0.70	0.8033	40	70	2.33	0.0246	0.25	0.70	0.9938
20	50	2.86	0.0208	0.25	0.75	0.8953	40	70	2.33	0.0246	0.25	0.75	0.9989
20	50	2.86	0.0208	0.30	0.45	0.0889	40	70	2.33	0.0246	0.30	0.45	0.2460
20	50	2.86	0.0208	0.30	0.50	0.1543	40	70	2.33	0.0246	0.30	0.50	0.4245
20	50	2.86	0.0208	0.30	0.55	0.2491	40	70	2.33	0.0246	0.30	0.55	0.6229
20	50	2.86	0.0208	0.30	0.60	0.3722	40	70	2.33	0.0246	0.30	0.60	0.7969
20	50	2.86	0.0208	0.30	0.65	0.5136	40	70	2.33	0.0246	0.30	0.65	0.9136
20	50	2.86	0.0208	0.30	0.70	0.6587	40	70	2.33	0.0246	0.30	0.70	0.9718
20	50	2.86	0.0208	0.35	0.50	0.0771	40	70	2.33	0.0246	0.35	0.50	0.2328
20	50	2.86	0.0208	0.35	0.55	0.1388	40	70	2.33	0.0246	0.35	0.55	0.4109
20	50	2.86	0.0208	0.35	0.60	0.2302	40	70	2.33	0.0246	0.35	0.60	0.6144
20	50	2.86	0.0208	0.35	0.65	0.3515	40	70	2.33	0.0246	0.35	0.65	0.7925
20	50	2.86	0.0208	0.40	0.55	0.0694	40	70	2.33	0.0246	0.40	0.55	0.2290
20	50	2.86	0.0208	0.40	0.60	0.1281	40	70	2.33	0.0246	0.40	0.60	0.4089
20	60	3.04	0.0236	0.05	0.15	0.2012	40	80	2.55	0.0198	0.05	0.15	0.3154
20	60	3.04	0.0236	0.05	0.20	0.3423	40	80	2.55	0.0198	0.05	0.20	0.5706
20	60	3.04	0.0236	0.05	0.25	0.4747	40	80	2.55	0.0198	0.05	0.25	0.7856
20	60	3.04	0.0236	0.05	0.30	0.6258	40	80	2.55	0.0198	0.05	0.30	0.9127
20	60	3.04	0.0236	0.05	0.35	0.7606	40	80	2.55	0.0198	0.05	0.35	0.9719
20	60	3.04	0.0236	0.05	0.40	0.8611	40	80	2.55	0.0198	0.05	0.40	0.9933
20	60	3.04	0.0236	0.05	0.45	0.9283	40	80	2.55	0.0198	0.05	0.45	0.9988
20	60	3.04	0.0236	0.10	0.25	0.2100	40	80	2.55	0.0198	0.10	0.25	0.4031
20	60	3.04	0.0236	0.10	0.30	0.3296	40	80	2.55	0.0198	0.10	0.30	0.6171
20	60	3.04	0.0236	0.10	0.35	0.4664	40	80	2.55	0.0198	0.10	0.35	0.8019
20	60	3.04	0.0236	0.10	0.40	0.6064	40	80	2.55	0.0198	0.10	0.40	0.9186
20	60	3.04	0.0236	0.10	0.45	0.7338	40	80	2.55	0.0198	0.10	0.45	0.9731
20	60	3.04	0.0236	0.10	0.50	0.8351	40	80	2.55	0.0198	0.10	0.50	0.9929
20	60	3.04	0.0236	0.10	0.55	0.9073	40	80	2.55	0.0198	0.10	0.55	0.9986
20	60	3.04	0.0236	0.10	0.60	0.9543	40	80	2.55	0.0198	0.10	0.60	0.9998
20	60	3.04	0.0236	0.15	0.30	0.1537	40	80	2.55	0.0198	0.15	0.30	0.3112
20	60	3.04	0.0236	0.15	0.35	0.2483	40	80	2.55	0.0198	0.15	0.35	0.5206
20	60	3.04	0.0236	0.15	0.40	0.3674	40	80	2.55	0.0198	0.15	0.40	0.7182
20	60	3.04	0.0236	0.15	0.45	0.5000	40	80	2.55	0.0198	0.15	0.45	0.8621
20	60	3.04	0.0236	0.15	0.50	0.6311	40	80	2.55	0.0198	0.15	0.50	0.9456
20	60	3.04	0.0236	0.15	0.55	0.7498	40	80	2.55	0.0198	0.15	0.55	0.9834
20	60	3.04	0.0236	0.15	0.60	0.8490	40	80	2.55	0.0198	0.15	0.60	0.9962
20	60	3.04	0.0236	0.15	0.65	0.9218	40	80	2.55	0.0198	0.15	0.65	0.9994
20	60	3.04	0.0236	0.20	0.35	0.1179	40	80	2.55	0.0198	0.20	0.35	0.2640
20	60	3.04	0.0236	0.20	0.40	0.1965	40	80	2.55	0.0198	0.20	0.40	0.4520
20	60	3.04	0.0236	0.20	0.45	0.2992	40	80	2.55	0.0198	0.20	0.45	0.6492
20	60	3.04	0.0236	0.20	0.50	0.4200	40	80	2.55	0.0198	0.20	0.50	0.8141
20	60	3.04	0.0236	0.20	0.55	0.5527	40	80	2.55	0.0198	0.20	0.55	0.9215
20	60	3.04	0.0236	0.20	0.60	0.6876	40	80	2.55	0.0198	0.20	0.60	0.9741
20	60	3.04	0.0236	0.20	0.65	0.8075	40	80	2.55	0.0198	0.20	0.65	0.9934
20	60	3.04	0.0236	0.20	0.70	0.8963	40	80	2.55	0.0198	0.20	0.70	0.9987
20	60	3.04	0.0236	0.25	0.40	0.0939	40	80	2.55	0.0198	0.25	0.40	0.2275

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	60	3.04	0.0236	0.25	0.45	0.1590	40	80	2.55	0.0198	0.25	0.45	0.4027
20	60	3.04	0.0236	0.25	0.50	0.2484	40	80	2.55	0.0198	0.25	0.50	0.6036
20	60	3.04	0.0236	0.25	0.55	0.3642	40	80	2.55	0.0198	0.25	0.55	0.7820
20	60	3.04	0.0236	0.25	0.60	0.5033	40	80	2.55	0.0198	0.25	0.60	0.9022
20	60	3.04	0.0236	0.25	0.65	0.6489	40	80	2.55	0.0198	0.25	0.65	0.9649
20	60	3.04	0.0236	0.25	0.70	0.7769	40	80	2.55	0.0198	0.25	0.70	0.9906
20	60	3.04	0.0236	0.25	0.75	0.8744	40	80	2.55	0.0198	0.25	0.75	0.9983
20	60	3.04	0.0236	0.30	0.45	0.0755	40	80	2.55	0.0198	0.30	0.45	0.2042
20	60	3.04	0.0236	0.30	0.50	0.1312	40	80	2.55	0.0198	0.30	0.50	0.3748
20	60	3.04	0.0236	0.30	0.55	0.2152	40	80	2.55	0.0198	0.30	0.55	0.5748
20	60	3.04	0.0236	0.30	0.60	0.3321	40	80	2.55	0.0198	0.30	0.60	0.7552
20	60	3.04	0.0236	0.30	0.65	0.4735	40	80	2.55	0.0198	0.30	0.65	0.8852
20	60	3.04	0.0236	0.30	0.70	0.6191	40	80	2.55	0.0198	0.30	0.70	0.9592
20	60	3.04	0.0236	0.35	0.50	0.0620	40	80	2.55	0.0198	0.35	0.50	0.1918
20	60	3.04	0.0236	0.35	0.55	0.1140	40	80	2.55	0.0198	0.35	0.55	0.3544
20	60	3.04	0.0236	0.35	0.60	0.1970	40	80	2.55	0.0198	0.35	0.60	0.5480
20	60	3.04	0.0236	0.35	0.65	0.3117	40	80	2.55	0.0198	0.35	0.65	0.7359
20	60	3.04	0.0236	0.40	0.55	0.0540	40	80	2.55	0.0198	0.40	0.55	0.1794
20	60	3.04	0.0236	0.40	0.60	0.1045	40	80	2.55	0.0198	0.40	0.60	0.3348
20	70	3.42	0.0191	0.05	0.15	0.1737	40	90	2.76	0.0171	0.05	0.15	0.2780
20	70	3.42	0.0191	0.05	0.20	0.3119	40	90	2.76	0.0171	0.05	0.20	0.5139
20	70	3.42	0.0191	0.05	0.25	0.4021	40	90	2.76	0.0171	0.05	0.25	0.7413
20	70	3.42	0.0191	0.05	0.30	0.5296	40	90	2.76	0.0171	0.05	0.30	0.8952
20	70	3.42	0.0191	0.05	0.35	0.6801	40	90	2.76	0.0171	0.05	0.35	0.9671
20	70	3.42	0.0191	0.05	0.40	0.8033	40	90	2.76	0.0171	0.05	0.40	0.9919
20	70	3.42	0.0191	0.05	0.45	0.8915	40	90	2.76	0.0171	0.05	0.45	0.9985
20	70	3.42	0.0191	0.10	0.25	0.1561	40	90	2.76	0.0171	0.10	0.25	0.3532
20	70	3.42	0.0191	0.10	0.30	0.2485	40	90	2.76	0.0171	0.10	0.30	0.5784
20	70	3.42	0.0191	0.10	0.35	0.3766	40	90	2.76	0.0171	0.10	0.35	0.7721
20	70	3.42	0.0191	0.10	0.40	0.5160	40	90	2.76	0.0171	0.10	0.40	0.9010
20	70	3.42	0.0191	0.10	0.45	0.6547	40	90	2.76	0.0171	0.10	0.45	0.9663
20	70	3.42	0.0191	0.10	0.50	0.7768	40	90	2.76	0.0171	0.10	0.50	0.9912
20	70	3.42	0.0191	0.10	0.55	0.8716	40	90	2.76	0.0171	0.10	0.55	0.9983
20	70	3.42	0.0191	0.10	0.60	0.9351	40	90	2.76	0.0171	0.10	0.60	0.9998
20	70	3.42	0.0191	0.15	0.30	0.1055	40	90	2.76	0.0171	0.15	0.30	0.2711
20	70	3.42	0.0191	0.15	0.35	0.1823	40	90	2.76	0.0171	0.15	0.35	0.4695
20	70	3.42	0.0191	0.15	0.40	0.2854	40	90	2.76	0.0171	0.15	0.40	0.6750
20	70	3.42	0.0191	0.15	0.45	0.4119	40	90	2.76	0.0171	0.15	0.45	0.8372
20	70	3.42	0.0191	0.15	0.50	0.5509	40	90	2.76	0.0171	0.15	0.50	0.9353
20	70	3.42	0.0191	0.15	0.55	0.6870	40	90	2.76	0.0171	0.15	0.55	0.9801
20	70	3.42	0.0191	0.15	0.60	0.8028	40	90	2.76	0.0171	0.15	0.60	0.9953
20	70	3.42	0.0191	0.15	0.65	0.8896	40	90	2.76	0.0171	0.15	0.65	0.9992
20	70	3.42	0.0191	0.20	0.35	0.0791	40	90	2.76	0.0171	0.20	0.35	0.2198
20	70	3.42	0.0191	0.20	0.40	0.1398	40	90	2.76	0.0171	0.20	0.40	0.4011
20	70	3.42	0.0191	0.20	0.45	0.2278	40	90	2.76	0.0171	0.20	0.45	0.6070
20	70	3.42	0.0191	0.20	0.50	0.3431	40	90	2.76	0.0171	0.20	0.50	0.7872
20	70	3.42	0.0191	0.20	0.55	0.4782	40	90	2.76	0.0171	0.20	0.55	0.9065
20	70	3.42	0.0191	0.20	0.60	0.6175	40	90	2.76	0.0171	0.20	0.60	0.9674
20	70	3.42	0.0191	0.20	0.65	0.7463	40	90	2.76	0.0171	0.20	0.65	0.9915
20	70	3.42	0.0191	0.20	0.70	0.8526	40	90	2.76	0.0171	0.20	0.70	0.9984

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	70	3.42	0.0191	0.25	0.40	0.0614	40	90	2.76	0.0171	0.25	0.40	0.1892
20	70	3.42	0.0191	0.25	0.45	0.1122	40	90	2.76	0.0171	0.25	0.45	0.3581
20	70	3.42	0.0191	0.25	0.50	0.1897	40	90	2.76	0.0171	0.25	0.50	0.5605
20	70	3.42	0.0191	0.25	0.55	0.2954	40	90	2.76	0.0171	0.25	0.55	0.7464
20	70	3.42	0.0191	0.25	0.60	0.4240	40	90	2.76	0.0171	0.25	0.60	0.8810
20	70	3.42	0.0191	0.25	0.65	0.5663	40	90	2.76	0.0171	0.25	0.65	0.9570
20	70	3.42	0.0191	0.25	0.70	0.7070	40	90	2.76	0.0171	0.25	0.70	0.9886
20	70	3.42	0.0191	0.25	0.75	0.8255	40	90	2.76	0.0171	0.25	0.75	0.9979
20	70	3.42	0.0191	0.30	0.45	0.0494	40	90	2.76	0.0171	0.30	0.45	0.1705
20	70	3.42	0.0191	0.30	0.50	0.0935	40	90	2.76	0.0171	0.30	0.50	0.3280
20	70	3.42	0.0191	0.30	0.55	0.1625	40	90	2.76	0.0171	0.30	0.55	0.5230
20	70	3.42	0.0191	0.30	0.60	0.2598	40	90	2.76	0.0171	0.30	0.60	0.7162
20	70	3.42	0.0191	0.30	0.65	0.3863	40	90	2.76	0.0171	0.30	0.65	0.8652
20	70	3.42	0.0191	0.30	0.70	0.5331	40	90	2.76	0.0171	0.30	0.70	0.9509
20	70	3.42	0.0191	0.35	0.50	0.0411	40	90	2.76	0.0171	0.35	0.50	0.1555
20	70	3.42	0.0191	0.35	0.55	0.0796	40	90	2.76	0.0171	0.35	0.55	0.3037
20	70	3.42	0.0191	0.35	0.60	0.1420	40	90	2.76	0.0171	0.35	0.60	0.4994
20	70	3.42	0.0191	0.35	0.65	0.2360	40	90	2.76	0.0171	0.35	0.65	0.7007
20	70	3.42	0.0191	0.40	0.55	0.0346	40	90	2.76	0.0171	0.40	0.55	0.1438
20	70	3.42	0.0191	0.40	0.60	0.0690	40	90	2.76	0.0171	0.40	0.60	0.2905
20	80	3.58	0.0219	0.05	0.15	0.1965	40	100	2.75	0.0227	0.05	0.15	0.3056
20	80	3.58	0.0219	0.05	0.20	0.3268	40	100	2.75	0.0227	0.05	0.20	0.5654
20	80	3.58	0.0219	0.05	0.25	0.4016	40	100	2.75	0.0227	0.05	0.25	0.7915
20	80	3.58	0.0219	0.05	0.30	0.5302	40	100	2.75	0.0227	0.05	0.30	0.9226
20	80	3.58	0.0219	0.05	0.35	0.6854	40	100	2.75	0.0227	0.05	0.35	0.9772
20	80	3.58	0.0219	0.05	0.40	0.8080	40	100	2.75	0.0227	0.05	0.40	0.9948
20	80	3.58	0.0219	0.05	0.45	0.8950	40	100	2.75	0.0227	0.05	0.45	0.9991
20	80	3.58	0.0219	0.10	0.25	0.1540	40	100	2.75	0.0227	0.10	0.25	0.4039
20	80	3.58	0.0219	0.10	0.30	0.2478	40	100	2.75	0.0227	0.10	0.30	0.6265
20	80	3.58	0.0219	0.10	0.35	0.3782	40	100	2.75	0.0227	0.10	0.35	0.8059
20	80	3.58	0.0219	0.10	0.40	0.5178	40	100	2.75	0.0227	0.10	0.40	0.9189
20	80	3.58	0.0219	0.10	0.45	0.6559	40	100	2.75	0.0227	0.10	0.45	0.9732
20	80	3.58	0.0219	0.10	0.50	0.7738	40	100	2.75	0.0227	0.10	0.50	0.9931
20	80	3.58	0.0219	0.10	0.55	0.8633	40	100	2.75	0.0227	0.10	0.55	0.9987
20	80	3.58	0.0219	0.10	0.60	0.9260	40	100	2.75	0.0227	0.10	0.60	0.9998
20	80	3.58	0.0219	0.15	0.30	0.1045	40	100	2.75	0.0227	0.15	0.30	0.3052
20	80	3.58	0.0219	0.15	0.35	0.1817	40	100	2.75	0.0227	0.15	0.35	0.5061
20	80	3.58	0.0219	0.15	0.40	0.2843	40	100	2.75	0.0227	0.15	0.40	0.7039
20	80	3.58	0.0219	0.15	0.45	0.4087	40	100	2.75	0.0227	0.15	0.45	0.8538
20	80	3.58	0.0219	0.15	0.50	0.5402	40	100	2.75	0.0227	0.15	0.50	0.9427
20	80	3.58	0.0219	0.15	0.55	0.6659	40	100	2.75	0.0227	0.15	0.55	0.9829
20	80	3.58	0.0219	0.15	0.60	0.7800	40	100	2.75	0.0227	0.15	0.60	0.9963
20	80	3.58	0.0219	0.15	0.65	0.8746	40	100	2.75	0.0227	0.15	0.65	0.9994
20	80	3.58	0.0219	0.20	0.35	0.0781	40	100	2.75	0.0227	0.20	0.35	0.2417
20	80	3.58	0.0219	0.20	0.40	0.1379	40	100	2.75	0.0227	0.20	0.40	0.4242
20	80	3.58	0.0219	0.20	0.45	0.2225	40	100	2.75	0.0227	0.20	0.45	0.6249
20	80	3.58	0.0219	0.20	0.50	0.3283	40	100	2.75	0.0227	0.20	0.50	0.7992
20	80	3.58	0.0219	0.20	0.55	0.4497	40	100	2.75	0.0227	0.20	0.55	0.9152
20	80	3.58	0.0219	0.20	0.60	0.5846	40	100	2.75	0.0227	0.20	0.60	0.9728
20	80	3.58	0.0219	0.20	0.65	0.7201	40	100	2.75	0.0227	0.20	0.65	0.9934

Table B.17: continue on next page

Table B.17: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	80	3.58	0.0219	0.20	0.70	0.8326	40	100	2.75	0.0227	0.20	0.70	0.9988
20	80	3.58	0.0219	0.25	0.40	0.0597	40	100	2.75	0.0227	0.25	0.40	0.2002
20	80	3.58	0.0219	0.25	0.45	0.1073	40	100	2.75	0.0227	0.25	0.45	0.3691
20	80	3.58	0.0219	0.25	0.50	0.1759	40	100	2.75	0.0227	0.25	0.50	0.5727
20	80	3.58	0.0219	0.25	0.55	0.2681	40	100	2.75	0.0227	0.25	0.55	0.7623
20	80	3.58	0.0219	0.25	0.60	0.3896	40	100	2.75	0.0227	0.25	0.60	0.8952
20	80	3.58	0.0219	0.25	0.65	0.5329	40	100	2.75	0.0227	0.25	0.65	0.9636
20	80	3.58	0.0219	0.25	0.70	0.6748	40	100	2.75	0.0227	0.25	0.70	0.9904
20	80	3.58	0.0219	0.25	0.75	0.7963	40	100	2.75	0.0227	0.25	0.75	0.9983
20	80	3.58	0.0219	0.30	0.45	0.0461	40	100	2.75	0.0227	0.30	0.45	0.1745
20	80	3.58	0.0219	0.30	0.50	0.0836	40	100	2.75	0.0227	0.30	0.50	0.3371
20	80	3.58	0.0219	0.30	0.55	0.1418	40	100	2.75	0.0227	0.30	0.55	0.5427
20	80	3.58	0.0219	0.30	0.60	0.2311	40	100	2.75	0.0227	0.30	0.60	0.7380
20	80	3.58	0.0219	0.30	0.65	0.3527	40	100	2.75	0.0227	0.30	0.65	0.8776
20	80	3.58	0.0219	0.30	0.70	0.4934	40	100	2.75	0.0227	0.30	0.70	0.9560
20	80	3.58	0.0219	0.35	0.50	0.0352	40	100	2.75	0.0227	0.35	0.50	0.1610
20	80	3.58	0.0219	0.35	0.55	0.0667	40	100	2.75	0.0227	0.35	0.55	0.3202
20	80	3.58	0.0219	0.35	0.60	0.1219	40	100	2.75	0.0227	0.35	0.60	0.5206
20	80	3.58	0.0219	0.35	0.65	0.2079	40	100	2.75	0.0227	0.35	0.65	0.7154
20	80	3.58	0.0219	0.40	0.55	0.0277	40	100	2.75	0.0227	0.40	0.55	0.1533
20	80	3.58	0.0219	0.40	0.60	0.0570	40	100	2.75	0.0227	0.40	0.60	0.3038

Table B.17: concluded from previous page

Table B.18: Achieved power and p-values calculated for the z-unpooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.01**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample; p-value: attained size of the test.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	3.29	0.0071	0.05	0.15	0.0035	20	90	4.42	0.0087	0.05	0.15	0.0666
10	20	3.29	0.0071	0.05	0.20	0.0193	20	90	4.42	0.0087	0.05	0.20	0.2314
10	20	3.29	0.0071	0.05	0.25	0.0613	20	90	4.42	0.0087	0.05	0.25	0.3375
10	20	3.29	0.0071	0.05	0.30	0.1380	20	90	4.42	0.0087	0.05	0.30	0.3958
10	20	3.29	0.0071	0.05	0.35	0.2451	20	90	4.42	0.0087	0.05	0.35	0.5141
10	20	3.29	0.0071	0.05	0.40	0.3677	20	90	4.42	0.0087	0.05	0.40	0.6657
10	20	3.29	0.0071	0.05	0.45	0.4895	20	90	4.42	0.0087	0.05	0.45	0.7830
10	20	3.29	0.0071	0.10	0.25	0.0359	20	90	4.42	0.0087	0.10	0.25	0.1158
10	20	3.29	0.0071	0.10	0.30	0.0814	20	90	4.42	0.0087	0.10	0.30	0.1491
10	20	3.29	0.0071	0.10	0.35	0.1468	20	90	4.42	0.0087	0.10	0.35	0.2343
10	20	3.29	0.0071	0.10	0.40	0.2259	20	90	4.42	0.0087	0.10	0.40	0.3539
10	20	3.29	0.0071	0.10	0.45	0.3127	20	90	4.42	0.0087	0.10	0.45	0.4773
10	20	3.29	0.0071	0.10	0.50	0.4044	20	90	4.42	0.0087	0.10	0.50	0.6069
10	20	3.29	0.0071	0.10	0.55	0.5000	20	90	4.42	0.0087	0.10	0.55	0.7236
10	20	3.29	0.0071	0.10	0.60	0.5973	20	90	4.42	0.0087	0.10	0.60	0.8243
10	20	3.29	0.0071	0.15	0.30	0.0466	20	90	4.42	0.0087	0.15	0.30	0.0529
10	20	3.29	0.0071	0.15	0.35	0.0854	20	90	4.42	0.0087	0.15	0.35	0.0966
10	20	3.29	0.0071	0.15	0.40	0.1351	20	90	4.42	0.0087	0.15	0.40	0.1634
10	20	3.29	0.0071	0.15	0.45	0.1945	20	90	4.42	0.0087	0.15	0.45	0.2488
10	20	3.29	0.0071	0.15	0.50	0.2643	20	90	4.42	0.0087	0.15	0.50	0.3568
10	20	3.29	0.0071	0.15	0.55	0.3453	20	90	4.42	0.0087	0.15	0.55	0.4758
10	20	3.29	0.0071	0.15	0.60	0.4364	20	90	4.42	0.0087	0.15	0.60	0.6057
10	20	3.29	0.0071	0.15	0.65	0.5341	20	90	4.42	0.0087	0.15	0.65	0.7305
10	20	3.29	0.0071	0.20	0.35	0.0482	20	90	4.42	0.0087	0.20	0.35	0.0362
10	20	3.29	0.0071	0.20	0.40	0.0784	20	90	4.42	0.0087	0.20	0.40	0.0674
10	20	3.29	0.0071	0.20	0.45	0.1174	20	90	4.42	0.0087	0.20	0.45	0.1146
10	20	3.29	0.0071	0.20	0.50	0.1673	20	90	4.42	0.0087	0.20	0.50	0.1828
10	20	3.29	0.0071	0.20	0.55	0.2301	20	90	4.42	0.0087	0.20	0.55	0.2718
10	20	3.29	0.0071	0.20	0.60	0.3062	20	90	4.42	0.0087	0.20	0.60	0.3875
10	20	3.29	0.0071	0.20	0.65	0.3946	20	90	4.42	0.0087	0.20	0.65	0.5191
10	20	3.29	0.0071	0.20	0.70	0.4932	20	90	4.42	0.0087	0.20	0.70	0.6482
10	20	3.29	0.0071	0.25	0.40	0.0440	20	90	4.42	0.0087	0.25	0.40	0.0251
10	20	3.29	0.0071	0.25	0.45	0.0685	20	90	4.42	0.0087	0.25	0.45	0.0472
10	20	3.29	0.0071	0.25	0.50	0.1023	20	90	4.42	0.0087	0.25	0.50	0.0829
10	20	3.29	0.0071	0.25	0.55	0.1476	20	90	4.42	0.0087	0.25	0.55	0.1370
10	20	3.29	0.0071	0.25	0.60	0.2064	20	90	4.42	0.0087	0.25	0.60	0.2181
10	20	3.29	0.0071	0.25	0.65	0.2796	20	90	4.42	0.0087	0.25	0.65	0.3246
10	20	3.29	0.0071	0.25	0.70	0.3678	20	90	4.42	0.0087	0.25	0.70	0.4474
10	20	3.29	0.0071	0.25	0.75	0.4700	20	90	4.42	0.0087	0.25	0.75	0.5808
10	20	3.29	0.0071	0.30	0.45	0.0385	20	90	4.42	0.0087	0.30	0.45	0.0174
10	20	3.29	0.0071	0.30	0.50	0.0602	20	90	4.42	0.0087	0.30	0.50	0.0335
10	20	3.29	0.0071	0.30	0.55	0.0910	20	90	4.42	0.0087	0.30	0.55	0.0613
10	20	3.29	0.0071	0.30	0.60	0.1334	20	90	4.42	0.0087	0.30	0.60	0.1086
10	20	3.29	0.0071	0.30	0.65	0.1899	20	90	4.42	0.0087	0.30	0.65	0.1792

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	3.29	0.0071	0.30	0.70	0.2629	20	90	4.42	0.0087	0.30	0.70	0.2731
10	20	3.29	0.0071	0.35	0.50	0.0339	20	90	4.42	0.0087	0.35	0.50	0.0120
10	20	3.29	0.0071	0.35	0.55	0.0537	20	90	4.42	0.0087	0.35	0.55	0.0243
10	20	3.29	0.0071	0.35	0.60	0.0826	20	90	4.42	0.0087	0.35	0.60	0.0479
10	20	3.29	0.0071	0.35	0.65	0.1235	20	90	4.42	0.0087	0.35	0.65	0.0873
10	20	3.29	0.0071	0.40	0.55	0.0302	20	90	4.42	0.0087	0.40	0.55	0.0085
10	20	3.29	0.0071	0.40	0.60	0.0487	20	90	4.42	0.0087	0.40	0.60	0.0186
10	30	3.88	0.0077	0.05	0.15	0.0018	20	100	4.69	0.0083	0.05	0.15	0.0584
10	30	3.88	0.0077	0.05	0.20	0.0153	20	100	4.69	0.0083	0.05	0.20	0.2287
10	30	3.88	0.0077	0.05	0.25	0.0633	20	100	4.69	0.0083	0.05	0.25	0.3369
10	30	3.88	0.0077	0.05	0.30	0.1615	20	100	4.69	0.0083	0.05	0.30	0.3769
10	30	3.88	0.0077	0.05	0.35	0.2952	20	100	4.69	0.0083	0.05	0.35	0.4710
10	30	3.88	0.0077	0.05	0.40	0.4268	20	100	4.69	0.0083	0.05	0.40	0.6252
10	30	3.88	0.0077	0.05	0.45	0.5284	20	100	4.69	0.0083	0.05	0.45	0.7460
10	30	3.88	0.0077	0.10	0.25	0.0369	20	100	4.69	0.0083	0.10	0.25	0.1147
10	30	3.88	0.0077	0.10	0.30	0.0941	20	100	4.69	0.0083	0.10	0.30	0.1354
10	30	3.88	0.0077	0.10	0.35	0.1722	20	100	4.69	0.0083	0.10	0.35	0.2024
10	30	3.88	0.0077	0.10	0.40	0.2503	20	100	4.69	0.0083	0.10	0.40	0.3166
10	30	3.88	0.0077	0.10	0.45	0.3146	20	100	4.69	0.0083	0.10	0.45	0.4269
10	30	3.88	0.0077	0.10	0.50	0.3704	20	100	4.69	0.0083	0.10	0.50	0.5525
10	30	3.88	0.0077	0.10	0.55	0.4348	20	100	4.69	0.0083	0.10	0.55	0.6849
10	30	3.88	0.0077	0.10	0.60	0.5180	20	100	4.69	0.0083	0.10	0.60	0.7961
10	30	3.88	0.0077	0.15	0.30	0.0531	20	100	4.69	0.0083	0.15	0.30	0.0458
10	30	3.88	0.0077	0.15	0.35	0.0974	20	100	4.69	0.0083	0.15	0.35	0.0798
10	30	3.88	0.0077	0.15	0.40	0.1424	20	100	4.69	0.0083	0.15	0.40	0.1398
10	30	3.88	0.0077	0.15	0.45	0.1819	20	100	4.69	0.0083	0.15	0.45	0.2094
10	30	3.88	0.0077	0.15	0.50	0.2222	20	100	4.69	0.0083	0.15	0.50	0.3093
10	30	3.88	0.0077	0.15	0.55	0.2761	20	100	4.69	0.0083	0.15	0.55	0.4336
10	30	3.88	0.0077	0.15	0.60	0.3508	20	100	4.69	0.0083	0.15	0.60	0.5635
10	30	3.88	0.0077	0.15	0.65	0.4405	20	100	4.69	0.0083	0.15	0.65	0.6836
10	30	3.88	0.0077	0.20	0.35	0.0532	20	100	4.69	0.0083	0.20	0.35	0.0289
10	30	3.88	0.0077	0.20	0.40	0.0783	20	100	4.69	0.0083	0.20	0.40	0.0552
10	30	3.88	0.0077	0.20	0.45	0.1019	20	100	4.69	0.0083	0.20	0.45	0.0911
10	30	3.88	0.0077	0.20	0.50	0.1292	20	100	4.69	0.0083	0.20	0.50	0.1519
10	30	3.88	0.0077	0.20	0.55	0.1696	20	100	4.69	0.0083	0.20	0.55	0.2384
10	30	3.88	0.0077	0.20	0.60	0.2280	20	100	4.69	0.0083	0.20	0.60	0.3453
10	30	3.88	0.0077	0.20	0.65	0.3009	20	100	4.69	0.0083	0.20	0.65	0.4631
10	30	3.88	0.0077	0.20	0.70	0.3816	20	100	4.69	0.0083	0.20	0.70	0.5940
10	30	3.88	0.0077	0.25	0.40	0.0415	20	100	4.69	0.0083	0.25	0.40	0.0197
10	30	3.88	0.0077	0.25	0.45	0.0550	20	100	4.69	0.0083	0.25	0.45	0.0356
10	30	3.88	0.0077	0.25	0.50	0.0726	20	100	4.69	0.0083	0.25	0.50	0.0663
10	30	3.88	0.0077	0.25	0.55	0.1003	20	100	4.69	0.0083	0.25	0.55	0.1156
10	30	3.88	0.0077	0.25	0.60	0.1419	20	100	4.69	0.0083	0.25	0.60	0.1854
10	30	3.88	0.0077	0.25	0.65	0.1958	20	100	4.69	0.0083	0.25	0.65	0.2751
10	30	3.88	0.0077	0.25	0.70	0.2596	20	100	4.69	0.0083	0.25	0.70	0.3928
10	30	3.88	0.0077	0.25	0.75	0.3352	20	100	4.69	0.0083	0.25	0.75	0.5291
10	30	3.88	0.0077	0.30	0.45	0.0285	20	100	4.69	0.0083	0.30	0.45	0.0125
10	30	3.88	0.0077	0.30	0.50	0.0392	20	100	4.69	0.0083	0.30	0.50	0.0258
10	30	3.88	0.0077	0.30	0.55	0.0570	20	100	4.69	0.0083	0.30	0.55	0.0497
10	30	3.88	0.0077	0.30	0.60	0.0844	20	100	4.69	0.0083	0.30	0.60	0.0878

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	30	3.88	0.0077	0.30	0.65	0.1213	20	100	4.69	0.0083	0.30	0.65	0.1441
10	30	3.88	0.0077	0.30	0.70	0.1678	20	100	4.69	0.0083	0.30	0.70	0.2293
10	30	3.88	0.0077	0.35	0.50	0.0202	20	100	4.69	0.0083	0.35	0.50	0.0090
10	30	3.88	0.0077	0.35	0.55	0.0308	20	100	4.69	0.0083	0.35	0.55	0.0190
10	30	3.88	0.0077	0.35	0.60	0.0477	20	100	4.69	0.0083	0.35	0.60	0.0367
10	30	3.88	0.0077	0.35	0.65	0.0713	20	100	4.69	0.0083	0.35	0.65	0.0666
10	30	3.88	0.0077	0.40	0.55	0.0158	20	100	4.69	0.0083	0.40	0.55	0.0064
10	30	3.88	0.0077	0.40	0.60	0.0255	20	100	4.69	0.0083	0.40	0.60	0.0135
10	40	4.39	0.0085	0.05	0.15	0.0008	30	40	2.50	0.0097	0.05	0.15	0.1710
10	40	4.39	0.0085	0.05	0.20	0.0116	30	40	2.50	0.0097	0.05	0.20	0.3431
10	40	4.39	0.0085	0.05	0.25	0.0618	30	40	2.50	0.0097	0.05	0.25	0.5307
10	40	4.39	0.0085	0.05	0.30	0.1777	30	40	2.50	0.0097	0.05	0.30	0.7021
10	40	4.39	0.0085	0.05	0.35	0.3349	30	40	2.50	0.0097	0.05	0.35	0.8351
10	40	4.39	0.0085	0.05	0.40	0.4727	30	40	2.50	0.0097	0.05	0.40	0.9217
10	40	4.39	0.0085	0.05	0.45	0.5565	30	40	2.50	0.0097	0.05	0.45	0.9685
10	40	4.39	0.0085	0.10	0.25	0.0360	30	40	2.50	0.0097	0.10	0.25	0.2339
10	40	4.39	0.0085	0.10	0.30	0.1035	30	40	2.50	0.0097	0.10	0.30	0.3895
10	40	4.39	0.0085	0.10	0.35	0.1950	30	40	2.50	0.0097	0.10	0.35	0.5627
10	40	4.39	0.0085	0.10	0.40	0.2755	30	40	2.50	0.0097	0.10	0.40	0.7230
10	40	4.39	0.0085	0.10	0.45	0.3258	30	40	2.50	0.0097	0.10	0.45	0.8473
10	40	4.39	0.0085	0.10	0.50	0.3576	30	40	2.50	0.0097	0.10	0.50	0.9282
10	40	4.39	0.0085	0.10	0.55	0.3989	30	40	2.50	0.0097	0.10	0.55	0.9718
10	40	4.39	0.0085	0.10	0.60	0.4719	30	40	2.50	0.0097	0.10	0.60	0.9910
10	40	4.39	0.0085	0.15	0.30	0.0584	30	40	2.50	0.0097	0.15	0.30	0.1834
10	40	4.39	0.0085	0.15	0.35	0.1101	30	40	2.50	0.0097	0.15	0.35	0.3205
10	40	4.39	0.0085	0.15	0.40	0.1557	30	40	2.50	0.0097	0.15	0.40	0.4862
10	40	4.39	0.0085	0.15	0.45	0.1851	30	40	2.50	0.0097	0.15	0.45	0.6544
10	40	4.39	0.0085	0.15	0.50	0.2071	30	40	2.50	0.0097	0.15	0.50	0.7973
10	40	4.39	0.0085	0.15	0.55	0.2423	30	40	2.50	0.0097	0.15	0.55	0.8981
10	40	4.39	0.0085	0.15	0.60	0.3076	30	40	2.50	0.0097	0.15	0.60	0.9569
10	40	4.39	0.0085	0.15	0.65	0.3990	30	40	2.50	0.0097	0.15	0.65	0.9849
10	40	4.39	0.0085	0.20	0.35	0.0601	30	40	2.50	0.0097	0.20	0.35	0.1588
10	40	4.39	0.0085	0.20	0.40	0.0850	30	40	2.50	0.0097	0.20	0.40	0.2855
10	40	4.39	0.0085	0.20	0.45	0.1016	30	40	2.50	0.0097	0.20	0.45	0.4460
10	40	4.39	0.0085	0.20	0.50	0.1161	30	40	2.50	0.0097	0.20	0.50	0.6157
10	40	4.39	0.0085	0.20	0.55	0.1427	30	40	2.50	0.0097	0.20	0.55	0.7654
10	40	4.39	0.0085	0.20	0.60	0.1932	30	40	2.50	0.0097	0.20	0.60	0.8759
10	40	4.39	0.0085	0.20	0.65	0.2647	30	40	2.50	0.0097	0.20	0.65	0.9443
10	40	4.39	0.0085	0.20	0.70	0.3408	30	40	2.50	0.0097	0.20	0.70	0.9794
10	40	4.39	0.0085	0.25	0.40	0.0447	30	40	2.50	0.0097	0.25	0.40	0.1480
10	40	4.39	0.0085	0.25	0.45	0.0537	30	40	2.50	0.0097	0.25	0.45	0.2687
10	40	4.39	0.0085	0.25	0.50	0.0628	30	40	2.50	0.0097	0.25	0.50	0.4232
10	40	4.39	0.0085	0.25	0.55	0.0811	30	40	2.50	0.0097	0.25	0.55	0.5895
10	40	4.39	0.0085	0.25	0.60	0.1165	30	40	2.50	0.0097	0.25	0.60	0.7410
10	40	4.39	0.0085	0.25	0.65	0.1672	30	40	2.50	0.0097	0.25	0.65	0.8582
10	40	4.39	0.0085	0.25	0.70	0.2234	30	40	2.50	0.0097	0.25	0.70	0.9348
10	40	4.39	0.0085	0.25	0.75	0.2851	30	40	2.50	0.0097	0.25	0.75	0.9759
10	40	4.39	0.0085	0.30	0.45	0.0272	30	40	2.50	0.0097	0.30	0.45	0.1428
10	40	4.39	0.0085	0.30	0.50	0.0326	30	40	2.50	0.0097	0.30	0.50	0.2573
10	40	4.39	0.0085	0.30	0.55	0.0443	30	40	2.50	0.0097	0.30	0.55	0.4052

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	40	4.39	0.0085	0.30	0.60	0.0671	30	40	2.50	0.0097	0.30	0.60	0.5683
10	40	4.39	0.0085	0.30	0.65	0.1004	30	40	2.50	0.0097	0.30	0.65	0.7228
10	40	4.39	0.0085	0.30	0.70	0.1389	30	40	2.50	0.0097	0.30	0.70	0.8474
10	40	4.39	0.0085	0.35	0.50	0.0161	30	40	2.50	0.0097	0.35	0.50	0.1377
10	40	4.39	0.0085	0.35	0.55	0.0231	30	40	2.50	0.0097	0.35	0.55	0.2464
10	40	4.39	0.0085	0.35	0.60	0.0368	30	40	2.50	0.0097	0.35	0.60	0.3901
10	40	4.39	0.0085	0.35	0.65	0.0571	30	40	2.50	0.0097	0.35	0.65	0.5540
10	40	4.39	0.0085	0.40	0.55	0.0114	30	40	2.50	0.0097	0.40	0.55	0.1317
10	40	4.39	0.0085	0.40	0.60	0.0191	30	40	2.50	0.0097	0.40	0.60	0.2373
10	50	4.86	0.0092	0.05	0.15	0.0004	30	50	2.86	0.0068	0.05	0.15	0.1260
10	50	4.86	0.0092	0.05	0.20	0.0086	30	50	2.86	0.0068	0.05	0.20	0.2884
10	50	4.86	0.0092	0.05	0.25	0.0589	30	50	2.86	0.0068	0.05	0.25	0.4873
10	50	4.86	0.0092	0.05	0.30	0.1893	30	50	2.86	0.0068	0.05	0.30	0.6796
10	50	4.86	0.0092	0.05	0.35	0.3659	30	50	2.86	0.0068	0.05	0.35	0.8279
10	50	4.86	0.0092	0.05	0.40	0.5053	30	50	2.86	0.0068	0.05	0.40	0.9214
10	50	4.86	0.0092	0.05	0.45	0.5735	30	50	2.86	0.0068	0.05	0.45	0.9698
10	50	4.86	0.0092	0.10	0.25	0.0343	30	50	2.86	0.0068	0.10	0.25	0.2008
10	50	4.86	0.0092	0.10	0.30	0.1102	30	50	2.86	0.0068	0.10	0.30	0.3575
10	50	4.86	0.0092	0.10	0.35	0.2131	30	50	2.86	0.0068	0.10	0.35	0.5371
10	50	4.86	0.0092	0.10	0.40	0.2943	30	50	2.86	0.0068	0.10	0.40	0.7056
10	50	4.86	0.0092	0.10	0.45	0.3341	30	50	2.86	0.0068	0.10	0.45	0.8360
10	50	4.86	0.0092	0.10	0.50	0.3490	30	50	2.86	0.0068	0.10	0.50	0.9210
10	50	4.86	0.0092	0.10	0.55	0.3649	30	50	2.86	0.0068	0.10	0.55	0.9679
10	50	4.86	0.0092	0.10	0.60	0.4091	30	50	2.86	0.0068	0.10	0.60	0.9894
10	50	4.86	0.0092	0.15	0.30	0.0622	30	50	2.86	0.0068	0.15	0.30	0.1565
10	50	4.86	0.0092	0.15	0.35	0.1203	30	50	2.86	0.0068	0.15	0.35	0.2866
10	50	4.86	0.0092	0.15	0.40	0.1662	30	50	2.86	0.0068	0.15	0.40	0.4477
10	50	4.86	0.0092	0.15	0.45	0.1888	30	50	2.86	0.0068	0.15	0.45	0.6146
10	50	4.86	0.0092	0.15	0.50	0.1980	30	50	2.86	0.0068	0.15	0.50	0.7628
10	50	4.86	0.0092	0.15	0.55	0.2115	30	50	2.86	0.0068	0.15	0.55	0.8746
10	50	4.86	0.0092	0.15	0.60	0.2511	30	50	2.86	0.0068	0.15	0.60	0.9442
10	50	4.86	0.0092	0.15	0.65	0.3322	30	50	2.86	0.0068	0.15	0.65	0.9795
10	50	4.86	0.0092	0.20	0.35	0.0656	30	50	2.86	0.0068	0.20	0.35	0.1293
10	50	4.86	0.0092	0.20	0.40	0.0906	30	50	2.86	0.0068	0.20	0.40	0.2392
10	50	4.86	0.0092	0.20	0.45	0.1030	30	50	2.86	0.0068	0.20	0.45	0.3849
10	50	4.86	0.0092	0.20	0.50	0.1086	30	50	2.86	0.0068	0.20	0.50	0.5509
10	50	4.86	0.0092	0.20	0.55	0.1187	30	50	2.86	0.0068	0.20	0.55	0.7105
10	50	4.86	0.0092	0.20	0.60	0.1493	30	50	2.86	0.0068	0.20	0.60	0.8381
10	50	4.86	0.0092	0.20	0.65	0.2120	30	50	2.86	0.0068	0.20	0.65	0.9229
10	50	4.86	0.0092	0.20	0.70	0.2931	30	50	2.86	0.0068	0.20	0.70	0.9697
10	50	4.86	0.0092	0.25	0.40	0.0475	30	50	2.86	0.0068	0.25	0.40	0.1094
10	50	4.86	0.0092	0.25	0.45	0.0541	30	50	2.86	0.0068	0.25	0.45	0.2073
10	50	4.86	0.0092	0.25	0.50	0.0573	30	50	2.86	0.0068	0.25	0.50	0.3453
10	50	4.86	0.0092	0.25	0.55	0.0643	30	50	2.86	0.0068	0.25	0.55	0.5087
10	50	4.86	0.0092	0.25	0.60	0.0856	30	50	2.86	0.0068	0.25	0.60	0.6715
10	50	4.86	0.0092	0.25	0.65	0.1295	30	50	2.86	0.0068	0.25	0.65	0.8087
10	50	4.86	0.0092	0.25	0.70	0.1867	30	50	2.86	0.0068	0.25	0.70	0.9066
10	50	4.86	0.0092	0.25	0.75	0.2383	30	50	2.86	0.0068	0.25	0.75	0.9641
10	50	4.86	0.0092	0.30	0.45	0.0271	30	50	2.86	0.0068	0.30	0.45	0.0966
10	50	4.86	0.0092	0.30	0.50	0.0290	30	50	2.86	0.0068	0.30	0.50	0.1875

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	50	4.86	0.0092	0.30	0.55	0.0334	30	50	2.86	0.0068	0.30	0.55	0.3178
10	50	4.86	0.0092	0.30	0.60	0.0472	30	50	2.86	0.0068	0.30	0.60	0.4765
10	50	4.86	0.0092	0.30	0.65	0.0755	30	50	2.86	0.0068	0.30	0.65	0.6426
10	50	4.86	0.0092	0.30	0.70	0.1127	30	50	2.86	0.0068	0.30	0.70	0.7915
10	50	4.86	0.0092	0.35	0.50	0.0139	30	50	2.86	0.0068	0.35	0.50	0.0880
10	50	4.86	0.0092	0.35	0.55	0.0165	30	50	2.86	0.0068	0.35	0.55	0.1721
10	50	4.86	0.0092	0.35	0.60	0.0248	30	50	2.86	0.0068	0.35	0.60	0.2963
10	50	4.86	0.0092	0.35	0.65	0.0418	30	50	2.86	0.0068	0.35	0.65	0.4555
10	50	4.86	0.0092	0.40	0.55	0.0078	30	50	2.86	0.0068	0.40	0.55	0.0804
10	50	4.86	0.0092	0.40	0.60	0.0123	30	50	2.86	0.0068	0.40	0.60	0.1603
10	60	5.28	0.0097	0.05	0.15	0.0002	30	60	3.04	0.0072	0.05	0.15	0.1394
10	60	5.28	0.0097	0.05	0.20	0.0064	30	60	3.04	0.0072	0.05	0.20	0.3023
10	60	5.28	0.0097	0.05	0.25	0.0554	30	60	3.04	0.0072	0.05	0.25	0.4976
10	60	5.28	0.0097	0.05	0.30	0.1981	30	60	3.04	0.0072	0.05	0.30	0.6833
10	60	5.28	0.0097	0.05	0.35	0.3911	30	60	3.04	0.0072	0.05	0.35	0.8257
10	60	5.28	0.0097	0.05	0.40	0.5287	30	60	3.04	0.0072	0.05	0.40	0.9177
10	60	5.28	0.0097	0.05	0.45	0.5840	30	60	3.04	0.0072	0.05	0.45	0.9677
10	60	5.28	0.0097	0.10	0.25	0.0322	30	60	3.04	0.0072	0.10	0.25	0.1943
10	60	5.28	0.0097	0.10	0.30	0.1154	30	60	3.04	0.0072	0.10	0.30	0.3395
10	60	5.28	0.0097	0.10	0.35	0.2278	30	60	3.04	0.0072	0.10	0.35	0.5088
10	60	5.28	0.0097	0.10	0.40	0.3079	30	60	3.04	0.0072	0.10	0.40	0.6778
10	60	5.28	0.0097	0.10	0.45	0.3401	30	60	3.04	0.0072	0.10	0.45	0.8188
10	60	5.28	0.0097	0.10	0.50	0.3481	30	60	3.04	0.0072	0.10	0.50	0.9147
10	60	5.28	0.0097	0.10	0.55	0.3535	30	60	3.04	0.0072	0.10	0.55	0.9671
10	60	5.28	0.0097	0.10	0.60	0.3765	30	60	3.04	0.0072	0.10	0.60	0.9897
10	60	5.28	0.0097	0.15	0.30	0.0651	30	60	3.04	0.0072	0.15	0.30	0.1366
10	60	5.28	0.0097	0.15	0.35	0.1286	30	60	3.04	0.0072	0.15	0.35	0.2521
10	60	5.28	0.0097	0.15	0.40	0.1738	30	60	3.04	0.0072	0.15	0.40	0.4082
10	60	5.28	0.0097	0.15	0.45	0.1921	30	60	3.04	0.0072	0.15	0.45	0.5843
10	60	5.28	0.0097	0.15	0.50	0.1967	30	60	3.04	0.0072	0.15	0.50	0.7468
10	60	5.28	0.0097	0.15	0.55	0.2012	30	60	3.04	0.0072	0.15	0.55	0.8682
10	60	5.28	0.0097	0.15	0.60	0.2218	30	60	3.04	0.0072	0.15	0.60	0.9419
10	60	5.28	0.0097	0.15	0.65	0.2844	30	60	3.04	0.0072	0.15	0.65	0.9787
10	60	5.28	0.0097	0.20	0.35	0.0701	30	60	3.04	0.0072	0.20	0.35	0.1050
10	60	5.28	0.0097	0.20	0.40	0.0948	30	60	3.04	0.0072	0.20	0.40	0.2064
10	60	5.28	0.0097	0.20	0.45	0.1048	30	60	3.04	0.0072	0.20	0.45	0.3529
10	60	5.28	0.0097	0.20	0.50	0.1074	30	60	3.04	0.0072	0.20	0.50	0.5259
10	60	5.28	0.0097	0.20	0.55	0.1108	30	60	3.04	0.0072	0.20	0.55	0.6929
10	60	5.28	0.0097	0.20	0.60	0.1267	30	60	3.04	0.0072	0.20	0.60	0.8268
10	60	5.28	0.0097	0.20	0.65	0.1750	30	60	3.04	0.0072	0.20	0.65	0.9169
10	60	5.28	0.0097	0.20	0.70	0.2586	30	60	3.04	0.0072	0.20	0.70	0.9676
10	60	5.28	0.0097	0.25	0.40	0.0497	30	60	3.04	0.0072	0.25	0.40	0.0893
10	60	5.28	0.0097	0.25	0.45	0.0549	30	60	3.04	0.0072	0.25	0.45	0.1818
10	60	5.28	0.0097	0.25	0.50	0.0564	30	60	3.04	0.0072	0.25	0.50	0.3173
10	60	5.28	0.0097	0.25	0.55	0.0587	30	60	3.04	0.0072	0.25	0.55	0.4810
10	60	5.28	0.0097	0.25	0.60	0.0698	30	60	3.04	0.0072	0.25	0.60	0.6476
10	60	5.28	0.0097	0.25	0.65	0.1036	30	60	3.04	0.0072	0.25	0.65	0.7924
10	60	5.28	0.0097	0.25	0.70	0.1621	30	60	3.04	0.0072	0.25	0.70	0.8987
10	60	5.28	0.0097	0.25	0.75	0.2170	30	60	3.04	0.0072	0.25	0.75	0.9613
10	60	5.28	0.0097	0.30	0.45	0.0276	30	60	3.04	0.0072	0.30	0.45	0.0802

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	60	5.28	0.0097	0.30	0.50	0.0283	30	60	3.04	0.0072	0.30	0.50	0.1638
10	60	5.28	0.0097	0.30	0.55	0.0298	30	60	3.04	0.0072	0.30	0.55	0.2875
10	60	5.28	0.0097	0.30	0.60	0.0369	30	60	3.04	0.0072	0.30	0.60	0.4439
10	60	5.28	0.0097	0.30	0.65	0.0587	30	60	3.04	0.0072	0.30	0.65	0.6149
10	60	5.28	0.0097	0.30	0.70	0.0965	30	60	3.04	0.0072	0.30	0.70	0.7734
10	60	5.28	0.0097	0.35	0.50	0.0135	30	60	3.04	0.0072	0.35	0.50	0.0722
10	60	5.28	0.0097	0.35	0.55	0.0144	30	60	3.04	0.0072	0.35	0.55	0.1473
10	60	5.28	0.0097	0.35	0.60	0.0187	30	60	3.04	0.0072	0.35	0.60	0.2637
10	60	5.28	0.0097	0.35	0.65	0.0317	30	60	3.04	0.0072	0.35	0.65	0.4210
10	60	5.28	0.0097	0.40	0.55	0.0066	30	60	3.04	0.0072	0.40	0.55	0.0643
10	60	5.28	0.0097	0.40	0.60	0.0089	30	60	3.04	0.0072	0.40	0.60	0.1348
10	70	5.86	0.0083	0.05	0.15	0.0000	30	70	3.22	0.0078	0.05	0.15	0.1507
10	70	5.86	0.0083	0.05	0.20	0.0022	30	70	3.22	0.0078	0.05	0.20	0.3125
10	70	5.86	0.0083	0.05	0.25	0.0313	30	70	3.22	0.0078	0.05	0.25	0.5071
10	70	5.86	0.0083	0.05	0.30	0.1521	30	70	3.22	0.0078	0.05	0.30	0.6939
10	70	5.86	0.0083	0.05	0.35	0.3558	30	70	3.22	0.0078	0.05	0.35	0.8382
10	70	5.86	0.0083	0.05	0.40	0.5175	30	70	3.22	0.0078	0.05	0.40	0.9277
10	70	5.86	0.0083	0.05	0.45	0.5830	30	70	3.22	0.0078	0.05	0.45	0.9725
10	70	5.86	0.0083	0.10	0.25	0.0182	30	70	3.22	0.0078	0.10	0.25	0.1948
10	70	5.86	0.0083	0.10	0.30	0.0886	30	70	3.22	0.0078	0.10	0.30	0.3450
10	70	5.86	0.0083	0.10	0.35	0.2072	30	70	3.22	0.0078	0.10	0.35	0.5214
10	70	5.86	0.0083	0.10	0.40	0.3014	30	70	3.22	0.0078	0.10	0.40	0.6886
10	70	5.86	0.0083	0.10	0.45	0.3395	30	70	3.22	0.0078	0.10	0.45	0.8213
10	70	5.86	0.0083	0.10	0.50	0.3477	30	70	3.22	0.0078	0.10	0.50	0.9121
10	70	5.86	0.0083	0.10	0.55	0.3489	30	70	3.22	0.0078	0.10	0.55	0.9644
10	70	5.86	0.0083	0.10	0.60	0.3521	30	70	3.22	0.0078	0.10	0.60	0.9885
10	70	5.86	0.0083	0.15	0.30	0.0500	30	70	3.22	0.0078	0.15	0.30	0.1380
10	70	5.86	0.0083	0.15	0.35	0.1170	30	70	3.22	0.0078	0.15	0.35	0.2560
10	70	5.86	0.0083	0.15	0.40	0.1702	30	70	3.22	0.0078	0.15	0.40	0.4063
10	70	5.86	0.0083	0.15	0.45	0.1917	30	70	3.22	0.0078	0.15	0.45	0.5709
10	70	5.86	0.0083	0.15	0.50	0.1963	30	70	3.22	0.0078	0.15	0.50	0.7277
10	70	5.86	0.0083	0.15	0.55	0.1971	30	70	3.22	0.0078	0.15	0.55	0.8533
10	70	5.86	0.0083	0.15	0.60	0.2000	30	70	3.22	0.0078	0.15	0.60	0.9347
10	70	5.86	0.0083	0.15	0.65	0.2191	30	70	3.22	0.0078	0.15	0.65	0.9768
10	70	5.86	0.0083	0.20	0.35	0.0638	30	70	3.22	0.0078	0.20	0.35	0.1034
10	70	5.86	0.0083	0.20	0.40	0.0928	30	70	3.22	0.0078	0.20	0.40	0.1962
10	70	5.86	0.0083	0.20	0.45	0.1046	30	70	3.22	0.0078	0.20	0.45	0.3282
10	70	5.86	0.0083	0.20	0.50	0.1071	30	70	3.22	0.0078	0.20	0.50	0.4920
10	70	5.86	0.0083	0.20	0.55	0.1075	30	70	3.22	0.0078	0.20	0.55	0.6627
10	70	5.86	0.0083	0.20	0.60	0.1098	30	70	3.22	0.0078	0.20	0.60	0.8091
10	70	5.86	0.0083	0.20	0.65	0.1245	30	70	3.22	0.0078	0.20	0.65	0.9105
10	70	5.86	0.0083	0.20	0.70	0.1773	30	70	3.22	0.0078	0.20	0.70	0.9657
10	70	5.86	0.0083	0.25	0.40	0.0487	30	70	3.22	0.0078	0.25	0.40	0.0793
10	70	5.86	0.0083	0.25	0.45	0.0548	30	70	3.22	0.0078	0.25	0.45	0.1584
10	70	5.86	0.0083	0.25	0.50	0.0562	30	70	3.22	0.0078	0.25	0.50	0.2818
10	70	5.86	0.0083	0.25	0.55	0.0564	30	70	3.22	0.0078	0.25	0.55	0.4440
10	70	5.86	0.0083	0.25	0.60	0.0580	30	70	3.22	0.0078	0.25	0.60	0.6212
10	70	5.86	0.0083	0.25	0.65	0.0683	30	70	3.22	0.0078	0.25	0.65	0.7784
10	70	5.86	0.0083	0.25	0.70	0.1052	30	70	3.22	0.0078	0.25	0.70	0.8904
10	70	5.86	0.0083	0.25	0.75	0.1721	30	70	3.22	0.0078	0.25	0.75	0.9566

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	70	5.86	0.0083	0.30	0.45	0.0275	30	70	3.22	0.0078	0.30	0.45	0.0649
10	70	5.86	0.0083	0.30	0.50	0.0282	30	70	3.22	0.0078	0.30	0.50	0.1373
10	70	5.86	0.0083	0.30	0.55	0.0283	30	70	3.22	0.0078	0.30	0.55	0.2551
10	70	5.86	0.0083	0.30	0.60	0.0293	30	70	3.22	0.0078	0.30	0.60	0.4151
10	70	5.86	0.0083	0.30	0.65	0.0360	30	70	3.22	0.0078	0.30	0.65	0.5921
10	70	5.86	0.0083	0.30	0.70	0.0598	30	70	3.22	0.0078	0.30	0.70	0.7535
10	70	5.86	0.0083	0.35	0.50	0.0134	30	70	3.22	0.0078	0.35	0.50	0.0569
10	70	5.86	0.0083	0.35	0.55	0.0135	30	70	3.22	0.0078	0.35	0.55	0.1253
10	70	5.86	0.0083	0.35	0.60	0.0141	30	70	3.22	0.0078	0.35	0.60	0.2387
10	70	5.86	0.0083	0.35	0.65	0.0181	30	70	3.22	0.0078	0.35	0.65	0.3925
10	70	5.86	0.0083	0.40	0.55	0.0061	30	70	3.22	0.0078	0.40	0.55	0.0523
10	70	5.86	0.0083	0.40	0.60	0.0064	30	70	3.22	0.0078	0.40	0.60	0.1168
10	80	6.21	0.0089	0.05	0.15	0.0000	30	80	3.39	0.0081	0.05	0.15	0.1527
10	80	6.21	0.0089	0.05	0.20	0.0017	30	80	3.39	0.0081	0.05	0.20	0.2888
10	80	6.21	0.0089	0.05	0.25	0.0299	30	80	3.39	0.0081	0.05	0.25	0.4810
10	80	6.21	0.0089	0.05	0.30	0.1603	30	80	3.39	0.0081	0.05	0.30	0.6820
10	80	6.21	0.0089	0.05	0.35	0.3792	30	80	3.39	0.0081	0.05	0.35	0.8325
10	80	6.21	0.0089	0.05	0.40	0.5366	30	80	3.39	0.0081	0.05	0.40	0.9234
10	80	6.21	0.0089	0.05	0.45	0.5895	30	80	3.39	0.0081	0.05	0.45	0.9701
10	80	6.21	0.0089	0.10	0.25	0.0174	30	80	3.39	0.0081	0.10	0.25	0.1786
10	80	6.21	0.0089	0.10	0.30	0.0933	30	80	3.39	0.0081	0.10	0.30	0.3292
10	80	6.21	0.0089	0.10	0.35	0.2209	30	80	3.39	0.0081	0.10	0.35	0.5019
10	80	6.21	0.0089	0.10	0.40	0.3125	30	80	3.39	0.0081	0.10	0.40	0.6679
10	80	6.21	0.0089	0.10	0.45	0.3433	30	80	3.39	0.0081	0.10	0.45	0.8078
10	80	6.21	0.0089	0.10	0.50	0.3483	30	80	3.39	0.0081	0.10	0.50	0.9080
10	80	6.21	0.0089	0.10	0.55	0.3487	30	80	3.39	0.0081	0.10	0.55	0.9645
10	80	6.21	0.0089	0.10	0.60	0.3493	30	80	3.39	0.0081	0.10	0.60	0.9889
10	80	6.21	0.0089	0.15	0.30	0.0527	30	80	3.39	0.0081	0.15	0.30	0.1264
10	80	6.21	0.0089	0.15	0.35	0.1247	30	80	3.39	0.0081	0.15	0.35	0.2355
10	80	6.21	0.0089	0.15	0.40	0.1765	30	80	3.39	0.0081	0.15	0.40	0.3801
10	80	6.21	0.0089	0.15	0.45	0.1938	30	80	3.39	0.0081	0.15	0.45	0.5503
10	80	6.21	0.0089	0.15	0.50	0.1966	30	80	3.39	0.0081	0.15	0.50	0.7188
10	80	6.21	0.0089	0.15	0.55	0.1969	30	80	3.39	0.0081	0.15	0.55	0.8508
10	80	6.21	0.0089	0.15	0.60	0.1975	30	80	3.39	0.0081	0.15	0.60	0.9338
10	80	6.21	0.0089	0.15	0.65	0.2041	30	80	3.39	0.0081	0.15	0.65	0.9765
10	80	6.21	0.0089	0.20	0.35	0.0680	30	80	3.39	0.0081	0.20	0.35	0.0905
10	80	6.21	0.0089	0.20	0.40	0.0962	30	80	3.39	0.0081	0.20	0.40	0.1767
10	80	6.21	0.0089	0.20	0.45	0.1057	30	80	3.39	0.0081	0.20	0.45	0.3096
10	80	6.21	0.0089	0.20	0.50	0.1072	30	80	3.39	0.0081	0.20	0.50	0.4795
10	80	6.21	0.0089	0.20	0.55	0.1074	30	80	3.39	0.0081	0.20	0.55	0.6542
10	80	6.21	0.0089	0.20	0.60	0.1078	30	80	3.39	0.0081	0.20	0.60	0.8027
10	80	6.21	0.0089	0.20	0.65	0.1130	30	80	3.39	0.0081	0.20	0.65	0.9070
10	80	6.21	0.0089	0.20	0.70	0.1437	30	80	3.39	0.0081	0.20	0.70	0.9646
10	80	6.21	0.0089	0.25	0.40	0.0505	30	80	3.39	0.0081	0.25	0.40	0.0689
10	80	6.21	0.0089	0.25	0.45	0.0554	30	80	3.39	0.0081	0.25	0.45	0.1459
10	80	6.21	0.0089	0.25	0.50	0.0562	30	80	3.39	0.0081	0.25	0.50	0.2690
10	80	6.21	0.0089	0.25	0.55	0.0563	30	80	3.39	0.0081	0.25	0.55	0.4297
10	80	6.21	0.0089	0.25	0.60	0.0566	30	80	3.39	0.0081	0.25	0.60	0.6071
10	80	6.21	0.0089	0.25	0.65	0.0602	30	80	3.39	0.0081	0.25	0.65	0.7686
10	80	6.21	0.0089	0.25	0.70	0.0817	30	80	3.39	0.0081	0.25	0.70	0.8859

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	80	6.21	0.0089	0.25	0.75	0.1421	30	80	3.39	0.0081	0.25	0.75	0.9540
10	80	6.21	0.0089	0.30	0.45	0.0278	30	80	3.39	0.0081	0.30	0.45	0.0581
10	80	6.21	0.0089	0.30	0.50	0.0282	30	80	3.39	0.0081	0.30	0.50	0.1272
10	80	6.21	0.0089	0.30	0.55	0.0283	30	80	3.39	0.0081	0.30	0.55	0.2399
10	80	6.21	0.0089	0.30	0.60	0.0284	30	80	3.39	0.0081	0.30	0.60	0.3965
10	80	6.21	0.0089	0.30	0.65	0.0308	30	80	3.39	0.0081	0.30	0.65	0.5760
10	80	6.21	0.0089	0.30	0.70	0.0446	30	80	3.39	0.0081	0.30	0.70	0.7426
10	80	6.21	0.0089	0.35	0.50	0.0134	30	80	3.39	0.0081	0.35	0.50	0.0507
10	80	6.21	0.0089	0.35	0.55	0.0135	30	80	3.39	0.0081	0.35	0.55	0.1135
10	80	6.21	0.0089	0.35	0.60	0.0136	30	80	3.39	0.0081	0.35	0.60	0.2213
10	80	6.21	0.0089	0.35	0.65	0.0150	30	80	3.39	0.0081	0.35	0.65	0.3740
10	80	6.21	0.0089	0.40	0.55	0.0060	30	80	3.39	0.0081	0.40	0.55	0.0453
10	80	6.21	0.0089	0.40	0.60	0.0061	30	80	3.39	0.0081	0.40	0.60	0.1046
10	90	6.55	0.0094	0.05	0.15	0.0000	30	90	3.55	0.0088	0.05	0.15	0.1616
10	90	6.55	0.0094	0.05	0.20	0.0012	30	90	3.55	0.0088	0.05	0.20	0.2935
10	90	6.55	0.0094	0.05	0.25	0.0283	30	90	3.55	0.0088	0.05	0.25	0.4755
10	90	6.55	0.0094	0.05	0.30	0.1672	30	90	3.55	0.0088	0.05	0.30	0.6613
10	90	6.55	0.0094	0.05	0.35	0.3996	30	90	3.55	0.0088	0.05	0.35	0.8174
10	90	6.55	0.0094	0.05	0.40	0.5510	30	90	3.55	0.0088	0.05	0.40	0.9198
10	90	6.55	0.0094	0.05	0.45	0.5932	30	90	3.55	0.0088	0.05	0.45	0.9706
10	90	6.55	0.0094	0.10	0.25	0.0165	30	90	3.55	0.0088	0.10	0.25	0.1666
10	90	6.55	0.0094	0.10	0.30	0.0974	30	90	3.55	0.0088	0.10	0.30	0.3029
10	90	6.55	0.0094	0.10	0.35	0.2327	30	90	3.55	0.0088	0.10	0.35	0.4814
10	90	6.55	0.0094	0.10	0.40	0.3209	30	90	3.55	0.0088	0.10	0.40	0.6613
10	90	6.55	0.0094	0.10	0.45	0.3455	30	90	3.55	0.0088	0.10	0.45	0.8063
10	90	6.55	0.0094	0.10	0.50	0.3485	30	90	3.55	0.0088	0.10	0.50	0.9054
10	90	6.55	0.0094	0.10	0.55	0.3487	30	90	3.55	0.0088	0.10	0.55	0.9621
10	90	6.55	0.0094	0.10	0.60	0.3487	30	90	3.55	0.0088	0.10	0.60	0.9878
10	90	6.55	0.0094	0.15	0.30	0.0550	30	90	3.55	0.0088	0.15	0.30	0.1114
10	90	6.55	0.0094	0.15	0.35	0.1314	30	90	3.55	0.0088	0.15	0.35	0.2218
10	90	6.55	0.0094	0.15	0.40	0.1812	30	90	3.55	0.0088	0.15	0.40	0.3720
10	90	6.55	0.0094	0.15	0.45	0.1951	30	90	3.55	0.0088	0.15	0.45	0.5411
10	90	6.55	0.0094	0.15	0.50	0.1968	30	90	3.55	0.0088	0.15	0.50	0.7053
10	90	6.55	0.0094	0.15	0.55	0.1969	30	90	3.55	0.0088	0.15	0.55	0.8387
10	90	6.55	0.0094	0.15	0.60	0.1969	30	90	3.55	0.0088	0.15	0.60	0.9255
10	90	6.55	0.0094	0.15	0.65	0.1979	30	90	3.55	0.0088	0.15	0.65	0.9714
10	90	6.55	0.0094	0.20	0.35	0.0717	30	90	3.55	0.0088	0.20	0.35	0.0838
10	90	6.55	0.0094	0.20	0.40	0.0988	30	90	3.55	0.0088	0.20	0.40	0.1695
10	90	6.55	0.0094	0.20	0.45	0.1064	30	90	3.55	0.0088	0.20	0.45	0.2956
10	90	6.55	0.0094	0.20	0.50	0.1073	30	90	3.55	0.0088	0.20	0.50	0.4572
10	90	6.55	0.0094	0.20	0.55	0.1074	30	90	3.55	0.0088	0.20	0.55	0.6295
10	90	6.55	0.0094	0.20	0.60	0.1074	30	90	3.55	0.0088	0.20	0.60	0.7793
10	90	6.55	0.0094	0.20	0.65	0.1082	30	90	3.55	0.0088	0.20	0.65	0.8882
10	90	6.55	0.0094	0.20	0.70	0.1178	30	90	3.55	0.0088	0.20	0.70	0.9547
10	90	6.55	0.0094	0.25	0.40	0.0518	30	90	3.55	0.0088	0.25	0.40	0.0641
10	90	6.55	0.0094	0.25	0.45	0.0558	30	90	3.55	0.0088	0.25	0.45	0.1338
10	90	6.55	0.0094	0.25	0.50	0.0563	30	90	3.55	0.0088	0.25	0.50	0.2467
10	90	6.55	0.0094	0.25	0.55	0.0563	30	90	3.55	0.0088	0.25	0.55	0.3988
10	90	6.55	0.0094	0.25	0.60	0.0563	30	90	3.55	0.0088	0.25	0.60	0.5685
10	90	6.55	0.0094	0.25	0.65	0.0569	30	90	3.55	0.0088	0.25	0.65	0.7304

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	90	6.55	0.0094	0.25	0.70	0.0636	30	90	3.55	0.0088	0.25	0.70	0.8609
10	90	6.55	0.0094	0.25	0.75	0.1005	30	90	3.55	0.0088	0.25	0.75	0.9421
10	90	6.55	0.0094	0.30	0.45	0.0280	30	90	3.55	0.0088	0.30	0.45	0.0507
10	90	6.55	0.0094	0.30	0.50	0.0282	30	90	3.55	0.0088	0.30	0.50	0.1114
10	90	6.55	0.0094	0.30	0.55	0.0282	30	90	3.55	0.0088	0.30	0.55	0.2121
10	90	6.55	0.0094	0.30	0.60	0.0283	30	90	3.55	0.0088	0.30	0.60	0.3530
10	90	6.55	0.0094	0.30	0.65	0.0286	30	90	3.55	0.0088	0.30	0.65	0.5246
10	90	6.55	0.0094	0.30	0.70	0.0330	30	90	3.55	0.0088	0.30	0.70	0.7008
10	90	6.55	0.0094	0.35	0.50	0.0135	30	90	3.55	0.0088	0.35	0.50	0.0421
10	90	6.55	0.0094	0.35	0.55	0.0135	30	90	3.55	0.0088	0.35	0.55	0.0945
10	90	6.55	0.0094	0.35	0.60	0.0135	30	90	3.55	0.0088	0.35	0.60	0.1851
10	90	6.55	0.0094	0.35	0.65	0.0137	30	90	3.55	0.0088	0.35	0.65	0.3234
10	90	6.55	0.0094	0.40	0.55	0.0060	30	90	3.55	0.0088	0.40	0.55	0.0351
10	90	6.55	0.0094	0.40	0.60	0.0061	30	90	3.55	0.0088	0.40	0.60	0.0814
10	100	6.86	0.0098	0.05	0.15	0.0000	30	100	3.70	0.0093	0.05	0.15	0.1656
10	100	6.86	0.0098	0.05	0.20	0.0009	30	100	3.70	0.0093	0.05	0.20	0.2749
10	100	6.86	0.0098	0.05	0.25	0.0267	30	100	3.70	0.0093	0.05	0.25	0.4548
10	100	6.86	0.0098	0.05	0.30	0.1732	30	100	3.70	0.0093	0.05	0.30	0.6515
10	100	6.86	0.0098	0.05	0.35	0.4174	30	100	3.70	0.0093	0.05	0.35	0.8057
10	100	6.86	0.0098	0.05	0.40	0.5619	30	100	3.70	0.0093	0.05	0.40	0.9082
10	100	6.86	0.0098	0.05	0.45	0.5954	30	100	3.70	0.0093	0.05	0.45	0.9657
10	100	6.86	0.0098	0.10	0.25	0.0155	30	100	3.70	0.0093	0.10	0.25	0.1555
10	100	6.86	0.0098	0.10	0.30	0.1009	30	100	3.70	0.0093	0.10	0.30	0.2889
10	100	6.86	0.0098	0.10	0.35	0.2431	30	100	3.70	0.0093	0.10	0.35	0.4523
10	100	6.86	0.0098	0.10	0.40	0.3272	30	100	3.70	0.0093	0.10	0.40	0.6298
10	100	6.86	0.0098	0.10	0.45	0.3468	30	100	3.70	0.0093	0.10	0.45	0.7888
10	100	6.86	0.0098	0.10	0.50	0.3486	30	100	3.70	0.0093	0.10	0.50	0.8979
10	100	6.86	0.0098	0.10	0.55	0.3487	30	100	3.70	0.0093	0.10	0.55	0.9579
10	100	6.86	0.0098	0.10	0.60	0.3487	30	100	3.70	0.0093	0.10	0.60	0.9855
10	100	6.86	0.0098	0.15	0.30	0.0570	30	100	3.70	0.0093	0.15	0.30	0.1014
10	100	6.86	0.0098	0.15	0.35	0.1372	30	100	3.70	0.0093	0.15	0.35	0.1969
10	100	6.86	0.0098	0.15	0.40	0.1848	30	100	3.70	0.0093	0.15	0.40	0.3410
10	100	6.86	0.0098	0.15	0.45	0.1958	30	100	3.70	0.0093	0.15	0.45	0.5173
10	100	6.86	0.0098	0.15	0.50	0.1968	30	100	3.70	0.0093	0.15	0.50	0.6868
10	100	6.86	0.0098	0.15	0.55	0.1969	30	100	3.70	0.0093	0.15	0.55	0.8217
10	100	6.86	0.0098	0.15	0.60	0.1969	30	100	3.70	0.0093	0.15	0.60	0.9139
10	100	6.86	0.0098	0.15	0.65	0.1970	30	100	3.70	0.0093	0.15	0.65	0.9665
10	100	6.86	0.0098	0.20	0.35	0.0749	30	100	3.70	0.0093	0.20	0.35	0.0704
10	100	6.86	0.0098	0.20	0.40	0.1008	30	100	3.70	0.0093	0.20	0.40	0.1500
10	100	6.86	0.0098	0.20	0.45	0.1068	30	100	3.70	0.0093	0.20	0.45	0.2749
10	100	6.86	0.0098	0.20	0.50	0.1074	30	100	3.70	0.0093	0.20	0.50	0.4319
10	100	6.86	0.0098	0.20	0.55	0.1074	30	100	3.70	0.0093	0.20	0.55	0.5988
10	100	6.86	0.0098	0.20	0.60	0.1074	30	100	3.70	0.0093	0.20	0.60	0.7537
10	100	6.86	0.0098	0.20	0.65	0.1075	30	100	3.70	0.0093	0.20	0.65	0.8738
10	100	6.86	0.0098	0.20	0.70	0.1098	30	100	3.70	0.0093	0.20	0.70	0.9471
10	100	6.86	0.0098	0.25	0.40	0.0529	30	100	3.70	0.0093	0.25	0.40	0.0549
10	100	6.86	0.0098	0.25	0.45	0.0560	30	100	3.70	0.0093	0.25	0.45	0.1203
10	100	6.86	0.0098	0.25	0.50	0.0563	30	100	3.70	0.0093	0.25	0.50	0.2238
10	100	6.86	0.0098	0.25	0.55	0.0563	30	100	3.70	0.0093	0.25	0.55	0.3649
10	100	6.86	0.0098	0.25	0.60	0.0563	30	100	3.70	0.0093	0.25	0.60	0.5342

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	100	6.86	0.0098	0.25	0.65	0.0564	30	100	3.70	0.0093	0.25	0.65	0.7042
10	100	6.86	0.0098	0.25	0.70	0.0580	30	100	3.70	0.0093	0.25	0.70	0.8409
10	100	6.86	0.0098	0.25	0.75	0.0750	30	100	3.70	0.0093	0.25	0.75	0.9307
10	100	6.86	0.0098	0.30	0.45	0.0281	30	100	3.70	0.0093	0.30	0.45	0.0438
10	100	6.86	0.0098	0.30	0.50	0.0282	30	100	3.70	0.0093	0.30	0.50	0.0963
10	100	6.86	0.0098	0.30	0.55	0.0282	30	100	3.70	0.0093	0.30	0.55	0.1856
10	100	6.86	0.0098	0.30	0.60	0.0282	30	100	3.70	0.0093	0.30	0.60	0.3205
10	100	6.86	0.0098	0.30	0.65	0.0283	30	100	3.70	0.0093	0.30	0.65	0.4909
10	100	6.86	0.0098	0.30	0.70	0.0293	30	100	3.70	0.0093	0.30	0.70	0.6665
10	100	6.86	0.0098	0.35	0.50	0.0135	30	100	3.70	0.0093	0.35	0.50	0.0344
10	100	6.86	0.0098	0.35	0.55	0.0135	30	100	3.70	0.0093	0.35	0.55	0.0788
10	100	6.86	0.0098	0.35	0.60	0.0135	30	100	3.70	0.0093	0.35	0.60	0.1616
10	100	6.86	0.0098	0.35	0.65	0.0135	30	100	3.70	0.0093	0.35	0.65	0.2909
10	100	6.86	0.0098	0.40	0.55	0.0060	30	100	3.70	0.0093	0.40	0.55	0.0279
10	100	6.86	0.0098	0.40	0.60	0.0060	30	100	3.70	0.0093	0.40	0.60	0.0680
20	30	2.74	0.0085	0.05	0.15	0.0584	40	50	2.50	0.0091	0.05	0.15	0.2261
20	30	2.74	0.0085	0.05	0.20	0.1645	40	50	2.50	0.0091	0.05	0.20	0.4491
20	30	2.74	0.0085	0.05	0.25	0.3121	40	50	2.50	0.0091	0.05	0.25	0.6638
20	30	2.74	0.0085	0.05	0.30	0.4734	40	50	2.50	0.0091	0.05	0.30	0.8255
20	30	2.74	0.0085	0.05	0.35	0.6254	40	50	2.50	0.0091	0.05	0.35	0.9255
20	30	2.74	0.0085	0.05	0.40	0.7538	40	50	2.50	0.0091	0.05	0.40	0.9747
20	30	2.74	0.0085	0.05	0.45	0.8522	40	50	2.50	0.0091	0.05	0.45	0.9933
20	30	2.74	0.0085	0.10	0.25	0.1391	40	50	2.50	0.0091	0.10	0.25	0.3053
20	30	2.74	0.0085	0.10	0.30	0.2408	40	50	2.50	0.0091	0.10	0.30	0.5043
20	30	2.74	0.0085	0.10	0.35	0.3643	40	50	2.50	0.0091	0.10	0.35	0.7010
20	30	2.74	0.0085	0.10	0.40	0.5002	40	50	2.50	0.0091	0.10	0.40	0.8494
20	30	2.74	0.0085	0.10	0.45	0.6362	40	50	2.50	0.0091	0.10	0.45	0.9369
20	30	2.74	0.0085	0.10	0.50	0.7582	40	50	2.50	0.0091	0.10	0.50	0.9783
20	30	2.74	0.0085	0.10	0.55	0.8552	40	50	2.50	0.0091	0.10	0.55	0.9940
20	30	2.74	0.0085	0.10	0.60	0.9230	40	50	2.50	0.0091	0.10	0.60	0.9987
20	30	2.74	0.0085	0.15	0.30	0.1127	40	50	2.50	0.0091	0.15	0.30	0.2460
20	30	2.74	0.0085	0.15	0.35	0.1930	40	50	2.50	0.0091	0.15	0.35	0.4295
20	30	2.74	0.0085	0.15	0.40	0.2998	40	50	2.50	0.0091	0.15	0.40	0.6231
20	30	2.74	0.0085	0.15	0.45	0.4279	40	50	2.50	0.0091	0.15	0.45	0.7868
20	30	2.74	0.0085	0.15	0.50	0.5654	40	50	2.50	0.0091	0.15	0.50	0.8990
20	30	2.74	0.0085	0.15	0.55	0.6967	40	50	2.50	0.0091	0.15	0.55	0.9608
20	30	2.74	0.0085	0.15	0.60	0.8084	40	50	2.50	0.0091	0.15	0.60	0.9879
20	30	2.74	0.0085	0.15	0.65	0.8928	40	50	2.50	0.0091	0.15	0.65	0.9971
20	30	2.74	0.0085	0.20	0.35	0.0944	40	50	2.50	0.0091	0.20	0.35	0.2143
20	30	2.74	0.0085	0.20	0.40	0.1648	40	50	2.50	0.0091	0.20	0.40	0.3789
20	30	2.74	0.0085	0.20	0.45	0.2628	40	50	2.50	0.0091	0.20	0.45	0.5665
20	30	2.74	0.0085	0.20	0.50	0.3847	40	50	2.50	0.0091	0.20	0.50	0.7396
20	30	2.74	0.0085	0.20	0.55	0.5208	40	50	2.50	0.0091	0.20	0.55	0.8687
20	30	2.74	0.0085	0.20	0.60	0.6571	40	50	2.50	0.0091	0.20	0.60	0.9460
20	30	2.74	0.0085	0.20	0.65	0.7787	40	50	2.50	0.0091	0.20	0.65	0.9825
20	30	2.74	0.0085	0.20	0.70	0.8737	40	50	2.50	0.0091	0.20	0.70	0.9957
20	30	2.74	0.0085	0.25	0.40	0.0835	40	50	2.50	0.0091	0.25	0.40	0.1919
20	30	2.74	0.0085	0.25	0.45	0.1483	40	50	2.50	0.0091	0.25	0.45	0.3453
20	30	2.74	0.0085	0.25	0.50	0.2403	40	50	2.50	0.0091	0.25	0.50	0.5290
20	30	2.74	0.0085	0.25	0.55	0.3583	40	50	2.50	0.0091	0.25	0.55	0.7078

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	30	2.74	0.0085	0.25	0.60	0.4944	40	50	2.50	0.0091	0.25	0.60	0.8482
20	30	2.74	0.0085	0.25	0.65	0.6342	40	50	2.50	0.0091	0.25	0.65	0.9359
20	30	2.74	0.0085	0.25	0.70	0.7602	40	50	2.50	0.0091	0.25	0.70	0.9787
20	30	2.74	0.0085	0.25	0.75	0.8595	40	50	2.50	0.0091	0.25	0.75	0.9947
20	30	2.74	0.0085	0.30	0.45	0.0770	40	50	2.50	0.0091	0.30	0.45	0.1777
20	30	2.74	0.0085	0.30	0.50	0.1382	40	50	2.50	0.0091	0.30	0.50	0.3245
20	30	2.74	0.0085	0.30	0.55	0.2272	40	50	2.50	0.0091	0.30	0.55	0.5063
20	30	2.74	0.0085	0.30	0.60	0.3435	40	50	2.50	0.0091	0.30	0.60	0.6884
20	30	2.74	0.0085	0.30	0.65	0.4786	40	50	2.50	0.0091	0.30	0.65	0.8351
20	30	2.74	0.0085	0.30	0.70	0.6173	40	50	2.50	0.0091	0.30	0.70	0.9294
20	30	2.74	0.0085	0.35	0.50	0.0731	40	50	2.50	0.0091	0.35	0.50	0.1694
20	30	2.74	0.0085	0.35	0.55	0.1326	40	50	2.50	0.0091	0.35	0.55	0.3122
20	30	2.74	0.0085	0.35	0.60	0.2194	40	50	2.50	0.0091	0.35	0.60	0.4918
20	30	2.74	0.0085	0.35	0.65	0.3323	40	50	2.50	0.0091	0.35	0.65	0.6754
20	30	2.74	0.0085	0.40	0.55	0.0707	40	50	2.50	0.0091	0.40	0.55	0.1636
20	30	2.74	0.0085	0.40	0.60	0.1279	40	50	2.50	0.0091	0.40	0.60	0.3026
20	40	3.11	0.0097	0.05	0.15	0.0880	40	60	2.62	0.0096	0.05	0.15	0.2138
20	40	3.11	0.0097	0.05	0.20	0.2093	40	60	2.62	0.0096	0.05	0.20	0.4534
20	40	3.11	0.0097	0.05	0.25	0.3344	40	60	2.62	0.0096	0.05	0.25	0.6909
20	40	3.11	0.0097	0.05	0.30	0.4630	40	60	2.62	0.0096	0.05	0.30	0.8559
20	40	3.11	0.0097	0.05	0.35	0.6054	40	60	2.62	0.0096	0.05	0.35	0.9443
20	40	3.11	0.0097	0.05	0.40	0.7449	40	60	2.62	0.0096	0.05	0.40	0.9822
20	40	3.11	0.0097	0.05	0.45	0.8558	40	60	2.62	0.0096	0.05	0.45	0.9954
20	40	3.11	0.0097	0.10	0.25	0.1308	40	60	2.62	0.0096	0.10	0.25	0.3276
20	40	3.11	0.0097	0.10	0.30	0.2143	40	60	2.62	0.0096	0.10	0.30	0.5309
20	40	3.11	0.0097	0.10	0.35	0.3360	40	60	2.62	0.0096	0.10	0.35	0.7178
20	40	3.11	0.0097	0.10	0.40	0.4840	40	60	2.62	0.0096	0.10	0.40	0.8574
20	40	3.11	0.0097	0.10	0.45	0.6329	40	60	2.62	0.0096	0.10	0.45	0.9417
20	40	3.11	0.0097	0.10	0.50	0.7611	40	60	2.62	0.0096	0.10	0.50	0.9813
20	40	3.11	0.0097	0.10	0.55	0.8581	40	60	2.62	0.0096	0.10	0.55	0.9955
20	40	3.11	0.0097	0.10	0.60	0.9236	40	60	2.62	0.0096	0.10	0.60	0.9992
20	40	3.11	0.0097	0.15	0.30	0.0933	40	60	2.62	0.0096	0.15	0.30	0.2463
20	40	3.11	0.0097	0.15	0.35	0.1705	40	60	2.62	0.0096	0.15	0.35	0.4229
20	40	3.11	0.0097	0.15	0.40	0.2807	40	60	2.62	0.0096	0.15	0.40	0.6185
20	40	3.11	0.0097	0.15	0.45	0.4131	40	60	2.62	0.0096	0.15	0.45	0.7901
20	40	3.11	0.0097	0.15	0.50	0.5518	40	60	2.62	0.0096	0.15	0.50	0.9065
20	40	3.11	0.0097	0.15	0.55	0.6817	40	60	2.62	0.0096	0.15	0.55	0.9667
20	40	3.11	0.0097	0.15	0.60	0.7922	40	60	2.62	0.0096	0.15	0.60	0.9905
20	40	3.11	0.0097	0.15	0.65	0.8780	40	60	2.62	0.0096	0.15	0.65	0.9979
20	40	3.11	0.0097	0.20	0.35	0.0794	40	60	2.62	0.0096	0.20	0.35	0.1994
20	40	3.11	0.0097	0.20	0.40	0.1471	40	60	2.62	0.0096	0.20	0.40	0.3666
20	40	3.11	0.0097	0.20	0.45	0.2413	40	60	2.62	0.0096	0.20	0.45	0.5658
20	40	3.11	0.0097	0.20	0.50	0.3571	40	60	2.62	0.0096	0.20	0.50	0.7482
20	40	3.11	0.0097	0.20	0.55	0.4855	40	60	2.62	0.0096	0.20	0.55	0.8779
20	40	3.11	0.0097	0.20	0.60	0.6167	40	60	2.62	0.0096	0.20	0.60	0.9515
20	40	3.11	0.0097	0.20	0.65	0.7404	40	60	2.62	0.0096	0.20	0.65	0.9848
20	40	3.11	0.0097	0.20	0.70	0.8456	40	60	2.62	0.0096	0.20	0.70	0.9965
20	40	3.11	0.0097	0.25	0.40	0.0700	40	60	2.62	0.0096	0.25	0.40	0.1802
20	40	3.11	0.0097	0.25	0.45	0.1271	40	60	2.62	0.0096	0.25	0.45	0.3397
20	40	3.11	0.0097	0.25	0.50	0.2077	40	60	2.62	0.0096	0.25	0.50	0.5304

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	40	3.11	0.0097	0.25	0.55	0.3114	40	60	2.62	0.0096	0.25	0.55	0.7118
20	40	3.11	0.0097	0.25	0.60	0.4355	40	60	2.62	0.0096	0.25	0.60	0.8520
20	40	3.11	0.0097	0.25	0.65	0.5733	40	60	2.62	0.0096	0.25	0.65	0.9389
20	40	3.11	0.0097	0.25	0.70	0.7113	40	60	2.62	0.0096	0.25	0.70	0.9808
20	40	3.11	0.0097	0.25	0.75	0.8303	40	60	2.62	0.0096	0.25	0.75	0.9958
20	40	3.11	0.0097	0.30	0.45	0.0605	40	60	2.62	0.0096	0.30	0.45	0.1691
20	40	3.11	0.0097	0.30	0.50	0.1089	40	60	2.62	0.0096	0.30	0.50	0.3159
20	40	3.11	0.0097	0.30	0.55	0.1804	40	60	2.62	0.0096	0.30	0.55	0.4984
20	40	3.11	0.0097	0.30	0.60	0.2792	40	60	2.62	0.0096	0.30	0.60	0.6838
20	40	3.11	0.0097	0.30	0.65	0.4064	40	60	2.62	0.0096	0.30	0.65	0.8358
20	40	3.11	0.0097	0.30	0.70	0.5533	40	60	2.62	0.0096	0.30	0.70	0.9336
20	40	3.11	0.0097	0.35	0.50	0.0515	40	60	2.62	0.0096	0.35	0.50	0.1565
20	40	3.11	0.0097	0.35	0.55	0.0945	40	60	2.62	0.0096	0.35	0.55	0.2957
20	40	3.11	0.0097	0.35	0.60	0.1626	40	60	2.62	0.0096	0.35	0.60	0.4780
20	40	3.11	0.0097	0.35	0.65	0.2629	40	60	2.62	0.0096	0.35	0.65	0.6716
20	40	3.11	0.0097	0.40	0.55	0.0447	40	60	2.62	0.0096	0.40	0.55	0.1471
20	40	3.11	0.0097	0.40	0.60	0.0858	40	60	2.62	0.0096	0.40	0.60	0.2856
20	50	3.32	0.0085	0.05	0.15	0.0751	40	70	2.79	0.0090	0.05	0.15	0.2205
20	50	3.32	0.0085	0.05	0.20	0.2049	40	70	2.79	0.0090	0.05	0.20	0.4410
20	50	3.32	0.0085	0.05	0.25	0.3374	40	70	2.79	0.0090	0.05	0.25	0.6674
20	50	3.32	0.0085	0.05	0.30	0.4681	40	70	2.79	0.0090	0.05	0.30	0.8415
20	50	3.32	0.0085	0.05	0.35	0.6097	40	70	2.79	0.0090	0.05	0.35	0.9407
20	50	3.32	0.0085	0.05	0.40	0.7424	40	70	2.79	0.0090	0.05	0.40	0.9828
20	50	3.32	0.0085	0.05	0.45	0.8471	40	70	2.79	0.0090	0.05	0.45	0.9961
20	50	3.32	0.0085	0.10	0.25	0.1290	40	70	2.79	0.0090	0.10	0.25	0.2920
20	50	3.32	0.0085	0.10	0.30	0.2094	40	70	2.79	0.0090	0.10	0.30	0.5031
20	50	3.32	0.0085	0.10	0.35	0.3217	40	70	2.79	0.0090	0.10	0.35	0.7093
20	50	3.32	0.0085	0.10	0.40	0.4551	40	70	2.79	0.0090	0.10	0.40	0.8606
20	50	3.32	0.0085	0.10	0.45	0.5956	40	70	2.79	0.0090	0.10	0.45	0.9459
20	50	3.32	0.0085	0.10	0.50	0.7283	40	70	2.79	0.0090	0.10	0.50	0.9832
20	50	3.32	0.0085	0.10	0.55	0.8377	40	70	2.79	0.0090	0.10	0.55	0.9958
20	50	3.32	0.0085	0.10	0.60	0.9145	40	70	2.79	0.0090	0.10	0.60	0.9992
20	50	3.32	0.0085	0.15	0.30	0.0864	40	70	2.79	0.0090	0.15	0.30	0.2266
20	50	3.32	0.0085	0.15	0.35	0.1519	40	70	2.79	0.0090	0.15	0.35	0.4131
20	50	3.32	0.0085	0.15	0.40	0.2452	40	70	2.79	0.0090	0.15	0.40	0.6169
20	50	3.32	0.0085	0.15	0.45	0.3657	40	70	2.79	0.0090	0.15	0.45	0.7890
20	50	3.32	0.0085	0.15	0.50	0.5058	40	70	2.79	0.0090	0.15	0.50	0.9029
20	50	3.32	0.0085	0.15	0.55	0.6479	40	70	2.79	0.0090	0.15	0.55	0.9635
20	50	3.32	0.0085	0.15	0.60	0.7713	40	70	2.79	0.0090	0.15	0.60	0.9893
20	50	3.32	0.0085	0.15	0.65	0.8647	40	70	2.79	0.0090	0.15	0.65	0.9977
20	50	3.32	0.0085	0.20	0.35	0.0652	40	70	2.79	0.0090	0.20	0.35	0.1893
20	50	3.32	0.0085	0.20	0.40	0.1188	40	70	2.79	0.0090	0.20	0.40	0.3537
20	50	3.32	0.0085	0.20	0.45	0.2007	40	70	2.79	0.0090	0.20	0.45	0.5457
20	50	3.32	0.0085	0.20	0.50	0.3129	40	70	2.79	0.0090	0.20	0.50	0.7247
20	50	3.32	0.0085	0.20	0.55	0.4467	40	70	2.79	0.0090	0.20	0.55	0.8613
20	50	3.32	0.0085	0.20	0.60	0.5845	40	70	2.79	0.0090	0.20	0.60	0.9443
20	50	3.32	0.0085	0.20	0.65	0.7120	40	70	2.79	0.0090	0.20	0.65	0.9830
20	50	3.32	0.0085	0.20	0.70	0.8221	40	70	2.79	0.0090	0.20	0.70	0.9963
20	50	3.32	0.0085	0.25	0.40	0.0523	40	70	2.79	0.0090	0.25	0.40	0.1624
20	50	3.32	0.0085	0.25	0.45	0.0995	40	70	2.79	0.0090	0.25	0.45	0.3065

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	50	3.32	0.0085	0.25	0.50	0.1739	40	70	2.79	0.0090	0.25	0.50	0.4886
20	50	3.32	0.0085	0.25	0.55	0.2756	40	70	2.79	0.0090	0.25	0.55	0.6771
20	50	3.32	0.0085	0.25	0.60	0.3972	40	70	2.79	0.0090	0.25	0.60	0.8326
20	50	3.32	0.0085	0.25	0.65	0.5314	40	70	2.79	0.0090	0.25	0.65	0.9320
20	50	3.32	0.0085	0.25	0.70	0.6711	40	70	2.79	0.0090	0.25	0.70	0.9795
20	50	3.32	0.0085	0.25	0.75	0.8003	40	70	2.79	0.0090	0.25	0.75	0.9956
20	50	3.32	0.0085	0.30	0.45	0.0446	40	70	2.79	0.0090	0.30	0.45	0.1397
20	50	3.32	0.0085	0.30	0.50	0.0870	40	70	2.79	0.0090	0.30	0.50	0.2726
20	50	3.32	0.0085	0.30	0.55	0.1523	40	70	2.79	0.0090	0.30	0.55	0.4538
20	50	3.32	0.0085	0.30	0.60	0.2422	40	70	2.79	0.0090	0.30	0.60	0.6514
20	50	3.32	0.0085	0.30	0.65	0.3587	40	70	2.79	0.0090	0.30	0.65	0.8196
20	50	3.32	0.0085	0.30	0.70	0.5013	40	70	2.79	0.0090	0.30	0.70	0.9275
20	50	3.32	0.0085	0.35	0.50	0.0390	40	70	2.79	0.0090	0.35	0.50	0.1253
20	50	3.32	0.0085	0.35	0.55	0.0754	40	70	2.79	0.0090	0.35	0.55	0.2552
20	50	3.32	0.0085	0.35	0.60	0.1326	40	70	2.79	0.0090	0.35	0.60	0.4395
20	50	3.32	0.0085	0.35	0.65	0.2186	40	70	2.79	0.0090	0.35	0.65	0.6440
20	50	3.32	0.0085	0.40	0.55	0.0333	40	70	2.79	0.0090	0.40	0.55	0.1193
20	50	3.32	0.0085	0.40	0.60	0.0649	40	70	2.79	0.0090	0.40	0.60	0.2507
20	60	3.68	0.0077	0.05	0.15	0.0648	40	80	2.99	0.0079	0.05	0.15	0.2088
20	60	3.68	0.0077	0.05	0.20	0.1995	40	80	2.99	0.0079	0.05	0.20	0.4353
20	60	3.68	0.0077	0.05	0.25	0.3261	40	80	2.99	0.0079	0.05	0.25	0.6677
20	60	3.68	0.0077	0.05	0.30	0.4395	40	80	2.99	0.0079	0.05	0.30	0.8428
20	60	3.68	0.0077	0.05	0.35	0.5775	40	80	2.99	0.0079	0.05	0.35	0.9420
20	60	3.68	0.0077	0.05	0.40	0.7177	40	80	2.99	0.0079	0.05	0.40	0.9834
20	60	3.68	0.0077	0.05	0.45	0.8301	40	80	2.99	0.0079	0.05	0.45	0.9963
20	60	3.68	0.0077	0.10	0.25	0.1184	40	80	2.99	0.0079	0.10	0.25	0.2820
20	60	3.68	0.0077	0.10	0.30	0.1851	40	80	2.99	0.0079	0.10	0.30	0.4912
20	60	3.68	0.0077	0.10	0.35	0.2898	40	80	2.99	0.0079	0.10	0.35	0.6985
20	60	3.68	0.0077	0.10	0.40	0.4206	40	80	2.99	0.0079	0.10	0.40	0.8518
20	60	3.68	0.0077	0.10	0.45	0.5603	40	80	2.99	0.0079	0.10	0.45	0.9400
20	60	3.68	0.0077	0.10	0.50	0.6936	40	80	2.99	0.0079	0.10	0.50	0.9805
20	60	3.68	0.0077	0.10	0.55	0.8048	40	80	2.99	0.0079	0.10	0.55	0.9952
20	60	3.68	0.0077	0.10	0.60	0.8871	40	80	2.99	0.0079	0.10	0.60	0.9991
20	60	3.68	0.0077	0.15	0.30	0.0725	40	80	2.99	0.0079	0.15	0.30	0.2103
20	60	3.68	0.0077	0.15	0.35	0.1304	40	80	2.99	0.0079	0.15	0.35	0.3885
20	60	3.68	0.0077	0.15	0.40	0.2155	40	80	2.99	0.0079	0.15	0.40	0.5868
20	60	3.68	0.0077	0.15	0.45	0.3264	40	80	2.99	0.0079	0.15	0.45	0.7628
20	60	3.68	0.0077	0.15	0.50	0.4556	40	80	2.99	0.0079	0.15	0.50	0.8884
20	60	3.68	0.0077	0.15	0.55	0.5885	40	80	2.99	0.0079	0.15	0.55	0.9585
20	60	3.68	0.0077	0.15	0.60	0.7127	40	80	2.99	0.0079	0.15	0.60	0.9882
20	60	3.68	0.0077	0.15	0.65	0.8200	40	80	2.99	0.0079	0.15	0.65	0.9975
20	60	3.68	0.0077	0.20	0.35	0.0533	40	80	2.99	0.0079	0.20	0.35	0.1657
20	60	3.68	0.0077	0.20	0.40	0.0989	40	80	2.99	0.0079	0.20	0.40	0.3154
20	60	3.68	0.0077	0.20	0.45	0.1684	40	80	2.99	0.0079	0.20	0.45	0.5040
20	60	3.68	0.0077	0.20	0.50	0.2630	40	80	2.99	0.0079	0.20	0.50	0.6947
20	60	3.68	0.0077	0.20	0.55	0.3781	40	80	2.99	0.0079	0.20	0.55	0.8457
20	60	3.68	0.0077	0.20	0.60	0.5075	40	80	2.99	0.0079	0.20	0.60	0.9377
20	60	3.68	0.0077	0.20	0.65	0.6440	40	80	2.99	0.0079	0.20	0.65	0.9803
20	60	3.68	0.0077	0.20	0.70	0.7728	40	80	2.99	0.0079	0.20	0.70	0.9954
20	60	3.68	0.0077	0.25	0.40	0.0410	40	80	2.99	0.0079	0.25	0.40	0.1340

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	60	3.68	0.0077	0.25	0.45	0.0778	40	80	2.99	0.0079	0.25	0.45	0.2680
20	60	3.68	0.0077	0.25	0.50	0.1351	40	80	2.99	0.0079	0.25	0.50	0.4512
20	60	3.68	0.0077	0.25	0.55	0.2155	40	80	2.99	0.0079	0.25	0.55	0.6480
20	60	3.68	0.0077	0.25	0.60	0.3219	40	80	2.99	0.0079	0.25	0.60	0.8123
20	60	3.68	0.0077	0.25	0.65	0.4546	40	80	2.99	0.0079	0.25	0.65	0.9193
20	60	3.68	0.0077	0.25	0.70	0.6024	40	80	2.99	0.0079	0.25	0.70	0.9738
20	60	3.68	0.0077	0.25	0.75	0.7405	40	80	2.99	0.0079	0.25	0.75	0.9941
20	60	3.68	0.0077	0.30	0.45	0.0323	40	80	2.99	0.0079	0.30	0.45	0.1150
20	60	3.68	0.0077	0.30	0.50	0.0620	40	80	2.99	0.0079	0.30	0.50	0.2398
20	60	3.68	0.0077	0.30	0.55	0.1096	40	80	2.99	0.0079	0.30	0.55	0.4165
20	60	3.68	0.0077	0.30	0.60	0.1825	40	80	2.99	0.0079	0.30	0.60	0.6127
20	60	3.68	0.0077	0.30	0.65	0.2882	40	80	2.99	0.0079	0.30	0.65	0.7869
20	60	3.68	0.0077	0.30	0.70	0.4244	40	80	2.99	0.0079	0.30	0.70	0.9087
20	60	3.68	0.0077	0.35	0.50	0.0254	40	80	2.99	0.0079	0.35	0.50	0.1036
20	60	3.68	0.0077	0.35	0.55	0.0498	40	80	2.99	0.0079	0.35	0.55	0.2200
20	60	3.68	0.0077	0.35	0.60	0.0926	40	80	2.99	0.0079	0.35	0.60	0.3895
20	60	3.68	0.0077	0.35	0.65	0.1638	40	80	2.99	0.0079	0.35	0.65	0.5902
20	60	3.68	0.0077	0.40	0.55	0.0201	40	80	2.99	0.0079	0.40	0.55	0.0943
20	60	3.68	0.0077	0.40	0.60	0.0419	40	80	2.99	0.0079	0.40	0.60	0.2047
20	70	3.92	0.0100	0.05	0.15	0.0877	40	90	3.17	0.0073	0.05	0.15	0.1937
20	70	3.92	0.0100	0.05	0.20	0.2386	40	90	3.17	0.0073	0.05	0.20	0.4063
20	70	3.92	0.0100	0.05	0.25	0.3412	40	90	3.17	0.0073	0.05	0.25	0.6416
20	70	3.92	0.0100	0.05	0.30	0.4233	40	90	3.17	0.0073	0.05	0.30	0.8281
20	70	3.92	0.0100	0.05	0.35	0.5529	40	90	3.17	0.0073	0.05	0.35	0.9354
20	70	3.92	0.0100	0.05	0.40	0.6990	40	90	3.17	0.0073	0.05	0.40	0.9812
20	70	3.92	0.0100	0.05	0.45	0.8173	40	90	3.17	0.0073	0.05	0.45	0.9957
20	70	3.92	0.0100	0.10	0.25	0.1200	40	90	3.17	0.0073	0.10	0.25	0.2547
20	70	3.92	0.0100	0.10	0.30	0.1700	40	90	3.17	0.0073	0.10	0.30	0.4586
20	70	3.92	0.0100	0.10	0.35	0.2672	40	90	3.17	0.0073	0.10	0.35	0.6694
20	70	3.92	0.0100	0.10	0.40	0.3964	40	90	3.17	0.0073	0.10	0.40	0.8325
20	70	3.92	0.0100	0.10	0.45	0.5361	40	90	3.17	0.0073	0.10	0.45	0.9310
20	70	3.92	0.0100	0.10	0.50	0.6721	40	90	3.17	0.0073	0.10	0.50	0.9777
20	70	3.92	0.0100	0.10	0.55	0.7874	40	90	3.17	0.0073	0.10	0.55	0.9945
20	70	3.92	0.0100	0.10	0.60	0.8736	40	90	3.17	0.0073	0.10	0.60	0.9990
20	70	3.92	0.0100	0.15	0.30	0.0639	40	90	3.17	0.0073	0.15	0.30	0.1834
20	70	3.92	0.0100	0.15	0.35	0.1161	40	90	3.17	0.0073	0.15	0.35	0.3519
20	70	3.92	0.0100	0.15	0.40	0.1962	40	90	3.17	0.0073	0.15	0.40	0.5504
20	70	3.92	0.0100	0.15	0.45	0.3023	40	90	3.17	0.0073	0.15	0.45	0.7369
20	70	3.92	0.0100	0.15	0.50	0.4286	40	90	3.17	0.0073	0.15	0.50	0.8743
20	70	3.92	0.0100	0.15	0.55	0.5605	40	90	3.17	0.0073	0.15	0.55	0.9525
20	70	3.92	0.0100	0.15	0.60	0.6847	40	90	3.17	0.0073	0.15	0.60	0.9865
20	70	3.92	0.0100	0.15	0.65	0.7935	40	90	3.17	0.0073	0.15	0.65	0.9972
20	70	3.92	0.0100	0.20	0.35	0.0459	40	90	3.17	0.0073	0.20	0.35	0.1404
20	70	3.92	0.0100	0.20	0.40	0.0869	40	90	3.17	0.0073	0.20	0.40	0.2805
20	70	3.92	0.0100	0.20	0.45	0.1507	40	90	3.17	0.0073	0.20	0.45	0.4676
20	70	3.92	0.0100	0.20	0.50	0.2393	40	90	3.17	0.0073	0.20	0.50	0.6643
20	70	3.92	0.0100	0.20	0.55	0.3484	40	90	3.17	0.0073	0.20	0.55	0.8268
20	70	3.92	0.0100	0.20	0.60	0.4712	40	90	3.17	0.0073	0.20	0.60	0.9299
20	70	3.92	0.0100	0.20	0.65	0.6020	40	90	3.17	0.0073	0.20	0.65	0.9784
20	70	3.92	0.0100	0.20	0.70	0.7308	40	90	3.17	0.0073	0.20	0.70	0.9950

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	70	3.92	0.0100	0.25	0.40	0.0347	40	90	3.17	0.0073	0.25	0.40	0.1121
20	70	3.92	0.0100	0.25	0.45	0.0672	40	90	3.17	0.0073	0.25	0.45	0.2357
20	70	3.92	0.0100	0.25	0.50	0.1185	40	90	3.17	0.0073	0.25	0.50	0.4135
20	70	3.92	0.0100	0.25	0.55	0.1912	40	90	3.17	0.0073	0.25	0.55	0.6163
20	70	3.92	0.0100	0.25	0.60	0.2866	40	90	3.17	0.0073	0.25	0.60	0.7944
20	70	3.92	0.0100	0.25	0.65	0.4063	40	90	3.17	0.0073	0.25	0.65	0.9121
20	70	3.92	0.0100	0.25	0.70	0.5459	40	90	3.17	0.0073	0.25	0.70	0.9709
20	70	3.92	0.0100	0.25	0.75	0.6896	40	90	3.17	0.0073	0.25	0.75	0.9931
20	70	3.92	0.0100	0.30	0.45	0.0268	40	90	3.17	0.0073	0.30	0.45	0.0948
20	70	3.92	0.0100	0.30	0.50	0.0523	40	90	3.17	0.0073	0.30	0.50	0.2086
20	70	3.92	0.0100	0.30	0.55	0.0932	40	90	3.17	0.0073	0.30	0.55	0.3821
20	70	3.92	0.0100	0.30	0.60	0.1547	40	90	3.17	0.0073	0.30	0.60	0.5861
20	70	3.92	0.0100	0.30	0.65	0.2442	40	90	3.17	0.0073	0.30	0.65	0.7697
20	70	3.92	0.0100	0.30	0.70	0.3655	40	90	3.17	0.0073	0.30	0.70	0.8978
20	70	3.92	0.0100	0.35	0.50	0.0206	40	90	3.17	0.0073	0.35	0.50	0.0850
20	70	3.92	0.0100	0.35	0.55	0.0403	40	90	3.17	0.0073	0.35	0.55	0.1936
20	70	3.92	0.0100	0.35	0.60	0.0742	40	90	3.17	0.0073	0.35	0.60	0.3611
20	70	3.92	0.0100	0.35	0.65	0.1306	40	90	3.17	0.0073	0.35	0.65	0.5620
20	70	3.92	0.0100	0.40	0.55	0.0154	40	90	3.17	0.0073	0.40	0.55	0.0792
20	70	3.92	0.0100	0.40	0.60	0.0315	40	90	3.17	0.0073	0.40	0.60	0.1817
20	80	4.12	0.0092	0.05	0.15	0.0762	40	100	3.34	0.0070	0.05	0.15	0.1832
20	80	4.12	0.0092	0.05	0.20	0.2348	40	100	3.34	0.0070	0.05	0.20	0.3839
20	80	4.12	0.0092	0.05	0.25	0.3431	40	100	3.34	0.0070	0.05	0.25	0.6191
20	80	4.12	0.0092	0.05	0.30	0.4297	40	100	3.34	0.0070	0.05	0.30	0.8145
20	80	4.12	0.0092	0.05	0.35	0.5675	40	100	3.34	0.0070	0.05	0.35	0.9272
20	80	4.12	0.0092	0.05	0.40	0.7073	40	100	3.34	0.0070	0.05	0.40	0.9778
20	80	4.12	0.0092	0.05	0.45	0.8130	40	100	3.34	0.0070	0.05	0.45	0.9951
20	80	4.12	0.0092	0.10	0.25	0.1206	40	100	3.34	0.0070	0.10	0.25	0.2332
20	80	4.12	0.0092	0.10	0.30	0.1738	40	100	3.34	0.0070	0.10	0.30	0.4280
20	80	4.12	0.0092	0.10	0.35	0.2750	40	100	3.34	0.0070	0.10	0.35	0.6369
20	80	4.12	0.0092	0.10	0.40	0.3945	40	100	3.34	0.0070	0.10	0.40	0.8145
20	80	4.12	0.0092	0.10	0.45	0.5193	40	100	3.34	0.0070	0.10	0.45	0.9251
20	80	4.12	0.0092	0.10	0.50	0.6451	40	100	3.34	0.0070	0.10	0.50	0.9759
20	80	4.12	0.0092	0.10	0.55	0.7570	40	100	3.34	0.0070	0.10	0.55	0.9938
20	80	4.12	0.0092	0.10	0.60	0.8520	40	100	3.34	0.0070	0.10	0.60	0.9988
20	80	4.12	0.0092	0.15	0.30	0.0655	40	100	3.34	0.0070	0.15	0.30	0.1592
20	80	4.12	0.0092	0.15	0.35	0.1186	40	100	3.34	0.0070	0.15	0.35	0.3182
20	80	4.12	0.0092	0.15	0.40	0.1903	40	100	3.34	0.0070	0.15	0.40	0.5239
20	80	4.12	0.0092	0.15	0.45	0.2829	40	100	3.34	0.0070	0.15	0.45	0.7198
20	80	4.12	0.0092	0.15	0.50	0.3946	40	100	3.34	0.0070	0.15	0.50	0.8626
20	80	4.12	0.0092	0.15	0.55	0.5184	40	100	3.34	0.0070	0.15	0.55	0.9454
20	80	4.12	0.0092	0.15	0.60	0.6499	40	100	3.34	0.0070	0.15	0.60	0.9833
20	80	4.12	0.0092	0.15	0.65	0.7699	40	100	3.34	0.0070	0.15	0.65	0.9963
20	80	4.12	0.0092	0.20	0.35	0.0462	40	100	3.34	0.0070	0.20	0.35	0.1211
20	80	4.12	0.0092	0.20	0.40	0.0818	40	100	3.34	0.0070	0.20	0.40	0.2579
20	80	4.12	0.0092	0.20	0.45	0.1357	40	100	3.34	0.0070	0.20	0.45	0.4422
20	80	4.12	0.0092	0.20	0.50	0.2105	40	100	3.34	0.0070	0.20	0.50	0.6366
20	80	4.12	0.0092	0.20	0.55	0.3095	40	100	3.34	0.0070	0.20	0.55	0.8025
20	80	4.12	0.0092	0.20	0.60	0.4342	40	100	3.34	0.0070	0.20	0.60	0.9146
20	80	4.12	0.0092	0.20	0.65	0.5695	40	100	3.34	0.0070	0.20	0.65	0.9720

Table B.18: continue on next page

Table B.18: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	80	4.12	0.0092	0.20	0.70	0.6989	40	100	3.34	0.0070	0.20	0.70	0.9934
20	80	4.12	0.0092	0.25	0.40	0.0316	40	100	3.34	0.0070	0.25	0.40	0.0986
20	80	4.12	0.0092	0.25	0.45	0.0580	40	100	3.34	0.0070	0.25	0.45	0.2124
20	80	4.12	0.0092	0.25	0.50	0.0995	40	100	3.34	0.0070	0.25	0.50	0.3775
20	80	4.12	0.0092	0.25	0.55	0.1633	40	100	3.34	0.0070	0.25	0.55	0.5733
20	80	4.12	0.0092	0.25	0.60	0.2559	40	100	3.34	0.0070	0.25	0.60	0.7579
20	80	4.12	0.0092	0.25	0.65	0.3726	40	100	3.34	0.0070	0.25	0.65	0.8918
20	80	4.12	0.0092	0.25	0.70	0.5053	40	100	3.34	0.0070	0.25	0.70	0.9636
20	80	4.12	0.0092	0.25	0.75	0.6472	40	100	3.34	0.0070	0.25	0.75	0.9913
20	80	4.12	0.0092	0.30	0.45	0.0222	40	100	3.34	0.0070	0.30	0.45	0.0802
20	80	4.12	0.0092	0.30	0.50	0.0419	40	100	3.34	0.0070	0.30	0.50	0.1782
20	80	4.12	0.0092	0.30	0.55	0.0766	40	100	3.34	0.0070	0.30	0.55	0.3345
20	80	4.12	0.0092	0.30	0.60	0.1336	40	100	3.34	0.0070	0.30	0.60	0.5337
20	80	4.12	0.0092	0.30	0.65	0.2160	40	100	3.34	0.0070	0.30	0.65	0.7313
20	80	4.12	0.0092	0.30	0.70	0.3253	40	100	3.34	0.0070	0.30	0.70	0.8782
20	80	4.12	0.0092	0.35	0.50	0.0157	40	100	3.34	0.0070	0.35	0.50	0.0669
20	80	4.12	0.0092	0.35	0.55	0.0319	40	100	3.34	0.0070	0.35	0.55	0.1573
20	80	4.12	0.0092	0.35	0.60	0.0619	40	100	3.34	0.0070	0.35	0.60	0.3103
20	80	4.12	0.0092	0.35	0.65	0.1108	40	100	3.34	0.0070	0.35	0.65	0.5129
20	80	4.12	0.0092	0.40	0.55	0.0118	40	100	3.34	0.0070	0.40	0.55	0.0591
20	80	4.12	0.0092	0.40	0.60	0.0253	40	100	3.34	0.0070	0.40	0.60	0.1462

Table B.18: concluded from previous page

Table B.19: P-values calculated for the z-pooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.05**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
10	20	1.88	0.316012	0.031574
10	30	1.83	0.69246	0.043865
10	40	2.03	0.930702	0.041712
10	50	1.74	0.54823	0.047843
10	60	2.08	0.689474	0.024907
10	70	1.79	0.801047	0.048862
10	80	1.83	0.951778	0.04821
10	90	1.97	0.893628	0.041246
10	100	2.04	0.948707	0.04527
20	30	1.69	0.403011	0.048092
20	40	1.78	0.694341	0.041944
20	50	1.76	0.593926	0.041183
20	60	1.73	0.771628	0.049473
20	70	1.75	0.824644	0.045176
20	80	1.74	0.679213	0.045884
20	90	1.83	0.783315	0.040713
20	100	1.71	0.650714	0.047264
30	40	1.68	0.434646	0.048898
30	50	1.7	0.758756	0.048607
30	60	1.69	0.668676	0.049881
30	70	1.76	0.848595	0.047319
30	80	1.69	0.644335	0.048985
30	90	1.71	0.683038	0.048022
30	100	1.72	0.782385	0.046544
40	50	1.68	0.574644	0.047961
40	60	1.72	0.794668	0.047196
40	70	1.67	0.631039	0.049362
40	80	1.69	0.700394	0.049079
40	90	1.7	0.520714	0.046451
40	100	1.72	0.720583	0.047146

Table B.19: concluded from previous page

Table B.20: P-values calculated for the z-pooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
10	30	2.17	0.5567	0.0176
10	40	2.16	0.8812	0.0246
10	50	2.39	0.8650	0.0166
10	60	2.08	0.6895	0.0249
10	70	2.67	0.9545	0.0163
10	80	2.24	0.8420	0.0239
10	90	3.02	0.9662	0.0099
10	100	3.18	0.9639	0.0086
20	30	1.97	0.6029	0.0246
20	40	2.06	0.6682	0.0217
20	50	2.00	0.3788	0.0237
20	60	2.21	0.6546	0.0157
20	70	2.10	0.8961	0.0242
20	80	2.04	0.6670	0.0245
20	90	2.16	0.8764	0.0243
20	100	2.24	0.8211	0.0185
30	40	2.10	0.8156	0.0222
30	50	2.02	0.7688	0.0237
30	60	2.01	0.8434	0.0250
30	70	2.10	0.8637	0.0226
30	80	2.12	0.8047	0.0232
30	90	2.08	0.8101	0.0243
30	100	2.10	0.6487	0.0206
40	50	2.00	0.5035	0.0225
40	60	1.98	0.3861	0.0249
40	70	1.99	0.3559	0.0250
40	80	2.07	0.5750	0.0212
40	90	2.03	0.6656	0.0242
40	100	2.02	0.6948	0.0245

Table B.20: concluded from previous page

Table B.21: P-values calculated for the z-pooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.01**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_p}$: critical value; p: value of the nuisance parameter; p-value: attained size of the test.

$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{z_p}$	p	pvalue
10	30	2.56	0.7475	0.0078
10	40	2.66	0.7236	0.0063
10	50	2.72	0.9549	0.0095
10	60	2.66	0.8842	0.0098
10	70	2.90	0.9440	0.0063
10	80	3.12	0.9371	0.0069
10	90	3.02	0.9662	0.0099
10	100	3.18	0.9639	0.0086
20	30	2.51	0.6623	0.0074
20	40	2.40	0.7736	0.0099
20	50	2.65	0.6937	0.0056
20	60	2.59	0.8560	0.0077
20	70	2.68	0.9212	0.0090
20	80	2.86	0.9343	0.0058
20	90	2.77	0.8797	0.0065
20	100	2.66	0.9111	0.0093
30	40	2.39	0.6151	0.0094
30	50	2.39	0.7384	0.0097
30	60	2.41	0.7563	0.0099
30	70	2.51	0.8980	0.0098
30	80	2.49	0.6520	0.0075
30	90	2.49	0.7514	0.0086
30	100	2.56	0.7776	0.0072
40	50	2.35	0.5576	0.0099

Table B.21: concluded from previous page

Table B.22: Achieved power and p-values calculated for the z-pooled statistic in cases of different sample sizes, $\alpha = 0.05$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	1.88	0.0316	0.05	0.15	0.0407	20	90	1.83	0.0407	0.05	0.15	0.1834
10	20	1.88	0.0316	0.05	0.20	0.1204	20	90	1.83	0.0407	0.05	0.20	0.4146
10	20	1.88	0.0316	0.05	0.25	0.2422	20	90	1.83	0.0407	0.05	0.25	0.6432
10	20	1.88	0.0316	0.05	0.30	0.3855	20	90	1.83	0.0407	0.05	0.30	0.8195
10	20	1.88	0.0316	0.05	0.35	0.5282	20	90	1.83	0.0407	0.05	0.35	0.9225
10	20	1.88	0.0316	0.05	0.40	0.6553	20	90	1.83	0.0407	0.05	0.40	0.9720
10	20	1.88	0.0316	0.05	0.45	0.7602	20	90	1.83	0.0407	0.05	0.45	0.9918
10	20	1.88	0.0316	0.10	0.25	0.1495	20	90	1.83	0.0407	0.10	0.25	0.3530
10	20	1.88	0.0316	0.10	0.30	0.2484	20	90	1.83	0.0407	0.10	0.30	0.5488
10	20	1.88	0.0316	0.10	0.35	0.3591	20	90	1.83	0.0407	0.10	0.35	0.7234
10	20	1.88	0.0316	0.10	0.40	0.4729	20	90	1.83	0.0407	0.10	0.40	0.8544
10	20	1.88	0.0316	0.10	0.45	0.5829	20	90	1.83	0.0407	0.10	0.45	0.9358
10	20	1.88	0.0316	0.10	0.50	0.6835	20	90	1.83	0.0407	0.10	0.50	0.9762
10	20	1.88	0.0316	0.10	0.55	0.7711	20	90	1.83	0.0407	0.10	0.55	0.9926
10	20	1.88	0.0316	0.10	0.60	0.8440	20	90	1.83	0.0407	0.10	0.60	0.9981
10	20	1.88	0.0316	0.15	0.30	0.1557	20	90	1.83	0.0407	0.15	0.30	0.3175
10	20	1.88	0.0316	0.15	0.35	0.2367	20	90	1.83	0.0407	0.15	0.35	0.4905
10	20	1.88	0.0316	0.15	0.40	0.3291	20	90	1.83	0.0407	0.15	0.40	0.6646
10	20	1.88	0.0316	0.15	0.45	0.4284	20	90	1.83	0.0407	0.15	0.45	0.8086
10	20	1.88	0.0316	0.15	0.50	0.5300	20	90	1.83	0.0407	0.15	0.50	0.9056
10	20	1.88	0.0316	0.15	0.55	0.6296	20	90	1.83	0.0407	0.15	0.55	0.9604
10	20	1.88	0.0316	0.15	0.60	0.7233	20	90	1.83	0.0407	0.15	0.60	0.9863
10	20	1.88	0.0316	0.15	0.65	0.8070	20	90	1.83	0.0407	0.15	0.65	0.9961
10	20	1.88	0.0316	0.20	0.35	0.1510	20	90	1.83	0.0407	0.20	0.35	0.2932
10	20	1.88	0.0316	0.20	0.40	0.2208	20	90	1.83	0.0407	0.20	0.40	0.4583
10	20	1.88	0.0316	0.20	0.45	0.3026	20	90	1.83	0.0407	0.20	0.45	0.6295
10	20	1.88	0.0316	0.20	0.50	0.3942	20	90	1.83	0.0407	0.20	0.50	0.7762
10	20	1.88	0.0316	0.20	0.55	0.4931	20	90	1.83	0.0407	0.20	0.55	0.8834
10	20	1.88	0.0316	0.20	0.60	0.5956	20	90	1.83	0.0407	0.20	0.60	0.9488
10	20	1.88	0.0316	0.20	0.65	0.6963	20	90	1.83	0.0407	0.20	0.65	0.9811
10	20	1.88	0.0316	0.20	0.70	0.7886	20	90	1.83	0.0407	0.20	0.70	0.9943
10	20	1.88	0.0316	0.25	0.40	0.1427	20	90	1.83	0.0407	0.25	0.40	0.2817
10	20	1.88	0.0316	0.25	0.45	0.2056	20	90	1.83	0.0407	0.25	0.45	0.4395
10	20	1.88	0.0316	0.25	0.50	0.2819	20	90	1.83	0.0407	0.25	0.50	0.6058
10	20	1.88	0.0316	0.25	0.55	0.3713	20	90	1.83	0.0407	0.25	0.55	0.7565
10	20	1.88	0.0316	0.25	0.60	0.4720	20	90	1.83	0.0407	0.25	0.60	0.8703
10	20	1.88	0.0316	0.25	0.65	0.5793	20	90	1.83	0.0407	0.25	0.65	0.9407
10	20	1.88	0.0316	0.25	0.70	0.6864	20	90	1.83	0.0407	0.25	0.70	0.9779
10	20	1.88	0.0316	0.25	0.75	0.7858	20	90	1.83	0.0407	0.25	0.75	0.9938
10	20	1.88	0.0316	0.30	0.45	0.1342	20	90	1.83	0.0407	0.30	0.45	0.2749
10	20	1.88	0.0316	0.30	0.50	0.1937	20	90	1.83	0.0407	0.30	0.50	0.4274
10	20	1.88	0.0316	0.30	0.55	0.2690	20	90	1.83	0.0407	0.30	0.55	0.5945
10	20	1.88	0.0316	0.30	0.60	0.3602	20	90	1.83	0.0407	0.30	0.60	0.7466
10	20	1.88	0.0316	0.30	0.65	0.4648	20	90	1.83	0.0407	0.30	0.65	0.8622

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	1.88	0.0316	0.30	0.70	0.5779	20	90	1.83	0.0407	0.30	0.70	0.9382
10	20	1.88	0.0316	0.35	0.50	0.1278	20	90	1.83	0.0407	0.35	0.50	0.2712
10	20	1.88	0.0316	0.35	0.55	0.1872	20	90	1.83	0.0407	0.35	0.55	0.4243
10	20	1.88	0.0316	0.35	0.60	0.2643	20	90	1.83	0.0407	0.35	0.60	0.5899
10	20	1.88	0.0316	0.35	0.65	0.3593	20	90	1.83	0.0407	0.35	0.65	0.7422
10	20	1.88	0.0316	0.40	0.55	0.1249	20	90	1.83	0.0407	0.40	0.55	0.2727
10	20	1.88	0.0316	0.40	0.60	0.1863	20	90	1.83	0.0407	0.40	0.60	0.4240
10	30	1.83	0.0439	0.05	0.15	0.0167	20	100	1.71	0.0473	0.05	0.15	0.2488
10	30	1.83	0.0439	0.05	0.20	0.0780	20	100	1.71	0.0473	0.05	0.20	0.4760
10	30	1.83	0.0439	0.05	0.25	0.2023	20	100	1.71	0.0473	0.05	0.25	0.6953
10	30	1.83	0.0439	0.05	0.30	0.3675	20	100	1.71	0.0473	0.05	0.30	0.8524
10	30	1.83	0.0439	0.05	0.35	0.5357	20	100	1.71	0.0473	0.05	0.35	0.9416
10	30	1.83	0.0439	0.05	0.40	0.6826	20	100	1.71	0.0473	0.05	0.40	0.9811
10	30	1.83	0.0439	0.05	0.45	0.7996	20	100	1.71	0.0473	0.05	0.45	0.9950
10	30	1.83	0.0439	0.10	0.25	0.1223	20	100	1.71	0.0473	0.10	0.25	0.3967
10	30	1.83	0.0439	0.10	0.30	0.2322	20	100	1.71	0.0473	0.10	0.30	0.5938
10	30	1.83	0.0439	0.10	0.35	0.3614	20	100	1.71	0.0473	0.10	0.35	0.7662
10	30	1.83	0.0439	0.10	0.40	0.4985	20	100	1.71	0.0473	0.10	0.40	0.8852
10	30	1.83	0.0439	0.10	0.45	0.6327	20	100	1.71	0.0473	0.10	0.45	0.9530
10	30	1.83	0.0439	0.10	0.50	0.7520	20	100	1.71	0.0473	0.10	0.50	0.9845
10	30	1.83	0.0439	0.10	0.55	0.8465	20	100	1.71	0.0473	0.10	0.55	0.9959
10	30	1.83	0.0439	0.10	0.60	0.9133	20	100	1.71	0.0473	0.10	0.60	0.9991
10	30	1.83	0.0439	0.15	0.30	0.1430	20	100	1.71	0.0473	0.15	0.30	0.3564
10	30	1.83	0.0439	0.15	0.35	0.2375	20	100	1.71	0.0473	0.15	0.35	0.5401
10	30	1.83	0.0439	0.15	0.40	0.3527	20	100	1.71	0.0473	0.15	0.40	0.7116
10	30	1.83	0.0439	0.15	0.45	0.4815	20	100	1.71	0.0473	0.15	0.45	0.8460
10	30	1.83	0.0439	0.15	0.50	0.6113	20	100	1.71	0.0473	0.15	0.50	0.9315
10	30	1.83	0.0439	0.15	0.55	0.7286	20	100	1.71	0.0473	0.15	0.55	0.9745
10	30	1.83	0.0439	0.15	0.60	0.8243	20	100	1.71	0.0473	0.15	0.60	0.9921
10	30	1.83	0.0439	0.15	0.65	0.8952	20	100	1.71	0.0473	0.15	0.65	0.9980
10	30	1.83	0.0439	0.20	0.35	0.1516	20	100	1.71	0.0473	0.20	0.35	0.3348
10	30	1.83	0.0439	0.20	0.40	0.2414	20	100	1.71	0.0473	0.20	0.40	0.5079
10	30	1.83	0.0439	0.20	0.45	0.3526	20	100	1.71	0.0473	0.20	0.45	0.6820
10	30	1.83	0.0439	0.20	0.50	0.4765	20	100	1.71	0.0473	0.20	0.50	0.8237
10	30	1.83	0.0439	0.20	0.55	0.6009	20	100	1.71	0.0473	0.20	0.55	0.9163
10	30	1.83	0.0439	0.20	0.60	0.7146	20	100	1.71	0.0473	0.20	0.60	0.9661
10	30	1.83	0.0439	0.20	0.65	0.8101	20	100	1.71	0.0473	0.20	0.65	0.9885
10	30	1.83	0.0439	0.20	0.70	0.8840	20	100	1.71	0.0473	0.20	0.70	0.9969
10	30	1.83	0.0439	0.25	0.40	0.1596	20	100	1.71	0.0473	0.25	0.40	0.3232
10	30	1.83	0.0439	0.25	0.45	0.2485	20	100	1.71	0.0473	0.25	0.45	0.4954
10	30	1.83	0.0439	0.25	0.50	0.3564	20	100	1.71	0.0473	0.25	0.50	0.6683
10	30	1.83	0.0439	0.25	0.55	0.4751	20	100	1.71	0.0473	0.25	0.55	0.8094
10	30	1.83	0.0439	0.25	0.60	0.5948	20	100	1.71	0.0473	0.25	0.60	0.9051
10	30	1.83	0.0439	0.25	0.65	0.7065	20	100	1.71	0.0473	0.25	0.65	0.9599
10	30	1.83	0.0439	0.25	0.70	0.8036	20	100	1.71	0.0473	0.25	0.70	0.9863
10	30	1.83	0.0439	0.25	0.75	0.8817	20	100	1.71	0.0473	0.25	0.75	0.9964
10	30	1.83	0.0439	0.30	0.45	0.1681	20	100	1.71	0.0473	0.30	0.45	0.3233
10	30	1.83	0.0439	0.30	0.50	0.2555	20	100	1.71	0.0473	0.30	0.50	0.4922
10	30	1.83	0.0439	0.30	0.55	0.3599	20	100	1.71	0.0473	0.30	0.55	0.6599
10	30	1.83	0.0439	0.30	0.60	0.4749	20	100	1.71	0.0473	0.30	0.60	0.7995

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	30	1.83	0.0439	0.30	0.65	0.5928	20	100	1.71	0.0473	0.30	0.65	0.8984
10	30	1.83	0.0439	0.30	0.70	0.7062	20	100	1.71	0.0473	0.30	0.70	0.9578
10	30	1.83	0.0439	0.35	0.50	0.1752	20	100	1.71	0.0473	0.35	0.50	0.3266
10	30	1.83	0.0439	0.35	0.55	0.2607	20	100	1.71	0.0473	0.35	0.55	0.4904
10	30	1.83	0.0439	0.35	0.60	0.3630	20	100	1.71	0.0473	0.35	0.60	0.6546
10	30	1.83	0.0439	0.35	0.65	0.4775	20	100	1.71	0.0473	0.35	0.65	0.7959
10	30	1.83	0.0439	0.40	0.55	0.1801	20	100	1.71	0.0473	0.40	0.55	0.3286
10	30	1.83	0.0439	0.40	0.60	0.2650	20	100	1.71	0.0473	0.40	0.60	0.4896
10	40	2.03	0.0417	0.05	0.15	0.0026	30	40	1.68	0.0489	0.05	0.15	0.3590
10	40	2.03	0.0417	0.05	0.20	0.0260	30	40	1.68	0.0489	0.05	0.20	0.5784
10	40	2.03	0.0417	0.05	0.25	0.1087	30	40	1.68	0.0489	0.05	0.25	0.7633
10	40	2.03	0.0417	0.05	0.30	0.2632	30	40	1.68	0.0489	0.05	0.30	0.8862
10	40	2.03	0.0417	0.05	0.35	0.4498	30	40	1.68	0.0489	0.05	0.35	0.9532
10	40	2.03	0.0417	0.05	0.40	0.6214	30	40	1.68	0.0489	0.05	0.40	0.9837
10	40	2.03	0.0417	0.05	0.45	0.7582	30	40	1.68	0.0489	0.05	0.45	0.9953
10	40	2.03	0.0417	0.10	0.25	0.0643	30	40	1.68	0.0489	0.10	0.25	0.4711
10	40	2.03	0.0417	0.10	0.30	0.1599	30	40	1.68	0.0489	0.10	0.30	0.6572
10	40	2.03	0.0417	0.10	0.35	0.2876	30	40	1.68	0.0489	0.10	0.35	0.8070
10	40	2.03	0.0417	0.10	0.40	0.4282	30	40	1.68	0.0489	0.10	0.40	0.9062
10	40	2.03	0.0417	0.10	0.45	0.5676	30	40	1.68	0.0489	0.10	0.45	0.9607
10	40	2.03	0.0417	0.10	0.50	0.6927	30	40	1.68	0.0489	0.10	0.50	0.9859
10	40	2.03	0.0417	0.10	0.55	0.7954	30	40	1.68	0.0489	0.10	0.55	0.9958
10	40	2.03	0.0417	0.10	0.60	0.8746	30	40	1.68	0.0489	0.10	0.60	0.9990
10	40	2.03	0.0417	0.15	0.30	0.0944	30	40	1.68	0.0489	0.15	0.30	0.4168
10	40	2.03	0.0417	0.15	0.35	0.1789	30	40	1.68	0.0489	0.15	0.35	0.5965
10	40	2.03	0.0417	0.15	0.40	0.2851	30	40	1.68	0.0489	0.15	0.40	0.7524
10	40	2.03	0.0417	0.15	0.45	0.4058	30	40	1.68	0.0489	0.15	0.45	0.8665
10	40	2.03	0.0417	0.15	0.50	0.5298	30	40	1.68	0.0489	0.15	0.50	0.9379
10	40	2.03	0.0417	0.15	0.55	0.6486	30	40	1.68	0.0489	0.15	0.55	0.9758
10	40	2.03	0.0417	0.15	0.60	0.7565	30	40	1.68	0.0489	0.15	0.60	0.9923
10	40	2.03	0.0417	0.15	0.65	0.8472	30	40	1.68	0.0489	0.15	0.65	0.9981
10	40	2.03	0.0417	0.20	0.35	0.1078	30	40	1.68	0.0489	0.20	0.35	0.3837
10	40	2.03	0.0417	0.20	0.40	0.1830	30	40	1.68	0.0489	0.20	0.40	0.5531
10	40	2.03	0.0417	0.20	0.45	0.2777	30	40	1.68	0.0489	0.20	0.45	0.7117
10	40	2.03	0.0417	0.20	0.50	0.3861	30	40	1.68	0.0489	0.20	0.50	0.8382
10	40	2.03	0.0417	0.20	0.55	0.5035	30	40	1.68	0.0489	0.20	0.55	0.9226
10	40	2.03	0.0417	0.20	0.60	0.6243	30	40	1.68	0.0489	0.20	0.60	0.9688
10	40	2.03	0.0417	0.20	0.65	0.7394	30	40	1.68	0.0489	0.20	0.65	0.9896
10	40	2.03	0.0417	0.20	0.70	0.8383	30	40	1.68	0.0489	0.20	0.70	0.9972
10	40	2.03	0.0417	0.25	0.40	0.1130	30	40	1.68	0.0489	0.25	0.40	0.3598
10	40	2.03	0.0417	0.25	0.45	0.1819	30	40	1.68	0.0489	0.25	0.45	0.5270
10	40	2.03	0.0417	0.25	0.50	0.2687	30	40	1.68	0.0489	0.25	0.50	0.6902
10	40	2.03	0.0417	0.25	0.55	0.3731	30	40	1.68	0.0489	0.25	0.55	0.8225
10	40	2.03	0.0417	0.25	0.60	0.4924	30	40	1.68	0.0489	0.25	0.60	0.9121
10	40	2.03	0.0417	0.25	0.65	0.6189	30	40	1.68	0.0489	0.25	0.65	0.9631
10	40	2.03	0.0417	0.25	0.70	0.7409	30	40	1.68	0.0489	0.25	0.70	0.9874
10	40	2.03	0.0417	0.25	0.75	0.8449	30	40	1.68	0.0489	0.25	0.75	0.9968
10	40	2.03	0.0417	0.30	0.45	0.1139	30	40	1.68	0.0489	0.30	0.45	0.3500
10	40	2.03	0.0417	0.30	0.50	0.1786	30	40	1.68	0.0489	0.30	0.50	0.5154
10	40	2.03	0.0417	0.30	0.55	0.2640	30	40	1.68	0.0489	0.30	0.55	0.6767

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	40	2.03	0.0417	0.30	0.60	0.3714	30	40	1.68	0.0489	0.30	0.60	0.8100
10	40	2.03	0.0417	0.30	0.65	0.4967	30	40	1.68	0.0489	0.30	0.65	0.9044
10	40	2.03	0.0417	0.30	0.70	0.6305	30	40	1.68	0.0489	0.30	0.70	0.9606
10	40	2.03	0.0417	0.35	0.50	0.1131	30	40	1.68	0.0489	0.35	0.50	0.3445
10	40	2.03	0.0417	0.35	0.55	0.1782	30	40	1.68	0.0489	0.35	0.55	0.5049
10	40	2.03	0.0417	0.35	0.60	0.2675	30	40	1.68	0.0489	0.35	0.60	0.6655
10	40	2.03	0.0417	0.35	0.65	0.3816	30	40	1.68	0.0489	0.35	0.65	0.8042
10	40	2.03	0.0417	0.40	0.55	0.1144	30	40	1.68	0.0489	0.40	0.55	0.3375
10	40	2.03	0.0417	0.40	0.60	0.1835	30	40	1.68	0.0489	0.40	0.60	0.4985
10	50	1.74	0.0478	0.05	0.15	0.0180	30	50	1.7	0.0486	0.05	0.15	0.3886
10	50	1.74	0.0478	0.05	0.20	0.1117	30	50	1.7	0.0486	0.05	0.20	0.6179
10	50	1.74	0.0478	0.05	0.25	0.2972	30	50	1.7	0.0486	0.05	0.25	0.7988
10	50	1.74	0.0478	0.05	0.30	0.4922	30	50	1.7	0.0486	0.05	0.30	0.9104
10	50	1.74	0.0478	0.05	0.35	0.6469	30	50	1.7	0.0486	0.05	0.35	0.9658
10	50	1.74	0.0478	0.05	0.40	0.7726	30	50	1.7	0.0486	0.05	0.40	0.9889
10	50	1.74	0.0478	0.05	0.45	0.8720	30	50	1.7	0.0486	0.05	0.45	0.9970
10	50	1.74	0.0478	0.10	0.25	0.1759	30	50	1.7	0.0486	0.10	0.25	0.4959
10	50	1.74	0.0478	0.10	0.30	0.3043	30	50	1.7	0.0486	0.10	0.30	0.6789
10	50	1.74	0.0478	0.10	0.35	0.4356	30	50	1.7	0.0486	0.10	0.35	0.8216
10	50	1.74	0.0478	0.10	0.40	0.5776	30	50	1.7	0.0486	0.10	0.40	0.9157
10	50	1.74	0.0478	0.10	0.45	0.7154	30	50	1.7	0.0486	0.10	0.45	0.9670
10	50	1.74	0.0478	0.10	0.50	0.8266	30	50	1.7	0.0486	0.10	0.50	0.9896
10	50	1.74	0.0478	0.10	0.55	0.9039	30	50	1.7	0.0486	0.10	0.55	0.9974
10	50	1.74	0.0478	0.10	0.60	0.9514	30	50	1.7	0.0486	0.10	0.60	0.9995
10	50	1.74	0.0478	0.15	0.30	0.1831	30	50	1.7	0.0486	0.15	0.30	0.4174
10	50	1.74	0.0478	0.15	0.35	0.2846	30	50	1.7	0.0486	0.15	0.35	0.5973
10	50	1.74	0.0478	0.15	0.40	0.4140	30	50	1.7	0.0486	0.15	0.40	0.7595
10	50	1.74	0.0478	0.15	0.45	0.5568	30	50	1.7	0.0486	0.15	0.45	0.8789
10	50	1.74	0.0478	0.15	0.50	0.6903	30	50	1.7	0.0486	0.15	0.50	0.9497
10	50	1.74	0.0478	0.15	0.55	0.8000	30	50	1.7	0.0486	0.15	0.55	0.9829
10	50	1.74	0.0478	0.15	0.60	0.8806	30	50	1.7	0.0486	0.15	0.60	0.9953
10	50	1.74	0.0478	0.15	0.65	0.9346	30	50	1.7	0.0486	0.15	0.65	0.9990
10	50	1.74	0.0478	0.20	0.35	0.1800	30	50	1.7	0.0486	0.20	0.35	0.3743
10	50	1.74	0.0478	0.20	0.40	0.2848	30	50	1.7	0.0486	0.20	0.40	0.5567
10	50	1.74	0.0478	0.20	0.45	0.4132	30	50	1.7	0.0486	0.20	0.45	0.7288
10	50	1.74	0.0478	0.20	0.50	0.5485	30	50	1.7	0.0486	0.20	0.50	0.8589
10	50	1.74	0.0478	0.20	0.55	0.6749	30	50	1.7	0.0486	0.20	0.55	0.9379
10	50	1.74	0.0478	0.20	0.60	0.7816	30	50	1.7	0.0486	0.20	0.60	0.9770
10	50	1.74	0.0478	0.20	0.65	0.8642	30	50	1.7	0.0486	0.20	0.65	0.9931
10	50	1.74	0.0478	0.20	0.70	0.9231	30	50	1.7	0.0486	0.20	0.70	0.9984
10	50	1.74	0.0478	0.25	0.40	0.1879	30	50	1.7	0.0486	0.25	0.40	0.3603
10	50	1.74	0.0478	0.25	0.45	0.2928	30	50	1.7	0.0486	0.25	0.45	0.5424
10	50	1.74	0.0478	0.25	0.50	0.4153	30	50	1.7	0.0486	0.25	0.50	0.7131
10	50	1.74	0.0478	0.25	0.55	0.5429	30	50	1.7	0.0486	0.25	0.55	0.8438
10	50	1.74	0.0478	0.25	0.60	0.6639	30	50	1.7	0.0486	0.25	0.60	0.9278
10	50	1.74	0.0478	0.25	0.65	0.7694	30	50	1.7	0.0486	0.25	0.65	0.9728
10	50	1.74	0.0478	0.25	0.70	0.8550	30	50	1.7	0.0486	0.25	0.70	0.9921
10	50	1.74	0.0478	0.25	0.75	0.9195	30	50	1.7	0.0486	0.25	0.75	0.9983
10	50	1.74	0.0478	0.30	0.45	0.1980	30	50	1.7	0.0486	0.30	0.45	0.3580
10	50	1.74	0.0478	0.30	0.50	0.2996	30	50	1.7	0.0486	0.30	0.50	0.5323

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	50	1.74	0.0478	0.30	0.55	0.4163	30	50	1.7	0.0486	0.30	0.55	0.6986
10	50	1.74	0.0478	0.30	0.60	0.5386	30	50	1.7	0.0486	0.30	0.60	0.8332
10	50	1.74	0.0478	0.30	0.65	0.6572	30	50	1.7	0.0486	0.30	0.65	0.9238
10	50	1.74	0.0478	0.30	0.70	0.7651	30	50	1.7	0.0486	0.30	0.70	0.9723
10	50	1.74	0.0478	0.35	0.50	0.2057	30	50	1.7	0.0486	0.35	0.50	0.3525
10	50	1.74	0.0478	0.35	0.55	0.3037	30	50	1.7	0.0486	0.35	0.55	0.5230
10	50	1.74	0.0478	0.35	0.60	0.4165	30	50	1.7	0.0486	0.35	0.60	0.6932
10	50	1.74	0.0478	0.35	0.65	0.5370	30	50	1.7	0.0486	0.35	0.65	0.8334
10	50	1.74	0.0478	0.40	0.55	0.2102	30	50	1.7	0.0486	0.40	0.55	0.3499
10	50	1.74	0.0478	0.40	0.60	0.3060	30	50	1.7	0.0486	0.40	0.60	0.5250
10	60	2.08	0.0249	0.05	0.15	0.0005	30	60	1.69	0.0499	0.05	0.15	0.3629
10	60	2.08	0.0249	0.05	0.20	0.0132	30	60	1.69	0.0499	0.05	0.20	0.6068
10	60	2.08	0.0249	0.05	0.25	0.0892	30	60	1.69	0.0499	0.05	0.25	0.8024
10	60	2.08	0.0249	0.05	0.30	0.2646	30	60	1.69	0.0499	0.05	0.30	0.9196
10	60	2.08	0.0249	0.05	0.35	0.4701	30	60	1.69	0.0499	0.05	0.35	0.9737
10	60	2.08	0.0249	0.05	0.40	0.6361	30	60	1.69	0.0499	0.05	0.40	0.9930
10	60	2.08	0.0249	0.05	0.45	0.7679	30	60	1.69	0.0499	0.05	0.45	0.9985
10	60	2.08	0.0249	0.10	0.25	0.0520	30	60	1.69	0.0499	0.10	0.25	0.5001
10	60	2.08	0.0249	0.10	0.30	0.1562	30	60	1.69	0.0499	0.10	0.30	0.7032
10	60	2.08	0.0249	0.10	0.35	0.2881	30	60	1.69	0.0499	0.10	0.35	0.8520
10	60	2.08	0.0249	0.10	0.40	0.4231	30	60	1.69	0.0499	0.10	0.40	0.9384
10	60	2.08	0.0249	0.10	0.45	0.5663	30	60	1.69	0.0499	0.10	0.45	0.9789
10	60	2.08	0.0249	0.10	0.50	0.7009	30	60	1.69	0.0499	0.10	0.50	0.9941
10	60	2.08	0.0249	0.10	0.55	0.8098	30	60	1.69	0.0499	0.10	0.55	0.9986
10	60	2.08	0.0249	0.10	0.60	0.8931	30	60	1.69	0.0499	0.10	0.60	0.9997
10	60	2.08	0.0249	0.15	0.30	0.0895	30	60	1.69	0.0499	0.15	0.30	0.4470
10	60	2.08	0.0249	0.15	0.35	0.1718	30	60	1.69	0.0499	0.15	0.35	0.6420
10	60	2.08	0.0249	0.15	0.40	0.2727	30	60	1.69	0.0499	0.15	0.40	0.8019
10	60	2.08	0.0249	0.15	0.45	0.3983	30	60	1.69	0.0499	0.15	0.45	0.9068
10	60	2.08	0.0249	0.15	0.50	0.5327	30	60	1.69	0.0499	0.15	0.50	0.9628
10	60	2.08	0.0249	0.15	0.55	0.6624	30	60	1.69	0.0499	0.15	0.55	0.9876
10	60	2.08	0.0249	0.15	0.60	0.7822	30	60	1.69	0.0499	0.15	0.60	0.9967
10	60	2.08	0.0249	0.15	0.65	0.8777	30	60	1.69	0.0499	0.15	0.65	0.9994
10	60	2.08	0.0249	0.20	0.35	0.0993	30	60	1.69	0.0499	0.20	0.35	0.4140
10	60	2.08	0.0249	0.20	0.40	0.1697	30	60	1.69	0.0499	0.20	0.40	0.6012
10	60	2.08	0.0249	0.20	0.45	0.2678	30	60	1.69	0.0499	0.20	0.45	0.7626
10	60	2.08	0.0249	0.20	0.50	0.3846	30	60	1.69	0.0499	0.20	0.50	0.8780
10	60	2.08	0.0249	0.20	0.55	0.5148	30	60	1.69	0.0499	0.20	0.55	0.9477
10	60	2.08	0.0249	0.20	0.60	0.6531	30	60	1.69	0.0499	0.20	0.60	0.9820
10	60	2.08	0.0249	0.20	0.65	0.7789	30	60	1.69	0.0499	0.20	0.65	0.9951
10	60	2.08	0.0249	0.20	0.70	0.8745	30	60	1.69	0.0499	0.20	0.70	0.9990
10	60	2.08	0.0249	0.25	0.40	0.1018	30	60	1.69	0.0499	0.25	0.40	0.3903
10	60	2.08	0.0249	0.25	0.45	0.1722	30	60	1.69	0.0499	0.25	0.45	0.5672
10	60	2.08	0.0249	0.25	0.50	0.2646	30	60	1.69	0.0499	0.25	0.50	0.7309
10	60	2.08	0.0249	0.25	0.55	0.3815	30	60	1.69	0.0499	0.25	0.55	0.8582
10	60	2.08	0.0249	0.25	0.60	0.5205	30	60	1.69	0.0499	0.25	0.60	0.9385
10	60	2.08	0.0249	0.25	0.65	0.6620	30	60	1.69	0.0499	0.25	0.65	0.9786
10	60	2.08	0.0249	0.25	0.70	0.7843	30	60	1.69	0.0499	0.25	0.70	0.9943
10	60	2.08	0.0249	0.25	0.75	0.8762	30	60	1.69	0.0499	0.25	0.75	0.9989
10	60	2.08	0.0249	0.30	0.45	0.1056	30	60	1.69	0.0499	0.30	0.45	0.3687

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	60	2.08	0.0249	0.30	0.50	0.1735	30	60	1.69	0.0499	0.30	0.50	0.5442
10	60	2.08	0.0249	0.30	0.55	0.2696	30	60	1.69	0.0499	0.30	0.55	0.7148
10	60	2.08	0.0249	0.30	0.60	0.3957	30	60	1.69	0.0499	0.30	0.60	0.8494
10	60	2.08	0.0249	0.30	0.65	0.5379	30	60	1.69	0.0499	0.30	0.65	0.9350
10	60	2.08	0.0249	0.30	0.70	0.6757	30	60	1.69	0.0499	0.30	0.70	0.9782
10	60	2.08	0.0249	0.35	0.50	0.1083	30	60	1.69	0.0499	0.35	0.50	0.3578
10	60	2.08	0.0249	0.35	0.55	0.1814	30	60	1.69	0.0499	0.35	0.55	0.5364
10	60	2.08	0.0249	0.35	0.60	0.2866	30	60	1.69	0.0499	0.35	0.60	0.7106
10	60	2.08	0.0249	0.35	0.65	0.4170	30	60	1.69	0.0499	0.35	0.65	0.8493
10	60	2.08	0.0249	0.40	0.55	0.1159	30	60	1.69	0.0499	0.40	0.55	0.3569
10	60	2.08	0.0249	0.40	0.60	0.1972	30	60	1.69	0.0499	0.40	0.60	0.5383
10	70	1.79	0.0489	0.05	0.15	0.0081	30	70	1.76	0.0473	0.05	0.15	0.3434
10	70	1.79	0.0489	0.05	0.20	0.0887	30	70	1.76	0.0473	0.05	0.20	0.6045
10	70	1.79	0.0489	0.05	0.25	0.2951	30	70	1.76	0.0473	0.05	0.25	0.8161
10	70	1.79	0.0489	0.05	0.30	0.5051	30	70	1.76	0.0473	0.05	0.30	0.9319
10	70	1.79	0.0489	0.05	0.35	0.6476	30	70	1.76	0.0473	0.05	0.35	0.9795
10	70	1.79	0.0489	0.05	0.40	0.7706	30	70	1.76	0.0473	0.05	0.40	0.9949
10	70	1.79	0.0489	0.05	0.45	0.8732	30	70	1.76	0.0473	0.05	0.45	0.9990
10	70	1.79	0.0489	0.10	0.25	0.1727	30	70	1.76	0.0473	0.10	0.25	0.5156
10	70	1.79	0.0489	0.10	0.30	0.3039	30	70	1.76	0.0473	0.10	0.30	0.7210
10	70	1.79	0.0489	0.10	0.35	0.4235	30	70	1.76	0.0473	0.10	0.35	0.8641
10	70	1.79	0.0489	0.10	0.40	0.5652	30	70	1.76	0.0473	0.10	0.40	0.9442
10	70	1.79	0.0489	0.10	0.45	0.7036	30	70	1.76	0.0473	0.10	0.45	0.9810
10	70	1.79	0.0489	0.10	0.50	0.8118	30	70	1.76	0.0473	0.10	0.50	0.9948
10	70	1.79	0.0489	0.10	0.55	0.8924	30	70	1.76	0.0473	0.10	0.55	0.9989
10	70	1.79	0.0489	0.10	0.60	0.9453	30	70	1.76	0.0473	0.10	0.60	0.9998
10	70	1.79	0.0489	0.15	0.30	0.1777	30	70	1.76	0.0473	0.15	0.30	0.4562
10	70	1.79	0.0489	0.15	0.35	0.2686	30	70	1.76	0.0473	0.15	0.35	0.6486
10	70	1.79	0.0489	0.15	0.40	0.3951	30	70	1.76	0.0473	0.15	0.40	0.8045
10	70	1.79	0.0489	0.15	0.45	0.5327	30	70	1.76	0.0473	0.15	0.45	0.9087
10	70	1.79	0.0489	0.15	0.50	0.6613	30	70	1.76	0.0473	0.15	0.50	0.9653
10	70	1.79	0.0489	0.15	0.55	0.7761	30	70	1.76	0.0473	0.15	0.55	0.9894
10	70	1.79	0.0489	0.15	0.60	0.8655	30	70	1.76	0.0473	0.15	0.60	0.9974
10	70	1.79	0.0489	0.15	0.65	0.9283	30	70	1.76	0.0473	0.15	0.65	0.9995
10	70	1.79	0.0489	0.20	0.35	0.1647	30	70	1.76	0.0473	0.20	0.35	0.4098
10	70	1.79	0.0489	0.20	0.40	0.2638	30	70	1.76	0.0473	0.20	0.40	0.5953
10	70	1.79	0.0489	0.20	0.45	0.3822	30	70	1.76	0.0473	0.20	0.45	0.7621
10	70	1.79	0.0489	0.20	0.50	0.5101	30	70	1.76	0.0473	0.20	0.50	0.8828
10	70	1.79	0.0489	0.20	0.55	0.6402	30	70	1.76	0.0473	0.20	0.55	0.9523
10	70	1.79	0.0489	0.20	0.60	0.7568	30	70	1.76	0.0473	0.20	0.60	0.9842
10	70	1.79	0.0489	0.20	0.65	0.8524	30	70	1.76	0.0473	0.20	0.65	0.9960
10	70	1.79	0.0489	0.20	0.70	0.9218	30	70	1.76	0.0473	0.20	0.70	0.9993
10	70	1.79	0.0489	0.25	0.40	0.1683	30	70	1.76	0.0473	0.25	0.40	0.3791
10	70	1.79	0.0489	0.25	0.45	0.2608	30	70	1.76	0.0473	0.25	0.45	0.5642
10	70	1.79	0.0489	0.25	0.50	0.3738	30	70	1.76	0.0473	0.25	0.50	0.7361
10	70	1.79	0.0489	0.25	0.55	0.5019	30	70	1.76	0.0473	0.25	0.55	0.8646
10	70	1.79	0.0489	0.25	0.60	0.6313	30	70	1.76	0.0473	0.25	0.60	0.9428
10	70	1.79	0.0489	0.25	0.65	0.7521	30	70	1.76	0.0473	0.25	0.65	0.9811
10	70	1.79	0.0489	0.25	0.70	0.8524	30	70	1.76	0.0473	0.25	0.70	0.9954
10	70	1.79	0.0489	0.25	0.75	0.9251	30	70	1.76	0.0473	0.25	0.75	0.9992

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	70	1.79	0.0489	0.30	0.45	0.1693	30	70	1.76	0.0473	0.30	0.45	0.3639
10	70	1.79	0.0489	0.30	0.50	0.2603	30	70	1.76	0.0473	0.30	0.50	0.5461
10	70	1.79	0.0489	0.30	0.55	0.3738	30	70	1.76	0.0473	0.30	0.55	0.7191
10	70	1.79	0.0489	0.30	0.60	0.5018	30	70	1.76	0.0473	0.30	0.60	0.8545
10	70	1.79	0.0489	0.30	0.65	0.6357	30	70	1.76	0.0473	0.30	0.65	0.9401
10	70	1.79	0.0489	0.30	0.70	0.7610	30	70	1.76	0.0473	0.30	0.70	0.9811
10	70	1.79	0.0489	0.35	0.50	0.1721	30	70	1.76	0.0473	0.35	0.50	0.3548
10	70	1.79	0.0489	0.35	0.55	0.2643	30	70	1.76	0.0473	0.35	0.55	0.5358
10	70	1.79	0.0489	0.35	0.60	0.3795	30	70	1.76	0.0473	0.35	0.60	0.7147
10	70	1.79	0.0489	0.35	0.65	0.5132	30	70	1.76	0.0473	0.35	0.65	0.8568
10	70	1.79	0.0489	0.40	0.55	0.1768	30	70	1.76	0.0473	0.40	0.55	0.3520
10	70	1.79	0.0489	0.40	0.60	0.2722	30	70	1.76	0.0473	0.40	0.60	0.5398
10	80	1.83	0.0482	0.05	0.15	0.0038	30	80	1.69	0.0490	0.05	0.15	0.3660
10	80	1.83	0.0482	0.05	0.20	0.0638	30	80	1.69	0.0490	0.05	0.20	0.6307
10	80	1.83	0.0482	0.05	0.25	0.2643	30	80	1.69	0.0490	0.05	0.25	0.8349
10	80	1.83	0.0482	0.05	0.30	0.4916	30	80	1.69	0.0490	0.05	0.30	0.9417
10	80	1.83	0.0482	0.05	0.35	0.6414	30	80	1.69	0.0490	0.05	0.35	0.9833
10	80	1.83	0.0482	0.05	0.40	0.7695	30	80	1.69	0.0490	0.05	0.40	0.9963
10	80	1.83	0.0482	0.05	0.45	0.8763	30	80	1.69	0.0490	0.05	0.45	0.9994
10	80	1.83	0.0482	0.10	0.25	0.1544	30	80	1.69	0.0490	0.10	0.25	0.5322
10	80	1.83	0.0482	0.10	0.30	0.2937	30	80	1.69	0.0490	0.10	0.30	0.7365
10	80	1.83	0.0482	0.10	0.35	0.4156	30	80	1.69	0.0490	0.10	0.35	0.8779
10	80	1.83	0.0482	0.10	0.40	0.5628	30	80	1.69	0.0490	0.10	0.40	0.9547
10	80	1.83	0.0482	0.10	0.45	0.7060	30	80	1.69	0.0490	0.10	0.45	0.9866
10	80	1.83	0.0482	0.10	0.50	0.8150	30	80	1.69	0.0490	0.10	0.50	0.9968
10	80	1.83	0.0482	0.10	0.55	0.8961	30	80	1.69	0.0490	0.10	0.55	0.9994
10	80	1.83	0.0482	0.10	0.60	0.9479	30	80	1.69	0.0490	0.10	0.60	0.9999
10	80	1.83	0.0482	0.15	0.30	0.1705	30	80	1.69	0.0490	0.15	0.30	0.4696
10	80	1.83	0.0482	0.15	0.35	0.2614	30	80	1.69	0.0490	0.15	0.35	0.6721
10	80	1.83	0.0482	0.15	0.40	0.3921	30	80	1.69	0.0490	0.15	0.40	0.8314
10	80	1.83	0.0482	0.15	0.45	0.5335	30	80	1.69	0.0490	0.15	0.45	0.9281
10	80	1.83	0.0482	0.15	0.50	0.6638	30	80	1.69	0.0490	0.15	0.50	0.9747
10	80	1.83	0.0482	0.15	0.55	0.7803	30	80	1.69	0.0490	0.15	0.55	0.9928
10	80	1.83	0.0482	0.15	0.60	0.8690	30	80	1.69	0.0490	0.15	0.60	0.9984
10	80	1.83	0.0482	0.15	0.65	0.9307	30	80	1.69	0.0490	0.15	0.65	0.9998
10	80	1.83	0.0482	0.20	0.35	0.1591	30	80	1.69	0.0490	0.20	0.35	0.4353
10	80	1.83	0.0482	0.20	0.40	0.2608	30	80	1.69	0.0490	0.20	0.40	0.6326
10	80	1.83	0.0482	0.20	0.45	0.3815	30	80	1.69	0.0490	0.20	0.45	0.7958
10	80	1.83	0.0482	0.20	0.50	0.5115	30	80	1.69	0.0490	0.20	0.50	0.9047
10	80	1.83	0.0482	0.20	0.55	0.6438	30	80	1.69	0.0490	0.20	0.55	0.9638
10	80	1.83	0.0482	0.20	0.60	0.7602	30	80	1.69	0.0490	0.20	0.60	0.9892
10	80	1.83	0.0482	0.20	0.65	0.8552	30	80	1.69	0.0490	0.20	0.65	0.9975
10	80	1.83	0.0482	0.20	0.70	0.9230	30	80	1.69	0.0490	0.20	0.70	0.9996
10	80	1.83	0.0482	0.25	0.40	0.1656	30	80	1.69	0.0490	0.25	0.40	0.4136
10	80	1.83	0.0482	0.25	0.45	0.2593	30	80	1.69	0.0490	0.25	0.45	0.6026
10	80	1.83	0.0482	0.25	0.50	0.3741	30	80	1.69	0.0490	0.25	0.50	0.7691
10	80	1.83	0.0482	0.25	0.55	0.5041	30	80	1.69	0.0490	0.25	0.55	0.8889
10	80	1.83	0.0482	0.25	0.60	0.6337	30	80	1.69	0.0490	0.25	0.60	0.9569
10	80	1.83	0.0482	0.25	0.65	0.7543	30	80	1.69	0.0490	0.25	0.65	0.9868
10	80	1.83	0.0482	0.25	0.70	0.8529	30	80	1.69	0.0490	0.25	0.70	0.9970

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	80	1.83	0.0482	0.25	0.75	0.9244	30	80	1.69	0.0490	0.25	0.75	0.9995
10	80	1.83	0.0482	0.30	0.45	0.1675	30	80	1.69	0.0490	0.30	0.45	0.3962
10	80	1.83	0.0482	0.30	0.50	0.2598	30	80	1.69	0.0490	0.30	0.50	0.5832
10	80	1.83	0.0482	0.30	0.55	0.3747	30	80	1.69	0.0490	0.30	0.55	0.7557
10	80	1.83	0.0482	0.30	0.60	0.5029	30	80	1.69	0.0490	0.30	0.60	0.8813
10	80	1.83	0.0482	0.30	0.65	0.6366	30	80	1.69	0.0490	0.30	0.65	0.9535
10	80	1.83	0.0482	0.30	0.70	0.7600	30	80	1.69	0.0490	0.30	0.70	0.9863
10	80	1.83	0.0482	0.35	0.50	0.1711	30	80	1.69	0.0490	0.35	0.50	0.3876
10	80	1.83	0.0482	0.35	0.55	0.2639	30	80	1.69	0.0490	0.35	0.55	0.5770
10	80	1.83	0.0482	0.35	0.60	0.3792	30	80	1.69	0.0490	0.35	0.60	0.7510
10	80	1.83	0.0482	0.35	0.65	0.5124	30	80	1.69	0.0490	0.35	0.65	0.8800
10	80	1.83	0.0482	0.40	0.55	0.1758	30	80	1.69	0.0490	0.40	0.55	0.3876
10	80	1.83	0.0482	0.40	0.60	0.2709	30	80	1.69	0.0490	0.40	0.60	0.5773
10	90	1.97	0.0412	0.05	0.15	0.0003	30	90	1.71	0.0480	0.05	0.15	0.3859
10	90	1.97	0.0412	0.05	0.20	0.0166	30	90	1.71	0.0480	0.05	0.20	0.6428
10	90	1.97	0.0412	0.05	0.25	0.1376	30	90	1.71	0.0480	0.05	0.25	0.8362
10	90	1.97	0.0412	0.05	0.30	0.3799	30	90	1.71	0.0480	0.05	0.30	0.9423
10	90	1.97	0.0412	0.05	0.35	0.5739	30	90	1.71	0.0480	0.05	0.35	0.9845
10	90	1.97	0.0412	0.05	0.40	0.7098	30	90	1.71	0.0480	0.05	0.40	0.9968
10	90	1.97	0.0412	0.05	0.45	0.8357	30	90	1.71	0.0480	0.05	0.45	0.9995
10	90	1.97	0.0412	0.10	0.25	0.0802	30	90	1.71	0.0480	0.10	0.25	0.5225
10	90	1.97	0.0412	0.10	0.30	0.2231	30	90	1.71	0.0480	0.10	0.30	0.7346
10	90	1.97	0.0412	0.10	0.35	0.3533	30	90	1.71	0.0480	0.10	0.35	0.8819
10	90	1.97	0.0412	0.10	0.40	0.4901	30	90	1.71	0.0480	0.10	0.40	0.9578
10	90	1.97	0.0412	0.10	0.45	0.6473	30	90	1.71	0.0480	0.10	0.45	0.9880
10	90	1.97	0.0412	0.10	0.50	0.7725	30	90	1.71	0.0480	0.10	0.50	0.9973
10	90	1.97	0.0412	0.10	0.55	0.8667	30	90	1.71	0.0480	0.10	0.55	0.9995
10	90	1.97	0.0412	0.10	0.60	0.9311	30	90	1.71	0.0480	0.10	0.60	0.9999
10	90	1.97	0.0412	0.15	0.30	0.1272	30	90	1.71	0.0480	0.15	0.30	0.4662
10	90	1.97	0.0412	0.15	0.35	0.2116	30	90	1.71	0.0480	0.15	0.35	0.6753
10	90	1.97	0.0412	0.15	0.40	0.3257	30	90	1.71	0.0480	0.15	0.40	0.8359
10	90	1.97	0.0412	0.15	0.45	0.4719	30	90	1.71	0.0480	0.15	0.45	0.9324
10	90	1.97	0.0412	0.15	0.50	0.6081	30	90	1.71	0.0480	0.15	0.50	0.9772
10	90	1.97	0.0412	0.15	0.55	0.7348	30	90	1.71	0.0480	0.15	0.55	0.9937
10	90	1.97	0.0412	0.15	0.60	0.8369	30	90	1.71	0.0480	0.15	0.60	0.9987
10	90	1.97	0.0412	0.15	0.65	0.9108	30	90	1.71	0.0480	0.15	0.65	0.9998
10	90	1.97	0.0412	0.20	0.35	0.1228	30	90	1.71	0.0480	0.20	0.35	0.4348
10	90	1.97	0.0412	0.20	0.40	0.2080	30	90	1.71	0.0480	0.20	0.40	0.6362
10	90	1.97	0.0412	0.20	0.45	0.3261	30	90	1.71	0.0480	0.20	0.45	0.8024
10	90	1.97	0.0412	0.20	0.50	0.4525	30	90	1.71	0.0480	0.20	0.50	0.9094
10	90	1.97	0.0412	0.20	0.55	0.5890	30	90	1.71	0.0480	0.20	0.55	0.9658
10	90	1.97	0.0412	0.20	0.60	0.7146	30	90	1.71	0.0480	0.20	0.60	0.9899
10	90	1.97	0.0412	0.20	0.65	0.8228	30	90	1.71	0.0480	0.20	0.65	0.9978
10	90	1.97	0.0412	0.20	0.70	0.9066	30	90	1.71	0.0480	0.20	0.70	0.9997
10	90	1.97	0.0412	0.25	0.40	0.1274	30	90	1.71	0.0480	0.25	0.40	0.4149
10	90	1.97	0.0412	0.25	0.45	0.2142	30	90	1.71	0.0480	0.25	0.45	0.6081
10	90	1.97	0.0412	0.25	0.50	0.3195	30	90	1.71	0.0480	0.25	0.50	0.7733
10	90	1.97	0.0412	0.25	0.55	0.4475	30	90	1.71	0.0480	0.25	0.55	0.8908
10	90	1.97	0.0412	0.25	0.60	0.5797	30	90	1.71	0.0480	0.25	0.60	0.9582
10	90	1.97	0.0412	0.25	0.65	0.7116	30	90	1.71	0.0480	0.25	0.65	0.9878

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	90	1.97	0.0412	0.25	0.70	0.8279	30	90	1.71	0.0480	0.25	0.70	0.9975
10	90	1.97	0.0412	0.25	0.75	0.9105	30	90	1.71	0.0480	0.25	0.75	0.9996
10	90	1.97	0.0412	0.30	0.45	0.1337	30	90	1.71	0.0480	0.30	0.45	0.3978
10	90	1.97	0.0412	0.30	0.50	0.2143	30	90	1.71	0.0480	0.30	0.50	0.5832
10	90	1.97	0.0412	0.30	0.55	0.3224	30	90	1.71	0.0480	0.30	0.55	0.7549
10	90	1.97	0.0412	0.30	0.60	0.4468	30	90	1.71	0.0480	0.30	0.60	0.8825
10	90	1.97	0.0412	0.30	0.65	0.5877	30	90	1.71	0.0480	0.30	0.65	0.9561
10	90	1.97	0.0412	0.30	0.70	0.7271	30	90	1.71	0.0480	0.30	0.70	0.9879
10	90	1.97	0.0412	0.35	0.50	0.1363	30	90	1.71	0.0480	0.35	0.50	0.3828
10	90	1.97	0.0412	0.35	0.55	0.2199	30	90	1.71	0.0480	0.35	0.55	0.5722
10	90	1.97	0.0412	0.35	0.60	0.3267	30	90	1.71	0.0480	0.35	0.60	0.7515
10	90	1.97	0.0412	0.35	0.65	0.4624	30	90	1.71	0.0480	0.35	0.65	0.8847
10	90	1.97	0.0412	0.40	0.55	0.1415	30	90	1.71	0.0480	0.40	0.55	0.3802
10	90	1.97	0.0412	0.40	0.60	0.2261	30	90	1.71	0.0480	0.40	0.60	0.5767
10	100	2.04	0.0453	0.05	0.15	0.0000	30	100	1.72	0.0465	0.05	0.15	0.3670
10	100	2.04	0.0453	0.05	0.20	0.0036	30	100	1.72	0.0465	0.05	0.20	0.6410
10	100	2.04	0.0453	0.05	0.25	0.0621	30	100	1.72	0.0465	0.05	0.25	0.8482
10	100	2.04	0.0453	0.05	0.30	0.2706	30	100	1.72	0.0465	0.05	0.30	0.9523
10	100	2.04	0.0453	0.05	0.35	0.5074	30	100	1.72	0.0465	0.05	0.35	0.9885
10	100	2.04	0.0453	0.05	0.40	0.6587	30	100	1.72	0.0465	0.05	0.40	0.9978
10	100	2.04	0.0453	0.05	0.45	0.7956	30	100	1.72	0.0465	0.05	0.45	0.9997
10	100	2.04	0.0453	0.10	0.25	0.0362	30	100	1.72	0.0465	0.10	0.25	0.5446
10	100	2.04	0.0453	0.10	0.30	0.1580	30	100	1.72	0.0465	0.10	0.30	0.7608
10	100	2.04	0.0453	0.10	0.35	0.3034	30	100	1.72	0.0465	0.10	0.35	0.8978
10	100	2.04	0.0453	0.10	0.40	0.4323	30	100	1.72	0.0465	0.10	0.40	0.9643
10	100	2.04	0.0453	0.10	0.45	0.5958	30	100	1.72	0.0465	0.10	0.45	0.9899
10	100	2.04	0.0453	0.10	0.50	0.7457	30	100	1.72	0.0465	0.10	0.50	0.9977
10	100	2.04	0.0453	0.10	0.55	0.8545	30	100	1.72	0.0465	0.10	0.55	0.9996
10	100	2.04	0.0453	0.10	0.60	0.9254	30	100	1.72	0.0465	0.10	0.60	1.0000
10	100	2.04	0.0453	0.15	0.30	0.0895	30	100	1.72	0.0465	0.15	0.30	0.4929
10	100	2.04	0.0453	0.15	0.35	0.1764	30	100	1.72	0.0465	0.15	0.35	0.6974
10	100	2.04	0.0453	0.15	0.40	0.2751	30	100	1.72	0.0465	0.15	0.40	0.8481
10	100	2.04	0.0453	0.15	0.45	0.4232	30	100	1.72	0.0465	0.15	0.45	0.9370
10	100	2.04	0.0453	0.15	0.50	0.5779	30	100	1.72	0.0465	0.15	0.50	0.9792
10	100	2.04	0.0453	0.15	0.55	0.7171	30	100	1.72	0.0465	0.15	0.55	0.9947
10	100	2.04	0.0453	0.15	0.60	0.8257	30	100	1.72	0.0465	0.15	0.60	0.9990
10	100	2.04	0.0453	0.15	0.65	0.9026	30	100	1.72	0.0465	0.15	0.65	0.9999
10	100	2.04	0.0453	0.20	0.35	0.0993	30	100	1.72	0.0465	0.20	0.35	0.4524
10	100	2.04	0.0453	0.20	0.40	0.1692	30	100	1.72	0.0465	0.20	0.40	0.6471
10	100	2.04	0.0453	0.20	0.45	0.2862	30	100	1.72	0.0465	0.20	0.45	0.8081
10	100	2.04	0.0453	0.20	0.50	0.4236	30	100	1.72	0.0465	0.20	0.50	0.9150
10	100	2.04	0.0453	0.20	0.55	0.5687	30	100	1.72	0.0465	0.20	0.55	0.9701
10	100	2.04	0.0453	0.20	0.60	0.6984	30	100	1.72	0.0465	0.20	0.60	0.9918
10	100	2.04	0.0453	0.20	0.65	0.8089	30	100	1.72	0.0465	0.20	0.65	0.9983
10	100	2.04	0.0453	0.20	0.70	0.8969	30	100	1.72	0.0465	0.20	0.70	0.9997
10	100	2.04	0.0453	0.25	0.40	0.1002	30	100	1.72	0.0465	0.25	0.40	0.4201
10	100	2.04	0.0453	0.25	0.45	0.1845	30	100	1.72	0.0465	0.25	0.45	0.6131
10	100	2.04	0.0453	0.25	0.50	0.2949	30	100	1.72	0.0465	0.25	0.50	0.7835
10	100	2.04	0.0453	0.25	0.55	0.4273	30	100	1.72	0.0465	0.25	0.55	0.9009
10	100	2.04	0.0453	0.25	0.60	0.5603	30	100	1.72	0.0465	0.25	0.60	0.9639

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	100	2.04	0.0453	0.25	0.65	0.6925	30	100	1.72	0.0465	0.25	0.65	0.9895
10	100	2.04	0.0453	0.25	0.70	0.8125	30	100	1.72	0.0465	0.25	0.70	0.9977
10	100	2.04	0.0453	0.25	0.75	0.9027	30	100	1.72	0.0465	0.25	0.75	0.9997
10	100	2.04	0.0453	0.30	0.45	0.1133	30	100	1.72	0.0465	0.30	0.45	0.4016
10	100	2.04	0.0453	0.30	0.50	0.1950	30	100	1.72	0.0465	0.30	0.50	0.5961
10	100	2.04	0.0453	0.30	0.55	0.3042	30	100	1.72	0.0465	0.30	0.55	0.7708
10	100	2.04	0.0453	0.30	0.60	0.4264	30	100	1.72	0.0465	0.30	0.60	0.8932
10	100	2.04	0.0453	0.30	0.65	0.5651	30	100	1.72	0.0465	0.30	0.65	0.9596
10	100	2.04	0.0453	0.30	0.70	0.7066	30	100	1.72	0.0465	0.30	0.70	0.9884
10	100	2.04	0.0453	0.35	0.50	0.1223	30	100	1.72	0.0465	0.35	0.50	0.3948
10	100	2.04	0.0453	0.35	0.55	0.2049	30	100	1.72	0.0465	0.35	0.55	0.5900
10	100	2.04	0.0453	0.35	0.60	0.3074	30	100	1.72	0.0465	0.35	0.60	0.7648
10	100	2.04	0.0453	0.35	0.65	0.4386	30	100	1.72	0.0465	0.35	0.65	0.8886
10	100	2.04	0.0453	0.40	0.55	0.1302	30	100	1.72	0.0465	0.40	0.55	0.3949
10	100	2.04	0.0453	0.40	0.60	0.2095	30	100	1.72	0.0465	0.40	0.60	0.5874
20	30	1.69	0.0481	0.05	0.15	0.3026	40	50	1.68	0.0480	0.05	0.15	0.4159
20	30	1.69	0.0481	0.05	0.20	0.4749	40	50	1.68	0.0480	0.05	0.20	0.6700
20	30	1.69	0.0481	0.05	0.25	0.6315	40	50	1.68	0.0480	0.05	0.25	0.8527
20	30	1.69	0.0481	0.05	0.30	0.7605	40	50	1.68	0.0480	0.05	0.30	0.9475
20	30	1.69	0.0481	0.05	0.35	0.8579	40	50	1.68	0.0480	0.05	0.35	0.9848
20	30	1.69	0.0481	0.05	0.40	0.9246	40	50	1.68	0.0480	0.05	0.40	0.9964
20	30	1.69	0.0481	0.05	0.45	0.9650	40	50	1.68	0.0480	0.05	0.45	0.9993
20	30	1.69	0.0481	0.10	0.25	0.3609	40	50	1.68	0.0480	0.10	0.25	0.5674
20	30	1.69	0.0481	0.10	0.30	0.5032	40	50	1.68	0.0480	0.10	0.30	0.7615
20	30	1.69	0.0481	0.10	0.35	0.6465	40	50	1.68	0.0480	0.10	0.35	0.8896
20	30	1.69	0.0481	0.10	0.40	0.7740	40	50	1.68	0.0480	0.10	0.40	0.9579
20	30	1.69	0.0481	0.10	0.45	0.8722	40	50	1.68	0.0480	0.10	0.45	0.9870
20	30	1.69	0.0481	0.10	0.50	0.9365	40	50	1.68	0.0480	0.10	0.50	0.9969
20	30	1.69	0.0481	0.10	0.55	0.9724	40	50	1.68	0.0480	0.10	0.55	0.9994
20	30	1.69	0.0481	0.10	0.60	0.9895	40	50	1.68	0.0480	0.10	0.60	0.9999
20	30	1.69	0.0481	0.15	0.30	0.3036	40	50	1.68	0.0480	0.15	0.30	0.4967
20	30	1.69	0.0481	0.15	0.35	0.4460	40	50	1.68	0.0480	0.15	0.35	0.6918
20	30	1.69	0.0481	0.15	0.40	0.5976	40	50	1.68	0.0480	0.15	0.40	0.8422
20	30	1.69	0.0481	0.15	0.45	0.7354	40	50	1.68	0.0480	0.15	0.45	0.9337
20	30	1.69	0.0481	0.15	0.50	0.8428	40	50	1.68	0.0480	0.15	0.50	0.9774
20	30	1.69	0.0481	0.15	0.55	0.9159	40	50	1.68	0.0480	0.15	0.55	0.9938
20	30	1.69	0.0481	0.15	0.60	0.9598	40	50	1.68	0.0480	0.15	0.60	0.9986
20	30	1.69	0.0481	0.15	0.65	0.9833	40	50	1.68	0.0480	0.15	0.65	0.9998
20	30	1.69	0.0481	0.20	0.35	0.2856	40	50	1.68	0.0480	0.20	0.35	0.4557
20	30	1.69	0.0481	0.20	0.40	0.4269	40	50	1.68	0.0480	0.20	0.40	0.6524
20	30	1.69	0.0481	0.20	0.45	0.5748	40	50	1.68	0.0480	0.20	0.45	0.8119
20	30	1.69	0.0481	0.20	0.50	0.7095	40	50	1.68	0.0480	0.20	0.50	0.9145
20	30	1.69	0.0481	0.20	0.55	0.8187	40	50	1.68	0.0480	0.20	0.55	0.9678
20	30	1.69	0.0481	0.20	0.60	0.8982	40	50	1.68	0.0480	0.20	0.60	0.9903
20	30	1.69	0.0481	0.20	0.65	0.9497	40	50	1.68	0.0480	0.20	0.65	0.9978
20	30	1.69	0.0481	0.20	0.70	0.9788	40	50	1.68	0.0480	0.20	0.70	0.9996
20	30	1.69	0.0481	0.25	0.40	0.2814	40	50	1.68	0.0480	0.25	0.40	0.4354
20	30	1.69	0.0481	0.25	0.45	0.4146	40	50	1.68	0.0480	0.25	0.45	0.6254
20	30	1.69	0.0481	0.25	0.50	0.5547	40	50	1.68	0.0480	0.25	0.50	0.7860
20	30	1.69	0.0481	0.25	0.55	0.6874	40	50	1.68	0.0480	0.25	0.55	0.8974

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	30	1.69	0.0481	0.25	0.60	0.8008	40	50	1.68	0.0480	0.25	0.60	0.9602
20	30	1.69	0.0481	0.25	0.65	0.8871	40	50	1.68	0.0480	0.25	0.65	0.9880
20	30	1.69	0.0481	0.25	0.70	0.9442	40	50	1.68	0.0480	0.25	0.70	0.9973
20	30	1.69	0.0481	0.25	0.75	0.9767	40	50	1.68	0.0480	0.25	0.75	0.9996
20	30	1.69	0.0481	0.30	0.45	0.2752	40	50	1.68	0.0480	0.30	0.45	0.4163
20	30	1.69	0.0481	0.30	0.50	0.4014	40	50	1.68	0.0480	0.30	0.50	0.6016
20	30	1.69	0.0481	0.30	0.55	0.5389	40	50	1.68	0.0480	0.30	0.55	0.7679
20	30	1.69	0.0481	0.30	0.60	0.6740	40	50	1.68	0.0480	0.30	0.60	0.8885
20	30	1.69	0.0481	0.30	0.65	0.7920	40	50	1.68	0.0480	0.30	0.65	0.9572
20	30	1.69	0.0481	0.30	0.70	0.8824	40	50	1.68	0.0480	0.30	0.70	0.9874
20	30	1.69	0.0481	0.35	0.50	0.2682	40	50	1.68	0.0480	0.35	0.50	0.4025
20	30	1.69	0.0481	0.35	0.55	0.3927	40	50	1.68	0.0480	0.35	0.55	0.5908
20	30	1.69	0.0481	0.35	0.60	0.5313	40	50	1.68	0.0480	0.35	0.60	0.7623
20	30	1.69	0.0481	0.35	0.65	0.6688	40	50	1.68	0.0480	0.35	0.65	0.8866
20	30	1.69	0.0481	0.40	0.55	0.2646	40	50	1.68	0.0480	0.40	0.55	0.3998
20	30	1.69	0.0481	0.40	0.60	0.3894	40	50	1.68	0.0480	0.40	0.60	0.5897
20	40	1.78	0.0419	0.05	0.15	0.2296	40	60	1.72	0.0472	0.05	0.15	0.4482
20	40	1.78	0.0419	0.05	0.20	0.4105	40	60	1.72	0.0472	0.05	0.20	0.6990
20	40	1.78	0.0419	0.05	0.25	0.5916	40	60	1.72	0.0472	0.05	0.25	0.8671
20	40	1.78	0.0419	0.05	0.30	0.7505	40	60	1.72	0.0472	0.05	0.30	0.9542
20	40	1.78	0.0419	0.05	0.35	0.8677	40	60	1.72	0.0472	0.05	0.35	0.9881
20	40	1.78	0.0419	0.05	0.40	0.9395	40	60	1.72	0.0472	0.05	0.40	0.9977
20	40	1.78	0.0419	0.05	0.45	0.9761	40	60	1.72	0.0472	0.05	0.45	0.9997
20	40	1.78	0.0419	0.10	0.25	0.3296	40	60	1.72	0.0472	0.10	0.25	0.5658
20	40	1.78	0.0419	0.10	0.30	0.4980	40	60	1.72	0.0472	0.10	0.30	0.7744
20	40	1.78	0.0419	0.10	0.35	0.6634	40	60	1.72	0.0472	0.10	0.35	0.9071
20	40	1.78	0.0419	0.10	0.40	0.7983	40	60	1.72	0.0472	0.10	0.40	0.9690
20	40	1.78	0.0419	0.10	0.45	0.8918	40	60	1.72	0.0472	0.10	0.45	0.9915
20	40	1.78	0.0419	0.10	0.50	0.9485	40	60	1.72	0.0472	0.10	0.50	0.9981
20	40	1.78	0.0419	0.10	0.55	0.9788	40	60	1.72	0.0472	0.10	0.55	0.9997
20	40	1.78	0.0419	0.10	0.60	0.9927	40	60	1.72	0.0472	0.10	0.60	1.0000
20	40	1.78	0.0419	0.15	0.30	0.2986	40	60	1.72	0.0472	0.15	0.30	0.5159
20	40	1.78	0.0419	0.15	0.35	0.4545	40	60	1.72	0.0472	0.15	0.35	0.7205
20	40	1.78	0.0419	0.15	0.40	0.6110	40	60	1.72	0.0472	0.15	0.40	0.8635
20	40	1.78	0.0419	0.15	0.45	0.7476	40	60	1.72	0.0472	0.15	0.45	0.9445
20	40	1.78	0.0419	0.15	0.50	0.8536	40	60	1.72	0.0472	0.15	0.50	0.9819
20	40	1.78	0.0419	0.15	0.55	0.9258	40	60	1.72	0.0472	0.15	0.55	0.9955
20	40	1.78	0.0419	0.15	0.60	0.9679	40	60	1.72	0.0472	0.15	0.60	0.9992
20	40	1.78	0.0419	0.15	0.65	0.9883	40	60	1.72	0.0472	0.15	0.65	0.9999
20	40	1.78	0.0419	0.20	0.35	0.2814	40	60	1.72	0.0472	0.20	0.35	0.4736
20	40	1.78	0.0419	0.20	0.40	0.4231	40	60	1.72	0.0472	0.20	0.40	0.6671
20	40	1.78	0.0419	0.20	0.45	0.5732	40	60	1.72	0.0472	0.20	0.45	0.8233
20	40	1.78	0.0419	0.20	0.50	0.7145	40	60	1.72	0.0472	0.20	0.50	0.9240
20	40	1.78	0.0419	0.20	0.55	0.8306	40	60	1.72	0.0472	0.20	0.55	0.9740
20	40	1.78	0.0419	0.20	0.60	0.9122	40	60	1.72	0.0472	0.20	0.60	0.9930
20	40	1.78	0.0419	0.20	0.65	0.9608	40	60	1.72	0.0472	0.20	0.65	0.9986
20	40	1.78	0.0419	0.20	0.70	0.9852	40	60	1.72	0.0472	0.20	0.70	0.9998
20	40	1.78	0.0419	0.25	0.40	0.2667	40	60	1.72	0.0472	0.25	0.40	0.4359
20	40	1.78	0.0419	0.25	0.45	0.4026	40	60	1.72	0.0472	0.25	0.45	0.6326
20	40	1.78	0.0419	0.25	0.50	0.5534	40	60	1.72	0.0472	0.25	0.50	0.8001

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	40	1.78	0.0419	0.25	0.55	0.6986	40	60	1.72	0.0472	0.25	0.55	0.9105
20	40	1.78	0.0419	0.25	0.60	0.8188	40	60	1.72	0.0472	0.25	0.60	0.9675
20	40	1.78	0.0419	0.25	0.65	0.9043	40	60	1.72	0.0472	0.25	0.65	0.9908
20	40	1.78	0.0419	0.25	0.70	0.9565	40	60	1.72	0.0472	0.25	0.70	0.9981
20	40	1.78	0.0419	0.25	0.75	0.9836	40	60	1.72	0.0472	0.25	0.75	0.9998
20	40	1.78	0.0419	0.30	0.45	0.2593	40	60	1.72	0.0472	0.30	0.45	0.4190
20	40	1.78	0.0419	0.30	0.50	0.3952	40	60	1.72	0.0472	0.30	0.50	0.6152
20	40	1.78	0.0419	0.30	0.55	0.5462	40	60	1.72	0.0472	0.30	0.55	0.7836
20	40	1.78	0.0419	0.30	0.60	0.6914	40	60	1.72	0.0472	0.30	0.60	0.8995
20	40	1.78	0.0419	0.30	0.65	0.8127	40	60	1.72	0.0472	0.30	0.65	0.9634
20	40	1.78	0.0419	0.30	0.70	0.9008	40	60	1.72	0.0472	0.30	0.70	0.9902
20	40	1.78	0.0419	0.35	0.50	0.2593	40	60	1.72	0.0472	0.35	0.50	0.4083
20	40	1.78	0.0419	0.35	0.55	0.3943	40	60	1.72	0.0472	0.35	0.55	0.5998
20	40	1.78	0.0419	0.35	0.60	0.5438	40	60	1.72	0.0472	0.35	0.60	0.7725
20	40	1.78	0.0419	0.35	0.65	0.6887	40	60	1.72	0.0472	0.35	0.65	0.8967
20	40	1.78	0.0419	0.40	0.55	0.2611	40	60	1.72	0.0472	0.40	0.55	0.3985
20	40	1.78	0.0419	0.40	0.60	0.3949	40	60	1.72	0.0472	0.40	0.60	0.5951
20	50	1.76	0.0412	0.05	0.15	0.2537	40	70	1.67	0.0494	0.05	0.15	0.4957
20	50	1.76	0.0412	0.05	0.20	0.4422	40	70	1.67	0.0494	0.05	0.20	0.7576
20	50	1.76	0.0412	0.05	0.25	0.6342	40	70	1.67	0.0494	0.05	0.25	0.9088
20	50	1.76	0.0412	0.05	0.30	0.7956	40	70	1.67	0.0494	0.05	0.30	0.9728
20	50	1.76	0.0412	0.05	0.35	0.9003	40	70	1.67	0.0494	0.05	0.35	0.9936
20	50	1.76	0.0412	0.05	0.40	0.9565	40	70	1.67	0.0494	0.05	0.40	0.9989
20	50	1.76	0.0412	0.05	0.45	0.9834	40	70	1.67	0.0494	0.05	0.45	0.9999
20	50	1.76	0.0412	0.10	0.25	0.3638	40	70	1.67	0.0494	0.10	0.25	0.6284
20	50	1.76	0.0412	0.10	0.30	0.5408	40	70	1.67	0.0494	0.10	0.30	0.8148
20	50	1.76	0.0412	0.10	0.35	0.6980	40	70	1.67	0.0494	0.10	0.35	0.9272
20	50	1.76	0.0412	0.10	0.40	0.8212	40	70	1.67	0.0494	0.10	0.40	0.9778
20	50	1.76	0.0412	0.10	0.45	0.9080	40	70	1.67	0.0494	0.10	0.45	0.9947
20	50	1.76	0.0412	0.10	0.50	0.9602	40	70	1.67	0.0494	0.10	0.50	0.9990
20	50	1.76	0.0412	0.10	0.55	0.9857	40	70	1.67	0.0494	0.10	0.55	0.9999
20	50	1.76	0.0412	0.10	0.60	0.9957	40	70	1.67	0.0494	0.10	0.60	1.0000
20	50	1.76	0.0412	0.15	0.30	0.3226	40	70	1.67	0.0494	0.15	0.30	0.5490
20	50	1.76	0.0412	0.15	0.35	0.4749	40	70	1.67	0.0494	0.15	0.35	0.7515
20	50	1.76	0.0412	0.15	0.40	0.6307	40	70	1.67	0.0494	0.15	0.40	0.8892
20	50	1.76	0.0412	0.15	0.45	0.7714	40	70	1.67	0.0494	0.15	0.45	0.9602
20	50	1.76	0.0412	0.15	0.50	0.8776	40	70	1.67	0.0494	0.15	0.50	0.9886
20	50	1.76	0.0412	0.15	0.55	0.9432	40	70	1.67	0.0494	0.15	0.55	0.9974
20	50	1.76	0.0412	0.15	0.60	0.9769	40	70	1.67	0.0494	0.15	0.60	0.9996
20	50	1.76	0.0412	0.15	0.65	0.9920	40	70	1.67	0.0494	0.15	0.65	0.9999
20	50	1.76	0.0412	0.20	0.35	0.2895	40	70	1.67	0.0494	0.20	0.35	0.5071
20	50	1.76	0.0412	0.20	0.40	0.4377	40	70	1.67	0.0494	0.20	0.40	0.7086
20	50	1.76	0.0412	0.20	0.45	0.5998	40	70	1.67	0.0494	0.20	0.45	0.8570
20	50	1.76	0.0412	0.20	0.50	0.7465	40	70	1.67	0.0494	0.20	0.50	0.9427
20	50	1.76	0.0412	0.20	0.55	0.8568	40	70	1.67	0.0494	0.20	0.55	0.9818
20	50	1.76	0.0412	0.20	0.60	0.9283	40	70	1.67	0.0494	0.20	0.60	0.9957
20	50	1.76	0.0412	0.20	0.65	0.9693	40	70	1.67	0.0494	0.20	0.65	0.9993
20	50	1.76	0.0412	0.20	0.70	0.9894	40	70	1.67	0.0494	0.20	0.70	0.9999
20	50	1.76	0.0412	0.25	0.40	0.2764	40	70	1.67	0.0494	0.25	0.40	0.4767
20	50	1.76	0.0412	0.25	0.45	0.4259	40	70	1.67	0.0494	0.25	0.45	0.6736

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	50	1.76	0.0412	0.25	0.50	0.5844	40	70	1.67	0.0494	0.25	0.50	0.8304
20	50	1.76	0.0412	0.25	0.55	0.7267	40	70	1.67	0.0494	0.25	0.55	0.9292
20	50	1.76	0.0412	0.25	0.60	0.8396	40	70	1.67	0.0494	0.25	0.60	0.9772
20	50	1.76	0.0412	0.25	0.65	0.9192	40	70	1.67	0.0494	0.25	0.65	0.9945
20	50	1.76	0.0412	0.25	0.70	0.9663	40	70	1.67	0.0494	0.25	0.70	0.9990
20	50	1.76	0.0412	0.25	0.75	0.9886	40	70	1.67	0.0494	0.25	0.75	0.9999
20	50	1.76	0.0412	0.30	0.45	0.2754	40	70	1.67	0.0494	0.30	0.45	0.4519
20	50	1.76	0.0412	0.30	0.50	0.4182	40	70	1.67	0.0494	0.30	0.50	0.6496
20	50	1.76	0.0412	0.30	0.55	0.5694	40	70	1.67	0.0494	0.30	0.55	0.8158
20	50	1.76	0.0412	0.30	0.60	0.7131	40	70	1.67	0.0494	0.30	0.60	0.9229
20	50	1.76	0.0412	0.30	0.65	0.8338	40	70	1.67	0.0494	0.30	0.65	0.9750
20	50	1.76	0.0412	0.30	0.70	0.9182	40	70	1.67	0.0494	0.30	0.70	0.9941
20	50	1.76	0.0412	0.35	0.50	0.2721	40	70	1.67	0.0494	0.35	0.50	0.4393
20	50	1.76	0.0412	0.35	0.55	0.4093	40	70	1.67	0.0494	0.35	0.55	0.6413
20	50	1.76	0.0412	0.35	0.60	0.5631	40	70	1.67	0.0494	0.35	0.60	0.8110
20	50	1.76	0.0412	0.35	0.65	0.7139	40	70	1.67	0.0494	0.35	0.65	0.9209
20	50	1.76	0.0412	0.40	0.55	0.2685	40	70	1.67	0.0494	0.40	0.55	0.4379
20	50	1.76	0.0412	0.40	0.60	0.4100	40	70	1.67	0.0494	0.40	0.60	0.6400
20	60	1.73	0.0495	0.05	0.15	0.2213	40	80	1.69	0.0491	0.05	0.15	0.4831
20	60	1.73	0.0495	0.05	0.20	0.4365	40	80	1.69	0.0491	0.05	0.20	0.7495
20	60	1.73	0.0495	0.05	0.25	0.6461	40	80	1.69	0.0491	0.05	0.25	0.9080
20	60	1.73	0.0495	0.05	0.30	0.8110	40	80	1.69	0.0491	0.05	0.30	0.9748
20	60	1.73	0.0495	0.05	0.35	0.9136	40	80	1.69	0.0491	0.05	0.35	0.9949
20	60	1.73	0.0495	0.05	0.40	0.9664	40	80	1.69	0.0491	0.05	0.40	0.9992
20	60	1.73	0.0495	0.05	0.45	0.9891	40	80	1.69	0.0491	0.05	0.45	0.9999
20	60	1.73	0.0495	0.10	0.25	0.3688	40	80	1.69	0.0491	0.10	0.25	0.6256
20	60	1.73	0.0495	0.10	0.30	0.5550	40	80	1.69	0.0491	0.10	0.30	0.8237
20	60	1.73	0.0495	0.10	0.35	0.7228	40	80	1.69	0.0491	0.10	0.35	0.9356
20	60	1.73	0.0495	0.10	0.40	0.8498	40	80	1.69	0.0491	0.10	0.40	0.9818
20	60	1.73	0.0495	0.10	0.45	0.9296	40	80	1.69	0.0491	0.10	0.45	0.9960
20	60	1.73	0.0495	0.10	0.50	0.9712	40	80	1.69	0.0491	0.10	0.50	0.9993
20	60	1.73	0.0495	0.10	0.55	0.9899	40	80	1.69	0.0491	0.10	0.55	0.9999
20	60	1.73	0.0495	0.10	0.60	0.9970	40	80	1.69	0.0491	0.10	0.60	1.0000
20	60	1.73	0.0495	0.15	0.30	0.3337	40	80	1.69	0.0491	0.15	0.30	0.5591
20	60	1.73	0.0495	0.15	0.35	0.5037	40	80	1.69	0.0491	0.15	0.35	0.7653
20	60	1.73	0.0495	0.15	0.40	0.6699	40	80	1.69	0.0491	0.15	0.40	0.8994
20	60	1.73	0.0495	0.15	0.45	0.8045	40	80	1.69	0.0491	0.15	0.45	0.9658
20	60	1.73	0.0495	0.15	0.50	0.8971	40	80	1.69	0.0491	0.15	0.50	0.9911
20	60	1.73	0.0495	0.15	0.55	0.9531	40	80	1.69	0.0491	0.15	0.55	0.9983
20	60	1.73	0.0495	0.15	0.60	0.9821	40	80	1.69	0.0491	0.15	0.60	0.9997
20	60	1.73	0.0495	0.15	0.65	0.9944	40	80	1.69	0.0491	0.15	0.65	1.0000
20	60	1.73	0.0495	0.20	0.35	0.3137	40	80	1.69	0.0491	0.20	0.35	0.5174
20	60	1.73	0.0495	0.20	0.40	0.4734	40	80	1.69	0.0491	0.20	0.40	0.7212
20	60	1.73	0.0495	0.20	0.45	0.6321	40	80	1.69	0.0491	0.20	0.45	0.8699
20	60	1.73	0.0495	0.20	0.50	0.7688	40	80	1.69	0.0491	0.20	0.50	0.9520
20	60	1.73	0.0495	0.20	0.55	0.8728	40	80	1.69	0.0491	0.20	0.55	0.9858
20	60	1.73	0.0495	0.20	0.60	0.9402	40	80	1.69	0.0491	0.20	0.60	0.9967
20	60	1.73	0.0495	0.20	0.65	0.9763	40	80	1.69	0.0491	0.20	0.65	0.9994
20	60	1.73	0.0495	0.20	0.70	0.9923	40	80	1.69	0.0491	0.20	0.70	0.9999
20	60	1.73	0.0495	0.25	0.40	0.3008	40	80	1.69	0.0491	0.25	0.40	0.4875

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	60	1.73	0.0495	0.25	0.45	0.4490	40	80	1.69	0.0491	0.25	0.45	0.6930
20	60	1.73	0.0495	0.25	0.50	0.6043	40	80	1.69	0.0491	0.25	0.50	0.8482
20	60	1.73	0.0495	0.25	0.55	0.7472	40	80	1.69	0.0491	0.25	0.55	0.9381
20	60	1.73	0.0495	0.25	0.60	0.8591	40	80	1.69	0.0491	0.25	0.60	0.9800
20	60	1.73	0.0495	0.25	0.65	0.9326	40	80	1.69	0.0491	0.25	0.65	0.9953
20	60	1.73	0.0495	0.25	0.70	0.9733	40	80	1.69	0.0491	0.25	0.70	0.9993
20	60	1.73	0.0495	0.25	0.75	0.9917	40	80	1.69	0.0491	0.25	0.75	0.9999
20	60	1.73	0.0495	0.30	0.45	0.2882	40	80	1.69	0.0491	0.30	0.45	0.4706
20	60	1.73	0.0495	0.30	0.50	0.4330	40	80	1.69	0.0491	0.30	0.50	0.6686
20	60	1.73	0.0495	0.30	0.55	0.5909	40	80	1.69	0.0491	0.30	0.55	0.8255
20	60	1.73	0.0495	0.30	0.60	0.7374	40	80	1.69	0.0491	0.30	0.60	0.9268
20	60	1.73	0.0495	0.30	0.65	0.8530	40	80	1.69	0.0491	0.30	0.65	0.9774
20	60	1.73	0.0495	0.30	0.70	0.9309	40	80	1.69	0.0491	0.30	0.70	0.9952
20	60	1.73	0.0495	0.35	0.50	0.2818	40	80	1.69	0.0491	0.35	0.50	0.4492
20	60	1.73	0.0495	0.35	0.55	0.4280	40	80	1.69	0.0491	0.35	0.55	0.6448
20	60	1.73	0.0495	0.35	0.60	0.5870	40	80	1.69	0.0491	0.35	0.60	0.8143
20	60	1.73	0.0495	0.35	0.65	0.7361	40	80	1.69	0.0491	0.35	0.65	0.9266
20	60	1.73	0.0495	0.40	0.55	0.2817	40	80	1.69	0.0491	0.40	0.55	0.4335
20	60	1.73	0.0495	0.40	0.60	0.4289	40	80	1.69	0.0491	0.40	0.60	0.6421
20	70	1.75	0.0452	0.05	0.15	0.2415	40	90	1.7	0.0465	0.05	0.15	0.4740
20	70	1.75	0.0452	0.05	0.20	0.4542	40	90	1.7	0.0465	0.05	0.20	0.7475
20	70	1.75	0.0452	0.05	0.25	0.6604	40	90	1.7	0.0465	0.05	0.25	0.9122
20	70	1.75	0.0452	0.05	0.30	0.8221	40	90	1.7	0.0465	0.05	0.30	0.9772
20	70	1.75	0.0452	0.05	0.35	0.9226	40	90	1.7	0.0465	0.05	0.35	0.9956
20	70	1.75	0.0452	0.05	0.40	0.9723	40	90	1.7	0.0465	0.05	0.40	0.9994
20	70	1.75	0.0452	0.05	0.45	0.9918	40	90	1.7	0.0465	0.05	0.45	0.9999
20	70	1.75	0.0452	0.10	0.25	0.3739	40	90	1.7	0.0465	0.10	0.25	0.6260
20	70	1.75	0.0452	0.10	0.30	0.5642	40	90	1.7	0.0465	0.10	0.30	0.8261
20	70	1.75	0.0452	0.10	0.35	0.7382	40	90	1.7	0.0465	0.10	0.35	0.9388
20	70	1.75	0.0452	0.10	0.40	0.8651	40	90	1.7	0.0465	0.10	0.40	0.9839
20	70	1.75	0.0452	0.10	0.45	0.9399	40	90	1.7	0.0465	0.10	0.45	0.9968
20	70	1.75	0.0452	0.10	0.50	0.9768	40	90	1.7	0.0465	0.10	0.50	0.9995
20	70	1.75	0.0452	0.10	0.55	0.9923	40	90	1.7	0.0465	0.10	0.55	0.9999
20	70	1.75	0.0452	0.10	0.60	0.9978	40	90	1.7	0.0465	0.10	0.60	1.0000
20	70	1.75	0.0452	0.15	0.30	0.3395	40	90	1.7	0.0465	0.15	0.30	0.5566
20	70	1.75	0.0452	0.15	0.35	0.5188	40	90	1.7	0.0465	0.15	0.35	0.7698
20	70	1.75	0.0452	0.15	0.40	0.6890	40	90	1.7	0.0465	0.15	0.40	0.9062
20	70	1.75	0.0452	0.15	0.45	0.8220	40	90	1.7	0.0465	0.15	0.45	0.9701
20	70	1.75	0.0452	0.15	0.50	0.9100	40	90	1.7	0.0465	0.15	0.50	0.9926
20	70	1.75	0.0452	0.15	0.55	0.9601	40	90	1.7	0.0465	0.15	0.55	0.9986
20	70	1.75	0.0452	0.15	0.60	0.9849	40	90	1.7	0.0465	0.15	0.60	0.9998
20	70	1.75	0.0452	0.15	0.65	0.9954	40	90	1.7	0.0465	0.15	0.65	1.0000
20	70	1.75	0.0452	0.20	0.35	0.3244	40	90	1.7	0.0465	0.20	0.35	0.5208
20	70	1.75	0.0452	0.20	0.40	0.4904	40	90	1.7	0.0465	0.20	0.40	0.7313
20	70	1.75	0.0452	0.20	0.45	0.6522	40	90	1.7	0.0465	0.20	0.45	0.8783
20	70	1.75	0.0452	0.20	0.50	0.7868	40	90	1.7	0.0465	0.20	0.50	0.9566
20	70	1.75	0.0452	0.20	0.55	0.8840	40	90	1.7	0.0465	0.20	0.55	0.9882
20	70	1.75	0.0452	0.20	0.60	0.9456	40	90	1.7	0.0465	0.20	0.60	0.9976
20	70	1.75	0.0452	0.20	0.65	0.9792	40	90	1.7	0.0465	0.20	0.65	0.9997
20	70	1.75	0.0452	0.20	0.70	0.9939	40	90	1.7	0.0465	0.20	0.70	1.0000

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	70	1.75	0.0452	0.25	0.40	0.3127	40	90	1.7	0.0465	0.25	0.40	0.4948
20	70	1.75	0.0452	0.25	0.45	0.4667	40	90	1.7	0.0465	0.25	0.45	0.7014
20	70	1.75	0.0452	0.25	0.50	0.6220	40	90	1.7	0.0465	0.25	0.50	0.8573
20	70	1.75	0.0452	0.25	0.55	0.7593	40	90	1.7	0.0465	0.25	0.55	0.9465
20	70	1.75	0.0452	0.25	0.60	0.8666	40	90	1.7	0.0465	0.25	0.60	0.9847
20	70	1.75	0.0452	0.25	0.65	0.9388	40	90	1.7	0.0465	0.25	0.65	0.9968
20	70	1.75	0.0452	0.25	0.70	0.9778	40	90	1.7	0.0465	0.25	0.70	0.9995
20	70	1.75	0.0452	0.25	0.75	0.9937	40	90	1.7	0.0465	0.25	0.75	1.0000
20	70	1.75	0.0452	0.30	0.45	0.3004	40	90	1.7	0.0465	0.30	0.45	0.4756
20	70	1.75	0.0452	0.30	0.50	0.4460	40	90	1.7	0.0465	0.30	0.50	0.6824
20	70	1.75	0.0452	0.30	0.55	0.6001	40	90	1.7	0.0465	0.30	0.55	0.8442
20	70	1.75	0.0452	0.30	0.60	0.7457	40	90	1.7	0.0465	0.30	0.60	0.9401
20	70	1.75	0.0452	0.30	0.65	0.8635	40	90	1.7	0.0465	0.30	0.65	0.9826
20	70	1.75	0.0452	0.30	0.70	0.9402	40	90	1.7	0.0465	0.30	0.70	0.9963
20	70	1.75	0.0452	0.35	0.50	0.2885	40	90	1.7	0.0465	0.35	0.50	0.4655
20	70	1.75	0.0452	0.35	0.55	0.4327	40	90	1.7	0.0465	0.35	0.55	0.6722
20	70	1.75	0.0452	0.35	0.60	0.5948	40	90	1.7	0.0465	0.35	0.60	0.8380
20	70	1.75	0.0452	0.35	0.65	0.7504	40	90	1.7	0.0465	0.35	0.65	0.9373
20	70	1.75	0.0452	0.40	0.55	0.2827	40	90	1.7	0.0465	0.40	0.55	0.4613
20	70	1.75	0.0452	0.40	0.60	0.4353	40	90	1.7	0.0465	0.40	0.60	0.6694
20	80	1.74	0.0459	0.05	0.15	0.2584	40	100	1.72	0.0471	0.05	0.15	0.4950
20	80	1.74	0.0459	0.05	0.20	0.4666	40	100	1.72	0.0471	0.05	0.20	0.7643
20	80	1.74	0.0459	0.05	0.25	0.6700	40	100	1.72	0.0471	0.05	0.25	0.9222
20	80	1.74	0.0459	0.05	0.30	0.8265	40	100	1.72	0.0471	0.05	0.30	0.9821
20	80	1.74	0.0459	0.05	0.35	0.9237	40	100	1.72	0.0471	0.05	0.35	0.9970
20	80	1.74	0.0459	0.05	0.40	0.9729	40	100	1.72	0.0471	0.05	0.40	0.9996
20	80	1.74	0.0459	0.05	0.45	0.9923	40	100	1.72	0.0471	0.05	0.45	1.0000
20	80	1.74	0.0459	0.10	0.25	0.3751	40	100	1.72	0.0471	0.10	0.25	0.6487
20	80	1.74	0.0459	0.10	0.30	0.5599	40	100	1.72	0.0471	0.10	0.30	0.8477
20	80	1.74	0.0459	0.10	0.35	0.7329	40	100	1.72	0.0471	0.10	0.35	0.9491
20	80	1.74	0.0459	0.10	0.40	0.8635	40	100	1.72	0.0471	0.10	0.40	0.9868
20	80	1.74	0.0459	0.10	0.45	0.9410	40	100	1.72	0.0471	0.10	0.45	0.9974
20	80	1.74	0.0459	0.10	0.50	0.9779	40	100	1.72	0.0471	0.10	0.50	0.9996
20	80	1.74	0.0459	0.10	0.55	0.9930	40	100	1.72	0.0471	0.10	0.55	1.0000
20	80	1.74	0.0459	0.10	0.60	0.9982	40	100	1.72	0.0471	0.10	0.60	1.0000
20	80	1.74	0.0459	0.15	0.30	0.3297	40	100	1.72	0.0471	0.15	0.30	0.5829
20	80	1.74	0.0459	0.15	0.35	0.5079	40	100	1.72	0.0471	0.15	0.35	0.7865
20	80	1.74	0.0459	0.15	0.40	0.6841	40	100	1.72	0.0471	0.15	0.40	0.9125
20	80	1.74	0.0459	0.15	0.45	0.8220	40	100	1.72	0.0471	0.15	0.45	0.9719
20	80	1.74	0.0459	0.15	0.50	0.9120	40	100	1.72	0.0471	0.15	0.50	0.9932
20	80	1.74	0.0459	0.15	0.55	0.9631	40	100	1.72	0.0471	0.15	0.55	0.9988
20	80	1.74	0.0459	0.15	0.60	0.9873	40	100	1.72	0.0471	0.15	0.60	0.9998
20	80	1.74	0.0459	0.15	0.65	0.9965	40	100	1.72	0.0471	0.15	0.65	1.0000
20	80	1.74	0.0459	0.20	0.35	0.3125	40	100	1.72	0.0471	0.20	0.35	0.5315
20	80	1.74	0.0459	0.20	0.40	0.4830	40	100	1.72	0.0471	0.20	0.40	0.7351
20	80	1.74	0.0459	0.20	0.45	0.6497	40	100	1.72	0.0471	0.20	0.45	0.8800
20	80	1.74	0.0459	0.20	0.50	0.7893	40	100	1.72	0.0471	0.20	0.50	0.9580
20	80	1.74	0.0459	0.20	0.55	0.8910	40	100	1.72	0.0471	0.20	0.55	0.9888
20	80	1.74	0.0459	0.20	0.60	0.9526	40	100	1.72	0.0471	0.20	0.60	0.9978
20	80	1.74	0.0459	0.20	0.65	0.9831	40	100	1.72	0.0471	0.20	0.65	0.9997

Table B.22: continue on next page

Table B.22: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	80	1.74	0.0459	0.20	0.70	0.9953	40	100	1.72	0.0471	0.20	0.70	1.0000
20	80	1.74	0.0459	0.25	0.40	0.3048	40	100	1.72	0.0471	0.25	0.40	0.4920
20	80	1.74	0.0459	0.25	0.45	0.4621	40	100	1.72	0.0471	0.25	0.45	0.7000
20	80	1.74	0.0459	0.25	0.50	0.6249	40	100	1.72	0.0471	0.25	0.50	0.8578
20	80	1.74	0.0459	0.25	0.55	0.7707	40	100	1.72	0.0471	0.25	0.55	0.9471
20	80	1.74	0.0459	0.25	0.60	0.8796	40	100	1.72	0.0471	0.25	0.60	0.9853
20	80	1.74	0.0459	0.25	0.65	0.9474	40	100	1.72	0.0471	0.25	0.65	0.9971
20	80	1.74	0.0459	0.25	0.70	0.9817	40	100	1.72	0.0471	0.25	0.70	0.9996
20	80	1.74	0.0459	0.25	0.75	0.9950	40	100	1.72	0.0471	0.25	0.75	1.0000
20	80	1.74	0.0459	0.30	0.45	0.2953	40	100	1.72	0.0471	0.30	0.45	0.4700
20	80	1.74	0.0459	0.30	0.50	0.4491	40	100	1.72	0.0471	0.30	0.50	0.6787
20	80	1.74	0.0459	0.30	0.55	0.6144	40	100	1.72	0.0471	0.30	0.55	0.8429
20	80	1.74	0.0459	0.30	0.60	0.7638	40	100	1.72	0.0471	0.30	0.60	0.9414
20	80	1.74	0.0459	0.30	0.65	0.8776	40	100	1.72	0.0471	0.30	0.65	0.9841
20	80	1.74	0.0459	0.30	0.70	0.9480	40	100	1.72	0.0471	0.30	0.70	0.9970
20	80	1.74	0.0459	0.35	0.50	0.2914	40	100	1.72	0.0471	0.35	0.50	0.4568
20	80	1.74	0.0459	0.35	0.55	0.4468	40	100	1.72	0.0471	0.35	0.55	0.6677
20	80	1.74	0.0459	0.35	0.60	0.6147	40	100	1.72	0.0471	0.35	0.60	0.8398
20	80	1.74	0.0459	0.35	0.65	0.7686	40	100	1.72	0.0471	0.35	0.65	0.9419
20	80	1.74	0.0459	0.40	0.55	0.2940	40	100	1.72	0.0471	0.40	0.55	0.4543
20	80	1.74	0.0459	0.40	0.60	0.4533	40	100	1.72	0.0471	0.40	0.60	0.6720

Table B.22: concluded from previous page

Table B.23: Achieved power and p-values calculated for the z-pooled statistic in cases of different sample sizes, $\boldsymbol{\alpha}$= **0.025**. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.08	0.0231	0.05	0.15	0.0132	20	90	2.16	0.0243	0.05	0.15	0.0438
10	20	2.08	0.0231	0.05	0.20	0.0527	20	90	2.16	0.0243	0.05	0.20	0.2123
10	20	2.08	0.0231	0.05	0.25	0.1326	20	90	2.16	0.0243	0.05	0.25	0.4385
10	20	2.08	0.0231	0.05	0.30	0.2499	20	90	2.16	0.0243	0.05	0.30	0.6529
10	20	2.08	0.0231	0.05	0.35	0.3881	20	90	2.16	0.0243	0.05	0.35	0.8152
10	20	2.08	0.0231	0.05	0.40	0.5278	20	90	2.16	0.0243	0.05	0.40	0.9196
10	20	2.08	0.0231	0.05	0.45	0.6543	20	90	2.16	0.0243	0.05	0.45	0.9728
10	20	2.08	0.0231	0.10	0.25	0.0801	20	90	2.16	0.0243	0.10	0.25	0.1963
10	20	2.08	0.0231	0.10	0.30	0.1555	20	90	2.16	0.0243	0.10	0.30	0.3590
10	20	2.08	0.0231	0.10	0.35	0.2518	20	90	2.16	0.0243	0.10	0.35	0.5441
10	20	2.08	0.0231	0.10	0.40	0.3607	20	90	2.16	0.0243	0.10	0.40	0.7253
10	20	2.08	0.0231	0.10	0.45	0.4742	20	90	2.16	0.0243	0.10	0.45	0.8620
10	20	2.08	0.0231	0.10	0.50	0.5853	20	90	2.16	0.0243	0.10	0.50	0.9414
10	20	2.08	0.0231	0.10	0.55	0.6885	20	90	2.16	0.0243	0.10	0.55	0.9789
10	20	2.08	0.0231	0.10	0.60	0.7799	20	90	2.16	0.0243	0.10	0.60	0.9937
10	20	2.08	0.0231	0.15	0.30	0.0942	20	90	2.16	0.0243	0.15	0.30	0.1745
10	20	2.08	0.0231	0.15	0.35	0.1590	20	90	2.16	0.0243	0.15	0.35	0.3167
10	20	2.08	0.0231	0.15	0.40	0.2393	20	90	2.16	0.0243	0.15	0.40	0.4992
10	20	2.08	0.0231	0.15	0.45	0.3321	20	90	2.16	0.0243	0.15	0.45	0.6797
10	20	2.08	0.0231	0.15	0.50	0.4339	20	90	2.16	0.0243	0.15	0.50	0.8213
10	20	2.08	0.0231	0.15	0.55	0.5406	20	90	2.16	0.0243	0.15	0.55	0.9137
10	20	2.08	0.0231	0.15	0.60	0.6480	20	90	2.16	0.0243	0.15	0.60	0.9650
10	20	2.08	0.0231	0.15	0.65	0.7503	20	90	2.16	0.0243	0.15	0.65	0.9888
10	20	2.08	0.0231	0.20	0.35	0.0975	20	90	2.16	0.0243	0.20	0.35	0.1647
10	20	2.08	0.0231	0.20	0.40	0.1539	20	90	2.16	0.0243	0.20	0.40	0.3044
10	20	2.08	0.0231	0.20	0.45	0.2251	20	90	2.16	0.0243	0.20	0.45	0.4764
10	20	2.08	0.0231	0.20	0.50	0.3109	20	90	2.16	0.0243	0.20	0.50	0.6473
10	20	2.08	0.0231	0.20	0.55	0.4105	20	90	2.16	0.0243	0.20	0.55	0.7906
10	20	2.08	0.0231	0.20	0.60	0.5214	20	90	2.16	0.0243	0.20	0.60	0.8942
10	20	2.08	0.0231	0.20	0.65	0.6375	20	90	2.16	0.0243	0.20	0.65	0.9567
10	20	2.08	0.0231	0.20	0.70	0.7487	20	90	2.16	0.0243	0.20	0.70	0.9861
10	20	2.08	0.0231	0.25	0.40	0.0957	20	90	2.16	0.0243	0.25	0.40	0.1660
10	20	2.08	0.0231	0.25	0.45	0.1476	20	90	2.16	0.0243	0.25	0.45	0.2978
10	20	2.08	0.0231	0.25	0.50	0.2158	20	90	2.16	0.0243	0.25	0.50	0.4581
10	20	2.08	0.0231	0.25	0.55	0.3023	20	90	2.16	0.0243	0.25	0.55	0.6244
10	20	2.08	0.0231	0.25	0.60	0.4071	20	90	2.16	0.0243	0.25	0.60	0.7745
10	20	2.08	0.0231	0.25	0.65	0.5255	20	90	2.16	0.0243	0.25	0.65	0.8876
10	20	2.08	0.0231	0.25	0.70	0.6473	20	90	2.16	0.0243	0.25	0.70	0.9545
10	20	2.08	0.0231	0.25	0.75	0.7592	20	90	2.16	0.0243	0.25	0.75	0.9854
10	20	2.08	0.0231	0.30	0.45	0.0936	20	90	2.16	0.0243	0.30	0.45	0.1665
10	20	2.08	0.0231	0.30	0.50	0.1451	20	90	2.16	0.0243	0.30	0.50	0.2907
10	20	2.08	0.0231	0.30	0.55	0.2159	20	90	2.16	0.0243	0.30	0.55	0.4466
10	20	2.08	0.0231	0.30	0.60	0.3081	20	90	2.16	0.0243	0.30	0.60	0.6180
10	20	2.08	0.0231	0.30	0.65	0.4193	20	90	2.16	0.0243	0.30	0.65	0.7752

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.08	0.0231	0.30	0.70	0.5412	20	90	2.16	0.0243	0.30	0.70	0.8897
10	20	2.08	0.0231	0.35	0.50	0.0944	20	90	2.16	0.0243	0.35	0.50	0.1650
10	20	2.08	0.0231	0.35	0.55	0.1493	20	90	2.16	0.0243	0.35	0.55	0.2878
10	20	2.08	0.0231	0.35	0.60	0.2254	20	90	2.16	0.0243	0.35	0.60	0.4498
10	20	2.08	0.0231	0.35	0.65	0.3228	20	90	2.16	0.0243	0.35	0.65	0.6276
10	20	2.08	0.0231	0.40	0.55	0.0995	20	90	2.16	0.0243	0.40	0.55	0.1663
10	20	2.08	0.0231	0.40	0.60	0.1588	20	90	2.16	0.0243	0.40	0.60	0.2960
10	30	2.17	0.0176	0.05	0.15	0.0018	20	100	2.24	0.0185	0.05	0.15	0.0239
10	30	2.17	0.0176	0.05	0.20	0.0154	20	100	2.24	0.0185	0.05	0.20	0.1655
10	30	2.17	0.0176	0.05	0.25	0.0642	20	100	2.24	0.0185	0.05	0.25	0.3852
10	30	2.17	0.0176	0.05	0.30	0.1668	20	100	2.24	0.0185	0.05	0.30	0.6101
10	30	2.17	0.0176	0.05	0.35	0.3156	20	100	2.24	0.0185	0.05	0.35	0.7945
10	30	2.17	0.0176	0.05	0.40	0.4811	20	100	2.24	0.0185	0.05	0.40	0.9108
10	30	2.17	0.0176	0.05	0.45	0.6352	20	100	2.24	0.0185	0.05	0.45	0.9687
10	30	2.17	0.0176	0.10	0.25	0.0379	20	100	2.24	0.0185	0.10	0.25	0.1623
10	30	2.17	0.0176	0.10	0.30	0.1007	20	100	2.24	0.0185	0.10	0.30	0.3224
10	30	2.17	0.0176	0.10	0.35	0.1978	20	100	2.24	0.0185	0.10	0.35	0.5154
10	30	2.17	0.0176	0.10	0.40	0.3192	20	100	2.24	0.0185	0.10	0.40	0.7011
10	30	2.17	0.0176	0.10	0.45	0.4533	20	100	2.24	0.0185	0.10	0.45	0.8430
10	30	2.17	0.0176	0.10	0.50	0.5894	20	100	2.24	0.0185	0.10	0.50	0.9306
10	30	2.17	0.0176	0.10	0.55	0.7154	20	100	2.24	0.0185	0.10	0.55	0.9752
10	30	2.17	0.0176	0.10	0.60	0.8199	20	100	2.24	0.0185	0.10	0.60	0.9930
10	30	2.17	0.0176	0.15	0.30	0.0591	20	100	2.24	0.0185	0.15	0.30	0.1518
10	30	2.17	0.0176	0.15	0.35	0.1208	20	100	2.24	0.0185	0.15	0.35	0.2903
10	30	2.17	0.0176	0.15	0.40	0.2064	20	100	2.24	0.0185	0.15	0.40	0.4665
10	30	2.17	0.0176	0.15	0.45	0.3140	20	100	2.24	0.0185	0.15	0.45	0.6458
10	30	2.17	0.0176	0.15	0.50	0.4387	20	100	2.24	0.0185	0.15	0.50	0.7973
10	30	2.17	0.0176	0.15	0.55	0.5696	20	100	2.24	0.0185	0.15	0.55	0.9033
10	30	2.17	0.0176	0.15	0.60	0.6932	20	100	2.24	0.0185	0.15	0.60	0.9620
10	30	2.17	0.0176	0.15	0.65	0.7979	20	100	2.24	0.0185	0.15	0.65	0.9880
10	30	2.17	0.0176	0.20	0.35	0.0717	20	100	2.24	0.0185	0.20	0.35	0.1456
10	30	2.17	0.0176	0.20	0.40	0.1297	20	100	2.24	0.0185	0.20	0.40	0.2735
10	30	2.17	0.0176	0.20	0.45	0.2108	20	100	2.24	0.0185	0.20	0.45	0.4373
10	30	2.17	0.0176	0.20	0.50	0.3146	20	100	2.24	0.0185	0.20	0.50	0.6144
10	30	2.17	0.0176	0.20	0.55	0.4351	20	100	2.24	0.0185	0.20	0.55	0.7729
10	30	2.17	0.0176	0.20	0.60	0.5612	20	100	2.24	0.0185	0.20	0.60	0.8867
10	30	2.17	0.0176	0.20	0.65	0.6806	20	100	2.24	0.0185	0.20	0.65	0.9536
10	30	2.17	0.0176	0.20	0.70	0.7840	20	100	2.24	0.0185	0.20	0.70	0.9855
10	30	2.17	0.0176	0.25	0.40	0.0790	20	100	2.24	0.0185	0.25	0.40	0.1429
10	30	2.17	0.0176	0.25	0.45	0.1367	20	100	2.24	0.0185	0.25	0.45	0.2636
10	30	2.17	0.0176	0.25	0.50	0.2173	20	100	2.24	0.0185	0.25	0.50	0.4246
10	30	2.17	0.0176	0.25	0.55	0.3190	20	100	2.24	0.0185	0.25	0.55	0.6020
10	30	2.17	0.0176	0.25	0.60	0.4352	20	100	2.24	0.0185	0.25	0.60	0.7611
10	30	2.17	0.0176	0.25	0.65	0.5565	20	100	2.24	0.0185	0.25	0.65	0.8804
10	30	2.17	0.0176	0.25	0.70	0.6731	20	100	2.24	0.0185	0.25	0.70	0.9532
10	30	2.17	0.0176	0.25	0.75	0.7771	20	100	2.24	0.0185	0.25	0.75	0.9862
10	30	2.17	0.0176	0.30	0.45	0.0855	20	100	2.24	0.0185	0.30	0.45	0.1421
10	30	2.17	0.0176	0.30	0.50	0.1442	20	100	2.24	0.0185	0.30	0.50	0.2630
10	30	2.17	0.0176	0.30	0.55	0.2242	20	100	2.24	0.0185	0.30	0.55	0.4236
10	30	2.17	0.0176	0.30	0.60	0.3232	20	100	2.24	0.0185	0.30	0.60	0.5996

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	30	2.17	0.0176	0.30	0.65	0.4357	20	100	2.24	0.0185	0.30	0.65	0.7633
10	30	2.17	0.0176	0.30	0.70	0.5545	20	100	2.24	0.0185	0.30	0.70	0.8875
10	30	2.17	0.0176	0.35	0.50	0.0916	20	100	2.24	0.0185	0.35	0.50	0.1458
10	30	2.17	0.0176	0.35	0.55	0.1506	20	100	2.24	0.0185	0.35	0.55	0.2679
10	30	2.17	0.0176	0.35	0.60	0.2293	20	100	2.24	0.0185	0.35	0.60	0.4293
10	30	2.17	0.0176	0.35	0.65	0.3261	20	100	2.24	0.0185	0.35	0.65	0.6125
10	30	2.17	0.0176	0.40	0.55	0.0964	20	100	2.24	0.0185	0.40	0.55	0.1514
10	30	2.17	0.0176	0.40	0.60	0.1549	20	100	2.24	0.0185	0.40	0.60	0.2771
10	40	2.16	0.0246	0.05	0.15	0.0008	30	40	2.10	0.0222	0.05	0.15	0.1760
10	40	2.16	0.0246	0.05	0.20	0.0116	30	40	2.10	0.0222	0.05	0.20	0.3654
10	40	2.16	0.0246	0.05	0.25	0.0623	30	40	2.10	0.0222	0.05	0.25	0.5758
10	40	2.16	0.0246	0.05	0.30	0.1823	30	40	2.10	0.0222	0.05	0.30	0.7568
10	40	2.16	0.0246	0.05	0.35	0.3569	30	40	2.10	0.0222	0.05	0.35	0.8808
10	40	2.16	0.0246	0.05	0.40	0.5388	30	40	2.10	0.0222	0.05	0.40	0.9503
10	40	2.16	0.0246	0.05	0.45	0.6939	30	40	2.10	0.0222	0.05	0.45	0.9827
10	40	2.16	0.0246	0.10	0.25	0.0367	30	40	2.10	0.0222	0.10	0.25	0.2891
10	40	2.16	0.0246	0.10	0.30	0.1092	30	40	2.10	0.0222	0.10	0.30	0.4724
10	40	2.16	0.0246	0.10	0.35	0.2223	30	40	2.10	0.0222	0.10	0.35	0.6549
10	40	2.16	0.0246	0.10	0.40	0.3576	30	40	2.10	0.0222	0.10	0.40	0.8039
10	40	2.16	0.0246	0.10	0.45	0.4991	30	40	2.10	0.0222	0.10	0.45	0.9041
10	40	2.16	0.0246	0.10	0.50	0.6333	30	40	2.10	0.0222	0.10	0.50	0.9598
10	40	2.16	0.0246	0.10	0.55	0.7494	30	40	2.10	0.0222	0.10	0.55	0.9857
10	40	2.16	0.0246	0.10	0.60	0.8431	30	40	2.10	0.0222	0.10	0.60	0.9957
10	40	2.16	0.0246	0.15	0.30	0.0636	30	40	2.10	0.0222	0.15	0.30	0.2524
10	40	2.16	0.0246	0.15	0.35	0.1347	30	40	2.10	0.0222	0.15	0.35	0.4187
10	40	2.16	0.0246	0.15	0.40	0.2302	30	40	2.10	0.0222	0.15	0.40	0.5954
10	40	2.16	0.0246	0.15	0.45	0.3448	30	40	2.10	0.0222	0.15	0.45	0.7500
10	40	2.16	0.0246	0.15	0.50	0.4696	30	40	2.10	0.0222	0.15	0.50	0.8639
10	40	2.16	0.0246	0.15	0.55	0.5951	30	40	2.10	0.0222	0.15	0.55	0.9358
10	40	2.16	0.0246	0.15	0.60	0.7154	30	40	2.10	0.0222	0.15	0.60	0.9745
10	40	2.16	0.0246	0.15	0.65	0.8216	30	40	2.10	0.0222	0.15	0.65	0.9918
10	40	2.16	0.0246	0.20	0.35	0.0791	30	40	2.10	0.0222	0.20	0.35	0.2329
10	40	2.16	0.0246	0.20	0.40	0.1434	30	40	2.10	0.0222	0.20	0.40	0.3840
10	40	2.16	0.0246	0.20	0.45	0.2290	30	40	2.10	0.0222	0.20	0.45	0.5495
10	40	2.16	0.0246	0.20	0.50	0.3328	30	40	2.10	0.0222	0.20	0.50	0.7047
10	40	2.16	0.0246	0.20	0.55	0.4513	30	40	2.10	0.0222	0.20	0.55	0.8303
10	40	2.16	0.0246	0.20	0.60	0.5807	30	40	2.10	0.0222	0.20	0.60	0.9169
10	40	2.16	0.0246	0.20	0.65	0.7092	30	40	2.10	0.0222	0.20	0.65	0.9664
10	40	2.16	0.0246	0.20	0.70	0.8179	30	40	2.10	0.0222	0.20	0.70	0.9893
10	40	2.16	0.0246	0.25	0.40	0.0861	30	40	2.10	0.0222	0.25	0.40	0.2157
10	40	2.16	0.0246	0.25	0.45	0.1460	30	40	2.10	0.0222	0.25	0.45	0.3539
10	40	2.16	0.0246	0.25	0.50	0.2259	30	40	2.10	0.0222	0.25	0.50	0.5143
10	40	2.16	0.0246	0.25	0.55	0.3277	30	40	2.10	0.0222	0.25	0.55	0.6747
10	40	2.16	0.0246	0.25	0.60	0.4518	30	40	2.10	0.0222	0.25	0.60	0.8110
10	40	2.16	0.0246	0.25	0.65	0.5872	30	40	2.10	0.0222	0.25	0.65	0.9074
10	40	2.16	0.0246	0.25	0.70	0.7137	30	40	2.10	0.0222	0.25	0.70	0.9630
10	40	2.16	0.0246	0.25	0.75	0.8168	30	40	2.10	0.0222	0.25	0.75	0.9885
10	40	2.16	0.0246	0.30	0.45	0.0892	30	40	2.10	0.0222	0.30	0.45	0.2008
10	40	2.16	0.0246	0.30	0.50	0.1468	30	40	2.10	0.0222	0.30	0.50	0.3346
10	40	2.16	0.0246	0.30	0.55	0.2280	30	40	2.10	0.0222	0.30	0.55	0.4963

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	40	2.16	0.0246	0.30	0.60	0.3367	30	40	2.10	0.0222	0.30	0.60	0.6621
10	40	2.16	0.0246	0.30	0.65	0.4656	30	40	2.10	0.0222	0.30	0.65	0.8044
10	40	2.16	0.0246	0.30	0.70	0.5973	30	40	2.10	0.0222	0.30	0.70	0.9055
10	40	2.16	0.0246	0.35	0.50	0.0911	30	40	2.10	0.0222	0.35	0.50	0.1938
10	40	2.16	0.0246	0.35	0.55	0.1518	30	40	2.10	0.0222	0.35	0.55	0.3280
10	40	2.16	0.0246	0.35	0.60	0.2400	30	40	2.10	0.0222	0.35	0.60	0.4920
10	40	2.16	0.0246	0.35	0.65	0.3527	30	40	2.10	0.0222	0.35	0.65	0.6610
10	40	2.16	0.0246	0.40	0.55	0.0963	30	40	2.10	0.0222	0.40	0.55	0.1932
10	40	2.16	0.0246	0.40	0.60	0.1629	30	40	2.10	0.0222	0.40	0.60	0.3289
10	50	2.39	0.0166	0.05	0.15	0.0000	30	50	2.02	0.0237	0.05	0.15	0.2164
10	50	2.39	0.0166	0.05	0.20	0.0006	30	50	2.02	0.0237	0.05	0.20	0.4375
10	50	2.39	0.0166	0.05	0.25	0.0083	30	50	2.02	0.0237	0.05	0.25	0.6570
10	50	2.39	0.0166	0.05	0.30	0.0511	30	50	2.02	0.0237	0.05	0.30	0.8260
10	50	2.39	0.0166	0.05	0.35	0.1670	30	50	2.02	0.0237	0.05	0.35	0.9273
10	50	2.39	0.0166	0.05	0.40	0.3496	30	50	2.02	0.0237	0.05	0.40	0.9746
10	50	2.39	0.0166	0.05	0.45	0.5434	30	50	2.02	0.0237	0.05	0.45	0.9925
10	50	2.39	0.0166	0.10	0.25	0.0049	30	50	2.02	0.0237	0.10	0.25	0.3495
10	50	2.39	0.0166	0.10	0.30	0.0299	30	50	2.02	0.0237	0.10	0.30	0.5515
10	50	2.39	0.0166	0.10	0.35	0.0993	30	50	2.02	0.0237	0.10	0.35	0.7303
10	50	2.39	0.0166	0.10	0.40	0.2155	30	50	2.02	0.0237	0.10	0.40	0.8581
10	50	2.39	0.0166	0.10	0.45	0.3583	30	50	2.02	0.0237	0.10	0.45	0.9359
10	50	2.39	0.0166	0.10	0.50	0.5116	30	50	2.02	0.0237	0.10	0.50	0.9763
10	50	2.39	0.0166	0.10	0.55	0.6615	30	50	2.02	0.0237	0.10	0.55	0.9931
10	50	2.39	0.0166	0.10	0.60	0.7898	30	50	2.02	0.0237	0.10	0.60	0.9985
10	50	2.39	0.0166	0.15	0.30	0.0170	30	50	2.02	0.0237	0.15	0.30	0.3054
10	50	2.39	0.0166	0.15	0.35	0.0574	30	50	2.02	0.0237	0.15	0.35	0.4805
10	50	2.39	0.0166	0.15	0.40	0.1293	30	50	2.02	0.0237	0.15	0.40	0.6545
10	50	2.39	0.0166	0.15	0.45	0.2296	30	50	2.02	0.0237	0.15	0.45	0.8026
10	50	2.39	0.0166	0.15	0.50	0.3562	30	50	2.02	0.0237	0.15	0.50	0.9062
10	50	2.39	0.0166	0.15	0.55	0.5007	30	50	2.02	0.0237	0.15	0.55	0.9635
10	50	2.39	0.0166	0.15	0.60	0.6459	30	50	2.02	0.0237	0.15	0.60	0.9884
10	50	2.39	0.0166	0.15	0.65	0.7753	30	50	2.02	0.0237	0.15	0.65	0.9970
10	50	2.39	0.0166	0.20	0.35	0.0321	30	50	2.02	0.0237	0.20	0.35	0.2686
10	50	2.39	0.0166	0.20	0.40	0.0752	30	50	2.02	0.0237	0.20	0.40	0.4337
10	50	2.39	0.0166	0.20	0.45	0.1425	30	50	2.02	0.0237	0.20	0.45	0.6151
10	50	2.39	0.0166	0.20	0.50	0.2388	30	50	2.02	0.0237	0.20	0.50	0.7754
10	50	2.39	0.0166	0.20	0.55	0.3624	30	50	2.02	0.0237	0.20	0.55	0.8883
10	50	2.39	0.0166	0.20	0.60	0.5040	30	50	2.02	0.0237	0.20	0.60	0.9533
10	50	2.39	0.0166	0.20	0.65	0.6491	30	50	2.02	0.0237	0.20	0.65	0.9841
10	50	2.39	0.0166	0.20	0.70	0.7786	30	50	2.02	0.0237	0.20	0.70	0.9958
10	50	2.39	0.0166	0.25	0.40	0.0423	30	50	2.02	0.0237	0.25	0.40	0.2523
10	50	2.39	0.0166	0.25	0.45	0.0855	30	50	2.02	0.0237	0.25	0.45	0.4179
10	50	2.39	0.0166	0.25	0.50	0.1539	30	50	2.02	0.0237	0.25	0.50	0.5977
10	50	2.39	0.0166	0.25	0.55	0.2512	30	50	2.02	0.0237	0.25	0.55	0.7568
10	50	2.39	0.0166	0.25	0.60	0.3760	30	50	2.02	0.0237	0.25	0.60	0.8743
10	50	2.39	0.0166	0.25	0.65	0.5198	30	50	2.02	0.0237	0.25	0.65	0.9462
10	50	2.39	0.0166	0.25	0.70	0.6645	30	50	2.02	0.0237	0.25	0.70	0.9816
10	50	2.39	0.0166	0.25	0.75	0.7896	30	50	2.02	0.0237	0.25	0.75	0.9952
10	50	2.39	0.0166	0.30	0.45	0.0493	30	50	2.02	0.0237	0.30	0.45	0.2498
10	50	2.39	0.0166	0.30	0.50	0.0951	30	50	2.02	0.0237	0.30	0.50	0.4090

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	50	2.39	0.0166	0.30	0.55	0.1667	30	50	2.02	0.0237	0.30	0.55	0.5835
10	50	2.39	0.0166	0.30	0.60	0.2683	30	50	2.02	0.0237	0.30	0.60	0.7444
10	50	2.39	0.0166	0.30	0.65	0.3981	30	50	2.02	0.0237	0.30	0.65	0.8671
10	50	2.39	0.0166	0.30	0.70	0.5432	30	50	2.02	0.0237	0.30	0.70	0.9432
10	50	2.39	0.0166	0.35	0.50	0.0561	30	50	2.02	0.0237	0.35	0.50	0.2463
10	50	2.39	0.0166	0.35	0.55	0.1056	30	50	2.02	0.0237	0.35	0.55	0.4017
10	50	2.39	0.0166	0.35	0.60	0.1827	30	50	2.02	0.0237	0.35	0.60	0.5766
10	50	2.39	0.0166	0.35	0.65	0.2910	30	50	2.02	0.0237	0.35	0.65	0.7400
10	50	2.39	0.0166	0.40	0.55	0.0636	30	50	2.02	0.0237	0.40	0.55	0.2442
10	50	2.39	0.0166	0.40	0.60	0.1184	30	50	2.02	0.0237	0.40	0.60	0.3997
10	60	2.08	0.0249	0.05	0.15	0.0005	30	60	2.01	0.0250	0.05	0.15	0.2183
10	60	2.08	0.0249	0.05	0.20	0.0132	30	60	2.01	0.0250	0.05	0.20	0.4465
10	60	2.08	0.0249	0.05	0.25	0.0892	30	60	2.01	0.0250	0.05	0.25	0.6767
10	60	2.08	0.0249	0.05	0.30	0.2646	30	60	2.01	0.0250	0.05	0.30	0.8461
10	60	2.08	0.0249	0.05	0.35	0.4701	30	60	2.01	0.0250	0.05	0.35	0.9409
10	60	2.08	0.0249	0.05	0.40	0.6361	30	60	2.01	0.0250	0.05	0.40	0.9818
10	60	2.08	0.0249	0.05	0.45	0.7679	30	60	2.01	0.0250	0.05	0.45	0.9955
10	60	2.08	0.0249	0.10	0.25	0.0520	30	60	2.01	0.0250	0.10	0.25	0.3587
10	60	2.08	0.0249	0.10	0.30	0.1562	30	60	2.01	0.0250	0.10	0.30	0.5708
10	60	2.08	0.0249	0.10	0.35	0.2881	30	60	2.01	0.0250	0.10	0.35	0.7573
10	60	2.08	0.0249	0.10	0.40	0.4231	30	60	2.01	0.0250	0.10	0.40	0.8842
10	60	2.08	0.0249	0.10	0.45	0.5663	30	60	2.01	0.0250	0.10	0.45	0.9534
10	60	2.08	0.0249	0.10	0.50	0.7009	30	60	2.01	0.0250	0.10	0.50	0.9843
10	60	2.08	0.0249	0.10	0.55	0.8098	30	60	2.01	0.0250	0.10	0.55	0.9957
10	60	2.08	0.0249	0.10	0.60	0.8931	30	60	2.01	0.0250	0.10	0.60	0.9991
10	60	2.08	0.0249	0.15	0.30	0.0895	30	60	2.01	0.0250	0.15	0.30	0.3187
10	60	2.08	0.0249	0.15	0.35	0.1718	30	60	2.01	0.0250	0.15	0.35	0.5113
10	60	2.08	0.0249	0.15	0.40	0.2727	30	60	2.01	0.0250	0.15	0.40	0.6934
10	60	2.08	0.0249	0.15	0.45	0.3983	30	60	2.01	0.0250	0.15	0.45	0.8337
10	60	2.08	0.0249	0.15	0.50	0.5327	30	60	2.01	0.0250	0.15	0.50	0.9235
10	60	2.08	0.0249	0.15	0.55	0.6624	30	60	2.01	0.0250	0.15	0.55	0.9711
10	60	2.08	0.0249	0.15	0.60	0.7822	30	60	2.01	0.0250	0.15	0.60	0.9914
10	60	2.08	0.0249	0.15	0.65	0.8777	30	60	2.01	0.0250	0.15	0.65	0.9981
10	60	2.08	0.0249	0.20	0.35	0.0993	30	60	2.01	0.0250	0.20	0.35	0.2914
10	60	2.08	0.0249	0.20	0.40	0.1697	30	60	2.01	0.0250	0.20	0.40	0.4657
10	60	2.08	0.0249	0.20	0.45	0.2678	30	60	2.01	0.0250	0.20	0.45	0.6431
10	60	2.08	0.0249	0.20	0.50	0.3846	30	60	2.01	0.0250	0.20	0.50	0.7945
10	60	2.08	0.0249	0.20	0.55	0.5148	30	60	2.01	0.0250	0.20	0.55	0.9014
10	60	2.08	0.0249	0.20	0.60	0.6531	30	60	2.01	0.0250	0.20	0.60	0.9618
10	60	2.08	0.0249	0.20	0.65	0.7789	30	60	2.01	0.0250	0.20	0.65	0.9883
10	60	2.08	0.0249	0.20	0.70	0.8745	30	60	2.01	0.0250	0.20	0.70	0.9972
10	60	2.08	0.0249	0.25	0.40	0.1018	30	60	2.01	0.0250	0.25	0.40	0.2678
10	60	2.08	0.0249	0.25	0.45	0.1722	30	60	2.01	0.0250	0.25	0.45	0.4322
10	60	2.08	0.0249	0.25	0.50	0.2646	30	60	2.01	0.0250	0.25	0.50	0.6119
10	60	2.08	0.0249	0.25	0.55	0.3815	30	60	2.01	0.0250	0.25	0.55	0.7736
10	60	2.08	0.0249	0.25	0.60	0.5205	30	60	2.01	0.0250	0.25	0.60	0.8900
10	60	2.08	0.0249	0.25	0.65	0.6620	30	60	2.01	0.0250	0.25	0.65	0.9565
10	60	2.08	0.0249	0.25	0.70	0.7843	30	60	2.01	0.0250	0.25	0.70	0.9865
10	60	2.08	0.0249	0.25	0.75	0.8762	30	60	2.01	0.0250	0.25	0.75	0.9969
10	60	2.08	0.0249	0.30	0.45	0.1056	30	60	2.01	0.0250	0.30	0.45	0.2524

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	60	2.08	0.0249	0.30	0.50	0.1735	30	60	2.01	0.0250	0.30	0.50	0.4165
10	60	2.08	0.0249	0.30	0.55	0.2696	30	60	2.01	0.0250	0.30	0.55	0.5999
10	60	2.08	0.0249	0.30	0.60	0.3957	30	60	2.01	0.0250	0.30	0.60	0.7650
10	60	2.08	0.0249	0.30	0.65	0.5379	30	60	2.01	0.0250	0.30	0.65	0.8848
10	60	2.08	0.0249	0.30	0.70	0.6757	30	60	2.01	0.0250	0.30	0.70	0.9548
10	60	2.08	0.0249	0.35	0.50	0.1083	30	60	2.01	0.0250	0.35	0.50	0.2486
10	60	2.08	0.0249	0.35	0.55	0.1814	30	60	2.01	0.0250	0.35	0.55	0.4136
10	60	2.08	0.0249	0.35	0.60	0.2866	30	60	2.01	0.0250	0.35	0.60	0.5968
10	60	2.08	0.0249	0.35	0.65	0.4170	30	60	2.01	0.0250	0.35	0.65	0.7633
10	60	2.08	0.0249	0.40	0.55	0.1159	30	60	2.01	0.0250	0.40	0.55	0.2502
10	60	2.08	0.0249	0.40	0.60	0.1972	30	60	2.01	0.0250	0.40	0.60	0.4150
10	70	2.67	0.0163	0.05	0.15	0.0000	30	70	2.10	0.0226	0.05	0.15	0.1894
10	70	2.67	0.0163	0.05	0.20	0.0000	30	70	2.10	0.0226	0.05	0.20	0.4244
10	70	2.67	0.0163	0.05	0.25	0.0002	30	70	2.10	0.0226	0.05	0.25	0.6612
10	70	2.67	0.0163	0.05	0.30	0.0048	30	70	2.10	0.0226	0.05	0.30	0.8395
10	70	2.67	0.0163	0.05	0.35	0.0408	30	70	2.10	0.0226	0.05	0.35	0.9398
10	70	2.67	0.0163	0.05	0.40	0.1631	30	70	2.10	0.0226	0.05	0.40	0.9820
10	70	2.67	0.0163	0.05	0.45	0.3700	30	70	2.10	0.0226	0.05	0.45	0.9957
10	70	2.67	0.0163	0.10	0.25	0.0001	30	70	2.10	0.0226	0.10	0.25	0.3339
10	70	2.67	0.0163	0.10	0.30	0.0028	30	70	2.10	0.0226	0.10	0.30	0.5494
10	70	2.67	0.0163	0.10	0.35	0.0238	30	70	2.10	0.0226	0.10	0.35	0.7437
10	70	2.67	0.0163	0.10	0.40	0.0961	30	70	2.10	0.0226	0.10	0.40	0.8782
10	70	2.67	0.0163	0.10	0.45	0.2250	30	70	2.10	0.0226	0.10	0.45	0.9525
10	70	2.67	0.0163	0.10	0.50	0.3787	30	70	2.10	0.0226	0.10	0.50	0.9852
10	70	2.67	0.0163	0.10	0.55	0.5422	30	70	2.10	0.0226	0.10	0.55	0.9964
10	70	2.67	0.0163	0.10	0.60	0.6984	30	70	2.10	0.0226	0.10	0.60	0.9993
10	70	2.67	0.0163	0.15	0.30	0.0016	30	70	2.10	0.0226	0.15	0.30	0.2930
10	70	2.67	0.0163	0.15	0.35	0.0135	30	70	2.10	0.0226	0.15	0.35	0.4864
10	70	2.67	0.0163	0.15	0.40	0.0550	30	70	2.10	0.0226	0.15	0.40	0.6778
10	70	2.67	0.0163	0.15	0.45	0.1331	30	70	2.10	0.0226	0.15	0.45	0.8303
10	70	2.67	0.0163	0.15	0.50	0.2407	30	70	2.10	0.0226	0.15	0.50	0.9268
10	70	2.67	0.0163	0.15	0.55	0.3784	30	70	2.10	0.0226	0.15	0.55	0.9745
10	70	2.67	0.0163	0.15	0.60	0.5323	30	70	2.10	0.0226	0.15	0.60	0.9929
10	70	2.67	0.0163	0.15	0.65	0.6828	30	70	2.10	0.0226	0.15	0.65	0.9985
10	70	2.67	0.0163	0.20	0.35	0.0074	30	70	2.10	0.0226	0.20	0.35	0.2667
10	70	2.67	0.0163	0.20	0.40	0.0304	30	70	2.10	0.0226	0.20	0.40	0.4465
10	70	2.67	0.0163	0.20	0.45	0.0764	30	70	2.10	0.0226	0.20	0.45	0.6382
10	70	2.67	0.0163	0.20	0.50	0.1481	30	70	2.10	0.0226	0.20	0.50	0.7999
10	70	2.67	0.0163	0.20	0.55	0.2530	30	70	2.10	0.0226	0.20	0.55	0.9078
10	70	2.67	0.0163	0.20	0.60	0.3860	30	70	2.10	0.0226	0.20	0.60	0.9653
10	70	2.67	0.0163	0.20	0.65	0.5384	30	70	2.10	0.0226	0.20	0.65	0.9897
10	70	2.67	0.0163	0.20	0.70	0.6973	30	70	2.10	0.0226	0.20	0.70	0.9977
10	70	2.67	0.0163	0.25	0.40	0.0162	30	70	2.10	0.0226	0.25	0.40	0.2520
10	70	2.67	0.0163	0.25	0.45	0.0423	30	70	2.10	0.0226	0.25	0.45	0.4266
10	70	2.67	0.0163	0.25	0.50	0.0878	30	70	2.10	0.0226	0.25	0.50	0.6155
10	70	2.67	0.0163	0.25	0.55	0.1621	30	70	2.10	0.0226	0.25	0.55	0.7792
10	70	2.67	0.0163	0.25	0.60	0.2670	30	70	2.10	0.0226	0.25	0.60	0.8944
10	70	2.67	0.0163	0.25	0.65	0.4050	30	70	2.10	0.0226	0.25	0.65	0.9592
10	70	2.67	0.0163	0.25	0.70	0.5688	30	70	2.10	0.0226	0.25	0.70	0.9876
10	70	2.67	0.0163	0.25	0.75	0.7274	30	70	2.10	0.0226	0.25	0.75	0.9972

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	70	2.67	0.0163	0.30	0.45	0.0225	30	70	2.10	0.0226	0.30	0.45	0.2465
10	70	2.67	0.0163	0.30	0.50	0.0500	30	70	2.10	0.0226	0.30	0.50	0.4151
10	70	2.67	0.0163	0.30	0.55	0.0992	30	70	2.10	0.0226	0.30	0.55	0.6006
10	70	2.67	0.0163	0.30	0.60	0.1763	30	70	2.10	0.0226	0.30	0.60	0.7673
10	70	2.67	0.0163	0.30	0.65	0.2908	30	70	2.10	0.0226	0.30	0.65	0.8875
10	70	2.67	0.0163	0.30	0.70	0.4431	30	70	2.10	0.0226	0.30	0.70	0.9560
10	70	2.67	0.0163	0.35	0.50	0.0272	30	70	2.10	0.0226	0.35	0.50	0.2429
10	70	2.67	0.0163	0.35	0.55	0.0578	30	70	2.10	0.0226	0.35	0.55	0.4083
10	70	2.67	0.0163	0.35	0.60	0.1108	30	70	2.10	0.0226	0.35	0.60	0.5943
10	70	2.67	0.0163	0.35	0.65	0.1989	30	70	2.10	0.0226	0.35	0.65	0.7626
10	70	2.67	0.0163	0.40	0.55	0.0319	30	70	2.10	0.0226	0.40	0.55	0.2417
10	70	2.67	0.0163	0.40	0.60	0.0661	30	70	2.10	0.0226	0.40	0.60	0.4072
10	80	2.24	0.0239	0.05	0.15	0.0000	30	80	2.12	0.0232	0.05	0.15	0.1939
10	80	2.24	0.0239	0.05	0.20	0.0008	30	80	2.12	0.0232	0.05	0.20	0.4321
10	80	2.24	0.0239	0.05	0.25	0.0177	30	80	2.12	0.0232	0.05	0.25	0.6765
10	80	2.24	0.0239	0.05	0.30	0.1172	30	80	2.12	0.0232	0.05	0.30	0.8502
10	80	2.24	0.0239	0.05	0.35	0.3290	30	80	2.12	0.0232	0.05	0.35	0.9432
10	80	2.24	0.0239	0.05	0.40	0.5410	30	80	2.12	0.0232	0.05	0.40	0.9828
10	80	2.24	0.0239	0.05	0.45	0.6994	30	80	2.12	0.0232	0.05	0.45	0.9960
10	80	2.24	0.0239	0.10	0.25	0.0103	30	80	2.12	0.0232	0.10	0.25	0.3387
10	80	2.24	0.0239	0.10	0.30	0.0684	30	80	2.12	0.0232	0.10	0.30	0.5475
10	80	2.24	0.0239	0.10	0.35	0.1945	30	80	2.12	0.0232	0.10	0.35	0.7377
10	80	2.24	0.0239	0.10	0.40	0.3367	30	80	2.12	0.0232	0.10	0.40	0.8762
10	80	2.24	0.0239	0.10	0.45	0.4846	30	80	2.12	0.0232	0.10	0.45	0.9538
10	80	2.24	0.0239	0.10	0.50	0.6448	30	80	2.12	0.0232	0.10	0.50	0.9864
10	80	2.24	0.0239	0.10	0.55	0.7805	30	80	2.12	0.0232	0.10	0.55	0.9968
10	80	2.24	0.0239	0.10	0.60	0.8777	30	80	2.12	0.0232	0.10	0.60	0.9994
10	80	2.24	0.0239	0.15	0.30	0.0387	30	80	2.12	0.0232	0.15	0.30	0.2814
10	80	2.24	0.0239	0.15	0.35	0.1116	30	80	2.12	0.0232	0.15	0.35	0.4720
10	80	2.24	0.0239	0.15	0.40	0.2038	30	80	2.12	0.0232	0.15	0.40	0.6712
10	80	2.24	0.0239	0.15	0.45	0.3236	30	80	2.12	0.0232	0.15	0.45	0.8302
10	80	2.24	0.0239	0.15	0.50	0.4740	30	80	2.12	0.0232	0.15	0.50	0.9280
10	80	2.24	0.0239	0.15	0.55	0.6231	30	80	2.12	0.0232	0.15	0.55	0.9754
10	80	2.24	0.0239	0.15	0.60	0.7528	30	80	2.12	0.0232	0.15	0.60	0.9935
10	80	2.24	0.0239	0.15	0.65	0.8511	30	80	2.12	0.0232	0.15	0.65	0.9987
10	80	2.24	0.0239	0.20	0.35	0.0620	30	80	2.12	0.0232	0.20	0.35	0.2522
10	80	2.24	0.0239	0.20	0.40	0.1197	30	80	2.12	0.0232	0.20	0.40	0.4361
10	80	2.24	0.0239	0.20	0.45	0.2080	30	80	2.12	0.0232	0.20	0.45	0.6326
10	80	2.24	0.0239	0.20	0.50	0.3314	30	80	2.12	0.0232	0.20	0.50	0.7972
10	80	2.24	0.0239	0.20	0.55	0.4711	30	80	2.12	0.0232	0.20	0.55	0.9081
10	80	2.24	0.0239	0.20	0.60	0.6113	30	80	2.12	0.0232	0.20	0.60	0.9670
10	80	2.24	0.0239	0.20	0.65	0.7350	30	80	2.12	0.0232	0.20	0.65	0.9908
10	80	2.24	0.0239	0.20	0.70	0.8412	30	80	2.12	0.0232	0.20	0.70	0.9981
10	80	2.24	0.0239	0.25	0.40	0.0678	30	80	2.12	0.0232	0.25	0.40	0.2408
10	80	2.24	0.0239	0.25	0.45	0.1283	30	80	2.12	0.0232	0.25	0.45	0.4152
10	80	2.24	0.0239	0.25	0.50	0.2208	30	80	2.12	0.0232	0.25	0.50	0.6070
10	80	2.24	0.0239	0.25	0.55	0.3383	30	80	2.12	0.0232	0.25	0.55	0.7777
10	80	2.24	0.0239	0.25	0.60	0.4709	30	80	2.12	0.0232	0.25	0.60	0.8971
10	80	2.24	0.0239	0.25	0.65	0.6043	30	80	2.12	0.0232	0.25	0.65	0.9619
10	80	2.24	0.0239	0.25	0.70	0.7369	30	80	2.12	0.0232	0.25	0.70	0.9893

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	80	2.24	0.0239	0.25	0.75	0.8522	30	80	2.12	0.0232	0.25	0.75	0.9979
10	80	2.24	0.0239	0.30	0.45	0.0758	30	80	2.12	0.0232	0.30	0.45	0.2337
10	80	2.24	0.0239	0.30	0.50	0.1402	30	80	2.12	0.0232	0.30	0.50	0.4033
10	80	2.24	0.0239	0.30	0.55	0.2310	30	80	2.12	0.0232	0.30	0.55	0.5965
10	80	2.24	0.0239	0.30	0.60	0.3441	30	80	2.12	0.0232	0.30	0.60	0.7695
10	80	2.24	0.0239	0.30	0.65	0.4728	30	80	2.12	0.0232	0.30	0.65	0.8922
10	80	2.24	0.0239	0.30	0.70	0.6180	30	80	2.12	0.0232	0.30	0.70	0.9613
10	80	2.24	0.0239	0.35	0.50	0.0845	30	80	2.12	0.0232	0.35	0.50	0.2319
10	80	2.24	0.0239	0.35	0.55	0.1495	30	80	2.12	0.0232	0.35	0.55	0.4021
10	80	2.24	0.0239	0.35	0.60	0.2384	30	80	2.12	0.0232	0.35	0.60	0.5943
10	80	2.24	0.0239	0.35	0.65	0.3515	30	80	2.12	0.0232	0.35	0.65	0.7697
10	80	2.24	0.0239	0.40	0.55	0.0915	30	80	2.12	0.0232	0.40	0.55	0.2349
10	80	2.24	0.0239	0.40	0.60	0.1560	30	80	2.12	0.0232	0.40	0.60	0.4050
10	90	3.02	0.0099	0.05	0.15	0.0000	30	90	2.08	0.0243	0.05	0.15	0.1977
10	90	3.02	0.0099	0.05	0.20	0.0000	30	90	2.08	0.0243	0.05	0.20	0.4396
10	90	3.02	0.0099	0.05	0.25	0.0000	30	90	2.08	0.0243	0.05	0.25	0.6996
10	90	3.02	0.0099	0.05	0.30	0.0000	30	90	2.08	0.0243	0.05	0.30	0.8755
10	90	3.02	0.0099	0.05	0.35	0.0007	30	90	2.08	0.0243	0.05	0.35	0.9590
10	90	3.02	0.0099	0.05	0.40	0.0128	30	90	2.08	0.0243	0.05	0.40	0.9892
10	90	3.02	0.0099	0.05	0.45	0.0872	30	90	2.08	0.0243	0.05	0.45	0.9978
10	90	3.02	0.0099	0.10	0.25	0.0000	30	90	2.08	0.0243	0.10	0.25	0.3653
10	90	3.02	0.0099	0.10	0.30	0.0000	30	90	2.08	0.0243	0.10	0.30	0.5927
10	90	3.02	0.0099	0.10	0.35	0.0004	30	90	2.08	0.0243	0.10	0.35	0.7817
10	90	3.02	0.0099	0.10	0.40	0.0074	30	90	2.08	0.0243	0.10	0.40	0.9045
10	90	3.02	0.0099	0.10	0.45	0.0511	30	90	2.08	0.0243	0.10	0.45	0.9667
10	90	3.02	0.0099	0.10	0.50	0.1684	30	90	2.08	0.0243	0.10	0.50	0.9908
10	90	3.02	0.0099	0.10	0.55	0.3366	30	90	2.08	0.0243	0.10	0.55	0.9981
10	90	3.02	0.0099	0.10	0.60	0.5249	30	90	2.08	0.0243	0.10	0.60	0.9997
10	90	3.02	0.0099	0.15	0.30	0.0000	30	90	2.08	0.0243	0.15	0.30	0.3196
10	90	3.02	0.0099	0.15	0.35	0.0002	30	90	2.08	0.0243	0.15	0.35	0.5217
10	90	3.02	0.0099	0.15	0.40	0.0042	30	90	2.08	0.0243	0.15	0.40	0.7157
10	90	3.02	0.0099	0.15	0.45	0.0290	30	90	2.08	0.0243	0.15	0.45	0.8599
10	90	3.02	0.0099	0.15	0.50	0.0980	30	90	2.08	0.0243	0.15	0.50	0.9439
10	90	3.02	0.0099	0.15	0.55	0.2095	30	90	2.08	0.0243	0.15	0.55	0.9825
10	90	3.02	0.0099	0.15	0.60	0.3642	30	90	2.08	0.0243	0.15	0.60	0.9959
10	90	3.02	0.0099	0.15	0.65	0.5507	30	90	2.08	0.0243	0.15	0.65	0.9993
10	90	3.02	0.0099	0.20	0.35	0.0001	30	90	2.08	0.0243	0.20	0.35	0.2884
10	90	3.02	0.0099	0.20	0.40	0.0023	30	90	2.08	0.0243	0.20	0.40	0.4789
10	90	3.02	0.0099	0.20	0.45	0.0160	30	90	2.08	0.0243	0.20	0.45	0.6719
10	90	3.02	0.0099	0.20	0.50	0.0552	30	90	2.08	0.0243	0.20	0.50	0.8280
10	90	3.02	0.0099	0.20	0.55	0.1264	30	90	2.08	0.0243	0.20	0.55	0.9277
10	90	3.02	0.0099	0.20	0.60	0.2429	30	90	2.08	0.0243	0.20	0.60	0.9760
10	90	3.02	0.0099	0.20	0.65	0.4048	30	90	2.08	0.0243	0.20	0.65	0.9938
10	90	3.02	0.0099	0.20	0.70	0.5825	30	90	2.08	0.0243	0.20	0.70	0.9988
10	90	3.02	0.0099	0.25	0.40	0.0012	30	90	2.08	0.0243	0.25	0.40	0.2706
10	90	3.02	0.0099	0.25	0.45	0.0084	30	90	2.08	0.0243	0.25	0.45	0.4522
10	90	3.02	0.0099	0.25	0.50	0.0300	30	90	2.08	0.0243	0.25	0.50	0.6470
10	90	3.02	0.0099	0.25	0.55	0.0737	30	90	2.08	0.0243	0.25	0.55	0.8113
10	90	3.02	0.0099	0.25	0.60	0.1554	30	90	2.08	0.0243	0.25	0.60	0.9179
10	90	3.02	0.0099	0.25	0.65	0.2836	30	90	2.08	0.0243	0.25	0.65	0.9714

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	90	3.02	0.0099	0.25	0.70	0.4452	30	90	2.08	0.0243	0.25	0.70	0.9924
10	90	3.02	0.0099	0.25	0.75	0.6174	30	90	2.08	0.0243	0.25	0.75	0.9986
10	90	3.02	0.0099	0.30	0.45	0.0043	30	90	2.08	0.0243	0.30	0.45	0.2605
10	90	3.02	0.0099	0.30	0.50	0.0157	30	90	2.08	0.0243	0.30	0.50	0.4416
10	90	3.02	0.0099	0.30	0.55	0.0413	30	90	2.08	0.0243	0.30	0.55	0.6375
10	90	3.02	0.0099	0.30	0.60	0.0952	30	90	2.08	0.0243	0.30	0.60	0.8025
10	90	3.02	0.0099	0.30	0.65	0.1894	30	90	2.08	0.0243	0.30	0.65	0.9119
10	90	3.02	0.0099	0.30	0.70	0.3235	30	90	2.08	0.0243	0.30	0.70	0.9694
10	90	3.02	0.0099	0.35	0.50	0.0078	30	90	2.08	0.0243	0.35	0.50	0.2601
10	90	3.02	0.0099	0.35	0.55	0.0222	30	90	2.08	0.0243	0.35	0.55	0.4401
10	90	3.02	0.0099	0.35	0.60	0.0556	30	90	2.08	0.0243	0.35	0.60	0.6332
10	90	3.02	0.0099	0.35	0.65	0.1203	30	90	2.08	0.0243	0.35	0.65	0.7987
10	90	3.02	0.0099	0.40	0.55	0.0113	30	90	2.08	0.0243	0.40	0.55	0.2626
10	90	3.02	0.0099	0.40	0.60	0.0308	30	90	2.08	0.0243	0.40	0.60	0.4404
10	100	3.18	0.0086	0.05	0.15	0.0000	30	100	2.10	0.0206	0.05	0.15	0.1778
10	100	3.18	0.0086	0.05	0.20	0.0000	30	100	2.10	0.0206	0.05	0.20	0.4241
10	100	3.18	0.0086	0.05	0.25	0.0000	30	100	2.10	0.0206	0.05	0.25	0.6862
10	100	3.18	0.0086	0.05	0.30	0.0000	30	100	2.10	0.0206	0.05	0.30	0.8696
10	100	3.18	0.0086	0.05	0.35	0.0001	30	100	2.10	0.0206	0.05	0.35	0.9571
10	100	3.18	0.0086	0.05	0.40	0.0035	30	100	2.10	0.0206	0.05	0.40	0.9887
10	100	3.18	0.0086	0.05	0.45	0.0397	30	100	2.10	0.0206	0.05	0.45	0.9978
10	100	3.18	0.0086	0.10	0.25	0.0000	30	100	2.10	0.0206	0.10	0.25	0.3463
10	100	3.18	0.0086	0.10	0.30	0.0000	30	100	2.10	0.0206	0.10	0.30	0.5762
10	100	3.18	0.0086	0.10	0.35	0.0001	30	100	2.10	0.0206	0.10	0.35	0.7694
10	100	3.18	0.0086	0.10	0.40	0.0020	30	100	2.10	0.0206	0.10	0.40	0.8985
10	100	3.18	0.0086	0.10	0.45	0.0232	30	100	2.10	0.0206	0.10	0.45	0.9655
10	100	3.18	0.0086	0.10	0.50	0.1100	30	100	2.10	0.0206	0.10	0.50	0.9912
10	100	3.18	0.0086	0.10	0.55	0.2670	30	100	2.10	0.0206	0.10	0.55	0.9983
10	100	3.18	0.0086	0.10	0.60	0.4482	30	100	2.10	0.0206	0.10	0.60	0.9998
10	100	3.18	0.0086	0.15	0.30	0.0000	30	100	2.10	0.0206	0.15	0.30	0.3011
10	100	3.18	0.0086	0.15	0.35	0.0000	30	100	2.10	0.0206	0.15	0.35	0.5012
10	100	3.18	0.0086	0.15	0.40	0.0011	30	100	2.10	0.0206	0.15	0.40	0.7019
10	100	3.18	0.0086	0.15	0.45	0.0131	30	100	2.10	0.0206	0.15	0.45	0.8568
10	100	3.18	0.0086	0.15	0.50	0.0629	30	100	2.10	0.0206	0.15	0.50	0.9456
10	100	3.18	0.0086	0.15	0.55	0.1593	30	100	2.10	0.0206	0.15	0.55	0.9837
10	100	3.18	0.0086	0.15	0.60	0.2950	30	100	2.10	0.0206	0.15	0.60	0.9962
10	100	3.18	0.0086	0.15	0.65	0.4749	30	100	2.10	0.0206	0.15	0.65	0.9993
10	100	3.18	0.0086	0.20	0.35	0.0000	30	100	2.10	0.0206	0.20	0.35	0.2689
10	100	3.18	0.0086	0.20	0.40	0.0006	30	100	2.10	0.0206	0.20	0.40	0.4625
10	100	3.18	0.0086	0.20	0.45	0.0072	30	100	2.10	0.0206	0.20	0.45	0.6677
10	100	3.18	0.0086	0.20	0.50	0.0348	30	100	2.10	0.0206	0.20	0.50	0.8306
10	100	3.18	0.0086	0.20	0.55	0.0921	30	100	2.10	0.0206	0.20	0.55	0.9296
10	100	3.18	0.0086	0.20	0.60	0.1874	30	100	2.10	0.0206	0.20	0.60	0.9768
10	100	3.18	0.0086	0.20	0.65	0.3341	30	100	2.10	0.0206	0.20	0.65	0.9943
10	100	3.18	0.0086	0.20	0.70	0.5166	30	100	2.10	0.0206	0.20	0.70	0.9990
10	100	3.18	0.0086	0.25	0.40	0.0003	30	100	2.10	0.0206	0.25	0.40	0.2575
10	100	3.18	0.0086	0.25	0.45	0.0038	30	100	2.10	0.0206	0.25	0.45	0.4476
10	100	3.18	0.0086	0.25	0.50	0.0185	30	100	2.10	0.0206	0.25	0.50	0.6478
10	100	3.18	0.0086	0.25	0.55	0.0515	30	100	2.10	0.0206	0.25	0.55	0.8118
10	100	3.18	0.0086	0.25	0.60	0.1145	30	100	2.10	0.0206	0.25	0.60	0.9189

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	100	3.18	0.0086	0.25	0.65	0.2244	30	100	2.10	0.0206	0.25	0.65	0.9735
10	100	3.18	0.0086	0.25	0.70	0.3835	30	100	2.10	0.0206	0.25	0.70	0.9937
10	100	3.18	0.0086	0.25	0.75	0.5814	30	100	2.10	0.0206	0.25	0.75	0.9989
10	100	3.18	0.0086	0.30	0.45	0.0019	30	100	2.10	0.0206	0.30	0.45	0.2560
10	100	3.18	0.0086	0.30	0.50	0.0095	30	100	2.10	0.0206	0.30	0.50	0.4387
10	100	3.18	0.0086	0.30	0.55	0.0276	30	100	2.10	0.0206	0.30	0.55	0.6346
10	100	3.18	0.0086	0.30	0.60	0.0671	30	100	2.10	0.0206	0.30	0.60	0.8036
10	100	3.18	0.0086	0.30	0.65	0.1438	30	100	2.10	0.0206	0.30	0.65	0.9174
10	100	3.18	0.0086	0.30	0.70	0.2714	30	100	2.10	0.0206	0.30	0.70	0.9737
10	100	3.18	0.0086	0.35	0.50	0.0046	30	100	2.10	0.0206	0.35	0.50	0.2548
10	100	3.18	0.0086	0.35	0.55	0.0142	30	100	2.10	0.0206	0.35	0.55	0.4343
10	100	3.18	0.0086	0.35	0.60	0.0375	30	100	2.10	0.0206	0.35	0.60	0.6348
10	100	3.18	0.0086	0.35	0.65	0.0877	30	100	2.10	0.0206	0.35	0.65	0.8089
10	100	3.18	0.0086	0.40	0.55	0.0069	30	100	2.10	0.0206	0.40	0.55	0.2564
10	100	3.18	0.0086	0.40	0.60	0.0199	30	100	2.10	0.0206	0.40	0.60	0.4426
20	30	1.97	0.0246	0.05	0.15	0.1148	40	50	2.00	0.0225	0.05	0.15	0.3152
20	30	1.97	0.0246	0.05	0.20	0.2588	40	50	2.00	0.0225	0.05	0.20	0.5644
20	30	1.97	0.0246	0.05	0.25	0.4303	40	50	2.00	0.0225	0.05	0.25	0.7726
20	30	1.97	0.0246	0.05	0.30	0.6017	40	50	2.00	0.0225	0.05	0.30	0.9020
20	30	1.97	0.0246	0.05	0.35	0.7496	40	50	2.00	0.0225	0.05	0.35	0.9653
20	30	1.97	0.0246	0.05	0.40	0.8597	40	50	2.00	0.0225	0.05	0.40	0.9901
20	30	1.97	0.0246	0.05	0.45	0.9303	40	50	2.00	0.0225	0.05	0.45	0.9978
20	30	1.97	0.0246	0.10	0.25	0.2197	40	50	2.00	0.0225	0.10	0.25	0.4345
20	30	1.97	0.0246	0.10	0.30	0.3605	40	50	2.00	0.0225	0.10	0.30	0.6428
20	30	1.97	0.0246	0.10	0.35	0.5172	40	50	2.00	0.0225	0.10	0.35	0.8116
20	30	1.97	0.0246	0.10	0.40	0.6669	40	50	2.00	0.0225	0.10	0.40	0.9184
20	30	1.97	0.0246	0.10	0.45	0.7916	40	50	2.00	0.0225	0.10	0.45	0.9713
20	30	1.97	0.0246	0.10	0.50	0.8831	40	50	2.00	0.0225	0.10	0.50	0.9918
20	30	1.97	0.0246	0.10	0.55	0.9422	40	50	2.00	0.0225	0.10	0.55	0.9982
20	30	1.97	0.0246	0.10	0.60	0.9753	40	50	2.00	0.0225	0.10	0.60	0.9997
20	30	1.97	0.0246	0.15	0.30	0.1997	40	50	2.00	0.0225	0.15	0.30	0.3671
20	30	1.97	0.0246	0.15	0.35	0.3254	40	50	2.00	0.0225	0.15	0.35	0.5704
20	30	1.97	0.0246	0.15	0.40	0.4703	40	50	2.00	0.0225	0.15	0.40	0.7519
20	30	1.97	0.0246	0.15	0.45	0.6171	40	50	2.00	0.0225	0.15	0.45	0.8795
20	30	1.97	0.0246	0.15	0.50	0.7487	40	50	2.00	0.0225	0.15	0.50	0.9514
20	30	1.97	0.0246	0.15	0.55	0.8522	40	50	2.00	0.0225	0.15	0.55	0.9841
20	30	1.97	0.0246	0.15	0.60	0.9230	40	50	2.00	0.0225	0.15	0.60	0.9959
20	30	1.97	0.0246	0.15	0.65	0.9647	40	50	2.00	0.0225	0.15	0.65	0.9992
20	30	1.97	0.0246	0.20	0.35	0.1885	40	50	2.00	0.0225	0.20	0.35	0.3333
20	30	1.97	0.0246	0.20	0.40	0.3050	40	50	2.00	0.0225	0.20	0.40	0.5251
20	30	1.97	0.0246	0.20	0.45	0.4439	40	50	2.00	0.0225	0.20	0.45	0.7070
20	30	1.97	0.0246	0.20	0.50	0.5896	40	50	2.00	0.0225	0.20	0.50	0.8466
20	30	1.97	0.0246	0.20	0.55	0.7235	40	50	2.00	0.0225	0.20	0.55	0.9335
20	30	1.97	0.0246	0.20	0.60	0.8313	40	50	2.00	0.0225	0.20	0.60	0.9769
20	30	1.97	0.0246	0.20	0.65	0.9078	40	50	2.00	0.0225	0.20	0.65	0.9938
20	30	1.97	0.0246	0.20	0.70	0.9561	40	50	2.00	0.0225	0.20	0.70	0.9988
20	30	1.97	0.0246	0.25	0.40	0.1830	40	50	2.00	0.0225	0.25	0.40	0.3089
20	30	1.97	0.0246	0.25	0.45	0.2954	40	50	2.00	0.0225	0.25	0.45	0.4907
20	30	1.97	0.0246	0.25	0.50	0.4301	40	50	2.00	0.0225	0.25	0.50	0.6737
20	30	1.97	0.0246	0.25	0.55	0.5718	40	50	2.00	0.0225	0.25	0.55	0.8233

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	30	1.97	0.0246	0.25	0.60	0.7040	40	50	2.00	0.0225	0.25	0.60	0.9214
20	30	1.97	0.0246	0.25	0.65	0.8148	40	50	2.00	0.0225	0.25	0.65	0.9723
20	30	1.97	0.0246	0.25	0.70	0.8983	40	50	2.00	0.0225	0.25	0.70	0.9926
20	30	1.97	0.0246	0.25	0.75	0.9532	40	50	2.00	0.0225	0.25	0.75	0.9986
20	30	1.97	0.0246	0.30	0.45	0.1816	40	50	2.00	0.0225	0.30	0.45	0.2909
20	30	1.97	0.0246	0.30	0.50	0.2896	40	50	2.00	0.0225	0.30	0.50	0.4687
20	30	1.97	0.0246	0.30	0.55	0.4184	40	50	2.00	0.0225	0.30	0.55	0.6544
20	30	1.97	0.0246	0.30	0.60	0.5564	40	50	2.00	0.0225	0.30	0.60	0.8108
20	30	1.97	0.0246	0.30	0.65	0.6911	40	50	2.00	0.0225	0.30	0.65	0.9158
20	30	1.97	0.0246	0.30	0.70	0.8094	40	50	2.00	0.0225	0.30	0.70	0.9708
20	30	1.97	0.0246	0.35	0.50	0.1792	40	50	2.00	0.0225	0.35	0.50	0.2812
20	30	1.97	0.0246	0.35	0.55	0.2823	40	50	2.00	0.0225	0.35	0.55	0.4581
20	30	1.97	0.0246	0.35	0.60	0.4087	40	50	2.00	0.0225	0.35	0.60	0.6465
20	30	1.97	0.0246	0.35	0.65	0.5506	40	50	2.00	0.0225	0.35	0.65	0.8071
20	30	1.97	0.0246	0.40	0.55	0.1752	40	50	2.00	0.0225	0.40	0.55	0.2779
20	30	1.97	0.0246	0.40	0.60	0.2783	40	50	2.00	0.0225	0.40	0.60	0.4557
20	40	2.06	0.0217	0.05	0.15	0.0923	40	60	1.98	0.0249	0.05	0.15	0.3284
20	40	2.06	0.0217	0.05	0.20	0.2385	40	60	1.98	0.0249	0.05	0.20	0.5862
20	40	2.06	0.0217	0.05	0.25	0.4209	40	60	1.98	0.0249	0.05	0.25	0.8006
20	40	2.06	0.0217	0.05	0.30	0.6097	40	60	1.98	0.0249	0.05	0.30	0.9254
20	40	2.06	0.0217	0.05	0.35	0.7724	40	60	1.98	0.0249	0.05	0.35	0.9781
20	40	2.06	0.0217	0.05	0.40	0.8858	40	60	1.98	0.0249	0.05	0.40	0.9949
20	40	2.06	0.0217	0.05	0.45	0.9502	40	60	1.98	0.0249	0.05	0.45	0.9991
20	40	2.06	0.0217	0.10	0.25	0.2082	40	60	1.98	0.0249	0.10	0.25	0.4712
20	40	2.06	0.0217	0.10	0.30	0.3640	40	60	1.98	0.0249	0.10	0.30	0.6915
20	40	2.06	0.0217	0.10	0.35	0.5392	40	60	1.98	0.0249	0.10	0.35	0.8514
20	40	2.06	0.0217	0.10	0.40	0.6995	40	60	1.98	0.0249	0.10	0.40	0.9415
20	40	2.06	0.0217	0.10	0.45	0.8239	40	60	1.98	0.0249	0.10	0.45	0.9816
20	40	2.06	0.0217	0.10	0.50	0.9079	40	60	1.98	0.0249	0.10	0.50	0.9955
20	40	2.06	0.0217	0.10	0.55	0.9572	40	60	1.98	0.0249	0.10	0.55	0.9992
20	40	2.06	0.0217	0.10	0.60	0.9826	40	60	1.98	0.0249	0.10	0.60	0.9999
20	40	2.06	0.0217	0.15	0.30	0.1994	40	60	1.98	0.0249	0.15	0.30	0.4059
20	40	2.06	0.0217	0.15	0.35	0.3379	40	60	1.98	0.0249	0.15	0.35	0.6143
20	40	2.06	0.0217	0.15	0.40	0.4940	40	60	1.98	0.0249	0.15	0.40	0.7908
20	40	2.06	0.0217	0.15	0.45	0.6456	40	60	1.98	0.0249	0.15	0.45	0.9076
20	40	2.06	0.0217	0.15	0.50	0.7740	40	60	1.98	0.0249	0.15	0.50	0.9674
20	40	2.06	0.0217	0.15	0.55	0.8698	40	60	1.98	0.0249	0.15	0.55	0.9909
20	40	2.06	0.0217	0.15	0.60	0.9335	40	60	1.98	0.0249	0.15	0.60	0.9980
20	40	2.06	0.0217	0.15	0.65	0.9709	40	60	1.98	0.0249	0.15	0.65	0.9997
20	40	2.06	0.0217	0.20	0.35	0.1920	40	60	1.98	0.0249	0.20	0.35	0.3633
20	40	2.06	0.0217	0.20	0.40	0.3152	40	60	1.98	0.0249	0.20	0.40	0.5668
20	40	2.06	0.0217	0.20	0.45	0.4578	40	60	1.98	0.0249	0.20	0.45	0.7518
20	40	2.06	0.0217	0.20	0.50	0.6025	40	60	1.98	0.0249	0.20	0.50	0.8823
20	40	2.06	0.0217	0.20	0.55	0.7334	40	60	1.98	0.0249	0.20	0.55	0.9545
20	40	2.06	0.0217	0.20	0.60	0.8401	40	60	1.98	0.0249	0.20	0.60	0.9860
20	40	2.06	0.0217	0.20	0.65	0.9170	40	60	1.98	0.0249	0.20	0.65	0.9967
20	40	2.06	0.0217	0.20	0.70	0.9641	40	60	1.98	0.0249	0.20	0.70	0.9994
20	40	2.06	0.0217	0.25	0.40	0.1826	40	60	1.98	0.0249	0.25	0.40	0.3416
20	40	2.06	0.0217	0.25	0.45	0.2944	40	60	1.98	0.0249	0.25	0.45	0.5384
20	40	2.06	0.0217	0.25	0.50	0.4273	40	60	1.98	0.0249	0.25	0.50	0.7233

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	40	2.06	0.0217	0.25	0.55	0.5697	40	60	1.98	0.0249	0.25	0.55	0.8612
20	40	2.06	0.0217	0.25	0.60	0.7077	40	60	1.98	0.0249	0.25	0.60	0.9432
20	40	2.06	0.0217	0.25	0.65	0.8256	40	60	1.98	0.0249	0.25	0.65	0.9818
20	40	2.06	0.0217	0.25	0.70	0.9119	40	60	1.98	0.0249	0.25	0.70	0.9957
20	40	2.06	0.0217	0.25	0.75	0.9641	40	60	1.98	0.0249	0.25	0.75	0.9993
20	40	2.06	0.0217	0.30	0.45	0.1720	40	60	1.98	0.0249	0.30	0.45	0.3266
20	40	2.06	0.0217	0.30	0.50	0.2762	40	60	1.98	0.0249	0.30	0.50	0.5155
20	40	2.06	0.0217	0.30	0.55	0.4067	40	60	1.98	0.0249	0.30	0.55	0.7000
20	40	2.06	0.0217	0.30	0.60	0.5541	40	60	1.98	0.0249	0.30	0.60	0.8453
20	40	2.06	0.0217	0.30	0.65	0.7012	40	60	1.98	0.0249	0.30	0.65	0.9364
20	40	2.06	0.0217	0.30	0.70	0.8274	40	60	1.98	0.0249	0.30	0.70	0.9803
20	40	2.06	0.0217	0.35	0.50	0.1628	40	60	1.98	0.0249	0.35	0.50	0.3126
20	40	2.06	0.0217	0.35	0.55	0.2664	40	60	1.98	0.0249	0.35	0.55	0.4974
20	40	2.06	0.0217	0.35	0.60	0.4016	40	60	1.98	0.0249	0.35	0.60	0.6860
20	40	2.06	0.0217	0.35	0.65	0.5574	40	60	1.98	0.0249	0.35	0.65	0.8396
20	40	2.06	0.0217	0.40	0.55	0.1597	40	60	1.98	0.0249	0.40	0.55	0.3026
20	40	2.06	0.0217	0.40	0.60	0.2683	40	60	1.98	0.0249	0.40	0.60	0.4900
20	50	2.00	0.0237	0.05	0.15	0.1241	40	70	1.99	0.0250	0.05	0.15	0.3271
20	50	2.00	0.0237	0.05	0.20	0.2928	40	70	1.99	0.0250	0.05	0.20	0.6111
20	50	2.00	0.0237	0.05	0.25	0.4820	40	70	1.99	0.0250	0.05	0.25	0.8212
20	50	2.00	0.0237	0.05	0.30	0.6704	40	70	1.99	0.0250	0.05	0.30	0.9344
20	50	2.00	0.0237	0.05	0.35	0.8236	40	70	1.99	0.0250	0.05	0.35	0.9816
20	50	2.00	0.0237	0.05	0.40	0.9207	40	70	1.99	0.0250	0.05	0.40	0.9962
20	50	2.00	0.0237	0.05	0.45	0.9697	40	70	1.99	0.0250	0.05	0.45	0.9994
20	50	2.00	0.0237	0.10	0.25	0.2393	40	70	1.99	0.0250	0.10	0.25	0.4743
20	50	2.00	0.0237	0.10	0.30	0.4083	40	70	1.99	0.0250	0.10	0.30	0.6983
20	50	2.00	0.0237	0.10	0.35	0.5930	40	70	1.99	0.0250	0.10	0.35	0.8644
20	50	2.00	0.0237	0.10	0.40	0.7530	40	70	1.99	0.0250	0.10	0.40	0.9528
20	50	2.00	0.0237	0.10	0.45	0.8676	40	70	1.99	0.0250	0.10	0.45	0.9872
20	50	2.00	0.0237	0.10	0.50	0.9374	40	70	1.99	0.0250	0.10	0.50	0.9973
20	50	2.00	0.0237	0.10	0.55	0.9741	40	70	1.99	0.0250	0.10	0.55	0.9996
20	50	2.00	0.0237	0.10	0.60	0.9908	40	70	1.99	0.0250	0.10	0.60	0.9999
20	50	2.00	0.0237	0.15	0.30	0.2254	40	70	1.99	0.0250	0.15	0.30	0.4117
20	50	2.00	0.0237	0.15	0.35	0.3801	40	70	1.99	0.0250	0.15	0.35	0.6371
20	50	2.00	0.0237	0.15	0.40	0.5486	40	70	1.99	0.0250	0.15	0.40	0.8176
20	50	2.00	0.0237	0.15	0.45	0.7025	40	70	1.99	0.0250	0.15	0.45	0.9259
20	50	2.00	0.0237	0.15	0.50	0.8238	40	70	1.99	0.0250	0.15	0.50	0.9759
20	50	2.00	0.0237	0.15	0.55	0.9073	40	70	1.99	0.0250	0.15	0.55	0.9938
20	50	2.00	0.0237	0.15	0.60	0.9577	40	70	1.99	0.0250	0.15	0.60	0.9988
20	50	2.00	0.0237	0.15	0.65	0.9838	40	70	1.99	0.0250	0.15	0.65	0.9998
20	50	2.00	0.0237	0.20	0.35	0.2196	40	70	1.99	0.0250	0.20	0.35	0.3841
20	50	2.00	0.0237	0.20	0.40	0.3587	40	70	1.99	0.0250	0.20	0.40	0.5972
20	50	2.00	0.0237	0.20	0.45	0.5133	40	70	1.99	0.0250	0.20	0.45	0.7793
20	50	2.00	0.0237	0.20	0.50	0.6625	40	70	1.99	0.0250	0.20	0.50	0.9003
20	50	2.00	0.0237	0.20	0.55	0.7895	40	70	1.99	0.0250	0.20	0.55	0.9636
20	50	2.00	0.0237	0.20	0.60	0.8847	40	70	1.99	0.0250	0.20	0.60	0.9895
20	50	2.00	0.0237	0.20	0.65	0.9461	40	70	1.99	0.0250	0.20	0.65	0.9978
20	50	2.00	0.0237	0.20	0.70	0.9790	40	70	1.99	0.0250	0.20	0.70	0.9997
20	50	2.00	0.0237	0.25	0.40	0.2118	40	70	1.99	0.0250	0.25	0.40	0.3622
20	50	2.00	0.0237	0.25	0.45	0.3389	40	70	1.99	0.0250	0.25	0.45	0.5634

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	50	2.00	0.0237	0.25	0.50	0.4850	40	70	1.99	0.0250	0.25	0.50	0.7461
20	50	2.00	0.0237	0.25	0.55	0.6342	40	70	1.99	0.0250	0.25	0.55	0.8777
20	50	2.00	0.0237	0.25	0.60	0.7684	40	70	1.99	0.0250	0.25	0.60	0.9531
20	50	2.00	0.0237	0.25	0.65	0.8723	40	70	1.99	0.0250	0.25	0.65	0.9865
20	50	2.00	0.0237	0.25	0.70	0.9401	40	70	1.99	0.0250	0.25	0.70	0.9973
20	50	2.00	0.0237	0.25	0.75	0.9772	40	70	1.99	0.0250	0.25	0.75	0.9996
20	50	2.00	0.0237	0.30	0.45	0.2024	40	70	1.99	0.0250	0.30	0.45	0.3412
20	50	2.00	0.0237	0.30	0.50	0.3227	40	70	1.99	0.0250	0.30	0.50	0.5343
20	50	2.00	0.0237	0.30	0.55	0.4673	40	70	1.99	0.0250	0.30	0.55	0.7204
20	50	2.00	0.0237	0.30	0.60	0.6203	40	70	1.99	0.0250	0.30	0.60	0.8637
20	50	2.00	0.0237	0.30	0.65	0.7596	40	70	1.99	0.0250	0.30	0.65	0.9488
20	50	2.00	0.0237	0.30	0.70	0.8684	40	70	1.99	0.0250	0.30	0.70	0.9859
20	50	2.00	0.0237	0.35	0.50	0.1949	40	70	1.99	0.0250	0.35	0.50	0.3231
20	50	2.00	0.0237	0.35	0.55	0.3145	40	70	1.99	0.0250	0.35	0.55	0.5160
20	50	2.00	0.0237	0.35	0.60	0.4612	40	70	1.99	0.0250	0.35	0.60	0.7108
20	50	2.00	0.0237	0.35	0.65	0.6171	40	70	1.99	0.0250	0.35	0.65	0.8624
20	50	2.00	0.0237	0.40	0.55	0.1923	40	70	1.99	0.0250	0.40	0.55	0.3156
20	50	2.00	0.0237	0.40	0.60	0.3135	40	70	1.99	0.0250	0.40	0.60	0.5151
20	60	2.21	0.0157	0.05	0.15	0.0390	40	80	2.07	0.0212	0.05	0.15	0.3106
20	60	2.21	0.0157	0.05	0.20	0.1683	40	80	2.07	0.0212	0.05	0.20	0.5731
20	60	2.21	0.0157	0.05	0.25	0.3660	40	80	2.07	0.0212	0.05	0.25	0.7971
20	60	2.21	0.0157	0.05	0.30	0.5769	40	80	2.07	0.0212	0.05	0.30	0.9282
20	60	2.21	0.0157	0.05	0.35	0.7580	40	80	2.07	0.0212	0.05	0.35	0.9812
20	60	2.21	0.0157	0.05	0.40	0.8823	40	80	2.07	0.0212	0.05	0.40	0.9964
20	60	2.21	0.0157	0.05	0.45	0.9514	40	80	2.07	0.0212	0.05	0.45	0.9995
20	60	2.21	0.0157	0.10	0.25	0.1629	40	80	2.07	0.0212	0.10	0.25	0.4407
20	60	2.21	0.0157	0.10	0.30	0.3129	40	80	2.07	0.0212	0.10	0.30	0.6795
20	60	2.21	0.0157	0.10	0.35	0.4935	40	80	2.07	0.0212	0.10	0.35	0.8548
20	60	2.21	0.0157	0.10	0.40	0.6689	40	80	2.07	0.0212	0.10	0.40	0.9481
20	60	2.21	0.0157	0.10	0.45	0.8110	40	80	2.07	0.0212	0.10	0.45	0.9855
20	60	2.21	0.0157	0.10	0.50	0.9071	40	80	2.07	0.0212	0.10	0.50	0.9970
20	60	2.21	0.0157	0.10	0.55	0.9607	40	80	2.07	0.0212	0.10	0.55	0.9996
20	60	2.21	0.0157	0.10	0.60	0.9859	40	80	2.07	0.0212	0.10	0.60	1.0000
20	60	2.21	0.0157	0.15	0.30	0.1539	40	80	2.07	0.0212	0.15	0.30	0.3826
20	60	2.21	0.0157	0.15	0.35	0.2844	40	80	2.07	0.0212	0.15	0.35	0.6070
20	60	2.21	0.0157	0.15	0.40	0.4468	40	80	2.07	0.0212	0.15	0.40	0.7948
20	60	2.21	0.0157	0.15	0.45	0.6164	40	80	2.07	0.0212	0.15	0.45	0.9152
20	60	2.21	0.0157	0.15	0.50	0.7639	40	80	2.07	0.0212	0.15	0.50	0.9734
20	60	2.21	0.0157	0.15	0.55	0.8717	40	80	2.07	0.0212	0.15	0.55	0.9938
20	60	2.21	0.0157	0.15	0.60	0.9404	40	80	2.07	0.0212	0.15	0.60	0.9989
20	60	2.21	0.0157	0.15	0.65	0.9778	40	80	2.07	0.0212	0.15	0.65	0.9999
20	60	2.21	0.0157	0.20	0.35	0.1479	40	80	2.07	0.0212	0.20	0.35	0.3440
20	60	2.21	0.0157	0.20	0.40	0.2674	40	80	2.07	0.0212	0.20	0.40	0.5574
20	60	2.21	0.0157	0.20	0.45	0.4198	40	80	2.07	0.0212	0.20	0.45	0.7563
20	60	2.21	0.0157	0.20	0.50	0.5816	40	80	2.07	0.0212	0.20	0.50	0.8943
20	60	2.21	0.0157	0.20	0.55	0.7296	40	80	2.07	0.0212	0.20	0.55	0.9640
20	60	2.21	0.0157	0.20	0.60	0.8495	40	80	2.07	0.0212	0.20	0.60	0.9903
20	60	2.21	0.0157	0.20	0.65	0.9315	40	80	2.07	0.0212	0.20	0.65	0.9981
20	60	2.21	0.0157	0.20	0.70	0.9751	40	80	2.07	0.0212	0.20	0.70	0.9998
20	60	2.21	0.0157	0.25	0.40	0.1446	40	80	2.07	0.0212	0.25	0.40	0.3226

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	60	2.21	0.0157	0.25	0.45	0.2573	40	80	2.07	0.0212	0.25	0.45	0.5355
20	60	2.21	0.0157	0.25	0.50	0.3999	40	80	2.07	0.0212	0.25	0.50	0.7367
20	60	2.21	0.0157	0.25	0.55	0.5590	40	80	2.07	0.0212	0.25	0.55	0.8778
20	60	2.21	0.0157	0.25	0.60	0.7168	40	80	2.07	0.0212	0.25	0.60	0.9548
20	60	2.21	0.0157	0.25	0.65	0.8469	40	80	2.07	0.0212	0.25	0.65	0.9877
20	60	2.21	0.0157	0.25	0.70	0.9311	40	80	2.07	0.0212	0.25	0.70	0.9978
20	60	2.21	0.0157	0.25	0.75	0.9744	40	80	2.07	0.0212	0.25	0.75	0.9997
20	60	2.21	0.0157	0.30	0.45	0.1422	40	80	2.07	0.0212	0.30	0.45	0.3178
20	60	2.21	0.0157	0.30	0.50	0.2487	40	80	2.07	0.0212	0.30	0.50	0.5228
20	60	2.21	0.0157	0.30	0.55	0.3913	40	80	2.07	0.0212	0.30	0.55	0.7176
20	60	2.21	0.0157	0.30	0.60	0.5599	40	80	2.07	0.0212	0.30	0.60	0.8654
20	60	2.21	0.0157	0.30	0.65	0.7241	40	80	2.07	0.0212	0.30	0.65	0.9520
20	60	2.21	0.0157	0.30	0.70	0.8516	40	80	2.07	0.0212	0.30	0.70	0.9877
20	60	2.21	0.0157	0.35	0.50	0.1399	40	80	2.07	0.0212	0.35	0.50	0.3111
20	60	2.21	0.0157	0.35	0.55	0.2498	40	80	2.07	0.0212	0.35	0.55	0.5086
20	60	2.21	0.0157	0.35	0.60	0.4022	40	80	2.07	0.0212	0.35	0.60	0.7110
20	60	2.21	0.0157	0.35	0.65	0.5752	40	80	2.07	0.0212	0.35	0.65	0.8677
20	60	2.21	0.0157	0.40	0.55	0.1449	40	80	2.07	0.0212	0.40	0.55	0.3059
20	60	2.21	0.0157	0.40	0.60	0.2636	40	80	2.07	0.0212	0.40	0.60	0.5129
20	70	2.10	0.0242	0.05	0.15	0.0587	40	90	2.03	0.0242	0.05	0.15	0.3118
20	70	2.10	0.0242	0.05	0.20	0.2319	40	90	2.03	0.0242	0.05	0.20	0.6167
20	70	2.10	0.0242	0.05	0.25	0.4653	40	90	2.03	0.0242	0.05	0.25	0.8385
20	70	2.10	0.0242	0.05	0.30	0.6793	40	90	2.03	0.0242	0.05	0.30	0.9465
20	70	2.10	0.0242	0.05	0.35	0.8329	40	90	2.03	0.0242	0.05	0.35	0.9869
20	70	2.10	0.0242	0.05	0.40	0.9241	40	90	2.03	0.0242	0.05	0.40	0.9978
20	70	2.10	0.0242	0.05	0.45	0.9705	40	90	2.03	0.0242	0.05	0.45	0.9997
20	70	2.10	0.0242	0.10	0.25	0.2242	40	90	2.03	0.0242	0.10	0.25	0.4833
20	70	2.10	0.0242	0.10	0.30	0.3966	40	90	2.03	0.0242	0.10	0.30	0.7140
20	70	2.10	0.0242	0.10	0.35	0.5760	40	90	2.03	0.0242	0.10	0.35	0.8798
20	70	2.10	0.0242	0.10	0.40	0.7340	40	90	2.03	0.0242	0.10	0.40	0.9614
20	70	2.10	0.0242	0.10	0.45	0.8546	40	90	2.03	0.0242	0.10	0.45	0.9905
20	70	2.10	0.0242	0.10	0.50	0.9327	40	90	2.03	0.0242	0.10	0.50	0.9982
20	70	2.10	0.0242	0.10	0.55	0.9742	40	90	2.03	0.0242	0.10	0.55	0.9998
20	70	2.10	0.0242	0.10	0.60	0.9920	40	90	2.03	0.0242	0.10	0.60	1.0000
20	70	2.10	0.0242	0.15	0.30	0.2044	40	90	2.03	0.0242	0.15	0.30	0.4142
20	70	2.10	0.0242	0.15	0.35	0.3460	40	90	2.03	0.0242	0.15	0.35	0.6467
20	70	2.10	0.0242	0.15	0.40	0.5084	40	90	2.03	0.0242	0.15	0.40	0.8281
20	70	2.10	0.0242	0.15	0.45	0.6709	40	90	2.03	0.0242	0.15	0.45	0.9341
20	70	2.10	0.0242	0.15	0.50	0.8083	40	90	2.03	0.0242	0.15	0.50	0.9805
20	70	2.10	0.0242	0.15	0.55	0.9050	40	90	2.03	0.0242	0.15	0.55	0.9957
20	70	2.10	0.0242	0.15	0.60	0.9608	40	90	2.03	0.0242	0.15	0.60	0.9993
20	70	2.10	0.0242	0.15	0.65	0.9866	40	90	2.03	0.0242	0.15	0.65	0.9999
20	70	2.10	0.0242	0.20	0.35	0.1848	40	90	2.03	0.0242	0.20	0.35	0.3793
20	70	2.10	0.0242	0.20	0.40	0.3126	40	90	2.03	0.0242	0.20	0.40	0.5988
20	70	2.10	0.0242	0.20	0.45	0.4706	40	90	2.03	0.0242	0.20	0.45	0.7883
20	70	2.10	0.0242	0.20	0.50	0.6364	40	90	2.03	0.0242	0.20	0.50	0.9111
20	70	2.10	0.0242	0.20	0.55	0.7824	40	90	2.03	0.0242	0.20	0.55	0.9711
20	70	2.10	0.0242	0.20	0.60	0.8885	40	90	2.03	0.0242	0.20	0.60	0.9930
20	70	2.10	0.0242	0.20	0.65	0.9516	40	90	2.03	0.0242	0.20	0.65	0.9988
20	70	2.10	0.0242	0.20	0.70	0.9829	40	90	2.03	0.0242	0.20	0.70	0.9999

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	70	2.10	0.0242	0.25	0.40	0.1724	40	90	2.03	0.0242	0.25	0.40	0.3543
20	70	2.10	0.0242	0.25	0.45	0.2965	40	90	2.03	0.0242	0.25	0.45	0.5670
20	70	2.10	0.0242	0.25	0.50	0.4536	40	90	2.03	0.0242	0.25	0.50	0.7604
20	70	2.10	0.0242	0.25	0.55	0.6213	40	90	2.03	0.0242	0.25	0.55	0.8944
20	70	2.10	0.0242	0.25	0.60	0.7695	40	90	2.03	0.0242	0.25	0.60	0.9641
20	70	2.10	0.0242	0.25	0.65	0.8790	40	90	2.03	0.0242	0.25	0.65	0.9910
20	70	2.10	0.0242	0.25	0.70	0.9477	40	90	2.03	0.0242	0.25	0.70	0.9985
20	70	2.10	0.0242	0.25	0.75	0.9825	40	90	2.03	0.0242	0.25	0.75	0.9998
20	70	2.10	0.0242	0.30	0.45	0.1683	40	90	2.03	0.0242	0.30	0.45	0.3385
20	70	2.10	0.0242	0.30	0.50	0.2924	40	90	2.03	0.0242	0.30	0.50	0.5468
20	70	2.10	0.0242	0.30	0.55	0.4497	40	90	2.03	0.0242	0.30	0.55	0.7437
20	70	2.10	0.0242	0.30	0.60	0.6156	40	90	2.03	0.0242	0.30	0.60	0.8846
20	70	2.10	0.0242	0.30	0.65	0.7647	40	90	2.03	0.0242	0.30	0.65	0.9610
20	70	2.10	0.0242	0.30	0.70	0.8794	40	90	2.03	0.0242	0.30	0.70	0.9908
20	70	2.10	0.0242	0.35	0.50	0.1702	40	90	2.03	0.0242	0.35	0.50	0.3298
20	70	2.10	0.0242	0.35	0.55	0.2950	40	90	2.03	0.0242	0.35	0.55	0.5366
20	70	2.10	0.0242	0.35	0.60	0.4504	40	90	2.03	0.0242	0.35	0.60	0.7366
20	70	2.10	0.0242	0.35	0.65	0.6181	40	90	2.03	0.0242	0.35	0.65	0.8846
20	70	2.10	0.0242	0.40	0.55	0.1743	40	90	2.03	0.0242	0.40	0.55	0.3265
20	70	2.10	0.0242	0.40	0.60	0.2991	40	90	2.03	0.0242	0.40	0.60	0.5370
20	80	2.04	0.0245	0.05	0.15	0.0786	40	100	2.02	0.0245	0.05	0.15	0.3210
20	80	2.04	0.0245	0.05	0.20	0.2751	40	100	2.02	0.0245	0.05	0.20	0.6268
20	80	2.04	0.0245	0.05	0.25	0.5077	40	100	2.02	0.0245	0.05	0.25	0.8518
20	80	2.04	0.0245	0.05	0.30	0.7110	40	100	2.02	0.0245	0.05	0.30	0.9562
20	80	2.04	0.0245	0.05	0.35	0.8541	40	100	2.02	0.0245	0.05	0.35	0.9906
20	80	2.04	0.0245	0.05	0.40	0.9388	40	100	2.02	0.0245	0.05	0.40	0.9986
20	80	2.04	0.0245	0.05	0.45	0.9794	40	100	2.02	0.0245	0.05	0.45	0.9998
20	80	2.04	0.0245	0.10	0.25	0.2462	40	100	2.02	0.0245	0.10	0.25	0.5060
20	80	2.04	0.0245	0.10	0.30	0.4208	40	100	2.02	0.0245	0.10	0.30	0.7417
20	80	2.04	0.0245	0.10	0.35	0.6051	40	100	2.02	0.0245	0.10	0.35	0.8972
20	80	2.04	0.0245	0.10	0.40	0.7694	40	100	2.02	0.0245	0.10	0.40	0.9687
20	80	2.04	0.0245	0.10	0.45	0.8869	40	100	2.02	0.0245	0.10	0.45	0.9927
20	80	2.04	0.0245	0.10	0.50	0.9530	40	100	2.02	0.0245	0.10	0.50	0.9987
20	80	2.04	0.0245	0.10	0.55	0.9832	40	100	2.02	0.0245	0.10	0.55	0.9998
20	80	2.04	0.0245	0.10	0.60	0.9951	40	100	2.02	0.0245	0.10	0.60	1.0000
20	80	2.04	0.0245	0.15	0.30	0.2189	40	100	2.02	0.0245	0.15	0.30	0.4394
20	80	2.04	0.0245	0.15	0.35	0.3732	40	100	2.02	0.0245	0.15	0.35	0.6715
20	80	2.04	0.0245	0.15	0.40	0.5537	40	100	2.02	0.0245	0.15	0.40	0.8453
20	80	2.04	0.0245	0.15	0.45	0.7226	40	100	2.02	0.0245	0.15	0.45	0.9422
20	80	2.04	0.0245	0.15	0.50	0.8485	40	100	2.02	0.0245	0.15	0.50	0.9835
20	80	2.04	0.0245	0.15	0.55	0.9282	40	100	2.02	0.0245	0.15	0.55	0.9966
20	80	2.04	0.0245	0.15	0.60	0.9718	40	100	2.02	0.0245	0.15	0.60	0.9995
20	80	2.04	0.0245	0.15	0.65	0.9913	40	100	2.02	0.0245	0.15	0.65	1.0000
20	80	2.04	0.0245	0.20	0.35	0.2052	40	100	2.02	0.0245	0.20	0.35	0.3986
20	80	2.04	0.0245	0.20	0.40	0.3542	40	100	2.02	0.0245	0.20	0.40	0.6175
20	80	2.04	0.0245	0.20	0.45	0.5263	40	100	2.02	0.0245	0.20	0.45	0.8010
20	80	2.04	0.0245	0.20	0.50	0.6877	40	100	2.02	0.0245	0.20	0.50	0.9192
20	80	2.04	0.0245	0.20	0.55	0.8193	40	100	2.02	0.0245	0.20	0.55	0.9755
20	80	2.04	0.0245	0.20	0.60	0.9119	40	100	2.02	0.0245	0.20	0.60	0.9946
20	80	2.04	0.0245	0.20	0.65	0.9653	40	100	2.02	0.0245	0.20	0.65	0.9992

Table B.23: continue on next page

Table B.23: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	80	2.04	0.0245	0.20	0.70	0.9893	40	100	2.02	0.0245	0.20	0.70	0.9999
20	80	2.04	0.0245	0.25	0.40	0.2029	40	100	2.02	0.0245	0.25	0.40	0.3657
20	80	2.04	0.0245	0.25	0.45	0.3429	40	100	2.02	0.0245	0.25	0.45	0.5789
20	80	2.04	0.0245	0.25	0.50	0.5033	40	100	2.02	0.0245	0.25	0.50	0.7743
20	80	2.04	0.0245	0.25	0.55	0.6653	40	100	2.02	0.0245	0.25	0.55	0.9062
20	80	2.04	0.0245	0.25	0.60	0.8063	40	100	2.02	0.0245	0.25	0.60	0.9704
20	80	2.04	0.0245	0.25	0.65	0.9072	40	100	2.02	0.0245	0.25	0.65	0.9932
20	80	2.04	0.0245	0.25	0.70	0.9640	40	100	2.02	0.0245	0.25	0.70	0.9989
20	80	2.04	0.0245	0.25	0.75	0.9889	40	100	2.02	0.0245	0.25	0.75	0.9999
20	80	2.04	0.0245	0.30	0.45	0.2001	40	100	2.02	0.0245	0.30	0.45	0.3465
20	80	2.04	0.0245	0.30	0.50	0.3318	40	100	2.02	0.0245	0.30	0.50	0.5630
20	80	2.04	0.0245	0.30	0.55	0.4925	40	100	2.02	0.0245	0.30	0.55	0.7632
20	80	2.04	0.0245	0.30	0.60	0.6617	40	100	2.02	0.0245	0.30	0.60	0.8993
20	80	2.04	0.0245	0.30	0.65	0.8086	40	100	2.02	0.0245	0.30	0.65	0.9678
20	80	2.04	0.0245	0.30	0.70	0.9099	40	100	2.02	0.0245	0.30	0.70	0.9927
20	80	2.04	0.0245	0.35	0.50	0.1966	40	100	2.02	0.0245	0.35	0.50	0.3433
20	80	2.04	0.0245	0.35	0.55	0.3306	40	100	2.02	0.0245	0.35	0.55	0.5591
20	80	2.04	0.0245	0.35	0.60	0.4987	40	100	2.02	0.0245	0.35	0.60	0.7590
20	80	2.04	0.0245	0.35	0.65	0.6730	40	100	2.02	0.0245	0.35	0.65	0.8980
20	80	2.04	0.0245	0.40	0.55	0.2000	40	100	2.02	0.0245	0.40	0.55	0.3451
20	80	2.04	0.0245	0.40	0.60	0.3420	40	100	2.02	0.0245	0.40	0.60	0.5604

Table B.23: concluded from previous page

Table B.24: Achieved power and p-values calculated for the z-pooled statistic in cases of different sample sizes, $\alpha = 0.01$. $\mathbf{n_1}$: size of sample 1; $\mathbf{n_2}$: size of sample 2; $\mathbf{z_u}$: critical value; p1: fixed value of the probability of success in the first sample; p2: fixed value of the probability of success in the second sample.

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.45	0.0083	0.05	0.15	0.0008	20	90	2.77	0.0065	0.05	0.15	0.0001
10	20	2.45	0.0083	0.05	0.20	0.0060	20	90	2.77	0.0065	0.05	0.20	0.0057
10	20	2.45	0.0083	0.05	0.25	0.0248	20	90	2.77	0.0065	0.05	0.25	0.0626
10	20	2.45	0.0083	0.05	0.30	0.0695	20	90	2.77	0.0065	0.05	0.30	0.2338
10	20	2.45	0.0083	0.05	0.35	0.1486	20	90	2.77	0.0065	0.05	0.35	0.4767
10	20	2.45	0.0083	0.05	0.40	0.2604	20	90	2.77	0.0065	0.05	0.40	0.7022
10	20	2.45	0.0083	0.05	0.45	0.3935	20	90	2.77	0.0065	0.05	0.45	0.8600
10	20	2.45	0.0083	0.10	0.25	0.0146	20	90	2.77	0.0065	0.10	0.25	0.0226
10	20	2.45	0.0083	0.10	0.30	0.0416	20	90	2.77	0.0065	0.10	0.30	0.0953
10	20	2.45	0.0083	0.10	0.35	0.0907	20	90	2.77	0.0065	0.10	0.35	0.2344
10	20	2.45	0.0083	0.10	0.40	0.1642	20	90	2.77	0.0065	0.10	0.40	0.4226
10	20	2.45	0.0083	0.10	0.45	0.2591	20	90	2.77	0.0065	0.10	0.45	0.6227
10	20	2.45	0.0083	0.10	0.50	0.3700	20	90	2.77	0.0065	0.10	0.50	0.7921
10	20	2.45	0.0083	0.10	0.55	0.4899	20	90	2.77	0.0065	0.10	0.55	0.9040
10	20	2.45	0.0083	0.10	0.60	0.6112	20	90	2.77	0.0065	0.10	0.60	0.9632
10	20	2.45	0.0083	0.15	0.30	0.0242	20	90	2.77	0.0065	0.15	0.30	0.0364
10	20	2.45	0.0083	0.15	0.35	0.0540	20	90	2.77	0.0065	0.15	0.35	0.1049
10	20	2.45	0.0083	0.15	0.40	0.1011	20	90	2.77	0.0065	0.15	0.40	0.2250
10	20	2.45	0.0083	0.15	0.45	0.1669	20	90	2.77	0.0065	0.15	0.45	0.3937
10	20	2.45	0.0083	0.15	0.50	0.2515	20	90	2.77	0.0065	0.15	0.50	0.5822
10	20	2.45	0.0083	0.15	0.55	0.3536	20	90	2.77	0.0065	0.15	0.55	0.7497
10	20	2.45	0.0083	0.15	0.60	0.4689	20	90	2.77	0.0065	0.15	0.60	0.8723
10	20	2.45	0.0083	0.15	0.65	0.5900	20	90	2.77	0.0065	0.15	0.65	0.9472
10	20	2.45	0.0083	0.20	0.35	0.0312	20	90	2.77	0.0065	0.20	0.35	0.0431
10	20	2.45	0.0083	0.20	0.40	0.0606	20	90	2.77	0.0065	0.20	0.40	0.1081
10	20	2.45	0.0083	0.20	0.45	0.1048	20	90	2.77	0.0065	0.20	0.45	0.2216
10	20	2.45	0.0083	0.20	0.50	0.1666	20	90	2.77	0.0065	0.20	0.50	0.3794
10	20	2.45	0.0083	0.20	0.55	0.2480	20	90	2.77	0.0065	0.20	0.55	0.5566
10	20	2.45	0.0083	0.20	0.60	0.3484	20	90	2.77	0.0065	0.20	0.60	0.7240
10	20	2.45	0.0083	0.20	0.65	0.4635	20	90	2.77	0.0065	0.20	0.65	0.8572
10	20	2.45	0.0083	0.20	0.70	0.5859	20	90	2.77	0.0065	0.20	0.70	0.9410
10	20	2.45	0.0083	0.25	0.40	0.0353	20	90	2.77	0.0065	0.25	0.40	0.0471
10	20	2.45	0.0083	0.25	0.45	0.0640	20	90	2.77	0.0065	0.25	0.45	0.1121
10	20	2.45	0.0083	0.25	0.50	0.1073	20	90	2.77	0.0065	0.25	0.50	0.2208
10	20	2.45	0.0083	0.25	0.55	0.1688	20	90	2.77	0.0065	0.25	0.55	0.3700
10	20	2.45	0.0083	0.25	0.60	0.2504	20	90	2.77	0.0065	0.25	0.60	0.5454
10	20	2.45	0.0083	0.25	0.65	0.3518	20	90	2.77	0.0065	0.25	0.65	0.7194
10	20	2.45	0.0083	0.25	0.70	0.4692	20	90	2.77	0.0065	0.25	0.70	0.8571
10	20	2.45	0.0083	0.25	0.75	0.5957	20	90	2.77	0.0065	0.25	0.75	0.9431
10	20	2.45	0.0083	0.30	0.45	0.0378	20	90	2.77	0.0065	0.30	0.45	0.0510
10	20	2.45	0.0083	0.30	0.50	0.0669	20	90	2.77	0.0065	0.30	0.50	0.1151
10	20	2.45	0.0083	0.30	0.55	0.1111	20	90	2.77	0.0065	0.30	0.55	0.2207
10	20	2.45	0.0083	0.30	0.60	0.1740	20	90	2.77	0.0065	0.30	0.60	0.3713
10	20	2.45	0.0083	0.30	0.65	0.2579	20	90	2.77	0.0065	0.30	0.65	0.5532

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	20	2.45	0.0083	0.30	0.70	0.3630	20	90	2.77	0.0065	0.30	0.70	0.7302
10	20	2.45	0.0083	0.35	0.50	0.0402	20	90	2.77	0.0065	0.35	0.50	0.0537
10	20	2.45	0.0083	0.35	0.55	0.0705	20	90	2.77	0.0065	0.35	0.55	0.1180
10	20	2.45	0.0083	0.35	0.60	0.1165	20	90	2.77	0.0065	0.35	0.60	0.2278
10	20	2.45	0.0083	0.35	0.65	0.1823	20	90	2.77	0.0065	0.35	0.65	0.3865
10	20	2.45	0.0083	0.40	0.55	0.0430	20	90	2.77	0.0065	0.40	0.55	0.0563
10	20	2.45	0.0083	0.40	0.60	0.0750	20	90	2.77	0.0065	0.40	0.60	0.1253
10	30	2.56	0.0078	0.05	0.15	0.0000	20	100	2.66	0.0093	0.05	0.15	0.0002
10	30	2.56	0.0078	0.05	0.20	0.0005	20	100	2.66	0.0093	0.05	0.20	0.0124
10	30	2.56	0.0078	0.05	0.25	0.0050	20	100	2.66	0.0093	0.05	0.25	0.1057
10	30	2.56	0.0078	0.05	0.30	0.0247	20	100	2.66	0.0093	0.05	0.30	0.3151
10	30	2.56	0.0078	0.05	0.35	0.0796	20	100	2.66	0.0093	0.05	0.35	0.5582
10	30	2.56	0.0078	0.05	0.40	0.1863	20	100	2.66	0.0093	0.05	0.40	0.7601
10	30	2.56	0.0078	0.05	0.45	0.3417	20	100	2.66	0.0093	0.05	0.45	0.8918
10	30	2.56	0.0078	0.10	0.25	0.0029	20	100	2.66	0.0093	0.10	0.25	0.0382
10	30	2.56	0.0078	0.10	0.30	0.0148	20	100	2.66	0.0093	0.10	0.30	0.1316
10	30	2.56	0.0078	0.10	0.35	0.0489	20	100	2.66	0.0093	0.10	0.35	0.2860
10	30	2.56	0.0078	0.10	0.40	0.1187	20	100	2.66	0.0093	0.10	0.40	0.4763
10	30	2.56	0.0078	0.10	0.45	0.2287	20	100	2.66	0.0093	0.10	0.45	0.6680
10	30	2.56	0.0078	0.10	0.50	0.3697	20	100	2.66	0.0093	0.10	0.50	0.8254
10	30	2.56	0.0078	0.10	0.55	0.5229	20	100	2.66	0.0093	0.10	0.55	0.9262
10	30	2.56	0.0078	0.10	0.60	0.6677	20	100	2.66	0.0093	0.10	0.60	0.9751
10	30	2.56	0.0078	0.15	0.30	0.0086	20	100	2.66	0.0093	0.15	0.30	0.0512
10	30	2.56	0.0078	0.15	0.35	0.0293	20	100	2.66	0.0093	0.15	0.35	0.1315
10	30	2.56	0.0078	0.15	0.40	0.0737	20	100	2.66	0.0093	0.15	0.40	0.2607
10	30	2.56	0.0078	0.15	0.45	0.1489	20	100	2.66	0.0093	0.15	0.45	0.4344
10	30	2.56	0.0078	0.15	0.50	0.2549	20	100	2.66	0.0093	0.15	0.50	0.6258
10	30	2.56	0.0078	0.15	0.55	0.3836	20	100	2.66	0.0093	0.15	0.55	0.7920
10	30	2.56	0.0078	0.15	0.60	0.5219	20	100	2.66	0.0093	0.15	0.60	0.9039
10	30	2.56	0.0078	0.15	0.65	0.6551	20	100	2.66	0.0093	0.15	0.65	0.9642
10	30	2.56	0.0078	0.20	0.35	0.0170	20	100	2.66	0.0093	0.20	0.35	0.0549
10	30	2.56	0.0078	0.20	0.40	0.0444	20	100	2.66	0.0093	0.20	0.40	0.1277
10	30	2.56	0.0078	0.20	0.45	0.0941	20	100	2.66	0.0093	0.20	0.45	0.2506
10	30	2.56	0.0078	0.20	0.50	0.1699	20	100	2.66	0.0093	0.20	0.50	0.4216
10	30	2.56	0.0078	0.20	0.55	0.2710	20	100	2.66	0.0093	0.20	0.55	0.6102
10	30	2.56	0.0078	0.20	0.60	0.3913	20	100	2.66	0.0093	0.20	0.60	0.7749
10	30	2.56	0.0078	0.20	0.65	0.5209	20	100	2.66	0.0093	0.20	0.65	0.8930
10	30	2.56	0.0078	0.20	0.70	0.6490	20	100	2.66	0.0093	0.20	0.70	0.9608
10	30	2.56	0.0078	0.25	0.40	0.0259	20	100	2.66	0.0093	0.25	0.40	0.0565
10	30	2.56	0.0078	0.25	0.45	0.0575	20	100	2.66	0.0093	0.25	0.45	0.1297
10	30	2.56	0.0078	0.25	0.50	0.1093	20	100	2.66	0.0093	0.25	0.50	0.2539
10	30	2.56	0.0078	0.25	0.55	0.1842	20	100	2.66	0.0093	0.25	0.55	0.4221
10	30	2.56	0.0078	0.25	0.60	0.2815	20	100	2.66	0.0093	0.25	0.60	0.6059
10	30	2.56	0.0078	0.25	0.65	0.3971	20	100	2.66	0.0093	0.25	0.65	0.7735
10	30	2.56	0.0078	0.25	0.70	0.5242	20	100	2.66	0.0093	0.25	0.70	0.8965
10	30	2.56	0.0078	0.25	0.75	0.6548	20	100	2.66	0.0093	0.25	0.75	0.9636
10	30	2.56	0.0078	0.30	0.45	0.0338	20	100	2.66	0.0093	0.30	0.45	0.0604
10	30	2.56	0.0078	0.30	0.50	0.0676	20	100	2.66	0.0093	0.30	0.50	0.1371
10	30	2.56	0.0078	0.30	0.55	0.1202	20	100	2.66	0.0093	0.30	0.55	0.2620
10	30	2.56	0.0078	0.30	0.60	0.1942	20	100	2.66	0.0093	0.30	0.60	0.4289

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	30	2.56	0.0078	0.30	0.65	0.2901	20	100	2.66	0.0093	0.30	0.65	0.6177
10	30	2.56	0.0078	0.30	0.70	0.4063	20	100	2.66	0.0093	0.30	0.70	0.7896
10	30	2.56	0.0078	0.35	0.50	0.0401	20	100	2.66	0.0093	0.35	0.50	0.0663
10	30	2.56	0.0078	0.35	0.55	0.0751	20	100	2.66	0.0093	0.35	0.55	0.1457
10	30	2.56	0.0078	0.35	0.60	0.1282	20	100	2.66	0.0093	0.35	0.60	0.2738
10	30	2.56	0.0078	0.35	0.65	0.2029	20	100	2.66	0.0093	0.35	0.65	0.4504
10	30	2.56	0.0078	0.40	0.55	0.0447	20	100	2.66	0.0093	0.40	0.55	0.0723
10	30	2.56	0.0078	0.40	0.60	0.0806	20	100	2.66	0.0093	0.40	0.60	0.1568
10	40	2.66	0.0063	0.05	0.15	0.0000	30	40	2.39	0.0094	0.05	0.15	0.1105
10	40	2.66	0.0063	0.05	0.20	0.0001	30	40	2.39	0.0094	0.05	0.20	0.2694
10	40	2.66	0.0063	0.05	0.25	0.0010	30	40	2.39	0.0094	0.05	0.25	0.4720
10	40	2.66	0.0063	0.05	0.30	0.0089	30	40	2.39	0.0094	0.05	0.30	0.6700
10	40	2.66	0.0063	0.05	0.35	0.0428	30	40	2.39	0.0094	0.05	0.35	0.8228
10	40	2.66	0.0063	0.05	0.40	0.1311	30	40	2.39	0.0094	0.05	0.40	0.9181
10	40	2.66	0.0063	0.05	0.45	0.2848	30	40	2.39	0.0094	0.05	0.45	0.9675
10	40	2.66	0.0063	0.10	0.25	0.0006	30	40	2.39	0.0094	0.10	0.25	0.2119
10	40	2.66	0.0063	0.10	0.30	0.0053	30	40	2.39	0.0094	0.10	0.30	0.3764
10	40	2.66	0.0063	0.10	0.35	0.0255	30	40	2.39	0.0094	0.10	0.35	0.5561
10	40	2.66	0.0063	0.10	0.40	0.0803	30	40	2.39	0.0094	0.10	0.40	0.7178
10	40	2.66	0.0063	0.10	0.45	0.1820	30	40	2.39	0.0094	0.10	0.45	0.8411
10	40	2.66	0.0063	0.10	0.50	0.3248	30	40	2.39	0.0094	0.10	0.50	0.9219
10	40	2.66	0.0063	0.10	0.55	0.4873	30	40	2.39	0.0094	0.10	0.55	0.9673
10	40	2.66	0.0063	0.10	0.60	0.6447	30	40	2.39	0.0094	0.10	0.60	0.9888
10	40	2.66	0.0063	0.15	0.30	0.0030	30	40	2.39	0.0094	0.15	0.30	0.1787
10	40	2.66	0.0063	0.15	0.35	0.0148	30	40	2.39	0.0094	0.15	0.35	0.3143
10	40	2.66	0.0063	0.15	0.40	0.0478	30	40	2.39	0.0094	0.15	0.40	0.4741
10	40	2.66	0.0063	0.15	0.45	0.1132	30	40	2.39	0.0094	0.15	0.45	0.6356
10	40	2.66	0.0063	0.15	0.50	0.2144	30	40	2.39	0.0094	0.15	0.50	0.7766
10	40	2.66	0.0063	0.15	0.55	0.3449	30	40	2.39	0.0094	0.15	0.55	0.8819
10	40	2.66	0.0063	0.15	0.60	0.4913	30	40	2.39	0.0094	0.15	0.60	0.9477
10	40	2.66	0.0063	0.15	0.65	0.6377	30	40	2.39	0.0094	0.15	0.65	0.9813
10	40	2.66	0.0063	0.20	0.35	0.0083	30	40	2.39	0.0094	0.20	0.35	0.1520
10	40	2.66	0.0063	0.20	0.40	0.0276	30	40	2.39	0.0094	0.20	0.40	0.2689
10	40	2.66	0.0063	0.20	0.45	0.0683	30	40	2.39	0.0094	0.20	0.45	0.4183
10	40	2.66	0.0063	0.20	0.50	0.1369	30	40	2.39	0.0094	0.20	0.50	0.5828
10	40	2.66	0.0063	0.20	0.55	0.2351	30	40	2.39	0.0094	0.20	0.55	0.7371
10	40	2.66	0.0063	0.20	0.60	0.3590	30	40	2.39	0.0094	0.20	0.60	0.8583
10	40	2.66	0.0063	0.20	0.65	0.5004	30	40	2.39	0.0094	0.20	0.65	0.9366
10	40	2.66	0.0063	0.20	0.70	0.6466	30	40	2.39	0.0094	0.20	0.70	0.9773
10	40	2.66	0.0063	0.25	0.40	0.0154	30	40	2.39	0.0094	0.25	0.40	0.1332
10	40	2.66	0.0063	0.25	0.45	0.0399	30	40	2.39	0.0094	0.25	0.45	0.2423
10	40	2.66	0.0063	0.25	0.50	0.0844	30	40	2.39	0.0094	0.25	0.50	0.3894
10	40	2.66	0.0063	0.25	0.55	0.1543	30	40	2.39	0.0094	0.25	0.55	0.5578
10	40	2.66	0.0063	0.25	0.60	0.2519	30	40	2.39	0.0094	0.25	0.60	0.7197
10	40	2.66	0.0063	0.25	0.65	0.3767	30	40	2.39	0.0094	0.25	0.65	0.8486
10	40	2.66	0.0063	0.25	0.70	0.5215	30	40	2.39	0.0094	0.25	0.70	0.9326
10	40	2.66	0.0063	0.25	0.75	0.6693	30	40	2.39	0.0094	0.25	0.75	0.9765
10	40	2.66	0.0063	0.30	0.45	0.0224	30	40	2.39	0.0094	0.30	0.45	0.1244
10	40	2.66	0.0063	0.30	0.50	0.0501	30	40	2.39	0.0094	0.30	0.50	0.2320
10	40	2.66	0.0063	0.30	0.55	0.0972	30	40	2.39	0.0094	0.30	0.55	0.3798

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	40	2.66	0.0063	0.30	0.60	0.1696	30	40	2.39	0.0094	0.30	0.60	0.5506
10	40	2.66	0.0063	0.30	0.65	0.2719	30	40	2.39	0.0094	0.30	0.65	0.7155
10	40	2.66	0.0063	0.30	0.70	0.4033	30	40	2.39	0.0094	0.30	0.70	0.8482
10	40	2.66	0.0063	0.35	0.50	0.0284	30	40	2.39	0.0094	0.35	0.50	0.1231
10	40	2.66	0.0063	0.35	0.55	0.0586	30	40	2.39	0.0094	0.35	0.55	0.2313
10	40	2.66	0.0063	0.35	0.60	0.1093	30	40	2.39	0.0094	0.35	0.60	0.3800
10	40	2.66	0.0063	0.35	0.65	0.1879	30	40	2.39	0.0094	0.35	0.65	0.5529
10	40	2.66	0.0063	0.40	0.55	0.0337	30	40	2.39	0.0094	0.40	0.55	0.1251
10	40	2.66	0.0063	0.40	0.60	0.0672	30	40	2.39	0.0094	0.40	0.60	0.2347
10	50	2.72	0.0095	0.05	0.15	0.0000	30	50	2.39	0.0097	0.05	0.15	0.0940
10	50	2.72	0.0095	0.05	0.20	0.0000	30	50	2.39	0.0097	0.05	0.20	0.2643
10	50	2.72	0.0095	0.05	0.25	0.0006	30	50	2.39	0.0097	0.05	0.25	0.4829
10	50	2.72	0.0095	0.05	0.30	0.0074	30	50	2.39	0.0097	0.05	0.30	0.6899
10	50	2.72	0.0095	0.05	0.35	0.0427	30	50	2.39	0.0097	0.05	0.35	0.8431
10	50	2.72	0.0095	0.05	0.40	0.1425	30	50	2.39	0.0097	0.05	0.40	0.9330
10	50	2.72	0.0095	0.05	0.45	0.3123	30	50	2.39	0.0097	0.05	0.45	0.9758
10	50	2.72	0.0095	0.10	0.25	0.0004	30	50	2.39	0.0097	0.10	0.25	0.2092
10	50	2.72	0.0095	0.10	0.30	0.0043	30	50	2.39	0.0097	0.10	0.30	0.3817
10	50	2.72	0.0095	0.10	0.35	0.0250	30	50	2.39	0.0097	0.10	0.35	0.5706
10	50	2.72	0.0095	0.10	0.40	0.0845	30	50	2.39	0.0097	0.10	0.40	0.7378
10	50	2.72	0.0095	0.10	0.45	0.1910	30	50	2.39	0.0097	0.10	0.45	0.8618
10	50	2.72	0.0095	0.10	0.50	0.3289	30	50	2.39	0.0097	0.10	0.50	0.9388
10	50	2.72	0.0095	0.10	0.55	0.4809	30	50	2.39	0.0097	0.10	0.55	0.9778
10	50	2.72	0.0095	0.10	0.60	0.6337	30	50	2.39	0.0097	0.10	0.60	0.9936
10	50	2.72	0.0095	0.15	0.30	0.0024	30	50	2.39	0.0097	0.15	0.30	0.1760
10	50	2.72	0.0095	0.15	0.35	0.0142	30	50	2.39	0.0097	0.15	0.35	0.3186
10	50	2.72	0.0095	0.15	0.40	0.0487	30	50	2.39	0.0097	0.15	0.40	0.4899
10	50	2.72	0.0095	0.15	0.45	0.1137	30	50	2.39	0.0097	0.15	0.45	0.6630
10	50	2.72	0.0095	0.15	0.50	0.2077	30	50	2.39	0.0097	0.15	0.50	0.8082
10	50	2.72	0.0095	0.15	0.55	0.3290	30	50	2.39	0.0097	0.15	0.55	0.9081
10	50	2.72	0.0095	0.15	0.60	0.4714	30	50	2.39	0.0097	0.15	0.60	0.9640
10	50	2.72	0.0095	0.15	0.65	0.6188	30	50	2.39	0.0097	0.15	0.65	0.9890
10	50	2.72	0.0095	0.20	0.35	0.0078	30	50	2.39	0.0097	0.20	0.35	0.1512
10	50	2.72	0.0095	0.20	0.40	0.0272	30	50	2.39	0.0097	0.20	0.40	0.2780
10	50	2.72	0.0095	0.20	0.45	0.0657	30	50	2.39	0.0097	0.20	0.45	0.4422
10	50	2.72	0.0095	0.20	0.50	0.1272	30	50	2.39	0.0097	0.20	0.50	0.6185
10	50	2.72	0.0095	0.20	0.55	0.2169	30	50	2.39	0.0097	0.20	0.55	0.7753
10	50	2.72	0.0095	0.20	0.60	0.3354	30	50	2.39	0.0097	0.20	0.60	0.8894
10	50	2.72	0.0095	0.20	0.65	0.4751	30	50	2.39	0.0097	0.20	0.65	0.9558
10	50	2.72	0.0095	0.20	0.70	0.6241	30	50	2.39	0.0097	0.20	0.70	0.9861
10	50	2.72	0.0095	0.25	0.40	0.0146	30	50	2.39	0.0097	0.25	0.40	0.1367
10	50	2.72	0.0095	0.25	0.45	0.0366	30	50	2.39	0.0097	0.25	0.45	0.2569
10	50	2.72	0.0095	0.25	0.50	0.0752	30	50	2.39	0.0097	0.25	0.50	0.4180
10	50	2.72	0.0095	0.25	0.55	0.1376	30	50	2.39	0.0097	0.25	0.55	0.5972
10	50	2.72	0.0095	0.25	0.60	0.2286	30	50	2.39	0.0097	0.25	0.60	0.7606
10	50	2.72	0.0095	0.25	0.65	0.3487	30	50	2.39	0.0097	0.25	0.65	0.8809
10	50	2.72	0.0095	0.25	0.70	0.4937	30	50	2.39	0.0097	0.25	0.70	0.9520
10	50	2.72	0.0095	0.25	0.75	0.6503	30	50	2.39	0.0097	0.25	0.75	0.9851
10	50	2.72	0.0095	0.30	0.45	0.0196	30	50	2.39	0.0097	0.30	0.45	0.1307
10	50	2.72	0.0095	0.30	0.50	0.0428	30	50	2.39	0.0097	0.30	0.50	0.2492

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	50	2.72	0.0095	0.30	0.55	0.0837	30	50	2.39	0.0097	0.30	0.55	0.4107
10	50	2.72	0.0095	0.30	0.60	0.1491	30	50	2.39	0.0097	0.30	0.60	0.5910
10	50	2.72	0.0095	0.30	0.65	0.2447	30	50	2.39	0.0097	0.30	0.65	0.7558
10	50	2.72	0.0095	0.30	0.70	0.3737	30	50	2.39	0.0097	0.30	0.70	0.8790
10	50	2.72	0.0095	0.35	0.50	0.0233	30	50	2.39	0.0097	0.35	0.50	0.1308
10	50	2.72	0.0095	0.35	0.55	0.0486	30	50	2.39	0.0097	0.35	0.55	0.2500
10	50	2.72	0.0095	0.35	0.60	0.0928	30	50	2.39	0.0097	0.35	0.60	0.4110
10	50	2.72	0.0095	0.35	0.65	0.1639	30	50	2.39	0.0097	0.35	0.65	0.5916
10	50	2.72	0.0095	0.40	0.55	0.0268	30	50	2.39	0.0097	0.40	0.55	0.1335
10	50	2.72	0.0095	0.40	0.60	0.0549	30	50	2.39	0.0097	0.40	0.60	0.2529
10	60	2.66	0.0098	0.05	0.15	0.0000	30	60	2.41	0.0099	0.05	0.15	0.0714
10	60	2.66	0.0098	0.05	0.20	0.0000	30	60	2.41	0.0099	0.05	0.20	0.2269
10	60	2.66	0.0098	0.05	0.25	0.0004	30	60	2.41	0.0099	0.05	0.25	0.4481
10	60	2.66	0.0098	0.05	0.30	0.0060	30	60	2.41	0.0099	0.05	0.30	0.6727
10	60	2.66	0.0098	0.05	0.35	0.0421	30	60	2.41	0.0099	0.05	0.35	0.8415
10	60	2.66	0.0098	0.05	0.40	0.1539	30	60	2.41	0.0099	0.05	0.40	0.9383
10	60	2.66	0.0098	0.05	0.45	0.3439	30	60	2.41	0.0099	0.05	0.45	0.9809
10	60	2.66	0.0098	0.10	0.25	0.0002	30	60	2.41	0.0099	0.10	0.25	0.1832
10	60	2.66	0.0098	0.10	0.30	0.0035	30	60	2.41	0.0099	0.10	0.30	0.3619
10	60	2.66	0.0098	0.10	0.35	0.0246	30	60	2.41	0.0099	0.10	0.35	0.5701
10	60	2.66	0.0098	0.10	0.40	0.0910	30	60	2.41	0.0099	0.10	0.40	0.7554
10	60	2.66	0.0098	0.10	0.45	0.2099	30	60	2.41	0.0099	0.10	0.45	0.8839
10	60	2.66	0.0098	0.10	0.50	0.3584	30	60	2.41	0.0099	0.10	0.50	0.9547
10	60	2.66	0.0098	0.10	0.55	0.5218	30	60	2.41	0.0099	0.10	0.55	0.9857
10	60	2.66	0.0098	0.10	0.60	0.6866	30	60	2.41	0.0099	0.10	0.60	0.9964
10	60	2.66	0.0098	0.15	0.30	0.0020	30	60	2.41	0.0099	0.15	0.30	0.1641
10	60	2.66	0.0098	0.15	0.35	0.0140	30	60	2.41	0.0099	0.15	0.35	0.3218
10	60	2.66	0.0098	0.15	0.40	0.0522	30	60	2.41	0.0099	0.15	0.40	0.5139
10	60	2.66	0.0098	0.15	0.45	0.1247	30	60	2.41	0.0099	0.15	0.45	0.6989
10	60	2.66	0.0098	0.15	0.50	0.2282	30	60	2.41	0.0099	0.15	0.50	0.8417
10	60	2.66	0.0098	0.15	0.55	0.3654	30	60	2.41	0.0099	0.15	0.55	0.9300
10	60	2.66	0.0098	0.15	0.60	0.5286	30	60	2.41	0.0099	0.15	0.60	0.9742
10	60	2.66	0.0098	0.15	0.65	0.6887	30	60	2.41	0.0099	0.15	0.65	0.9925
10	60	2.66	0.0098	0.20	0.35	0.0077	30	60	2.41	0.0099	0.20	0.35	0.1547
10	60	2.66	0.0098	0.20	0.40	0.0290	30	60	2.41	0.0099	0.20	0.40	0.2978
10	60	2.66	0.0098	0.20	0.45	0.0719	30	60	2.41	0.0099	0.20	0.45	0.4778
10	60	2.66	0.0098	0.20	0.50	0.1410	30	60	2.41	0.0099	0.20	0.50	0.6590
10	60	2.66	0.0098	0.20	0.55	0.2467	30	60	2.41	0.0099	0.20	0.55	0.8068
10	60	2.66	0.0098	0.20	0.60	0.3891	30	60	2.41	0.0099	0.20	0.60	0.9077
10	60	2.66	0.0098	0.20	0.65	0.5487	30	60	2.41	0.0099	0.20	0.65	0.9648
10	60	2.66	0.0098	0.20	0.70	0.7002	30	60	2.41	0.0099	0.20	0.70	0.9901
10	60	2.66	0.0098	0.25	0.40	0.0155	30	60	2.41	0.0099	0.25	0.40	0.1485
10	60	2.66	0.0098	0.25	0.45	0.0400	30	60	2.41	0.0099	0.25	0.45	0.2816
10	60	2.66	0.0098	0.25	0.50	0.0843	30	60	2.41	0.0099	0.25	0.50	0.4498
10	60	2.66	0.0098	0.25	0.55	0.1602	30	60	2.41	0.0099	0.25	0.55	0.6257
10	60	2.66	0.0098	0.25	0.60	0.2740	30	60	2.41	0.0099	0.25	0.60	0.7822
10	60	2.66	0.0098	0.25	0.65	0.4171	30	60	2.41	0.0099	0.25	0.65	0.8974
10	60	2.66	0.0098	0.25	0.70	0.5722	30	60	2.41	0.0099	0.25	0.70	0.9633
10	60	2.66	0.0098	0.25	0.75	0.7223	30	60	2.41	0.0099	0.25	0.75	0.9905
10	60	2.66	0.0098	0.30	0.45	0.0215	30	60	2.41	0.0099	0.30	0.45	0.1428

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	60	2.66	0.0098	0.30	0.50	0.0485	30	60	2.41	0.0099	0.30	0.50	0.2658
10	60	2.66	0.0098	0.30	0.55	0.0999	30	60	2.41	0.0099	0.30	0.55	0.4278
10	60	2.66	0.0098	0.30	0.60	0.1844	30	60	2.41	0.0099	0.30	0.60	0.6107
10	60	2.66	0.0098	0.30	0.65	0.3024	30	60	2.41	0.0099	0.30	0.65	0.7803
10	60	2.66	0.0098	0.30	0.70	0.4467	30	60	2.41	0.0099	0.30	0.70	0.9022
10	60	2.66	0.0098	0.35	0.50	0.0267	30	60	2.41	0.0099	0.35	0.50	0.1357
10	60	2.66	0.0098	0.35	0.55	0.0595	30	60	2.41	0.0099	0.35	0.55	0.2566
10	60	2.66	0.0098	0.35	0.60	0.1184	30	60	2.41	0.0099	0.35	0.60	0.4267
10	60	2.66	0.0098	0.35	0.65	0.2089	30	60	2.41	0.0099	0.35	0.65	0.6218
10	60	2.66	0.0098	0.40	0.55	0.0337	30	60	2.41	0.0099	0.40	0.55	0.1347
10	60	2.66	0.0098	0.40	0.60	0.0721	30	60	2.41	0.0099	0.40	0.60	0.2645
10	70	2.90	0.0063	0.05	0.15	0.0000	30	70	2.51	0.0098	0.05	0.15	0.0574
10	70	2.90	0.0063	0.05	0.20	0.0000	30	70	2.51	0.0098	0.05	0.20	0.2007
10	70	2.90	0.0063	0.05	0.25	0.0000	30	70	2.51	0.0098	0.05	0.25	0.4200
10	70	2.90	0.0063	0.05	0.30	0.0005	30	70	2.51	0.0098	0.05	0.30	0.6559
10	70	2.90	0.0063	0.05	0.35	0.0080	30	70	2.51	0.0098	0.05	0.35	0.8330
10	70	2.90	0.0063	0.05	0.40	0.0544	30	70	2.51	0.0098	0.05	0.40	0.9339
10	70	2.90	0.0063	0.05	0.45	0.1909	30	70	2.51	0.0098	0.05	0.45	0.9796
10	70	2.90	0.0063	0.10	0.25	0.0000	30	70	2.51	0.0098	0.10	0.25	0.1622
10	70	2.90	0.0063	0.10	0.30	0.0003	30	70	2.51	0.0098	0.10	0.30	0.3342
10	70	2.90	0.0063	0.10	0.35	0.0046	30	70	2.51	0.0098	0.10	0.35	0.5388
10	70	2.90	0.0063	0.10	0.40	0.0318	30	70	2.51	0.0098	0.10	0.40	0.7330
10	70	2.90	0.0063	0.10	0.45	0.1129	30	70	2.51	0.0098	0.10	0.45	0.8757
10	70	2.90	0.0063	0.10	0.50	0.2465	30	70	2.51	0.0098	0.10	0.50	0.9536
10	70	2.90	0.0063	0.10	0.55	0.4029	30	70	2.51	0.0098	0.10	0.55	0.9860
10	70	2.90	0.0063	0.10	0.60	0.5729	30	70	2.51	0.0098	0.10	0.60	0.9967
10	70	2.90	0.0063	0.15	0.30	0.0002	30	70	2.51	0.0098	0.15	0.30	0.1403
10	70	2.90	0.0063	0.15	0.35	0.0026	30	70	2.51	0.0098	0.15	0.35	0.2868
10	70	2.90	0.0063	0.15	0.40	0.0180	30	70	2.51	0.0098	0.15	0.40	0.4832
10	70	2.90	0.0063	0.15	0.45	0.0648	30	70	2.51	0.0098	0.15	0.45	0.6820
10	70	2.90	0.0063	0.15	0.50	0.1471	30	70	2.51	0.0098	0.15	0.50	0.8349
10	70	2.90	0.0063	0.15	0.55	0.2603	30	70	2.51	0.0098	0.15	0.55	0.9288
10	70	2.90	0.0063	0.15	0.60	0.4096	30	70	2.51	0.0098	0.15	0.60	0.9754
10	70	2.90	0.0063	0.15	0.65	0.5799	30	70	2.51	0.0098	0.15	0.65	0.9935
10	70	2.90	0.0063	0.20	0.35	0.0014	30	70	2.51	0.0098	0.20	0.35	0.1304
10	70	2.90	0.0063	0.20	0.40	0.0099	30	70	2.51	0.0098	0.20	0.40	0.2706
10	70	2.90	0.0063	0.20	0.45	0.0360	30	70	2.51	0.0098	0.20	0.45	0.4548
10	70	2.90	0.0063	0.20	0.50	0.0851	30	70	2.51	0.0098	0.20	0.50	0.6440
10	70	2.90	0.0063	0.20	0.55	0.1628	30	70	2.51	0.0098	0.20	0.55	0.8026
10	70	2.90	0.0063	0.20	0.60	0.2809	30	70	2.51	0.0098	0.20	0.60	0.9104
10	70	2.90	0.0063	0.20	0.65	0.4348	30	70	2.51	0.0098	0.20	0.65	0.9683
10	70	2.90	0.0063	0.20	0.70	0.6044	30	70	2.51	0.0098	0.20	0.70	0.9918
10	70	2.90	0.0063	0.25	0.40	0.0052	30	70	2.51	0.0098	0.25	0.40	0.1295
10	70	2.90	0.0063	0.25	0.45	0.0193	30	70	2.51	0.0098	0.25	0.45	0.2591
10	70	2.90	0.0063	0.25	0.50	0.0476	30	70	2.51	0.0098	0.25	0.50	0.4311
10	70	2.90	0.0063	0.25	0.55	0.0983	30	70	2.51	0.0098	0.25	0.55	0.6188
10	70	2.90	0.0063	0.25	0.60	0.1847	30	70	2.51	0.0098	0.25	0.60	0.7855
10	70	2.90	0.0063	0.25	0.65	0.3114	30	70	2.51	0.0098	0.25	0.65	0.9037
10	70	2.90	0.0063	0.25	0.70	0.4709	30	70	2.51	0.0098	0.25	0.70	0.9675
10	70	2.90	0.0063	0.25	0.75	0.6403	30	70	2.51	0.0098	0.25	0.75	0.9922

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	70	2.90	0.0063	0.30	0.45	0.0099	30	70	2.51	0.0098	0.30	0.45	0.1264
10	70	2.90	0.0063	0.30	0.50	0.0256	30	70	2.51	0.0098	0.30	0.50	0.2494
10	70	2.90	0.0063	0.30	0.55	0.0570	30	70	2.51	0.0098	0.30	0.55	0.4194
10	70	2.90	0.0063	0.30	0.60	0.1163	30	70	2.51	0.0098	0.30	0.60	0.6121
10	70	2.90	0.0063	0.30	0.65	0.2129	30	70	2.51	0.0098	0.30	0.65	0.7872
10	70	2.90	0.0063	0.30	0.70	0.3500	30	70	2.51	0.0098	0.30	0.70	0.9089
10	70	2.90	0.0063	0.35	0.50	0.0132	30	70	2.51	0.0098	0.35	0.50	0.1244
10	70	2.90	0.0063	0.35	0.55	0.0316	30	70	2.51	0.0098	0.35	0.55	0.2480
10	70	2.90	0.0063	0.35	0.60	0.0698	30	70	2.51	0.0098	0.35	0.60	0.4243
10	70	2.90	0.0063	0.35	0.65	0.1387	30	70	2.51	0.0098	0.35	0.65	0.6257
10	70	2.90	0.0063	0.40	0.55	0.0167	30	70	2.51	0.0098	0.40	0.55	0.1273
10	70	2.90	0.0063	0.40	0.60	0.0398	30	70	2.51	0.0098	0.40	0.60	0.2588
10	80	3.12	0.0069	0.05	0.15	0.0000	30	80	2.49	0.0075	0.05	0.15	0.0502
10	80	3.12	0.0069	0.05	0.20	0.0000	30	80	2.49	0.0075	0.05	0.20	0.2017
10	80	3.12	0.0069	0.05	0.25	0.0000	30	80	2.49	0.0075	0.05	0.25	0.4363
10	80	3.12	0.0069	0.05	0.30	0.0000	30	80	2.49	0.0075	0.05	0.30	0.6830
10	80	3.12	0.0069	0.05	0.35	0.0006	30	80	2.49	0.0075	0.05	0.35	0.8617
10	80	3.12	0.0069	0.05	0.40	0.0095	30	80	2.49	0.0075	0.05	0.40	0.9526
10	80	3.12	0.0069	0.05	0.45	0.0653	30	80	2.49	0.0075	0.05	0.45	0.9871
10	80	3.12	0.0069	0.10	0.25	0.0000	30	80	2.49	0.0075	0.10	0.25	0.1700
10	80	3.12	0.0069	0.10	0.30	0.0000	30	80	2.49	0.0075	0.10	0.30	0.3625
10	80	3.12	0.0069	0.10	0.35	0.0003	30	80	2.49	0.0075	0.10	0.35	0.5852
10	80	3.12	0.0069	0.10	0.40	0.0055	30	80	2.49	0.0075	0.10	0.40	0.7742
10	80	3.12	0.0069	0.10	0.45	0.0383	30	80	2.49	0.0075	0.10	0.45	0.8999
10	80	3.12	0.0069	0.10	0.50	0.1350	30	80	2.49	0.0075	0.10	0.50	0.9649
10	80	3.12	0.0069	0.10	0.55	0.2910	30	80	2.49	0.0075	0.10	0.55	0.9903
10	80	3.12	0.0069	0.10	0.60	0.4719	30	80	2.49	0.0075	0.10	0.60	0.9979
10	80	3.12	0.0069	0.15	0.30	0.0000	30	80	2.49	0.0075	0.15	0.30	0.1585
10	80	3.12	0.0069	0.15	0.35	0.0002	30	80	2.49	0.0075	0.15	0.35	0.3218
10	80	3.12	0.0069	0.15	0.40	0.0031	30	80	2.49	0.0075	0.15	0.40	0.5220
10	80	3.12	0.0069	0.15	0.45	0.0218	30	80	2.49	0.0075	0.15	0.45	0.7156
10	80	3.12	0.0069	0.15	0.50	0.0784	30	80	2.49	0.0075	0.15	0.50	0.8601
10	80	3.12	0.0069	0.15	0.55	0.1785	30	80	2.49	0.0075	0.15	0.55	0.9439
10	80	3.12	0.0069	0.15	0.60	0.3181	30	80	2.49	0.0075	0.15	0.60	0.9822
10	80	3.12	0.0069	0.15	0.65	0.4883	30	80	2.49	0.0075	0.15	0.65	0.9958
10	80	3.12	0.0069	0.20	0.35	0.0001	30	80	2.49	0.0075	0.20	0.35	0.1478
10	80	3.12	0.0069	0.20	0.40	0.0017	30	80	2.49	0.0075	0.20	0.40	0.2953
10	80	3.12	0.0069	0.20	0.45	0.0120	30	80	2.49	0.0075	0.20	0.45	0.4862
10	80	3.12	0.0069	0.20	0.50	0.0441	30	80	2.49	0.0075	0.20	0.50	0.6780
10	80	3.12	0.0069	0.20	0.55	0.1062	30	80	2.49	0.0075	0.20	0.55	0.8307
10	80	3.12	0.0069	0.20	0.60	0.2064	30	80	2.49	0.0075	0.20	0.60	0.9282
10	80	3.12	0.0069	0.20	0.65	0.3469	30	80	2.49	0.0075	0.20	0.65	0.9767
10	80	3.12	0.0069	0.20	0.70	0.5162	30	80	2.49	0.0075	0.20	0.70	0.9944
10	80	3.12	0.0069	0.25	0.40	0.0009	30	80	2.49	0.0075	0.25	0.40	0.1418
10	80	3.12	0.0069	0.25	0.45	0.0063	30	80	2.49	0.0075	0.25	0.45	0.2815
10	80	3.12	0.0069	0.25	0.50	0.0239	30	80	2.49	0.0075	0.25	0.50	0.4632
10	80	3.12	0.0069	0.25	0.55	0.0610	30	80	2.49	0.0075	0.25	0.55	0.6538
10	80	3.12	0.0069	0.25	0.60	0.1287	30	80	2.49	0.0075	0.25	0.60	0.8153
10	80	3.12	0.0069	0.25	0.65	0.2354	30	80	2.49	0.0075	0.25	0.65	0.9219
10	80	3.12	0.0069	0.25	0.70	0.3843	30	80	2.49	0.0075	0.25	0.70	0.9746

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	80	3.12	0.0069	0.25	0.75	0.5689	30	80	2.49	0.0075	0.25	0.75	0.9940
10	80	3.12	0.0069	0.30	0.45	0.0032	30	80	2.49	0.0075	0.30	0.45	0.1390
10	80	3.12	0.0069	0.30	0.50	0.0124	30	80	2.49	0.0075	0.30	0.50	0.2724
10	80	3.12	0.0069	0.30	0.55	0.0337	30	80	2.49	0.0075	0.30	0.55	0.4520
10	80	3.12	0.0069	0.30	0.60	0.0768	30	80	2.49	0.0075	0.30	0.60	0.6476
10	80	3.12	0.0069	0.30	0.65	0.1525	30	80	2.49	0.0075	0.30	0.65	0.8139
10	80	3.12	0.0069	0.30	0.70	0.2731	30	80	2.49	0.0075	0.30	0.70	0.9221
10	80	3.12	0.0069	0.35	0.50	0.0062	30	80	2.49	0.0075	0.35	0.50	0.1374
10	80	3.12	0.0069	0.35	0.55	0.0178	30	80	2.49	0.0075	0.35	0.55	0.2716
10	80	3.12	0.0069	0.35	0.60	0.0437	30	80	2.49	0.0075	0.35	0.60	0.4558
10	80	3.12	0.0069	0.35	0.65	0.0942	30	80	2.49	0.0075	0.35	0.65	0.6540
10	80	3.12	0.0069	0.40	0.55	0.0089	30	80	2.49	0.0075	0.40	0.55	0.1408
10	80	3.12	0.0069	0.40	0.60	0.0236	30	80	2.49	0.0075	0.40	0.60	0.2799
10	90	3.02	0.0099	0.05	0.15	0.0000	30	90	2.49	0.0086	0.05	0.15	0.0443
10	90	3.02	0.0099	0.05	0.20	0.0000	30	90	2.49	0.0086	0.05	0.20	0.2058
10	90	3.02	0.0099	0.05	0.25	0.0000	30	90	2.49	0.0086	0.05	0.25	0.4627
10	90	3.02	0.0099	0.05	0.30	0.0000	30	90	2.49	0.0086	0.05	0.30	0.7107
10	90	3.02	0.0099	0.05	0.35	0.0007	30	90	2.49	0.0086	0.05	0.35	0.8747
10	90	3.02	0.0099	0.05	0.40	0.0128	30	90	2.49	0.0086	0.05	0.40	0.9579
10	90	3.02	0.0099	0.05	0.45	0.0872	30	90	2.49	0.0086	0.05	0.45	0.9894
10	90	3.02	0.0099	0.10	0.25	0.0000	30	90	2.49	0.0086	0.10	0.25	0.1826
10	90	3.02	0.0099	0.10	0.30	0.0000	30	90	2.49	0.0086	0.10	0.30	0.3751
10	90	3.02	0.0099	0.10	0.35	0.0004	30	90	2.49	0.0086	0.10	0.35	0.5948
10	90	3.02	0.0099	0.10	0.40	0.0074	30	90	2.49	0.0086	0.10	0.40	0.7858
10	90	3.02	0.0099	0.10	0.45	0.0511	30	90	2.49	0.0086	0.10	0.45	0.9075
10	90	3.02	0.0099	0.10	0.50	0.1684	30	90	2.49	0.0086	0.10	0.50	0.9676
10	90	3.02	0.0099	0.10	0.55	0.3366	30	90	2.49	0.0086	0.10	0.55	0.9914
10	90	3.02	0.0099	0.10	0.60	0.5249	30	90	2.49	0.0086	0.10	0.60	0.9984
10	90	3.02	0.0099	0.15	0.30	0.0000	30	90	2.49	0.0086	0.15	0.30	0.1605
10	90	3.02	0.0099	0.15	0.35	0.0002	30	90	2.49	0.0086	0.15	0.35	0.3266
10	90	3.02	0.0099	0.15	0.40	0.0042	30	90	2.49	0.0086	0.15	0.40	0.5315
10	90	3.02	0.0099	0.15	0.45	0.0290	30	90	2.49	0.0086	0.15	0.45	0.7213
10	90	3.02	0.0099	0.15	0.50	0.0980	30	90	2.49	0.0086	0.15	0.50	0.8636
10	90	3.02	0.0099	0.15	0.55	0.2095	30	90	2.49	0.0086	0.15	0.55	0.9479
10	90	3.02	0.0099	0.15	0.60	0.3642	30	90	2.49	0.0086	0.15	0.60	0.9849
10	90	3.02	0.0099	0.15	0.65	0.5507	30	90	2.49	0.0086	0.15	0.65	0.9967
10	90	3.02	0.0099	0.20	0.35	0.0001	30	90	2.49	0.0086	0.20	0.35	0.1492
10	90	3.02	0.0099	0.20	0.40	0.0023	30	90	2.49	0.0086	0.20	0.40	0.2977
10	90	3.02	0.0099	0.20	0.45	0.0160	30	90	2.49	0.0086	0.20	0.45	0.4857
10	90	3.02	0.0099	0.20	0.50	0.0552	30	90	2.49	0.0086	0.20	0.50	0.6810
10	90	3.02	0.0099	0.20	0.55	0.1264	30	90	2.49	0.0086	0.20	0.55	0.8394
10	90	3.02	0.0099	0.20	0.60	0.2429	30	90	2.49	0.0086	0.20	0.60	0.9357
10	90	3.02	0.0099	0.20	0.65	0.4048	30	90	2.49	0.0086	0.20	0.65	0.9799
10	90	3.02	0.0099	0.20	0.70	0.5825	30	90	2.49	0.0086	0.20	0.70	0.9953
10	90	3.02	0.0099	0.25	0.40	0.0012	30	90	2.49	0.0086	0.25	0.40	0.1398
10	90	3.02	0.0099	0.25	0.45	0.0084	30	90	2.49	0.0086	0.25	0.45	0.2773
10	90	3.02	0.0099	0.25	0.50	0.0300	30	90	2.49	0.0086	0.25	0.50	0.4656
10	90	3.02	0.0099	0.25	0.55	0.0737	30	90	2.49	0.0086	0.25	0.55	0.6655
10	90	3.02	0.0099	0.25	0.60	0.1554	30	90	2.49	0.0086	0.25	0.60	0.8272
10	90	3.02	0.0099	0.25	0.65	0.2836	30	90	2.49	0.0086	0.25	0.65	0.9284

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	90	3.02	0.0099	0.25	0.70	0.4452	30	90	2.49	0.0086	0.25	0.70	0.9777
10	90	3.02	0.0099	0.25	0.75	0.6174	30	90	2.49	0.0086	0.25	0.75	0.9952
10	90	3.02	0.0099	0.30	0.45	0.0043	30	90	2.49	0.0086	0.30	0.45	0.1350
10	90	3.02	0.0099	0.30	0.50	0.0157	30	90	2.49	0.0086	0.30	0.50	0.2740
10	90	3.02	0.0099	0.30	0.55	0.0413	30	90	2.49	0.0086	0.30	0.55	0.4623
10	90	3.02	0.0099	0.30	0.60	0.0952	30	90	2.49	0.0086	0.30	0.60	0.6596
10	90	3.02	0.0099	0.30	0.65	0.1894	30	90	2.49	0.0086	0.30	0.65	0.8229
10	90	3.02	0.0099	0.30	0.70	0.3235	30	90	2.49	0.0086	0.30	0.70	0.9290
10	90	3.02	0.0099	0.35	0.50	0.0078	30	90	2.49	0.0086	0.35	0.50	0.1381
10	90	3.02	0.0099	0.35	0.55	0.0222	30	90	2.49	0.0086	0.35	0.55	0.2776
10	90	3.02	0.0099	0.35	0.60	0.0556	30	90	2.49	0.0086	0.35	0.60	0.4639
10	90	3.02	0.0099	0.35	0.65	0.1203	30	90	2.49	0.0086	0.35	0.65	0.6634
10	90	3.02	0.0099	0.40	0.55	0.0113	30	90	2.49	0.0086	0.40	0.55	0.1426
10	90	3.02	0.0099	0.40	0.60	0.0308	30	90	2.49	0.0086	0.40	0.60	0.2832
10	100	3.18	0.0086	0.05	0.15	0.0000	30	100	2.56	0.0072	0.05	0.15	0.0370
10	100	3.18	0.0086	0.05	0.20	0.0000	30	100	2.56	0.0072	0.05	0.20	0.1844
10	100	3.18	0.0086	0.05	0.25	0.0000	30	100	2.56	0.0072	0.05	0.25	0.4244
10	100	3.18	0.0086	0.05	0.30	0.0000	30	100	2.56	0.0072	0.05	0.30	0.6754
10	100	3.18	0.0086	0.05	0.35	0.0001	30	100	2.56	0.0072	0.05	0.35	0.8555
10	100	3.18	0.0086	0.05	0.40	0.0035	30	100	2.56	0.0072	0.05	0.40	0.9506
10	100	3.18	0.0086	0.05	0.45	0.0397	30	100	2.56	0.0072	0.05	0.45	0.9874
10	100	3.18	0.0086	0.10	0.25	0.0000	30	100	2.56	0.0072	0.10	0.25	0.1540
10	100	3.18	0.0086	0.10	0.30	0.0000	30	100	2.56	0.0072	0.10	0.30	0.3347
10	100	3.18	0.0086	0.10	0.35	0.0001	30	100	2.56	0.0072	0.10	0.35	0.5557
10	100	3.18	0.0086	0.10	0.40	0.0020	30	100	2.56	0.0072	0.10	0.40	0.7586
10	100	3.18	0.0086	0.10	0.45	0.0232	30	100	2.56	0.0072	0.10	0.45	0.8959
10	100	3.18	0.0086	0.10	0.50	0.1100	30	100	2.56	0.0072	0.10	0.50	0.9651
10	100	3.18	0.0086	0.10	0.55	0.2670	30	100	2.56	0.0072	0.10	0.55	0.9912
10	100	3.18	0.0086	0.10	0.60	0.4482	30	100	2.56	0.0072	0.10	0.60	0.9984
10	100	3.18	0.0086	0.15	0.30	0.0000	30	100	2.56	0.0072	0.15	0.30	0.1344
10	100	3.18	0.0086	0.15	0.35	0.0000	30	100	2.56	0.0072	0.15	0.35	0.2887
10	100	3.18	0.0086	0.15	0.40	0.0011	30	100	2.56	0.0072	0.15	0.40	0.4948
10	100	3.18	0.0086	0.15	0.45	0.0131	30	100	2.56	0.0072	0.15	0.45	0.7002
10	100	3.18	0.0086	0.15	0.50	0.0629	30	100	2.56	0.0072	0.15	0.50	0.8564
10	100	3.18	0.0086	0.15	0.55	0.1593	30	100	2.56	0.0072	0.15	0.55	0.9461
10	100	3.18	0.0086	0.15	0.60	0.2950	30	100	2.56	0.0072	0.15	0.60	0.9845
10	100	3.18	0.0086	0.15	0.65	0.4749	30	100	2.56	0.0072	0.15	0.65	0.9967
10	100	3.18	0.0086	0.20	0.35	0.0000	30	100	2.56	0.0072	0.20	0.35	0.1247
10	100	3.18	0.0086	0.20	0.40	0.0006	30	100	2.56	0.0072	0.20	0.40	0.2673
10	100	3.18	0.0086	0.20	0.45	0.0072	30	100	2.56	0.0072	0.20	0.45	0.4624
10	100	3.18	0.0086	0.20	0.50	0.0348	30	100	2.56	0.0072	0.20	0.50	0.6680
10	100	3.18	0.0086	0.20	0.55	0.0921	30	100	2.56	0.0072	0.20	0.55	0.8327
10	100	3.18	0.0086	0.20	0.60	0.1874	30	100	2.56	0.0072	0.20	0.60	0.9332
10	100	3.18	0.0086	0.20	0.65	0.3341	30	100	2.56	0.0072	0.20	0.65	0.9792
10	100	3.18	0.0086	0.20	0.70	0.5166	30	100	2.56	0.0072	0.20	0.70	0.9951
10	100	3.18	0.0086	0.25	0.40	0.0003	30	100	2.56	0.0072	0.25	0.40	0.1215
10	100	3.18	0.0086	0.25	0.45	0.0038	30	100	2.56	0.0072	0.25	0.45	0.2584
10	100	3.18	0.0086	0.25	0.50	0.0185	30	100	2.56	0.0072	0.25	0.50	0.4488
10	100	3.18	0.0086	0.25	0.55	0.0515	30	100	2.56	0.0072	0.25	0.55	0.6525
10	100	3.18	0.0086	0.25	0.60	0.1145	30	100	2.56	0.0072	0.25	0.60	0.8202

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
10	100	3.18	0.0086	0.25	0.65	0.2244	30	100	2.56	0.0072	0.25	0.65	0.9247
10	100	3.18	0.0086	0.25	0.70	0.3835	30	100	2.56	0.0072	0.25	0.70	0.9759
10	100	3.18	0.0086	0.25	0.75	0.5814	30	100	2.56	0.0072	0.25	0.75	0.9949
10	100	3.18	0.0086	0.30	0.45	0.0019	30	100	2.56	0.0072	0.30	0.45	0.1225
10	100	3.18	0.0086	0.30	0.50	0.0095	30	100	2.56	0.0072	0.30	0.50	0.2579
10	100	3.18	0.0086	0.30	0.55	0.0276	30	100	2.56	0.0072	0.30	0.55	0.4457
10	100	3.18	0.0086	0.30	0.60	0.0671	30	100	2.56	0.0072	0.30	0.60	0.6467
10	100	3.18	0.0086	0.30	0.65	0.1438	30	100	2.56	0.0072	0.30	0.65	0.8126
10	100	3.18	0.0086	0.30	0.70	0.2714	30	100	2.56	0.0072	0.30	0.70	0.9231
10	100	3.18	0.0086	0.35	0.50	0.0046	30	100	2.56	0.0072	0.35	0.50	0.1262
10	100	3.18	0.0086	0.35	0.55	0.0142	30	100	2.56	0.0072	0.35	0.55	0.2619
10	100	3.18	0.0086	0.35	0.60	0.0375	30	100	2.56	0.0072	0.35	0.60	0.4465
10	100	3.18	0.0086	0.35	0.65	0.0877	30	100	2.56	0.0072	0.35	0.65	0.6449
10	100	3.18	0.0086	0.40	0.55	0.0069	30	100	2.56	0.0072	0.40	0.55	0.1310
10	100	3.18	0.0086	0.40	0.60	0.0199	30	100	2.56	0.0072	0.40	0.60	0.2654
20	30	2.51	0.0074	0.05	0.15	0.0262	40	50	2.35	0.0099	0.05	0.15	0.1587
20	30	2.51	0.0074	0.05	0.20	0.0960	40	50	2.35	0.0099	0.05	0.20	0.3698
20	30	2.51	0.0074	0.05	0.25	0.2183	40	50	2.35	0.0099	0.05	0.25	0.6096
20	30	2.51	0.0074	0.05	0.30	0.3763	40	50	2.35	0.0099	0.05	0.30	0.8026
20	30	2.51	0.0074	0.05	0.35	0.5454	40	50	2.35	0.0099	0.05	0.35	0.9193
20	30	2.51	0.0074	0.05	0.40	0.7009	40	50	2.35	0.0099	0.05	0.40	0.9736
20	30	2.51	0.0074	0.05	0.45	0.8245	40	50	2.35	0.0099	0.05	0.45	0.9931
20	30	2.51	0.0074	0.10	0.25	0.0943	40	50	2.35	0.0099	0.10	0.25	0.2834
20	30	2.51	0.0074	0.10	0.30	0.1877	40	50	2.35	0.0099	0.10	0.30	0.4942
20	30	2.51	0.0074	0.10	0.35	0.3158	40	50	2.35	0.0099	0.10	0.35	0.6981
20	30	2.51	0.0074	0.10	0.40	0.4659	40	50	2.35	0.0099	0.10	0.40	0.8488
20	30	2.51	0.0074	0.10	0.45	0.6174	40	50	2.35	0.0099	0.10	0.45	0.9368
20	30	2.51	0.0074	0.10	0.50	0.7504	40	50	2.35	0.0099	0.10	0.50	0.9783
20	30	2.51	0.0074	0.10	0.55	0.8528	40	50	2.35	0.0099	0.10	0.55	0.9940
20	30	2.51	0.0074	0.10	0.60	0.9225	40	50	2.35	0.0099	0.10	0.60	0.9987
20	30	2.51	0.0074	0.15	0.30	0.0886	40	50	2.35	0.0099	0.15	0.30	0.2436
20	30	2.51	0.0074	0.15	0.35	0.1700	40	50	2.35	0.0099	0.15	0.35	0.4288
20	30	2.51	0.0074	0.15	0.40	0.2830	40	50	2.35	0.0099	0.15	0.40	0.6230
20	30	2.51	0.0074	0.15	0.45	0.4186	40	50	2.35	0.0099	0.15	0.45	0.7868
20	30	2.51	0.0074	0.15	0.50	0.5615	40	50	2.35	0.0099	0.15	0.50	0.8990
20	30	2.51	0.0074	0.15	0.55	0.6955	40	50	2.35	0.0099	0.15	0.55	0.9609
20	30	2.51	0.0074	0.15	0.60	0.8083	40	50	2.35	0.0099	0.15	0.60	0.9880
20	30	2.51	0.0074	0.15	0.65	0.8931	40	50	2.35	0.0099	0.15	0.65	0.9972
20	30	2.51	0.0074	0.20	0.35	0.0850	40	50	2.35	0.0099	0.20	0.35	0.2142
20	30	2.51	0.0074	0.20	0.40	0.1579	40	50	2.35	0.0099	0.20	0.40	0.3789
20	30	2.51	0.0074	0.20	0.45	0.2590	40	50	2.35	0.0099	0.20	0.45	0.5667
20	30	2.51	0.0074	0.20	0.50	0.3831	40	50	2.35	0.0099	0.20	0.50	0.7401
20	30	2.51	0.0074	0.20	0.55	0.5204	40	50	2.35	0.0099	0.20	0.55	0.8697
20	30	2.51	0.0074	0.20	0.60	0.6576	40	50	2.35	0.0099	0.20	0.60	0.9474
20	30	2.51	0.0074	0.20	0.65	0.7805	40	50	2.35	0.0099	0.20	0.65	0.9836
20	30	2.51	0.0074	0.20	0.70	0.8771	40	50	2.35	0.0099	0.20	0.70	0.9963
20	30	2.51	0.0074	0.25	0.40	0.0810	40	50	2.35	0.0099	0.25	0.40	0.1920
20	30	2.51	0.0074	0.25	0.45	0.1469	40	50	2.35	0.0099	0.25	0.45	0.3459
20	30	2.51	0.0074	0.25	0.50	0.2399	40	50	2.35	0.0099	0.25	0.50	0.5311
20	30	2.51	0.0074	0.25	0.55	0.3587	40	50	2.35	0.0099	0.25	0.55	0.7123

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	30	2.51	0.0074	0.25	0.60	0.4963	40	50	2.35	0.0099	0.25	0.60	0.8544
20	30	2.51	0.0074	0.25	0.65	0.6393	40	50	2.35	0.0099	0.25	0.65	0.9413
20	30	2.51	0.0074	0.25	0.70	0.7703	40	50	2.35	0.0099	0.25	0.70	0.9818
20	30	2.51	0.0074	0.25	0.75	0.8746	40	50	2.35	0.0099	0.25	0.75	0.9960
20	30	2.51	0.0074	0.30	0.45	0.0766	40	50	2.35	0.0099	0.30	0.45	0.1790
20	30	2.51	0.0074	0.30	0.50	0.1383	40	50	2.35	0.0099	0.30	0.50	0.3290
20	30	2.51	0.0074	0.30	0.55	0.2283	40	50	2.35	0.0099	0.30	0.55	0.5164
20	30	2.51	0.0074	0.30	0.60	0.3474	40	50	2.35	0.0099	0.30	0.60	0.7032
20	30	2.51	0.0074	0.30	0.65	0.4888	40	50	2.35	0.0099	0.30	0.65	0.8499
20	30	2.51	0.0074	0.30	0.70	0.6381	40	50	2.35	0.0099	0.30	0.70	0.9400
20	30	2.51	0.0074	0.35	0.50	0.0735	40	50	2.35	0.0099	0.35	0.50	0.1754
20	30	2.51	0.0074	0.35	0.55	0.1342	40	50	2.35	0.0099	0.35	0.55	0.3263
20	30	2.51	0.0074	0.35	0.60	0.2253	40	50	2.35	0.0099	0.35	0.60	0.5147
20	30	2.51	0.0074	0.35	0.65	0.3479	40	50	2.35	0.0099	0.35	0.65	0.7028
20	30	2.51	0.0074	0.40	0.55	0.0728	40	50	2.35	0.0099	0.40	0.55	0.1771
20	30	2.51	0.0074	0.40	0.60	0.1350	40	50	2.35	0.0099	0.40	0.60	0.3284
20	40	2.40	0.0099	0.05	0.15	0.0246	40	60	2.36	0.0099	0.05	0.15	0.1849
20	40	2.40	0.0099	0.05	0.20	0.1037	40	60	2.36	0.0099	0.05	0.20	0.4160
20	40	2.40	0.0099	0.05	0.25	0.2422	40	60	2.36	0.0099	0.05	0.25	0.6616
20	40	2.40	0.0099	0.05	0.30	0.4131	40	60	2.36	0.0099	0.05	0.30	0.8446
20	40	2.40	0.0099	0.05	0.35	0.5890	40	60	2.36	0.0099	0.05	0.35	0.9429
20	40	2.40	0.0099	0.05	0.40	0.7455	40	60	2.36	0.0099	0.05	0.40	0.9832
20	40	2.40	0.0099	0.05	0.45	0.8640	40	60	2.36	0.0099	0.05	0.45	0.9961
20	40	2.40	0.0099	0.10	0.25	0.0997	40	60	2.36	0.0099	0.10	0.25	0.3146
20	40	2.40	0.0099	0.10	0.30	0.1990	40	60	2.36	0.0099	0.10	0.30	0.5327
20	40	2.40	0.0099	0.10	0.35	0.3374	40	60	2.36	0.0099	0.10	0.35	0.7328
20	40	2.40	0.0099	0.10	0.40	0.5026	40	60	2.36	0.0099	0.10	0.40	0.8755
20	40	2.40	0.0099	0.10	0.45	0.6687	40	60	2.36	0.0099	0.10	0.45	0.9536
20	40	2.40	0.0099	0.10	0.50	0.8070	40	60	2.36	0.0099	0.10	0.50	0.9862
20	40	2.40	0.0099	0.10	0.55	0.9021	40	60	2.36	0.0099	0.10	0.55	0.9967
20	40	2.40	0.0099	0.10	0.60	0.9565	40	60	2.36	0.0099	0.10	0.60	0.9994
20	40	2.40	0.0099	0.15	0.30	0.0903	40	60	2.36	0.0099	0.15	0.30	0.2599
20	40	2.40	0.0099	0.15	0.35	0.1794	40	60	2.36	0.0099	0.15	0.35	0.4564
20	40	2.40	0.0099	0.15	0.40	0.3103	40	60	2.36	0.0099	0.15	0.40	0.6604
20	40	2.40	0.0099	0.15	0.45	0.4705	40	60	2.36	0.0099	0.15	0.45	0.8218
20	40	2.40	0.0099	0.15	0.50	0.6325	40	60	2.36	0.0099	0.15	0.50	0.9225
20	40	2.40	0.0099	0.15	0.55	0.7698	40	60	2.36	0.0099	0.15	0.55	0.9730
20	40	2.40	0.0099	0.15	0.60	0.8700	40	60	2.36	0.0099	0.15	0.60	0.9929
20	40	2.40	0.0099	0.15	0.65	0.9352	40	60	2.36	0.0099	0.15	0.65	0.9986
20	40	2.40	0.0099	0.20	0.35	0.0890	40	60	2.36	0.0099	0.20	0.35	0.2305
20	40	2.40	0.0099	0.20	0.40	0.1767	40	60	2.36	0.0099	0.20	0.40	0.4098
20	40	2.40	0.0099	0.20	0.45	0.3020	40	60	2.36	0.0099	0.20	0.45	0.6051
20	40	2.40	0.0099	0.20	0.50	0.4504	40	60	2.36	0.0099	0.20	0.50	0.7765
20	40	2.40	0.0099	0.20	0.55	0.6003	40	60	2.36	0.0099	0.20	0.55	0.8973
20	40	2.40	0.0099	0.20	0.60	0.7346	40	60	2.36	0.0099	0.20	0.60	0.9633
20	40	2.40	0.0099	0.20	0.65	0.8439	40	60	2.36	0.0099	0.20	0.65	0.9901
20	40	2.40	0.0099	0.20	0.70	0.9225	40	60	2.36	0.0099	0.20	0.70	0.9981
20	40	2.40	0.0099	0.25	0.40	0.0927	40	60	2.36	0.0099	0.25	0.40	0.2083
20	40	2.40	0.0099	0.25	0.45	0.1768	40	60	2.36	0.0099	0.25	0.45	0.3737
20	40	2.40	0.0099	0.25	0.50	0.2912	40	60	2.36	0.0099	0.25	0.50	0.5691

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	40	2.40	0.0099	0.25	0.55	0.4267	40	60	2.36	0.0099	0.25	0.55	0.7525
20	40	2.40	0.0099	0.25	0.60	0.5721	40	60	2.36	0.0099	0.25	0.60	0.8853
20	40	2.40	0.0099	0.25	0.65	0.7145	40	60	2.36	0.0099	0.25	0.65	0.9585
20	40	2.40	0.0099	0.25	0.70	0.8368	40	60	2.36	0.0099	0.25	0.70	0.9887
20	40	2.40	0.0099	0.25	0.75	0.9240	40	60	2.36	0.0099	0.25	0.75	0.9978
20	40	2.40	0.0099	0.30	0.45	0.0942	40	60	2.36	0.0099	0.30	0.45	0.1937
20	40	2.40	0.0099	0.30	0.50	0.1710	40	60	2.36	0.0099	0.30	0.50	0.3579
20	40	2.40	0.0099	0.30	0.55	0.2766	40	60	2.36	0.0099	0.30	0.55	0.5569
20	40	2.40	0.0099	0.30	0.60	0.4103	40	60	2.36	0.0099	0.30	0.60	0.7442
20	40	2.40	0.0099	0.30	0.65	0.5643	40	60	2.36	0.0099	0.30	0.65	0.8805
20	40	2.40	0.0099	0.30	0.70	0.7189	40	60	2.36	0.0099	0.30	0.70	0.9566
20	40	2.40	0.0099	0.35	0.50	0.0911	40	60	2.36	0.0099	0.35	0.50	0.1913
20	40	2.40	0.0099	0.35	0.55	0.1638	40	60	2.36	0.0099	0.35	0.55	0.3560
20	40	2.40	0.0099	0.35	0.60	0.2710	40	60	2.36	0.0099	0.35	0.60	0.5545
20	40	2.40	0.0099	0.35	0.65	0.4143	40	60	2.36	0.0099	0.35	0.65	0.7421
20	40	2.40	0.0099	0.40	0.55	0.0885	40	60	2.36	0.0099	0.40	0.55	0.1933
20	40	2.40	0.0099	0.40	0.60	0.1646	40	60	2.36	0.0099	0.40	0.60	0.3572
20	50	2.65	0.0056	0.05	0.15	0.0019	40	70	2.39	0.0094	0.05	0.15	0.1615
20	50	2.65	0.0056	0.05	0.20	0.0227	40	70	2.39	0.0094	0.05	0.20	0.4057
20	50	2.65	0.0056	0.05	0.25	0.1017	40	70	2.39	0.0094	0.05	0.25	0.6627
20	50	2.65	0.0056	0.05	0.30	0.2562	40	70	2.39	0.0094	0.05	0.30	0.8497
20	50	2.65	0.0056	0.05	0.35	0.4576	40	70	2.39	0.0094	0.05	0.35	0.9480
20	50	2.65	0.0056	0.05	0.40	0.6581	40	70	2.39	0.0094	0.05	0.40	0.9861
20	50	2.65	0.0056	0.05	0.45	0.8171	40	70	2.39	0.0094	0.05	0.45	0.9972
20	50	2.65	0.0056	0.10	0.25	0.0392	40	70	2.39	0.0094	0.10	0.25	0.3042
20	50	2.65	0.0056	0.10	0.30	0.1128	40	70	2.39	0.0094	0.10	0.30	0.5301
20	50	2.65	0.0056	0.10	0.35	0.2389	40	70	2.39	0.0094	0.10	0.35	0.7386
20	50	2.65	0.0056	0.10	0.40	0.4087	40	70	2.39	0.0094	0.10	0.40	0.8838
20	50	2.65	0.0056	0.10	0.45	0.5914	40	70	2.39	0.0094	0.10	0.45	0.9599
20	50	2.65	0.0056	0.10	0.50	0.7514	40	70	2.39	0.0094	0.10	0.50	0.9894
20	50	2.65	0.0056	0.10	0.55	0.8676	40	70	2.39	0.0094	0.10	0.55	0.9979
20	50	2.65	0.0056	0.10	0.60	0.9392	40	70	2.39	0.0094	0.10	0.60	0.9997
20	50	2.65	0.0056	0.15	0.30	0.0470	40	70	2.39	0.0094	0.15	0.30	0.2519
20	50	2.65	0.0056	0.15	0.35	0.1159	40	70	2.39	0.0094	0.15	0.35	0.4548
20	50	2.65	0.0056	0.15	0.40	0.2300	40	70	2.39	0.0094	0.15	0.40	0.6686
20	50	2.65	0.0056	0.15	0.45	0.3821	40	70	2.39	0.0094	0.15	0.45	0.8366
20	50	2.65	0.0056	0.15	0.50	0.5491	40	70	2.39	0.0094	0.15	0.50	0.9355
20	50	2.65	0.0056	0.15	0.55	0.7046	40	70	2.39	0.0094	0.15	0.55	0.9799
20	50	2.65	0.0056	0.15	0.60	0.8298	40	70	2.39	0.0094	0.15	0.60	0.9951
20	50	2.65	0.0056	0.15	0.65	0.9170	40	70	2.39	0.0094	0.15	0.65	0.9991
20	50	2.65	0.0056	0.20	0.35	0.0521	40	70	2.39	0.0094	0.20	0.35	0.2252
20	50	2.65	0.0056	0.20	0.40	0.1182	40	70	2.39	0.0094	0.20	0.40	0.4164
20	50	2.65	0.0056	0.20	0.45	0.2228	40	70	2.39	0.0094	0.20	0.45	0.6260
20	50	2.65	0.0056	0.20	0.50	0.3611	40	70	2.39	0.0094	0.20	0.50	0.8004
20	50	2.65	0.0056	0.20	0.55	0.5183	40	70	2.39	0.0094	0.20	0.55	0.9131
20	50	2.65	0.0056	0.20	0.60	0.6754	40	70	2.39	0.0094	0.20	0.60	0.9700
20	50	2.65	0.0056	0.20	0.65	0.8121	40	70	2.39	0.0094	0.20	0.65	0.9922
20	50	2.65	0.0056	0.20	0.70	0.9113	40	70	2.39	0.0094	0.20	0.70	0.9986
20	50	2.65	0.0056	0.25	0.40	0.0556	40	70	2.39	0.0094	0.25	0.40	0.2127
20	50	2.65	0.0056	0.25	0.45	0.1180	40	70	2.39	0.0094	0.25	0.45	0.3911

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	50	2.65	0.0056	0.25	0.50	0.2150	40	70	2.39	0.0094	0.25	0.50	0.5922
20	50	2.65	0.0056	0.25	0.55	0.3465	40	70	2.39	0.0094	0.25	0.55	0.7704
20	50	2.65	0.0056	0.25	0.60	0.5051	40	70	2.39	0.0094	0.25	0.60	0.8955
20	50	2.65	0.0056	0.25	0.65	0.6718	40	70	2.39	0.0094	0.25	0.65	0.9636
20	50	2.65	0.0056	0.25	0.70	0.8176	40	70	2.39	0.0094	0.25	0.70	0.9909
20	50	2.65	0.0056	0.25	0.75	0.9184	40	70	2.39	0.0094	0.25	0.75	0.9985
20	50	2.65	0.0056	0.30	0.45	0.0568	40	70	2.39	0.0094	0.30	0.45	0.2017
20	50	2.65	0.0056	0.30	0.50	0.1163	40	70	2.39	0.0094	0.30	0.50	0.3692
20	50	2.65	0.0056	0.30	0.55	0.2113	40	70	2.39	0.0094	0.30	0.55	0.5669
20	50	2.65	0.0056	0.30	0.60	0.3472	40	70	2.39	0.0094	0.30	0.60	0.7532
20	50	2.65	0.0056	0.30	0.65	0.5162	40	70	2.39	0.0094	0.30	0.65	0.8892
20	50	2.65	0.0056	0.30	0.70	0.6909	40	70	2.39	0.0094	0.30	0.70	0.9628
20	50	2.65	0.0056	0.35	0.50	0.0572	40	70	2.39	0.0094	0.35	0.50	0.1915
20	50	2.65	0.0056	0.35	0.55	0.1177	40	70	2.39	0.0094	0.35	0.55	0.3558
20	50	2.65	0.0056	0.35	0.60	0.2192	40	70	2.39	0.0094	0.35	0.60	0.5588
20	50	2.65	0.0056	0.35	0.65	0.3665	40	70	2.39	0.0094	0.35	0.65	0.7530
20	50	2.65	0.0056	0.40	0.55	0.0598	40	70	2.39	0.0094	0.40	0.55	0.1880
20	50	2.65	0.0056	0.40	0.60	0.1267	40	70	2.39	0.0094	0.40	0.60	0.3570
20	60	2.59	0.0077	0.05	0.15	0.0022	40	80	2.42	0.0097	0.05	0.15	0.1582
20	60	2.59	0.0077	0.05	0.20	0.0295	40	80	2.42	0.0097	0.05	0.20	0.4113
20	60	2.59	0.0077	0.05	0.25	0.1359	40	80	2.42	0.0097	0.05	0.25	0.6826
20	60	2.59	0.0077	0.05	0.30	0.3325	40	80	2.42	0.0097	0.05	0.30	0.8674
20	60	2.59	0.0077	0.05	0.35	0.5597	40	80	2.42	0.0097	0.05	0.35	0.9564
20	60	2.59	0.0077	0.05	0.40	0.7517	40	80	2.42	0.0097	0.05	0.40	0.9888
20	60	2.59	0.0077	0.05	0.45	0.8801	40	80	2.42	0.0097	0.05	0.45	0.9978
20	60	2.59	0.0077	0.10	0.25	0.0546	40	80	2.42	0.0097	0.10	0.25	0.3153
20	60	2.59	0.0077	0.10	0.30	0.1550	40	80	2.42	0.0097	0.10	0.30	0.5433
20	60	2.59	0.0077	0.10	0.35	0.3098	40	80	2.42	0.0097	0.10	0.35	0.7483
20	60	2.59	0.0077	0.10	0.40	0.4923	40	80	2.42	0.0097	0.10	0.40	0.8898
20	60	2.59	0.0077	0.10	0.45	0.6680	40	80	2.42	0.0097	0.10	0.45	0.9632
20	60	2.59	0.0077	0.10	0.50	0.8107	40	80	2.42	0.0097	0.10	0.50	0.9908
20	60	2.59	0.0077	0.10	0.55	0.9078	40	80	2.42	0.0097	0.10	0.55	0.9983
20	60	2.59	0.0077	0.10	0.60	0.9621	40	80	2.42	0.0097	0.10	0.60	0.9998
20	60	2.59	0.0077	0.15	0.30	0.0669	40	80	2.42	0.0097	0.15	0.30	0.2522
20	60	2.59	0.0077	0.15	0.35	0.1549	40	80	2.42	0.0097	0.15	0.35	0.4539
20	60	2.59	0.0077	0.15	0.40	0.2856	40	80	2.42	0.0097	0.15	0.40	0.6698
20	60	2.59	0.0077	0.15	0.45	0.4473	40	80	2.42	0.0097	0.15	0.45	0.8398
20	60	2.59	0.0077	0.15	0.50	0.6170	40	80	2.42	0.0097	0.15	0.50	0.9385
20	60	2.59	0.0077	0.15	0.55	0.7663	40	80	2.42	0.0097	0.15	0.55	0.9820
20	60	2.59	0.0077	0.15	0.60	0.8769	40	80	2.42	0.0097	0.15	0.60	0.9962
20	60	2.59	0.0077	0.15	0.65	0.9464	40	80	2.42	0.0097	0.15	0.65	0.9994
20	60	2.59	0.0077	0.20	0.35	0.0706	40	80	2.42	0.0097	0.20	0.35	0.2180
20	60	2.59	0.0077	0.20	0.40	0.1495	40	80	2.42	0.0097	0.20	0.40	0.4100
20	60	2.59	0.0077	0.20	0.45	0.2687	40	80	2.42	0.0097	0.20	0.45	0.6234
20	60	2.59	0.0077	0.20	0.50	0.4215	40	80	2.42	0.0097	0.20	0.50	0.8035
20	60	2.59	0.0077	0.20	0.55	0.5868	40	80	2.42	0.0097	0.20	0.55	0.9199
20	60	2.59	0.0077	0.20	0.60	0.7405	40	80	2.42	0.0097	0.20	0.60	0.9754
20	60	2.59	0.0077	0.20	0.65	0.8626	40	80	2.42	0.0097	0.20	0.65	0.9945
20	60	2.59	0.0077	0.20	0.70	0.9405	40	80	2.42	0.0097	0.20	0.70	0.9991
20	60	2.59	0.0077	0.25	0.40	0.0711	40	80	2.42	0.0097	0.25	0.40	0.2034

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	60	2.59	0.0077	0.25	0.45	0.1459	40	80	2.42	0.0097	0.25	0.45	0.3838
20	60	2.59	0.0077	0.25	0.50	0.2597	40	80	2.42	0.0097	0.25	0.50	0.5955
20	60	2.59	0.0077	0.25	0.55	0.4075	40	80	2.42	0.0097	0.25	0.55	0.7847
20	60	2.59	0.0077	0.25	0.60	0.5749	40	80	2.42	0.0097	0.25	0.60	0.9102
20	60	2.59	0.0077	0.25	0.65	0.7361	40	80	2.42	0.0097	0.25	0.65	0.9714
20	60	2.59	0.0077	0.25	0.70	0.8615	40	80	2.42	0.0097	0.25	0.70	0.9933
20	60	2.59	0.0077	0.25	0.75	0.9405	40	80	2.42	0.0097	0.25	0.75	0.9989
20	60	2.59	0.0077	0.30	0.45	0.0718	40	80	2.42	0.0097	0.30	0.45	0.1949
20	60	2.59	0.0077	0.30	0.50	0.1448	40	80	2.42	0.0097	0.30	0.50	0.3732
20	60	2.59	0.0077	0.30	0.55	0.2570	40	80	2.42	0.0097	0.30	0.55	0.5863
20	60	2.59	0.0077	0.30	0.60	0.4087	40	80	2.42	0.0097	0.30	0.60	0.7769
20	60	2.59	0.0077	0.30	0.65	0.5815	40	80	2.42	0.0097	0.30	0.65	0.9049
20	60	2.59	0.0077	0.30	0.70	0.7428	40	80	2.42	0.0097	0.30	0.70	0.9694
20	60	2.59	0.0077	0.35	0.50	0.0730	40	80	2.42	0.0097	0.35	0.50	0.1951
20	60	2.59	0.0077	0.35	0.55	0.1472	40	80	2.42	0.0097	0.35	0.55	0.3730
20	60	2.59	0.0077	0.35	0.60	0.2649	40	80	2.42	0.0097	0.35	0.60	0.5836
20	60	2.59	0.0077	0.35	0.65	0.4216	40	80	2.42	0.0097	0.35	0.65	0.7736
20	60	2.59	0.0077	0.40	0.55	0.0763	40	80	2.42	0.0097	0.40	0.55	0.1981
20	60	2.59	0.0077	0.40	0.60	0.1557	40	80	2.42	0.0097	0.40	0.60	0.3741
20	70	2.68	0.0090	0.05	0.15	0.0010	40	90	2.44	0.0090	0.05	0.15	0.1350
20	70	2.68	0.0090	0.05	0.20	0.0198	40	90	2.44	0.0090	0.05	0.20	0.3795
20	70	2.68	0.0090	0.05	0.25	0.1085	40	90	2.44	0.0090	0.05	0.25	0.6590
20	70	2.68	0.0090	0.05	0.30	0.2805	40	90	2.44	0.0090	0.05	0.30	0.8624
20	70	2.68	0.0090	0.05	0.35	0.4919	40	90	2.44	0.0090	0.05	0.35	0.9591
20	70	2.68	0.0090	0.05	0.40	0.6991	40	90	2.44	0.0090	0.05	0.40	0.9909
20	70	2.68	0.0090	0.05	0.45	0.8561	40	90	2.44	0.0090	0.05	0.45	0.9985
20	70	2.68	0.0090	0.10	0.25	0.0393	40	90	2.44	0.0090	0.10	0.25	0.2951
20	70	2.68	0.0090	0.10	0.30	0.1159	40	90	2.44	0.0090	0.10	0.30	0.5412
20	70	2.68	0.0090	0.10	0.35	0.2490	40	90	2.44	0.0090	0.10	0.35	0.7604
20	70	2.68	0.0090	0.10	0.40	0.4353	40	90	2.44	0.0090	0.10	0.40	0.9015
20	70	2.68	0.0090	0.10	0.45	0.6333	40	90	2.44	0.0090	0.10	0.45	0.9690
20	70	2.68	0.0090	0.10	0.50	0.7954	40	90	2.44	0.0090	0.10	0.50	0.9927
20	70	2.68	0.0090	0.10	0.55	0.9023	40	90	2.44	0.0090	0.10	0.55	0.9987
20	70	2.68	0.0090	0.10	0.60	0.9606	40	90	2.44	0.0090	0.10	0.60	0.9998
20	70	2.68	0.0090	0.15	0.30	0.0454	40	90	2.44	0.0090	0.15	0.30	0.2529
20	70	2.68	0.0090	0.15	0.35	0.1167	40	90	2.44	0.0090	0.15	0.35	0.4664
20	70	2.68	0.0090	0.15	0.40	0.2430	40	90	2.44	0.0090	0.15	0.40	0.6856
20	70	2.68	0.0090	0.15	0.45	0.4130	40	90	2.44	0.0090	0.15	0.45	0.8519
20	70	2.68	0.0090	0.15	0.50	0.5940	40	90	2.44	0.0090	0.15	0.50	0.9450
20	70	2.68	0.0090	0.15	0.55	0.7526	40	90	2.44	0.0090	0.15	0.55	0.9845
20	70	2.68	0.0090	0.15	0.60	0.8705	40	90	2.44	0.0090	0.15	0.60	0.9968
20	70	2.68	0.0090	0.15	0.65	0.9445	40	90	2.44	0.0090	0.15	0.65	0.9996
20	70	2.68	0.0090	0.20	0.35	0.0506	40	90	2.44	0.0090	0.20	0.35	0.2237
20	70	2.68	0.0090	0.20	0.40	0.1229	40	90	2.44	0.0090	0.20	0.40	0.4202
20	70	2.68	0.0090	0.20	0.45	0.2410	40	90	2.44	0.0090	0.20	0.45	0.6353
20	70	2.68	0.0090	0.20	0.50	0.3958	40	90	2.44	0.0090	0.20	0.50	0.8128
20	70	2.68	0.0090	0.20	0.55	0.5659	40	90	2.44	0.0090	0.20	0.55	0.9252
20	70	2.68	0.0090	0.20	0.60	0.7269	40	90	2.44	0.0090	0.20	0.60	0.9776
20	70	2.68	0.0090	0.20	0.65	0.8563	40	90	2.44	0.0090	0.20	0.65	0.9952
20	70	2.68	0.0090	0.20	0.70	0.9395	40	90	2.44	0.0090	0.20	0.70	0.9993

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	70	2.68	0.0090	0.25	0.40	0.0566	40	90	2.44	0.0090	0.25	0.40	0.2066
20	70	2.68	0.0090	0.25	0.45	0.1267	40	90	2.44	0.0090	0.25	0.45	0.3892
20	70	2.68	0.0090	0.25	0.50	0.2367	40	90	2.44	0.0090	0.25	0.50	0.6015
20	70	2.68	0.0090	0.25	0.55	0.3838	40	90	2.44	0.0090	0.25	0.55	0.7898
20	70	2.68	0.0090	0.25	0.60	0.5549	40	90	2.44	0.0090	0.25	0.60	0.9138
20	70	2.68	0.0090	0.25	0.65	0.7240	40	90	2.44	0.0090	0.25	0.65	0.9742
20	70	2.68	0.0090	0.25	0.70	0.8582	40	90	2.44	0.0090	0.25	0.70	0.9948
20	70	2.68	0.0090	0.25	0.75	0.9411	40	90	2.44	0.0090	0.25	0.75	0.9993
20	70	2.68	0.0090	0.30	0.45	0.0601	40	90	2.44	0.0090	0.30	0.45	0.1944
20	70	2.68	0.0090	0.30	0.50	0.1276	40	90	2.44	0.0090	0.30	0.50	0.3727
20	70	2.68	0.0090	0.30	0.55	0.2351	40	90	2.44	0.0090	0.30	0.55	0.5868
20	70	2.68	0.0090	0.30	0.60	0.3859	40	90	2.44	0.0090	0.30	0.60	0.7810
20	70	2.68	0.0090	0.30	0.65	0.5649	40	90	2.44	0.0090	0.30	0.65	0.9125
20	70	2.68	0.0090	0.30	0.70	0.7365	40	90	2.44	0.0090	0.30	0.70	0.9752
20	70	2.68	0.0090	0.35	0.50	0.0619	40	90	2.44	0.0090	0.35	0.50	0.1907
20	70	2.68	0.0090	0.35	0.55	0.1301	40	90	2.44	0.0090	0.35	0.55	0.3691
20	70	2.68	0.0090	0.35	0.60	0.2437	40	90	2.44	0.0090	0.35	0.60	0.5880
20	70	2.68	0.0090	0.35	0.65	0.4034	40	90	2.44	0.0090	0.35	0.65	0.7886
20	70	2.68	0.0090	0.40	0.55	0.0649	40	90	2.44	0.0090	0.40	0.55	0.1933
20	70	2.68	0.0090	0.40	0.60	0.1392	40	90	2.44	0.0090	0.40	0.60	0.3792
20	80	2.86	0.0058	0.05	0.15	0.0001	40	100	2.60	0.0083	0.05	0.15	0.0877
20	80	2.86	0.0058	0.05	0.20	0.0041	40	100	2.60	0.0083	0.05	0.20	0.3172
20	80	2.86	0.0058	0.05	0.25	0.0461	40	100	2.60	0.0083	0.05	0.25	0.6036
20	80	2.86	0.0058	0.05	0.30	0.1824	40	100	2.60	0.0083	0.05	0.30	0.8228
20	80	2.86	0.0058	0.05	0.35	0.3964	40	100	2.60	0.0083	0.05	0.35	0.9405
20	80	2.86	0.0058	0.05	0.40	0.6233	40	100	2.60	0.0083	0.05	0.40	0.9858
20	80	2.86	0.0058	0.05	0.45	0.8058	40	100	2.60	0.0083	0.05	0.45	0.9977
20	80	2.86	0.0058	0.10	0.25	0.0163	40	100	2.60	0.0083	0.10	0.25	0.2362
20	80	2.86	0.0058	0.10	0.30	0.0709	40	100	2.60	0.0083	0.10	0.30	0.4612
20	80	2.86	0.0058	0.10	0.35	0.1832	40	100	2.60	0.0083	0.10	0.35	0.6975
20	80	2.86	0.0058	0.10	0.40	0.3527	40	100	2.60	0.0083	0.10	0.40	0.8707
20	80	2.86	0.0058	0.10	0.45	0.5493	40	100	2.60	0.0083	0.10	0.45	0.9583
20	80	2.86	0.0058	0.10	0.50	0.7293	40	100	2.60	0.0083	0.10	0.50	0.9898
20	80	2.86	0.0058	0.10	0.55	0.8639	40	100	2.60	0.0083	0.10	0.55	0.9982
20	80	2.86	0.0058	0.10	0.60	0.9447	40	100	2.60	0.0083	0.10	0.60	0.9998
20	80	2.86	0.0058	0.15	0.30	0.0260	40	100	2.60	0.0083	0.15	0.30	0.1909
20	80	2.86	0.0058	0.15	0.35	0.0785	40	100	2.60	0.0083	0.15	0.35	0.3938
20	80	2.86	0.0058	0.15	0.40	0.1790	40	100	2.60	0.0083	0.15	0.40	0.6269
20	80	2.86	0.0058	0.15	0.45	0.3285	40	100	2.60	0.0083	0.15	0.45	0.8159
20	80	2.86	0.0058	0.15	0.50	0.5089	40	100	2.60	0.0083	0.15	0.50	0.9290
20	80	2.86	0.0058	0.15	0.55	0.6893	40	100	2.60	0.0083	0.15	0.55	0.9797
20	80	2.86	0.0058	0.15	0.60	0.8346	40	100	2.60	0.0083	0.15	0.60	0.9959
20	80	2.86	0.0058	0.15	0.65	0.9275	40	100	2.60	0.0083	0.15	0.65	0.9994
20	80	2.86	0.0058	0.20	0.35	0.0311	40	100	2.60	0.0083	0.20	0.35	0.1730
20	80	2.86	0.0058	0.20	0.40	0.0825	40	100	2.60	0.0083	0.20	0.40	0.3572
20	80	2.86	0.0058	0.20	0.45	0.1760	40	100	2.60	0.0083	0.20	0.45	0.5770
20	80	2.86	0.0058	0.20	0.50	0.3167	40	100	2.60	0.0083	0.20	0.50	0.7748
20	80	2.86	0.0058	0.20	0.55	0.4933	40	100	2.60	0.0083	0.20	0.55	0.9081
20	80	2.86	0.0058	0.20	0.60	0.6729	40	100	2.60	0.0083	0.20	0.60	0.9723
20	80	2.86	0.0058	0.20	0.65	0.8213	40	100	2.60	0.0083	0.20	0.65	0.9940

Table B.24: continue on next page

Table B.24: –continued from previous page

n_1	n_2	z_u	pvalue	p_1	p_2	power	n_1	n_2	z_u	pvalue	p_1	p_2	power
20	80	2.86	0.0058	0.20	0.70	0.9220	40	100	2.60	0.0083	0.20	0.70	0.9991
20	80	2.86	0.0058	0.25	0.40	0.0347	40	100	2.60	0.0083	0.25	0.40	0.1614
20	80	2.86	0.0058	0.25	0.45	0.0852	40	100	2.60	0.0083	0.25	0.45	0.3311
20	80	2.86	0.0058	0.25	0.50	0.1774	40	100	2.60	0.0083	0.25	0.50	0.5481
20	80	2.86	0.0058	0.25	0.55	0.3177	40	100	2.60	0.0083	0.25	0.55	0.7550
20	80	2.86	0.0058	0.25	0.60	0.4920	40	100	2.60	0.0083	0.25	0.60	0.8972
20	80	2.86	0.0058	0.25	0.65	0.6719	40	100	2.60	0.0083	0.25	0.65	0.9676
20	80	2.86	0.0058	0.25	0.70	0.8265	40	100	2.60	0.0083	0.25	0.70	0.9928
20	80	2.86	0.0058	0.25	0.75	0.9298	40	100	2.60	0.0083	0.25	0.75	0.9990
20	80	2.86	0.0058	0.30	0.45	0.0374	40	100	2.60	0.0083	0.30	0.45	0.1538
20	80	2.86	0.0058	0.30	0.50	0.0897	40	100	2.60	0.0083	0.30	0.50	0.3215
20	80	2.86	0.0058	0.30	0.55	0.1843	40	100	2.60	0.0083	0.30	0.55	0.5397
20	80	2.86	0.0058	0.30	0.60	0.3254	40	100	2.60	0.0083	0.30	0.60	0.7469
20	80	2.86	0.0058	0.30	0.65	0.5037	40	100	2.60	0.0083	0.30	0.65	0.8921
20	80	2.86	0.0058	0.30	0.70	0.6925	40	100	2.60	0.0083	0.30	0.70	0.9670
20	80	2.86	0.0058	0.35	0.50	0.0409	40	100	2.60	0.0083	0.35	0.50	0.1545
20	80	2.86	0.0058	0.35	0.55	0.0962	40	100	2.60	0.0083	0.35	0.55	0.3226
20	80	2.86	0.0058	0.35	0.60	0.1943	40	100	2.60	0.0083	0.35	0.60	0.5385
20	80	2.86	0.0058	0.35	0.65	0.3441	40	100	2.60	0.0083	0.35	0.65	0.7472
20	80	2.86	0.0058	0.40	0.55	0.0450	40	100	2.60	0.0083	0.40	0.55	0.1582
20	80	2.86	0.0058	0.40	0.60	0.1044	40	100	2.60	0.0083	0.40	0.60	0.3263

Table B.24: concluded from previous page

Appendix C

Figures

Figure C.1: Comparison of the p-values for the Z exact test for the unpooled and pooled statistics in case of equal sample size, $\boldsymbol{\alpha}$= **0.05**.

		z		p		p-value	
n1	n2	S-U	S-P	S-U	S-P	S-U	S-P
10	10	1.96	1.79	0.7007	0.7007	0.0474	0.0474
11	11	1.92	1.78	0.8034	0.8034	0.0454	0.0454
12	12	1.86	1.74	0.8154	0.8154	0.0468	0.0468
13	13	1.81	1.70	0.8258	0.8258	0.0480	0.0480
14	14	1.77	1.68	0.8349	0.8349	0.0491	0.0491
15	15	1.74	1.66	0.5000	0.5000	0.0495	0.0495
16	16	1.92	1.82	0.1181	0.3212	0.0416	0.0361
17	17	1.90	1.80	0.8880	0.8880	0.0420	0.0420
18	18	1.88	1.79	0.1065	0.1065	0.0424	0.0424
19	19	1.86	1.78	0.7183	0.7183	0.0415	0.0415
20	20	1.85	1.78	0.5000	0.5000	0.0404	0.0404
21	21	1.83	1.76	0.5000	0.5000	0.0442	0.0442
22	22	1.81	1.75	0.5000	0.5000	0.0481	0.0481
23	23	1.84	1.78	0.6151	0.6151	0.0438	0.0438
24	24	1.80	1.74	0.3670	0.3670	0.0455	0.0455
25	25	1.77	1.71	0.3546	0.3546	0.0472	0.0472
26	26	1.75	1.70	0.3439	0.3439	0.0489	0.0489
27	27	1.79	1.74	0.2580	0.2580	0.0413	0.0413
28	28	1.78	1.73	0.7464	0.7464	0.0423	0.0423
29	29	1.78	1.73	0.7508	0.7508	0.0432	0.0432
30	30	1.77	1.73	0.7550	0.7550	0.0440	0.0440
31	31	1.72	1.68	0.5000	0.5000	0.0490	0.0490
32	32	1.80	1.76	0.5966	0.6279	0.0458	0.0432
33	33	1.77	1.73	0.6118	0.6118	0.0471	0.0471
34	34	1.75	1.71	0.6289	0.6289	0.0488	0.0488
35	35	1.75	1.71	0.3468	0.3468	0.0470	0.0470
36	36	1.75	1.71	0.1520	0.1520	0.0435	0.0435
37	37	1.70	1.67	0.2186	0.2186	0.0492	0.0492
38	38	1.71	1.68	0.7884	0.7884	0.0497	0.0497
39	39	1.74	1.70	0.8539	0.8539	0.0445	0.0445
40	40	1.73	1.70	0.8556	0.8556	0.0448	0.0448
50	50	1.71	1.69	0.1289	0.8711	0.0476	0.0476
60	60	1.70	1.68	0.1608	0.1608	0.0500	0.0500
70	70	1.72	1.70	0.6132	0.6020	0.0476	0.0486
80	80	1.68	1.67	0.6877	0.6877	0.0494	0.0494
90	90	1.69	1.67	0.3616	0.3616	0.0494	0.0494
100	100	1.68	1.67	0.8758	0.8758	0.0495	0.0495
150	150	1.67	1.66	0.3544	0.3544	0.0498	0.0498

z: critical value; p: nuisance parameter point of maximum; p-value: attained size of the test; n1: sample size 1; n2: sample size 2; S-U: Suissa Unpooled; S-P: Suissa Pooled. Green cell: larger p-value; Orange cell: lower p-value.

Figure C.2: Comparison of the p-values for the Z exact test for the unpooled and pooled statistics in case of equal sample size, $\boldsymbol{\alpha} = \mathbf{0.05}$.

		z		p		p-value	
n1	**n2**	**S-U**	**S-P**	**S-U**	**S-P**	**S-U**	**S-P**
10	10	2.17	1.96	0.5000	0.5000	0.0211	0.0211
11	11	2.40	2.14	0.6449	0.6449	0.0207	0.0207
12	12	2.26	2.05	0.3184	0.3184	0.0225	0.0225
13	13	2.16	1.99	0.3038	0.3038	0.0243	0.0243
14	14	2.19	2.03	0.7879	0.7879	0.0208	0.0208
15	15	2.14	2.00	0.7962	0.7962	0.0216	0.0216
16	16	2.29	2.13	0.8033	0.8033	0.0224	0.0224
17	17	2.21	2.07	0.1910	0.1910	0.0231	0.0231
18	18	2.14	2.02	0.3308	0.3308	0.0239	0.0239
19	19	2.14	2.02	0.1776	0.1776	0.0243	0.0243
20	20	2.10	1.99	0.1736	0.1736	0.0249	0.0249
21	21	2.17	2.05	0.8465	0.8465	0.0248	0.0248
22	22	2.14	2.04	0.5000	0.5000	0.0244	0.0244
23	23	2.17	2.07	0.5585	0.5585	0.0237	0.0237
24	24	2.12	2.03	0.6050	0.6050	0.0245	0.0245
25	25	2.10	2.01	0.3416	0.3416	0.0232	0.0232
26	26	2.06	1.98	0.3330	0.3330	0.0243	0.0243
27	27	2.11	2.03	0.2867	0.2867	0.0223	0.0223
28	28	2.10	2.03	0.7180	0.7180	0.0231	0.0231
29	29	2.09	2.02	0.7224	0.5000	0.0238	0.0240
30	30	2.15	2.07	0.7875	0.4471	0.0216	0.0235
31	31	2.11	2.04	0.5936	0.5936	0.0240	0.0240
32	32	2.09	2.02	0.3606	0.3606	0.0233	0.0233
33	33	2.06	2.00	0.3530	0.3530	0.0243	0.0243
34	34	2.06	2.00	0.1975	0.1975	0.0233	0.0233
35	35	2.06	2.00	0.3043	0.3043	0.0240	0.0240
36	36	2.05	1.99	0.3002	0.3002	0.0247	0.0247
37	37	2.05	1.99	0.8105	0.8105	0.0244	0.0244
38	38	2.04	1.99	0.8114	0.8114	0.0247	0.0247
39	39	2.10	2.04	0.5987	0.4543	0.0230	0.0248
40	40	2.08	2.02	0.6084	0.6084	0.0238	0.0238
50	50	2.05	2.01	0.6056	0.6056	0.0244	0.0244
60	60	2.05	2.02	0.5875	0.6023	0.0245	0.0238
70	70	2.00	1.98	0.8245	0.8245	0.0249	0.0249
80	80	2.01	1.98	0.3210	0.3210	0.0245	0.0245
90	90	2.00	1.98	0.3654	0.3654	0.0250	0.0250
100	100	2.01	1.99	0.5967	0.5967	0.0248	0.0248
150	150	2.00	1.99	0.6112	0.6112	0.0244	0.0244

z: critical value; p: nuisance parameter point of maximum; p-value: attained size of the test; n1: sample size 1; n2: sample size 2; S-U: Suissa Unpooled; S-P: Suissa Pooled. Green cell: larger p-value; Orange cell: lower p-value.

Figure C.3: Comparison of the p-values for the Z exact test for the unpooled and pooled statistics in case of equal sample size, $\boldsymbol{\alpha}$= **0.05**.

		z		p		p-value	
n1	**n2**	**S-U**	**S-P**	**S-U**	**S-P**	**S-U**	**S-P**
10	10	2.76	2.4	0.5000	0.5000	0.0064	0.0064
11	11	2.63	2.3	0.5000	0.5000	0.0087	0.0087
12	12	2.83	2.5	0.6114	0.6114	0.0087	0.0087
13	13	2.67	2.4	0.6577	0.6577	0.0096	0.0096
14	14	2.65	2.4	0.2519	0.2519	0.0083	0.0083
15	15	2.57	2.3	0.7560	0.7560	0.0088	0.0088
16	16	2.51	2.3	0.7612	0.7612	0.0094	0.0094
17	17	2.66	2.4	0.7714	0.7714	0.0099	0.0099
18	18	2.63	2.4	0.6552	0.3519	0.0084	0.0083
19	19	2.59	2.4	0.3353	0.3353	0.0091	0.0091
20	20	2.56	2.4	0.5000	0.5000	0.0084	0.0084
21	21	2.54	2.4	0.5000	0.5000	0.0098	0.0098
22	22	2.59	2.4	0.5519	0.5519	0.0097	0.0097
23	23	2.55	2.4	0.3287	0.3287	0.0091	0.0091
24	24	2.49	2.4	0.3236	0.3236	0.0097	0.0097
25	25	2.51	2.4	0.7387	0.7387	0.0093	0.0093
26	26	2.47	2.3	0.7534	0.7534	0.0098	0.0098
27	27	2.50	2.4	0.5000	0.5000	0.0100	0.0100
28	28	2.55	2.4	0.5908	0.5908	0.0091	0.0091
29	29	2.50	2.4	0.6087	0.6087	0.0096	0.0096
30	30	2.48	2.4	0.3498	0.3498	0.0092	0.0092
31	31	2.44	2.3	0.3434	0.3434	0.0097	0.0097
32	32	2.46	2.4	0.7043	0.7043	0.0091	0.0091
33	33	2.43	2.3	0.7063	0.7063	0.0094	0.0094
34	34	2.54	2.4	0.4659	0.6136	0.0093	0.0084
35	35	2.50	2.4	0.5821	0.6215	0.0095	0.0089
36	36	2.48	2.4	0.7760	0.7760	0.0094	0.0094
37	37	2.44	2.4	0.3649	0.3649	0.0098	0.0098
38	38	2.44	2.4	0.2197	0.2197	0.0098	0.0098
39	39	2.45	2.4	0.7277	0.7277	0.0093	0.0093
40	40	2.44	2.4	0.7304	0.7304	0.0096	0.0096
50	50	2.48	2.4	0.5818	0.6033	0.0091	0.0086
60	60	2.44	2.4	0.5839	0.5839	0.0096	0.0096
70	70	2.42	2.4	0.5838	0.5684	0.0097	0.0100
80	80	2.39	2.4	0.7375	0.7375	0.0097	0.0097
90	90	2.38	2.3	0.7609	0.7609	0.0097	0.0097
100	100	2.37	2.3	0.1185	0.1185	0.0099	0.0099
150	150	2.37	2.3	0.6167	0.6121	0.0097	0.0099

z: critical value; p: nuisance parameter point of maximum; p-value: attained size of the test; n1: sample size 1; n2: sample size 2; S-U: Suissa Unpooled; S-P: Suissa Pooled. Green cell: larger p-value; Orange cell: lower p-value.

Figure C.4: Comparison of the p-values for the Z exact test for the unpooled and pooled statistics for different sample sizes, $\boldsymbol{\alpha} = \mathbf{0.05}$.

		z		p		p-value	
n1	**n2**	**S-U**	**S-P**	**S-U**	**S-P**	**S-U**	**S-P**
10	20	2.24	1.88	0.2119	0.3160	0.0427	0.0316
10	30	2.74	1.83	0.2087	0.6925	0.0427	0.0439
10	40	3.17	2.03	0.2132	0.9307	0.0445	0.0417
10	50	3.54	1.74	0.2171	0.5482	0.0463	0.0478
10	60	3.88	2.08	0.2197	0.6895	0.0479	0.0249
10	70	4.19	1.79	0.2214	0.8010	0.0494	0.0489
10	80	4.65	1.83	0.2338	0.9518	0.0430	0.0482
10	90	4.91	1.97	0.2335	0.8936	0.0448	0.0412
10	100	5.16	2.04	0.2332	0.9487	0.0464	0.0453
20	30	1.87	1.69	0.4135	0.4030	0.0412	0.0481
20	40	2.14	1.78	0.1048	0.6943	0.0467	0.0419
20	50	2.36	1.76	0.1069	0.5939	0.0480	0.0412
20	60	2.59	1.73	0.1067	0.7716	0.0486	0.0495
20	70	2.79	1.75	0.1079	0.8246	0.0498	0.0452
20	80	3.19	1.74	0.1194	0.6792	0.0385	0.0459
20	90	3.36	1.83	0.1194	0.7833	0.0405	0.0407
20	100	3.52	1.71	0.1194	0.6507	0.0423	0.0473
30	40	1.79	1.68	0.2770	0.4346	0.0459	0.0489
30	50	1.84	1.70	0.2094	0.7588	0.0468	0.0486
30	60	2.08	1.69	0.0714	0.6687	0.0489	0.0499
30	70	2.33	1.76	0.0750	0.8486	0.0427	0.0473
30	80	2.55	1.69	0.0782	0.6443	0.0387	0.0490
30	90	2.76	1.71	0.0810	0.6830	0.0359	0.0480
30	100	2.75	1.72	0.0748	0.7824	0.0462	0.0465
40	50	1.78	1.68	0.2003	0.5746	0.0442	0.0480
40	60	1.86	1.72	0.3169	0.7947	0.0381	0.0472
40	70	1.79	1.67	0.3262	0.6310	0.0473	0.0494
40	80	2.10	1.69	0.0540	0.7004	0.0500	0.0491
40	90	2.31	1.70	0.0577	0.5207	0.0402	0.0465
40	100	2.52	1.72	0.0526	0.7206	0.0498	0.0471

z: critical value; p: nuisance parameter point of maximum; p-value: attained size of the test; n1: sample size 1; n2: sample size 2; S-U: Suissa Unpooled; S-P: Suissa Pooled. Green cell: larger p-value; Orange cell: lower p-value.

Figure C.5: Comparison of the p-values for the Z exact test for the unpooled and pooled statistics for different sample sizes, $\alpha = \mathbf{0.025}$.

		z		p		p-value	
n1	**n2**	**S-U**	**S-P**	**S-U**	**S-P**	**S-U**	**S-P**
10	20	2.59	2.08	0.2478	0.6055	0.0242	0.0231
10	30	3.31	2.17	0.2569	0.5567	0.0185	0.0176
10	40	3.66	2.16	0.2529	0.8812	0.0235	0.0246
10	50	4.20	2.39	0.2668	0.8650	0.0211	0.0166
10	60	4.48	2.08	0.2624	0.6895	0.0247	0.0249
10	70	4.93	2.67	0.2713	0.9545	0.0230	0.0163
10	80	5.34	2.24	0.2781	0.8420	0.0218	0.0239
10	90	5.56	3.02	0.2735	0.9662	0.0245	0.0099
10	100	5.93	3.18	0.2787	0.9639	0.0234	0.0086
20	30	2.30	1.97	0.3053	0.6029	0.0209	0.0246
20	40	2.66	2.06	0.1430	0.6682	0.0171	0.0217
20	50	2.86	2.00	0.1388	0.3788	0.0208	0.0237
20	60	3.04	2.21	0.1331	0.6546	0.0236	0.0157
20	70	3.42	2.10	0.1419	0.8961	0.0191	0.0242
20	80	3.58	2.04	0.1397	0.6670	0.0219	0.0245
20	90	3.73	2.16	0.1380	0.8764	0.0244	0.0243
20	100	4.04	2.24	0.1450	0.8211	0.0212	0.0185
30	40	2.21	2.10	0.1329	0.8156	0.0236	0.0222
30	50	2.36	2.02	0.1012	0.7688	0.0200	0.0237
30	60	2.59	2.01	0.0980	0.8434	0.0188	0.0250
30	70	2.79	2.10	0.0977	0.8637	0.0183	0.0226
30	80	2.99	2.12	0.0982	0.8047	0.0180	0.0232
30	90	3.17	2.08	0.0977	0.8101	0.0177	0.0243
30	100	3.15	2.10	0.0909	0.6487	0.0245	0.0206
40	50	2.05	2.00	0.3855	0.5035	0.0245	0.0225
40	60	2.06	1.98	0.3861	0.3861	0.0249	0.0249
40	70	2.33	1.99	0.0802	0.3559	0.0246	0.0250
40	80	2.55	2.07	0.0749	0.5750	0.0198	0.0212
40	90	2.76	2.03	0.0754	0.6656	0.0171	0.0242
40	100	2.75	2.02	0.0690	0.6948	0.0227	0.0245

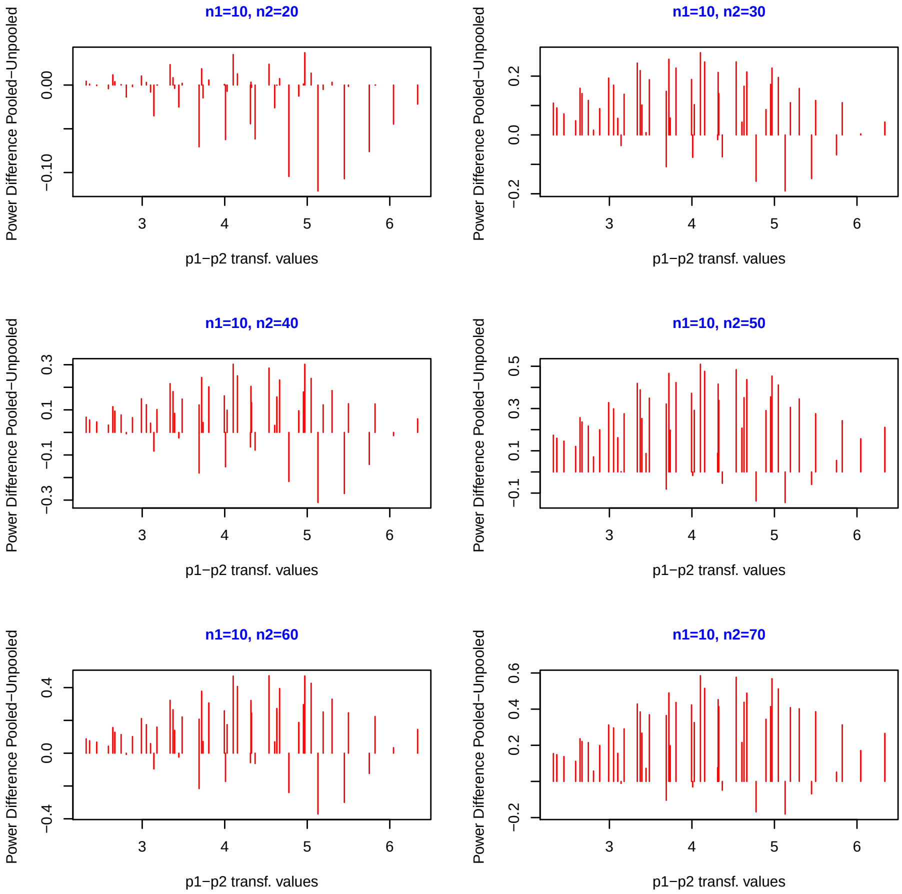
z: critical value; p: nuisance parameter point of maximum; p-value: attained size of the test; n1: sample size 1; n2: sample size 2; S-U: Suissa Unpooled; S-P: Suissa Pooled. Green cell: larger p-value; Orange cell: lower p-value.

Figure C.6: Comparison of the p-values for the Z exact test for the unpooled and pooled statistics for different sample sizes, $\alpha = 0.01$.

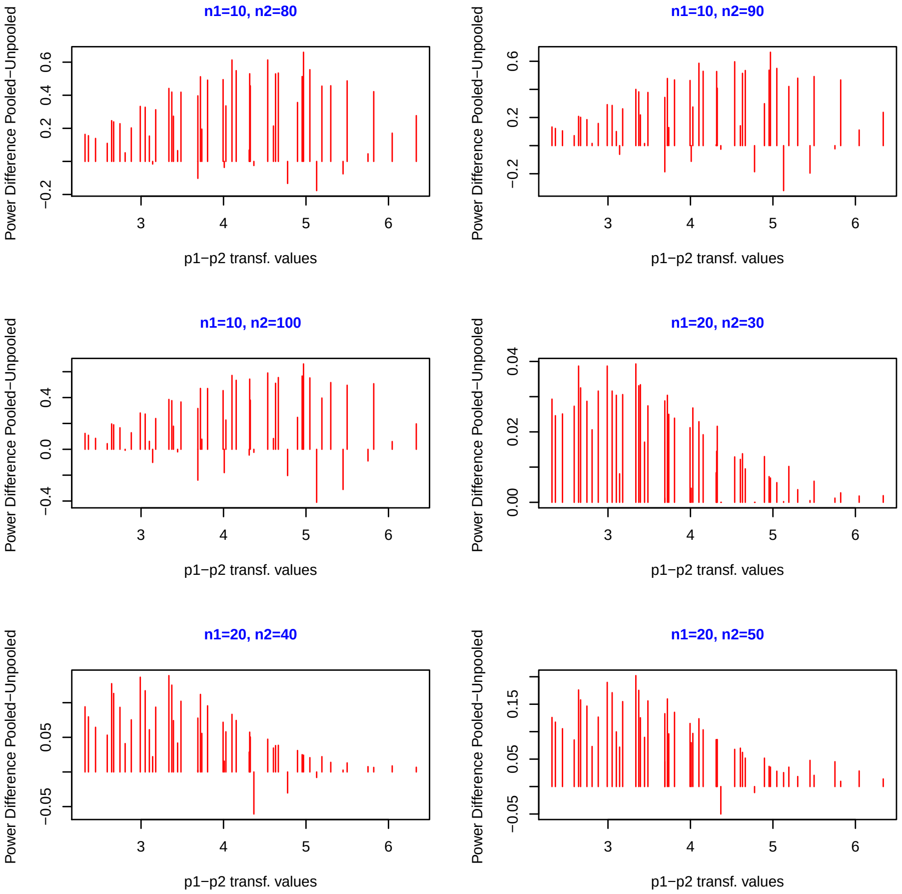
		z		p		p-value	
n1	n2	S-U	S-P	S-U	S-P	S-U	S-P
10	20	3.29	2.45	0.3138	0.6813	0.0071	0.0083
10	30	3.88	2.56	0.3056	0.7475	0.0077	0.0078
10	40	4.39	2.66	0.3116	0.7236	0.0085	0.0063
10	50	4.86	2.72	0.3159	0.9549	0.0092	0.0095
10	60	5.28	2.66	0.3187	0.8842	0.0097	0.0098
10	70	5.86	2.90	0.3328	0.9440	0.0083	0.0063
10	80	6.21	3.12	0.3328	0.9371	0.0089	0.0069
10	90	6.55	3.02	0.3327	0.9662	0.0094	0.0099
10	100	6.86	3.18	0.3326	0.9639	0.0098	0.0086
20	30	2.74	2.51	0.2031	0.6623	0.0085	0.0074
20	40	3.11	2.40	0.1540	0.7736	0.0097	0.0099
20	50	3.32	2.65	0.1644	0.6937	0.0085	0.0056
20	60	3.68	2.59	0.1703	0.8560	0.0077	0.0077
20	70	3.92	2.68	0.1642	0.9212	0.0100	0.0090
20	80	4.12	2.86	0.1701	0.9343	0.0092	0.0058
20	90	4.42	2.77	0.1747	0.8797	0.0087	0.0065
20	100	4.69	2.66	0.1786	0.9111	0.0083	0.0093
30	40	2.50	2.39	0.4129	0.6151	0.0097	0.0094
30	50	2.86	2.39	0.1391	0.7384	0.0068	0.0097
30	60	3.04	2.41	0.1253	0.7563	0.0072	0.0099
30	70	3.22	2.51	0.1207	0.8980	0.0078	0.0098
30	80	3.39	2.49	0.1154	0.6520	0.0081	0.0075
30	90	3.55	2.49	0.1151	0.7514	0.0088	0.0086
30	100	3.70	2.56	0.1144	0.7776	0.0093	0.0072
40	50	2.50	2.35	0.2674	0.5576	0.0091	0.0099
40	60	2.62	2.36	0.1579	0.5247	0.0096	0.0099
40	70	2.79	2.39	0.1016	0.6716	0.0090	0.0094
40	80	2.99	2.42	0.0969	0.8112	0.0079	0.0097
40	90	3.17	2.44	0.0934	0.6478	0.0073	0.0090
40	100	3.34	2.60	0.0928	0.9206	0.0070	0.0083

z: critical value; p: nuisance parameter point of maximum; p-value: attained size of the test; n1: sample size 1; n2: sample size 2; S-U: Suissa Unpooled; S-P: Suissa Pooled. Green cell: larger p-value; Orange cell: lower p-value.

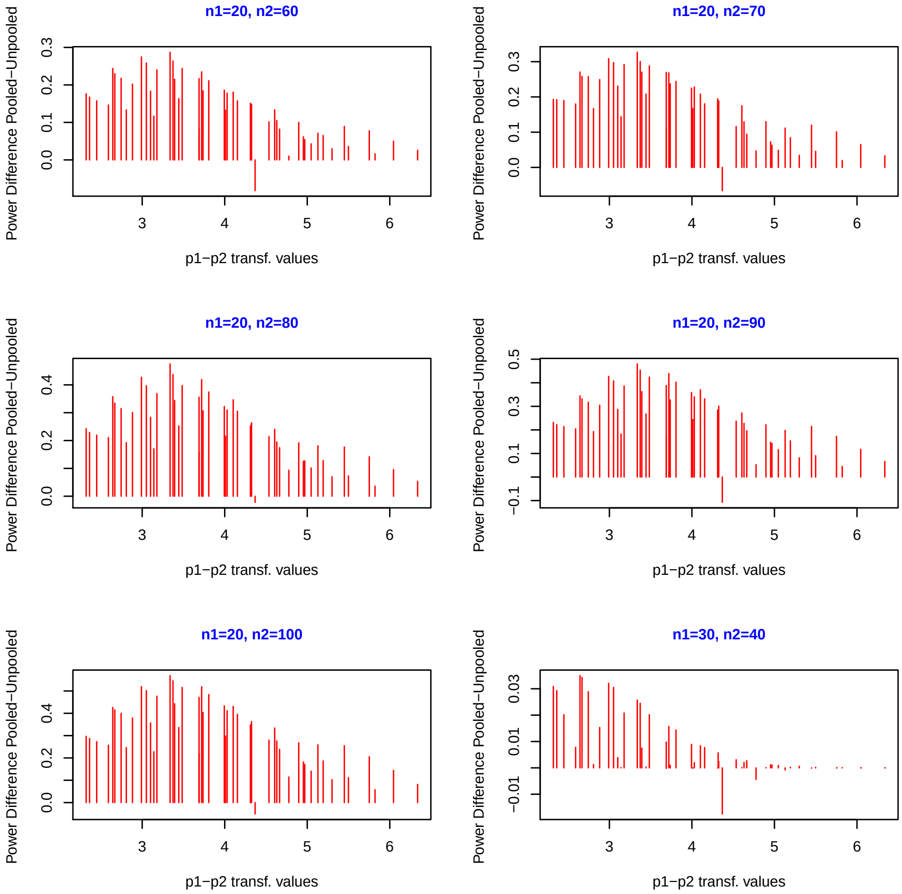
Figure C.7: Comparison of power between the unpooled and the pooled Z Exact Tests for different sample sizes, $\boldsymbol{\alpha}=\mathbf{0.05}$.



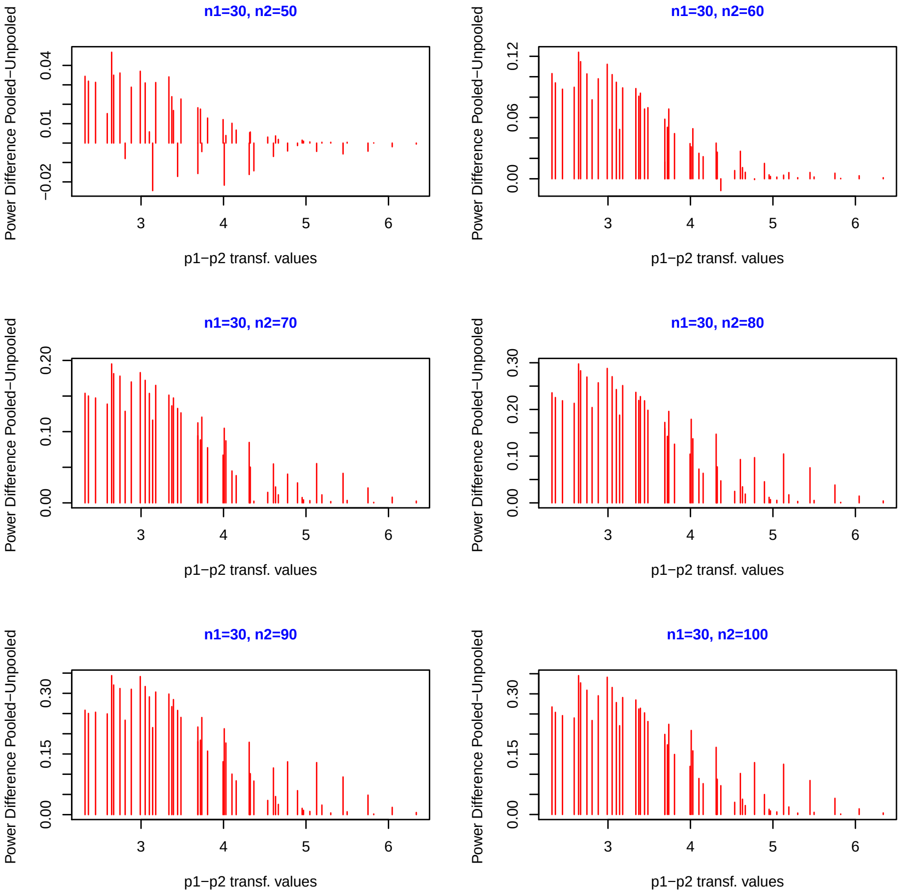
X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



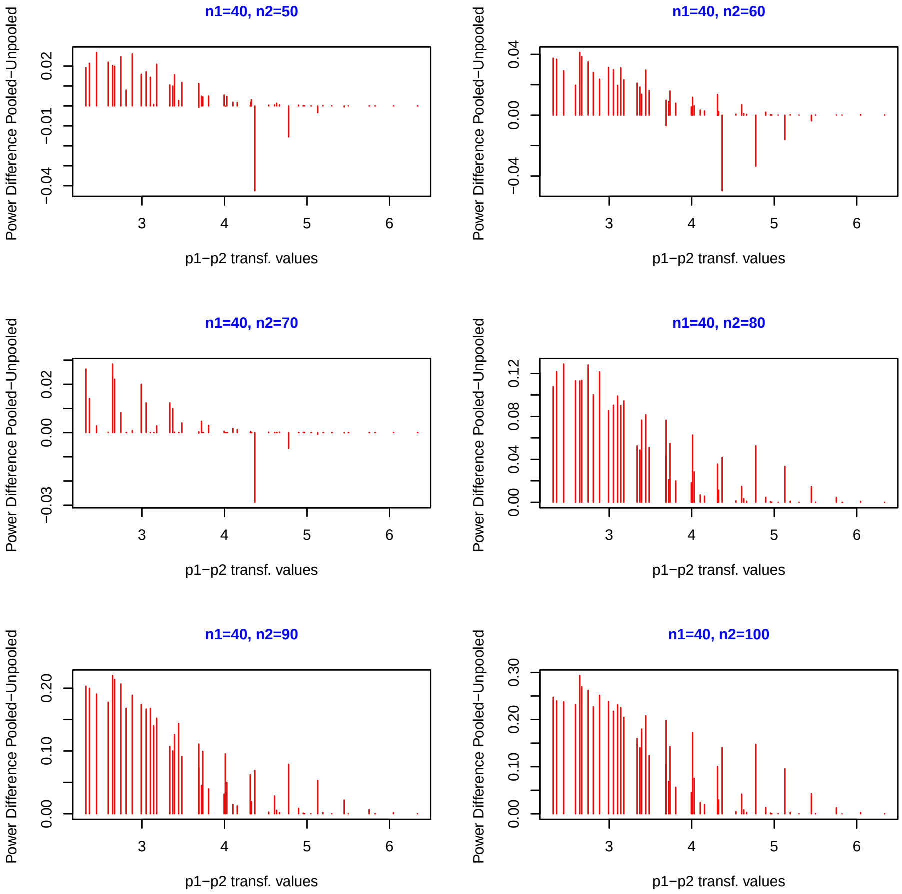
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

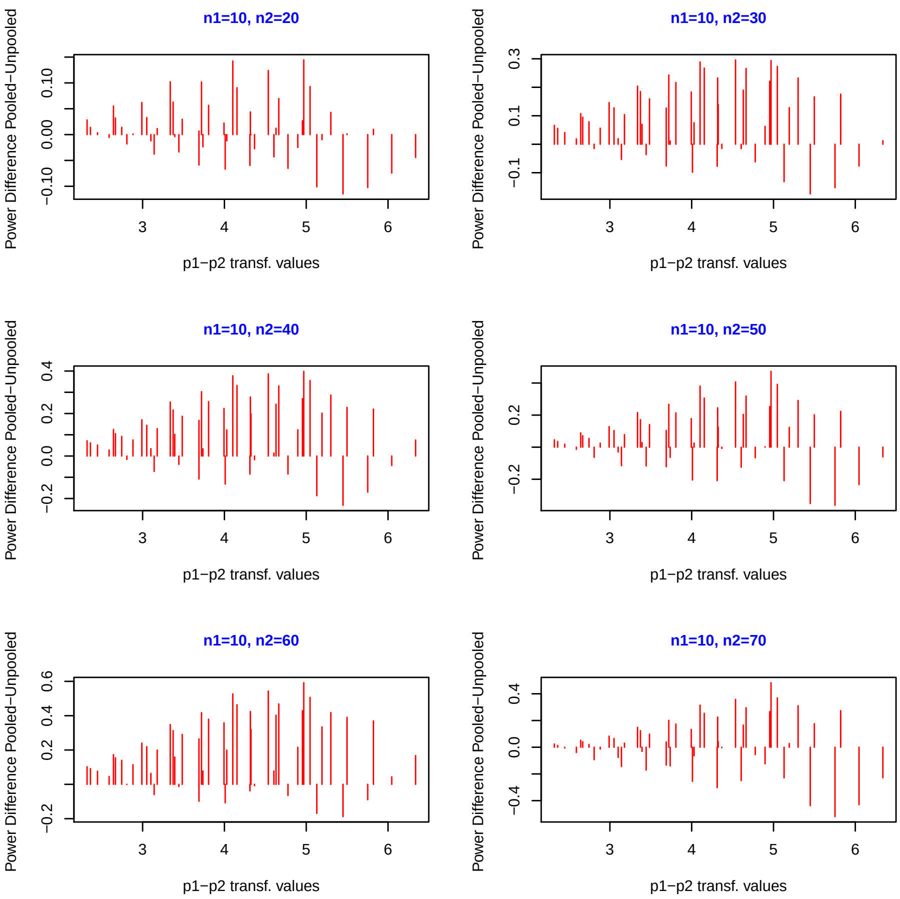


X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

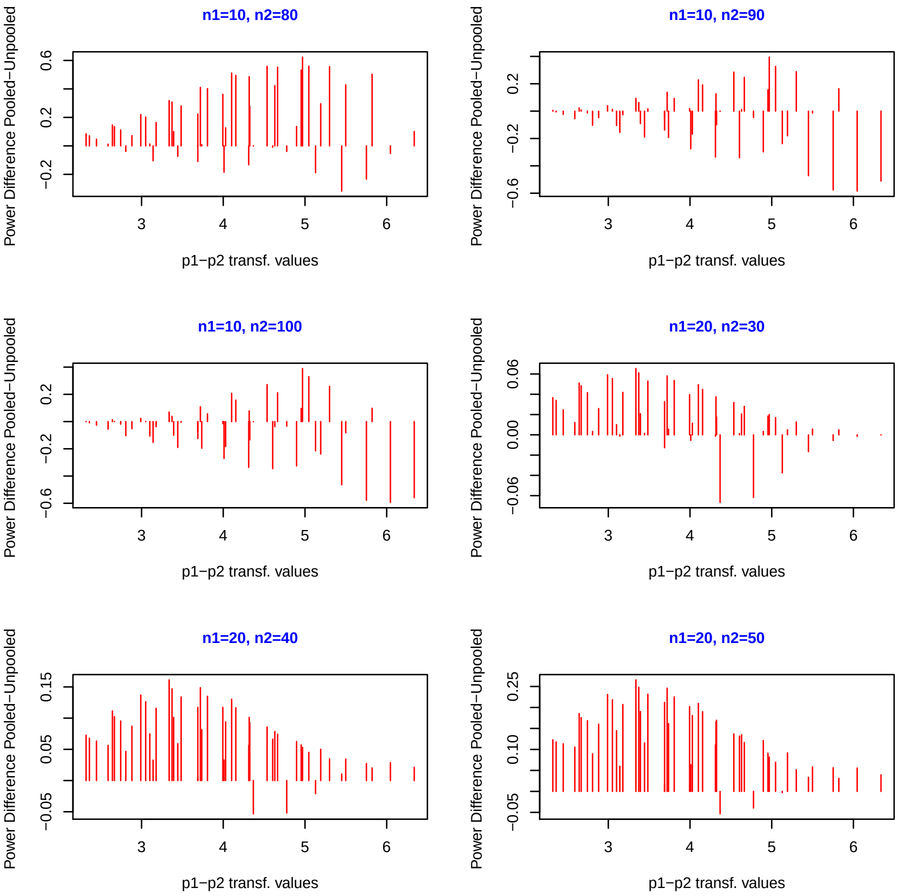


X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

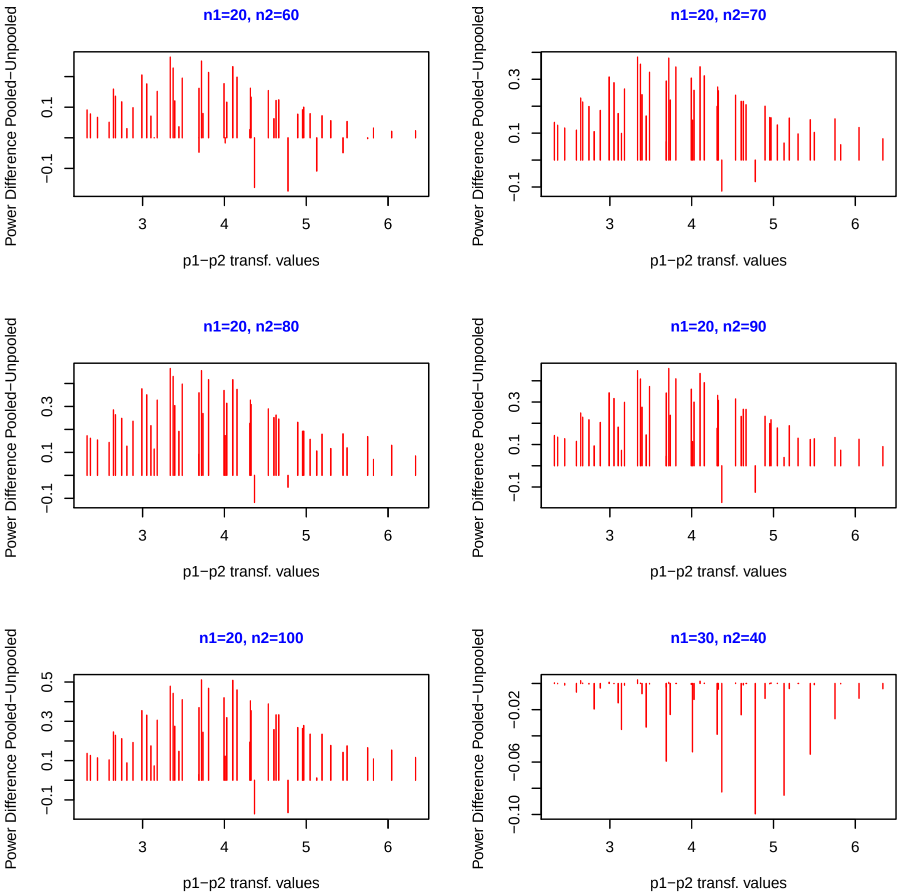
Figure C.8: Comparison of power between unpooled and pooled Z Exact Tests for different sample sizes, $\boldsymbol{\alpha}$= **0.025**.



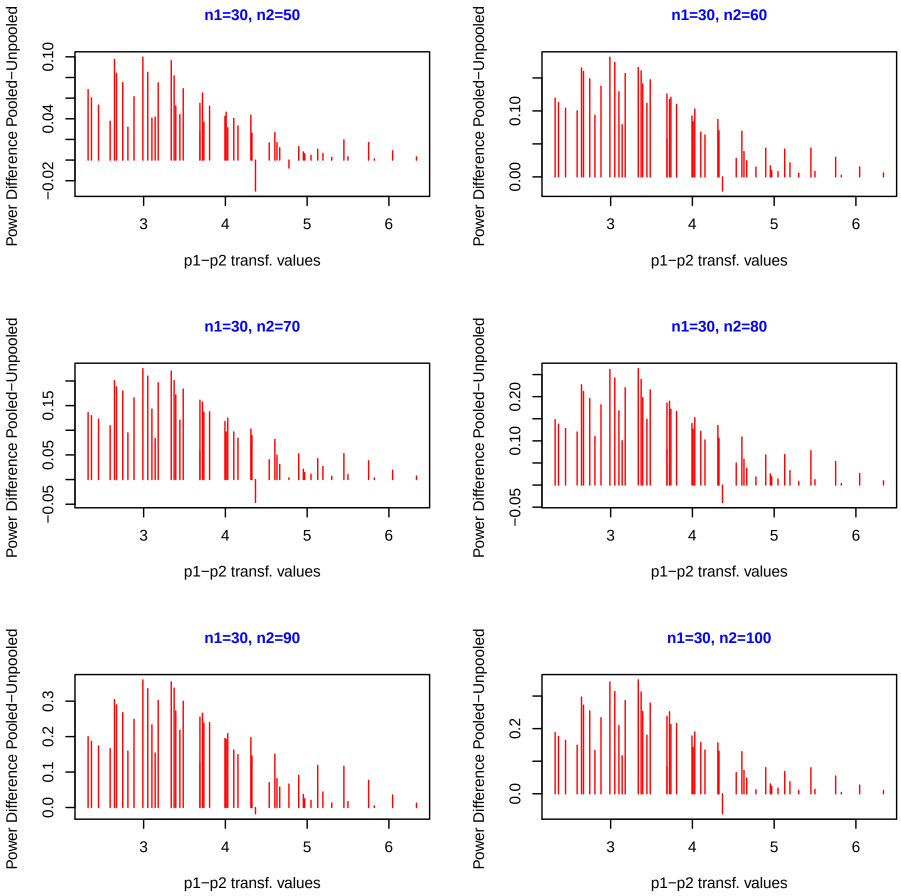
X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



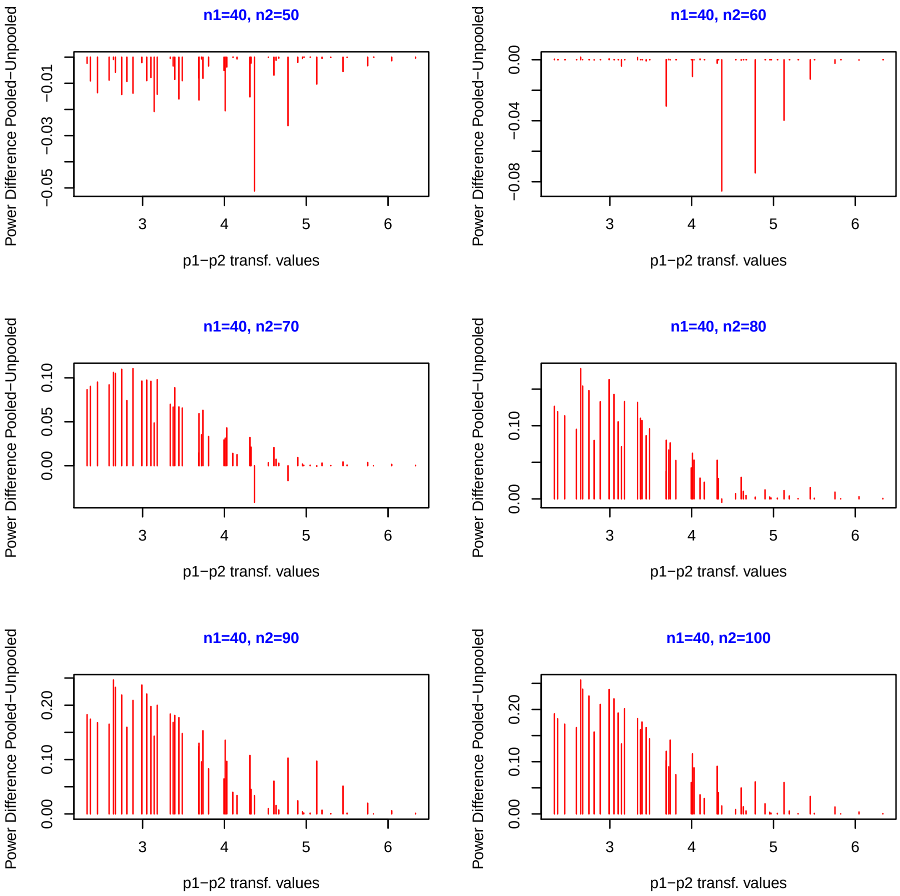
X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

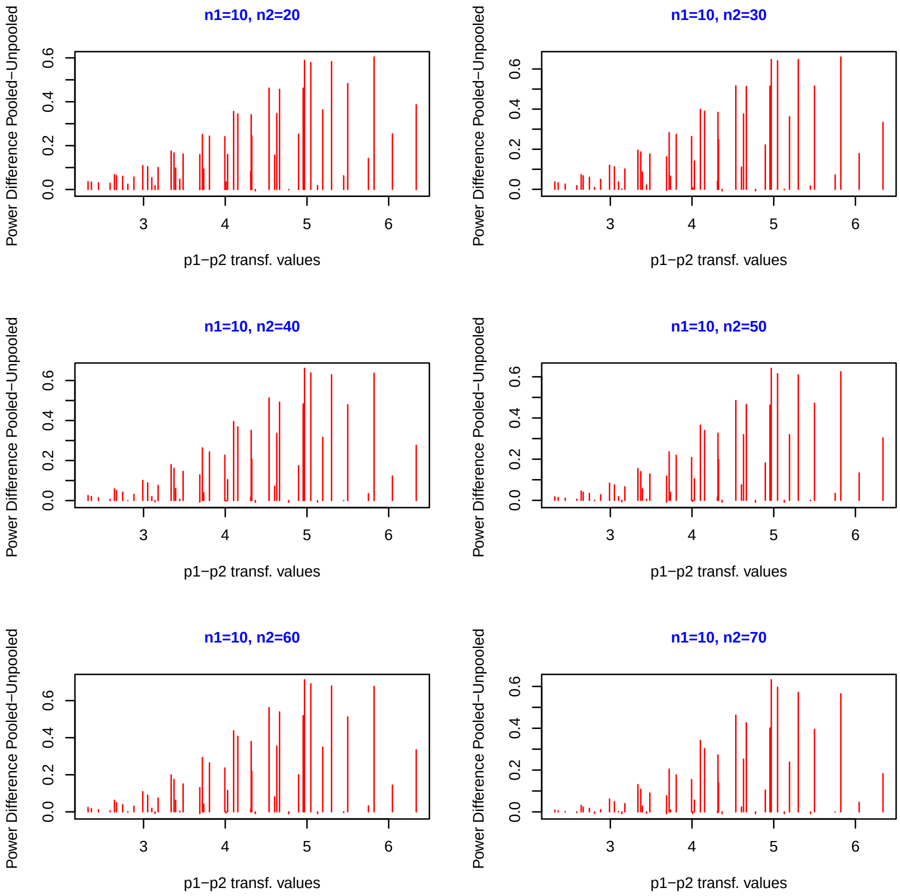


X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

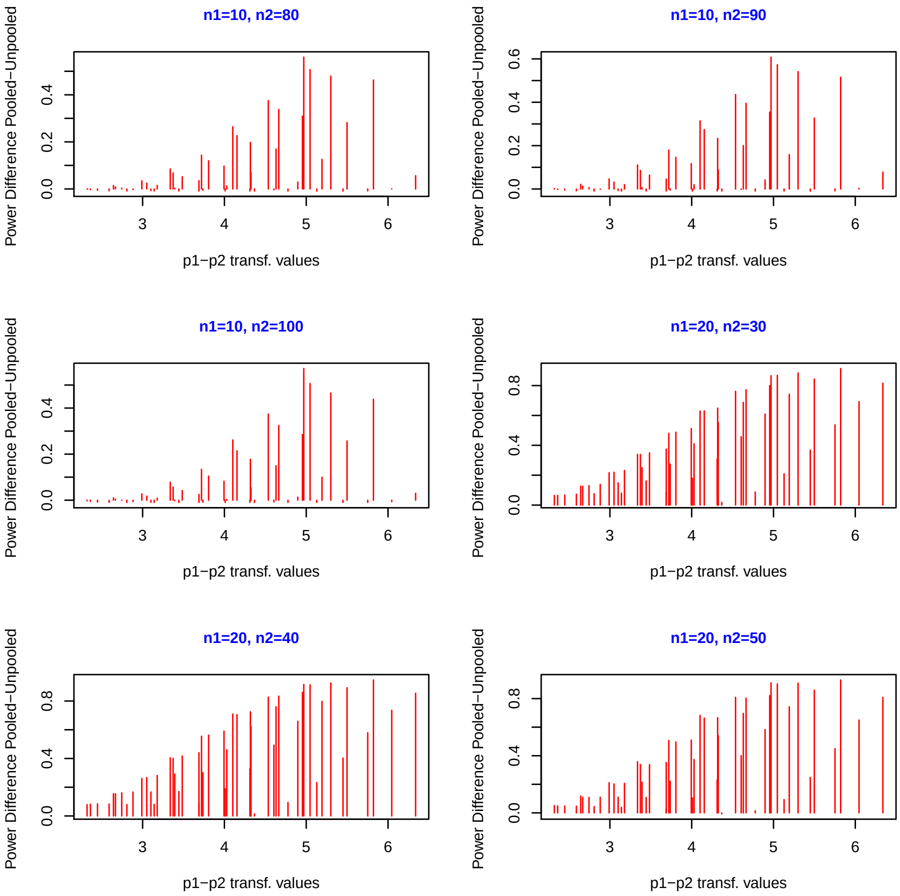


X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

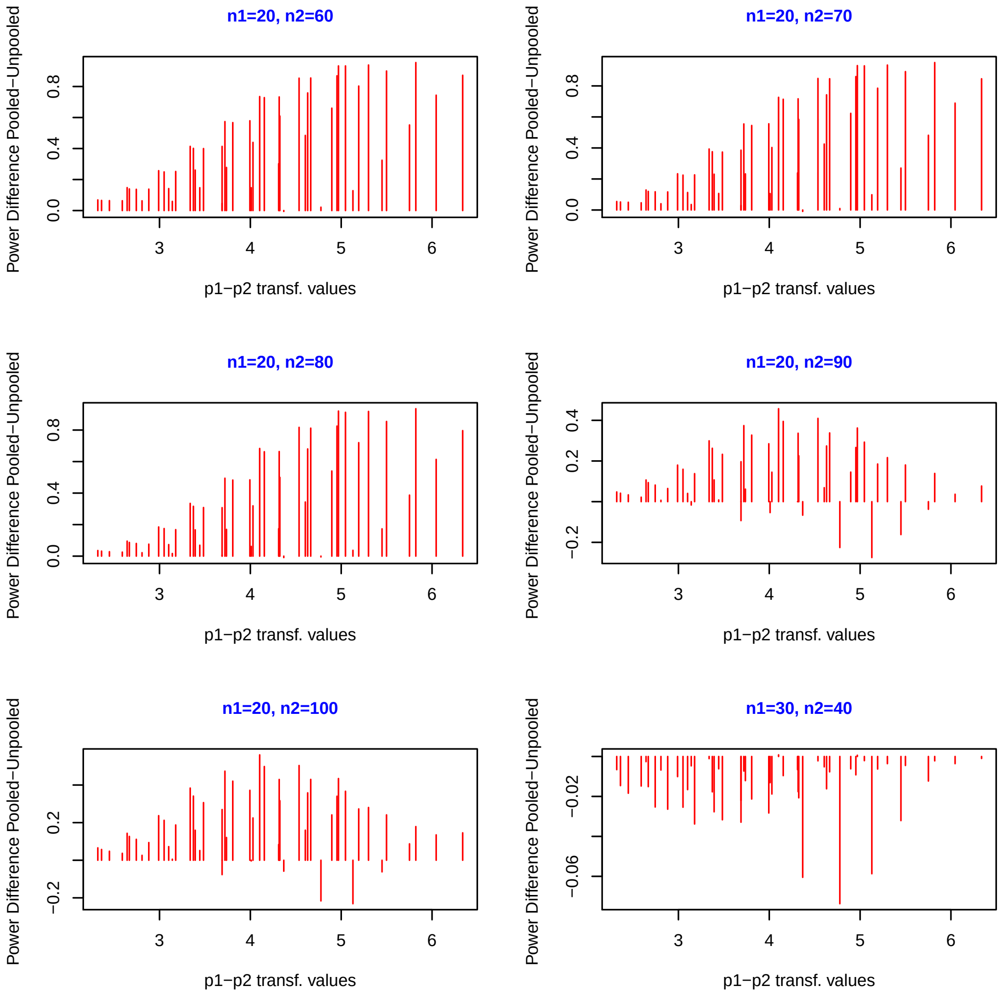
Figure C.9: Comparison of power between unpooled and pooled Z Exact Tests for different sample sizes, $\alpha = \mathbf{0.01}$.



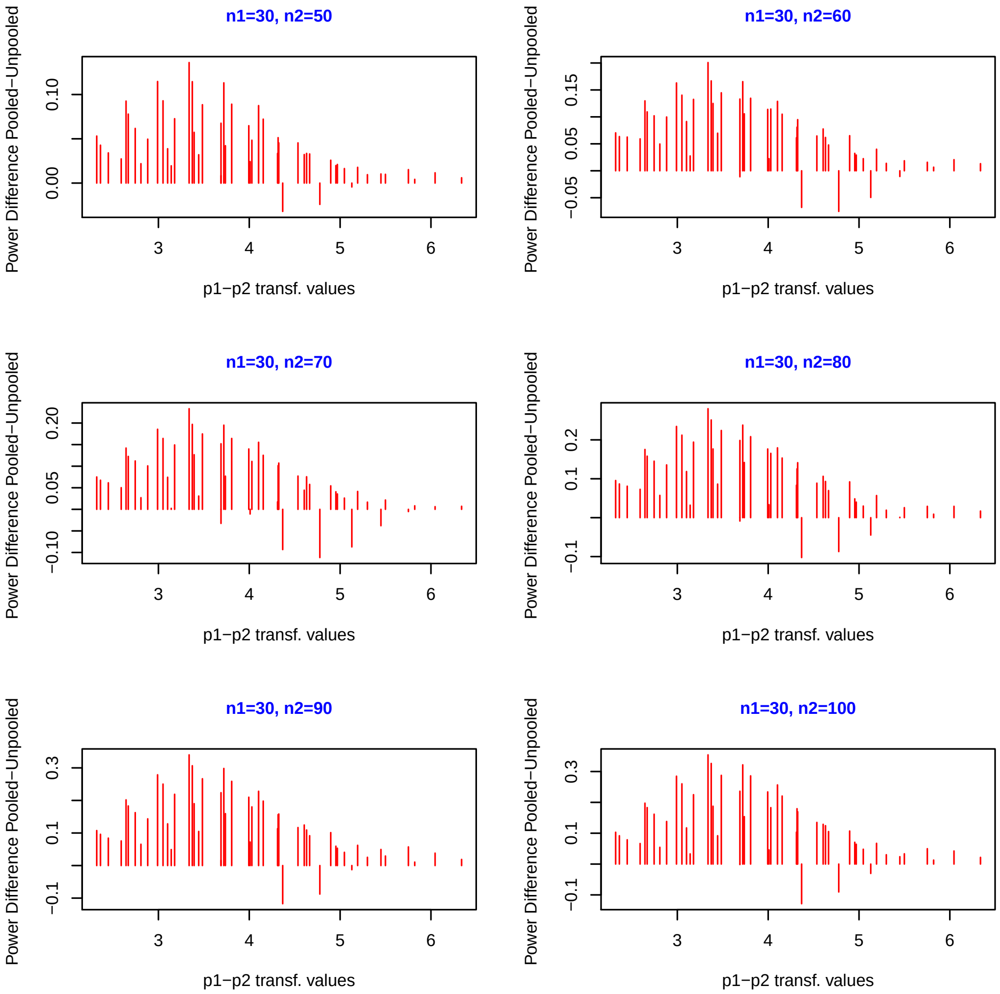
X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



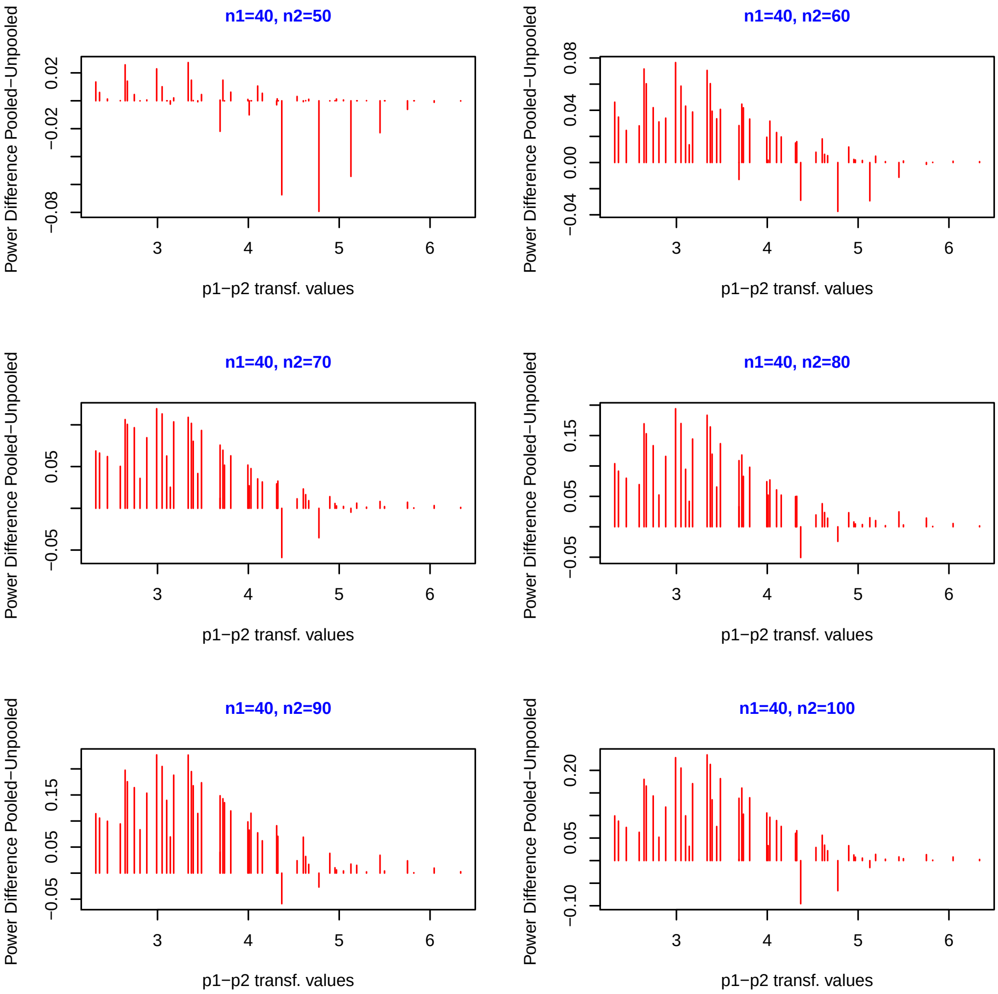
X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



X-axis represents the values of the trasformed variable: $log((p_2*(1-p_1))/(p_1*(1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.



X-axis represents the values of the trasformed variable: $log((p_2 * (1-p_1))/(p_1 * (1-p_2))^2)$ whereas on the y-axis is indicated the power difference between the pooled test and the unpooled test.

Figure C.10: Comparison of p-values for the unpoooled Z test calculated with both the classical Lehmann (1959) procedure and the Berger and Boos (1994) procedure for $\alpha = \mathbf{0.05}$.

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.10	2.24	2.24	2.24	2.24	0.2119	0.1053	0.1063	0.1072	0.0427	0.0182	0.0177	0.0180
10	30	0.10	2.74	2.45	2.45	2.45	0.2087	0.1045	0.1055	0.1063	0.0427	0.0298	0.0295	0.0300
10	40	0.10	3.17	2.66	2.66	2.66	0.2132	0.1040	0.1048	0.1055	0.0445	0.0398	0.0398	0.0404
10	50	0.10	3.54	2.86	2.86	2.86	0.2171	0.1037	0.1044	0.1051	0.0463	0.0485	0.0485	0.0494
10	60	0.10	3.88	3.26	3.26	3.26	0.2197	0.1035	0.1042	0.1048	0.0479	0.0304	0.0302	0.0309
10	70	0.10	4.19	3.42	3.42	3.42	0.2214	0.1033	0.1039	0.1044	0.0494	0.0359	0.0358	0.0365
10	80	0.10	4.65	3.58	3.58	3.58	0.2338	0.1031	0.1037	0.1042	0.0430	0.0410	0.0411	0.0419
10	90	0.10	4.91	3.73	3.73	3.73	0.2335	0.1031	0.1036	0.1041	0.0448	0.0460	0.0461	0.0469
10	100	0.10	5.16	4.04	4.04	4.04	0.2332	0.1029	0.1034	0.1039	0.0464	0.0306	0.0305	0.0312
20	30	0.10	1.87	2.01	2.01	2.01	0.4135	0.1015	0.1016	0.1016	0.0412	0.0461	0.0452	0.0451
20	40	0.10	2.14	2.14	2.14	2.14	0.1048	0.1036	0.1043	0.1048	0.0467	0.0477	0.0468	0.0467
20	50	0.10	2.36	2.36	2.36	2.36	0.1069	0.1034	0.1040	0.1046	0.0480	0.0489	0.0481	0.0480
20	60	0.10	2.59	2.59	2.59	2.59	0.1067	0.1033	0.1039	0.1044	0.0486	0.0495	0.0486	0.0486
20	70	0.10	2.79	3.01	2.79	2.79	0.1079	0.1030	0.1036	0.1041	0.0498	0.0343	0.0496	0.0496
20	80	0.10	3.19	3.19	3.19	3.19	0.1194	0.1029	0.1035	0.1040	0.0385	0.0360	0.0353	0.0354
20	90	0.10	3.36	3.36	3.36	3.36	0.1194	0.1029	0.1034	0.1039	0.0405	0.0375	0.0369	0.0370
20	100	0.10	3.52	3.52	3.52	3.52	0.1194	0.1027	0.1032	0.1037	0.0423	0.0387	0.0381	0.0383
30	40	0.10	1.79	1.81	1.81	1.81	0.2770	0.0970	0.0970	0.0970	0.0459	0.0434	0.0425	0.0424
30	50	0.10	1.84	2.07	2.07	2.07	0.2094	0.0964	0.0958	0.0953	0.0468	0.0434	0.0428	0.0430
30	60	0.10	2.08	2.08	2.08	2.08	0.0714	0.0967	0.0961	0.0956	0.0489	0.0444	0.0437	0.0438
30	70	0.10	2.33	2.28	2.28	2.28	0.0750	0.0969	0.0963	0.0958	0.0427	0.0452	0.0447	0.0450
30	80	0.10	2.55	2.26	2.26	2.26	0.0782	0.0971	0.0965	0.0960	0.0387	0.0498	0.0493	0.0496
30	90	0.10	2.76	2.31	2.31	2.31	0.0810	0.0973	0.0967	0.0963	0.0359	0.0499	0.0494	0.0496
30	100	0.10	2.75	2.41	2.41	2.41	0.0748	0.0973	0.0968	0.0964	0.0462	0.0491	0.0487	0.0490
40	50	0.10	1.78	1.79	1.79	1.79	0.2003	0.0966	0.0960	0.0955	0.0442	0.0488	0.0480	0.0480
40	60	0.10	1.86	1.91	1.91	1.91	0.3169	0.0968	0.0963	0.0958	0.0381	0.0419	0.0411	0.0410
40	70	0.10	1.79	1.97	1.94	1.94	0.3262	0.0970	0.0964	0.0959	0.0473	0.0406	0.0495	0.0495
40	80	0.10	2.1	2.04	2.04	2.04	0.0540	0.0971	0.0966	0.0961	0.0500	0.0426	0.0417	0.0417
40	90	0.10	2.31	2.06	2.06	2.06	0.0577	0.0973	0.0968	0.0964	0.0402	0.0485	0.0478	0.0479
40	100	0.10	2.52	2.05	2.02	2.02	0.0526	0.0974	0.0969	0.0965	0.0498	0.0497	0.0493	0.0494

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.25	2.24	2.24	2.24	2.24	0.2119	0.2408	0.2393	0.2380	0.0427	0.0426	0.0418	0.0418
10	30	0.25	2.74	2.74	2.55	2.74	0.2087	0.2425	0.2412	0.2400	0.0427	0.0406	0.0497	0.0400
10	40	0.25	3.17	2.92	2.92	2.92	0.2132	0.2432	0.2420	0.2410	0.0445	0.0500	0.0495	0.0498
10	50	0.25	3.54	3.54	3.54	3.54	0.2171	0.2433	0.2422	0.2413	0.0463	0.0442	0.0435	0.0436
10	60	0.25	3.88	3.88	3.88	3.88	0.2197	0.2441	0.2432	0.2423	0.0479	0.0458	0.0451	0.0452
10	70	0.25	4.19	4.19	4.19	4.19	0.2214	0.2443	0.2434	0.2426	0.0494	0.0473	0.0466	0.0467
10	80	0.25	4.65	4.48	4.48	4.48	0.2338	0.2450	0.2441	0.2433	0.0430	0.0484	0.0477	0.0478
10	90	0.25	4.91	4.75	4.75	4.75	0.2335	0.2453	0.2445	0.2437	0.0448	0.0495	0.0488	0.0489
10	100	0.25	5.16	5.16	5.01	5.01	0.2332	0.2455	0.2447	0.2440	0.0464	0.0463	0.0497	0.0499
20	30	0.25	1.87	1.84	1.84	1.84	0.4135	0.2438	0.2426	0.2416	0.0412	0.0494	0.0486	0.0486
20	40	0.25	2.14	1.88	1.88	1.88	0.1048	0.2442	0.2431	0.2422	0.0467	0.0478	0.0469	0.0469
20	50	0.25	2.36	1.95	1.95	1.95	0.1069	0.2442	0.2432	0.2423	0.0480	0.0472	0.0464	0.0464
20	60	0.25	2.59	1.99	1.99	1.99	0.1067	0.2448	0.2439	0.2431	0.0486	0.0487	0.0479	0.0480
20	70	0.25	2.79	2.01	2.01	2.01	0.1079	0.2450	0.2441	0.2433	0.0498	0.0477	0.0469	0.0470
20	80	0.25	3.19	2.09	2.09	2.09	0.1194	0.2455	0.2446	0.2439	0.0385	0.0499	0.0491	0.0492
20	90	0.25	3.36	2.05	2.05	2.05	0.1194	0.2457	0.2449	0.2442	0.0405	0.0488	0.0480	0.0479
20	100	0.25	3.52	2.12	2.10	2.10	0.1194	0.2459	0.2451	0.2444	0.0423	0.0453	0.0500	0.0500
30	40	0.25	1.79	1.75	1.75	1.75	0.2770	0.2554	0.2563	0.2572	0.0459	0.0467	0.0459	0.0458
30	50	0.25	1.84	1.82	1.82	1.82	0.2094	0.2446	0.2437	0.2429	0.0468	0.0474	0.0466	0.0466
30	60	0.25	2.08	1.83	1.83	1.83	0.0714	0.2452	0.2443	0.2436	0.0489	0.0475	0.0467	0.0466
30	70	0.25	2.33	1.86	1.86	1.86	0.0750	0.2453	0.2445	0.2437	0.0427	0.0462	0.0454	0.0454
30	80	0.25	2.55	1.90	1.90	1.90	0.0782	0.2457	0.2449	0.2443	0.0387	0.0478	0.0469	0.0469
30	90	0.25	2.76	1.88	1.86	1.86	0.0810	0.2460	0.2452	0.2445	0.0359	0.0495	0.0492	0.0492
30	100	0.25	2.75	1.92	1.89	1.89	0.0748	0.2461	0.2454	0.2447	0.0462	0.0462	0.0499	0.0499
40	50	0.25	1.78	1.74	1.73	1.73	0.2003	0.2449	0.2440	0.2433	0.0442	0.0500	0.0495	0.0495
40	60	0.25	1.86	1.74	1.70	1.70	0.3169	0.2454	0.2446	0.2439	0.0381	0.0497	0.0498	0.0497
40	70	0.25	1.79	1.78	1.74	1.74	0.3262	0.2455	0.2447	0.2440	0.0473	0.0499	0.0493	0.0493
40	80	0.25	2.1	1.82	1.76	1.76	0.0540	0.2459	0.2451	0.2444	0.0500	0.0453	0.0497	0.0497
40	90	0.25	2.31	1.80	1.76	1.76	0.0577	0.2461	0.2454	0.2447	0.0402	0.0491	0.0496	0.0495
40	100	0.25	2.52	1.81	1.81	1.81	0.0526	0.2462	0.2455	0.2448	0.0498	0.0489	0.0480	0.0480

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.50	2.24	1.78	1.78	1.78	0.2119	0.4905	0.4888	0.4873	0.0427	0.0487	0.0478	0.0477
10	30	0.50	2.74	1.91	1.83	1.83	0.2087	0.4917	0.4902	0.4889	0.0427	0.0497	0.0499	0.0499
10	40	0.50	3.17	1.85	1.85	1.85	0.2132	0.4925	0.4912	0.4900	0.0445	0.0467	0.0459	0.0459
10	50	0.50	3.54	1.87	1.87	1.87	0.2171	0.4930	0.4918	0.4907	0.0463	0.0491	0.0484	0.0485
10	60	0.50	3.88	1.88	1.88	1.88	0.2197	0.4933	0.4922	0.4911	0.0479	0.0500	0.0491	0.0491
10	70	0.50	4.19	1.92	1.92	1.92	0.2214	0.4928	0.4917	0.4908	0.0494	0.0492	0.0485	0.0486
10	80	0.50	4.65	1.90	1.90	1.90	0.2338	0.4941	0.4931	0.4923	0.0430	0.0492	0.0484	0.0484
10	90	0.50	4.91	1.95	1.95	1.95	0.2335	0.4945	0.4935	0.4927	0.0448	0.0474	0.0466	0.0466
10	100	0.50	5.16	1.92	1.92	1.92	0.2332	0.4943	0.4934	0.4926	0.0464	0.0494	0.0486	0.0486
20	30	0.50	1.87	1.71	1.71	1.71	0.4135	0.4925	0.4911	0.4899	0.0412	0.0487	0.0478	0.0477
20	40	0.50	2.14	1.71	1.71	1.71	0.1048	0.4931	0.4918	0.4907	0.0467	0.0495	0.0488	0.0488
20	50	0.50	2.36	1.77	1.76	1.76	0.1069	0.5058	0.4923	0.4913	0.0480	0.0458	0.0495	0.0495
20	60	0.50	2.59	1.75	1.75	1.75	0.1067	0.4933	0.4923	0.4913	0.0486	0.0475	0.0467	0.0467
20	70	0.50	2.79	1.73	1.70	1.70	0.1079	0.4929	0.4919	0.4911	0.0498	0.0493	0.0500	0.0499
20	80	0.50	3.19	1.77	1.74	1.74	0.1194	0.4941	0.4932	0.4924	0.0385	0.0470	0.0495	0.0495
20	90	0.50	3.36	1.74	1.74	1.74	0.1194	0.4945	0.4936	0.4928	0.0405	0.0490	0.0481	0.0481
20	100	0.50	3.52	1.76	1.76	1.76	0.1194	0.4945	0.4936	0.4928	0.0423	0.0483	0.0475	0.0474
30	40	0.50	1.79	1.70	1.70	1.70	0.2770	0.4939	0.4927	0.4917	0.0459	0.0492	0.0483	0.0483
30	50	0.50	1.84	1.72	1.71	1.71	0.2094	0.4941	0.4931	0.4922	0.0468	0.0460	0.0492	0.0492
30	60	0.50	2.08	1.69	1.69	1.69	0.0714	0.4935	0.4925	0.4916	0.0489	0.0494	0.0486	0.0486
30	70	0.50	2.33	1.73	1.72	1.69	0.0750	0.4930	0.4921	0.4913	0.0427	0.0479	0.0499	0.0500
30	80	0.50	2.55	1.74	1.70	1.70	0.0782	0.4942	0.4932	0.4925	0.0387	0.0490	0.0498	0.0497
30	90	0.50	2.76	1.72	1.72	1.72	0.0810	0.4945	0.4936	0.4928	0.0359	0.0492	0.0484	0.0484
30	100	0.50	2.75	1.72	1.72	1.72	0.0748	0.4945	0.4937	0.4929	0.0462	0.0482	0.0474	0.0473
40	50	0.50	1.78	1.68	1.68	1.68	0.2003	0.4943	0.4933	0.4924	0.0442	0.0499	0.0490	0.0489
40	60	0.50	1.86	1.68	1.68	1.68	0.3169	0.4937	0.4927	0.4919	0.0381	0.0487	0.0478	0.0477
40	70	0.50	1.79	1.71	1.69	1.69	0.3262	0.5031	0.4924	0.4916	0.0473	0.0480	0.0493	0.0492
40	80	0.50	2.1	1.71	1.71	1.71	0.0540	0.4944	0.4935	0.4927	0.0500	0.0481	0.0473	0.0472
40	90	0.50	2.31	1.71	1.69	1.69	0.0577	0.4946	0.4937	0.4930	0.0402	0.0478	0.0495	0.0494
40	100	0.50	2.52	1.70	1.70	1.70	0.0526	0.4947	0.4938	0.4931	0.0498	0.0485	0.0476	0.0475

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.75	2.24	1.66	1.66	1.66	0.2119	0.7428	0.7413	0.7400	0.0427	0.0418	0.0409	0.0409
10	30	0.75	2.74	1.60	1.60	1.60	0.2087	0.7434	0.7421	0.7409	0.0427	0.0448	0.0441	0.0441
10	40	0.75	3.17	1.61	1.61	1.61	0.2132	0.7442	0.7430	0.7420	0.0445	0.0423	0.0414	0.0414
10	50	0.75	3.54	1.54	1.54	1.54	0.2171	0.7452	0.7442	0.7432	0.0463	0.0494	0.0486	0.0486
10	60	0.75	3.88	1.60	1.55	1.55	0.2197	0.7452	0.7442	0.7434	0.0479	0.0431	0.0494	0.0494
10	70	0.75	4.19	1.55	1.55	1.55	0.2214	0.7457	0.7448	0.7440	0.0494	0.0473	0.0465	0.0465
10	80	0.75	4.65	1.57	1.53	1.53	0.2338	0.7457	0.7448	0.7440	0.0430	0.0492	0.0498	0.0498
10	90	0.75	4.91	1.56	1.56	1.56	0.2335	0.7458	0.7450	0.7443	0.0448	0.0466	0.0458	0.0458
10	100	0.75	5.16	1.53	1.53	1.53	0.2332	0.7461	0.7453	0.7446	0.0464	0.0496	0.0488	0.0488
20	30	0.75	1.87	1.72	1.72	1.72	0.4135	0.7562	0.7574	0.7584	0.0412	0.0494	0.0486	0.0485
20	40	0.75	2.14	1.59	1.59	1.59	0.1048	0.7443	0.7432	0.7423	0.0467	0.0493	0.0485	0.0484
20	50	0.75	2.36	1.61	1.61	1.61	0.1069	0.7452	0.7442	0.7434	0.0480	0.0494	0.0486	0.0486
20	60	0.75	2.59	1.59	1.57	1.57	0.1067	0.7452	0.7443	0.7435	0.0486	0.0492	0.0495	0.0495
20	70	0.75	2.79	1.55	1.55	1.55	0.1079	0.7457	0.7448	0.7441	0.0498	0.0499	0.0491	0.0491
20	80	0.75	3.19	1.58	1.55	1.55	0.1194	0.7457	0.7448	0.7441	0.0385	0.0458	0.0498	0.0498
20	90	0.75	3.36	1.55	1.52	1.52	0.1194	0.7458	0.7450	0.7443	0.0405	0.0496	0.0497	0.0496
20	100	0.75	3.52	1.54	1.54	1.54	0.1194	0.7461	0.7453	0.7446	0.0423	0.0494	0.0486	0.0486
30	40	0.75	1.79	1.62	1.62	1.62	0.2770	0.7553	0.7563	0.7571	0.0459	0.0498	0.0489	0.0488
30	50	0.75	1.84	1.65	1.60	1.60	0.2094	0.7454	0.7445	0.7437	0.0468	0.0472	0.0494	0.0493
30	60	0.75	2.08	1.64	1.60	1.60	0.0714	0.7454	0.7445	0.7438	0.0489	0.0455	0.0493	0.0492
30	70	0.75	2.33	1.67	1.55	1.55	0.0750	0.7458	0.7450	0.7443	0.0427	0.0431	0.0500	0.0499
30	80	0.75	2.55	1.61	1.60	1.60	0.0782	0.7458	0.7450	0.7443	0.0387	0.0474	0.0497	0.0496
30	90	0.75	2.76	1.59	1.59	1.59	0.0810	0.7459	0.7452	0.7445	0.0359	0.0472	0.0463	0.0463
30	100	0.75	2.75	1.62	1.62	1.62	0.0748	0.7462	0.7454	0.7448	0.0462	0.0448	0.0439	0.0438
40	50	0.75	1.78	1.61	1.61	1.61	0.2003	0.7457	0.7448	0.7441	0.0442	0.0483	0.0474	0.0474
40	60	0.75	1.86	1.65	1.65	1.65	0.3169	0.7546	0.7554	0.7561	0.0381	0.0475	0.0466	0.0466
40	70	0.75	1.79	1.62	1.60	1.60	0.3262	0.7461	0.7453	0.7446	0.0473	0.0488	0.0493	0.0492
40	80	0.75	2.1	1.60	1.60	1.60	0.0540	0.7460	0.7453	0.7446	0.0500	0.0499	0.0490	0.0490
40	90	0.75	2.31	1.61	1.60	1.60	0.0577	0.7462	0.7454	0.7448	0.0402	0.0463	0.0500	0.0499
40	100	0.75	2.52	1.61	1.60	1.60	0.0526	0.7463	0.7457	0.7450	0.0498	0.0500	0.0497	0.0497

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.90	2.24	1.59	1.59	1.59	0.2119	0.8947	0.8937	0.8928	0.0427	0.0348	0.0343	0.0346
10	30	0.90	2.74	1.30	1.30	1.30	0.2087	0.8955	0.8945	0.8937	0.0427	0.0463	0.0457	0.0458
10	40	0.90	3.17	1.36	1.36	1.36	0.2132	0.8960	0.8952	0.8945	0.0445	0.0411	0.0405	0.0406
10	50	0.90	3.54	1.33	1.33	1.33	0.2171	0.8963	0.8956	0.8949	0.0463	0.0456	0.0448	0.0449
10	60	0.90	3.88	1.34	1.34	1.34	0.2197	0.8965	0.8958	0.8952	0.0479	0.0421	0.0413	0.0414
10	70	0.90	4.19	1.34	1.34	1.34	0.2214	0.8967	0.8961	0.8956	0.0494	0.0409	0.0402	0.0403
10	80	0.90	4.65	1.35	1.35	1.35	0.2338	0.8969	0.8963	0.8958	0.0430	0.0419	0.0411	0.0411
10	90	0.90	4.91	1.31	1.31	1.31	0.2335	0.8969	0.8964	0.8959	0.0448	0.0496	0.0489	0.0490
10	100	0.90	5.16	1.29	1.29	1.29	0.2332	0.8971	0.8966	0.8961	0.0464	0.0496	0.0489	0.0489
20	30	0.90	1.87	1.50	1.50	1.50	0.4135	0.8960	0.8952	0.8945	0.0412	0.0476	0.0469	0.0470
20	40	0.90	2.14	1.50	1.50	1.50	0.1048	0.8964	0.8957	0.8950	0.0467	0.0478	0.0472	0.0473
20	50	0.90	2.36	1.47	1.47	1.47	0.1069	0.8966	0.8960	0.8954	0.0480	0.0420	0.0412	0.0412
20	60	0.90	2.59	1.41	1.41	1.41	0.1067	0.8967	0.8961	0.8956	0.0486	0.0470	0.0464	0.0465
20	70	0.90	2.79	1.42	1.36	1.36	0.1079	0.8970	0.8964	0.8959	0.0498	0.0495	0.0496	0.0497
20	80	0.90	3.19	1.37	1.37	1.37	0.1194	0.8971	0.8965	0.8960	0.0385	0.0490	0.0482	0.0483
20	90	0.90	3.36	1.43	1.43	1.43	0.1194	0.8971	0.8966	0.8961	0.0405	0.0488	0.0480	0.0480
20	100	0.90	3.52	1.40	1.39	1.39	0.1194	0.8973	0.8968	0.8963	0.0423	0.0429	0.0497	0.0497
30	40	0.90	1.79	1.63	1.53	1.53	0.2770	0.8965	0.9045	0.9051	0.0459	0.0394	0.0500	0.0499
30	50	0.90	1.84	1.47	1.46	1.46	0.2094	0.8967	0.8961	0.8955	0.0468	0.0497	0.0499	0.0499
30	60	0.90	2.08	1.51	1.51	1.51	0.0714	0.8968	0.8962	0.8957	0.0489	0.0488	0.0480	0.0481
30	70	0.90	2.33	1.50	1.50	1.50	0.0750	0.8970	0.8964	0.8959	0.0427	0.0456	0.0448	0.0448
30	80	0.90	2.55	1.43	1.43	1.43	0.0782	0.8971	0.8966	0.8961	0.0387	0.0490	0.0482	0.0481
30	90	0.90	2.76	1.46	1.41	1.41	0.0810	0.8972	0.8966	0.8962	0.0359	0.0474	0.0493	0.0493
30	100	0.90	2.75	1.45	1.44	1.44	0.0748	0.8973	0.8968	0.8964	0.0462	0.0499	0.0495	0.0495
40	50	0.90	1.78	1.63	1.63	1.63	0.2003	0.8976	0.8976	0.8976	0.0442	0.0495	0.0486	0.0485
40	60	0.90	1.86	1.59	1.59	1.59	0.3169	0.8970	0.8965	0.8960	0.0381	0.0485	0.0477	0.0476
40	70	0.90	1.79	1.54	1.54	1.54	0.3262	0.8972	0.8967	0.8962	0.0473	0.0454	0.0446	0.0446
40	80	0.90	2.1	1.51	1.51	1.51	0.0540	0.8973	0.8968	0.8963	0.0500	0.0493	0.0484	0.0484
40	90	0.90	2.31	1.54	1.51	1.51	0.0577	0.8973	0.8968	0.8964	0.0402	0.0450	0.0498	0.0498
40	100	0.90	2.52	1.47	1.47	1.47	0.0526	0.8975	0.8970	0.8965	0.0498	0.0475	0.0466	0.0466

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

Figure C.11: Comparison of p-values for the unpoooled Z test calculated with both the classical Lehmann (1959) procedure and the Berger and Boos (1994) procedure for α= **0.025**.

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.10	2.59	2.24	2.24	2.24	0.2478	0.1053	0.1063	0.1072	0.0242	0.0182	0.0177	0.0180
10	30	0.10	3.31	2.74	2.74	2.74	0.2569	0.1045	0.1055	0.1063	0.0185	0.0116	0.0111	0.0113
10	40	0.10	3.66	2.92	2.92	2.92	0.2529	0.1040	0.1048	0.1055	0.0235	0.0180	0.0176	0.0180
10	50	0.10	4.2	3.09	3.09	3.09	0.2668	0.1037	0.1044	0.1051	0.0211	0.0243	0.0240	0.0245
10	60	0.10	4.48	3.47	3.47	3.47	0.2624	0.1035	0.1042	0.1048	0.0247	0.0152	0.0148	0.0152
10	70	0.10	4.93	3.62	3.62	3.62	0.2713	0.1033	0.1039	0.1044	0.0230	0.0192	0.0188	0.0192
10	80	0.10	5.34	3.76	3.76	3.76	0.2781	0.1031	0.1037	0.1042	0.0218	0.0231	0.0229	0.0234
10	90	0.10	5.56	4.08	4.08	4.08	0.2735	0.1031	0.1036	0.1041	0.0245	0.0151	0.0147	0.0150
10	100	0.10	5.93	4.21	4.21	4.21	0.2787	0.1029	0.1034	0.1039	0.0234	0.0177	0.0174	0.0178
20	30	0.10	2.3	2.30	2.15	2.15	0.3053	0.1040	0.1048	0.1055	0.0209	0.0236	0.0247	0.0248
20	40	0.10	2.66	2.66	2.66	2.66	0.143	0.1036	0.1043	0.1050	0.0171	0.0140	0.0133	0.0133
20	50	0.10	2.86	2.86	2.86	2.86	0.1388	0.1034	0.1040	0.1046	0.0208	0.0169	0.0162	0.0163
20	60	0.10	3.04	3.04	3.04	3.04	0.1331	0.1033	0.1039	0.1044	0.0236	0.0194	0.0187	0.0188
20	70	0.10	3.42	3.22	3.22	3.22	0.1419	0.1030	0.1036	0.1041	0.0191	0.0216	0.0209	0.0210
20	80	0.10	3.58	3.39	3.39	3.39	0.1397	0.1029	0.1035	0.1040	0.0219	0.0235	0.0229	0.0230
20	90	0.10	3.73	3.73	3.55	3.55	0.138	0.1029	0.1034	0.1039	0.0244	0.0160	0.0247	0.0248
20	100	0.10	4.04	3.87	3.87	3.87	0.145	0.1027	0.1032	0.1037	0.0212	0.0175	0.0169	0.0170
30	40	0.10	2.21	2.11	2.11	2.11	0.1329	0.1035	0.1042	0.1048	0.0236	0.0241	0.0233	0.0232
30	50	0.10	2.36	2.36	2.36	2.36	0.1012	0.1012	0.1012	0.1012	0.0200	0.0210	0.0201	0.0200
30	60	0.10	2.59	2.59	2.59	2.59	0.098	0.0980	0.0980	0.0980	0.0188	0.0198	0.0189	0.0188
30	70	0.10	2.79	2.79	2.79	2.79	0.0977	0.0977	0.0977	0.0977	0.0183	0.0193	0.0184	0.0183
30	80	0.10	2.99	2.99	2.99	2.99	0.0982	0.0982	0.0982	0.0982	0.0180	0.0190	0.0181	0.0180
30	90	0.10	3.17	3.17	2.97	2.97	0.0977	0.0977	0.0967	0.0963	0.0177	0.0187	0.0245	0.0245
30	100	0.10	3.15	3.15	3.15	3.15	0.0909	0.0973	0.0968	0.0964	0.0245	0.0250	0.0242	0.0241
40	50	0.10	2.05	2.10	2.10	2.10	0.3855	0.1030	0.1036	0.1041	0.0245	0.0217	0.0208	0.0208
40	60	0.10	2.06	2.20	2.20	2.20	0.3861	0.0968	0.0963	0.0958	0.0249	0.0240	0.0232	0.0231
40	70	0.10	2.33	2.35	2.33	2.33	0.0802	0.0970	0.0964	0.0959	0.0246	0.0238	0.0243	0.0243
40	80	0.10	2.55	2.46	2.46	2.46	0.0749	0.0971	0.0966	0.0961	0.0198	0.0221	0.0213	0.0213
40	90	0.10	2.76	2.49	2.49	2.49	0.0754	0.0973	0.0968	0.0964	0.0171	0.0235	0.0227	0.0228
40	100	0.10	2.75	2.52	2.52	2.52	0.069	0.0974	0.0969	0.0965	0.0227	0.0246	0.0239	0.0239

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.25	2.59	2.73	2.59	2.59	0.2478	0.2408	0.2478	0.2478	0.0242	0.0236	0.0243	0.0242
10	30	0.25	3.31	3.31	3.31	3.31	0.2569	0.2566	0.2568	0.2568	0.0185	0.0195	0.0186	0.0185
10	40	0.25	3.66	3.66	3.66	3.66	0.2529	0.2529	0.2529	0.2529	0.0235	0.0245	0.0236	0.0235
10	50	0.25	4.2	4.20	4.20	4.20	0.2668	0.2548	0.2558	0.2568	0.0211	0.0218	0.0209	0.0209
10	60	0.25	4.48	4.68	4.48	4.48	0.2624	0.2548	0.2558	0.2566	0.0247	0.0196	0.0247	0.0247
10	70	0.25	4.93	4.93	4.93	4.93	0.2713	0.2543	0.2552	0.2560	0.0230	0.0231	0.0223	0.0223
10	80	0.25	5.34	5.34	5.34	5.34	0.2781	0.2543	0.2552	0.2560	0.0218	0.0210	0.0202	0.0202
10	90	0.25	5.56	5.56	5.56	5.56	0.2735	0.2542	0.2550	0.2557	0.0245	0.0240	0.0232	0.0233
10	100	0.25	5.93	5.93	5.93	5.93	0.2787	0.2539	0.2547	0.2554	0.0234	0.0220	0.0212	0.0213
20	30	0.25	2.3	2.15	2.14	2.14	0.3053	0.2438	0.2426	0.2416	0.0209	0.0250	0.0244	0.0244
20	40	0.25	2.66	2.38	2.26	2.26	0.143	0.2442	0.2431	0.2422	0.0171	0.0216	0.0244	0.0244
20	50	0.25	2.86	2.45	2.37	2.37	0.1388	0.2442	0.2432	0.2423	0.0208	0.0222	0.0245	0.0245
20	60	0.25	3.04	2.51	2.46	2.46	0.1331	0.2448	0.2439	0.2431	0.0236	0.0227	0.0247	0.0247
20	70	0.25	3.42	2.56	2.53	2.53	0.1419	0.2450	0.2441	0.2433	0.0191	0.0232	0.0250	0.0250
20	80	0.25	3.58	2.60	2.60	2.60	0.1397	0.2455	0.2446	0.2439	0.0219	0.0237	0.0228	0.0228
20	90	0.25	3.73	2.63	2.63	2.63	0.138	0.2457	0.2449	0.2442	0.0244	0.0240	0.0232	0.0232
20	100	0.25	4.04	2.66	2.66	2.66	0.145	0.2459	0.2451	0.2444	0.0212	0.0244	0.0236	0.0235
30	40	0.25	2.21	2.21	2.11	2.11	0.1329	0.2447	0.2437	0.2429	0.0236	0.0221	0.0244	0.0244
30	50	0.25	2.36	2.17	2.15	2.15	0.1012	0.2546	0.2555	0.2563	0.0200	0.0249	0.0241	0.0240
30	60	0.25	2.59	2.24	2.17	2.17	0.098	0.2452	0.2443	0.2436	0.0188	0.0250	0.0243	0.0243
30	70	0.25	2.79	2.25	2.25	2.25	0.0977	0.2453	0.2445	0.2437	0.0183	0.0240	0.0231	0.0230
30	80	0.25	2.99	2.26	2.26	2.26	0.0982	0.2457	0.2449	0.2443	0.0180	0.0247	0.0238	0.0238
30	90	0.25	3.17	2.32	2.32	2.32	0.0977	0.2460	0.2452	0.2445	0.0177	0.0235	0.0226	0.0226
30	100	0.25	3.15	2.35	2.29	2.29	0.0909	0.2461	0.2454	0.2447	0.0245	0.0244	0.0246	0.0245
40	50	0.25	2.05	2.11	2.05	2.05	0.3855	0.2543	0.2440	0.2433	0.0245	0.0226	0.0241	0.0241
40	60	0.25	2.06	2.06	2.05	2.05	0.3861	0.2454	0.2551	0.2558	0.0249	0.0248	0.0248	0.0247
40	70	0.25	2.33	2.14	2.14	2.14	0.0802	0.2455	0.2447	0.2440	0.0246	0.0243	0.0234	0.0234
40	80	0.25	2.55	2.18	2.13	2.13	0.0749	0.2459	0.2451	0.2444	0.0198	0.0248	0.0249	0.0248
40	90	0.25	2.76	2.17	2.17	2.17	0.0754	0.2461	0.2454	0.2447	0.0171	0.0243	0.0234	0.0234
40	100	0.25	2.75	2.20	2.20	2.20	0.069	0.2462	0.2455	0.2448	0.0227	0.0244	0.0235	0.0235

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.50	2.59	2.26	2.26	2.26	0.2478	0.4905	0.4888	0.4873	0.0242	0.0238	0.0230	0.0230
10	30	0.50	3.31	2.36	2.36	2.36	0.2569	0.4917	0.4902	0.4889	0.0185	0.0208	0.0200	0.0199
10	40	0.50	3.66	2.35	2.35	2.35	0.2529	0.4925	0.4912	0.4900	0.0235	0.0220	0.0212	0.0212
10	50	0.50	4.2	2.35	2.35	2.35	0.2668	0.4930	0.4918	0.4907	0.0211	0.0233	0.0225	0.0225
10	60	0.50	4.48	2.35	2.35	2.35	0.2624	0.4933	0.4922	0.4911	0.0247	0.0239	0.0230	0.0230
10	70	0.50	4.93	2.35	2.35	2.35	0.2713	0.4928	0.4917	0.4908	0.0230	0.0245	0.0236	0.0236
10	80	0.50	5.34	2.36	2.36	2.36	0.2781	0.4941	0.4931	0.4923	0.0218	0.0248	0.0239	0.0239
10	90	0.50	5.56	2.44	2.36	2.36	0.2735	0.4945	0.4935	0.4927	0.0245	0.0221	0.0243	0.0243
10	100	0.50	5.93	2.43	2.36	2.36	0.2787	0.4943	0.4934	0.4926	0.0234	0.0225	0.0246	0.0246
20	30	0.50	2.3	2.09	2.07	2.07	0.3053	0.4925	0.4911	0.4899	0.0209	0.0248	0.0248	0.0248
20	40	0.50	2.66	2.10	2.10	2.10	0.143	0.4931	0.4918	0.4907	0.0171	0.0243	0.0235	0.0234
20	50	0.50	2.86	2.10	2.10	2.10	0.1388	0.4934	0.4923	0.4913	0.0208	0.0243	0.0234	0.0234
20	60	0.50	3.04	2.15	2.13	2.07	0.1331	0.4933	0.4923	0.4913	0.0236	0.0234	0.0243	0.0250
20	70	0.50	3.42	2.18	2.08	2.08	0.1419	0.4929	0.4919	0.4911	0.0191	0.0219	0.0248	0.0248
20	80	0.50	3.58	2.15	2.13	2.13	0.1397	0.4941	0.4932	0.4924	0.0219	0.0229	0.0244	0.0244
20	90	0.50	3.73	2.13	2.13	2.13	0.138	0.4945	0.4936	0.4928	0.0244	0.0244	0.0235	0.0235
20	100	0.50	4.04	2.14	2.12	2.12	0.145	0.4945	0.4936	0.4928	0.0212	0.0244	0.0242	0.0242
30	40	0.50	2.21	2.07	2.07	2.07	0.1329	0.4939	0.4927	0.4917	0.0236	0.0244	0.0235	0.0235
30	50	0.50	2.36	2.05	2.05	2.05	0.1012	0.4941	0.4931	0.4922	0.0200	0.0243	0.0234	0.0233
30	60	0.50	2.59	2.06	2.02	2.02	0.098	0.4935	0.4925	0.4916	0.0188	0.0237	0.0243	0.0243
30	70	0.50	2.79	2.07	2.06	2.04	0.0977	0.4930	0.4921	0.4913	0.0183	0.0242	0.0250	0.0250
30	80	0.50	2.99	2.12	2.03	2.03	0.0982	0.4942	0.4932	0.4925	0.0180	0.0220	0.0244	0.0244
30	90	0.50	3.17	2.07	2.07	2.07	0.0977	0.4945	0.4936	0.4928	0.0177	0.0247	0.0239	0.0238
30	100	0.50	3.15	2.08	2.06	2.06	0.0909	0.4945	0.4937	0.4929	0.0245	0.0235	0.0248	0.0247
40	50	0.50	2.05	2.04	2.04	2.04	0.3855	0.4943	0.4933	0.4924	0.0245	0.0238	0.0229	0.0228
40	60	0.50	2.06	2.02	2.02	2.02	0.3861	0.4937	0.4927	0.4919	0.0249	0.0244	0.0235	0.0234
40	70	0.50	2.33	2.04	2.01	2.01	0.0802	0.4933	0.5040	0.5048	0.0246	0.0239	0.0249	0.0248
40	80	0.50	2.55	2.03	2.00	2.00	0.0749	0.4944	0.4935	0.4927	0.0198	0.0243	0.0245	0.0244
40	90	0.50	2.76	2.05	2.03	2.03	0.0754	0.4946	0.4937	0.4930	0.0171	0.0242	0.0244	0.0243
40	100	0.50	2.75	2.03	2.03	2.03	0.069	0.4947	0.4938	0.4931	0.0227	0.0249	0.0241	0.0240

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.75	2.59	1.98	1.98	1.98	0.2478	0.7428	0.7413	0.7400	0.0242	0.0205	0.0196	0.0196
10	30	0.75	3.31	1.94	1.94	1.94	0.2569	0.7434	0.7421	0.7409	0.0185	0.0205	0.0197	0.0196
10	40	0.75	3.66	1.93	1.91	1.91	0.2529	0.7442	0.7430	0.7420	0.0235	0.0207	0.0247	0.0247
10	50	0.75	4.2	1.92	1.92	1.92	0.2668	0.7452	0.7442	0.7432	0.0211	0.0209	0.0200	0.0200
10	60	0.75	4.48	1.91	1.91	1.91	0.2624	0.7452	0.7442	0.7434	0.0247	0.0229	0.0221	0.0221
10	70	0.75	4.93	1.91	1.89	1.89	0.2713	0.7457	0.7448	0.7440	0.0230	0.0228	0.0249	0.0249
10	80	0.75	5.34	1.91	1.84	1.84	0.2781	0.7457	0.7448	0.7440	0.0218	0.0227	0.0245	0.0245
10	90	0.75	5.56	1.85	1.85	1.85	0.2735	0.7458	0.7450	0.7443	0.0245	0.0249	0.0241	0.0241
10	100	0.75	5.93	1.86	1.84	1.84	0.2787	0.7461	0.7453	0.7446	0.0234	0.0245	0.0246	0.0246
20	30	0.75	2.3	2.07	1.97	1.97	0.3053	0.7562	0.7574	0.7584	0.0209	0.0248	0.0243	0.0242
20	40	0.75	2.66	1.96	1.91	1.91	0.143	0.7443	0.7432	0.7423	0.0171	0.0219	0.0246	0.0245
20	50	0.75	2.86	1.88	1.88	1.88	0.1388	0.7452	0.7442	0.7434	0.0208	0.0249	0.0240	0.0240
20	60	0.75	3.04	1.90	1.90	1.90	0.1331	0.7452	0.7443	0.7435	0.0236	0.0230	0.0221	0.0221
20	70	0.75	3.42	1.90	1.85	1.85	0.1419	0.7457	0.7448	0.7441	0.0191	0.0249	0.0243	0.0242
20	80	0.75	3.58	1.87	1.87	1.87	0.1397	0.7457	0.7448	0.7441	0.0219	0.0242	0.0234	0.0233
20	90	0.75	3.73	1.91	1.84	1.84	0.138	0.7458	0.7450	0.7443	0.0244	0.0213	0.0245	0.0245
20	100	0.75	4.04	1.85	1.85	1.85	0.145	0.7461	0.7453	0.7446	0.0212	0.0244	0.0235	0.0235
30	40	0.75	2.21	2.07	2.07	2.07	0.1329	0.7446	0.7437	0.7428	0.0236	0.0243	0.0235	0.0234
30	50	0.75	2.36	1.96	1.96	1.96	0.1012	0.7454	0.7445	0.7437	0.0200	0.0242	0.0234	0.0234
30	60	0.75	2.59	1.94	1.90	1.90	0.098	0.7454	0.7445	0.7438	0.0188	0.0232	0.0248	0.0248
30	70	0.75	2.79	1.98	1.86	1.86	0.0977	0.7458	0.7450	0.7443	0.0183	0.0196	0.0246	0.0246
30	80	0.75	2.99	1.92	1.87	1.87	0.0982	0.7458	0.7450	0.7443	0.0180	0.0235	0.0246	0.0246
30	90	0.75	3.17	1.89	1.87	1.87	0.0977	0.7459	0.7452	0.7445	0.0177	0.0250	0.0249	0.0249
30	100	0.75	3.15	1.86	1.84	1.84	0.0909	0.7462	0.7454	0.7448	0.0245	0.0248	0.0248	0.0248
40	50	0.75	2.05	2.08	2.08	2.08	0.3855	0.7457	0.7448	0.7441	0.0245	0.0218	0.0209	0.0208
40	60	0.75	2.06	1.97	1.96	1.96	0.3861	0.7457	0.7554	0.7561	0.0249	0.0239	0.0242	0.0241
40	70	0.75	2.33	1.94	1.94	1.94	0.0802	0.7461	0.7453	0.7446	0.0246	0.0250	0.0241	0.0240
40	80	0.75	2.55	1.92	1.92	1.92	0.0749	0.7460	0.7453	0.7446	0.0198	0.0249	0.0241	0.0240
40	90	0.75	2.76	1.89	1.88	1.88	0.0754	0.7462	0.7546	0.7553	0.0171	0.0240	0.0245	0.0244
40	100	0.75	2.75	1.91	1.89	1.89	0.069	0.7463	0.7457	0.7450	0.0227	0.0238	0.0247	0.0247

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.90	2.59	1.64	1.64	1.64	0.2478	0.8947	0.8937	0.8928	0.0242	0.0185	0.0178	0.0180
10	30	0.90	3.31	1.59	1.59	1.59	0.2569	0.8955	0.8945	0.8937	0.0185	0.0237	0.0230	0.0232
10	40	0.90	3.66	1.68	1.59	1.59	0.2529	0.8960	0.8952	0.8945	0.0235	0.0170	0.0245	0.0246
10	50	0.90	4.2	1.62	1.62	1.62	0.2668	0.8963	0.8956	0.8949	0.0211	0.0183	0.0175	0.0176
10	60	0.90	4.48	1.58	1.58	1.58	0.2624	0.8965	0.8958	0.8952	0.0247	0.0211	0.0203	0.0203
10	70	0.90	4.93	1.55	1.55	1.55	0.2713	0.8967	0.8961	0.8956	0.0230	0.0227	0.0219	0.0219
10	80	0.90	5.34	1.53	1.53	1.53	0.2781	0.8969	0.8963	0.8958	0.0218	0.0240	0.0232	0.0232
10	90	0.90	5.56	1.54	1.51	1.51	0.2735	0.8969	0.8964	0.8959	0.0245	0.0246	0.0242	0.0242
10	100	0.90	5.93	1.57	1.51	1.51	0.2787	0.8971	0.8966	0.8961	0.0234	0.0206	0.0247	0.0247
20	30	0.90	2.3	1.75	1.75	1.75	0.3053	0.8960	0.8952	0.8945	0.0209	0.0245	0.0237	0.0236
20	40	0.90	2.66	1.78	1.78	1.78	0.143	0.8964	0.8957	0.8950	0.0171	0.0240	0.0232	0.0231
20	50	0.90	2.86	1.71	1.71	1.71	0.1388	0.8966	0.8960	0.8954	0.0208	0.0213	0.0205	0.0205
20	60	0.90	3.04	1.64	1.64	1.64	0.1331	0.8967	0.8961	0.8956	0.0236	0.0244	0.0236	0.0237
20	70	0.90	3.42	1.70	1.70	1.70	0.1419	0.8970	0.8964	0.8959	0.0191	0.0205	0.0197	0.0197
20	80	0.90	3.58	1.62	1.62	1.62	0.1397	0.8971	0.8965	0.8960	0.0219	0.0234	0.0226	0.0226
20	90	0.90	3.73	1.65	1.59	1.59	0.138	0.8971	0.8966	0.8961	0.0244	0.0242	0.0246	0.0246
20	100	0.90	4.04	1.63	1.63	1.63	0.145	0.8973	0.8968	0.8963	0.0212	0.0235	0.0227	0.0227
30	40	0.90	2.21	1.86	1.86	1.86	0.1329	0.8965	0.8958	0.8952	0.0236	0.0236	0.0227	0.0226
30	50	0.90	2.36	1.78	1.75	1.75	0.1012	0.8967	0.8961	0.8955	0.0200	0.0219	0.0248	0.0248
30	60	0.90	2.59	1.82	1.77	1.77	0.098	0.8968	0.9039	0.9044	0.0188	0.0239	0.0249	0.0249
30	70	0.90	2.79	1.76	1.76	1.76	0.0977	0.8970	0.8964	0.8959	0.0183	0.0228	0.0219	0.0219
30	80	0.90	2.99	1.75	1.75	1.75	0.0982	0.8971	0.8966	0.8961	0.0180	0.0243	0.0234	0.0233
30	90	0.90	3.17	1.72	1.72	1.72	0.0977	0.8972	0.8966	0.8962	0.0177	0.0230	0.0222	0.0222
30	100	0.90	3.15	1.69	1.69	1.69	0.0909	0.8973	0.8968	0.8964	0.0245	0.0238	0.0230	0.0230
40	50	0.90	2.05	1.90	1.90	1.90	0.3855	0.8970	0.8964	0.8959	0.0245	0.0250	0.0241	0.0241
40	60	0.90	2.06	1.89	1.89	1.89	0.3861	0.9032	0.9037	0.9042	0.0249	0.0223	0.0214	0.0213
40	70	0.90	2.33	1.81	1.79	1.79	0.0802	0.8972	0.8967	0.8962	0.0246	0.0248	0.0242	0.0242
40	80	0.90	2.55	1.80	1.80	1.80	0.0749	0.8973	0.8968	0.8963	0.0198	0.0244	0.0235	0.0234
40	90	0.90	2.76	1.77	1.77	1.77	0.0754	0.8973	0.8968	0.8964	0.0171	0.0236	0.0228	0.0227
40	100	0.90	2.75	1.75	1.75	1.75	0.069	0.8975	0.8970	0.8965	0.0227	0.0248	0.0239	0.0239

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

Figure C.12: Comparison of p-values for the unpoooled Z test calculated with both the classical Lehmann (1959) procedure and the Berger and Boos (1994) procedure for $\boldsymbol{\alpha}$= **0.01**.

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.10	3.29	2.59	2.59	2.59	0.3138	0.1053	0.1063	0.1072	0.0071	0.0057	0.0050	0.0050
10	30	0.10	3.88	3.03	3.03	3.03	0.3056	0.1045	0.1055	0.1063	0.0077	0.0044	0.0036	0.0036
10	40	0.10	4.39	3.17	3.17	3.17	0.3116	0.1040	0.1048	0.1055	0.0085	0.0075	0.0069	0.0070
10	50	0.10	4.86	3.54	3.54	3.54	0.3159	0.1037	0.1044	0.1051	0.0092	0.0051	0.0043	0.0044
10	60	0.10	5.28	3.68	3.68	3.68	0.3187	0.1035	0.1042	0.1048	0.0097	0.0073	0.0066	0.0068
10	70	0.10	5.86	3.81	3.81	3.81	0.3328	0.1033	0.1039	0.1044	0.0083	0.0097	0.0091	0.0093
10	80	0.10	6.21	4.12	4.12	4.12	0.3328	0.1031	0.1037	0.1042	0.0089	0.0064	0.0057	0.0058
10	90	0.10	6.55	4.25	4.25	4.25	0.3327	0.1031	0.1036	0.1041	0.0094	0.0081	0.0075	0.0077
10	100	0.10	6.86	4.37	4.37	4.37	0.3326	0.1029	0.1034	0.1039	0.0098	0.0099	0.0093	0.0096
20	30	0.10	2.74	2.74	2.59	2.59	0.2031	0.1040	0.1048	0.1055	0.0085	0.0046	0.0098	0.0099
20	40	0.10	3.11	2.92	2.92	2.92	0.1540	0.1036	0.1043	0.1050	0.0097	0.0066	0.0058	0.0059
20	50	0.10	3.32	3.09	3.09	3.09	0.1644	0.1034	0.1040	0.1046	0.0085	0.0087	0.0080	0.0080
20	60	0.10	3.68	3.47	3.47	3.47	0.1703	0.1033	0.1039	0.1044	0.0077	0.0057	0.0049	0.0049
20	70	0.10	3.92	3.62	3.62	3.62	0.1642	0.1030	0.1036	0.1041	0.0100	0.0071	0.0063	0.0063
20	80	0.10	4.12	3.76	3.76	3.76	0.1701	0.1029	0.1035	0.1040	0.0092	0.0084	0.0076	0.0077
20	90	0.10	4.42	3.90	3.90	3.90	0.1747	0.1029	0.1034	0.1039	0.0087	0.0097	0.0090	0.0091
20	100	0.10	4.69	4.21	4.21	4.21	0.1786	0.1027	0.1032	0.1037	0.0083	0.0066	0.0059	0.0059
30	40	0.10	2.50	2.66	2.61	2.61	0.4129	0.1035	0.1042	0.1048	0.0097	0.0063	0.0097	0.0096
30	50	0.10	2.86	2.86	2.86	2.86	0.1391	0.1033	0.1039	0.1045	0.0068	0.0069	0.0060	0.0060
30	60	0.10	3.04	3.04	3.04	3.04	0.1253	0.1032	0.1038	0.1043	0.0072	0.0075	0.0067	0.0066
30	70	0.10	3.22	3.22	3.22	3.22	0.1207	0.1030	0.1036	0.1041	0.0078	0.0082	0.0073	0.0072
30	80	0.10	3.39	3.39	3.39	3.39	0.1154	0.1029	0.1034	0.1039	0.0081	0.0086	0.0078	0.0077
30	90	0.10	3.55	3.55	3.55	3.55	0.1151	0.1028	0.1034	0.1038	0.0088	0.0092	0.0084	0.0083
30	100	0.10	3.70	3.70	3.70	3.70	0.1144	0.1027	0.1032	0.1036	0.0093	0.0097	0.0089	0.0088
40	50	0.10	2.50	2.60	2.60	2.60	0.2674	0.0966	0.0960	0.0955	0.0091	0.0089	0.0080	0.0080
40	60	0.10	2.62	2.62	2.62	2.62	0.1579	0.1030	0.1035	0.1040	0.0096	0.0100	0.0091	0.0090
40	70	0.10	2.79	2.86	2.79	2.79	0.1016	0.0970	0.1016	0.1016	0.0090	0.0085	0.0091	0.0090
40	80	0.10	2.99	2.99	2.99	2.99	0.0969	0.0971	0.0969	0.0969	0.0079	0.0089	0.0080	0.0079
40	90	0.10	3.17	3.17	3.06	3.06	0.0934	0.0973	0.0968	0.0964	0.0073	0.0083	0.0097	0.0097
40	100	0.10	3.34	3.34	3.15	3.15	0.0928	0.0974	0.0969	0.0965	0.0070	0.0079	0.0099	0.0098

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.25	3.29	3.29	3.29	3.29	0.3138	0.2572	0.2587	0.2600	0.0071	0.0072	0.0063	0.0063
10	30	0.25	3.88	3.88	3.88	3.88	0.3056	0.2566	0.2579	0.2591	0.0077	0.0073	0.0065	0.0065
10	40	0.25	4.39	4.39	4.39	4.39	0.3116	0.2558	0.2570	0.2580	0.0085	0.0072	0.0064	0.0064
10	50	0.25	4.86	4.86	4.63	4.63	0.3159	0.2548	0.2558	0.2568	0.0092	0.0070	0.0099	0.0099
10	60	0.25	5.28	5.08	5.08	5.08	0.3187	0.2548	0.2558	0.2566	0.0097	0.0100	0.0092	0.0092
10	70	0.25	5.86	5.48	5.48	5.48	0.3328	0.2543	0.2552	0.2560	0.0083	0.0092	0.0085	0.0085
10	80	0.25	6.21	5.86	5.86	5.86	0.3328	0.2543	0.2552	0.2560	0.0089	0.0086	0.0079	0.0079
10	90	0.25	6.55	6.22	6.22	6.22	0.3327	0.2542	0.2550	0.2557	0.0094	0.0080	0.0073	0.0073
10	100	0.25	6.86	6.55	6.40	6.40	0.3326	0.2539	0.2547	0.2554	0.0098	0.0075	0.0095	0.0095
20	30	0.25	2.74	2.69	2.69	2.69	0.2031	0.2438	0.2426	0.2416	0.0085	0.0097	0.0089	0.0088
20	40	0.25	3.11	2.87	2.87	2.87	0.1540	0.2442	0.2431	0.2422	0.0097	0.0098	0.0089	0.0089
20	50	0.25	3.32	3.09	2.92	2.92	0.1644	0.2442	0.2432	0.2423	0.0085	0.0085	0.0098	0.0097
20	60	0.25	3.68	3.09	3.08	3.08	0.1703	0.2448	0.2439	0.2431	0.0077	0.0096	0.0092	0.0092
20	70	0.25	3.92	3.25	3.22	3.22	0.1642	0.2450	0.2441	0.2433	0.0100	0.0089	0.0099	0.0098
20	80	0.25	4.12	3.33	3.23	3.23	0.1701	0.2455	0.2446	0.2439	0.0092	0.0099	0.0092	0.0091
20	90	0.25	4.42	3.36	3.36	3.36	0.1747	0.2457	0.2449	0.2442	0.0087	0.0094	0.0085	0.0084
20	100	0.25	4.69	3.48	3.34	3.34	0.1786	0.2459	0.2451	0.2444	0.0083	0.0088	0.0095	0.0094
30	40	0.25	2.50	2.56	2.48	2.48	0.4129	0.2447	0.2563	0.2572	0.0097	0.0099	0.0099	0.0098
30	50	0.25	2.86	2.67	2.57	2.57	0.1391	0.2446	0.2437	0.2429	0.0068	0.0096	0.0098	0.0098
30	60	0.25	3.04	2.74	2.67	2.67	0.1253	0.2452	0.2443	0.2436	0.0072	0.0090	0.0095	0.0095
30	70	0.25	3.22	2.75	2.75	2.75	0.1207	0.2453	0.2445	0.2437	0.0078	0.0096	0.0087	0.0087
30	80	0.25	3.39	2.82	2.80	2.80	0.1154	0.2457	0.2449	0.2443	0.0081	0.0096	0.0099	0.0098
30	90	0.25	3.55	2.88	2.88	2.79	0.1151	0.2460	0.2452	0.2445	0.0088	0.0099	0.0090	0.0100
30	100	0.25	3.70	2.92	2.91	2.89	0.1144	0.2461	0.2454	0.2447	0.0093	0.0099	0.0100	0.0100
40	50	0.25	2.50	2.53	2.50	2.50	0.2674	0.2543	0.2552	0.2559	0.0091	0.0088	0.0092	0.0091
40	60	0.25	2.62	2.58	2.52	2.52	0.1579	0.2454	0.2551	0.2558	0.0096	0.0099	0.0100	0.0099
40	70	0.25	2.79	2.59	2.58	2.58	0.1016	0.2455	0.2447	0.2440	0.0090	0.0097	0.0098	0.0097
40	80	0.25	2.99	2.71	2.58	2.58	0.0969	0.2459	0.2451	0.2444	0.0079	0.0084	0.0095	0.0094
40	90	0.25	3.17	2.66	2.61	2.61	0.0934	0.2461	0.2454	0.2447	0.0073	0.0099	0.0100	0.0099
40	100	0.25	3.34	2.76	2.66	2.66	0.0928	0.2462	0.2455	0.2448	0.0070	0.0092	0.0095	0.0095

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.50	3.29	2.73	2.73	2.73	0.3138	0.4905	0.4888	0.4873	0.0071	0.0094	0.0086	0.0085
10	30	0.50	3.88	3.04	2.82	2.82	0.3056	0.4917	0.4902	0.4889	0.0077	0.0086	0.0095	0.0095
10	40	0.50	4.39	3.04	3.04	2.99	0.3116	0.4925	0.4912	0.4900	0.0085	0.0095	0.0086	0.0100
10	50	0.50	4.86	3.07	3.05	3.05	0.3159	0.4930	0.4918	0.4907	0.0092	0.0096	0.0094	0.0093
10	60	0.50	5.28	3.20	3.06	3.06	0.3187	0.4933	0.4922	0.4911	0.0097	0.0090	0.0099	0.0099
10	70	0.50	5.86	3.19	3.19	3.19	0.3328	0.4928	0.4917	0.4908	0.0083	0.0098	0.0090	0.0089
10	80	0.50	6.21	3.30	3.19	3.19	0.3328	0.4941	0.4931	0.4923	0.0089	0.0094	0.0095	0.0095
10	90	0.50	6.55	3.35	3.18	3.18	0.3327	0.4945	0.4935	0.4927	0.0094	0.0100	0.0099	0.0099
10	100	0.50	6.86	3.36	3.27	3.27	0.3326	0.4943	0.4934	0.4926	0.0098	0.0098	0.0097	0.0097
20	30	0.50	2.74	2.59	2.47	2.47	0.2031	0.4925	0.4911	0.4899	0.0085	0.0097	0.0097	0.0096
20	40	0.50	3.11	2.55	2.55	2.55	0.1540	0.4931	0.4918	0.4907	0.0097	0.0097	0.0088	0.0087
20	50	0.50	3.32	2.60	2.60	2.60	0.1644	0.4934	0.4923	0.4913	0.0085	0.0091	0.0082	0.0081
20	60	0.50	3.68	2.59	2.58	2.58	0.1703	0.4933	0.4923	0.4913	0.0077	0.0096	0.0099	0.0098
20	70	0.50	3.92	2.58	2.58	2.58	0.1642	0.4929	0.4919	0.4911	0.0100	0.0099	0.0090	0.0090
20	80	0.50	4.12	2.61	2.58	2.58	0.1701	0.4941	0.4932	0.4924	0.0092	0.0097	0.0100	0.0099
20	90	0.50	4.42	2.63	2.58	2.58	0.1747	0.4945	0.4936	0.4928	0.0087	0.0100	0.0097	0.0096
20	100	0.50	4.69	2.65	2.58	2.58	0.1786	0.4945	0.4936	0.4928	0.0083	0.0099	0.0098	0.0097
30	40	0.50	2.50	2.52	2.45	2.45	0.4129	0.4939	0.4927	0.4917	0.0097	0.0095	0.0094	0.0093
30	50	0.50	2.86	2.49	2.42	2.42	0.1391	0.4941	0.4931	0.4922	0.0068	0.0100	0.0099	0.0098
30	60	0.50	3.04	2.50	2.48	2.48	0.1253	0.4935	0.4925	0.4916	0.0072	0.0095	0.0097	0.0096
30	70	0.50	3.22	2.51	2.47	2.47	0.1207	0.4930	0.4921	0.4913	0.0078	0.0093	0.0097	0.0096
30	80	0.50	3.39	2.51	2.49	2.49	0.1154	0.4942	0.4932	0.4925	0.0081	0.0092	0.0092	0.0091
30	90	0.50	3.55	2.52	2.48	2.48	0.1151	0.4945	0.4936	0.4928	0.0088	0.0100	0.0096	0.0095
30	100	0.50	3.70	2.53	2.47	2.47	0.1144	0.4945	0.4937	0.4929	0.0093	0.0099	0.0098	0.0097
40	50	0.50	2.50	2.46	2.45	2.42	0.2674	0.4943	0.4933	0.4924	0.0091	0.0096	0.0091	0.0100
40	60	0.50	2.62	2.45	2.44	2.41	0.1579	0.4937	0.4927	0.4919	0.0096	0.0100	0.0098	0.0099
40	70	0.50	2.79	2.45	2.44	2.44	0.1016	0.4960	0.4924	0.4916	0.0090	0.0100	0.0098	0.0097
40	80	0.50	2.99	2.46	2.41	2.41	0.0969	0.4944	0.4935	0.4927	0.0079	0.0096	0.0099	0.0098
40	90	0.50	3.17	2.49	2.42	2.42	0.0934	0.4946	0.4937	0.4930	0.0073	0.0091	0.0100	0.0099
40	100	0.50	3.34	2.48	2.41	2.41	0.0928	0.4947	0.4938	0.4931	0.0070	0.0098	0.0100	0.0099

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.75	3.29	2.33	2.33	2.33	0.3138	0.7428	0.7413	0.7400	0.0071	0.0092	0.0083	0.0083
10	30	0.75	3.88	2.34	2.34	2.34	0.3056	0.7434	0.7421	0.7409	0.0077	0.0096	0.0088	0.0087
10	40	0.75	4.39	2.40	2.26	2.26	0.3116	0.7442	0.7430	0.7420	0.0085	0.0081	0.0095	0.0095
10	50	0.75	4.86	2.30	2.30	2.30	0.3159	0.7452	0.7442	0.7432	0.0092	0.0098	0.0089	0.0089
10	60	0.75	5.28	2.35	2.24	2.24	0.3187	0.7452	0.7442	0.7434	0.0097	0.0084	0.0097	0.0097
10	70	0.75	5.86	2.29	2.29	2.29	0.3328	0.7457	0.7448	0.7440	0.0083	0.0097	0.0088	0.0088
10	80	0.75	6.21	2.32	2.24	2.24	0.3328	0.7457	0.7448	0.7440	0.0089	0.0090	0.0099	0.0098
10	90	0.75	6.55	2.28	2.28	2.28	0.3327	0.7458	0.7450	0.7443	0.0094	0.0099	0.0091	0.0090
10	100	0.75	6.86	2.31	2.25	2.25	0.3326	0.7461	0.7453	0.7446	0.0098	0.0093	0.0100	0.0099
20	30	0.75	2.74	2.45	2.45	2.45	0.2031	0.7436	0.7425	0.7414	0.0085	0.0087	0.0078	0.0077
20	40	0.75	3.11	2.34	2.30	2.30	0.1540	0.7443	0.7432	0.7423	0.0097	0.0091	0.0096	0.0095
20	50	0.75	3.32	2.28	2.22	2.22	0.1644	0.7452	0.7442	0.7434	0.0085	0.0100	0.0096	0.0095
20	60	0.75	3.68	2.29	2.26	2.26	0.1703	0.7452	0.7443	0.7435	0.0077	0.0089	0.0096	0.0096
20	70	0.75	3.92	2.23	2.22	2.22	0.1642	0.7457	0.7448	0.7441	0.0100	0.0100	0.0092	0.0091
20	80	0.75	4.12	2.27	2.20	2.20	0.1701	0.7457	0.7448	0.7441	0.0092	0.0089	0.0097	0.0097
20	90	0.75	4.42	2.22	2.21	2.21	0.1747	0.7458	0.7450	0.7443	0.0087	0.0098	0.0099	0.0099
20	100	0.75	4.69	2.26	2.21	2.21	0.1786	0.7461	0.7453	0.7446	0.0083	0.0100	0.0094	0.0093
30	40	0.75	2.50	2.38	2.38	2.37	0.4129	0.7446	0.7437	0.7428	0.0097	0.0088	0.0079	0.0100
30	50	0.75	2.86	2.33	2.33	2.33	0.1391	0.7454	0.7445	0.7437	0.0068	0.0096	0.0088	0.0087
30	60	0.75	3.04	2.30	2.27	2.27	0.1253	0.7454	0.7445	0.7438	0.0072	0.0096	0.0099	0.0098
30	70	0.75	3.22	2.29	2.29	2.29	0.1207	0.7458	0.7450	0.7443	0.0078	0.0092	0.0083	0.0083
30	80	0.75	3.39	2.28	2.25	2.25	0.1154	0.7458	0.7450	0.7443	0.0081	0.0095	0.0096	0.0095
30	90	0.75	3.55	2.27	2.22	2.22	0.1151	0.7459	0.7452	0.7445	0.0088	0.0096	0.0096	0.0095
30	100	0.75	3.70	2.26	2.26	2.26	0.1144	0.7462	0.7454	0.7448	0.0093	0.0098	0.0089	0.0088
40	50	0.75	2.50	2.36	2.34	2.34	0.2674	0.7551	0.7560	0.7567	0.0091	0.0091	0.0095	0.0094
40	60	0.75	2.62	2.36	2.31	2.31	0.1579	0.7457	0.7449	0.7442	0.0096	0.0093	0.0095	0.0094
40	70	0.75	2.79	2.31	2.30	2.30	0.1016	0.7461	0.7453	0.7446	0.0090	0.0099	0.0092	0.0091
40	80	0.75	2.99	2.29	2.29	2.29	0.0969	0.7460	0.7453	0.7446	0.0079	0.0100	0.0091	0.0090
40	90	0.75	3.17	2.28	2.27	2.27	0.0934	0.7462	0.7454	0.7448	0.0073	0.0093	0.0093	0.0093
40	100	0.75	3.34	2.28	2.27	2.27	0.0928	0.7463	0.7457	0.7450	0.0070	0.0097	0.0095	0.0095

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_u				p				p-value			
n1	n2	P_Pop	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001	S-U	B-U-001	B-U-0001	B-U-00001
10	20	0.90	3.29	2.08	2.08	2.08	0.3138	0.8947	0.8937	0.8928	0.0071	0.0072	0.0064	0.0064
10	30	0.90	3.88	1.94	1.83	1.83	0.3056	0.8955	0.8945	0.8937	0.0077	0.0099	0.0093	0.0093
10	40	0.90	4.39	1.88	1.88	1.88	0.3116	0.8960	0.8952	0.8945	0.0085	0.0086	0.0078	0.0078
10	50	0.90	4.86	1.87	1.87	1.87	0.3159	0.8963	0.8956	0.8949	0.0092	0.0096	0.0088	0.0088
10	60	0.90	5.28	1.88	1.82	1.82	0.3187	0.8965	0.8958	0.8952	0.0097	0.0086	0.0099	0.0099
10	70	0.90	5.86	1.89	1.86	1.86	0.3328	0.8967	0.8961	0.8956	0.0083	0.0082	0.0093	0.0093
10	80	0.90	6.21	1.89	1.81	1.81	0.3328	0.8969	0.8963	0.8958	0.0089	0.0098	0.0095	0.0094
10	90	0.90	6.55	1.83	1.83	1.83	0.3327	0.8969	0.8964	0.8959	0.0094	0.0099	0.0090	0.0090
10	100	0.90	6.86	1.84	1.84	1.84	0.3326	0.8971	0.8966	0.8961	0.0098	0.0099	0.0091	0.0090
20	30	0.90	2.74	2.12	2.12	2.12	0.2031	0.8960	0.8952	0.8945	0.0085	0.0090	0.0082	0.0081
20	40	0.90	3.11	2.04	1.95	1.95	0.1540	0.8964	0.8957	0.8950	0.0097	0.0087	0.0100	0.0100
20	50	0.90	3.32	2.02	2.02	2.02	0.1644	0.8966	0.8960	0.8954	0.0085	0.0091	0.0082	0.0082
20	60	0.90	3.68	2.00	1.99	1.99	0.1703	0.8967	0.8961	0.8956	0.0077	0.0084	0.0092	0.0092
20	70	0.90	3.92	1.95	1.92	1.92	0.1642	0.8970	0.8964	0.8959	0.0100	0.0099	0.0093	0.0093
20	80	0.90	4.12	1.99	1.93	1.93	0.1701	0.8971	0.8965	0.8960	0.0092	0.0089	0.0095	0.0094
20	90	0.90	4.42	1.95	1.95	1.95	0.1747	0.8971	0.8966	0.8961	0.0087	0.0092	0.0083	0.0083
20	100	0.90	4.69	1.91	1.91	1.91	0.1786	0.8973	0.8968	0.8963	0.0083	0.0094	0.0086	0.0086
30	40	0.90	2.50	2.28	2.17	2.17	0.4129	0.8965	0.8958	0.8952	0.0097	0.0071	0.0094	0.0093
30	50	0.90	2.86	2.09	2.07	2.07	0.1391	0.8967	0.8961	0.8955	0.0068	0.0090	0.0094	0.0093
30	60	0.90	3.04	2.15	2.08	2.08	0.1253	0.8968	0.8962	0.8957	0.0072	0.0093	0.0098	0.0097
30	70	0.90	3.22	2.05	2.05	2.05	0.1207	0.8970	0.8964	0.8959	0.0078	0.0099	0.0090	0.0090
30	80	0.90	3.39	2.07	2.02	2.02	0.1154	0.8971	0.8966	0.8961	0.0081	0.0094	0.0097	0.0097
30	90	0.90	3.55	2.05	2.05	2.05	0.1151	0.8972	0.8966	0.8962	0.0088	0.0085	0.0077	0.0076
30	100	0.90	3.70	2.01	1.97	1.97	0.1144	0.8973	0.8968	0.8964	0.0093	0.0088	0.0098	0.0097
40	50	0.90	2.50	2.32	2.23	2.23	0.2674	0.8970	0.8964	0.8959	0.0091	0.0081	0.0093	0.0093
40	60	0.90	2.62	2.21	2.17	2.17	0.1579	0.8970	0.8965	0.8960	0.0096	0.0081	0.0097	0.0096
40	70	0.90	2.79	2.11	2.11	2.11	0.1016	0.8972	0.8967	0.8962	0.0090	0.0094	0.0085	0.0085
40	80	0.90	2.99	2.16	2.12	2.12	0.0969	0.8973	0.8968	0.8963	0.0079	0.0082	0.0094	0.0093
40	90	0.90	3.17	2.14	2.06	2.06	0.0934	0.8973	0.8968	0.8964	0.0073	0.0085	0.0094	0.0093
40	100	0.90	3.34	2.08	2.04	2.04	0.0928	0.8975	0.8970	0.8965	0.0070	0.0092	0.0099	0.0098

$\mathbf{z_u}$: Z unpooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

Figure C.13: Comparison of p-values for the poooled Z test calculated with both the classical Lehmann (1959) procedure and the Berger and Boos (1994) procedure for α= **0.05**.

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.10	1.88	1.52	1.52	1.52	0.3160	0.1053	0.1063	0.1072	0.0316	0.0184	0.0179	0.0182
10	30	0.10	1.83	1.39	1.39	1.39	0.6925	0.1045	0.1055	0.1063	0.0439	0.0300	0.0298	0.0303
10	40	0.10	2.03	1.31	1.31	1.31	0.9307	0.1040	0.1048	0.1055	0.0417	0.0399	0.0399	0.0405
10	50	0.10	1.74	1.26	1.26	1.26	0.5482	0.1037	0.1044	0.1051	0.0478	0.0485	0.0486	0.0494
10	60	0.10	2.08	1.32	1.32	1.32	0.6895	0.1035	0.1042	0.1048	0.0249	0.0304	0.0303	0.0309
10	70	0.10	1.79	1.28	1.28	1.28	0.8010	0.1033	0.1039	0.1044	0.0489	0.0359	0.0358	0.0365
10	80	0.10	1.83	1.26	1.26	1.26	0.9518	0.1031	0.1037	0.1042	0.0482	0.0410	0.0411	0.0419
10	90	0.10	1.97	1.24	1.24	1.24	0.8936	0.1031	0.1036	0.1041	0.0412	0.0460	0.0461	0.0469
10	100	0.10	2.04	1.27	1.27	1.27	0.9487	0.1029	0.1034	0.1039	0.0453	0.0306	0.0305	0.0312
20	30	0.10	1.69	1.71	1.71	1.71	0.4030	0.1040	0.1048	0.1055	0.0481	0.0311	0.0305	0.0307
20	40	0.10	1.78	1.66	1.66	1.66	0.6943	0.1036	0.1043	0.1050	0.0419	0.0319	0.0313	0.0315
20	50	0.10	1.76	1.63	1.63	1.63	0.5939	0.1034	0.1040	0.1046	0.0412	0.0329	0.0323	0.0325
20	60	0.10	1.73	1.60	1.60	1.60	0.7716	0.1033	0.1039	0.1044	0.0495	0.0343	0.0336	0.0338
20	70	0.10	1.75	1.59	1.59	1.59	0.8246	0.1030	0.1036	0.1041	0.0452	0.0355	0.0349	0.0350
20	80	0.10	1.74	1.58	1.58	1.58	0.6792	0.1029	0.1035	0.1040	0.0459	0.0378	0.0372	0.0374
20	90	0.10	1.83	1.57	1.57	1.57	0.7833	0.1029	0.1034	0.1039	0.0407	0.0386	0.0381	0.0382
20	100	0.10	1.71	1.56	1.56	1.56	0.6507	0.1027	0.1032	0.1037	0.0473	0.0394	0.0389	0.0390
30	40	0.10	1.68	1.62	1.62	1.62	0.4346	0.1035	0.1042	0.1048	0.0489	0.0435	0.0426	0.0425
30	50	0.10	1.70	1.59	1.59	1.59	0.7588	0.1033	0.1039	0.1045	0.0486	0.0490	0.0482	0.0482
30	60	0.10	1.69	1.63	1.63	1.63	0.6687	0.1032	0.1038	0.1043	0.0499	0.0492	0.0485	0.0485
30	70	0.10	1.76	1.61	1.61	1.61	0.8486	0.0969	0.0963	0.0958	0.0473	0.0458	0.0450	0.0449
30	80	0.10	1.69	1.57	1.57	1.57	0.6443	0.1029	0.1034	0.1039	0.0490	0.0462	0.0453	0.0452
30	90	0.10	1.71	1.58	1.58	1.58	0.6830	0.1028	0.1034	0.1038	0.0480	0.0484	0.0476	0.0476
30	100	0.10	1.72	1.60	1.60	1.60	0.7824	0.1027	0.1032	0.1036	0.0465	0.0490	0.0483	0.0483
40	50	0.10	1.68	1.68	1.68	1.68	0.5746	0.1030	0.1036	0.1041	0.0480	0.0381	0.0372	0.0371
40	60	0.10	1.72	1.66	1.66	1.66	0.7947	0.1030	0.1035	0.1040	0.0472	0.0441	0.0433	0.0432
40	70	0.10	1.67	1.65	1.65	1.65	0.6310	0.1028	0.1033	0.1038	0.0494	0.0456	0.0448	0.0448
40	80	0.10	1.69	1.63	1.62	1.62	0.7004	0.0971	0.0966	0.0961	0.0491	0.0491	0.0494	0.0493
40	90	0.10	1.70	1.63	1.63	1.63	0.5207	0.1027	0.1032	0.1036	0.0465	0.0441	0.0433	0.0433
40	100	0.10	1.72	1.63	1.63	1.63	0.7206	0.1025	0.1030	0.1035	0.0471	0.0454	0.0446	0.0446

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: sample size 1; n2: sample size 2; $\mathbf{P_{pop}}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test at confidence level 0.001; B-U-0001: Berger Unpooled test at confidence level 0.0001; B-U-00001: Berger Unpooled test at confidence level 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.25	1.88	1.70	1.70	1.70	0.3160	0.2408	0.2393	0.2380	0.0316	0.0433	0.0424	0.0424
10	30	0.25	1.83	1.60	1.60	1.60	0.6925	0.2425	0.2412	0.2400	0.0439	0.0481	0.0472	0.0471
10	40	0.25	2.03	1.66	1.58	1.58	0.9307	0.2558	0.2520	0.2520	0.0417	0.0438	0.0499	0.0498
10	50	0.25	1.74	1.62	1.62	1.62	0.5482	0.2433	0.2422	0.2413	0.0478	0.0486	0.0477	0.0477
10	60	0.25	2.08	1.64	1.58	1.58	0.6895	0.2548	0.2432	0.2423	0.0249	0.0443	0.0495	0.0495
10	70	0.25	1.79	1.63	1.63	1.63	0.8010	0.2447	0.2447	0.2447	0.0489	0.0438	0.0429	0.0428
10	80	0.25	1.83	1.62	1.62	1.62	0.9518	0.2450	0.2441	0.2435	0.0482	0.0457	0.0448	0.0447
10	90	0.25	1.97	1.62	1.62	1.62	0.8936	0.2453	0.2445	0.2437	0.0412	0.0473	0.0465	0.0464
10	100	0.25	2.04	1.62	1.62	1.62	0.9487	0.2455	0.2447	0.2440	0.0453	0.0477	0.0468	0.0468
20	30	0.25	1.69	1.68	1.68	1.68	0.4030	0.2564	0.2575	0.2586	0.0481	0.0426	0.0417	0.0416
20	40	0.25	1.78	1.63	1.63	1.63	0.6943	0.2442	0.2431	0.2422	0.0419	0.0479	0.0470	0.0470
20	50	0.25	1.76	1.63	1.63	1.63	0.5939	0.2548	0.2558	0.2566	0.0412	0.0453	0.0444	0.0444
20	60	0.25	1.73	1.63	1.59	1.58	0.7716	0.2548	0.2557	0.2565	0.0495	0.0498	0.0499	0.0500
20	70	0.25	1.75	1.60	1.60	1.60	0.8246	0.2543	0.2552	0.2559	0.0452	0.0481	0.0473	0.0473
20	80	0.25	1.74	1.64	1.64	1.64	0.6792	0.2543	0.2552	0.2559	0.0459	0.0430	0.0421	0.0420
20	90	0.25	1.83	1.61	1.59	1.59	0.7833	0.2542	0.2550	0.2557	0.0407	0.0494	0.0498	0.0498
20	100	0.25	1.71	1.63	1.62	1.62	0.6507	0.2539	0.2547	0.2554	0.0473	0.0448	0.0491	0.0490
30	40	0.25	1.68	1.65	1.65	1.65	0.4346	0.2554	0.2563	0.2572	0.0489	0.0481	0.0473	0.0473
30	50	0.25	1.70	1.69	1.69	1.69	0.7588	0.2446	0.2437	0.2429	0.0486	0.0469	0.0460	0.0460
30	60	0.25	1.69	1.67	1.65	1.65	0.6687	0.2452	0.2555	0.2562	0.0499	0.0466	0.0497	0.0496
30	70	0.25	1.76	1.64	1.64	1.64	0.8486	0.2542	0.2550	0.2557	0.0473	0.0479	0.0471	0.0471
30	80	0.25	1.69	1.65	1.63	1.63	0.6443	0.2457	0.2550	0.2557	0.0490	0.0473	0.0497	0.0497
30	90	0.25	1.71	1.61	1.61	1.61	0.6830	0.2541	0.2548	0.2555	0.0480	0.0500	0.0491	0.0491
30	100	0.25	1.72	1.64	1.64	1.64	0.7824	0.2461	0.2454	0.2447	0.0465	0.0463	0.0454	0.0454
40	50	0.25	1.68	1.68	1.67	1.67	0.5746	0.2543	0.2440	0.2433	0.0480	0.0451	0.0495	0.0494
40	60	0.25	1.72	1.67	1.62	1.62	0.7947	0.2454	0.2446	0.2439	0.0472	0.0497	0.0497	0.0496
40	70	0.25	1.67	1.62	1.62	1.62	0.6310	0.2455	0.2447	0.2440	0.0494	0.0499	0.0490	0.0490
40	80	0.25	1.69	1.66	1.66	1.63	0.7004	0.2459	0.2451	0.2554	0.0491	0.0464	0.0455	0.0500
40	90	0.25	1.70	1.66	1.62	1.62	0.5207	0.2461	0.2454	0.2447	0.0465	0.0480	0.0495	0.0494
40	100	0.25	1.72	1.63	1.63	1.63	0.7206	0.2537	0.2543	0.2550	0.0471	0.0478	0.0469	0.0469

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_p}$**op**: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.50	1.88	1.59	1.59	1.59	0.3160	0.5094	0.5111	0.5126	0.0316	0.0499	0.0490	0.0490
10	30	0.50	1.83	1.67	1.67	1.67	0.6925	0.5081	0.5096	0.5109	0.0439	0.0464	0.0456	0.0456
10	40	0.50	2.03	1.71	1.71	1.71	0.9307	0.5071	0.5085	0.5096	0.0417	0.0413	0.0405	0.0404
10	50	0.50	1.74	1.64	1.64	1.64	0.5482	0.5063	0.5075	0.5086	0.0478	0.0497	0.0488	0.0488
10	60	0.50	2.08	1.67	1.67	1.67	0.6895	0.5056	0.5067	0.5077	0.0249	0.0456	0.0448	0.0447
10	70	0.50	1.79	1.70	1.70	1.70	0.8010	0.5043	0.5053	0.5063	0.0489	0.0430	0.0421	0.0421
10	80	0.50	1.83	1.65	1.65	1.65	0.9518	0.5050	0.5060	0.5068	0.0482	0.0483	0.0475	0.0474
10	90	0.50	1.97	1.68	1.68	1.68	0.8936	0.5048	0.5057	0.5066	0.0412	0.0460	0.0451	0.0450
10	100	0.50	2.04	1.70	1.64	1.64	0.9487	0.5041	0.5050	0.5058	0.0453	0.0442	0.0492	0.0491
20	30	0.50	1.69	1.63	1.63	1.63	0.4030	0.5070	0.5084	0.5096	0.0481	0.0497	0.0488	0.0487
20	40	0.50	1.78	1.66	1.66	1.66	0.6943	0.5063	0.5076	0.5087	0.0419	0.0466	0.0458	0.0457
20	50	0.50	1.76	1.67	1.67	1.67	0.5939	0.5058	0.5069	0.5079	0.0412	0.0495	0.0487	0.0487
20	60	0.50	1.73	1.68	1.68	1.68	0.7716	0.4933	0.4923	0.4913	0.0495	0.0499	0.0490	0.0489
20	70	0.50	1.75	1.67	1.67	1.65	0.8246	0.5038	0.5048	0.5056	0.0452	0.0499	0.0491	0.0500
20	80	0.50	1.74	1.71	1.65	1.65	0.6792	0.5045	0.5054	0.5062	0.0459	0.0439	0.0498	0.0497
20	90	0.50	1.83	1.67	1.67	1.67	0.7833	0.4945	0.4936	0.4928	0.0407	0.0482	0.0473	0.0472
20	100	0.50	1.71	1.65	1.64	1.64	0.6507	0.4945	0.5047	0.5054	0.0473	0.0491	0.0496	0.0496
30	40	0.50	1.68	1.66	1.66	1.66	0.4346	0.4939	0.4927	0.4917	0.0489	0.0492	0.0483	0.0483
30	50	0.50	1.70	1.68	1.68	1.68	0.7588	0.5057	0.5067	0.5076	0.0486	0.0474	0.0465	0.0464
30	60	0.50	1.69	1.65	1.65	1.65	0.6687	0.5044	0.5053	0.5062	0.0499	0.0496	0.0488	0.0487
30	70	0.50	1.76	1.67	1.67	1.67	0.8486	0.5033	0.5043	0.5051	0.0473	0.0495	0.0486	0.0486
30	80	0.50	1.69	1.68	1.66	1.66	0.6443	0.5039	0.5049	0.5056	0.0490	0.0480	0.0493	0.0493
30	90	0.50	1.71	1.69	1.69	1.69	0.6830	0.5038	0.5047	0.5055	0.0480	0.0492	0.0483	0.0482
30	100	0.50	1.72	1.67	1.65	1.65	0.7824	0.5035	0.5043	0.5051	0.0465	0.0478	0.0499	0.0498
40	50	0.50	1.68	1.66	1.66	1.66	0.5746	0.4943	0.4933	0.4924	0.0480	0.0499	0.0490	0.0489
40	60	0.50	1.72	1.65	1.65	1.65	0.7947	0.5040	0.5049	0.5057	0.0472	0.0491	0.0482	0.0481
40	70	0.50	1.67	1.67	1.67	1.67	0.6310	0.5031	0.5040	0.5048	0.0494	0.0481	0.0472	0.0471
40	80	0.50	1.69	1.68	1.68	1.68	0.7004	0.5037	0.5046	0.5053	0.0491	0.0490	0.0481	0.0480
40	90	0.50	1.70	1.67	1.64	1.64	0.5207	0.5036	0.4937	0.4930	0.0465	0.0480	0.0499	0.0498
40	100	0.50	1.72	1.67	1.66	1.66	0.7206	0.4947	0.5041	0.5048	0.0471	0.0484	0.0494	0.0493

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_p op}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.75	1.88	1.70	1.70	1.70	0.3160	0.7592	0.7607	0.7620	0.0316	0.0484	0.0477	0.0477
10	30	0.75	1.83	1.83	1.83	1.83	0.6925	0.7434	0.7421	0.7409	0.0439	0.0440	0.0431	0.0431
10	40	0.75	2.03	1.77	1.77	1.77	0.9307	0.7568	0.7580	0.7590	0.0417	0.0412	0.0404	0.0403
10	50	0.75	1.74	1.74	1.74	1.74	0.5482	0.7452	0.7442	0.7432	0.0478	0.0476	0.0467	0.0466
10	60	0.75	2.08	1.76	1.76	1.76	0.6895	0.7559	0.7568	0.7577	0.0249	0.0449	0.0441	0.0440
10	70	0.75	1.79	1.71	1.71	1.71	0.8010	0.7557	0.7566	0.7574	0.0489	0.0496	0.0488	0.0487
10	80	0.75	1.83	1.77	1.77	1.77	0.9518	0.7550	0.7559	0.7567	0.0482	0.0470	0.0461	0.0461
10	90	0.75	1.97	1.75	1.73	1.73	0.8936	0.7547	0.7555	0.7563	0.0412	0.0499	0.0494	0.0493
10	100	0.75	2.04	1.78	1.77	1.77	0.9487	0.7545	0.7453	0.7446	0.0453	0.0446	0.0493	0.0492
20	30	0.75	1.69	1.81	1.81	1.81	0.4030	0.7562	0.7574	0.7584	0.0481	0.0461	0.0453	0.0452
20	40	0.75	1.78	1.66	1.66	1.66	0.6943	0.7443	0.7432	0.7423	0.0419	0.0494	0.0486	0.0485
20	50	0.75	1.76	1.74	1.73	1.73	0.5939	0.7558	0.7568	0.7577	0.0412	0.0469	0.0492	0.0491
20	60	0.75	1.73	1.74	1.70	1.70	0.7716	0.7452	0.7561	0.7569	0.0495	0.0455	0.0494	0.0494
20	70	0.75	1.75	1.73	1.68	1.68	0.8246	0.7457	0.7559	0.7567	0.0452	0.0459	0.0495	0.0495
20	80	0.75	1.74	1.74	1.72	1.72	0.6792	0.7457	0.7554	0.7561	0.0459	0.0451	0.0499	0.0499
20	90	0.75	1.83	1.72	1.72	1.72	0.7833	0.7458	0.7450	0.7443	0.0407	0.0493	0.0484	0.0484
20	100	0.75	1.71	1.71	1.71	1.71	0.6507	0.7541	0.7549	0.7556	0.0473	0.0469	0.0460	0.0459
30	40	0.75	1.68	1.62	1.62	1.62	0.4346	0.7553	0.7563	0.7571	0.0489	0.0498	0.0489	0.0488
30	50	0.75	1.70	1.70	1.68	1.68	0.7588	0.7554	0.7445	0.7437	0.0486	0.0496	0.0494	0.0493
30	60	0.75	1.69	1.70	1.68	1.68	0.6687	0.7454	0.7445	0.7438	0.0499	0.0500	0.0495	0.0494
30	70	0.75	1.76	1.75	1.69	1.69	0.8486	0.7547	0.7450	0.7443	0.0473	0.0460	0.0494	0.0493
30	80	0.75	1.69	1.69	1.69	1.66	0.6443	0.7543	0.7551	0.7443	0.0490	0.0480	0.0471	0.0500
30	90	0.75	1.71	1.71	1.71	1.71	0.6830	0.7459	0.7452	0.7445	0.0480	0.0480	0.0471	0.0470
30	100	0.75	1.72	1.71	1.71	1.71	0.7824	0.7478	0.7478	0.7478	0.0465	0.0496	0.0487	0.0486
40	50	0.75	1.68	1.62	1.62	1.62	0.5746	0.7457	0.7448	0.7441	0.0480	0.0488	0.0480	0.0480
40	60	0.75	1.72	1.68	1.68	1.68	0.7947	0.7546	0.7554	0.7561	0.0472	0.0481	0.0472	0.0471
40	70	0.75	1.67	1.66	1.66	1.66	0.6310	0.7545	0.7553	0.7560	0.0494	0.0496	0.0488	0.0487
40	80	0.75	1.69	1.68	1.68	1.68	0.7004	0.7460	0.7453	0.7446	0.0491	0.0492	0.0483	0.0482
40	90	0.75	1.70	1.68	1.68	1.68	0.5207	0.7539	0.7546	0.7553	0.0465	0.0491	0.0483	0.0483
40	100	0.75	1.72	1.72	1.72	1.72	0.7206	0.7463	0.7457	0.7450	0.0471	0.0474	0.0465	0.0465

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_p op}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.90	1.88	1.90	1.90	1.90	0.3160	0.9049	0.9049	0.9049	0.0316	0.0406	0.0397	0.0396
10	30	0.90	1.83	1.76	1.76	1.76	0.6925	0.8955	0.8945	0.8937	0.0439	0.0447	0.0441	0.0442
10	40	0.90	2.03	1.96	1.96	1.96	0.9307	0.9047	0.9055	0.9062	0.0417	0.0475	0.0470	0.0472
10	50	0.90	1.74	1.86	1.86	1.86	0.5482	0.8963	0.8956	0.8949	0.0478	0.0458	0.0449	0.0448
10	60	0.90	2.08	1.75	1.75	1.75	0.6895	0.9038	0.9045	0.9051	0.0249	0.0493	0.0485	0.0484
10	70	0.90	1.79	1.93	1.93	1.93	0.8010	0.8967	0.8961	0.8956	0.0489	0.0433	0.0424	0.0423
10	80	0.90	1.83	1.83	1.83	1.83	0.9518	0.9034	0.9039	0.9045	0.0482	0.0459	0.0450	0.0450
10	90	0.90	1.97	1.85	1.85	1.85	0.8936	0.9031	0.9036	0.9041	0.0412	0.0492	0.0484	0.0485
10	100	0.90	2.04	1.87	1.87	1.87	0.9487	0.9029	0.9035	0.9040	0.0453	0.0443	0.0435	0.0434
20	30	0.90	1.69	1.77	1.77	1.77	0.4030	0.8960	0.8952	0.8945	0.0481	0.0475	0.0469	0.0469
20	40	0.90	1.78	1.83	1.83	1.83	0.6943	0.8964	0.8957	0.8950	0.0419	0.0366	0.0358	0.0358
20	50	0.90	1.76	1.77	1.77	1.77	0.5939	0.8966	0.8960	0.8954	0.0412	0.0419	0.0410	0.0410
20	60	0.90	1.73	1.73	1.73	1.73	0.7716	0.9036	0.9042	0.9048	0.0495	0.0479	0.0472	0.0472
20	70	0.90	1.75	1.75	1.70	1.70	0.8246	0.9034	0.8964	0.8959	0.0452	0.0458	0.0500	0.0499
20	80	0.90	1.74	1.79	1.79	1.79	0.6792	0.9032	0.9038	0.9043	0.0459	0.0488	0.0481	0.0481
20	90	0.90	1.83	1.83	1.83	1.83	0.7833	0.9029	0.9035	0.9040	0.0407	0.0460	0.0451	0.0451
20	100	0.90	1.71	1.84	1.84	1.84	0.6507	0.8973	0.8968	0.8963	0.0473	0.0449	0.0440	0.0439
30	40	0.90	1.68	1.75	1.66	1.66	0.4346	0.8965	0.9045	0.9051	0.0489	0.0394	0.0500	0.0499
30	50	0.90	1.70	1.62	1.59	1.59	0.7588	0.8967	0.8961	0.8955	0.0486	0.0468	0.0498	0.0499
30	60	0.90	1.69	1.80	1.80	1.80	0.6687	0.9033	0.9039	0.9044	0.0499	0.0482	0.0473	0.0473
30	70	0.90	1.76	1.76	1.76	1.76	0.8486	0.8970	0.8964	0.8959	0.0473	0.0449	0.0440	0.0440
30	80	0.90	1.69	1.70	1.70	1.70	0.6443	0.9029	0.9035	0.9040	0.0490	0.0484	0.0475	0.0475
30	90	0.90	1.71	1.70	1.70	1.70	0.6830	0.9027	0.9033	0.9037	0.0480	0.0477	0.0468	0.0468
30	100	0.90	1.72	1.85	1.72	1.72	0.7824	0.9027	0.9032	0.9036	0.0465	0.0439	0.0499	0.0499
40	50	0.90	1.68	1.67	1.67	1.67	0.5746	0.8976	0.8976	0.8976	0.0480	0.0495	0.0486	0.0485
40	60	0.90	1.72	1.72	1.72	1.72	0.7947	0.9032	0.9037	0.9042	0.0472	0.0433	0.0425	0.0425
40	70	0.90	1.67	1.68	1.68	1.68	0.6310	0.8972	0.8967	0.8962	0.0494	0.0454	0.0446	0.0446
40	80	0.90	1.69	1.76	1.76	1.76	0.7004	0.9029	0.9034	0.9039	0.0491	0.0480	0.0472	0.0473
40	90	0.90	1.70	1.70	1.67	1.67	0.5207	0.9027	0.8968	0.8964	0.0465	0.0494	0.0499	0.0499
40	100	0.90	1.72	1.72	1.72	1.72	0.7206	0.8975	0.8970	0.8965	0.0471	0.0474	0.0466	0.0465

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

Figure C.14: Comparison of p-values for the Pooled Z test calculated with both the classical Lehmann (1959) procedure and the Berger and Boos (1994) procedure for $\boldsymbol{\alpha} = \mathbf{0.025}$.

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.10	2.08	1.52	1.52	1.52	0.606	0.105	0.106	0.107	0.0231	0.0184	0.0179	0.0182
10	30	0.10	2.17	1.54	1.54	1.54	0.557	0.105	0.105	0.106	0.0176	0.0117	0.0111	0.0113
10	40	0.10	2.16	1.43	1.43	1.43	0.881	0.104	0.105	0.106	0.0246	0.0180	0.0176	0.0180
10	50	0.10	2.39	1.36	1.36	1.36	0.865	0.104	0.104	0.105	0.0166	0.0243	0.0240	0.0245
10	60	0.10	2.08	1.40	1.40	1.40	0.689	0.104	0.104	0.105	0.0249	0.0152	0.0148	0.0152
10	70	0.10	2.67	1.35	1.35	1.35	0.955	0.103	0.104	0.104	0.0163	0.0192	0.0188	0.0192
10	80	0.10	2.24	1.32	1.32	1.32	0.842	0.103	0.104	0.104	0.0239	0.0231	0.0229	0.0234
10	90	0.10	3.02	1.35	1.35	1.35	0.966	0.103	0.104	0.104	0.0099	0.0151	0.0147	0.0150
10	100	0.10	3.18	1.32	1.32	1.32	0.964	0.103	0.103	0.104	0.0086	0.0177	0.0174	0.0178
20	30	0.10	1.97	1.93	1.74	1.74	0.603	0.104	0.105	0.106	0.0246	0.0130	0.0249	0.0249
20	40	0.10	2.06	1.83	1.83	1.83	0.668	0.104	0.104	0.105	0.0217	0.0156	0.0149	0.0150
20	50	0.10	2.00	1.77	1.77	1.77	0.379	0.103	0.104	0.105	0.0237	0.0179	0.0172	0.0173
20	60	0.10	2.21	1.73	1.73	1.73	0.655	0.103	0.104	0.104	0.0157	0.0201	0.0194	0.0196
20	70	0.10	2.10	1.70	1.70	1.70	0.896	0.103	0.104	0.104	0.0242	0.0220	0.0214	0.0215
20	80	0.10	2.04	1.67	1.67	1.67	0.667	0.103	0.103	0.104	0.0245	0.0243	0.0237	0.0238
20	90	0.10	2.16	1.74	1.69	1.74	0.876	0.103	0.103	0.104	0.0243	0.0162	0.0249	0.0157
20	100	0.10	2.24	1.71	1.71	1.71	0.821	0.103	0.103	0.104	0.0185	0.0176	0.0170	0.0172
30	40	0.10	2.10	1.85	1.85	1.85	0.816	0.104	0.104	0.105	0.0222	0.0241	0.0233	0.0232
30	50	0.10	2.02	1.93	1.93	1.93	0.769	0.103	0.104	0.104	0.0237	0.0216	0.0207	0.0207
30	60	0.10	2.01	1.83	1.83	1.83	0.843	0.103	0.104	0.104	0.0250	0.0233	0.0225	0.0224
30	70	0.10	2.10	1.89	1.80	1.80	0.864	0.103	0.104	0.104	0.0226	0.0214	0.0249	0.0249
30	80	0.10	2.12	1.82	1.82	1.82	0.805	0.103	0.103	0.104	0.0232	0.0226	0.0218	0.0218
30	90	0.10	2.08	1.81	1.81	1.81	0.810	0.103	0.103	0.104	0.0243	0.0239	0.0231	0.0231
30	100	0.10	2.10	1.81	1.81	1.81	0.649	0.103	0.103	0.104	0.0206	0.0221	0.0212	0.0212
40	50	0.10	2.00	1.91	1.91	1.91	0.503	0.103	0.104	0.104	0.0225	0.0219	0.0210	0.0210
40	60	0.10	1.98	1.90	1.88	1.88	0.386	0.103	0.104	0.104	0.0249	0.0243	0.0243	0.0243
40	70	0.10	1.99	1.91	1.84	1.84	0.356	0.103	0.103	0.104	0.0250	0.0231	0.0247	0.0246
40	80	0.10	2.07	1.90	1.90	1.90	0.575	0.097	0.097	0.096	0.0212	0.0249	0.0240	0.0240
40	90	0.10	2.03	1.91	1.91	1.91	0.666	0.103	0.103	0.104	0.0242	0.0213	0.0205	0.0204
40	100	0.10	2.02	1.88	1.88	1.88	0.695	0.103	0.103	0.103	0.0245	0.0209	0.0200	0.0200

$\mathbf{z_P}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_Pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.25	2.08	1.94	1.92	1.92	0.606	0.257	0.253	0.253	0.0231	0.0165	0.0245	0.0244
10	30	0.25	2.17	1.83	1.83	1.83	0.557	0.257	0.258	0.259	0.0176	0.0245	0.0237	0.0238
10	40	0.25	2.16	1.88	1.88	1.88	0.881	0.256	0.257	0.258	0.0246	0.0200	0.0193	0.0193
10	50	0.25	2.39	1.83	1.83	1.83	0.865	0.255	0.256	0.257	0.0166	0.0232	0.0224	0.0224
10	60	0.25	2.08	1.86	1.86	1.86	0.689	0.255	0.256	0.257	0.0249	0.0204	0.0196	0.0197
10	70	0.25	2.67	1.83	1.83	1.83	0.955	0.254	0.255	0.256	0.0163	0.0240	0.0233	0.0233
10	80	0.25	2.24	1.86	1.86	1.86	0.842	0.254	0.255	0.256	0.0239	0.0213	0.0205	0.0205
10	90	0.25	3.02	1.83	1.83	1.83	0.966	0.254	0.255	0.256	0.0099	0.0243	0.0236	0.0236
10	100	0.25	3.18	1.85	1.85	1.85	0.964	0.254	0.255	0.255	0.0086	0.0222	0.0214	0.0215
20	30	0.25	1.97	1.93	1.93	1.90	0.603	0.244	0.243	0.242	0.0246	0.0246	0.0238	0.0250
20	40	0.25	2.06	1.90	1.90	1.90	0.668	0.256	0.257	0.258	0.0217	0.0237	0.0228	0.0228
20	50	0.25	2.00	1.91	1.91	1.91	0.379	0.255	0.256	0.257	0.0237	0.0229	0.0220	0.0220
20	60	0.25	2.21	1.91	1.91	1.91	0.655	0.255	0.256	0.257	0.0157	0.0241	0.0232	0.0231
20	70	0.25	2.10	1.91	1.91	1.91	0.896	0.254	0.255	0.256	0.0242	0.0249	0.0241	0.0240
20	80	0.25	2.04	1.92	1.88	1.88	0.667	0.254	0.255	0.256	0.0245	0.0217	0.0245	0.0245
20	90	0.25	2.16	1.89	1.86	1.86	0.876	0.254	0.255	0.256	0.0243	0.0250	0.0249	0.0248
20	100	0.25	2.24	1.91	1.85	1.85	0.821	0.254	0.255	0.255	0.0185	0.0231	0.0244	0.0243
30	40	0.25	2.10	2.02	1.99	1.99	0.816	0.255	0.244	0.243	0.0222	0.0212	0.0244	0.0244
30	50	0.25	2.02	1.93	1.91	1.91	0.769	0.255	0.256	0.256	0.0237	0.0249	0.0241	0.0241
30	60	0.25	2.01	1.96	1.95	1.95	0.843	0.249	0.255	0.256	0.0250	0.0240	0.0248	0.0247
30	70	0.25	2.10	1.91	1.90	1.90	0.864	0.254	0.255	0.256	0.0226	0.0242	0.0249	0.0249
30	80	0.25	2.12	1.92	1.90	1.90	0.805	0.254	0.245	0.244	0.0232	0.0247	0.0246	0.0245
30	90	0.25	2.08	1.91	1.91	1.91	0.810	0.254	0.255	0.255	0.0243	0.0237	0.0228	0.0227
30	100	0.25	2.10	1.92	1.92	1.92	0.649	0.248	0.248	0.248	0.0206	0.0240	0.0231	0.0230
40	50	0.25	2.00	1.99	1.95	1.95	0.503	0.254	0.244	0.243	0.0225	0.0226	0.0241	0.0241
40	60	0.25	1.98	1.95	1.91	1.91	0.386	0.254	0.255	0.256	0.0249	0.0243	0.0245	0.0245
40	70	0.25	1.99	1.94	1.94	1.94	0.356	0.254	0.255	0.255	0.0250	0.0241	0.0232	0.0231
40	80	0.25	2.07	1.94	1.92	1.92	0.575	0.254	0.255	0.255	0.0212	0.0248	0.0249	0.0248
40	90	0.25	2.03	1.93	1.93	1.93	0.666	0.254	0.255	0.255	0.0242	0.0240	0.0231	0.0230
40	100	0.25	2.02	1.94	1.94	1.94	0.695	0.246	0.245	0.245	0.0245	0.0244	0.0235	0.0234

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

					z_p				p				p-value		
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.50	2.08	2.08	2.08	2.08	0.606	0.509	0.511	0.513	0.0231	0.0218	0.0210	0.0209
10	30	0.50	2.17	2.02	2.02	2.02	0.557	0.508	0.510	0.511	0.0176	0.0235	0.0227	0.0227
10	40	0.50	2.16	1.99	1.99	1.99	0.881	0.507	0.508	0.510	0.0246	0.0244	0.0235	0.0235
10	50	0.50	2.39	1.97	1.97	1.97	0.865	0.506	0.508	0.509	0.0166	0.0249	0.0241	0.0240
10	60	0.50	2.08	1.99	1.96	1.96	0.689	0.506	0.507	0.508	0.0249	0.0237	0.0245	0.0245
10	70	0.50	2.67	1.98	1.95	1.95	0.955	0.504	0.505	0.506	0.0163	0.0244	0.0248	0.0247
10	80	0.50	2.24	1.97	1.97	1.97	0.842	0.505	0.506	0.507	0.0239	0.0249	0.0240	0.0239
10	90	0.50	3.02	2.00	1.97	1.97	0.966	0.505	0.506	0.507	0.0099	0.0221	0.0245	0.0244
10	100	0.50	3.18	1.99	1.97	1.97	0.964	0.504	0.505	0.506	0.0086	0.0226	0.0248	0.0248
20	30	0.50	1.97	1.99	1.97	1.97	0.603	0.507	0.491	0.490	0.0246	0.0236	0.0246	0.0245
20	40	0.50	2.06	2.02	2.01	2.01	0.668	0.506	0.508	0.509	0.0217	0.0226	0.0246	0.0245
20	50	0.50	2.00	1.97	1.97	1.97	0.379	0.506	0.507	0.508	0.0237	0.0250	0.0241	0.0241
20	60	0.50	2.21	1.96	1.96	1.96	0.655	0.505	0.506	0.507	0.0157	0.0249	0.0240	0.0239
20	70	0.50	2.10	1.99	1.98	1.98	0.896	0.504	0.492	0.491	0.0242	0.0236	0.0241	0.0240
20	80	0.50	2.04	2.01	2.01	2.01	0.667	0.504	0.505	0.506	0.0245	0.0241	0.0233	0.0232
20	90	0.50	2.16	1.98	1.98	1.98	0.876	0.504	0.505	0.506	0.0243	0.0240	0.0231	0.0230
20	100	0.50	2.24	1.97	1.97	1.97	0.821	0.504	0.505	0.505	0.0185	0.0238	0.0229	0.0229
30	40	0.50	2.10	2.01	1.98	1.98	0.816	0.506	0.505	0.505	0.0222	0.0234	0.0246	0.0245
30	50	0.50	2.02	1.99	1.97	1.97	0.769	0.494	0.507	0.508	0.0237	0.0243	0.0247	0.0246
30	60	0.50	2.01	1.95	1.95	1.95	0.843	0.504	0.505	0.506	0.0250	0.0247	0.0238	0.0237
30	70	0.50	2.10	1.98	1.98	1.98	0.864	0.503	0.504	0.505	0.0226	0.0245	0.0236	0.0235
30	80	0.50	2.12	2.00	1.98	1.98	0.805	0.504	0.505	0.506	0.0232	0.0235	0.0247	0.0247
30	90	0.50	2.08	2.01	2.01	2.01	0.810	0.504	0.505	0.505	0.0243	0.0223	0.0214	0.0213
30	100	0.50	2.10	1.99	1.96	1.96	0.649	0.503	0.494	0.493	0.0206	0.0238	0.0248	0.0247
40	50	0.50	2.00	1.99	1.99	1.99	0.503	0.505	0.506	0.507	0.0225	0.0245	0.0237	0.0236
40	60	0.50	1.98	1.98	1.97	1.97	0.386	0.494	0.505	0.506	0.0249	0.0244	0.0242	0.0241
40	70	0.50	1.99	1.99	1.97	1.97	0.356	0.503	0.504	0.505	0.0250	0.0241	0.0249	0.0248
40	80	0.50	2.07	1.95	1.95	1.95	0.575	0.504	0.505	0.505	0.0212	0.0248	0.0239	0.0238
40	90	0.50	2.03	2.00	1.98	1.98	0.666	0.495	0.504	0.505	0.0242	0.0240	0.0243	0.0242
40	100	0.50	2.02	1.99	1.98	1.98	0.695	0.503	0.504	0.505	0.0245	0.0242	0.0241	0.0240

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.75	2.08	2.05	2.05	2.05	0.606	0.743	0.741	0.740	0.0231	0.0212	0.0203	0.0202
10	30	0.75	2.17	2.11	2.11	2.11	0.557	0.757	0.759	0.760	0.0176	0.0242	0.0233	0.0233
10	40	0.75	2.16	2.13	2.13	2.13	0.881	0.757	0.758	0.759	0.0246	0.0248	0.0239	0.0239
10	50	0.75	2.39	2.17	2.11	2.11	0.865	0.757	0.758	0.759	0.0166	0.0234	0.0248	0.0247
10	60	0.75	2.08	2.11	2.08	2.08	0.689	0.756	0.744	0.743	0.0249	0.0237	0.0246	0.0245
10	70	0.75	2.67	2.10	2.09	2.09	0.955	0.756	0.757	0.757	0.0163	0.0240	0.0244	0.0244
10	80	0.75	2.24	2.12	2.12	2.12	0.842	0.755	0.756	0.757	0.0239	0.0230	0.0221	0.0220
10	90	0.75	3.02	2.14	2.14	2.14	0.966	0.755	0.756	0.756	0.0099	0.0230	0.0221	0.0220
10	100	0.75	3.18	2.16	2.12	2.12	0.964	0.746	0.755	0.756	0.0086	0.0224	0.0245	0.0245
20	30	0.75	1.97	2.03	1.96	1.96	0.603	0.756	0.757	0.758	0.0246	0.0248	0.0243	0.0243
20	40	0.75	2.06	2.06	2.03	2.03	0.668	0.744	0.757	0.758	0.0217	0.0220	0.0244	0.0243
20	50	0.75	2.00	2.08	1.99	1.99	0.379	0.745	0.757	0.758	0.0237	0.0246	0.0245	0.0245
20	60	0.75	2.21	2.03	2.03	2.03	0.655	0.755	0.756	0.757	0.0157	0.0245	0.0236	0.0235
20	70	0.75	2.10	2.09	2.07	2.07	0.896	0.755	0.756	0.757	0.0242	0.0236	0.0243	0.0243
20	80	0.75	2.04	2.04	2.03	2.03	0.667	0.746	0.755	0.756	0.0245	0.0243	0.0248	0.0248
20	90	0.75	2.16	2.05	2.04	2.04	0.876	0.754	0.745	0.744	0.0243	0.0248	0.0248	0.0247
20	100	0.75	2.24	2.06	2.06	2.06	0.821	0.754	0.755	0.756	0.0185	0.0240	0.0231	0.0230
30	40	0.75	2.10	2.10	2.10	2.10	0.816	0.755	0.756	0.757	0.0222	0.0214	0.0205	0.0205
30	50	0.75	2.02	2.02	2.02	2.02	0.769	0.755	0.756	0.757	0.0237	0.0246	0.0237	0.0236
30	60	0.75	2.01	2.03	2.03	2.01	0.843	0.755	0.756	0.744	0.0250	0.0233	0.0224	0.0250
30	70	0.75	2.10	2.06	2.05	2.02	0.864	0.747	0.745	0.744	0.0226	0.0244	0.0244	0.0250
30	80	0.75	2.12	2.02	1.99	1.99	0.805	0.754	0.745	0.744	0.0232	0.0239	0.0246	0.0245
30	90	0.75	2.08	2.05	2.04	2.04	0.810	0.754	0.755	0.755	0.0243	0.0237	0.0248	0.0248
30	100	0.75	2.10	2.06	2.02	2.02	0.649	0.754	0.745	0.745	0.0206	0.0240	0.0246	0.0245
40	50	0.75	2.00	2.08	2.08	2.08	0.503	0.755	0.756	0.757	0.0225	0.0240	0.0231	0.0231
40	60	0.75	1.98	2.04	2.02	2.02	0.386	0.755	0.755	0.756	0.0249	0.0244	0.0242	0.0241
40	70	0.75	1.99	2.01	2.01	2.01	0.356	0.755	0.755	0.756	0.0250	0.0242	0.0233	0.0232
40	80	0.75	2.07	2.04	2.01	2.01	0.575	0.746	0.755	0.756	0.0212	0.0233	0.0245	0.0245
40	90	0.75	2.03	2.03	1.99	1.99	0.666	0.746	0.755	0.755	0.0242	0.0239	0.0245	0.0245
40	100	0.75	2.02	2.02	2.02	2.02	0.695	0.746	0.746	0.745	0.0245	0.0244	0.0235	0.0234

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

n1	n2	P_Pop	z_p S-P	z_p B-P-001	z_p B-P-0001	z_p B-P-00001	p S-P	p B-P-001	p B-P-0001	p B-P-00001	p-value S-P	p-value B-P-001	p-value B-P-0001	p-value B-P-00001
10	20	0.90	2.08	2.08	2.08	2.08	0.606	0.895	0.894	0.893	0.0231	0.0141	0.0134	0.0134
10	30	0.90	2.17	2.44	2.44	2.44	0.557	0.905	0.906	0.907	0.0176	0.0178	0.0170	0.0170
10	40	0.90	2.16	2.32	2.09	2.09	0.881	0.905	0.895	0.894	0.0246	0.0230	0.0246	0.0245
10	50	0.90	2.39	2.31	2.31	2.31	0.865	0.904	0.905	0.906	0.0166	0.0230	0.0222	0.0222
10	60	0.90	2.08	2.28	2.28	2.28	0.689	0.904	0.904	0.905	0.0249	0.0211	0.0203	0.0203
10	70	0.90	2.67	2.33	2.26	2.26	0.955	0.904	0.904	0.905	0.0163	0.0213	0.0247	0.0247
10	80	0.90	2.24	2.24	2.24	2.24	0.842	0.903	0.904	0.904	0.0239	0.0243	0.0234	0.0234
10	90	0.90	3.02	2.30	2.30	2.30	0.966	0.903	0.904	0.904	0.0099	0.0237	0.0228	0.0228
10	100	0.90	3.18	2.40	2.26	2.26	0.964	0.903	0.904	0.904	0.0086	0.0243	0.0244	0.0244
20	30	0.90	1.97	1.93	1.93	1.93	0.603	0.896	0.895	0.894	0.0246	0.0240	0.0231	0.0230
20	40	0.90	2.06	2.04	2.04	2.04	0.668	0.896	0.896	0.895	0.0217	0.0240	0.0231	0.0231
20	50	0.90	2.00	2.17	2.17	2.17	0.379	0.897	0.896	0.895	0.0237	0.0203	0.0194	0.0193
20	60	0.90	2.21	2.15	2.06	2.06	0.655	0.904	0.896	0.896	0.0157	0.0249	0.0242	0.0241
20	70	0.90	2.10	2.25	2.10	2.10	0.896	0.903	0.896	0.896	0.0242	0.0200	0.0243	0.0242
20	80	0.90	2.04	2.22	2.22	2.22	0.667	0.903	0.904	0.904	0.0245	0.0232	0.0223	0.0222
20	90	0.90	2.16	2.14	2.14	2.14	0.876	0.897	0.897	0.896	0.0243	0.0249	0.0241	0.0240
20	100	0.90	2.24	2.24	2.23	2.23	0.821	0.903	0.903	0.904	0.0185	0.0222	0.0249	0.0249
30	40	0.90	2.10	2.05	2.05	2.05	0.816	0.896	0.896	0.895	0.0222	0.0236	0.0227	0.0226
30	50	0.90	2.02	2.03	2.03	2.03	0.769	0.897	0.896	0.896	0.0237	0.0203	0.0194	0.0194
30	60	0.90	2.01	2.15	2.03	2.03	0.843	0.903	0.904	0.904	0.0250	0.0248	0.0249	0.0248
30	70	0.90	2.10	2.10	2.10	2.10	0.864	0.897	0.896	0.896	0.0226	0.0226	0.0218	0.0217
30	80	0.90	2.12	2.15	2.15	2.15	0.805	0.903	0.904	0.904	0.0232	0.0220	0.0212	0.0211
30	90	0.90	2.08	2.11	2.11	2.11	0.810	0.903	0.903	0.904	0.0243	0.0226	0.0218	0.0217
30	100	0.90	2.10	2.11	2.11	2.11	0.649	0.903	0.903	0.904	0.0206	0.0222	0.0213	0.0212
40	50	0.90	2.00	1.99	1.99	1.99	0.503	0.897	0.896	0.896	0.0225	0.0250	0.0241	0.0241
40	60	0.90	1.98	2.05	2.05	2.05	0.386	0.903	0.904	0.904	0.0249	0.0221	0.0213	0.0212
40	70	0.90	1.99	2.01	2.00	2.00	0.356	0.897	0.897	0.896	0.0250	0.0221	0.0248	0.0248
40	80	0.90	2.07	2.02	2.02	2.02	0.575	0.903	0.903	0.904	0.0212	0.0249	0.0240	0.0239
40	90	0.90	2.03	2.09	2.09	2.09	0.666	0.897	0.897	0.896	0.0242	0.0229	0.0221	0.0220
40	100	0.90	2.02	2.12	2.10	2.10	0.695	0.903	0.903	0.904	0.0245	0.0217	0.0248	0.0248

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

Figure C.15: Comparison of p-values for the Poooled Z test calculated with both the classical Lehmann (1959) procedure and the Berger and Boos (1994) procedure for $\boldsymbol{\alpha}= \mathbf{0.01}$.

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.10	2.45	1.74	1.74	1.74	0.6813	0.1053	0.1063	0.1072	0.0083	0.0057	0.0050	0.0051
10	30	0.10	2.56	1.69	1.69	1.69	0.7475	0.1045	0.1055	0.1063	0.0078	0.0044	0.0036	0.0036
10	40	0.10	2.66	1.55	1.55	1.55	0.7236	0.1040	0.1048	0.1055	0.0063	0.0075	0.0069	0.0070
10	50	0.10	2.72	1.55	1.55	1.55	0.9549	0.1037	0.1044	0.1051	0.0095	0.0051	0.0043	0.0044
10	60	0.10	2.66	1.48	1.48	1.48	0.8842	0.1035	0.1042	0.1048	0.0098	0.0073	0.0066	0.0068
10	70	0.10	2.90	1.43	1.43	1.43	0.9440	0.1033	0.1039	0.1044	0.0063	0.0097	0.0091	0.0093
10	80	0.10	3.12	1.44	1.44	1.44	0.9371	0.1031	0.1037	0.1042	0.0069	0.0064	0.0057	0.0058
10	90	0.10	3.02	1.41	1.41	1.41	0.9662	0.1031	0.1036	0.1041	0.0099	0.0081	0.0075	0.0077
10	100	0.10	3.18	1.37	1.37	1.37	0.9639	0.1029	0.1034	0.1039	0.0086	0.0099	0.0093	0.0096
20	30	0.10	2.51	2.14	2.14	2.14	0.6623	0.1040	0.1048	0.1055	0.0074	0.0052	0.0044	0.0044
20	40	0.10	2.40	2.00	2.00	2.00	0.7736	0.1036	0.1043	0.1050	0.0099	0.0071	0.0064	0.0064
20	50	0.10	2.65	1.91	1.91	1.91	0.6937	0.1034	0.1040	0.1046	0.0056	0.0091	0.0083	0.0084
20	60	0.10	2.59	1.96	1.96	1.96	0.8560	0.1033	0.1039	0.1044	0.0077	0.0058	0.0050	0.0050
20	70	0.10	2.68	1.90	1.90	1.90	0.9212	0.1030	0.1036	0.1041	0.0090	0.0072	0.0065	0.0065
20	80	0.10	2.86	1.85	1.85	1.85	0.9343	0.1029	0.1035	0.1040	0.0058	0.0085	0.0078	0.0078
20	90	0.10	2.77	1.81	1.81	1.81	0.8797	0.1029	0.1034	0.1039	0.0065	0.0098	0.0091	0.0091
20	100	0.10	2.66	1.86	1.86	1.86	0.9111	0.1027	0.1032	0.1037	0.0093	0.0066	0.0059	0.0059
30	40	0.10	2.39	2.22	2.22	2.22	0.6151	0.1035	0.1042	0.1048	0.0094	0.0079	0.0071	0.0071
30	50	0.10	2.39	2.15	2.15	2.15	0.7384	0.1033	0.1039	0.1045	0.0097	0.0079	0.0071	0.0071
30	60	0.10	2.41	2.10	2.10	2.10	0.7563	0.1032	0.1038	0.1043	0.0099	0.0097	0.0089	0.0088
30	70	0.10	2.51	2.06	2.06	2.06	0.8980	0.1030	0.1036	0.1041	0.0098	0.0095	0.0086	0.0086
30	80	0.10	2.49	2.05	2.04	2.04	0.6520	0.1029	0.1034	0.1039	0.0075	0.0095	0.0099	0.0099
30	90	0.10	2.49	2.07	2.01	2.01	0.7514	0.1028	0.1034	0.1038	0.0086	0.0098	0.0097	0.0097
30	100	0.10	2.56	2.09	2.00	2.00	0.7776	0.1027	0.1032	0.1036	0.0072	0.0069	0.0097	0.0097
40	50	0.10	2.35	2.28	2.27	2.27	0.5576	0.1030	0.1036	0.1041	0.0099	0.0091	0.0093	0.0092
40	60	0.10	2.36	2.24	2.22	2.22	0.5247	0.1030	0.1035	0.1040	0.0099	0.0100	0.0092	0.0091
40	70	0.10	2.39	2.23	2.15	2.15	0.6716	0.1028	0.1033	0.1038	0.0094	0.0086	0.0096	0.0095
40	80	0.10	2.42	2.21	2.21	2.21	0.8112	0.1027	0.1032	0.1037	0.0097	0.0092	0.0084	0.0083
40	90	0.10	2.44	2.16	2.16	2.16	0.6478	0.1027	0.1032	0.1036	0.0090	0.0099	0.0090	0.0089
40	100	0.10	2.60	2.19	2.11	2.11	0.9206	0.1025	0.1030	0.1035	0.0083	0.0086	0.0094	0.0093

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_p op}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.25	2.45	2.15	2.14	2.14	0.6813	0.2572	0.2587	0.2600	0.0083	0.0079	0.0093	0.0093
10	30	0.25	2.56	2.11	2.11	2.11	0.7475	0.2566	0.2579	0.2591	0.0078	0.0080	0.0072	0.0072
10	40	0.25	2.66	2.10	2.10	2.10	0.7236	0.2558	0.2570	0.2580	0.0063	0.0077	0.0069	0.0069
10	50	0.25	2.72	2.09	2.09	2.09	0.9549	0.2548	0.2558	0.2568	0.0095	0.0072	0.0064	0.0064
10	60	0.25	2.66	2.09	2.01	2.01	0.8842	0.2548	0.2558	0.2566	0.0098	0.0069	0.0093	0.0094
10	70	0.25	2.90	2.02	2.02	2.02	0.9440	0.2543	0.2552	0.2560	0.0063	0.0093	0.0086	0.0086
10	80	0.25	3.12	2.03	2.03	2.03	0.9371	0.2543	0.2552	0.2560	0.0069	0.0087	0.0079	0.0079
10	90	0.25	3.02	2.03	2.03	2.03	0.9662	0.2542	0.2550	0.2557	0.0099	0.0081	0.0073	0.0073
10	100	0.25	3.18	2.04	1.99	1.99	0.9639	0.2539	0.2547	0.2554	0.0086	0.0075	0.0095	0.0095
20	30	0.25	2.51	2.32	2.32	2.32	0.6623	0.2438	0.2426	0.2416	0.0074	0.0093	0.0084	0.0083
20	40	0.25	2.40	2.23	2.23	2.23	0.7736	0.2557	0.2568	0.2577	0.0099	0.0096	0.0088	0.0087
20	50	0.25	2.65	2.26	2.26	2.26	0.6937	0.2548	0.2558	0.2566	0.0056	0.0092	0.0084	0.0083
20	60	0.25	2.59	2.26	2.17	2.17	0.8560	0.2548	0.2557	0.2565	0.0077	0.0095	0.0097	0.0096
20	70	0.25	2.68	2.22	2.20	2.20	0.9212	0.2543	0.2552	0.2559	0.0090	0.0091	0.0092	0.0092
20	80	0.25	2.86	2.23	2.19	2.19	0.9343	0.2543	0.2552	0.2559	0.0058	0.0087	0.0094	0.0093
20	90	0.25	2.77	2.17	2.17	2.17	0.8797	0.2542	0.2550	0.2557	0.0065	0.0100	0.0091	0.0090
20	100	0.25	2.66	2.20	2.20	2.20	0.9111	0.2539	0.2547	0.2554	0.0093	0.0094	0.0085	0.0085
30	40	0.25	2.39	2.31	2.26	2.26	0.6151	0.2554	0.2563	0.2572	0.0094	0.0098	0.0100	0.0099
30	50	0.25	2.39	2.31	2.24	2.24	0.7384	0.2546	0.2555	0.2563	0.0097	0.0098	0.0099	0.0099
30	60	0.25	2.41	2.27	2.26	2.26	0.7563	0.2546	0.2555	0.2562	0.0099	0.0100	0.0093	0.0092
30	70	0.25	2.51	2.27	2.27	2.27	0.8980	0.2542	0.2550	0.2557	0.0098	0.0096	0.0087	0.0086
30	80	0.25	2.49	2.28	2.25	2.25	0.6520	0.2542	0.2550	0.2557	0.0075	0.0090	0.0094	0.0093
30	90	0.25	2.49	2.29	2.21	2.21	0.7514	0.2541	0.2548	0.2555	0.0086	0.0092	0.0096	0.0096
30	100	0.25	2.56	2.26	2.21	2.21	0.7776	0.2538	0.2546	0.2552	0.0072	0.0099	0.0097	0.0096
40	50	0.25	2.35	2.35	2.32	2.32	0.5576	0.2543	0.2552	0.2559	0.0099	0.0100	0.0091	0.0090
40	60	0.25	2.36	2.36	2.30	2.26	0.5247	0.2543	0.2551	0.2558	0.0099	0.0098	0.0099	0.0100
40	70	0.25	2.39	2.33	2.29	2.29	0.6716	0.2455	0.2547	0.2554	0.0094	0.0095	0.0099	0.0098
40	80	0.25	2.42	2.30	2.30	2.30	0.8112	0.2540	0.2547	0.2554	0.0097	0.0099	0.0090	0.0090
40	90	0.25	2.44	2.27	2.26	2.26	0.6478	0.2538	0.2546	0.2552	0.0090	0.0098	0.0099	0.0098
40	100	0.25	2.60	2.30	2.27	2.27	0.9206	0.2537	0.2543	0.2550	0.0083	0.0093	0.0092	0.0091

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.50	2.45	2.38	2.38	2.38	0.6813	0.5094	0.5111	0.5126	0.0083	0.0078	0.0070	0.0069
10	30	0.50	2.56	2.38	2.38	2.38	0.7475	0.5081	0.5096	0.5109	0.0078	0.0094	0.0085	0.0084
10	40	0.50	2.66	2.42	2.32	2.30	0.7236	0.5071	0.5085	0.5096	0.0063	0.0084	0.0099	0.0100
10	50	0.50	2.72	2.34	2.32	2.32	0.9549	0.5063	0.5075	0.5086	0.0095	0.0094	0.0095	0.0095
10	60	0.50	2.66	2.36	2.36	2.36	0.8842	0.5056	0.5067	0.5077	0.0098	0.0086	0.0078	0.0077
10	70	0.50	2.90	2.38	2.30	2.30	0.9440	0.5043	0.5053	0.5063	0.0063	0.0081	0.0093	0.0092
10	80	0.50	3.12	2.33	2.32	2.32	0.9371	0.5050	0.5060	0.5068	0.0069	0.0095	0.0095	0.0094
10	90	0.50	3.02	2.35	2.29	2.29	0.9662	0.5048	0.5057	0.5066	0.0099	0.0090	0.0098	0.0098
10	100	0.50	3.18	2.37	2.31	2.31	0.9639	0.5041	0.5050	0.5058	0.0086	0.0086	0.0092	0.0091
20	30	0.50	2.51	2.36	2.36	2.36	0.6623	0.5070	0.5084	0.5096	0.0074	0.0097	0.0088	0.0087
20	40	0.50	2.40	2.38	2.38	2.38	0.7736	0.5063	0.5076	0.5087	0.0099	0.0094	0.0085	0.0084
20	50	0.50	2.65	2.37	2.35	2.35	0.6937	0.5058	0.5069	0.5079	0.0056	0.0094	0.0093	0.0092
20	60	0.50	2.59	2.36	2.33	2.33	0.8560	0.5048	0.5059	0.5068	0.0077	0.0093	0.0094	0.0093
20	70	0.50	2.68	2.38	2.33	2.32	0.9212	0.4929	0.5048	0.5056	0.0090	0.0095	0.0100	0.0100
20	80	0.50	2.86	2.39	2.31	2.31	0.9343	0.5045	0.5054	0.5062	0.0058	0.0100	0.0099	0.0098
20	90	0.50	2.77	2.36	2.35	2.33	0.8797	0.5043	0.4936	0.5060	0.0065	0.0098	0.0093	0.0100
20	100	0.50	2.66	2.37	2.31	2.31	0.9111	0.5038	0.5047	0.5054	0.0093	0.0097	0.0100	0.0099
30	40	0.50	2.39	2.38	2.36	2.36	0.6151	0.5062	0.4927	0.4917	0.0094	0.0096	0.0094	0.0093
30	50	0.50	2.39	2.38	2.36	2.35	0.7384	0.4941	0.5067	0.5076	0.0097	0.0097	0.0096	0.0100
30	60	0.50	2.41	2.39	2.39	2.39	0.7563	0.5044	0.5053	0.5062	0.0099	0.0095	0.0086	0.0085
30	70	0.50	2.51	2.36	2.32	2.32	0.8980	0.5033	0.5043	0.5051	0.0098	0.0099	0.0099	0.0099
30	80	0.50	2.49	2.38	2.34	2.34	0.6520	0.5039	0.5049	0.5056	0.0075	0.0093	0.0094	0.0094
30	90	0.50	2.49	2.34	2.34	2.33	0.7514	0.5038	0.5047	0.5055	0.0086	0.0100	0.0091	0.0099
30	100	0.50	2.56	2.38	2.34	2.34	0.7776	0.5035	0.5043	0.5051	0.0072	0.0094	0.0100	0.0099
40	50	0.50	2.35	2.36	2.35	2.35	0.5576	0.5052	0.5062	0.5070	0.0099	0.0099	0.0099	0.0098
40	60	0.50	2.36	2.38	2.35	2.33	0.5247	0.5040	0.5049	0.5057	0.0099	0.0095	0.0100	0.0099
40	70	0.50	2.39	2.38	2.35	2.33	0.6716	0.5031	0.5040	0.5048	0.0094	0.0093	0.0094	0.0100
40	80	0.50	2.42	2.34	2.33	2.33	0.8112	0.5037	0.5046	0.5053	0.0097	0.0098	0.0098	0.0097
40	90	0.50	2.44	2.38	2.35	2.34	0.6478	0.4946	0.5044	0.5052	0.0090	0.0097	0.0097	0.0099
40	100	0.50	2.60	2.37	2.33	2.33	0.9206	0.5033	0.5041	0.5048	0.0083	0.0096	0.0100	0.0099

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

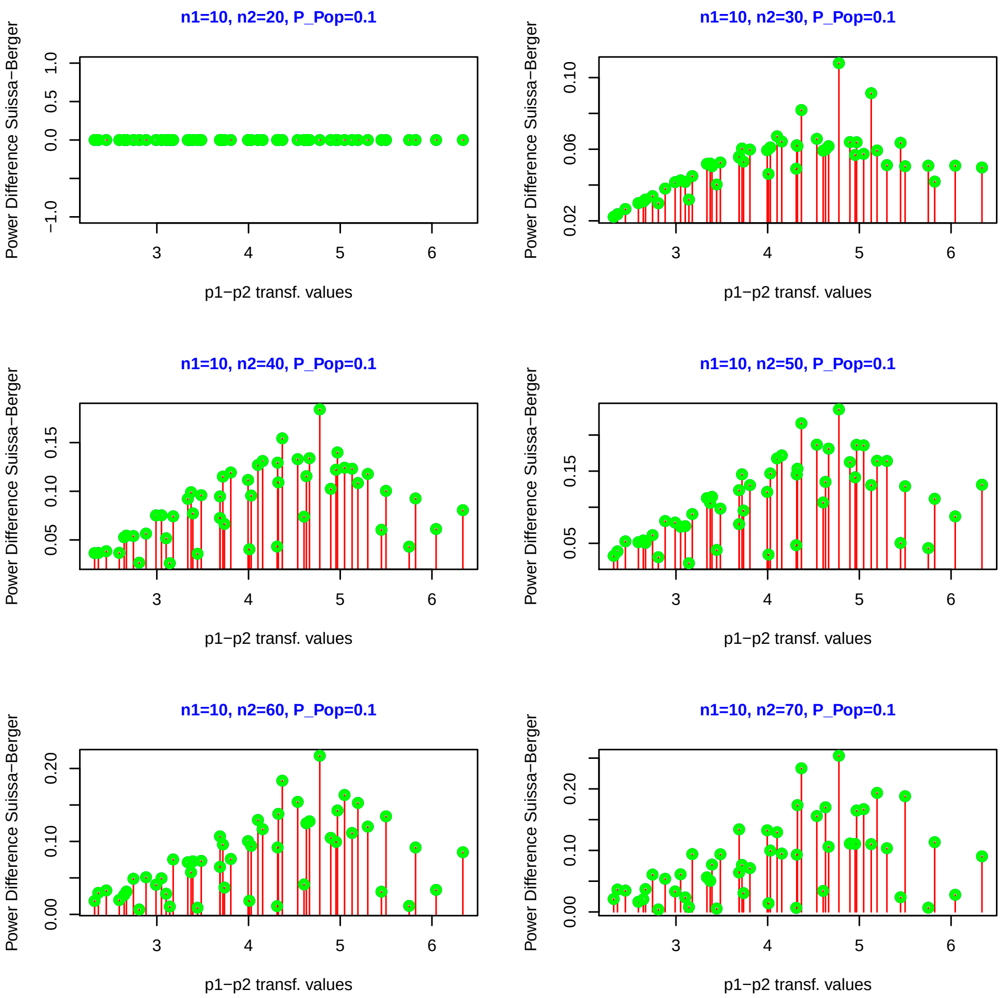
			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.75	2.45	2.45	2.45	2.45	0.6813	0.7428	0.7413	0.7400	0.0083	0.0090	0.0081	0.0080
10	30	0.75	2.56	2.56	2.44	2.44	0.7475	0.7475	0.7588	0.7600	0.0078	0.0088	0.0098	0.0098
10	40	0.75	2.66	2.52	2.52	2.52	0.7236	0.7568	0.7580	0.7590	0.0063	0.0096	0.0088	0.0087
10	50	0.75	2.72	2.60	2.55	2.55	0.9549	0.7567	0.7578	0.7587	0.0095	0.0091	0.0099	0.0099
10	60	0.75	2.66	2.57	2.53	2.53	0.8842	0.7559	0.7568	0.7577	0.0098	0.0087	0.0097	0.0096
10	70	0.75	2.90	2.60	2.54	2.54	0.9440	0.7557	0.7566	0.7574	0.0063	0.0084	0.0094	0.0093
10	80	0.75	3.12	2.53	2.53	2.53	0.9371	0.7550	0.7559	0.7567	0.0069	0.0097	0.0088	0.0088
10	90	0.75	3.02	2.59	2.51	2.51	0.9662	0.7547	0.7555	0.7563	0.0099	0.0093	0.0098	0.0097
10	100	0.75	3.18	2.61	2.54	2.54	0.9639	0.7545	0.7553	0.7560	0.0086	0.0094	0.0094	0.0093
20	30	0.75	2.51	2.51	2.51	2.51	0.6623	0.7436	0.7425	0.7414	0.0074	0.0079	0.0070	0.0069
20	40	0.75	2.40	2.44	2.40	2.40	0.7736	0.7443	0.7569	0.7578	0.0099	0.0092	0.0099	0.0099
20	50	0.75	2.65	2.51	2.40	2.40	0.6937	0.7558	0.7568	0.7577	0.0056	0.0085	0.0095	0.0095
20	60	0.75	2.59	2.43	2.43	2.41	0.8560	0.7552	0.7561	0.7435	0.0077	0.0100	0.0091	0.0100
20	70	0.75	2.68	2.50	2.43	2.43	0.9212	0.7550	0.7559	0.7567	0.0090	0.0100	0.0098	0.0098
20	80	0.75	2.86	2.47	2.46	2.46	0.9343	0.7545	0.7554	0.7561	0.0058	0.0098	0.0092	0.0091
20	90	0.75	2.77	2.49	2.48	2.48	0.8797	0.7543	0.7551	0.7558	0.0065	0.0096	0.0099	0.0098
20	100	0.75	2.66	2.51	2.47	2.47	0.9111	0.7541	0.7549	0.7556	0.0093	0.0092	0.0093	0.0092
30	40	0.75	2.39	2.39	2.38	2.38	0.6151	0.7553	0.7563	0.7571	0.0094	0.0092	0.0098	0.0098
30	50	0.75	2.39	2.41	2.39	2.39	0.7384	0.7454	0.7445	0.7437	0.0097	0.0093	0.0098	0.0097
30	60	0.75	2.41	2.43	2.43	2.41	0.7563	0.7454	0.7445	0.7563	0.0099	0.0097	0.0088	0.0099
30	70	0.75	2.51	2.46	2.41	2.41	0.8980	0.7547	0.7555	0.7563	0.0098	0.0091	0.0093	0.0092
30	80	0.75	2.49	2.48	2.48	2.48	0.6520	0.7543	0.7551	0.7557	0.0075	0.0093	0.0084	0.0083
30	90	0.75	2.49	2.47	2.44	2.44	0.7514	0.7539	0.7548	0.7555	0.0086	0.0096	0.0098	0.0097
30	100	0.75	2.56	2.45	2.45	2.45	0.7776	0.7539	0.7546	0.7553	0.0072	0.0097	0.0088	0.0087
40	50	0.75	2.35	2.35	2.35	2.35	0.5576	0.7551	0.7560	0.7567	0.0099	0.0100	0.0091	0.0090
40	60	0.75	2.36	2.40	2.36	2.36	0.5247	0.7457	0.7449	0.7442	0.0099	0.0092	0.0093	0.0093
40	70	0.75	2.39	2.42	2.39	2.39	0.6716	0.7545	0.7553	0.7560	0.0094	0.0099	0.0092	0.0092
40	80	0.75	2.42	2.43	2.42	2.42	0.8112	0.7460	0.7549	0.7556	0.0097	0.0097	0.0092	0.0091
40	90	0.75	2.44	2.44	2.40	2.40	0.6478	0.7539	0.7546	0.7553	0.0090	0.0095	0.0094	0.0093
40	100	0.75	2.60	2.45	2.45	2.45	0.9206	0.7538	0.7545	0.7552	0.0083	0.0097	0.0088	0.0087

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

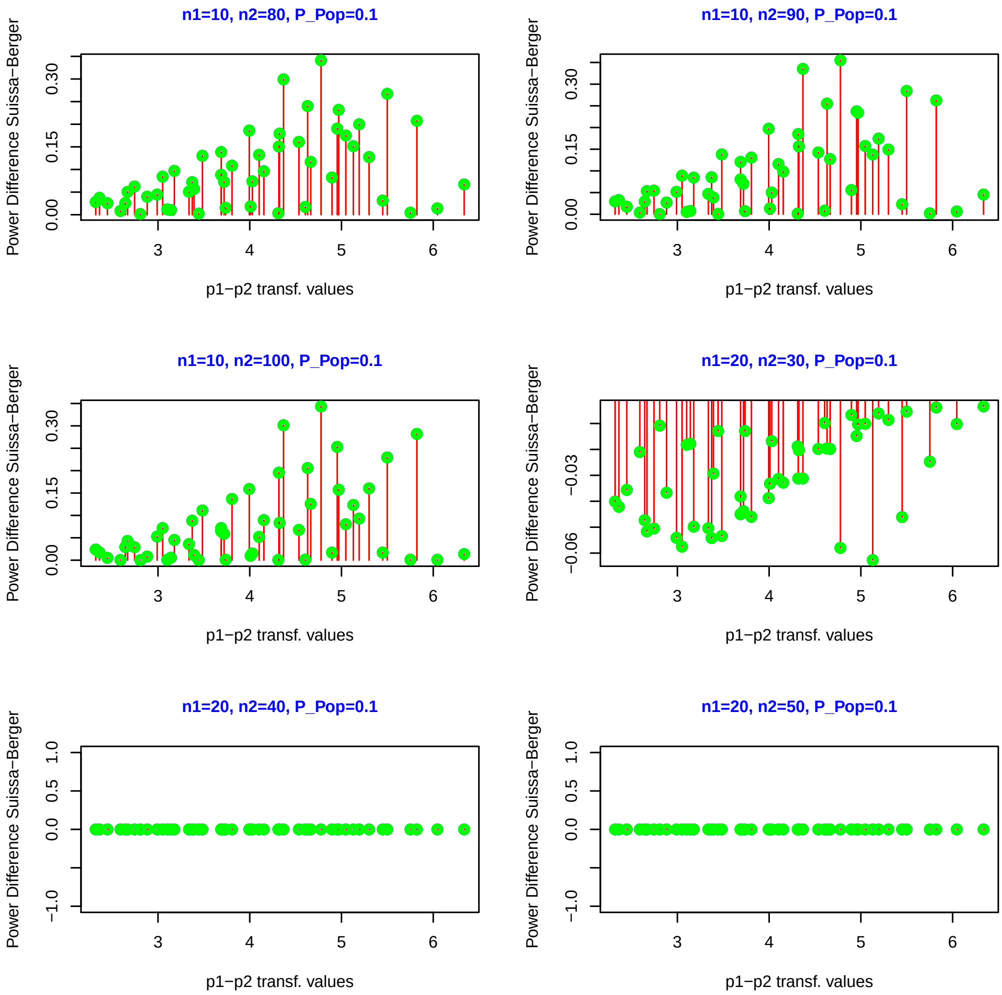
			z_p				p				p-value			
n1	n2	P_Pop	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001	S-P	B-P-001	B-P-0001	B-P-00001
10	20	0.90	2.45	2.59	2.43	2.43	0.6813	0.8947	0.8937	0.8928	0.0083	0.0032	0.0099	0.0099
10	30	0.90	2.56	2.52	2.52	2.52	0.7475	0.8955	0.8945	0.8937	0.0078	0.0095	0.0087	0.0087
10	40	0.90	2.66	2.87	2.87	2.87	0.7236	0.9047	0.9055	0.9062	0.0063	0.0086	0.0077	0.0077
10	50	0.90	2.72	2.72	2.72	2.72	0.9549	0.9042	0.9050	0.9056	0.0095	0.0082	0.0073	0.0072
10	60	0.90	2.66	2.77	2.66	2.66	0.8842	0.9038	0.8958	0.8952	0.0098	0.0088	0.0098	0.0097
10	70	0.90	2.90	2.89	2.89	2.89	0.9440	0.9036	0.9042	0.9048	0.0063	0.0083	0.0074	0.0074
10	80	0.90	3.12	2.83	2.79	2.79	0.9371	0.9034	0.9039	0.9045	0.0069	0.0100	0.0092	0.0091
10	90	0.90	3.02	2.88	2.73	2.73	0.9662	0.9031	0.9036	0.9041	0.0099	0.0090	0.0096	0.0095
10	100	0.90	3.18	2.90	2.90	2.90	0.9639	0.9029	0.9035	0.9040	0.0086	0.0097	0.0088	0.0088
20	30	0.90	2.51	2.31	2.31	2.31	0.6623	0.8960	0.8952	0.8945	0.0074	0.0090	0.0081	0.0081
20	40	0.90	2.40	2.52	2.52	2.52	0.7736	0.8964	0.8957	0.8950	0.0099	0.0081	0.0073	0.0072
20	50	0.90	2.65	2.65	2.65	2.65	0.6937	0.8966	0.8960	0.8954	0.0056	0.0069	0.0060	0.0059
20	60	0.90	2.59	2.59	2.59	2.49	0.8560	0.8967	0.8961	0.8956	0.0077	0.0082	0.0073	0.0100
20	70	0.90	2.68	2.60	2.60	2.60	0.9212	0.9034	0.9040	0.9045	0.0090	0.0100	0.0091	0.0090
20	80	0.90	2.86	2.55	2.55	2.55	0.9343	0.9032	0.9038	0.9043	0.0058	0.0098	0.0089	0.0088
20	90	0.90	2.77	2.74	2.57	2.57	0.8797	0.9029	0.9035	0.9040	0.0065	0.0086	0.0098	0.0097
20	100	0.90	2.66	2.69	2.62	2.62	0.9111	0.8973	0.9034	0.9038	0.0093	0.0082	0.0097	0.0096
30	40	0.90	2.39	2.42	2.38	2.38	0.6151	0.8965	0.8958	0.8952	0.0094	0.0070	0.0094	0.0093
30	50	0.90	2.39	2.42	2.42	2.42	0.7384	0.8967	0.8961	0.8955	0.0097	0.0086	0.0077	0.0076
30	60	0.90	2.41	2.61	2.41	2.41	0.7563	0.9033	0.9039	0.9044	0.0099	0.0088	0.0099	0.0099
30	70	0.90	2.51	2.52	2.51	2.51	0.8980	0.8970	0.8980	0.8980	0.0098	0.0086	0.0099	0.0098
30	80	0.90	2.49	2.56	2.44	2.44	0.6520	0.9029	0.9035	0.9040	0.0075	0.0089	0.0096	0.0095
30	90	0.90	2.49	2.55	2.54	2.54	0.7514	0.9027	0.8966	0.8962	0.0086	0.0088	0.0095	0.0094
30	100	0.90	2.56	2.59	2.54	2.54	0.7776	0.9027	0.9032	0.9036	0.0072	0.0086	0.0095	0.0094
40	50	0.90	2.35	2.40	2.29	2.29	0.5576	0.8970	0.8964	0.8959	0.0099	0.0081	0.0093	0.0093
40	60	0.90	2.36	2.43	2.35	2.35	0.5247	0.9032	0.9037	0.9042	0.0099	0.0085	0.0100	0.0099
40	70	0.90	2.39	2.36	2.36	2.36	0.6716	0.9030	0.9036	0.9041	0.0094	0.0096	0.0087	0.0086
40	80	0.90	2.42	2.57	2.48	2.41	0.8112	0.9029	0.9034	0.9039	0.0097	0.0092	0.0099	0.0099
40	90	0.90	2.44	2.47	2.47	2.47	0.6478	0.8973	0.8968	0.8964	0.0090	0.0095	0.0086	0.0085
40	100	0.90	2.60	2.50	2.50	2.50	0.9206	0.9026	0.9031	0.9035	0.0083	0.0095	0.0086	0.0085

$\mathbf{z_p}$: Z pooled critical value; p: point of maximum for the nuisance parameter; p-value: attained size of the test. n1: first sample size; n2: second sample size; $\mathbf{P_pop}$: theoretical value of the parameter P in the population used for the Monte Carlo simulations; S-U: Suissa Unpooled test; B-U-001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.001; B-U-0001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.0001; B-U-00001: Berger Unpooled test when γ, confidence level for the nuisance parameter is fixed at 0.00001. The cells containing the p-values have been painted according to the different degree of conservatorism, ranging from green (less conservative), yellow, orange, and to pink (most conservative).

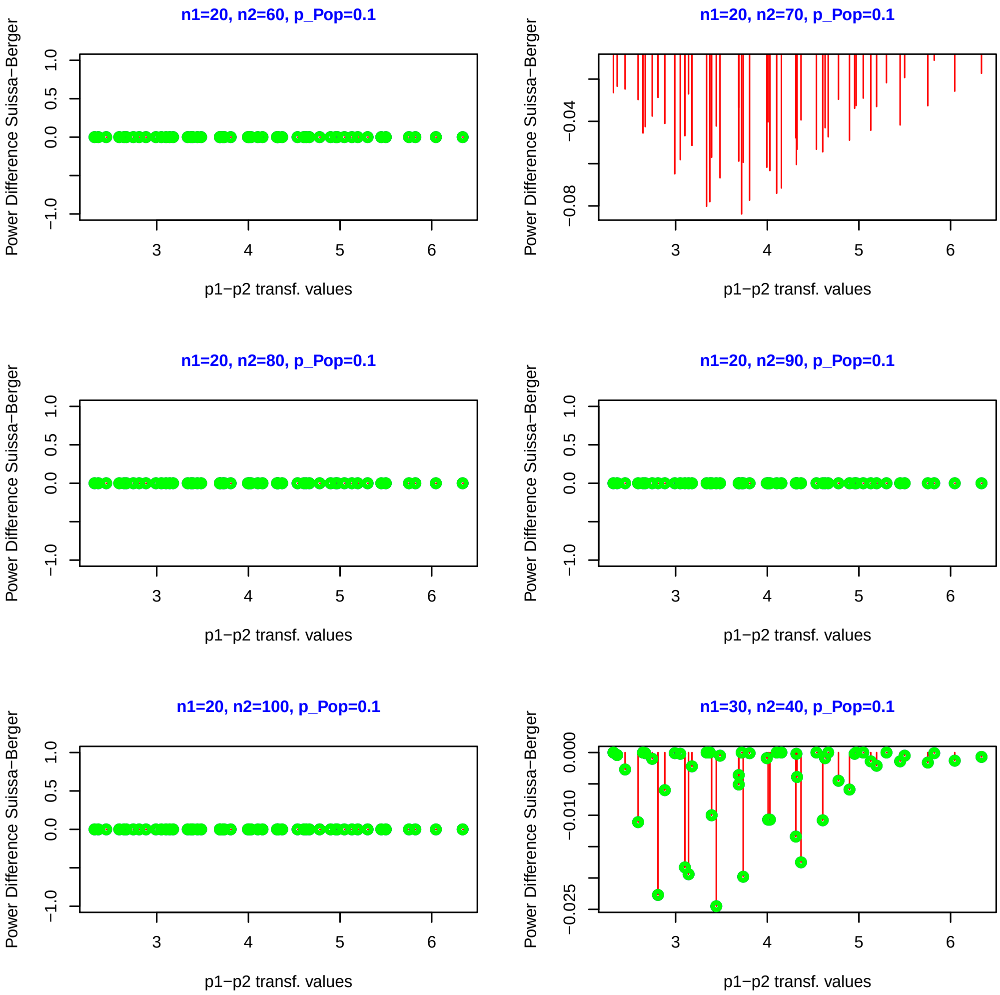
Figure C.16: Comparison of power between the Suissa unpooled test and the Berger unpooled test for different sample sizes, α= **0.05**.



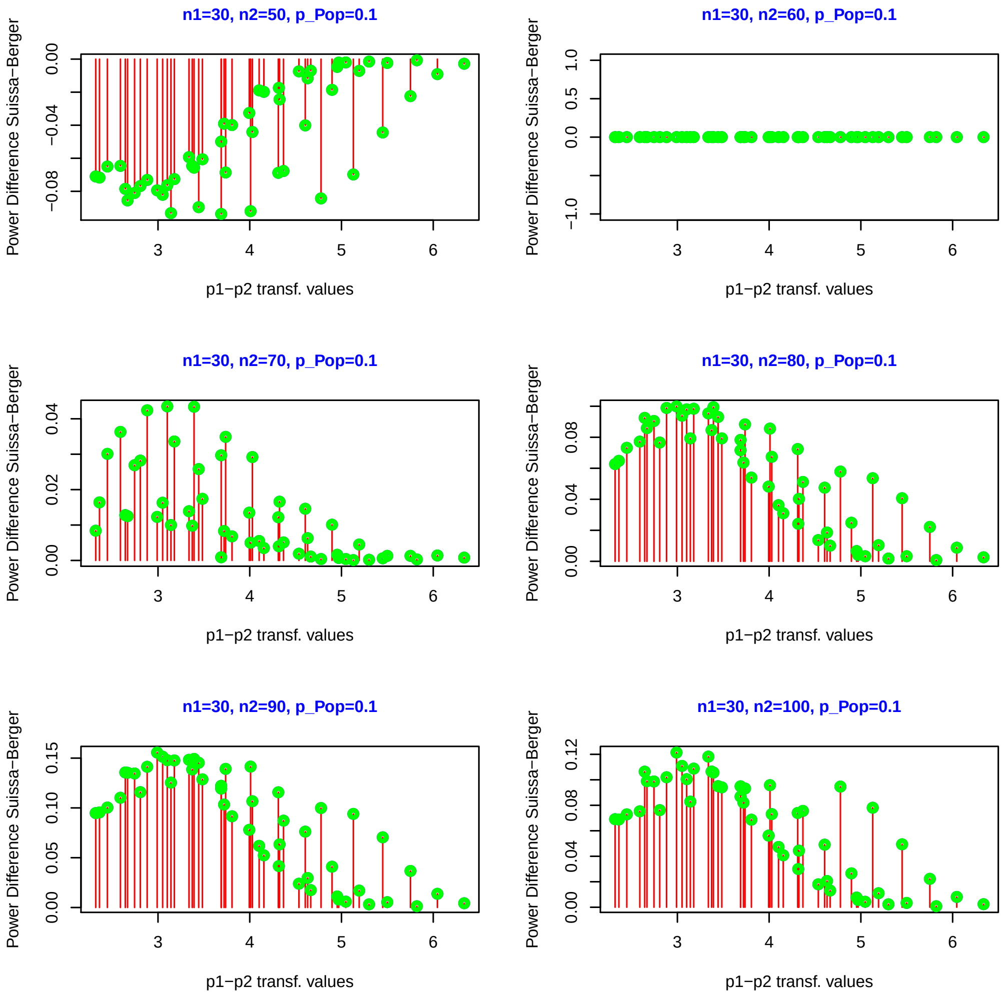
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test (γ = 0.001) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test (γ = 0.0001) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test (γ = 0.00001) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test (γ = 0.0001) and the Berger unpooled test (γ = 0.00001) achieve the same level of power, only the green dots are drawn.



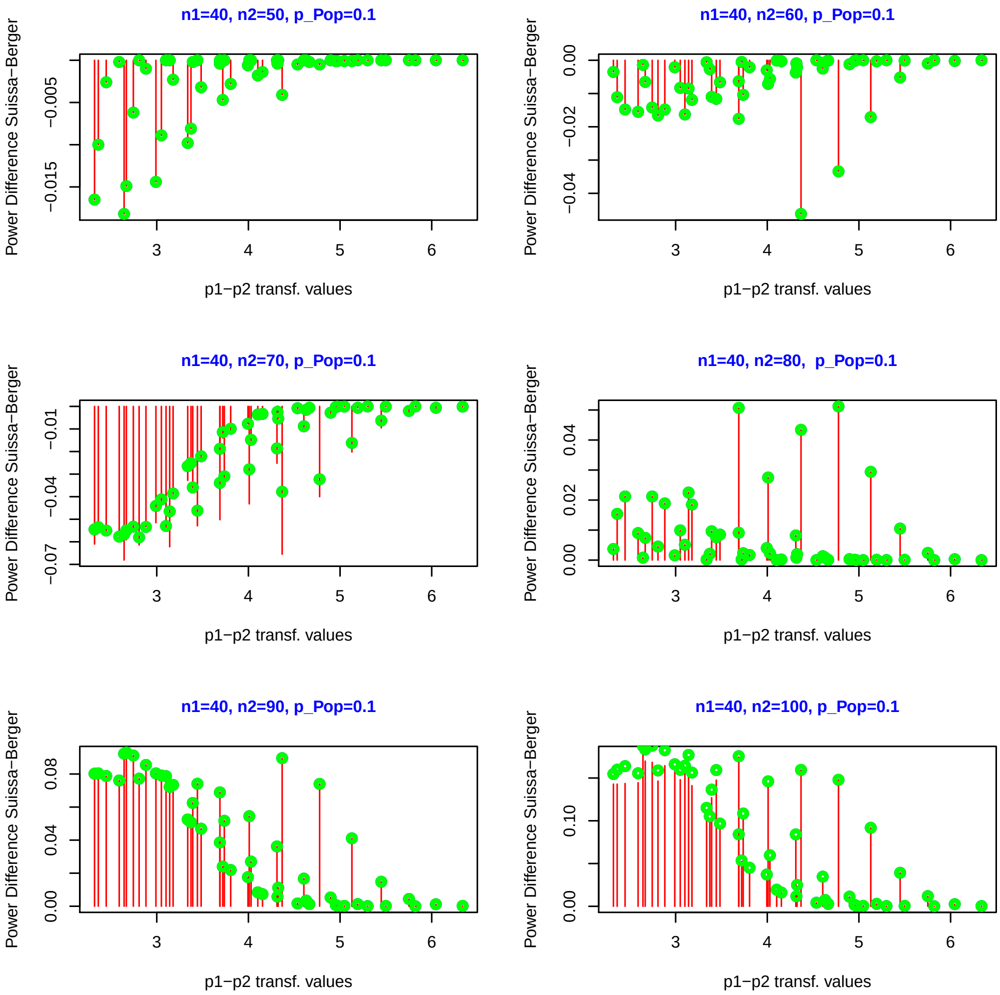
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



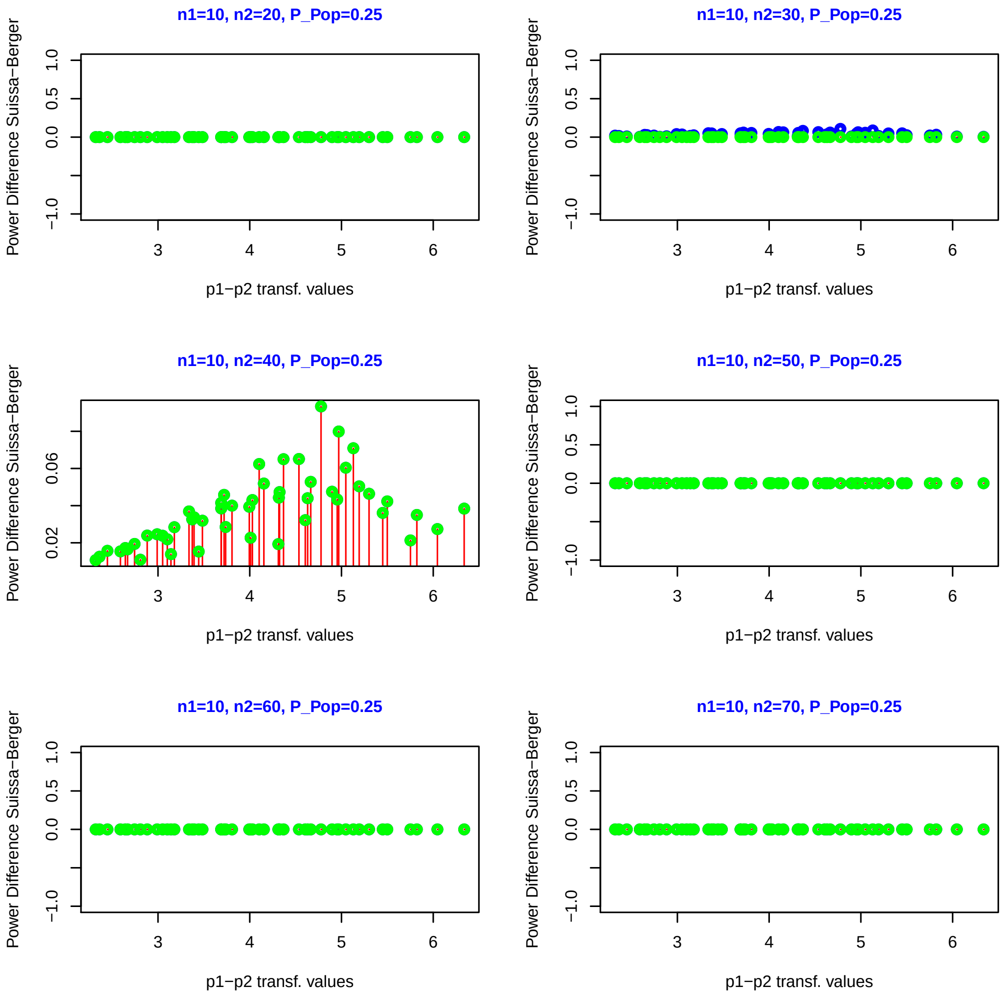
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



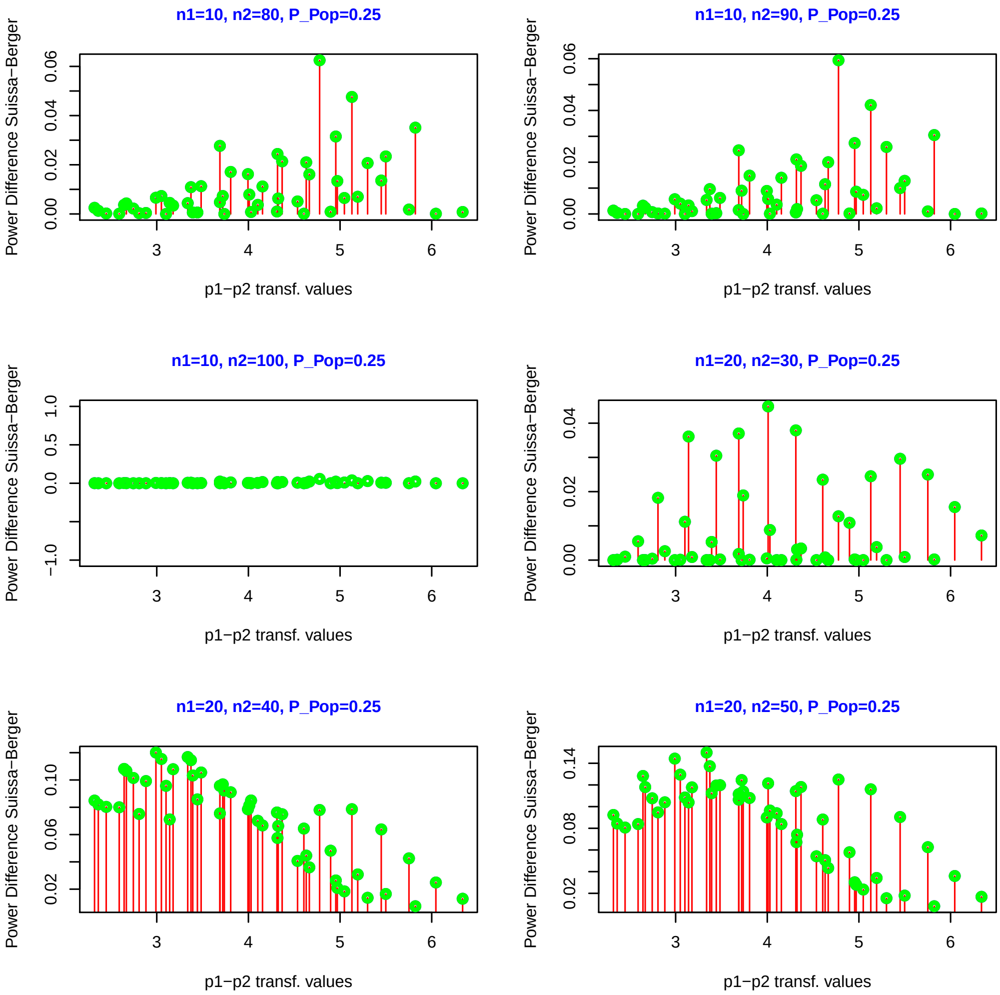
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



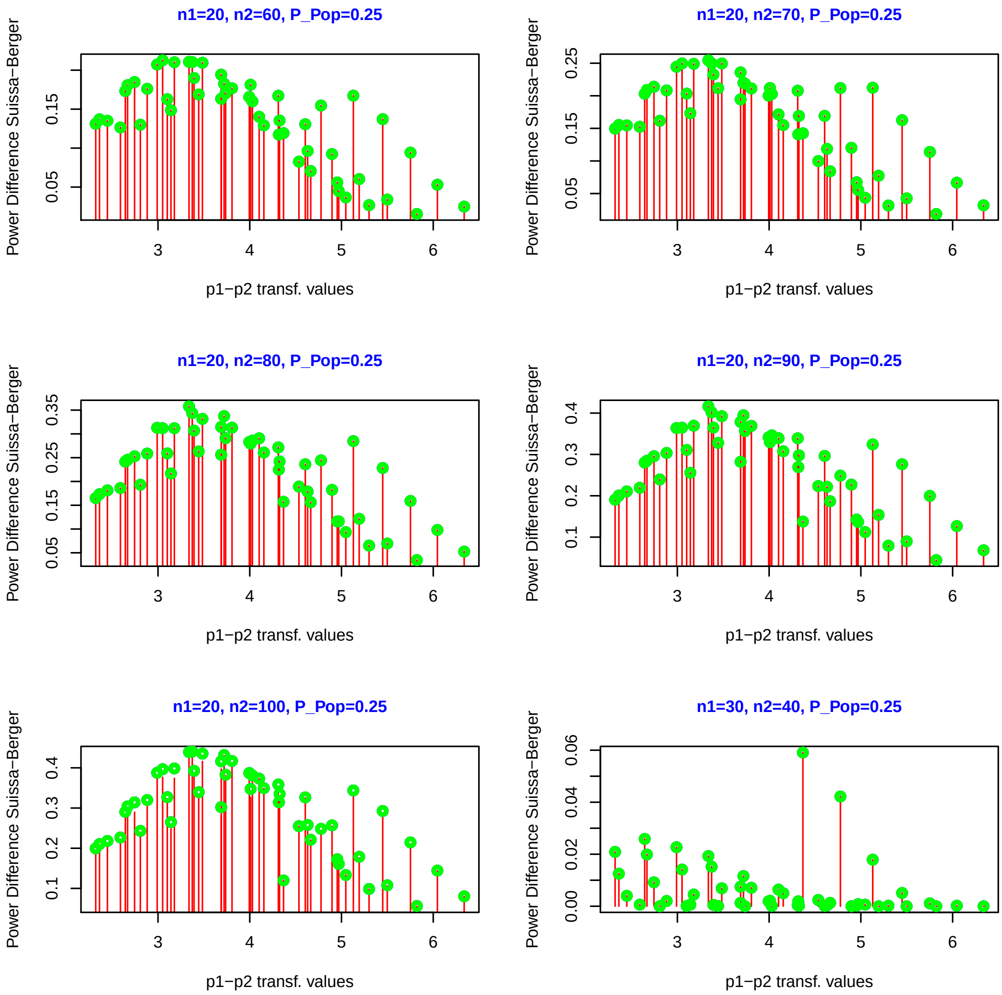
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



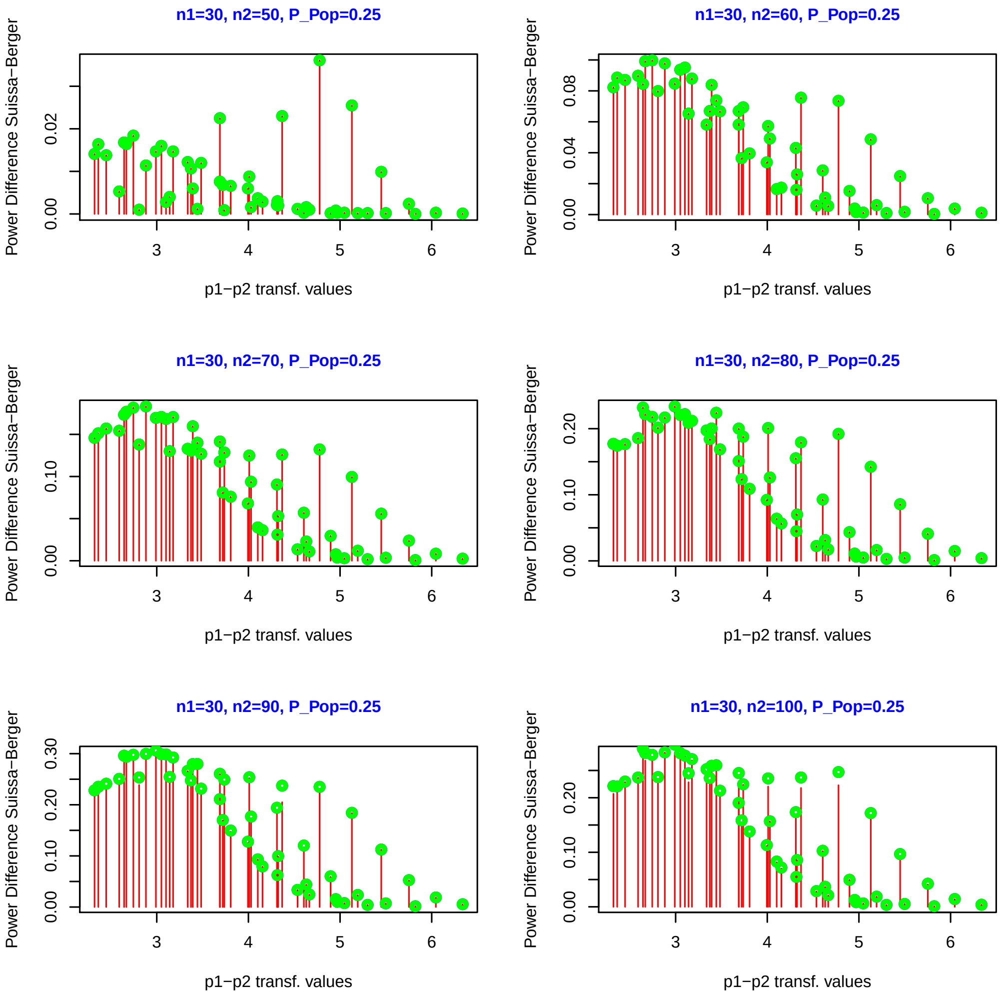
X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger unpooled test ($\gamma = 0.001$) and the Suissa unpooled test (red bars). Power difference between the Berger unpooled test ($\gamma = 0.0001$) and the Suissa unpooled test is represented by green dots whereas power difference between the Berger unpooled test ($\gamma = 0.00001$) and the Suissa unpooled test is represented by blue dots. In case the Berger unpooled test ($\gamma = 0.0001$) and the Berger unpooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



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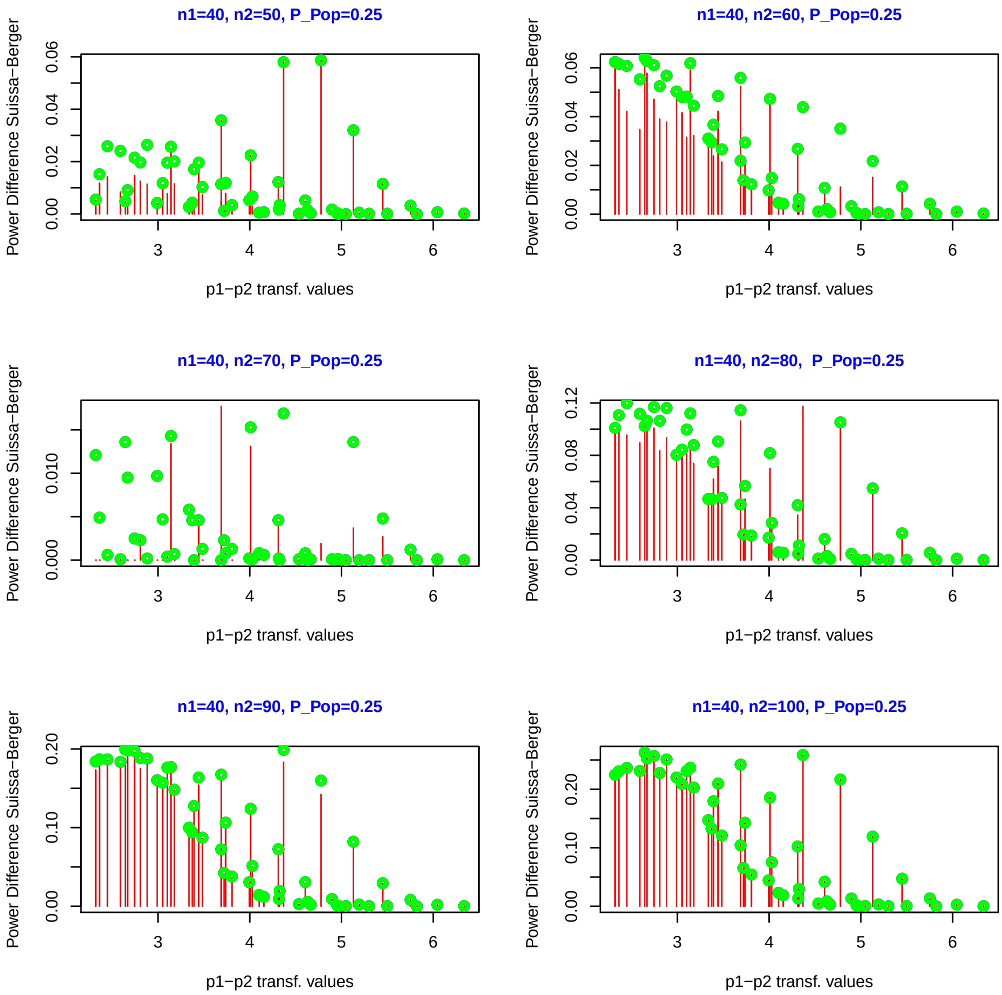

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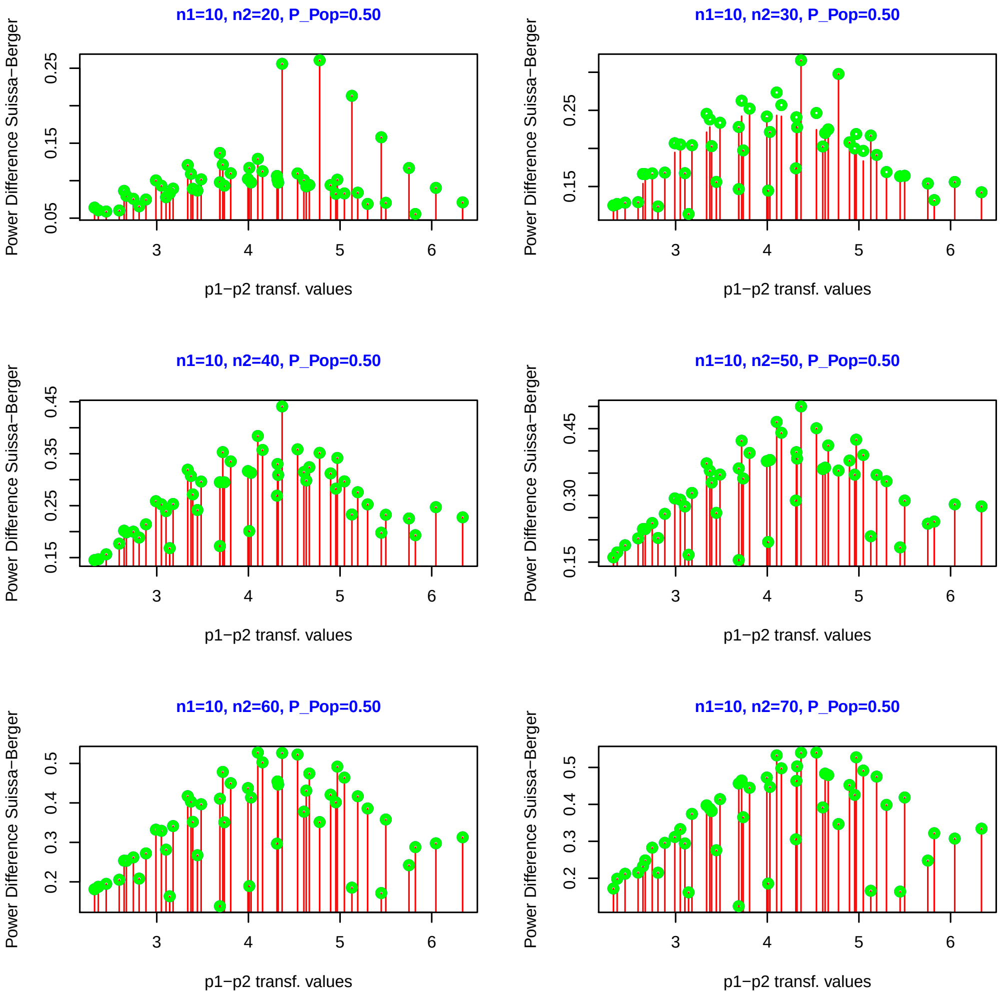

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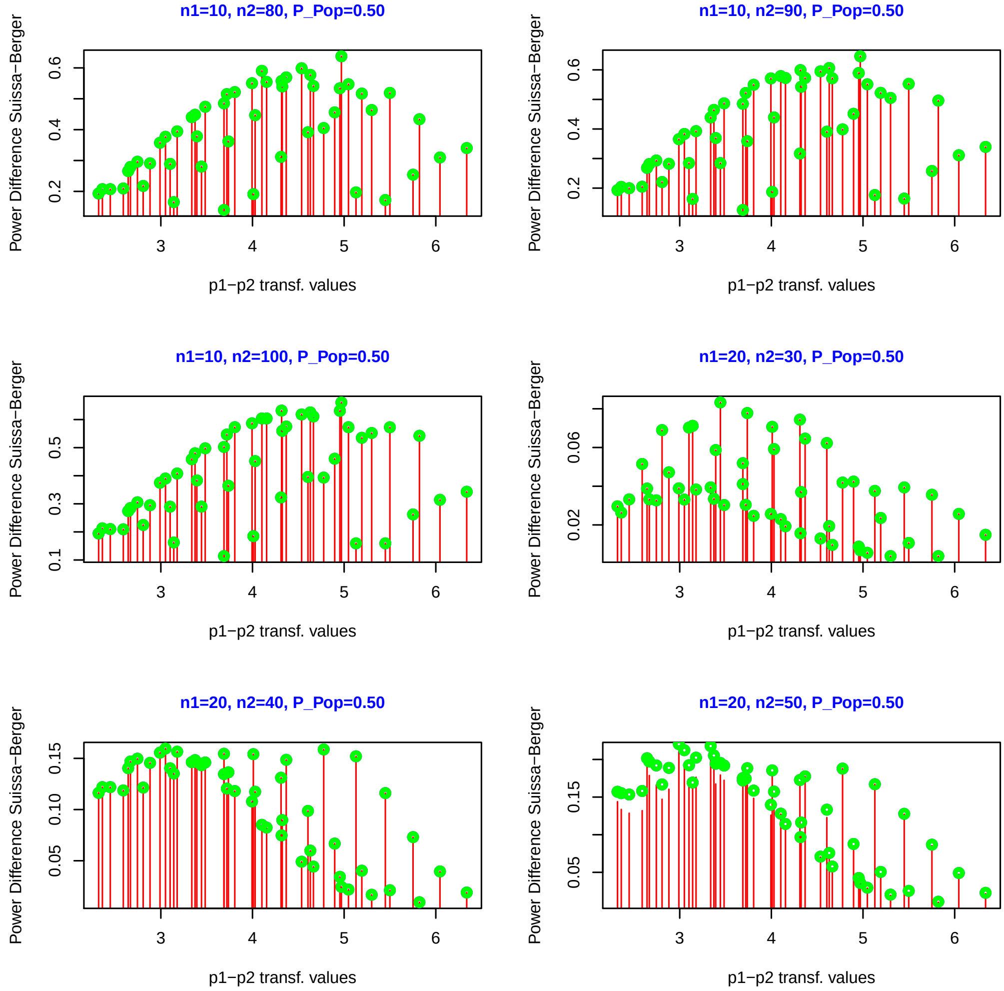

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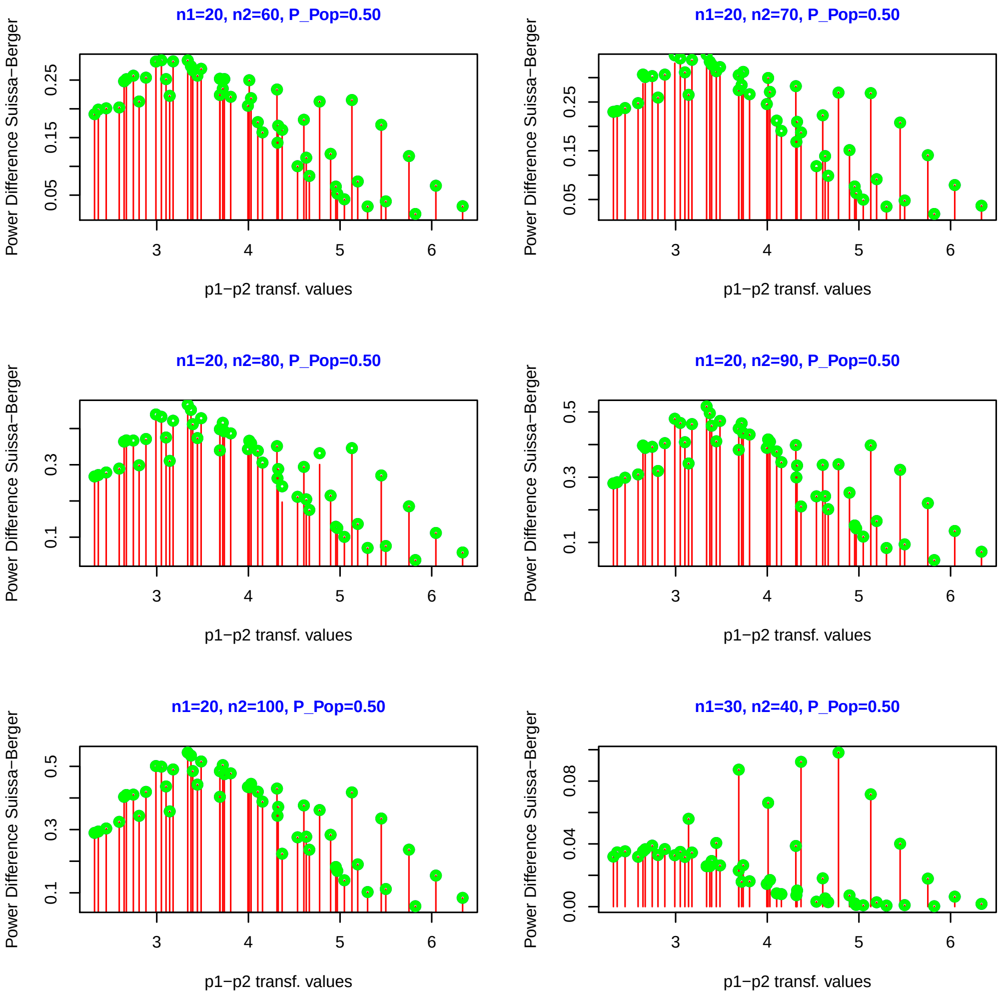

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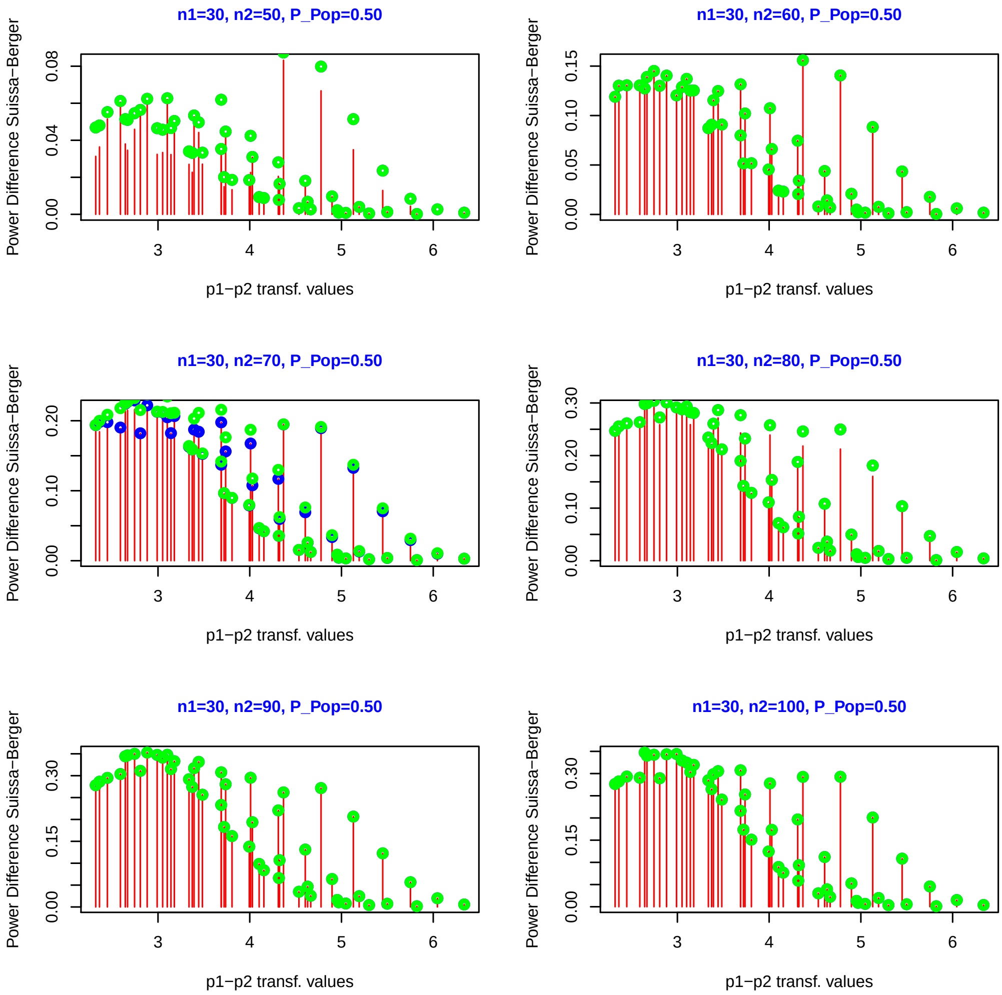

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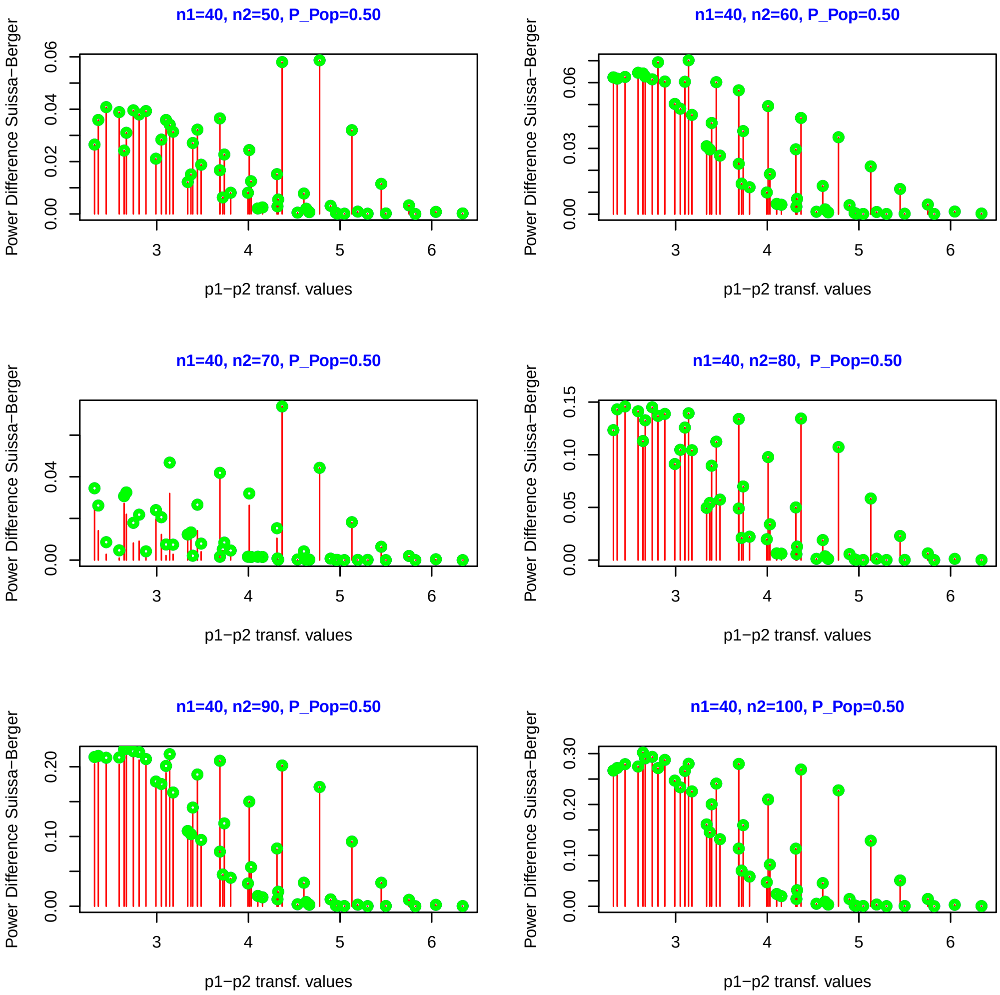

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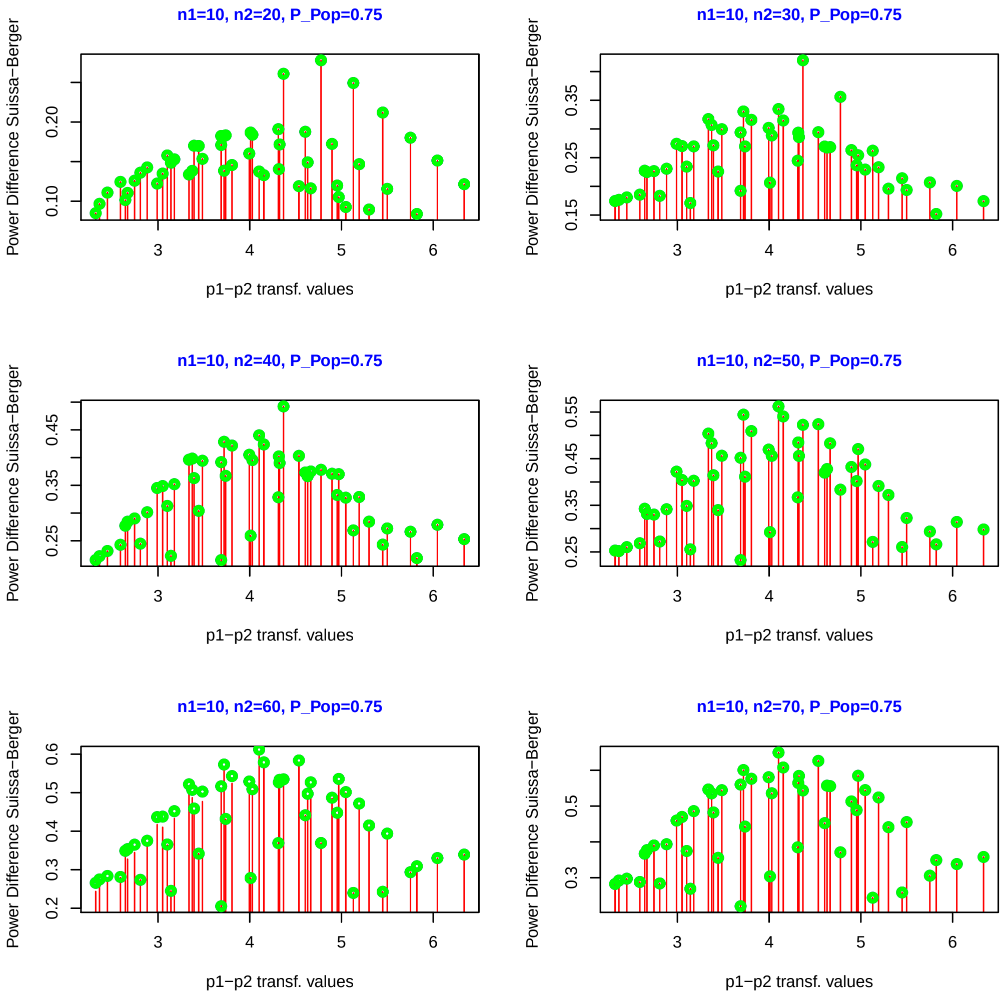

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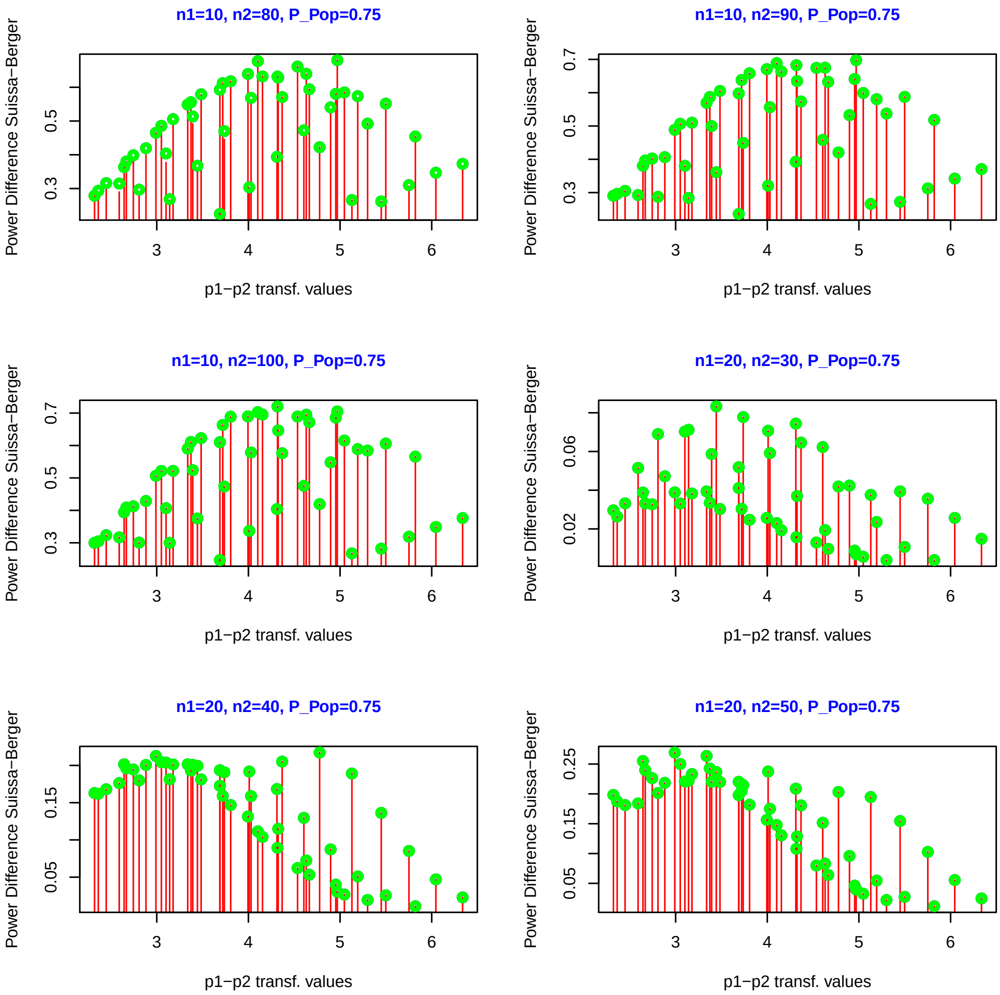

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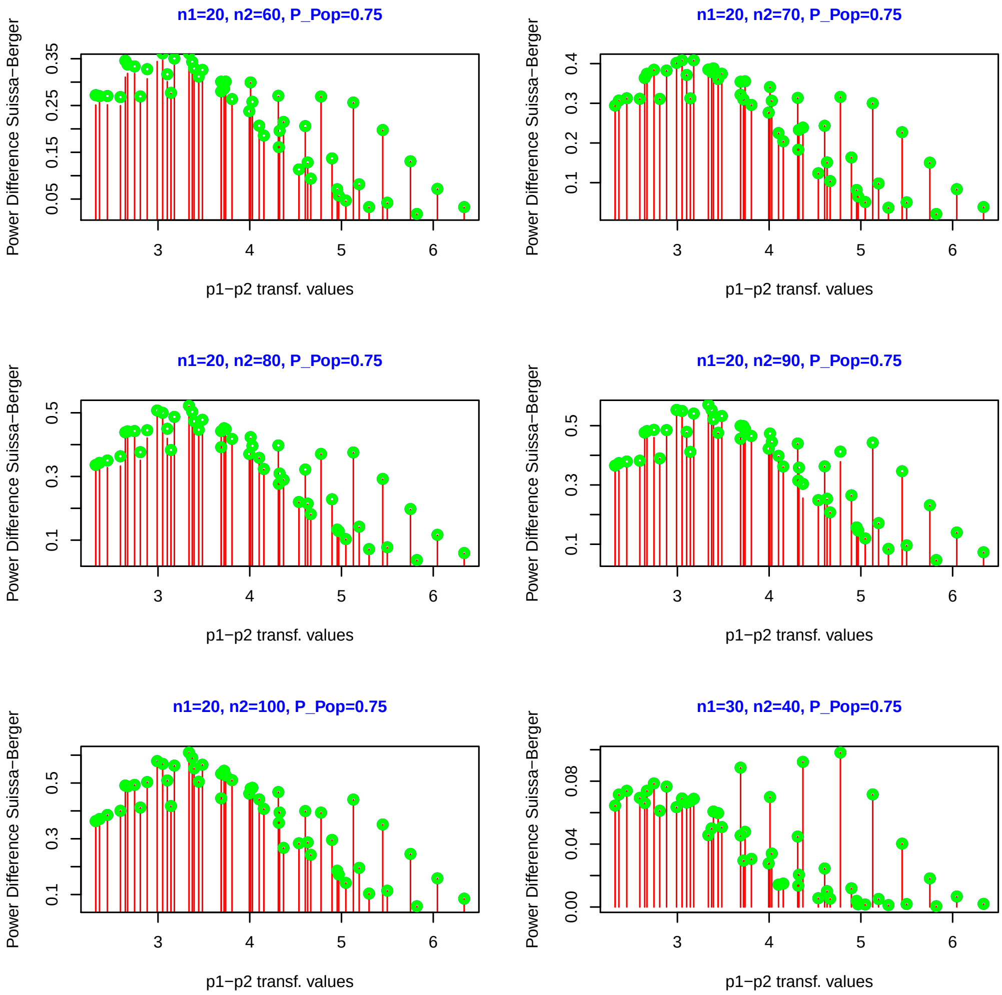

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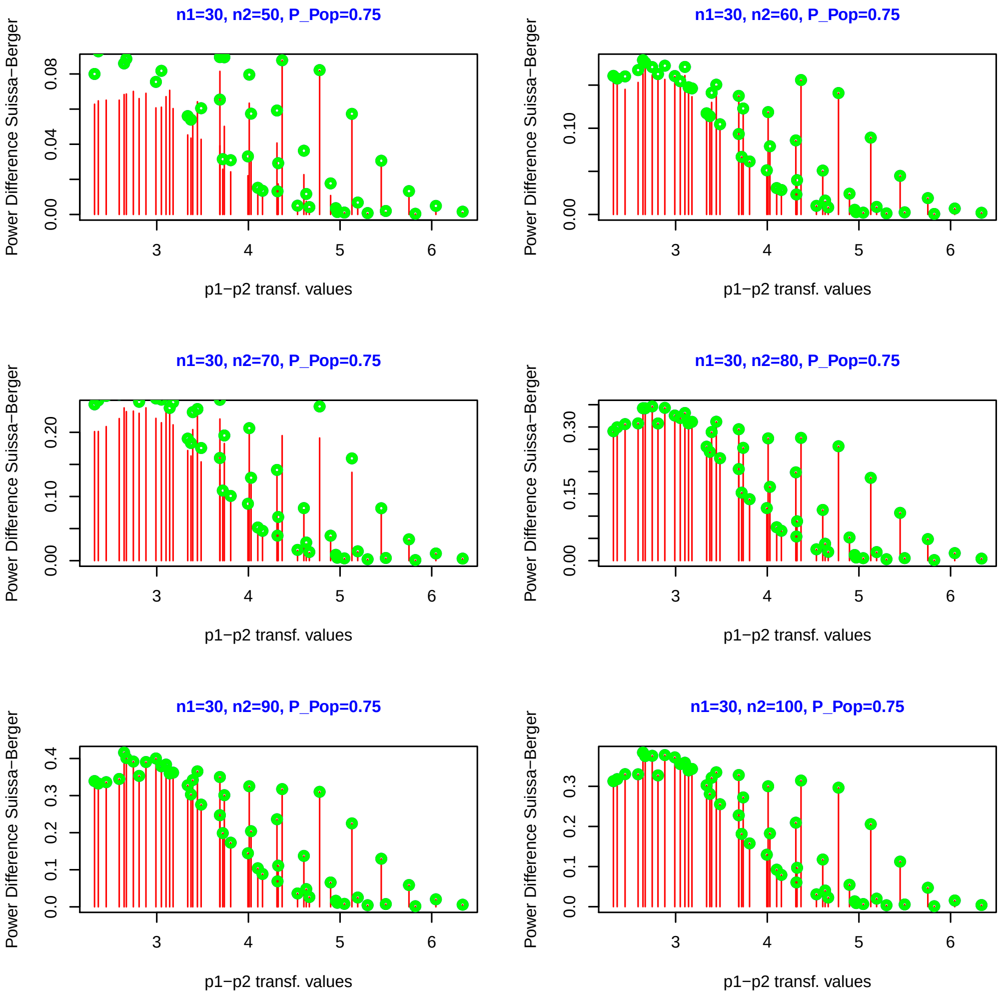

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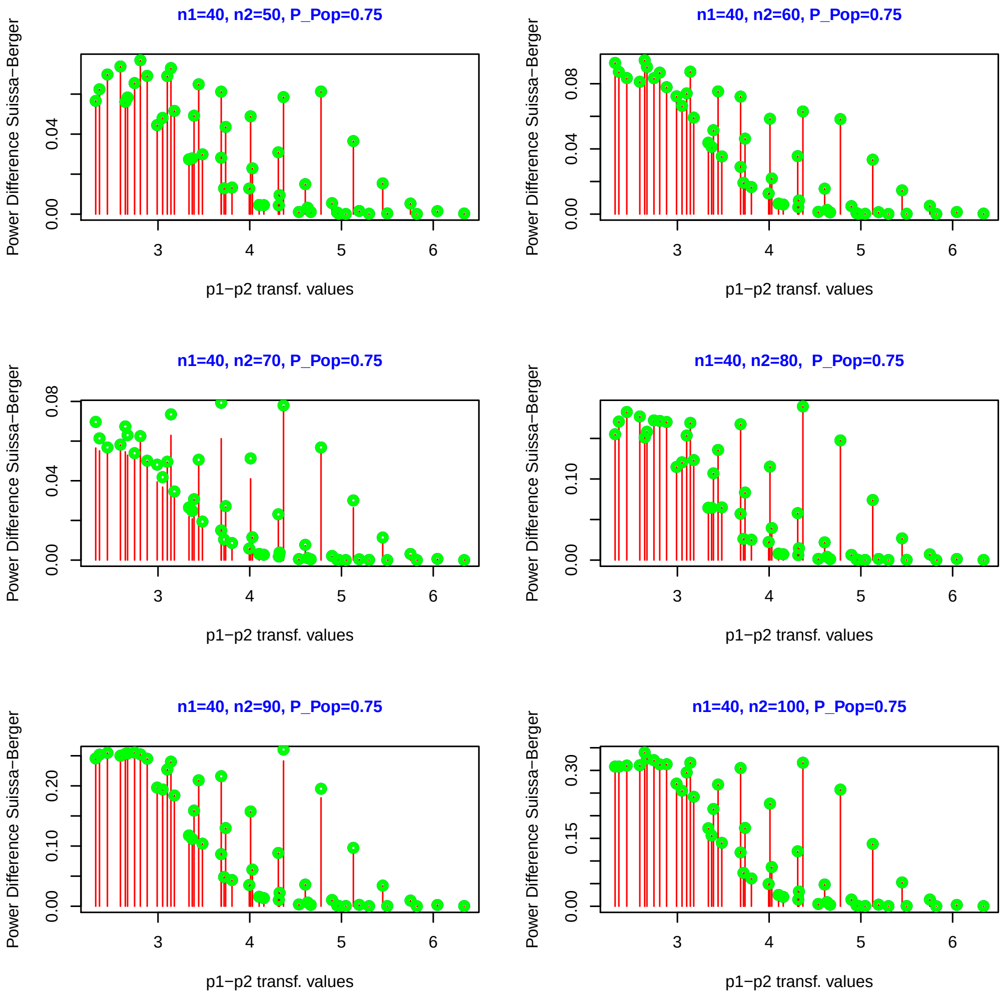

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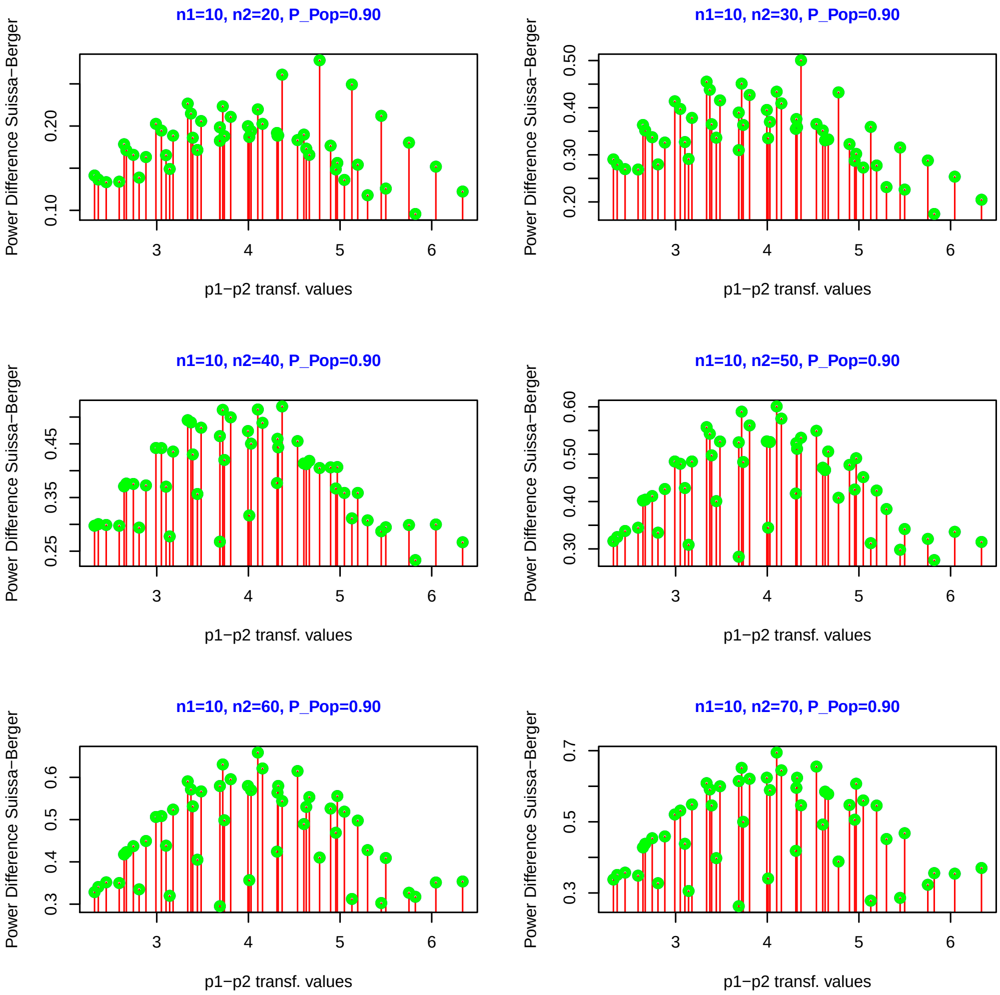

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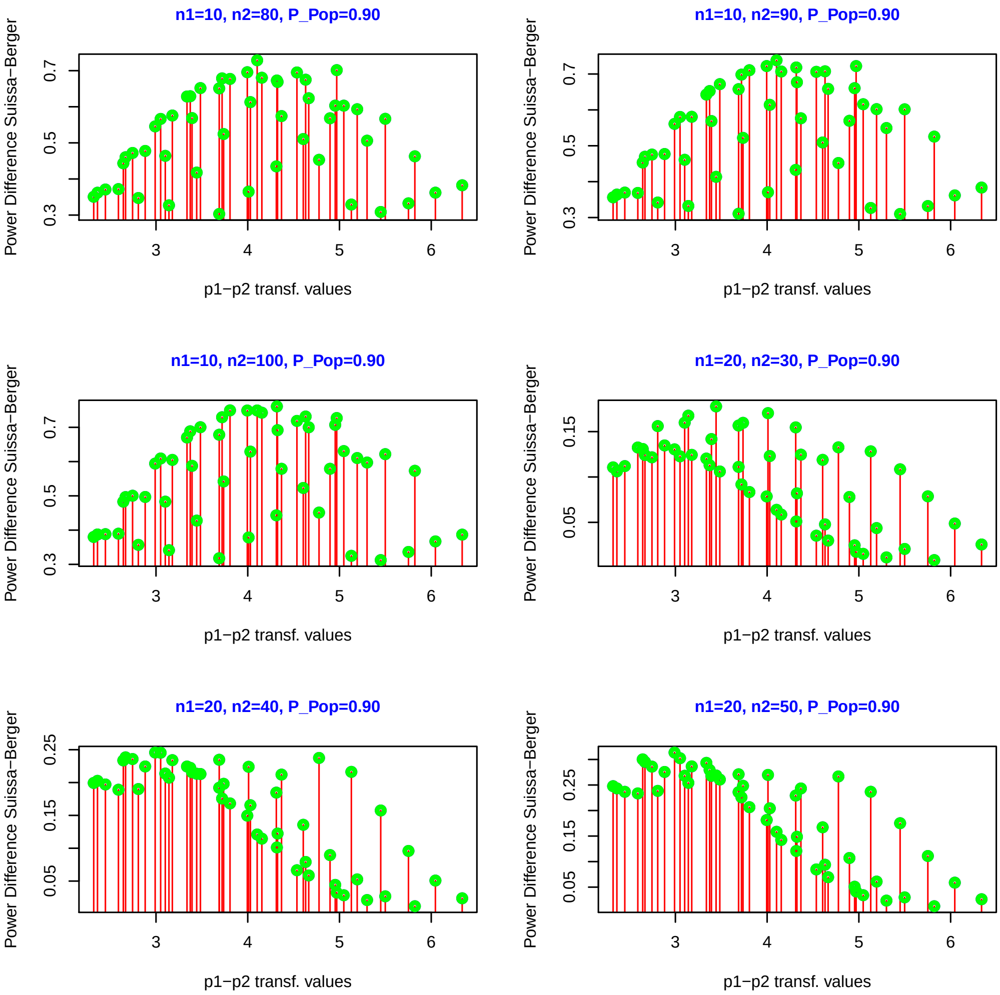

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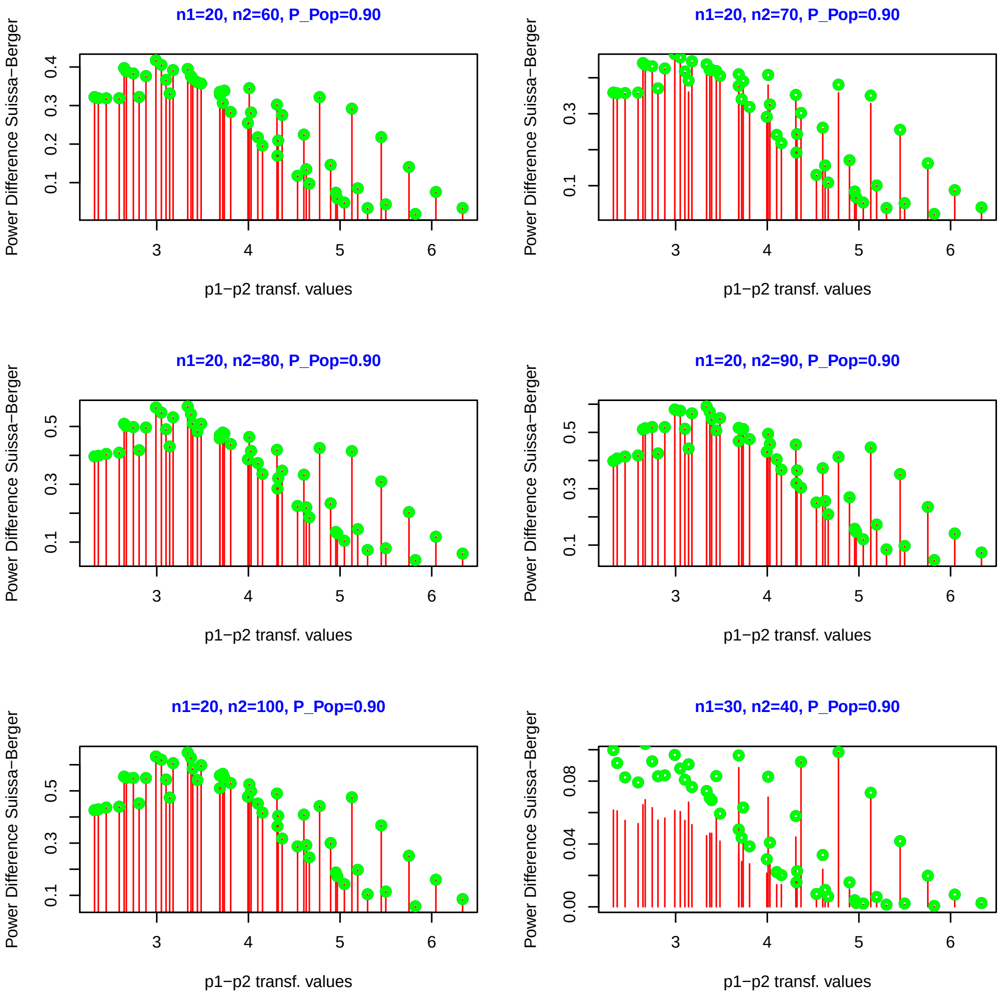

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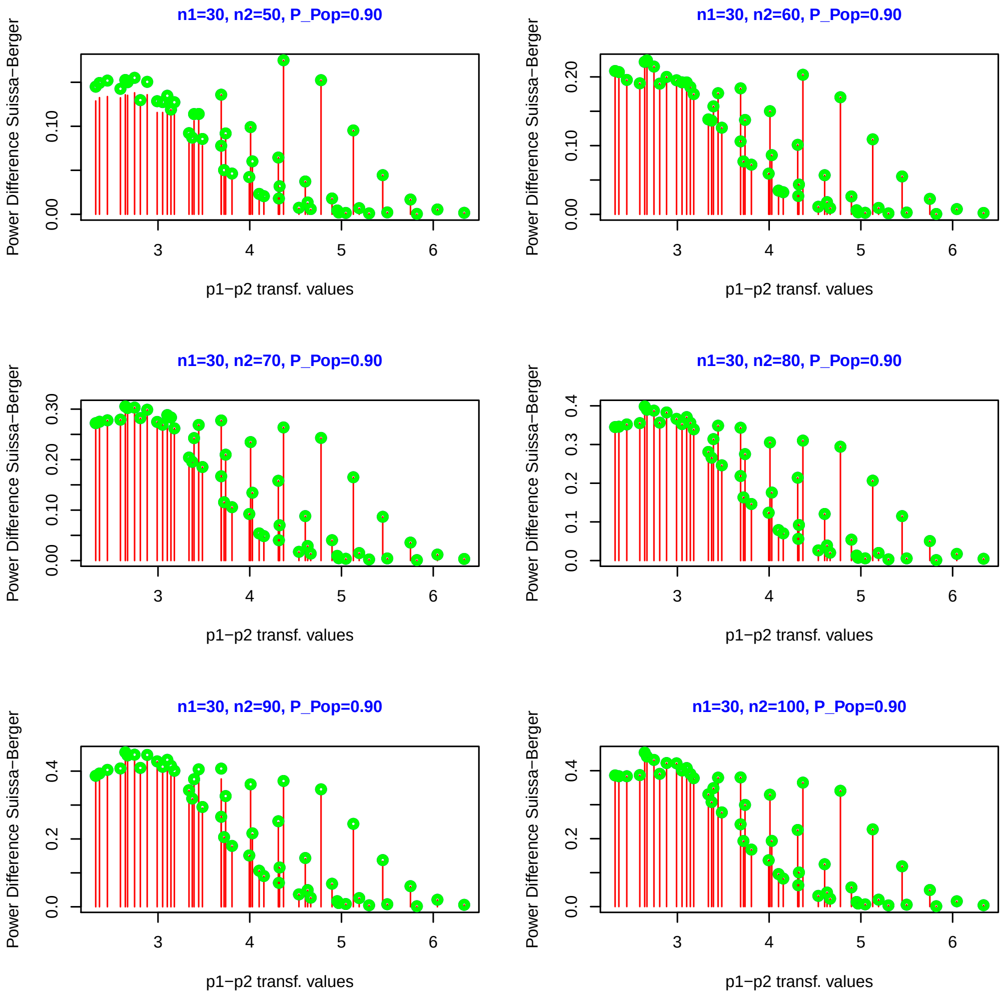

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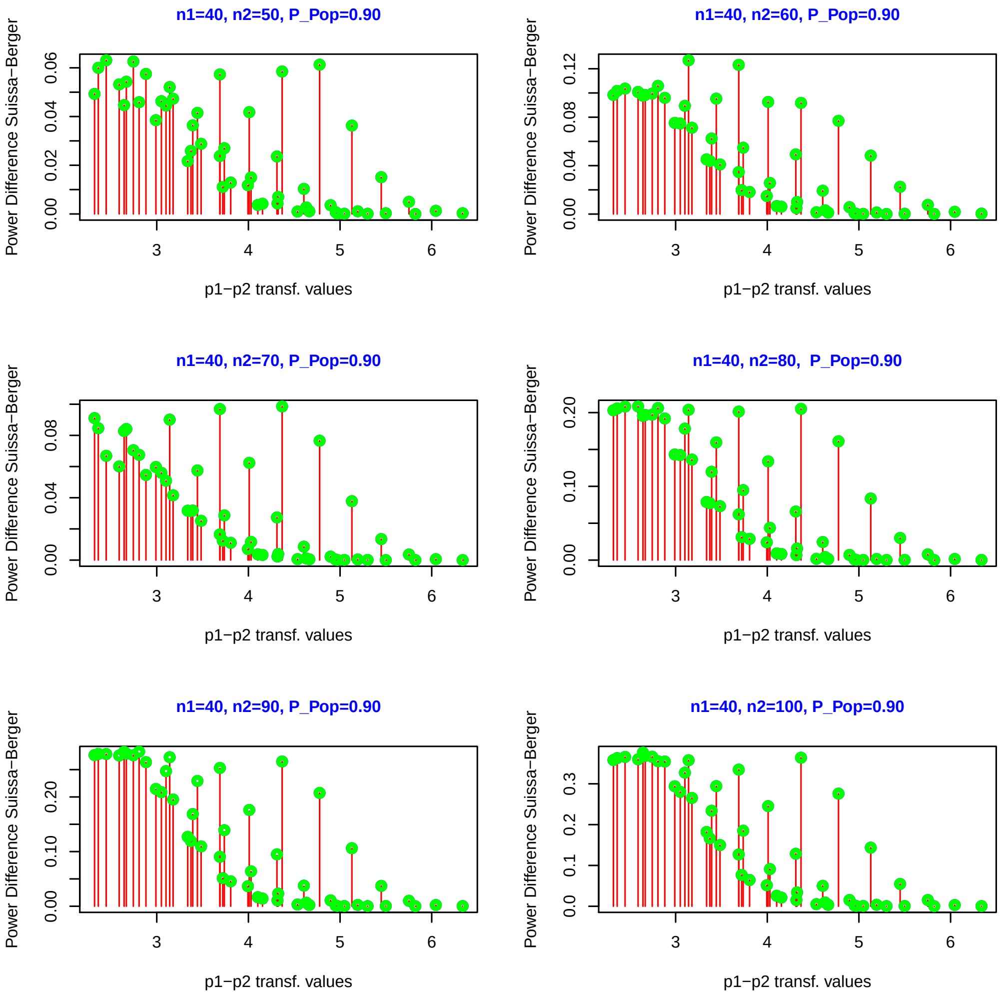

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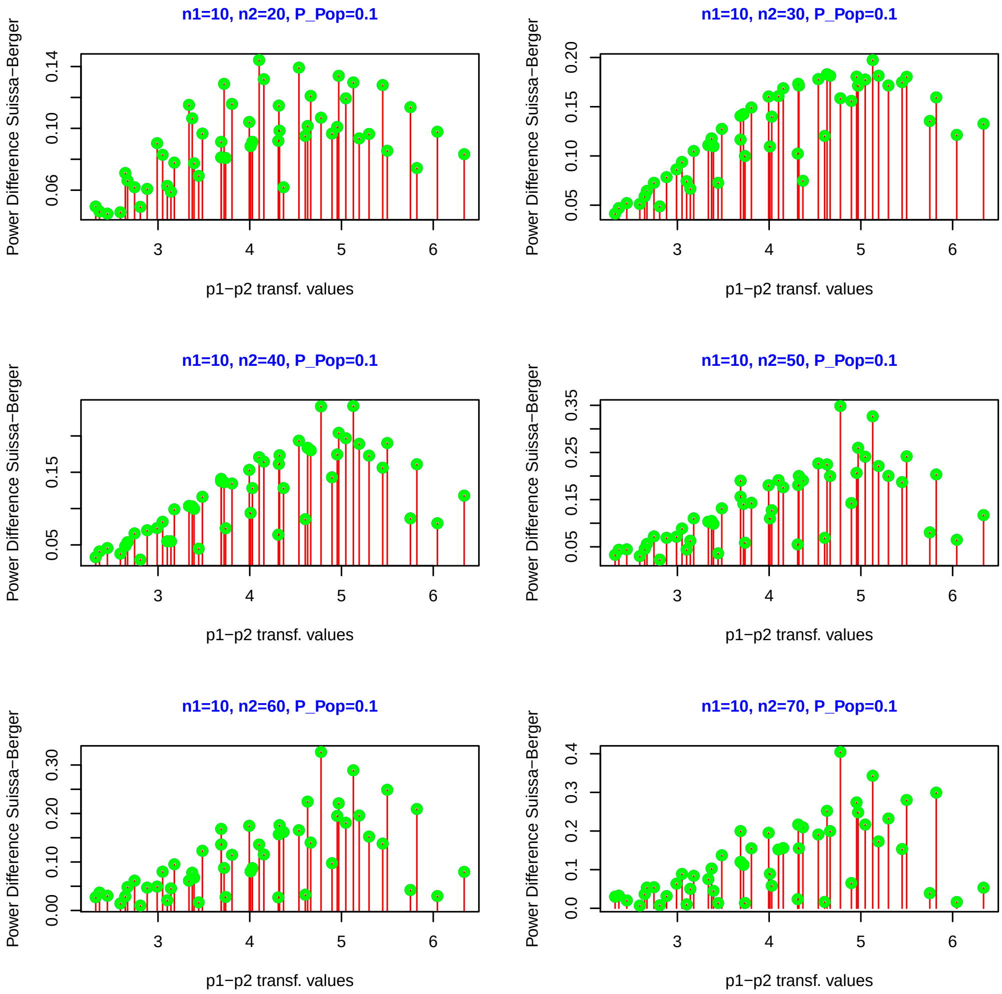
Figure C.17: Comparison of power between the Suissa unpooled test and the Berger unpooled test for different sample sizes, $\boldsymbol{\alpha} = \mathbf{0.025}$.



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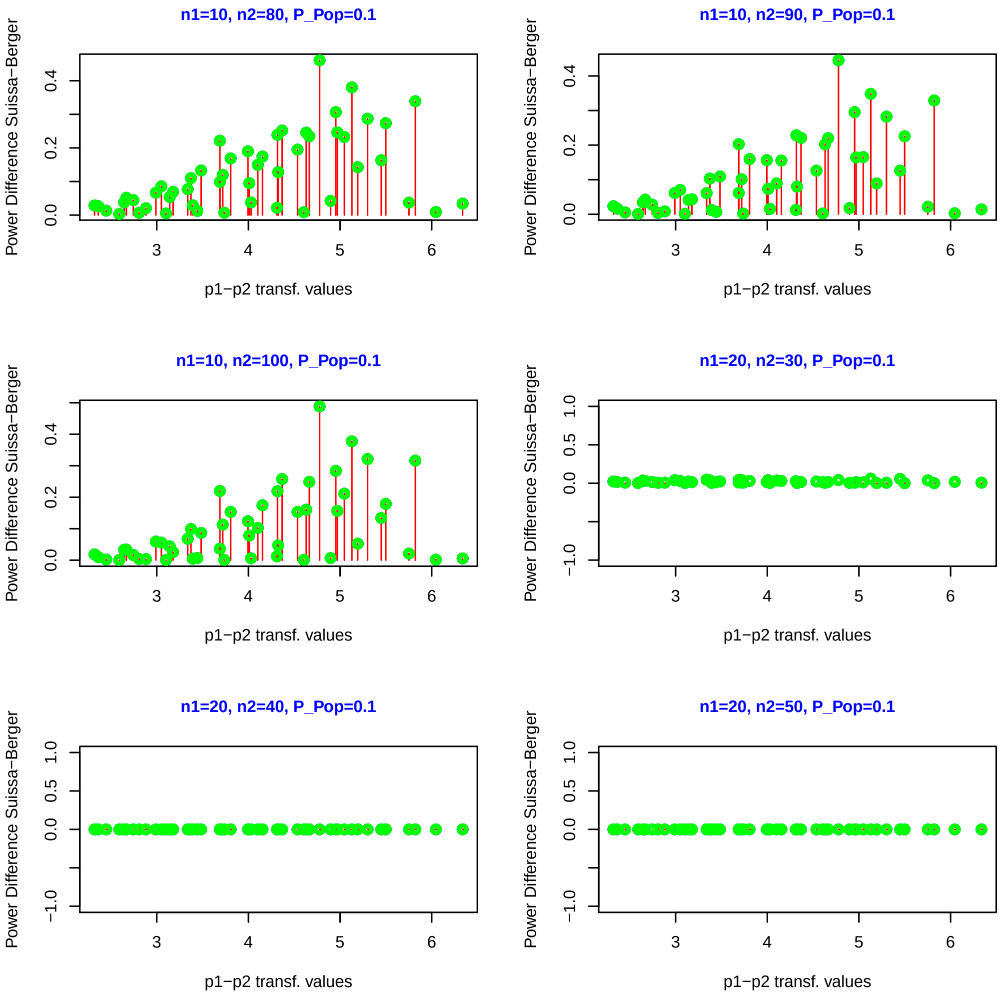

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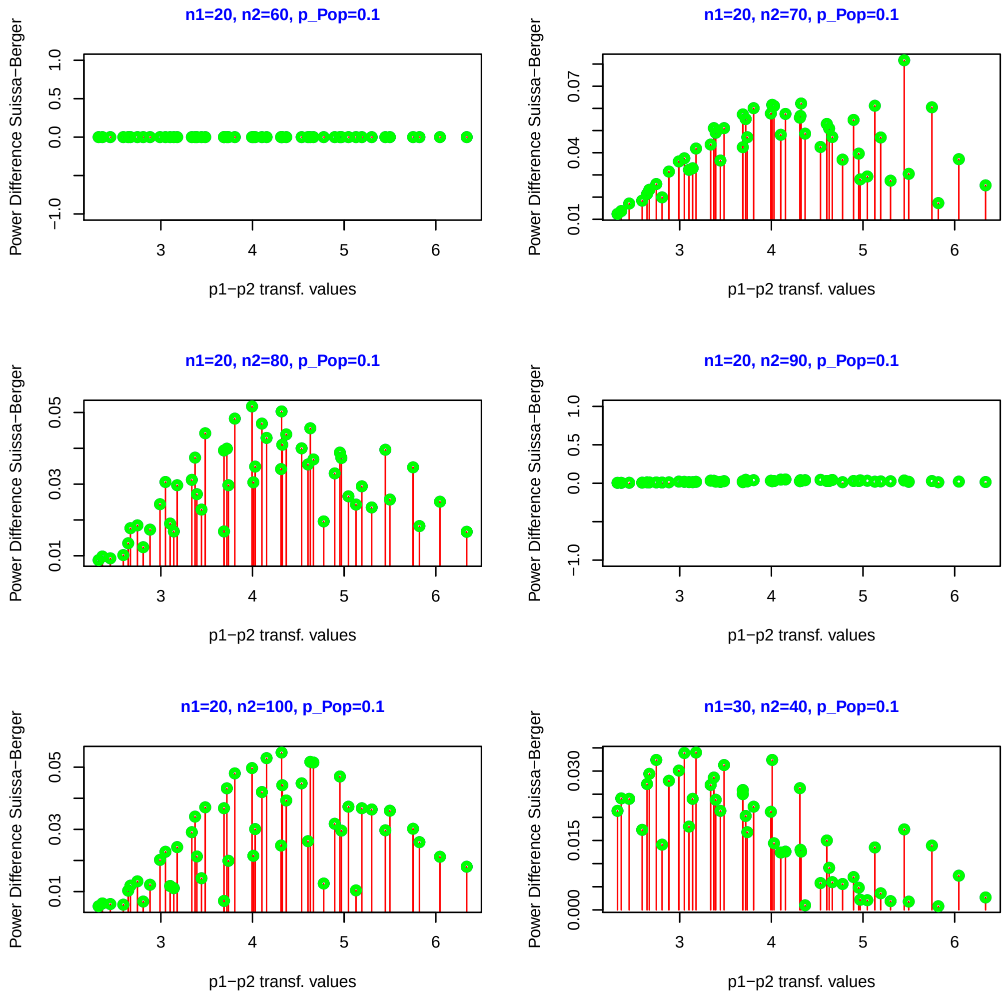

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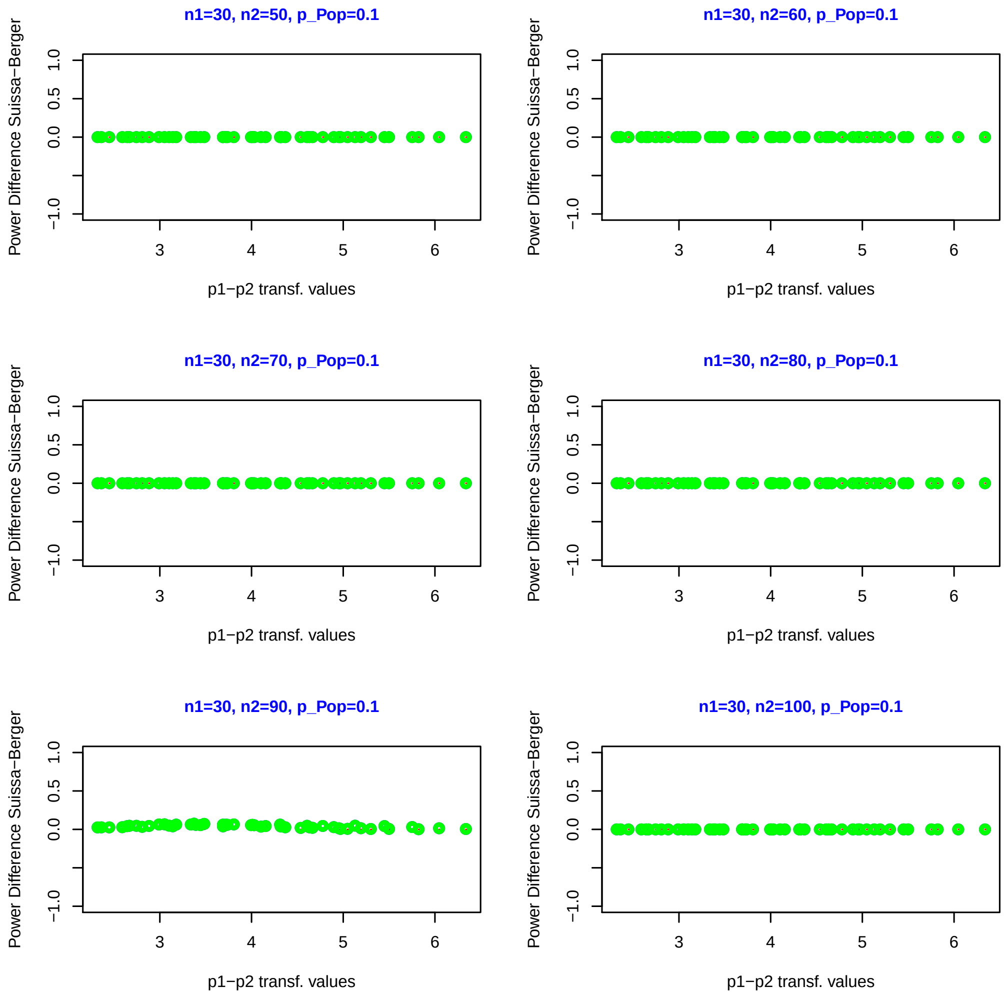

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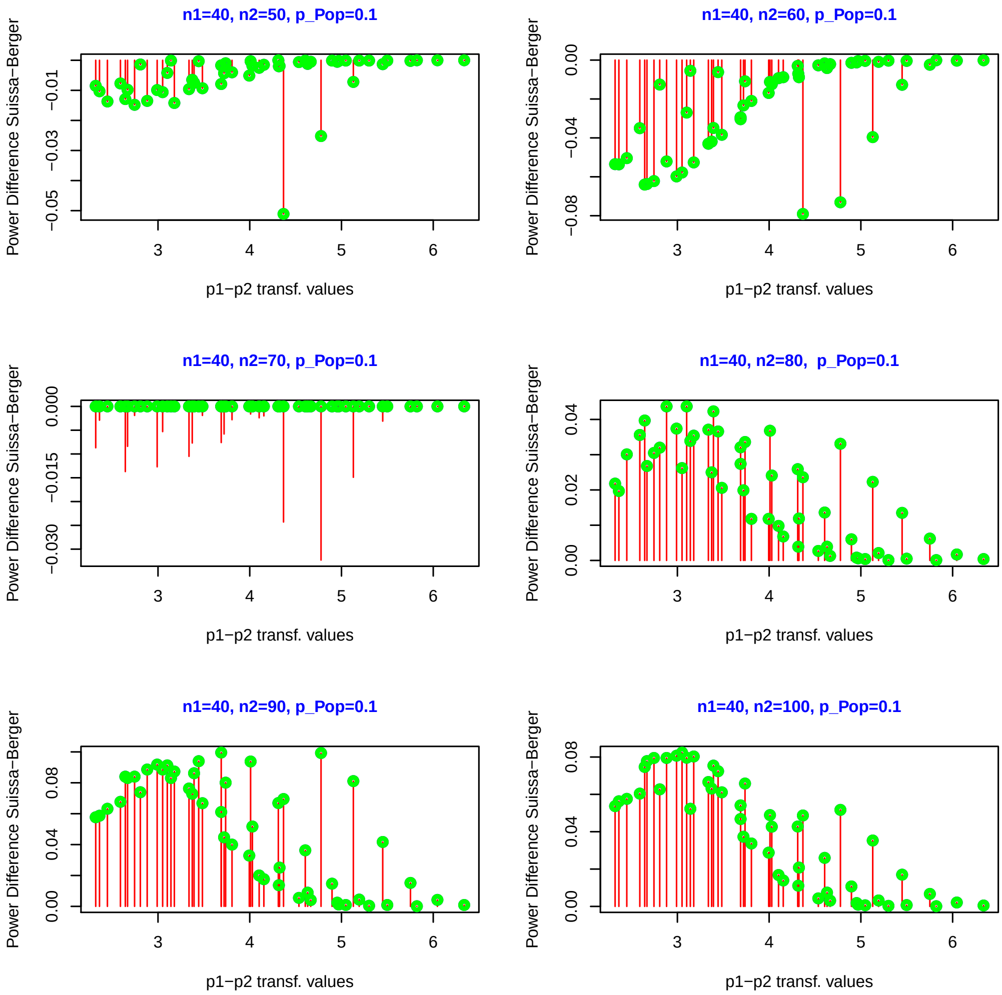

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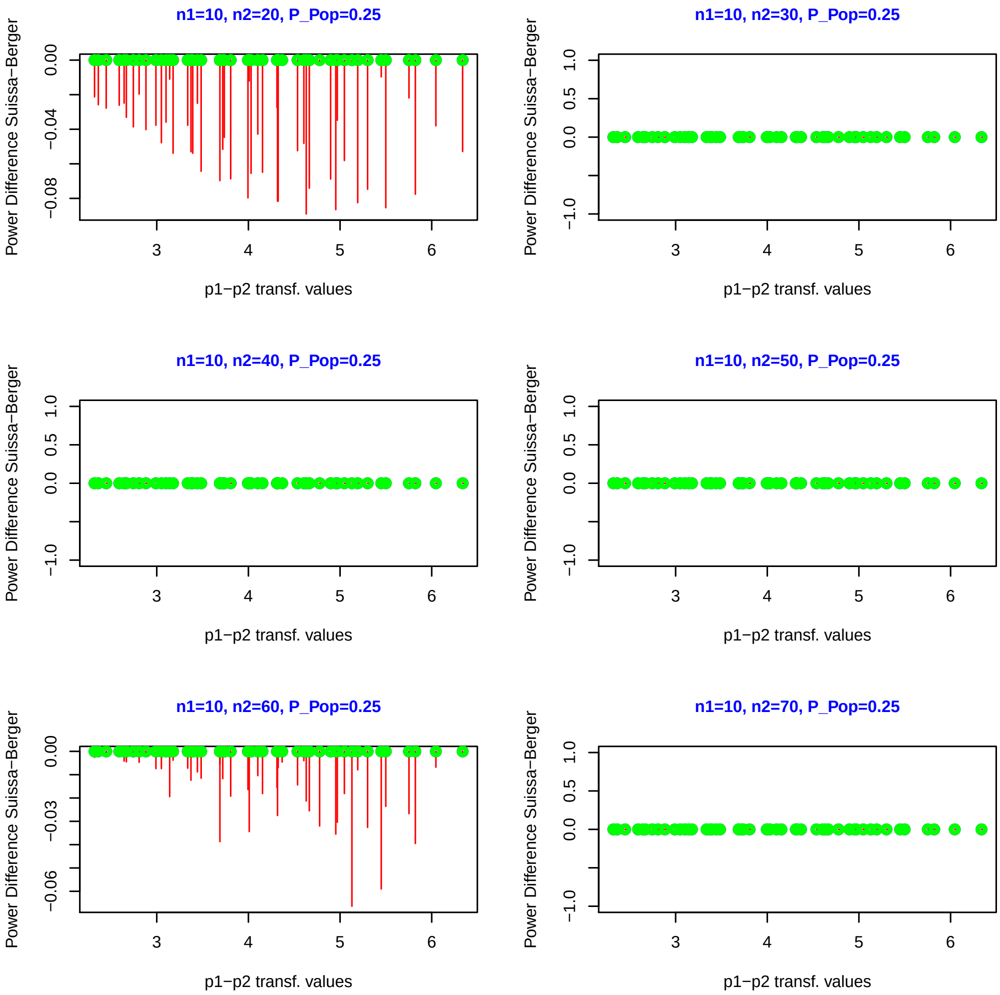

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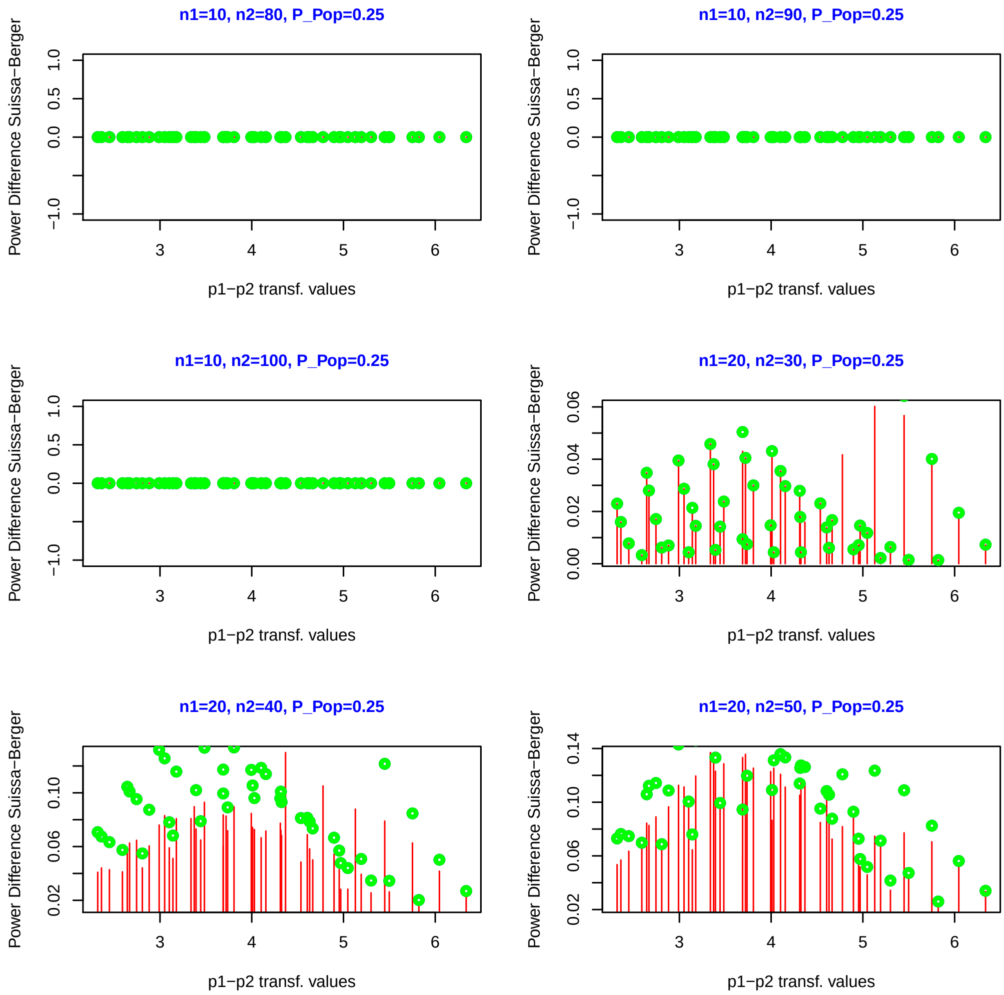

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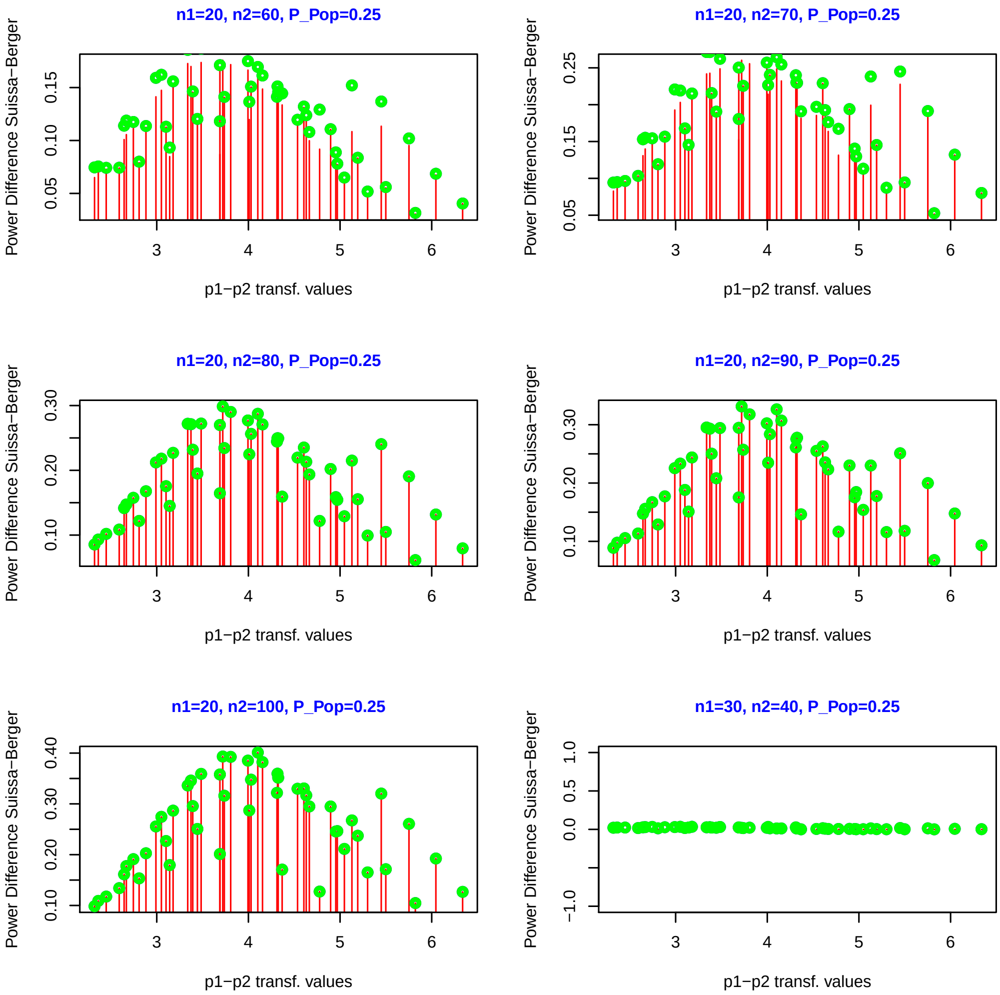

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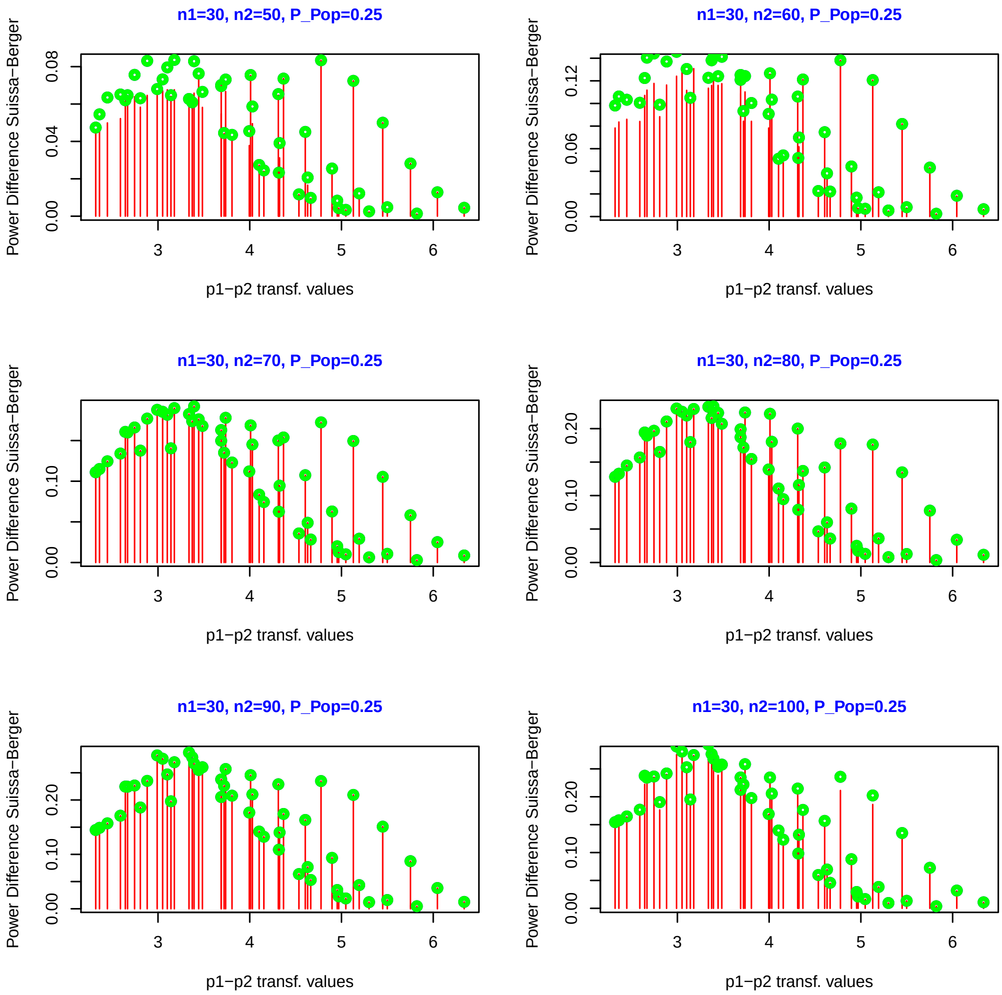

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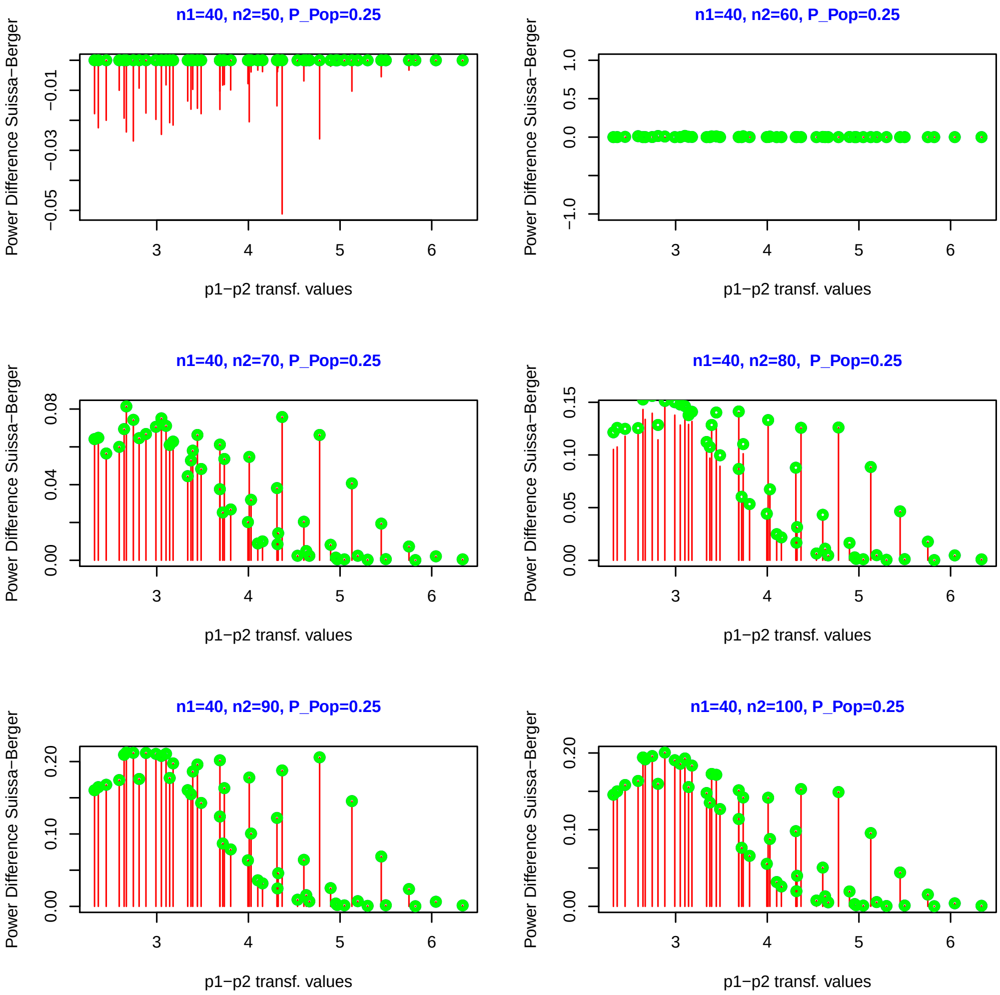

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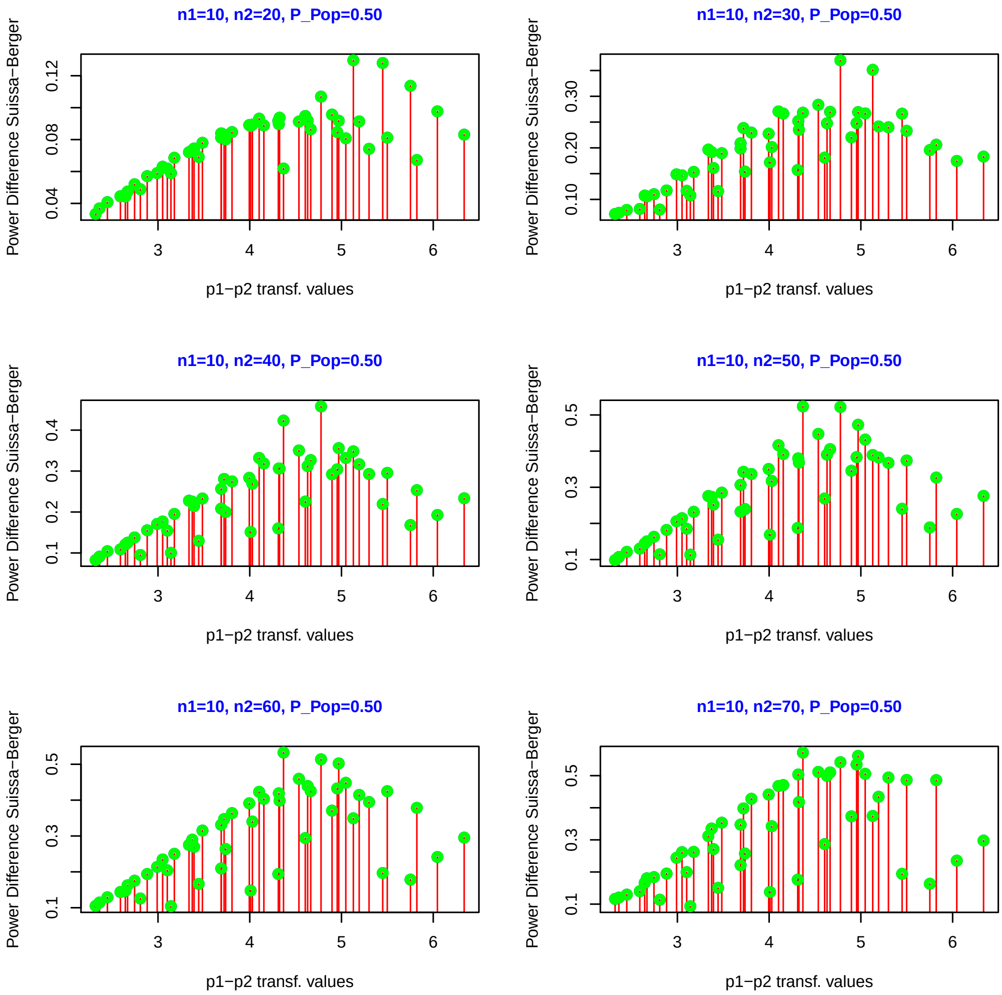

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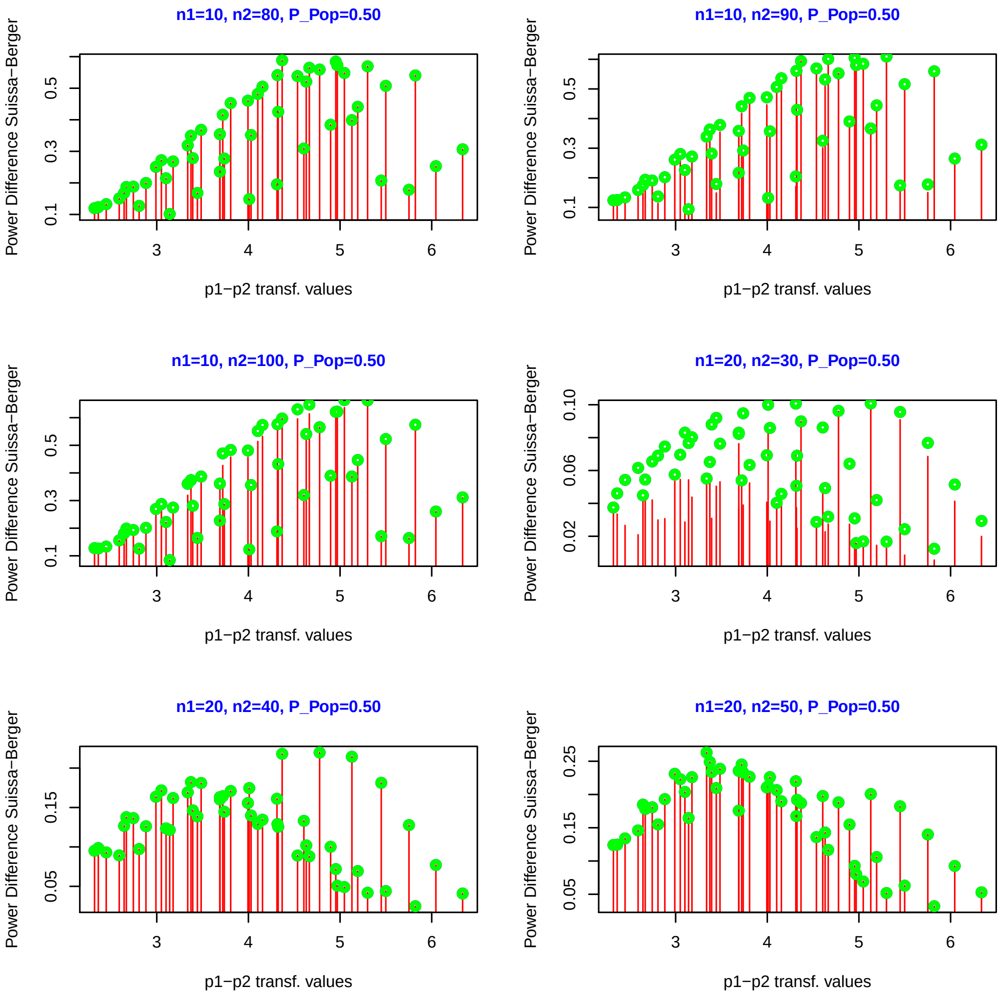

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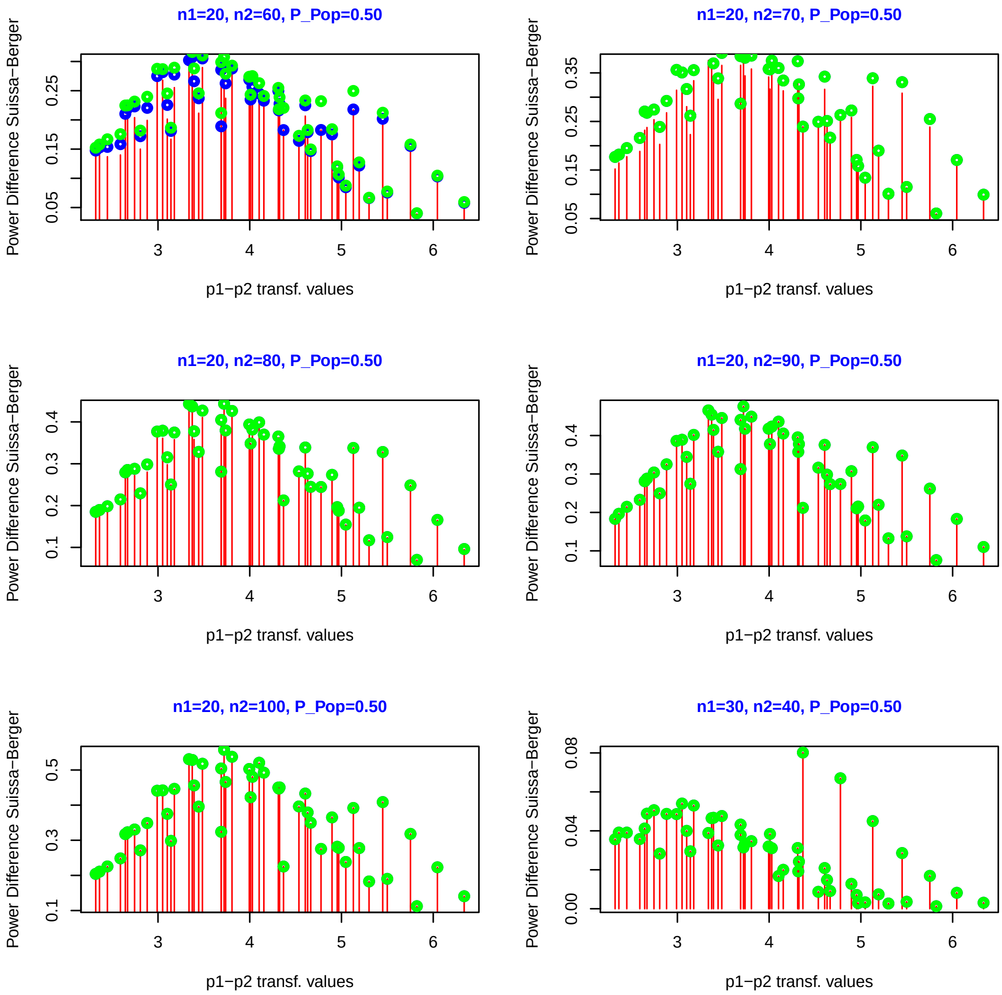

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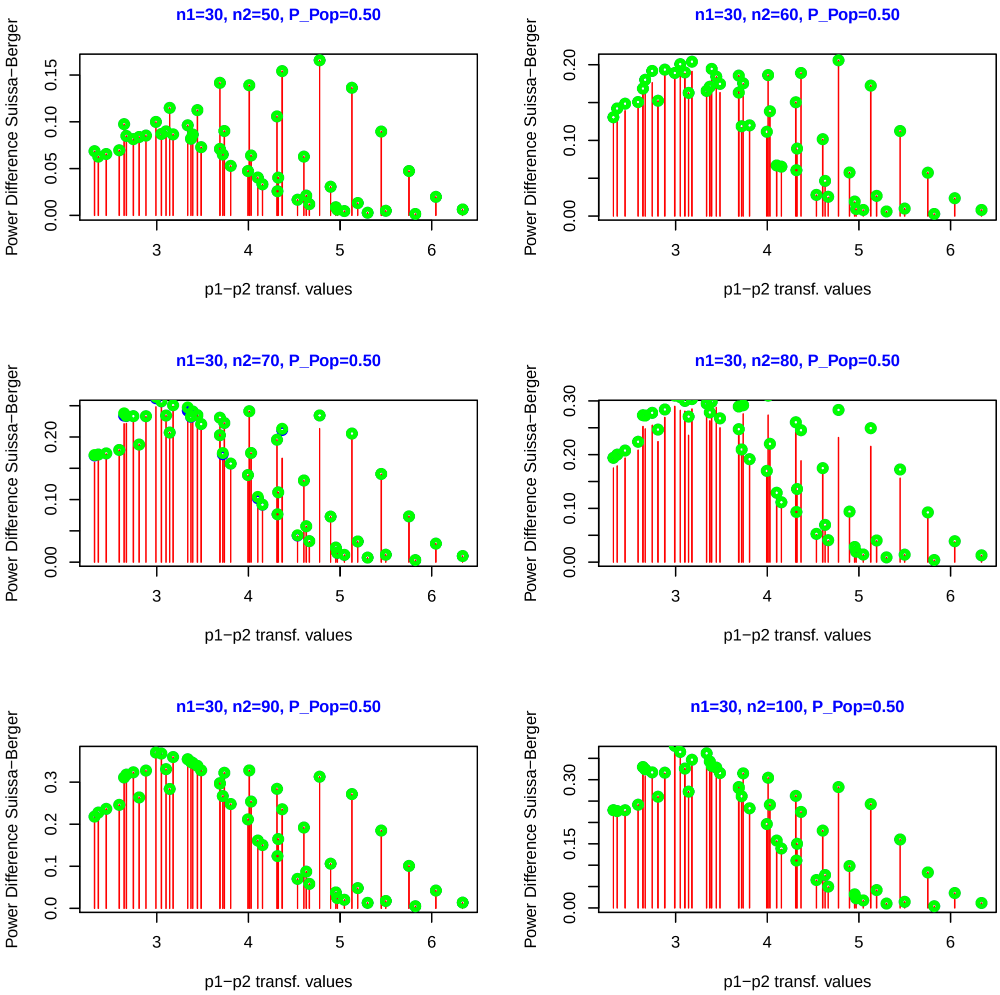

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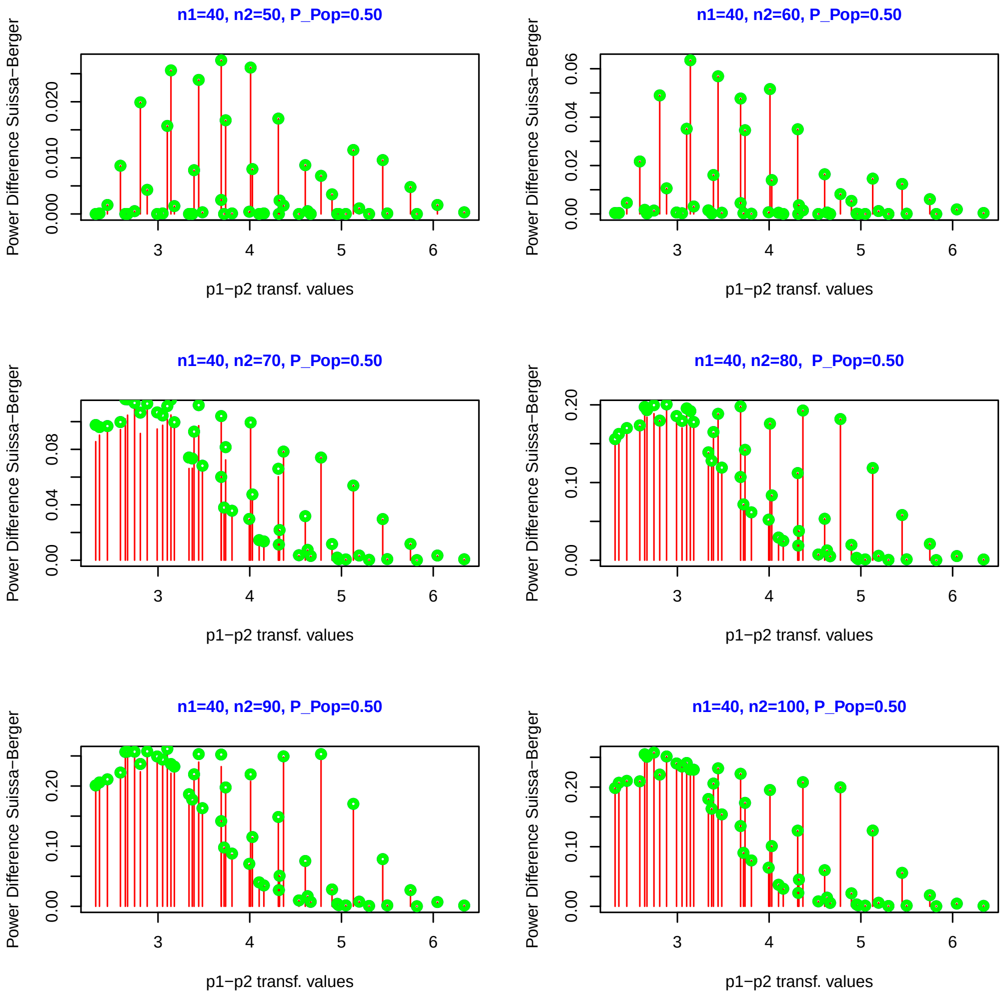

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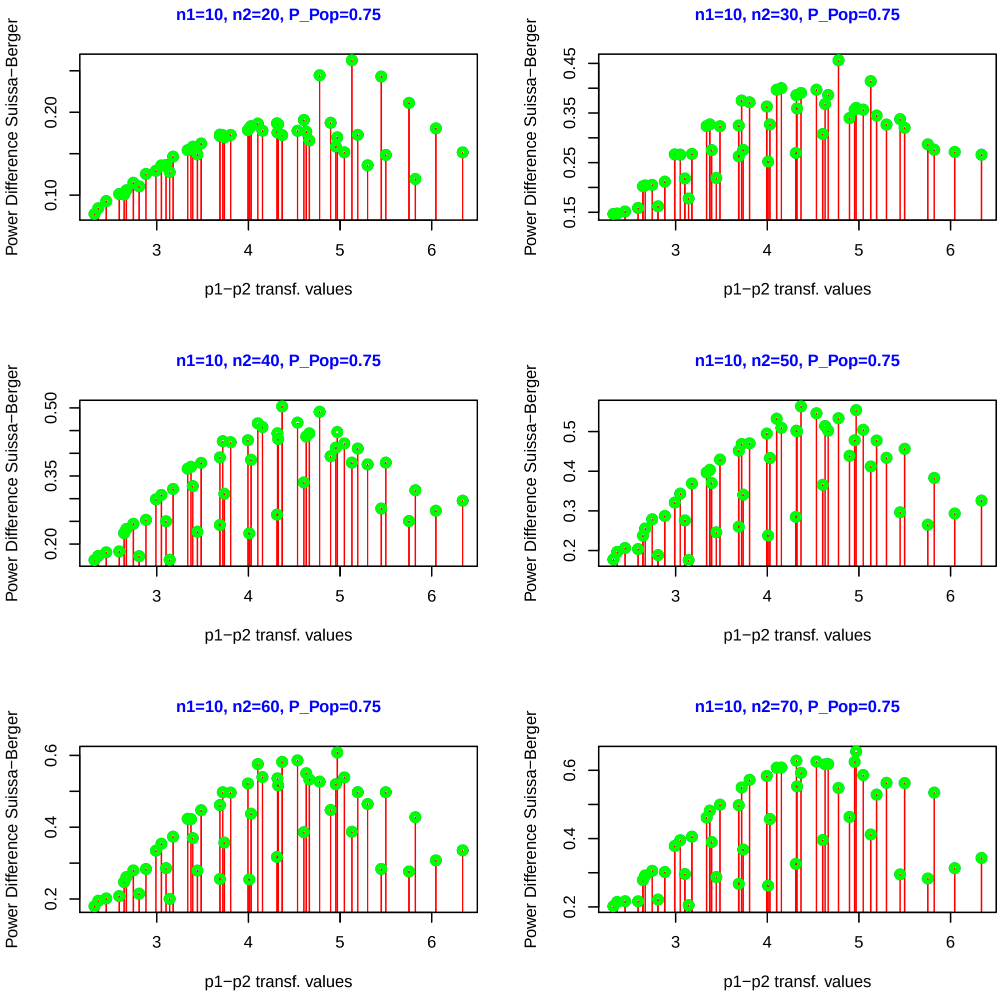

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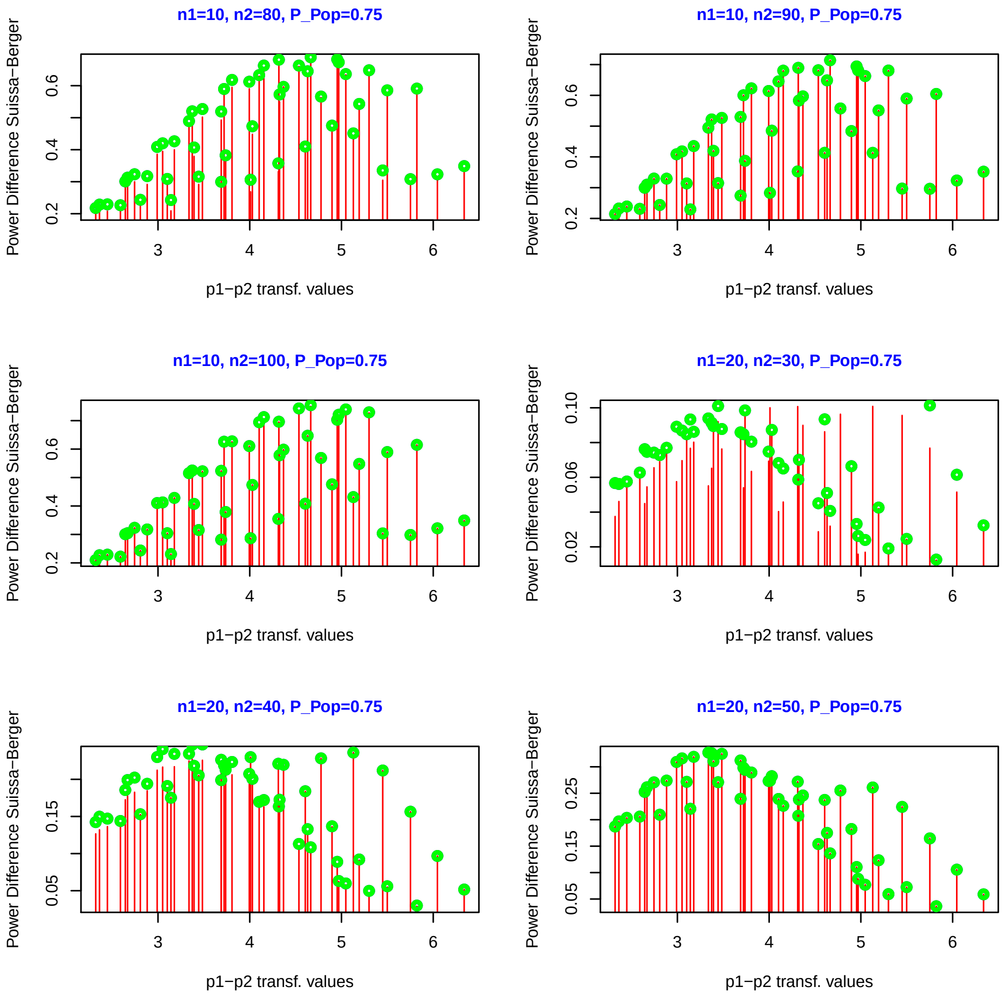

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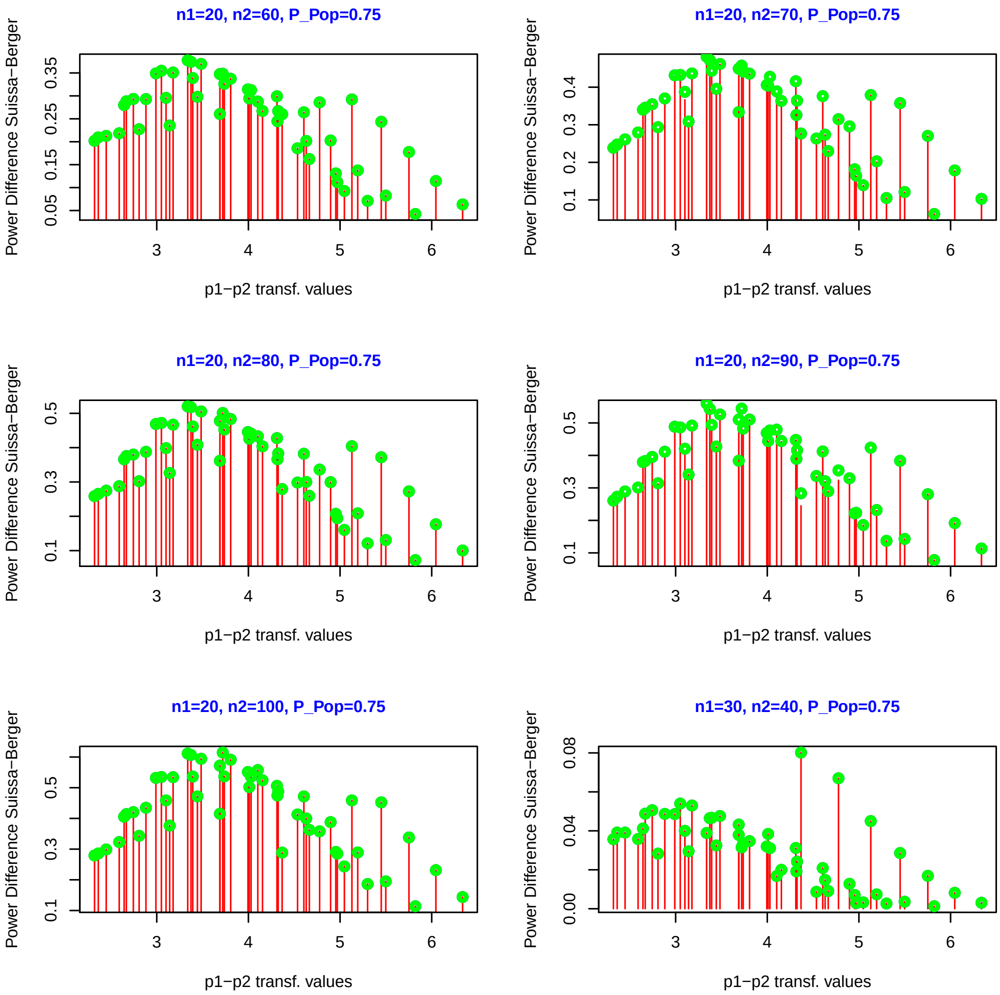

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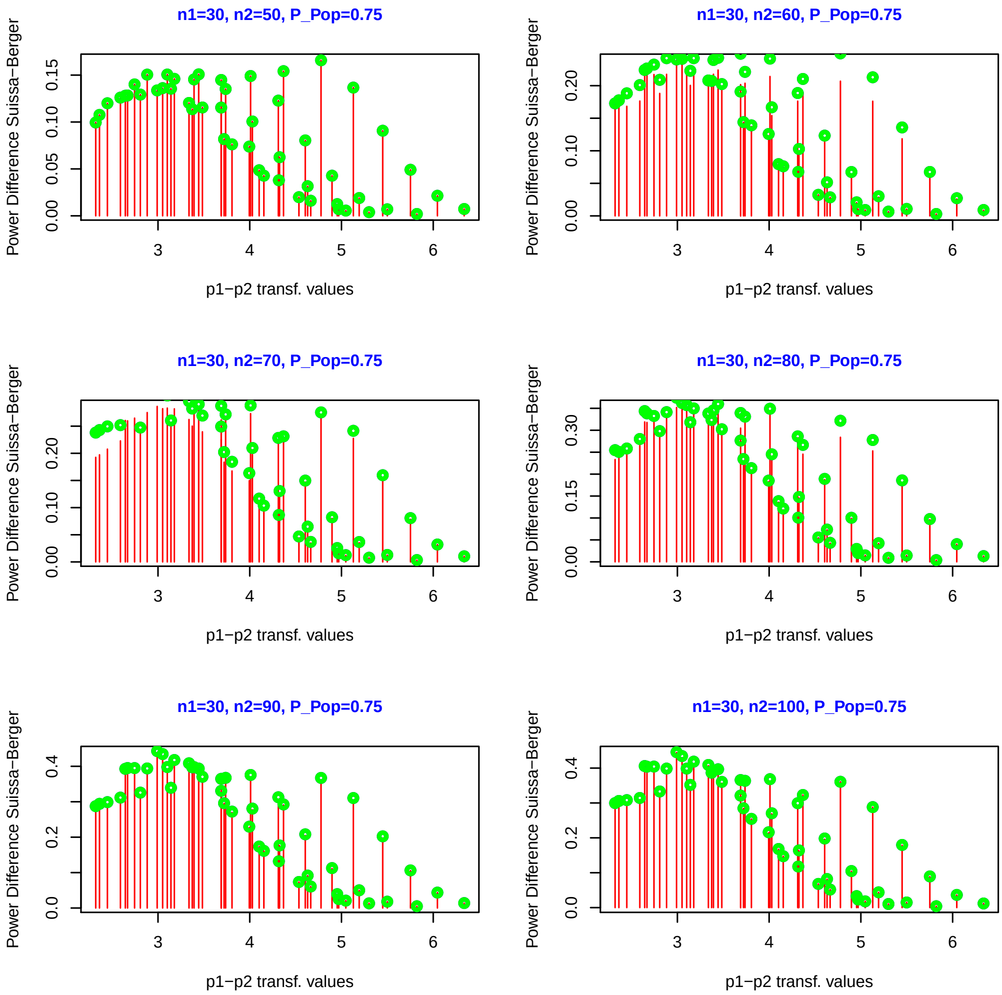

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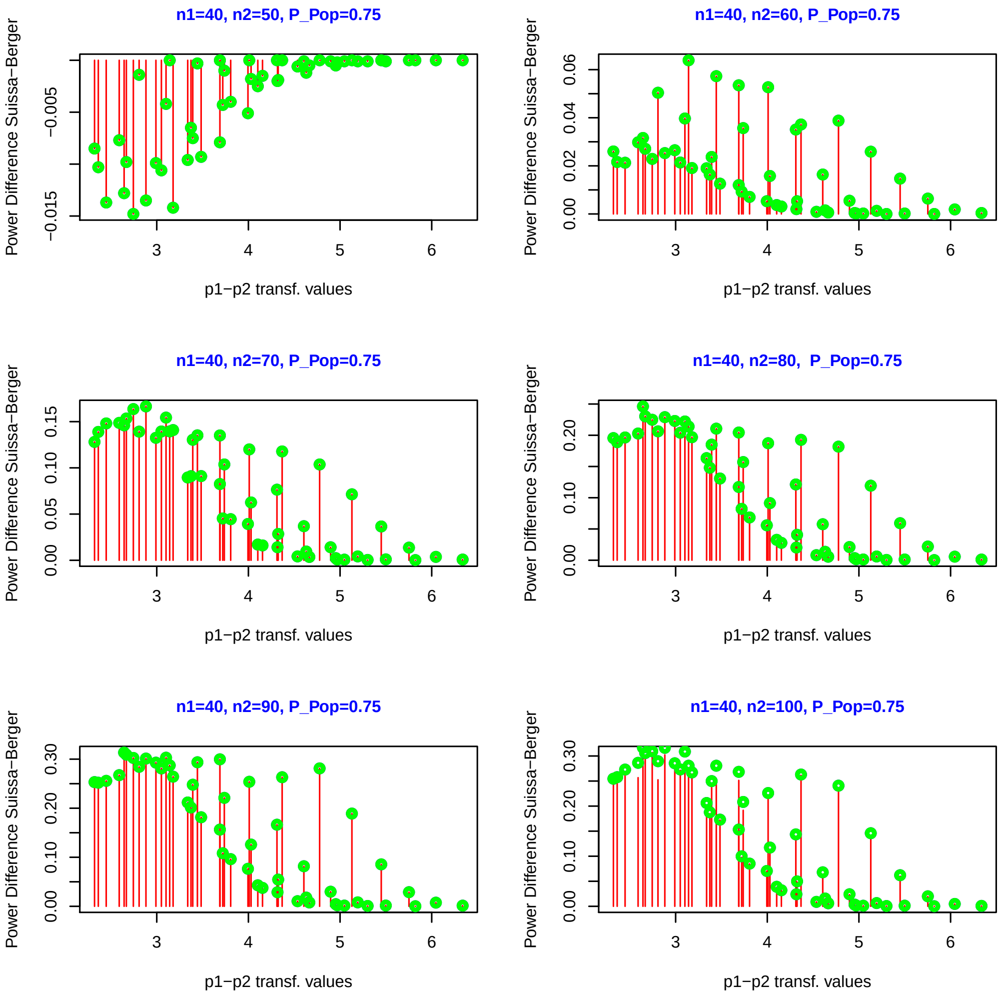

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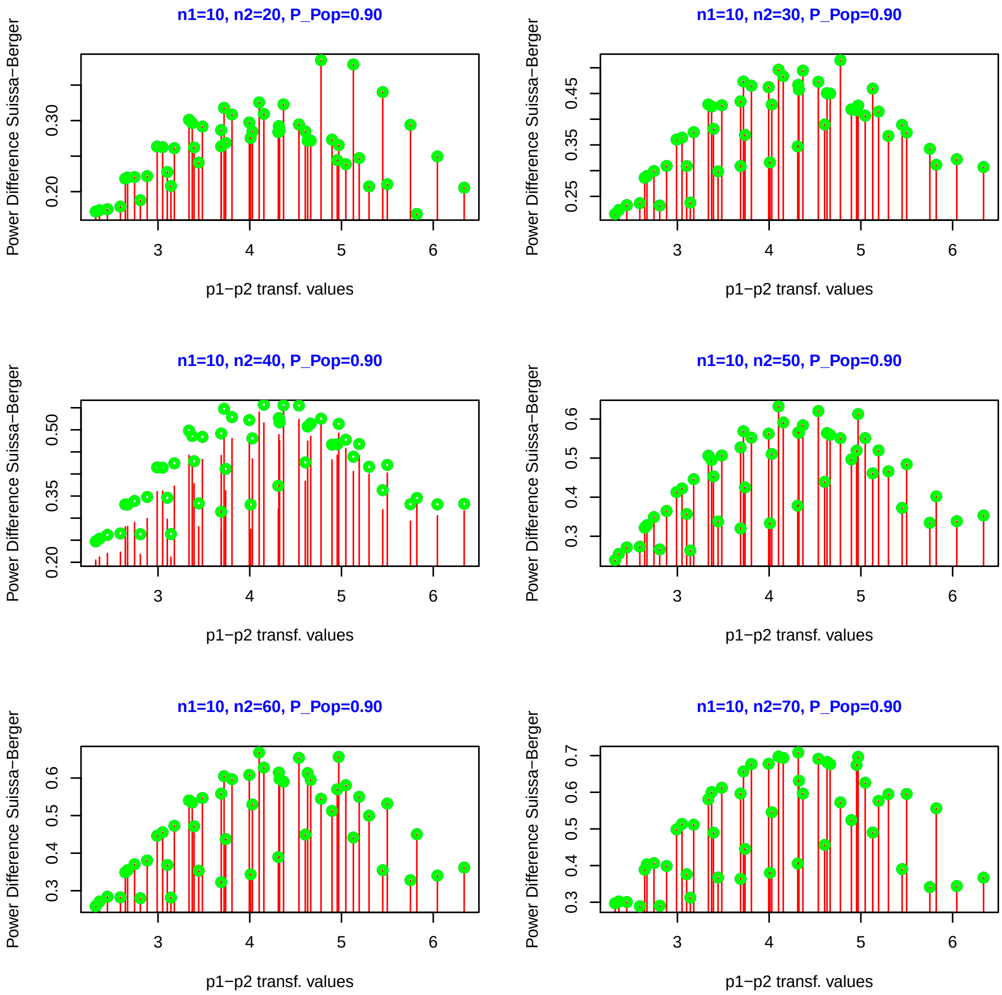

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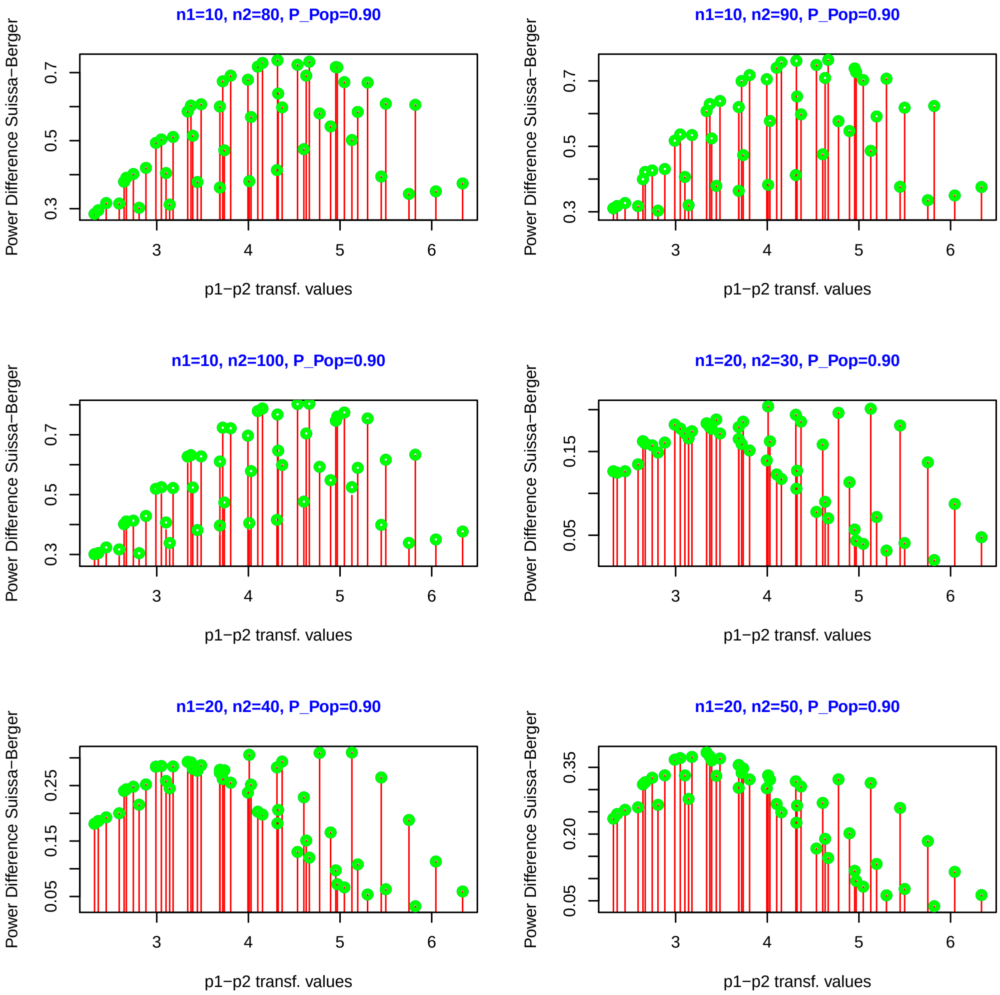

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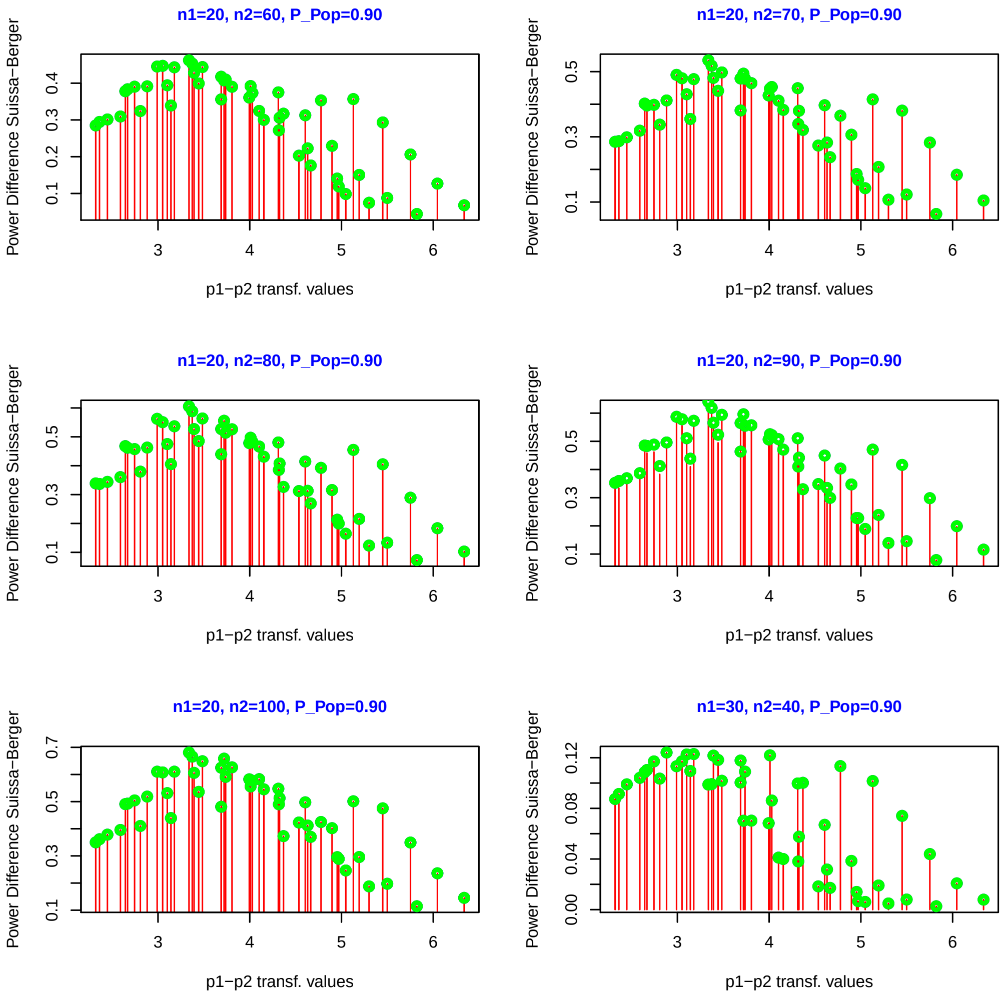

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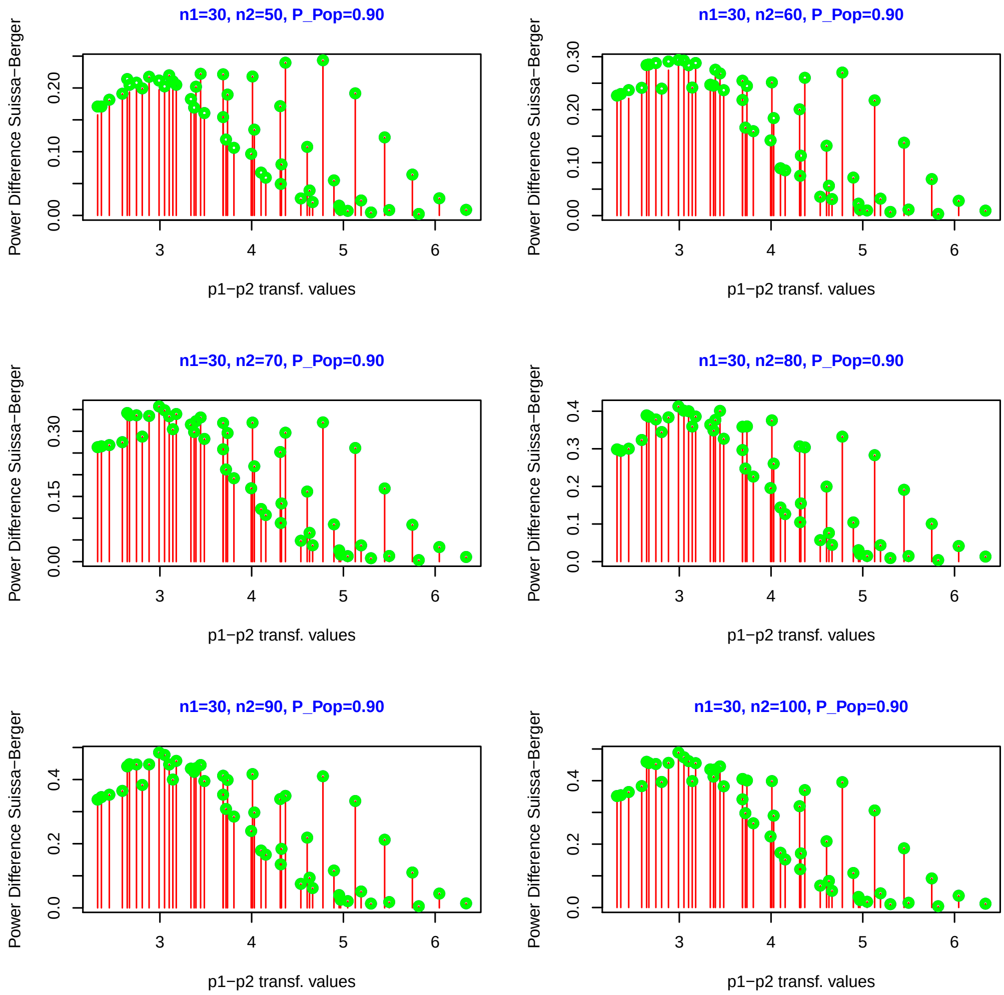

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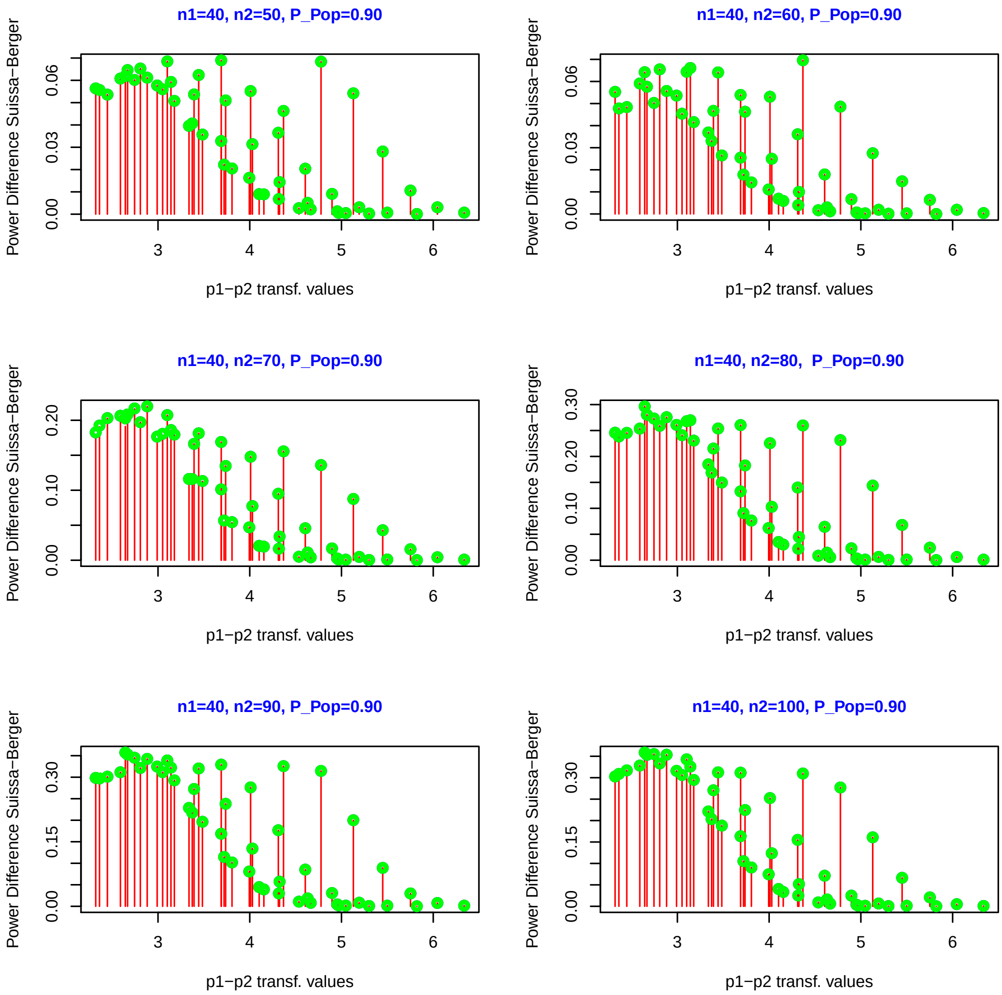

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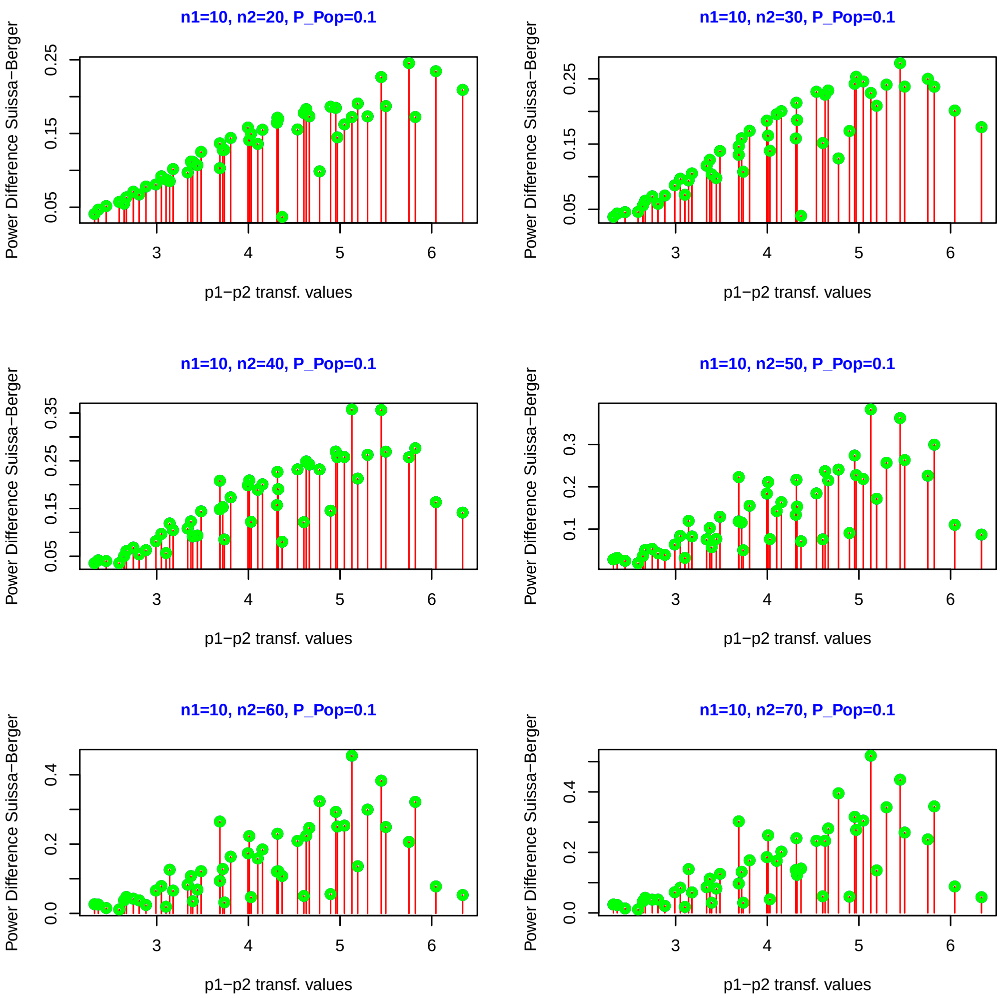
Figure C.18: Comparison of power between the Suissa unpooled test and the Berger unpooled test for different sample sizes, $\boldsymbol{\alpha}$= **0.01**.



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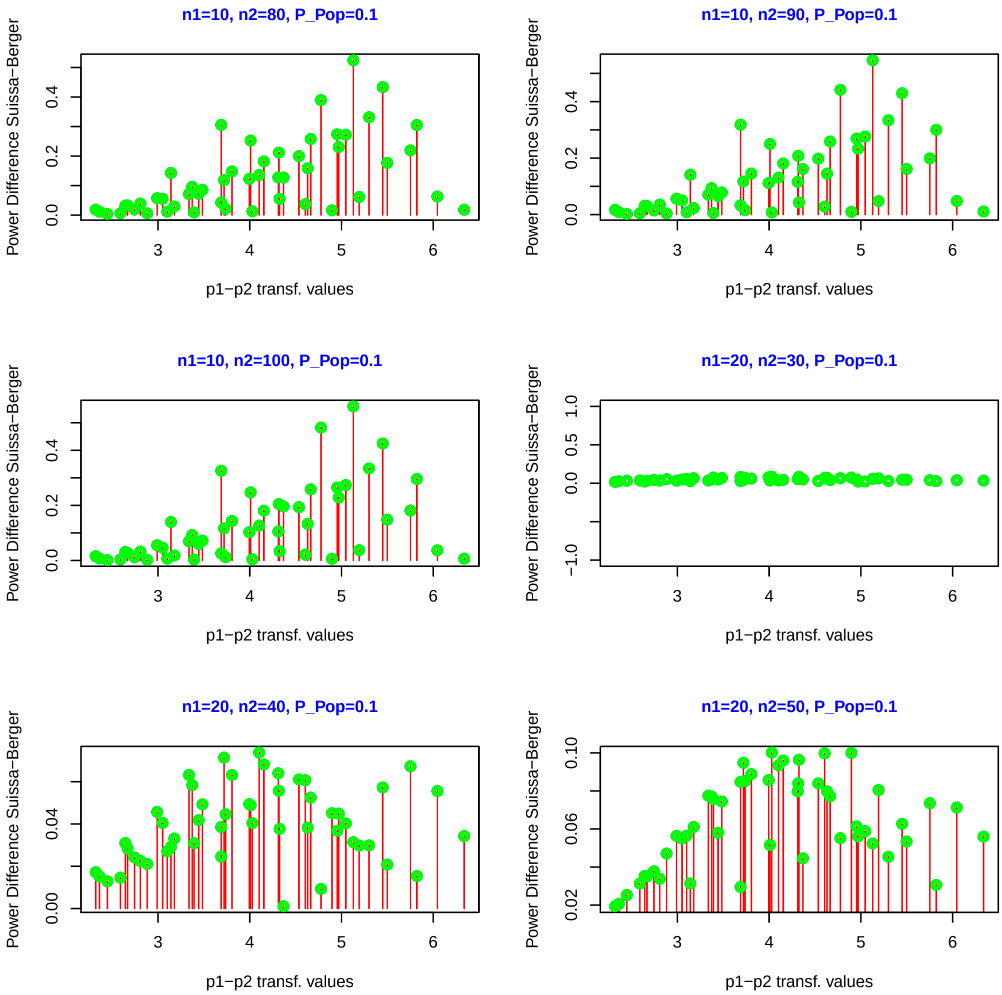

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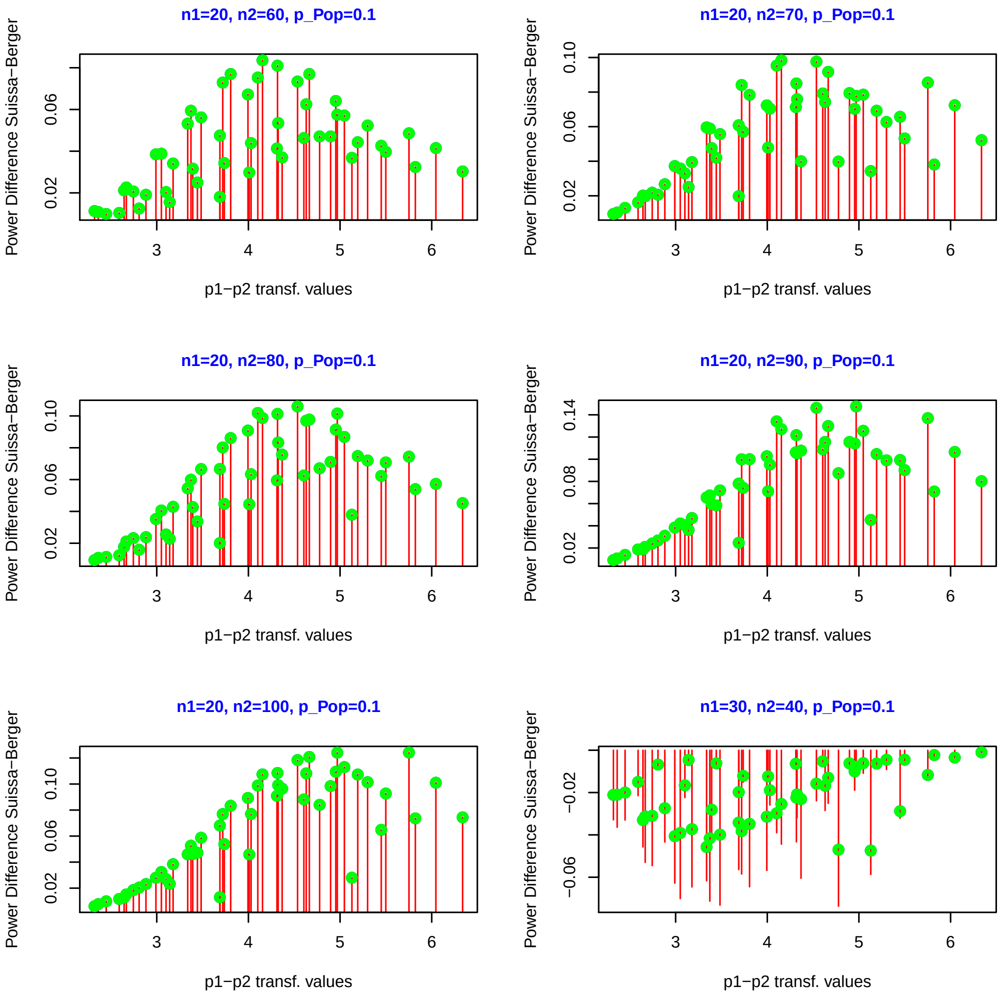

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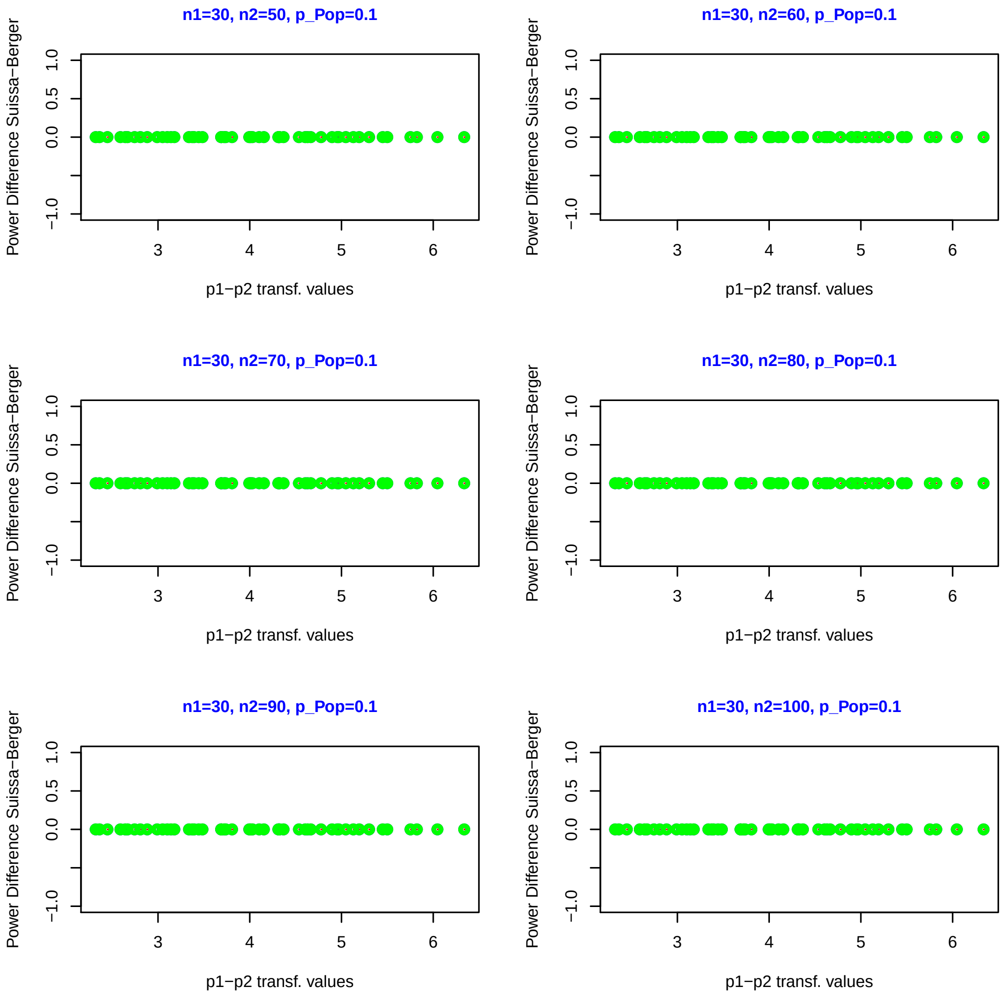

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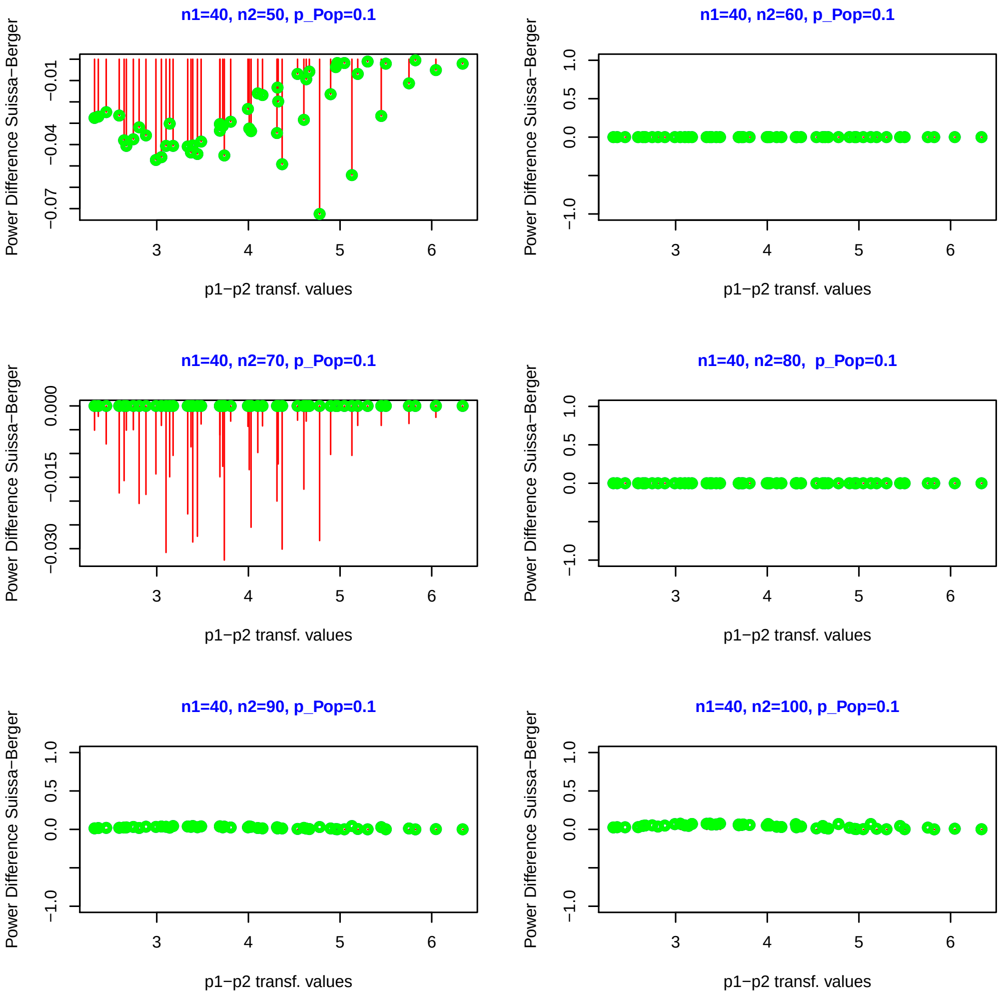

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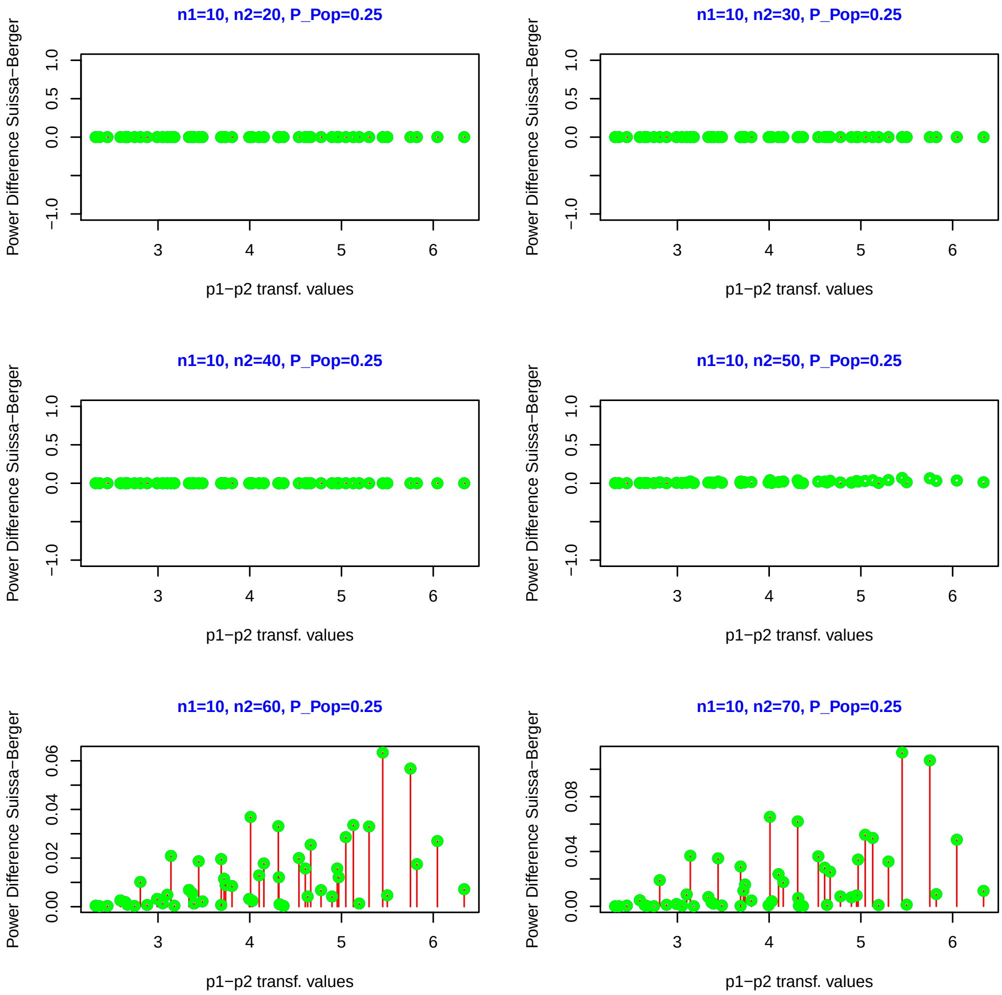

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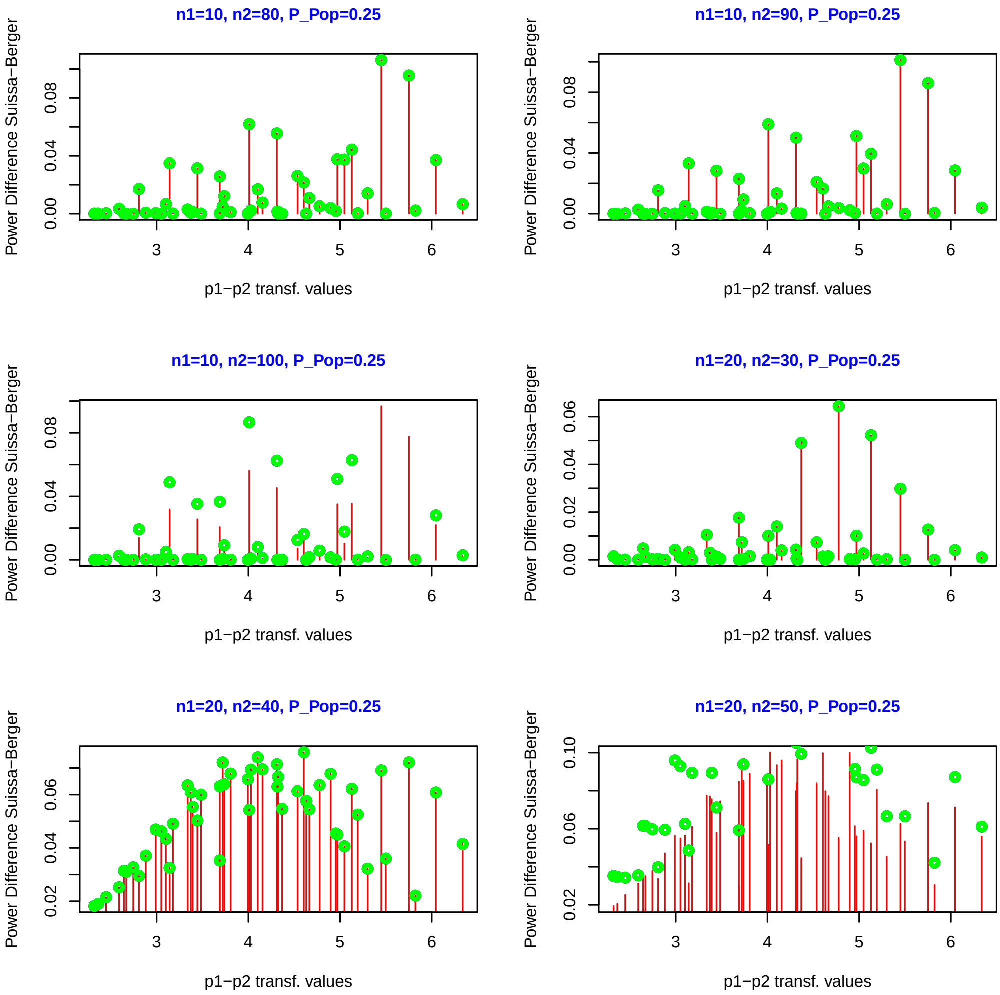

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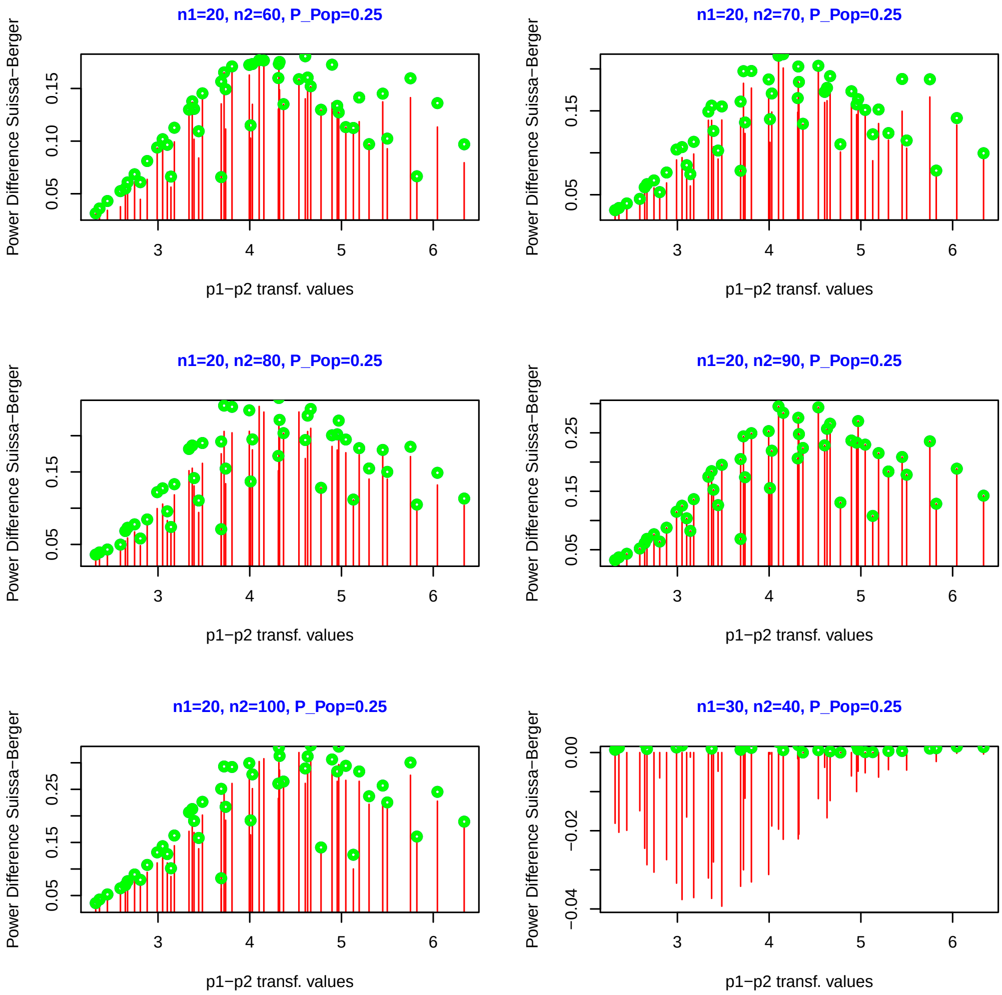

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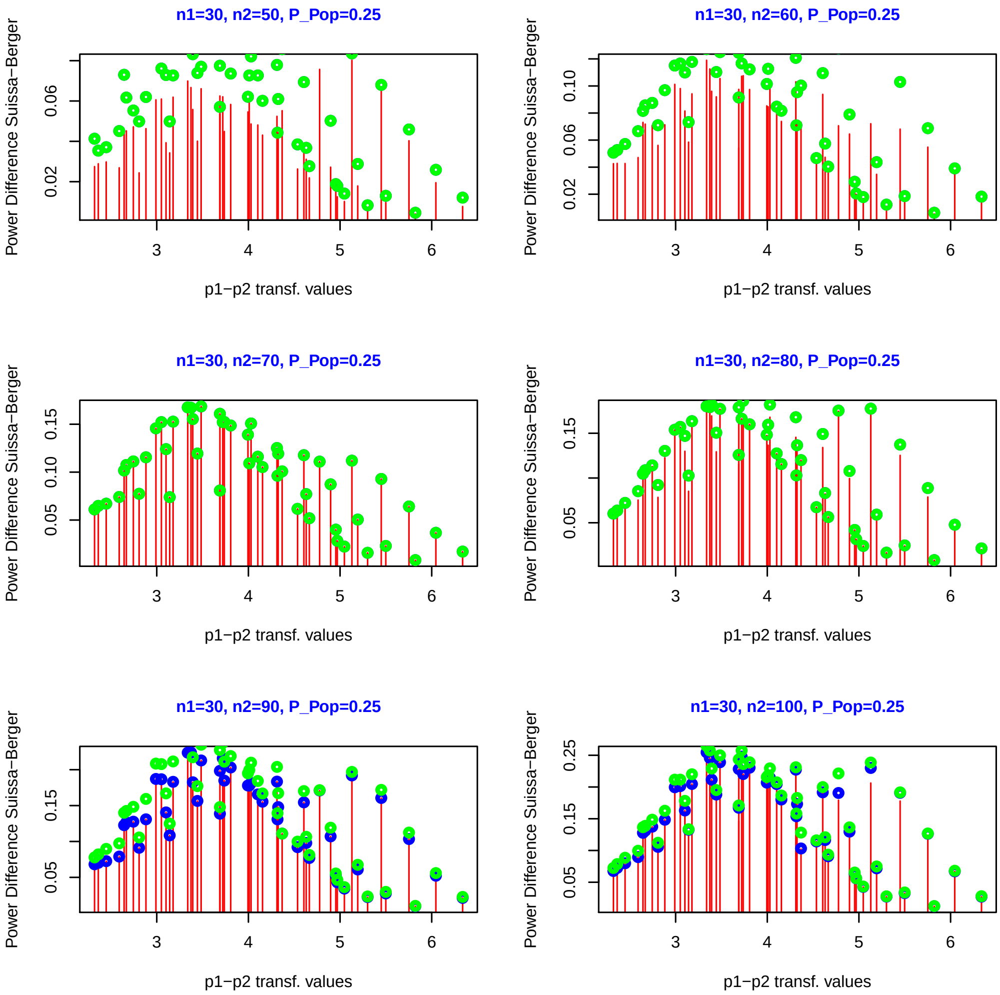

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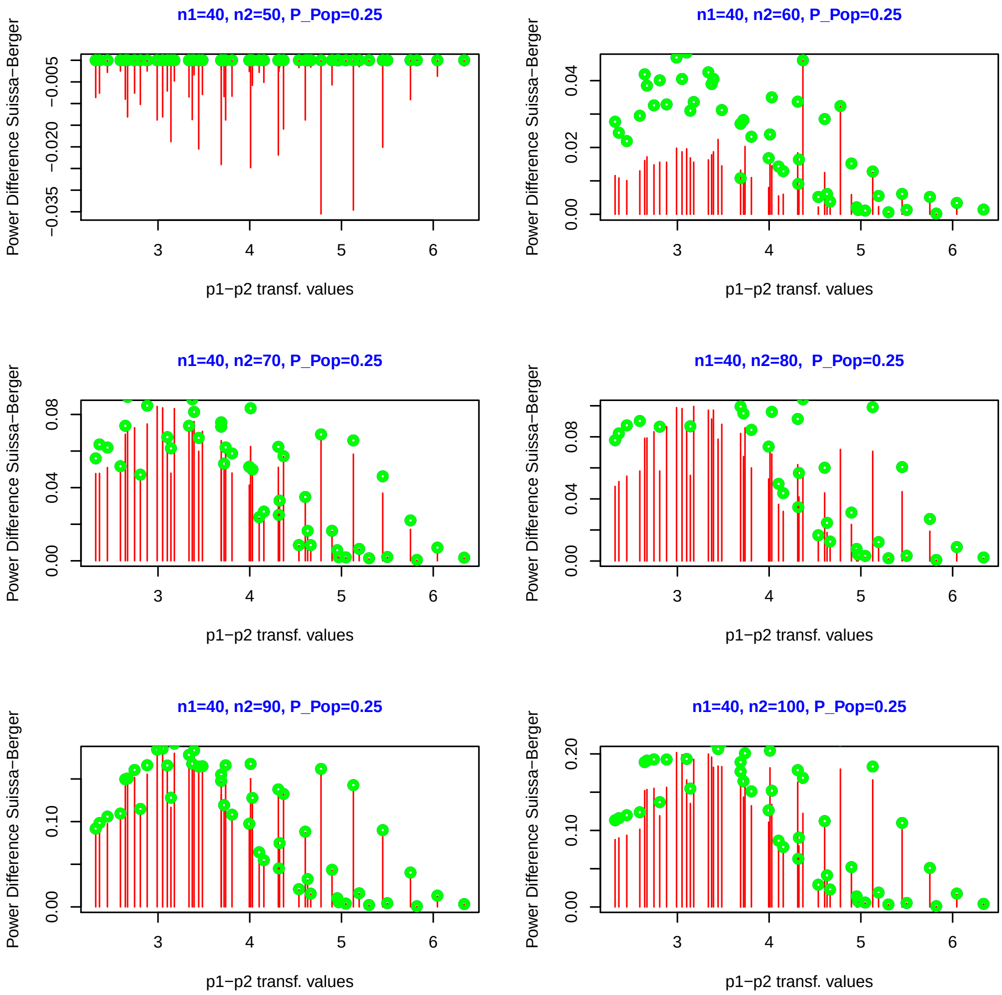

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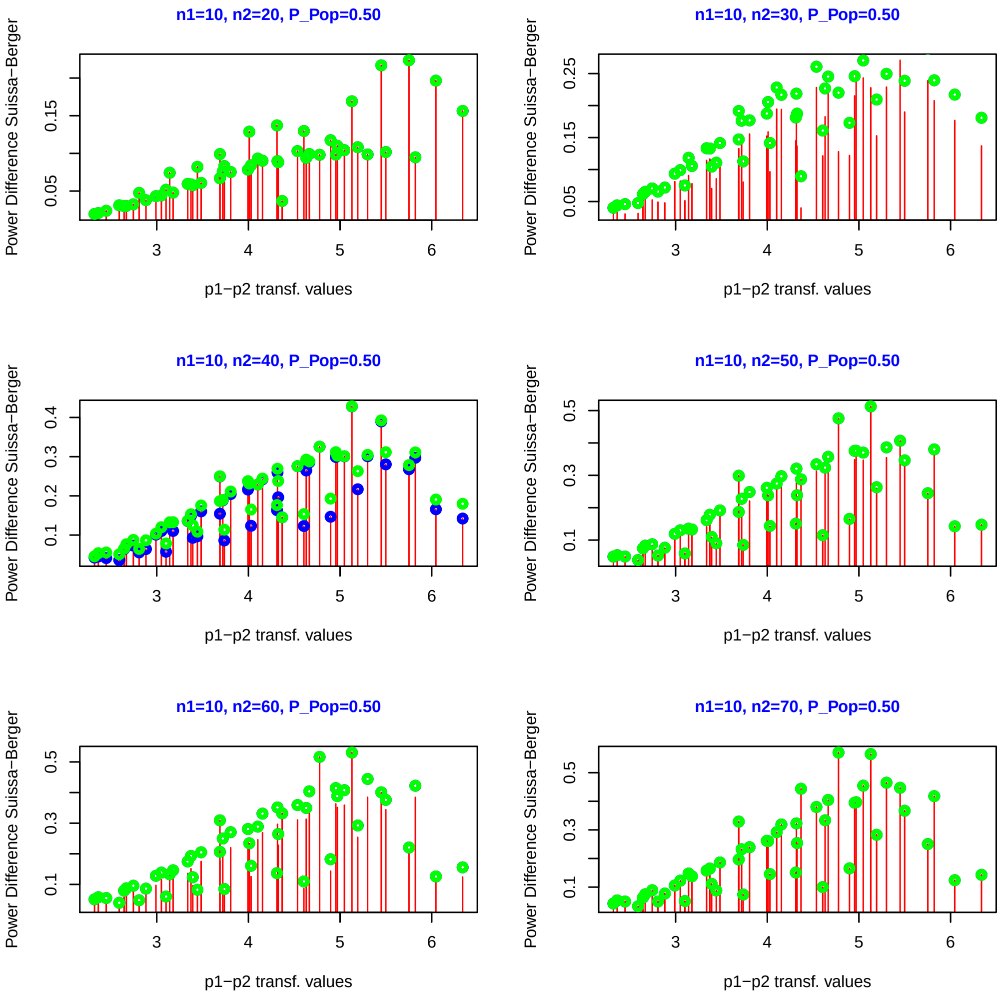

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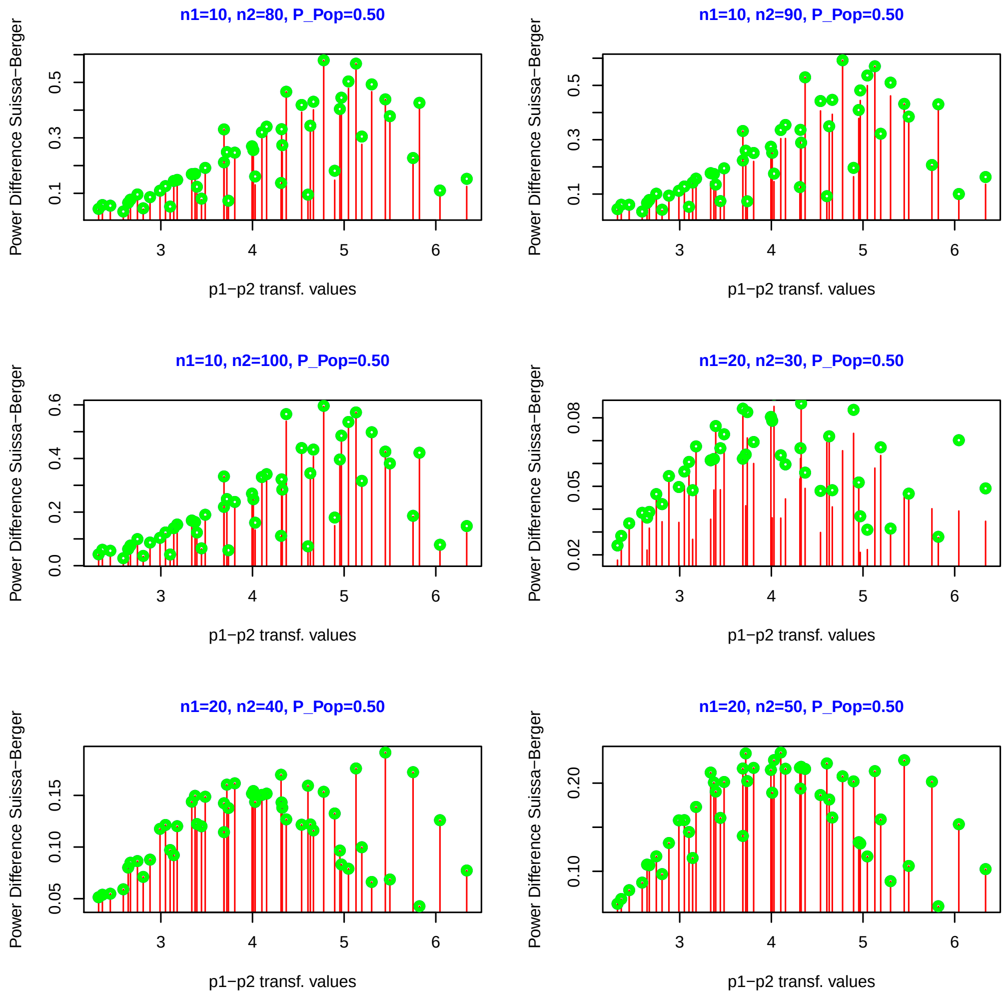

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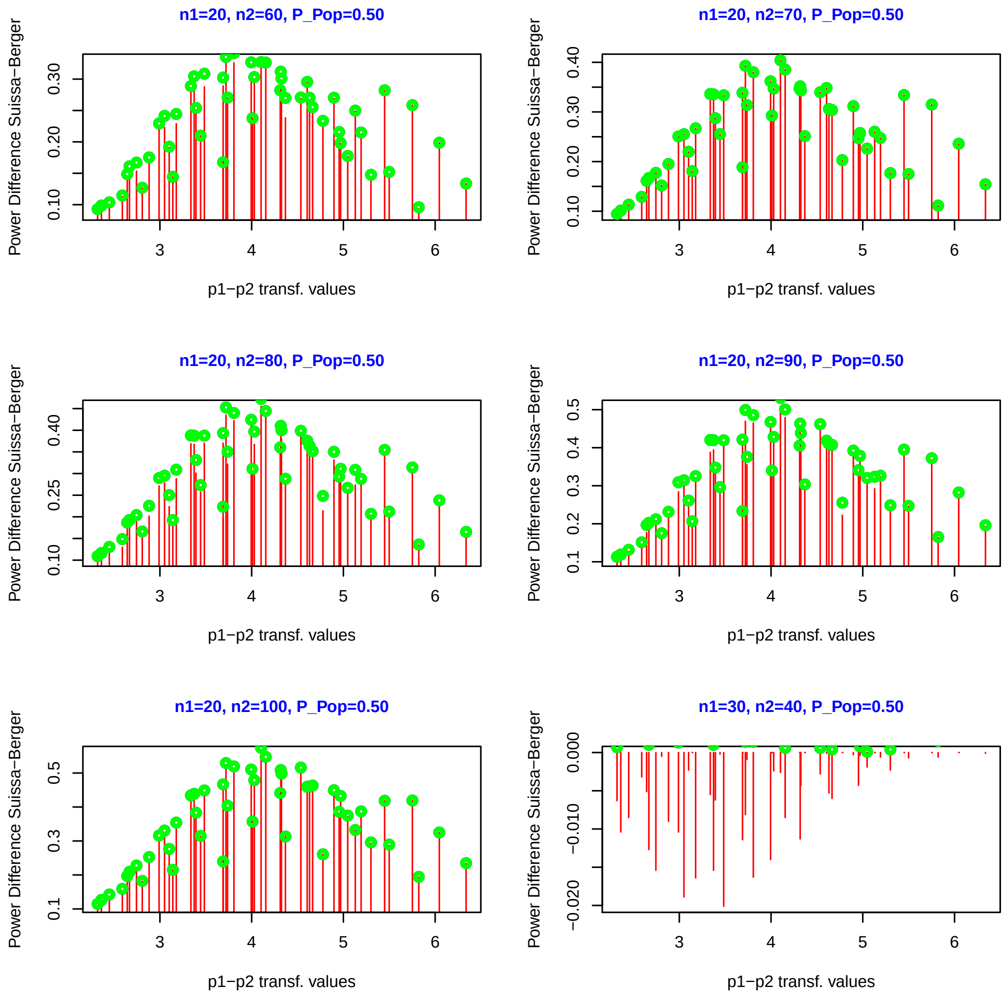

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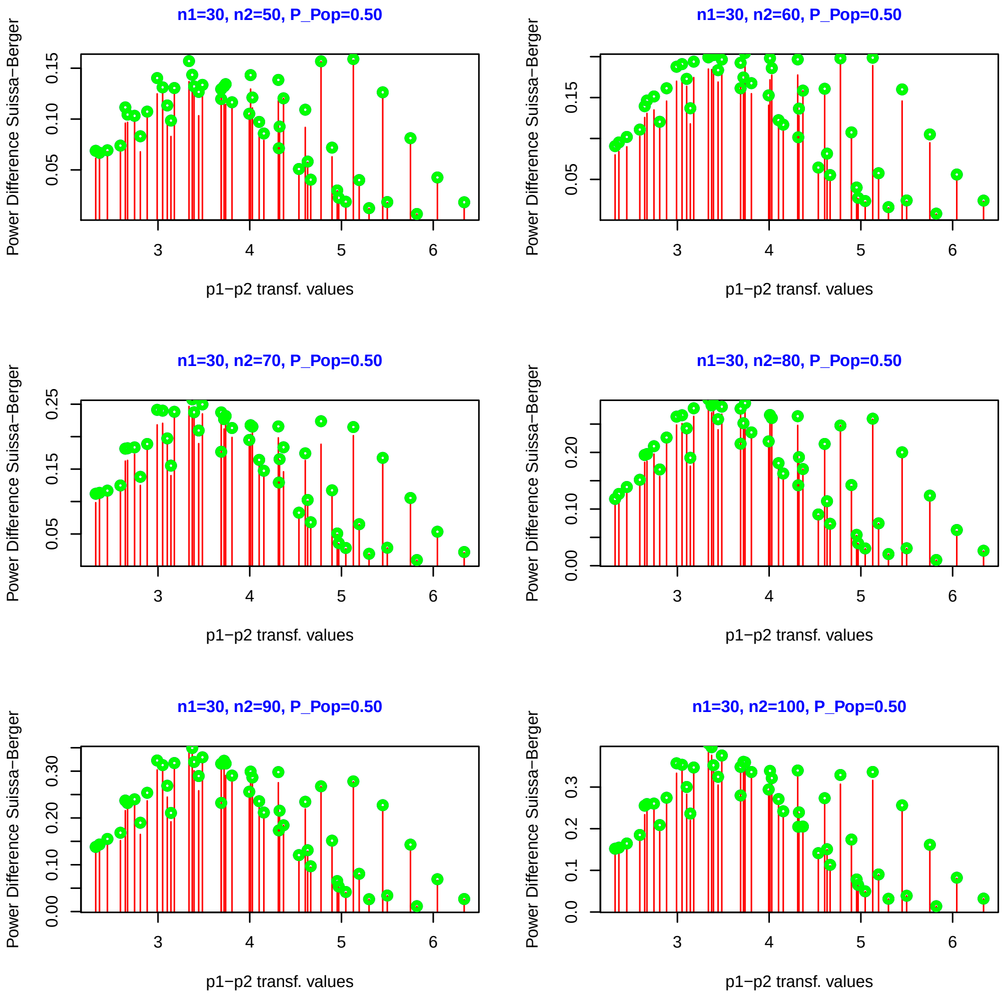

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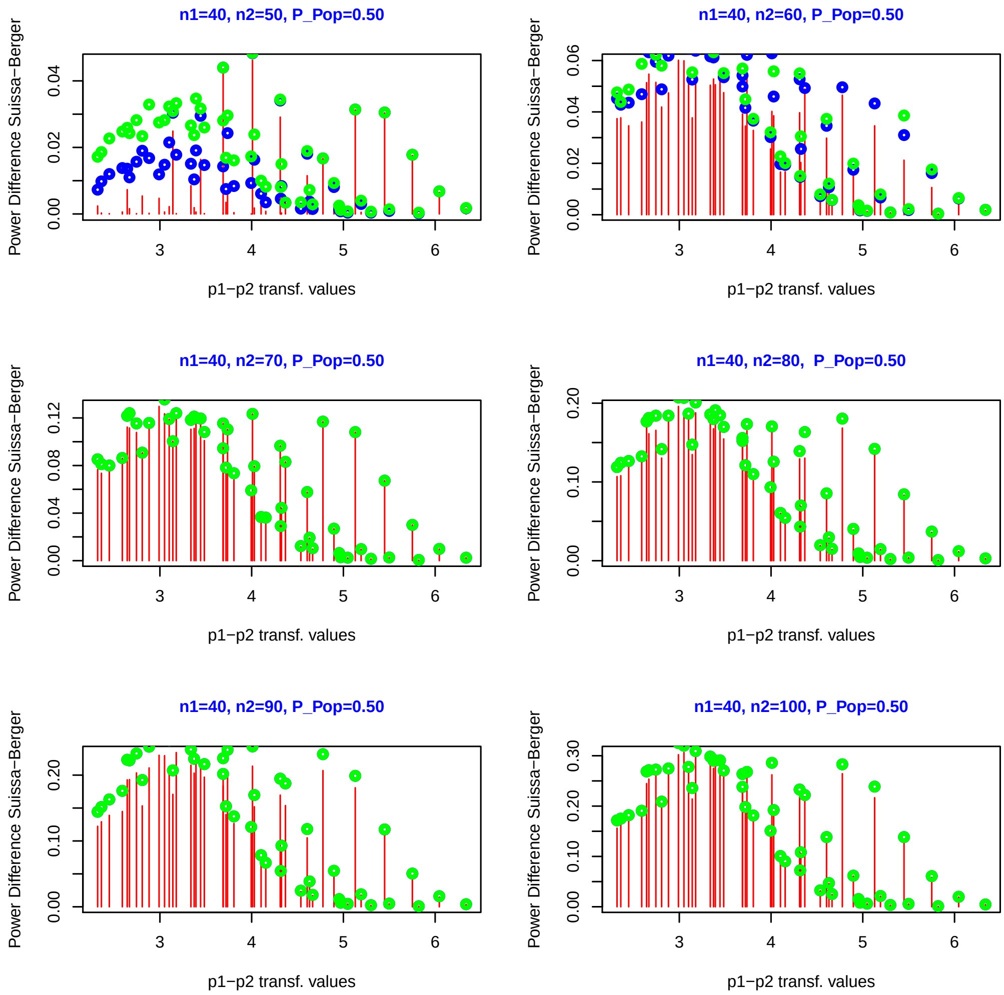

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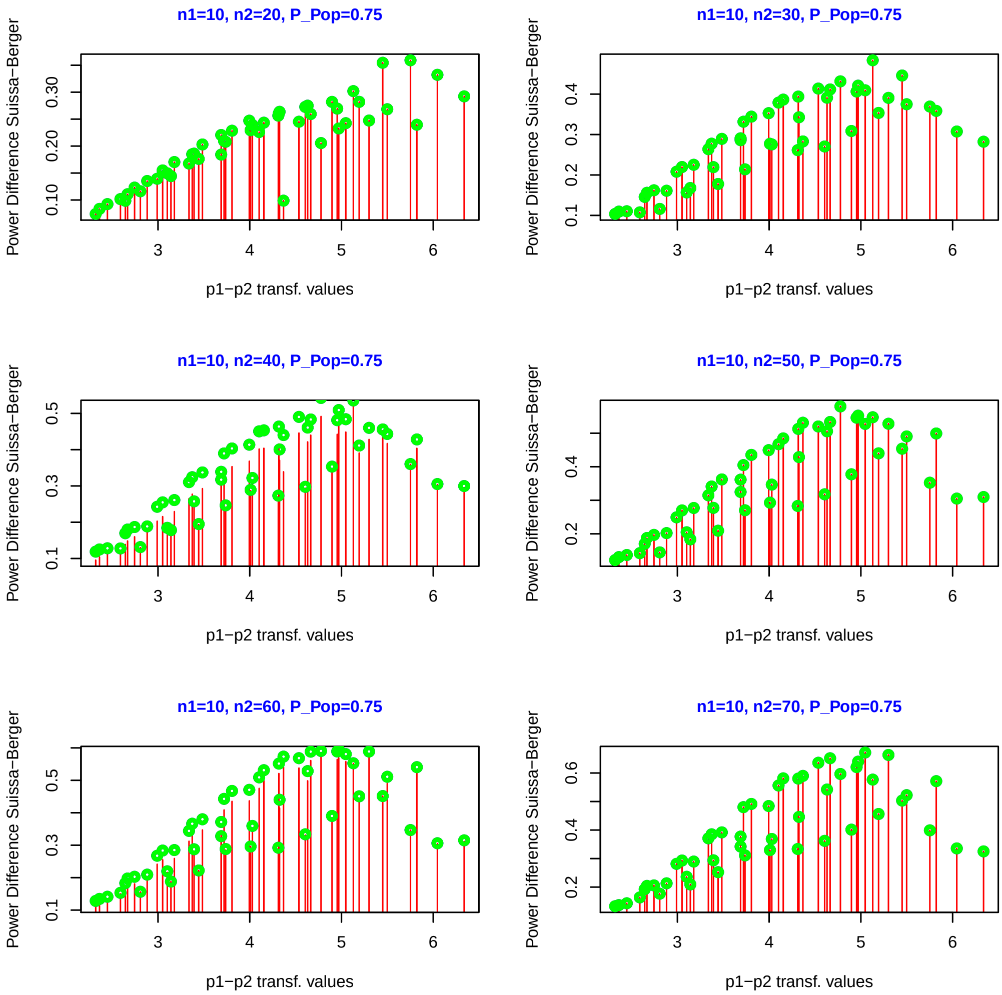

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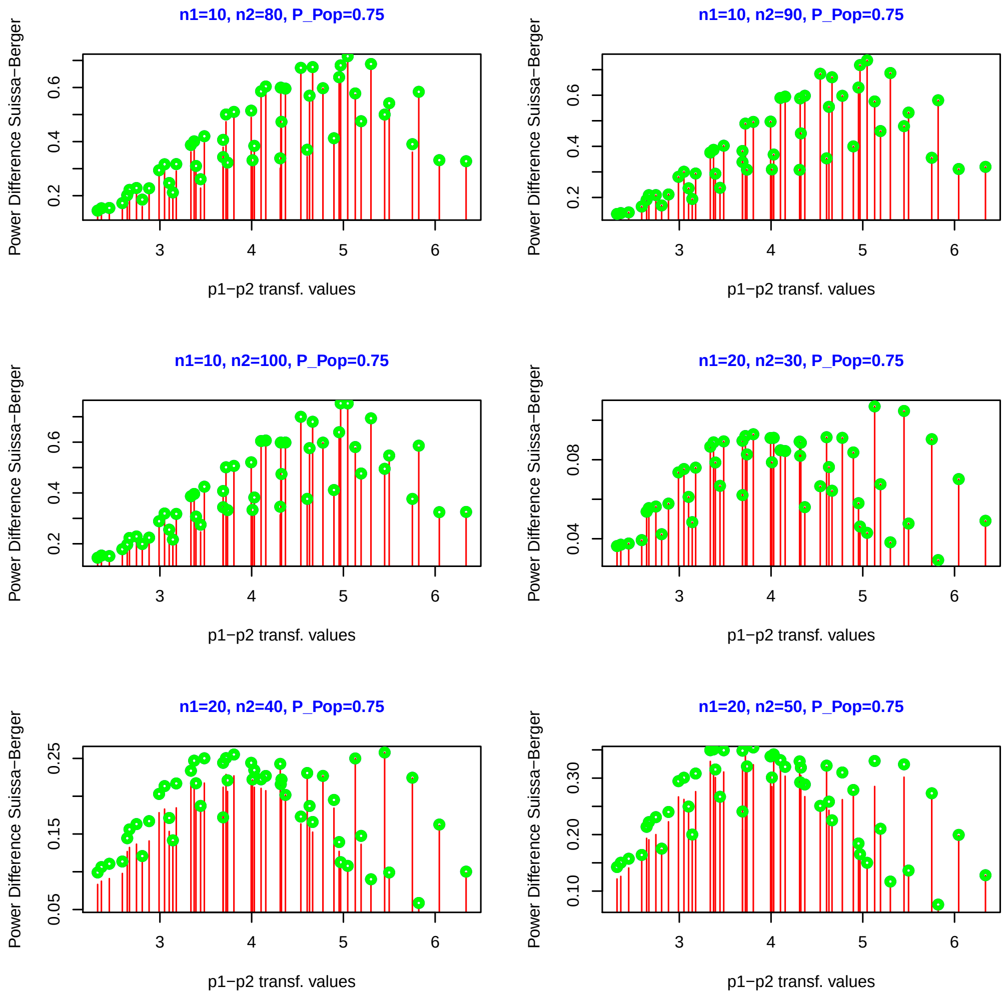

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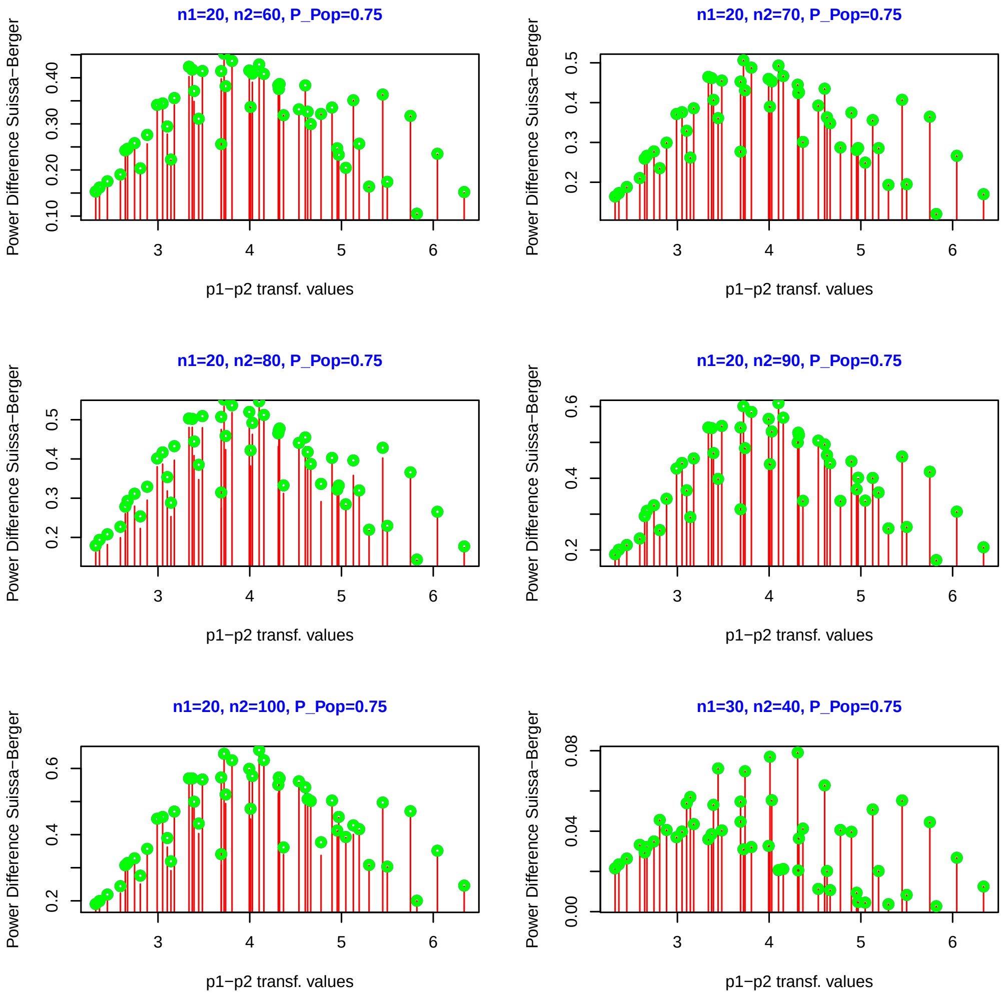

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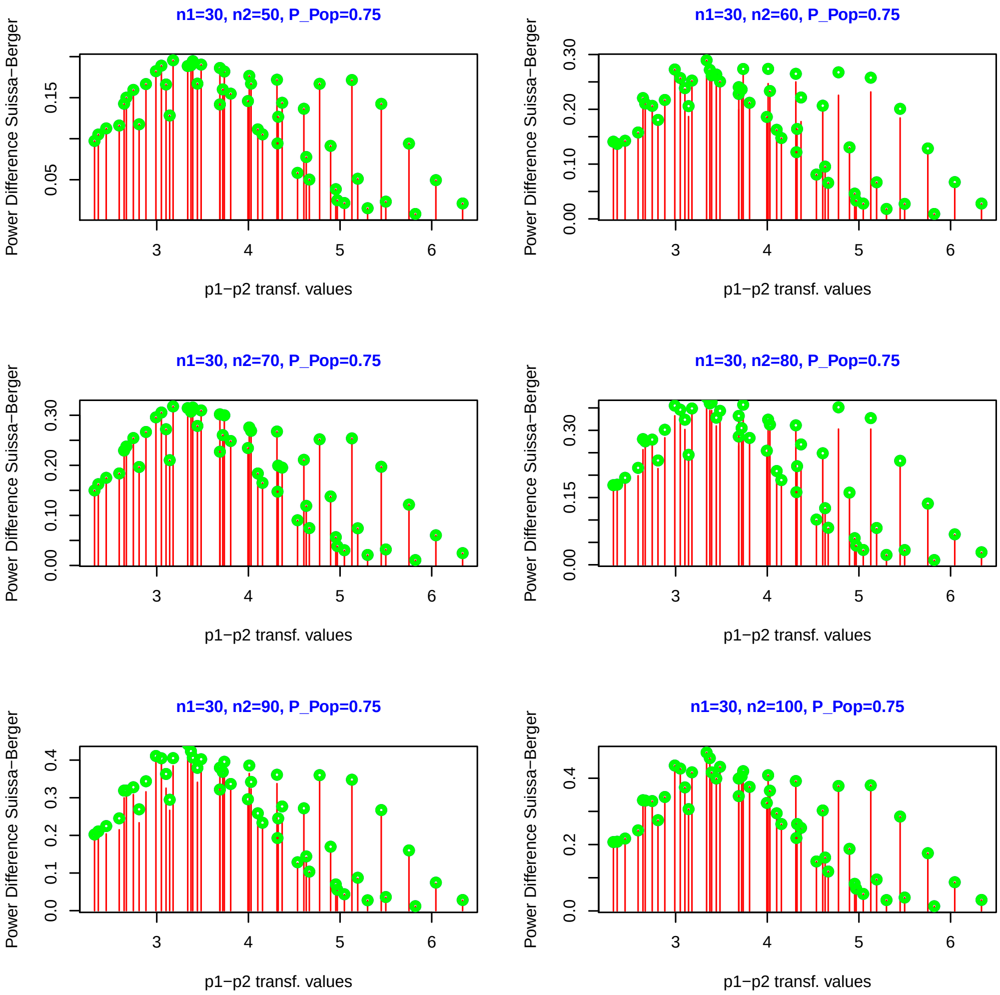

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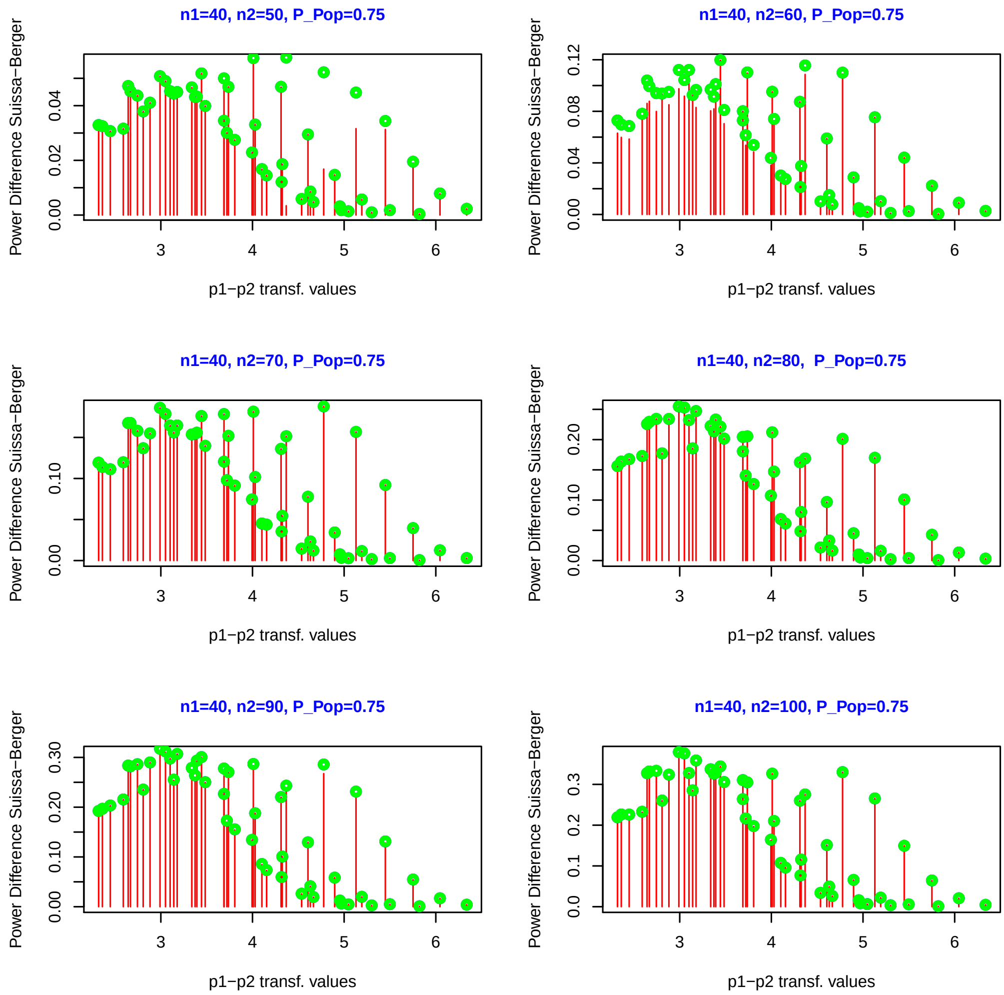

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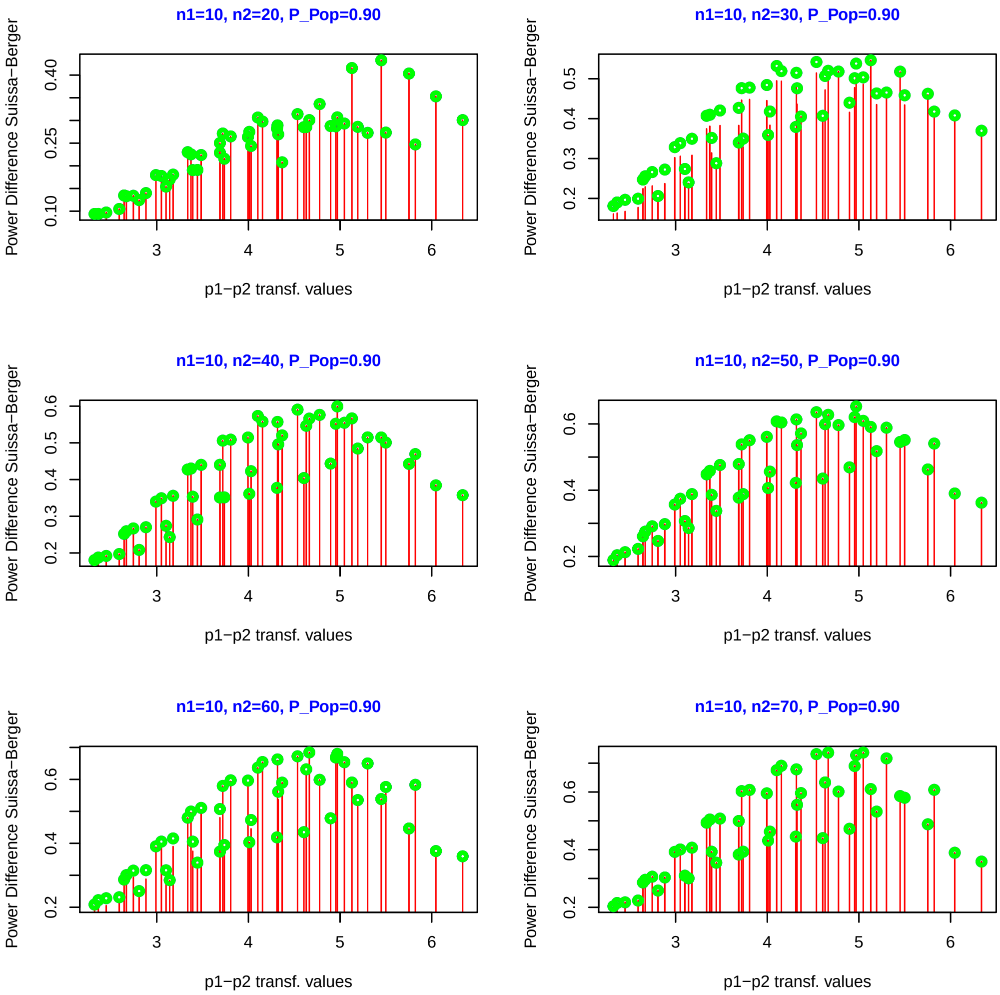

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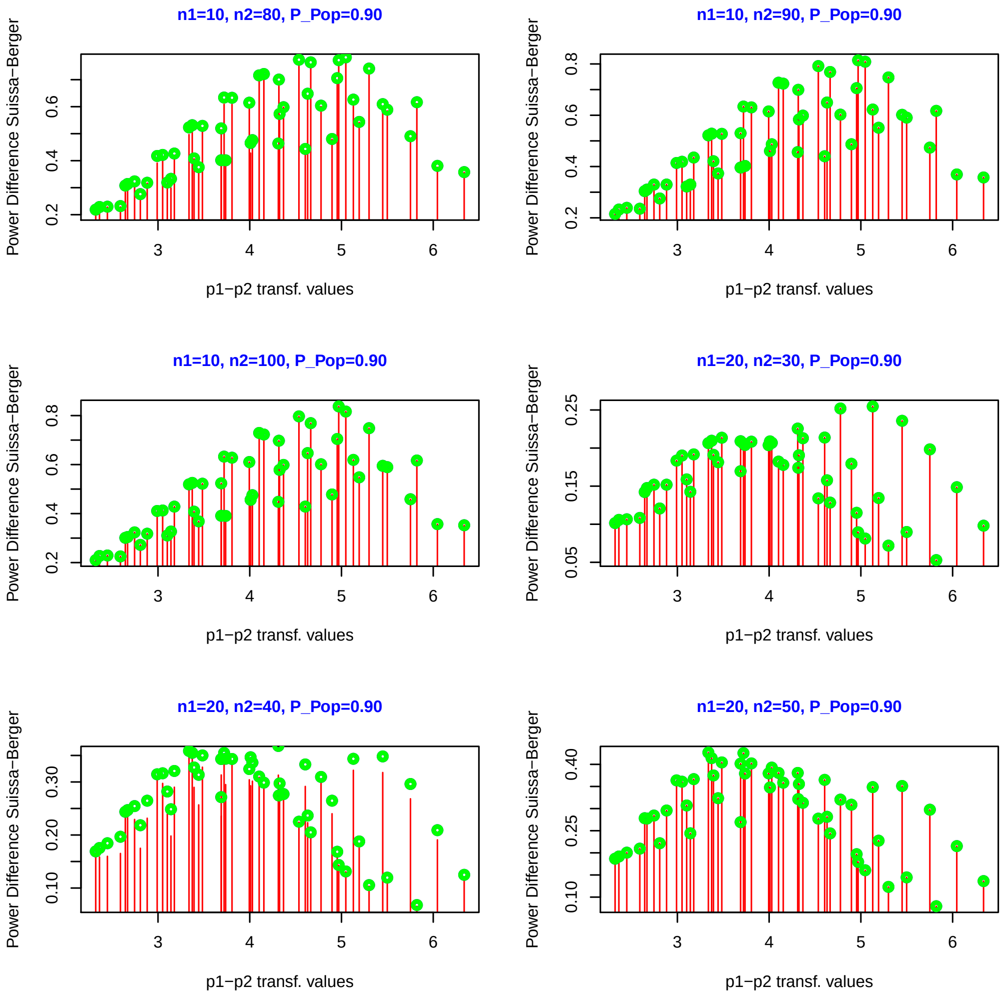

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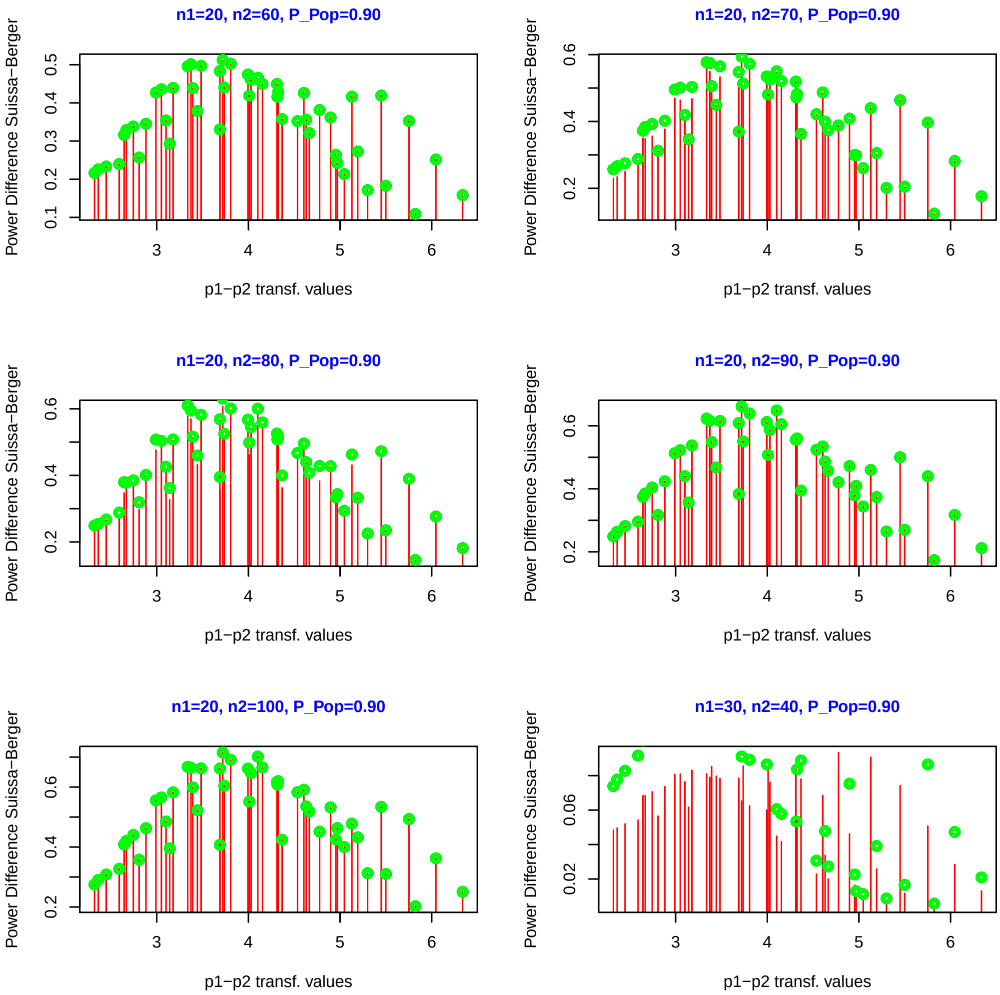

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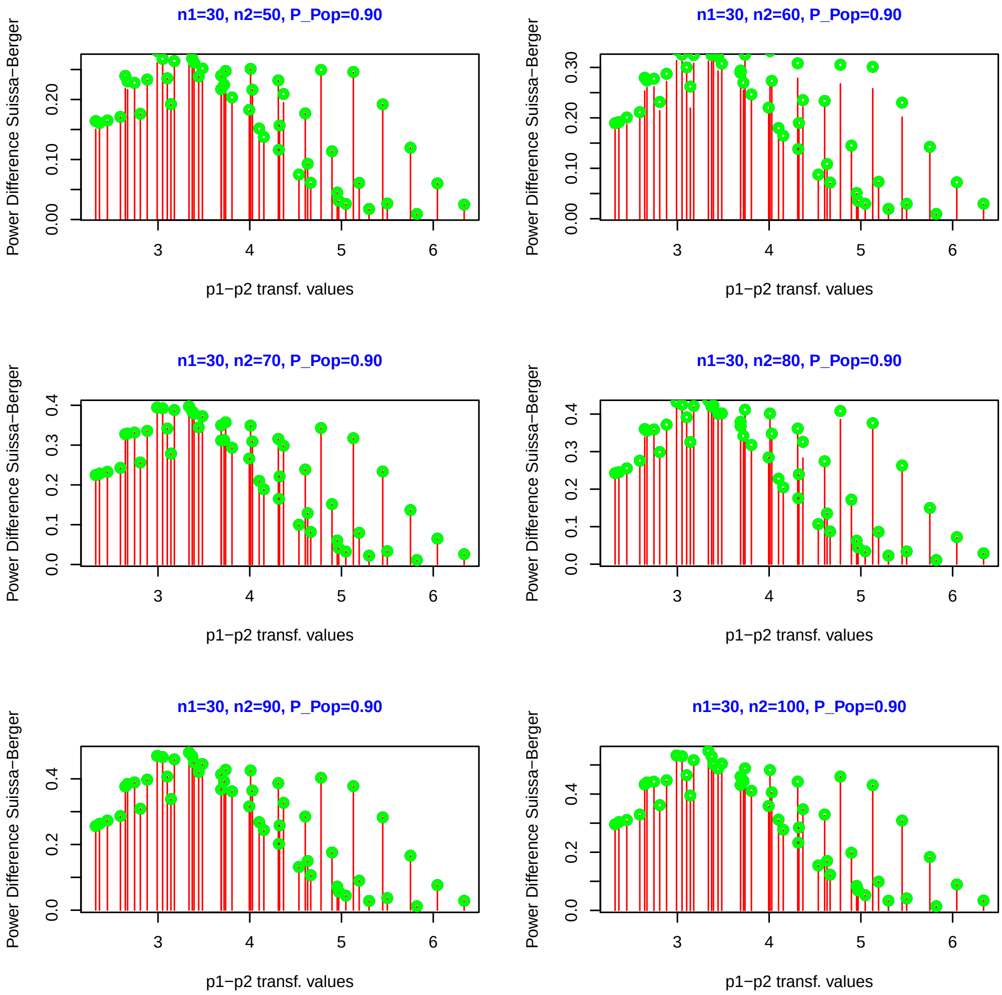

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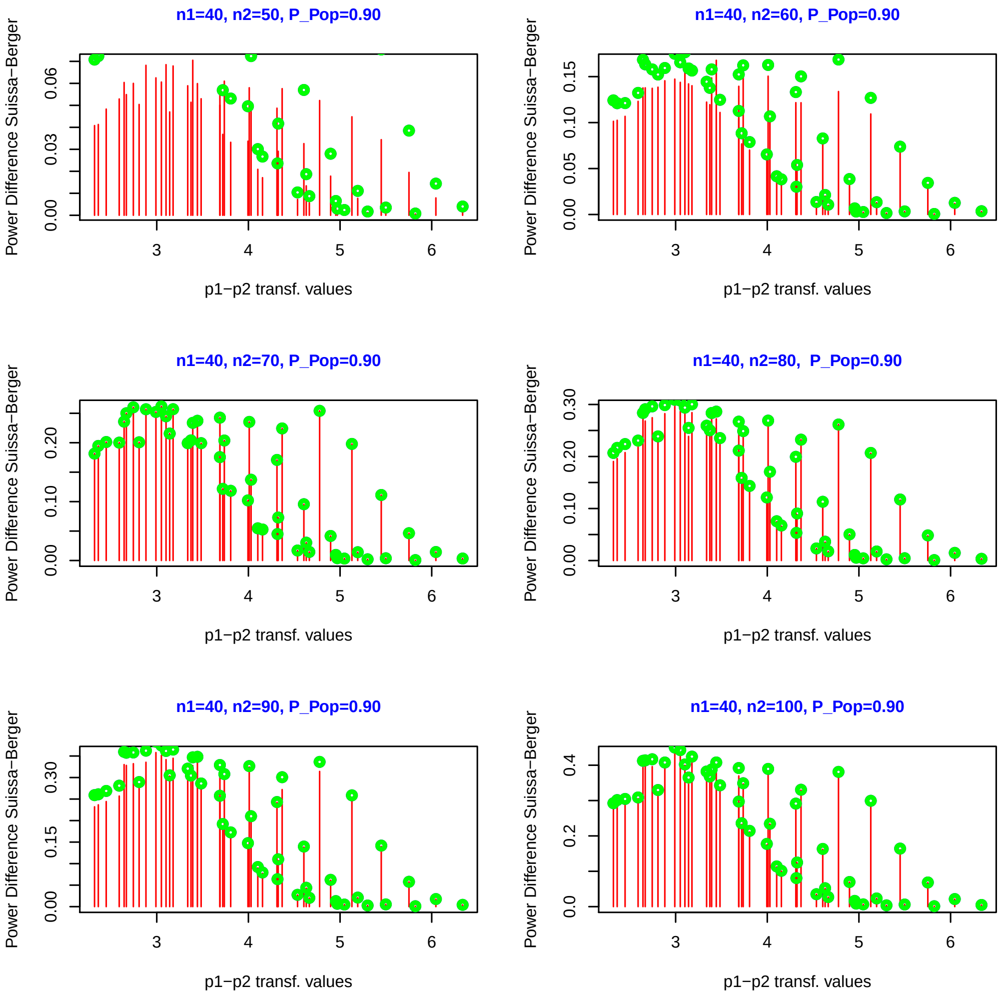

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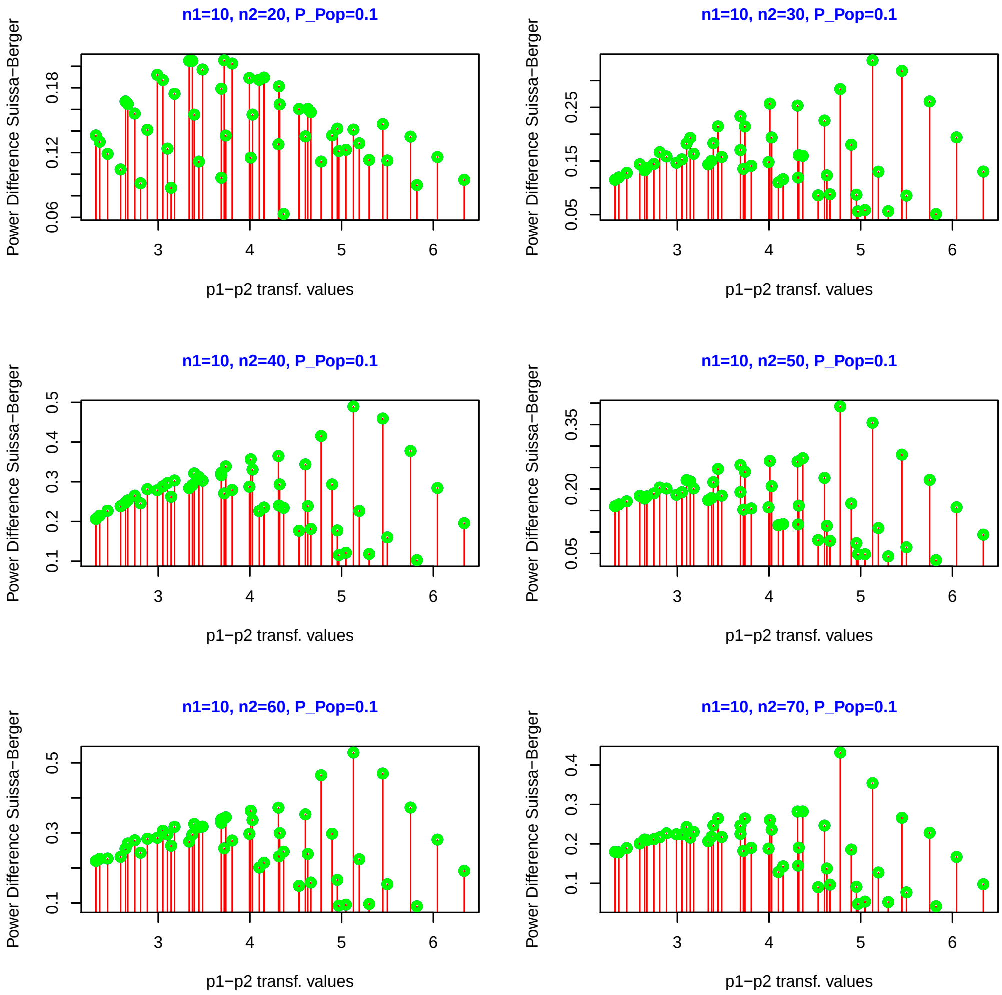
Figure C.19: Comparison of power between the Suissa pooled test and the Berger pooled test for different sample sizes, $\boldsymbol{\alpha}= \mathbf{0.05}$.



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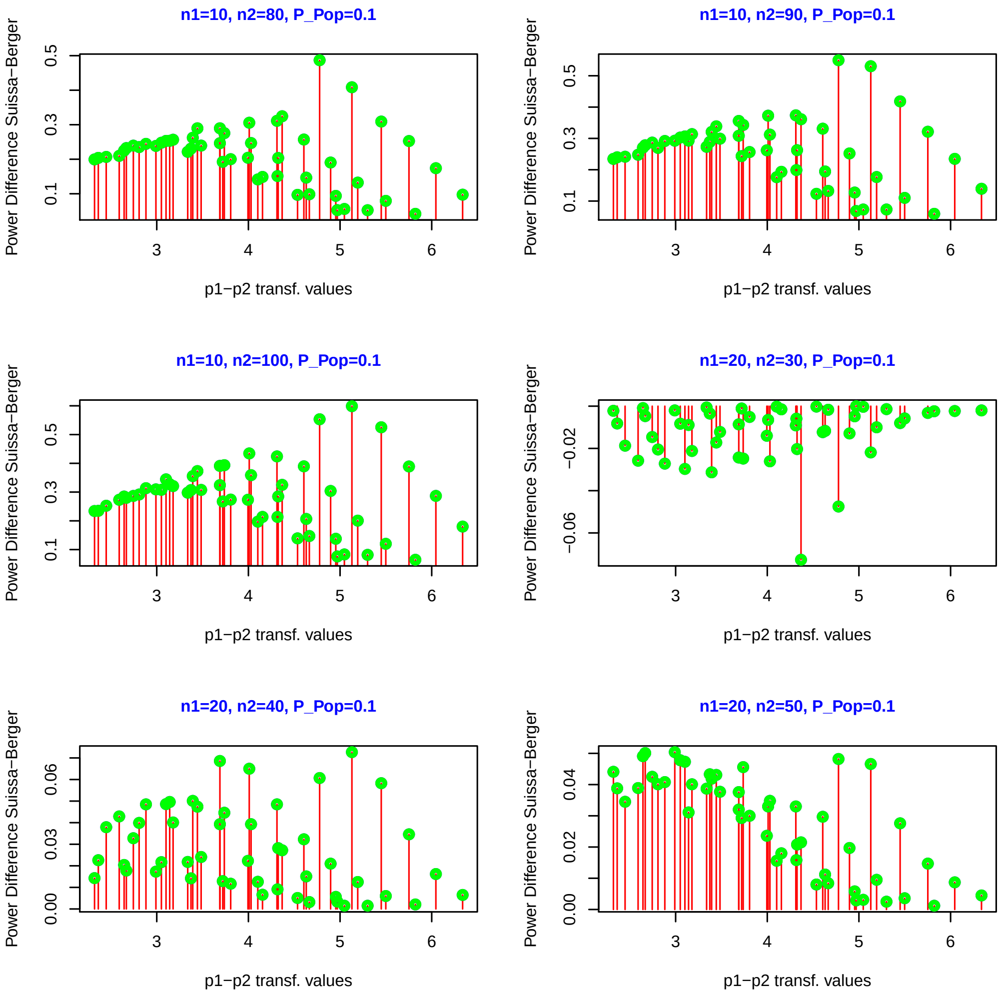

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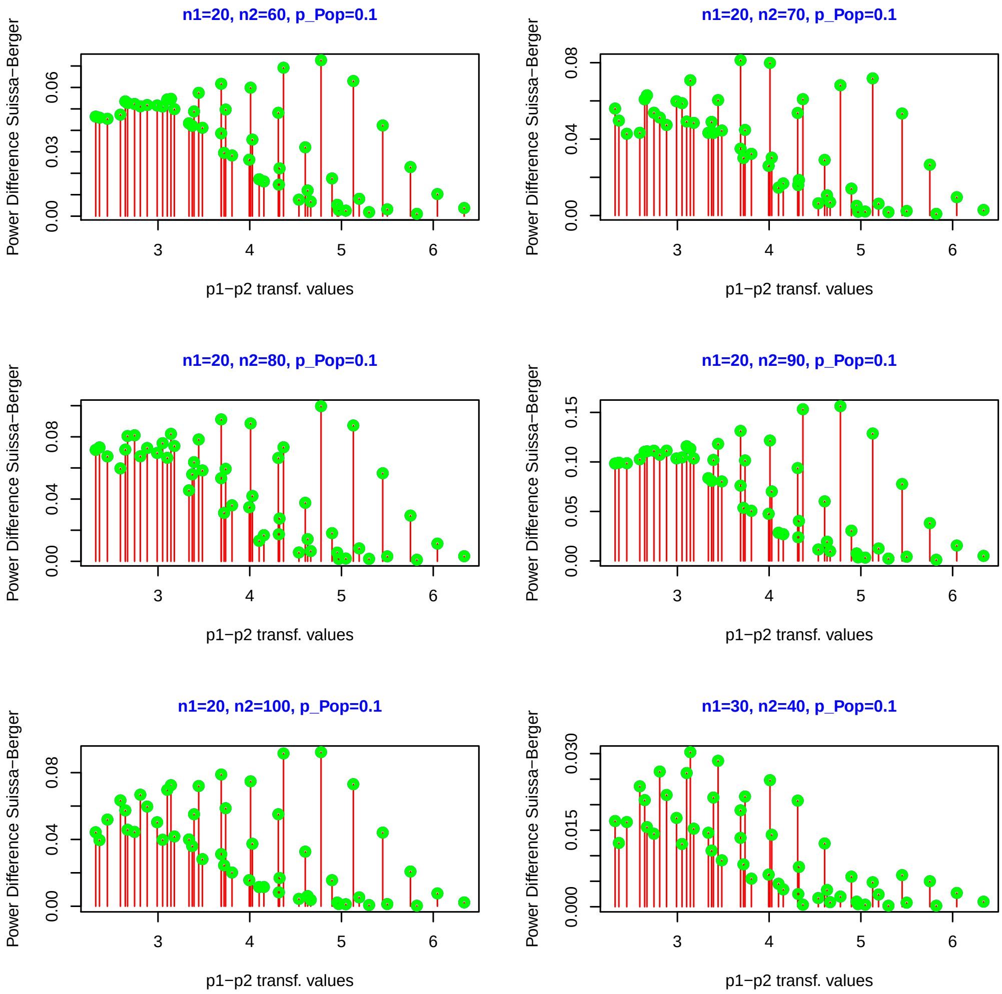

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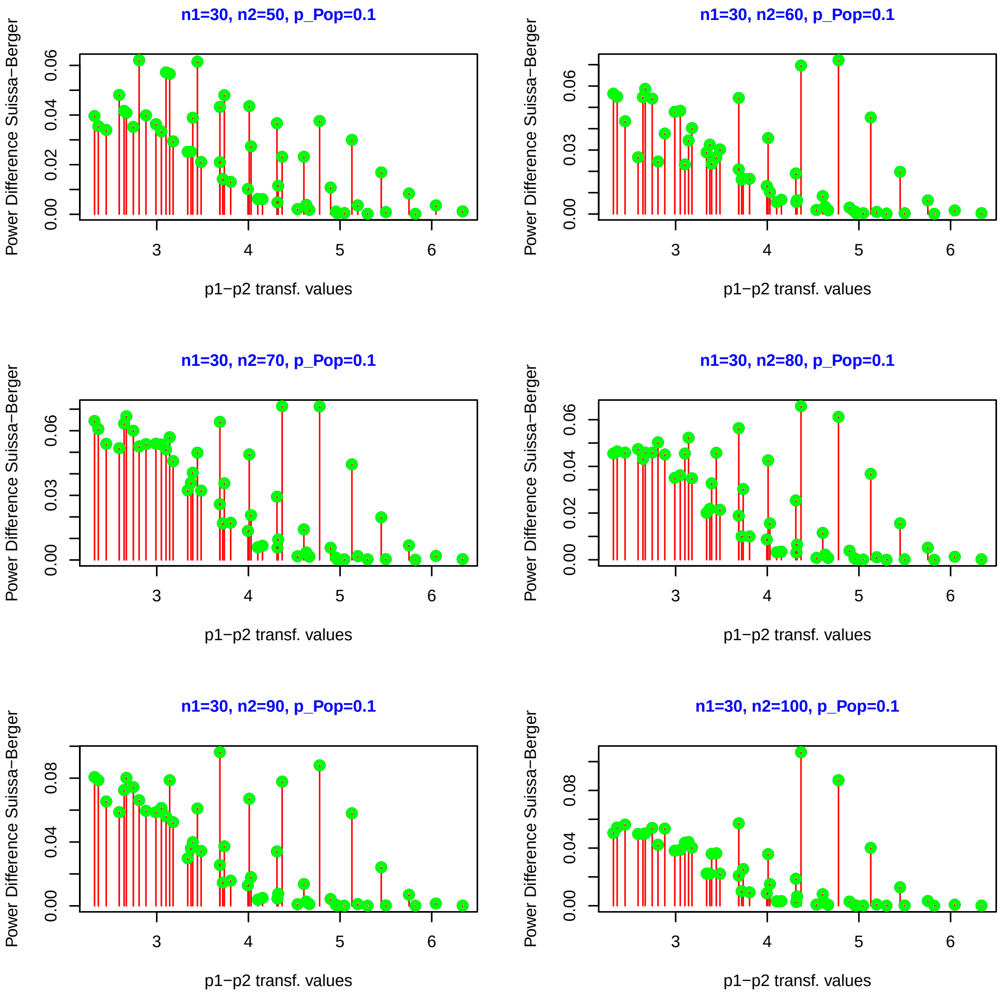

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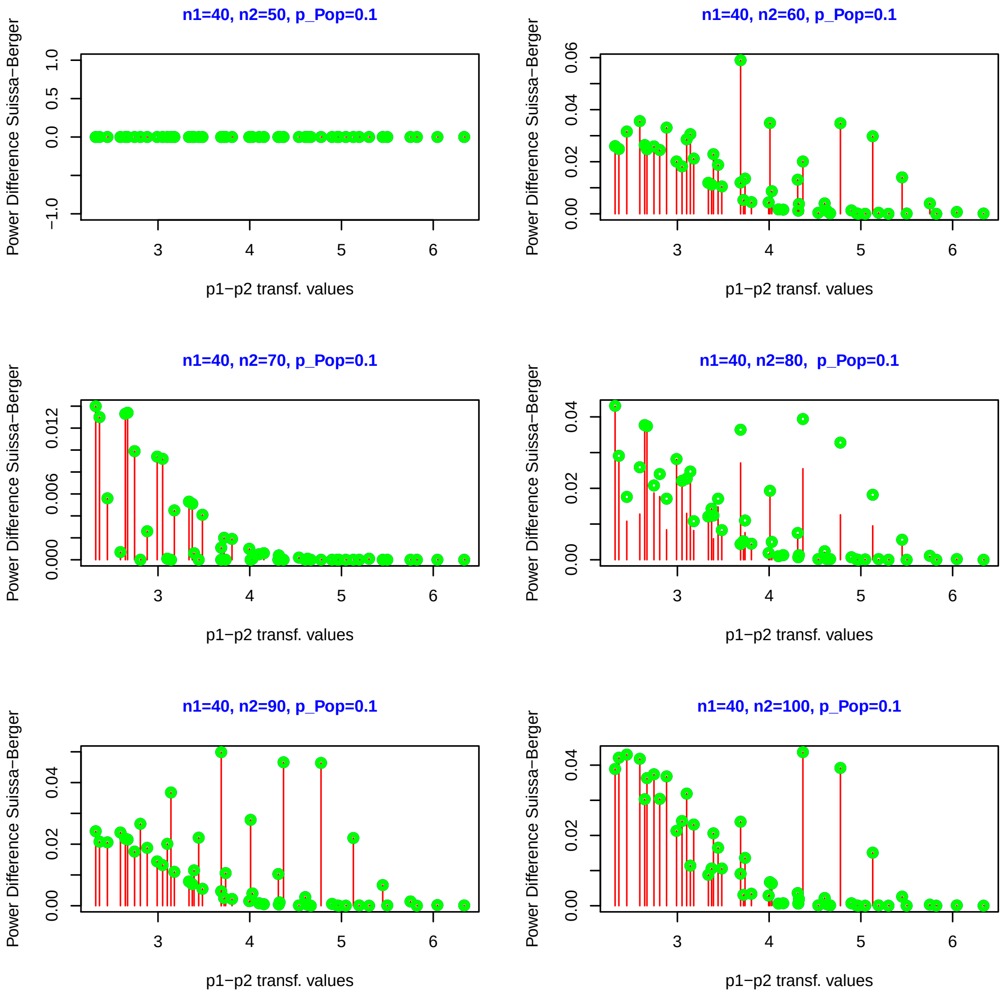

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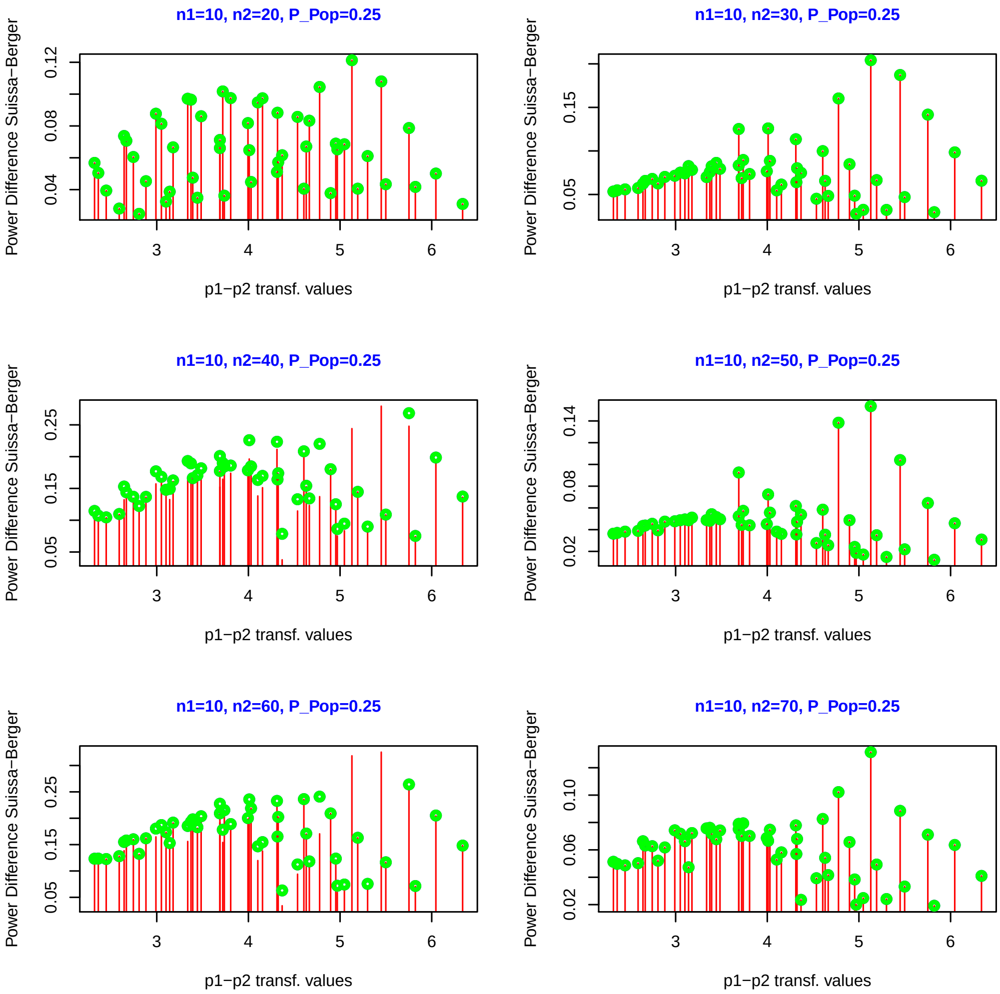

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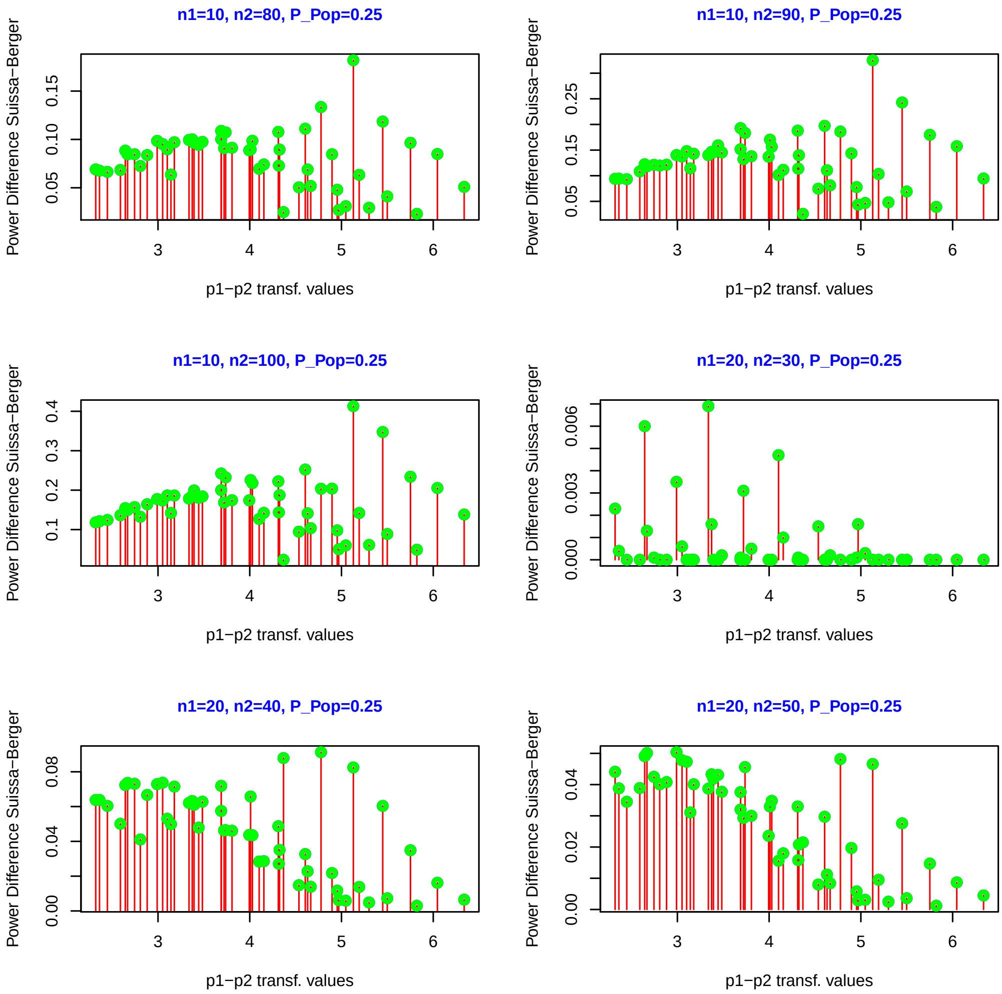

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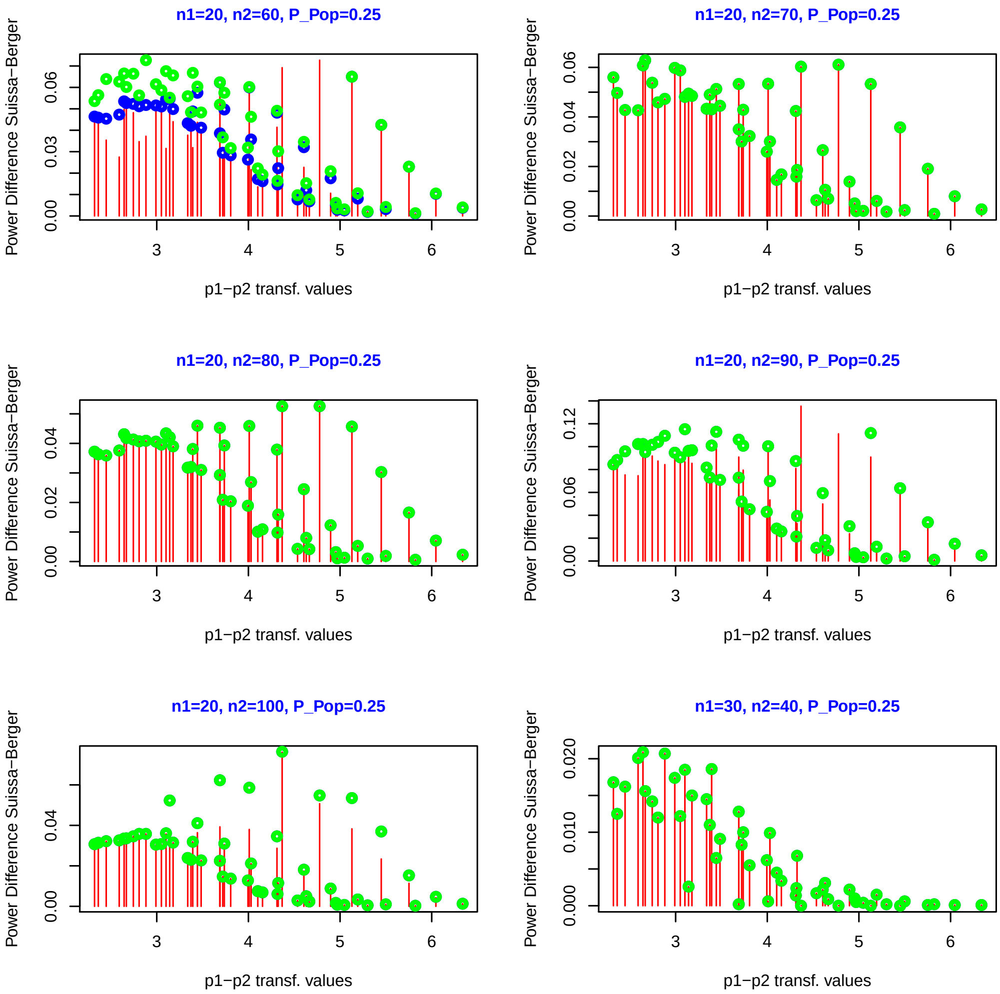

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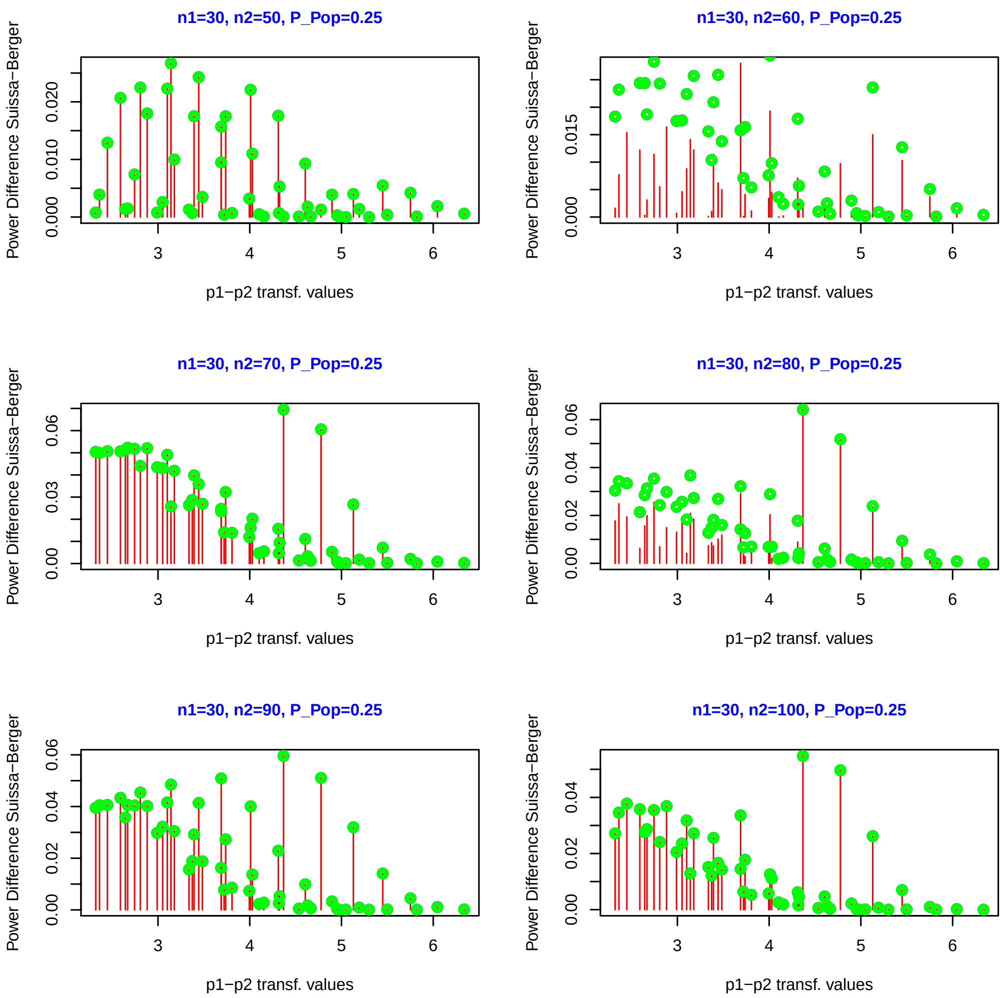

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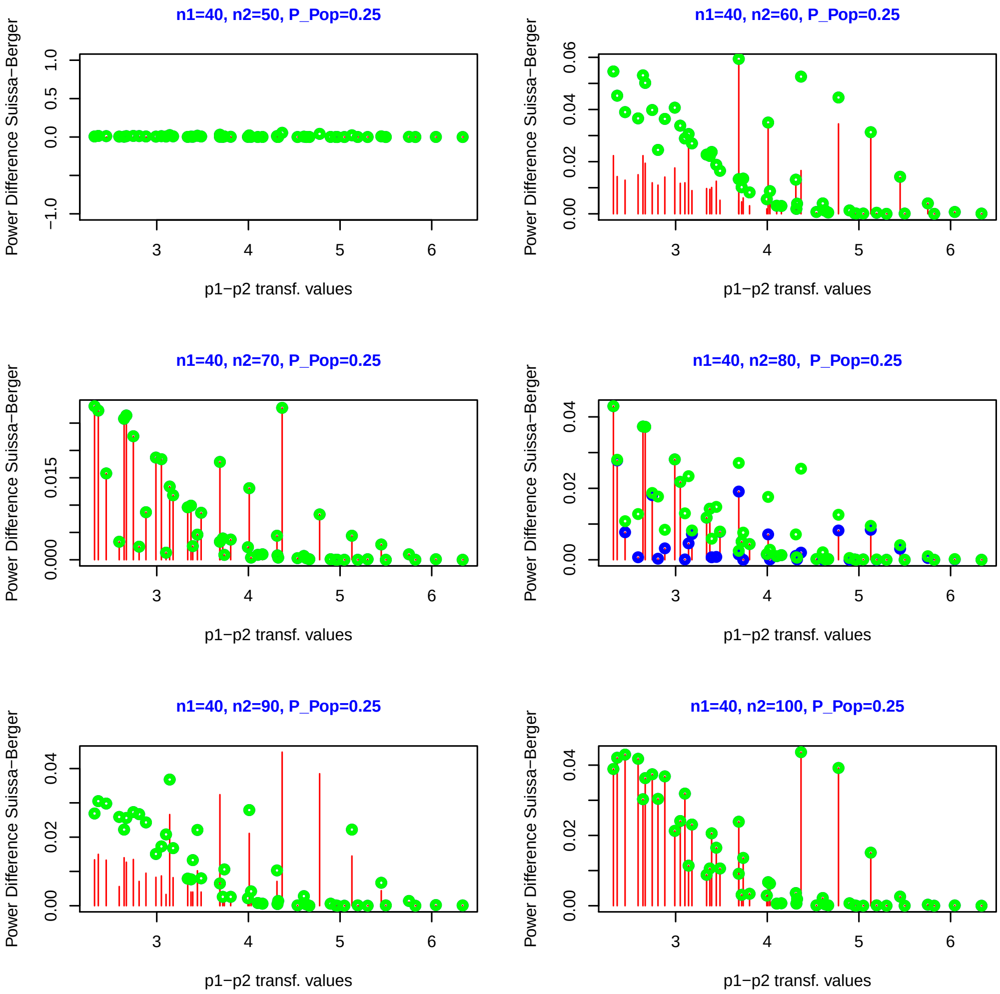

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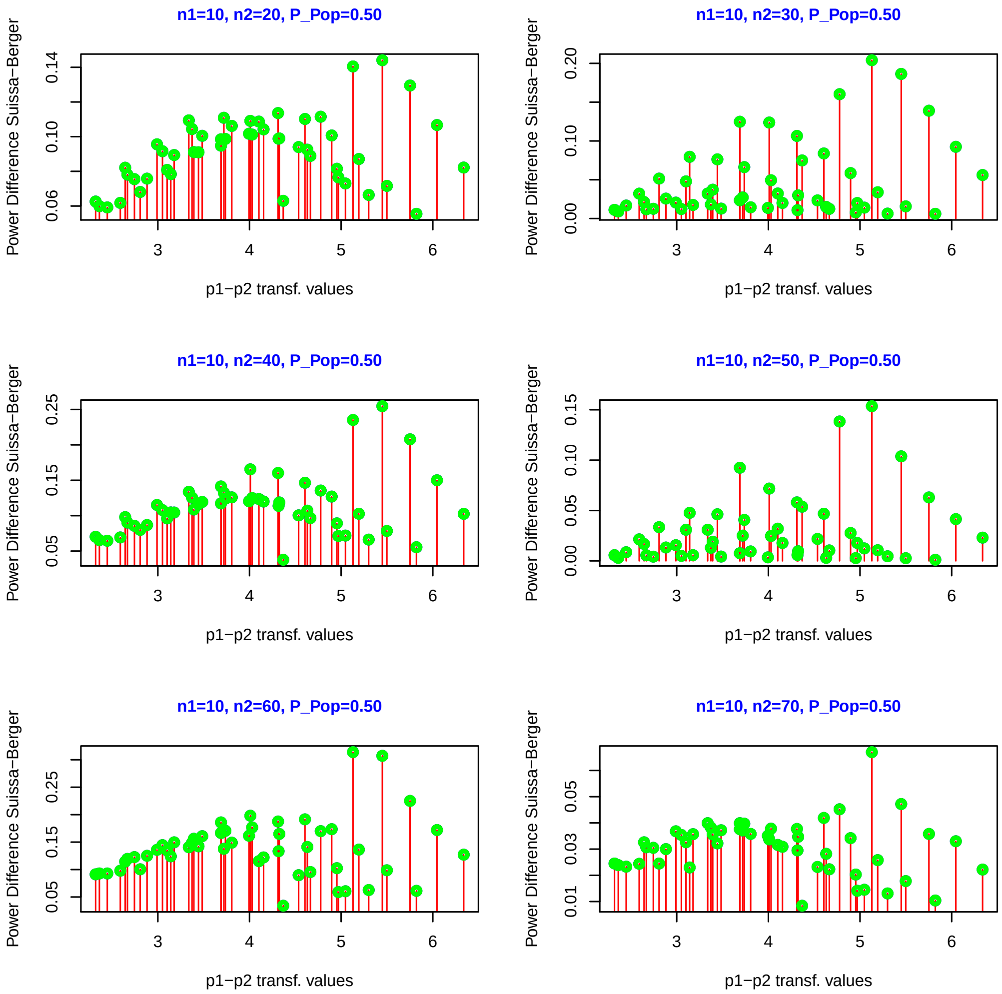

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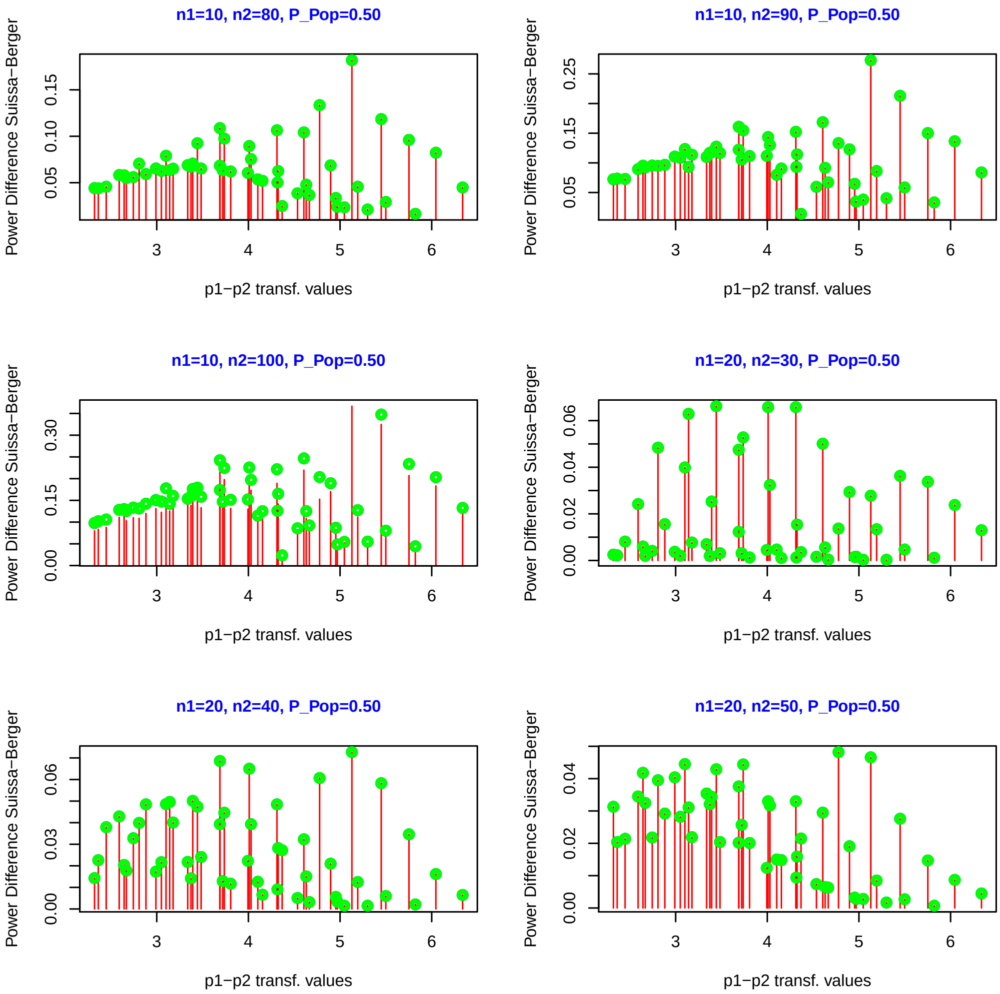

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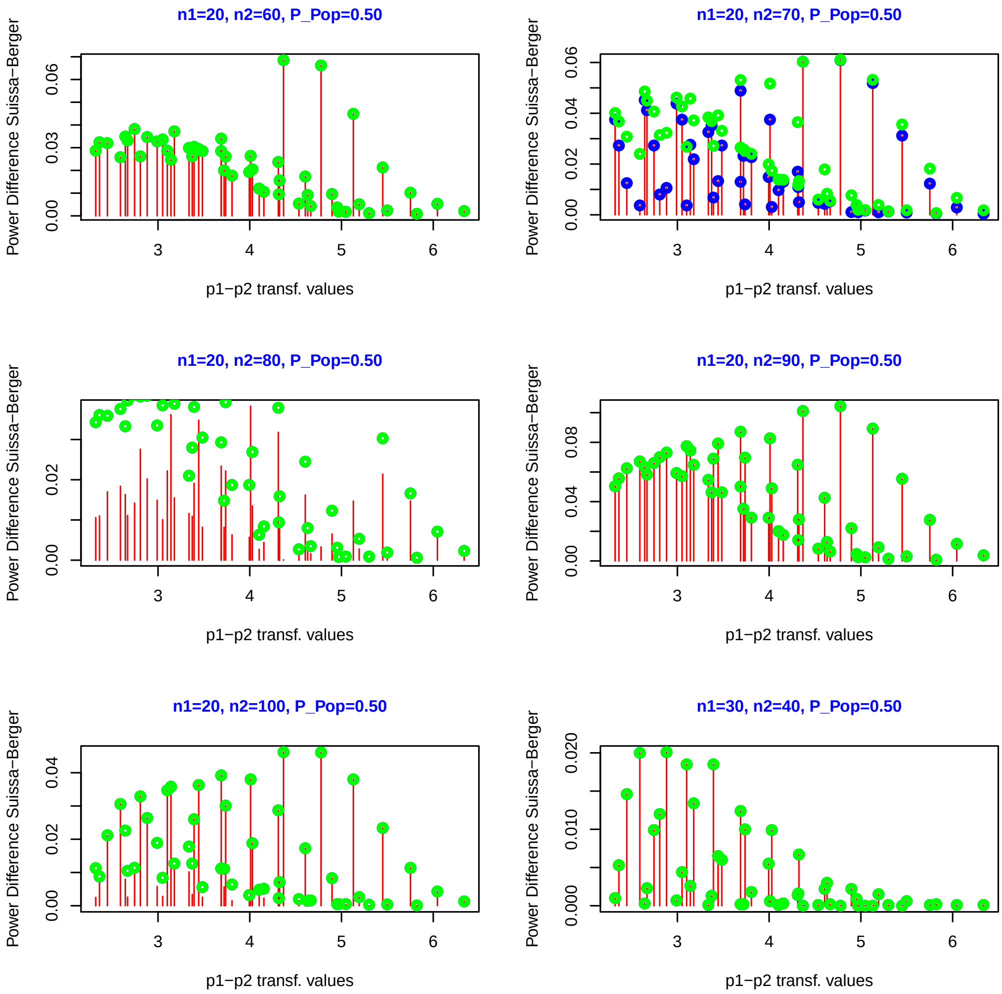

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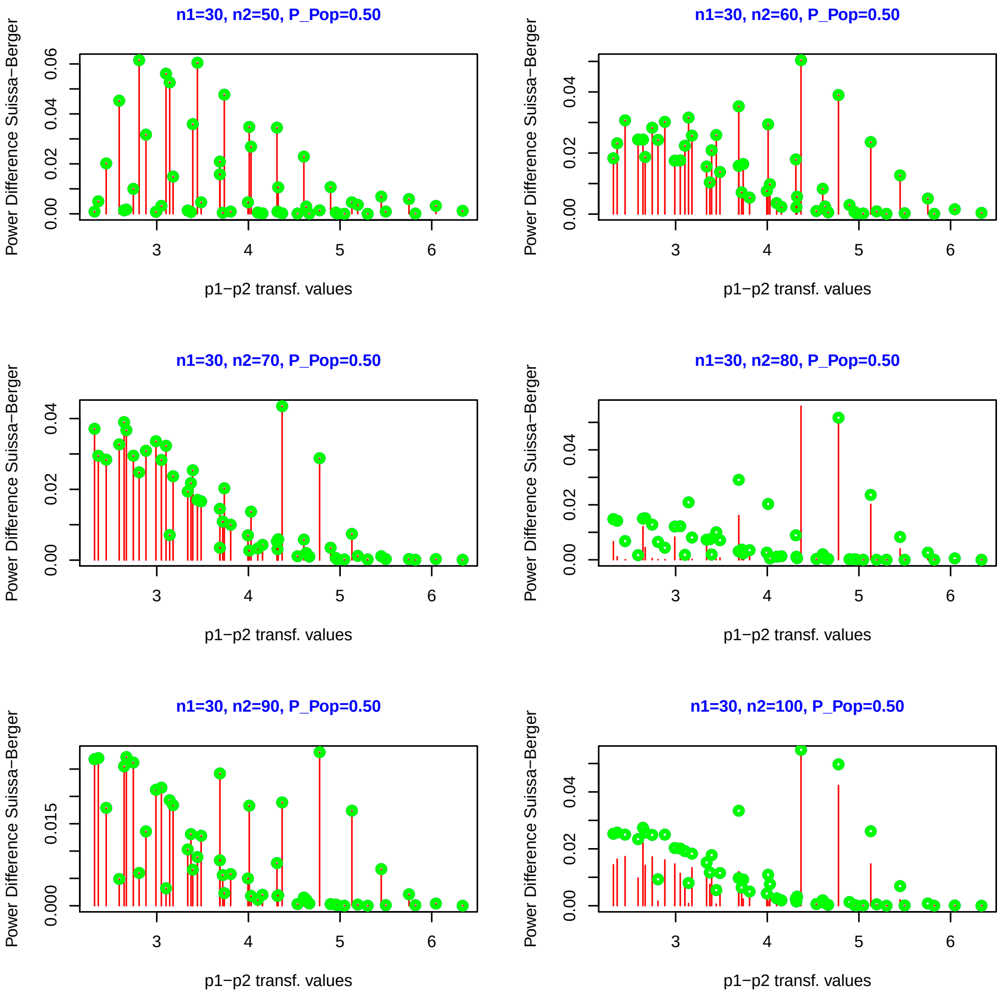

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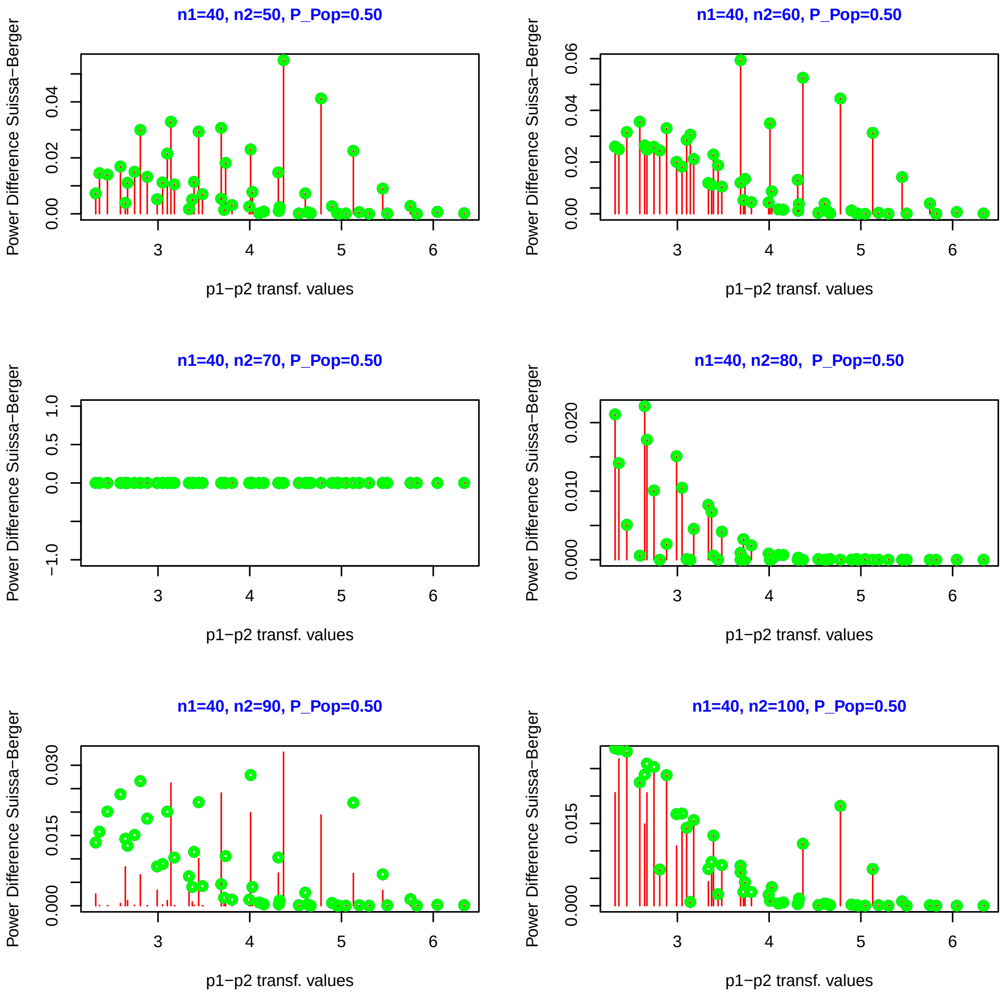

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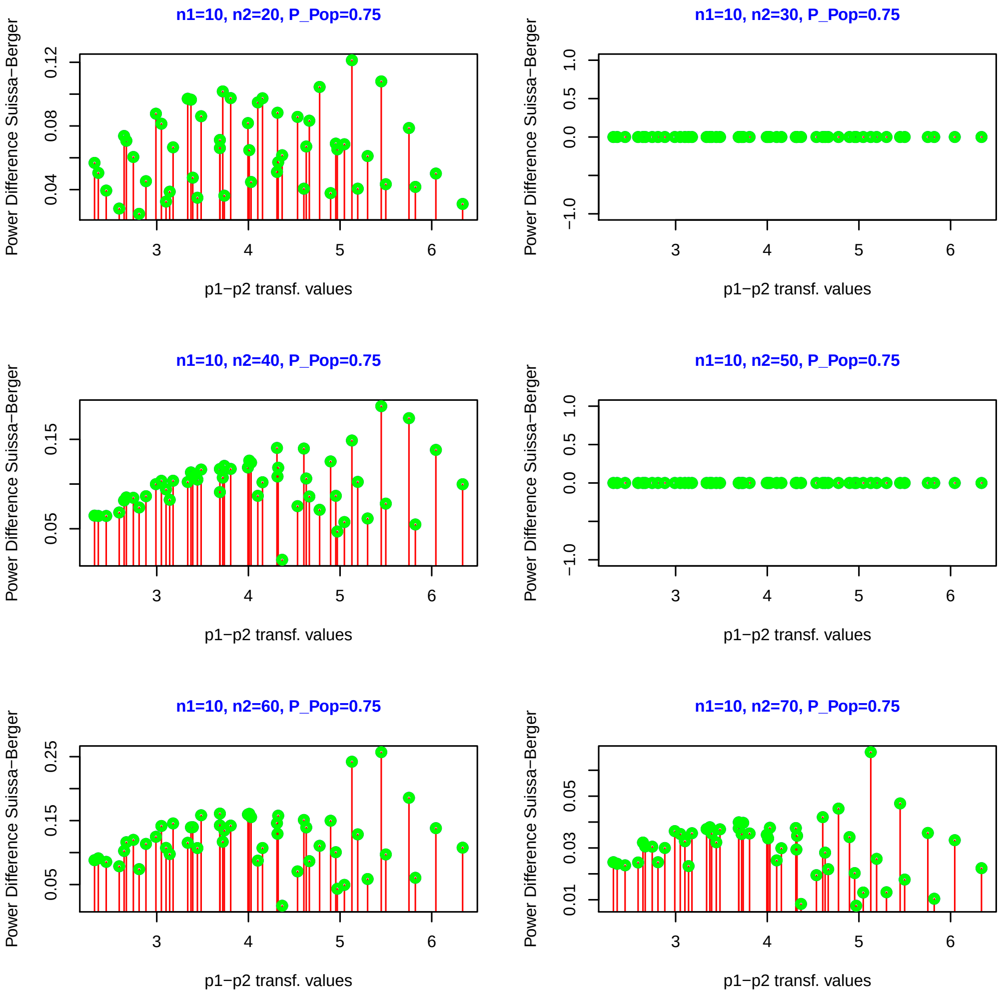

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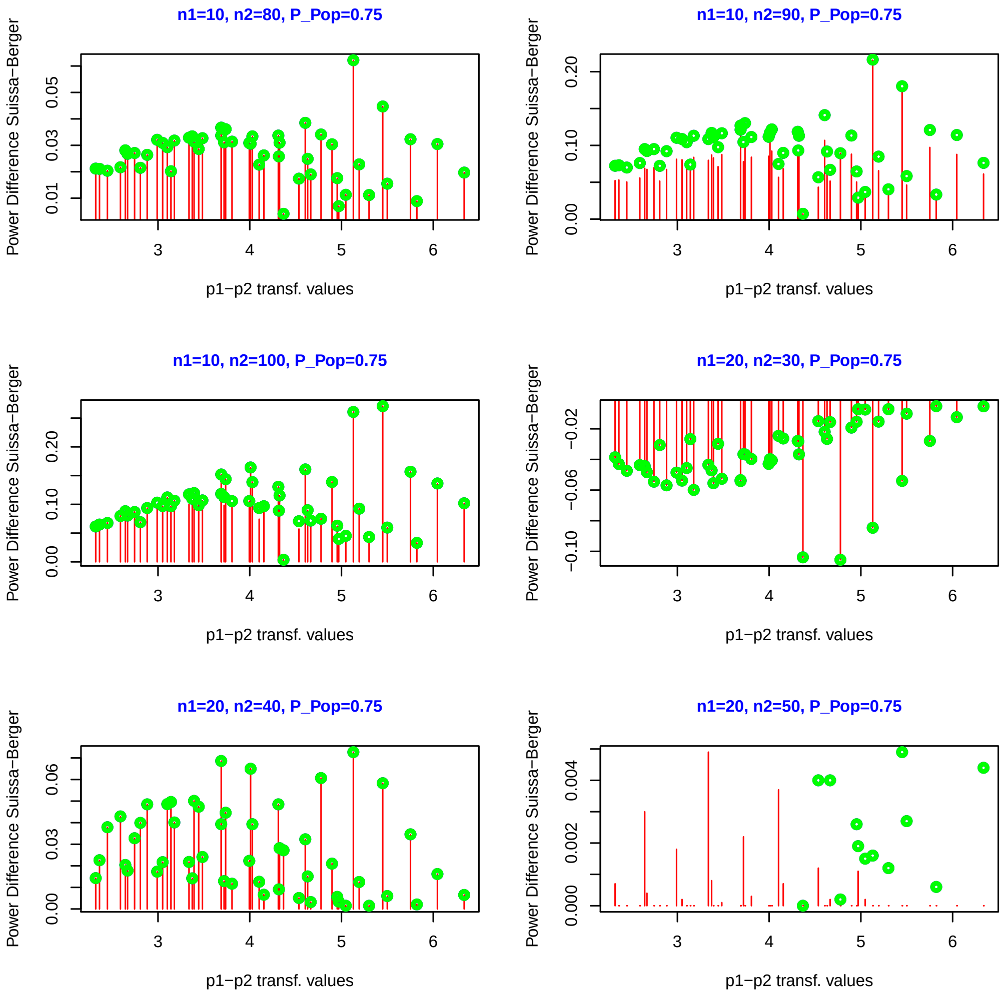

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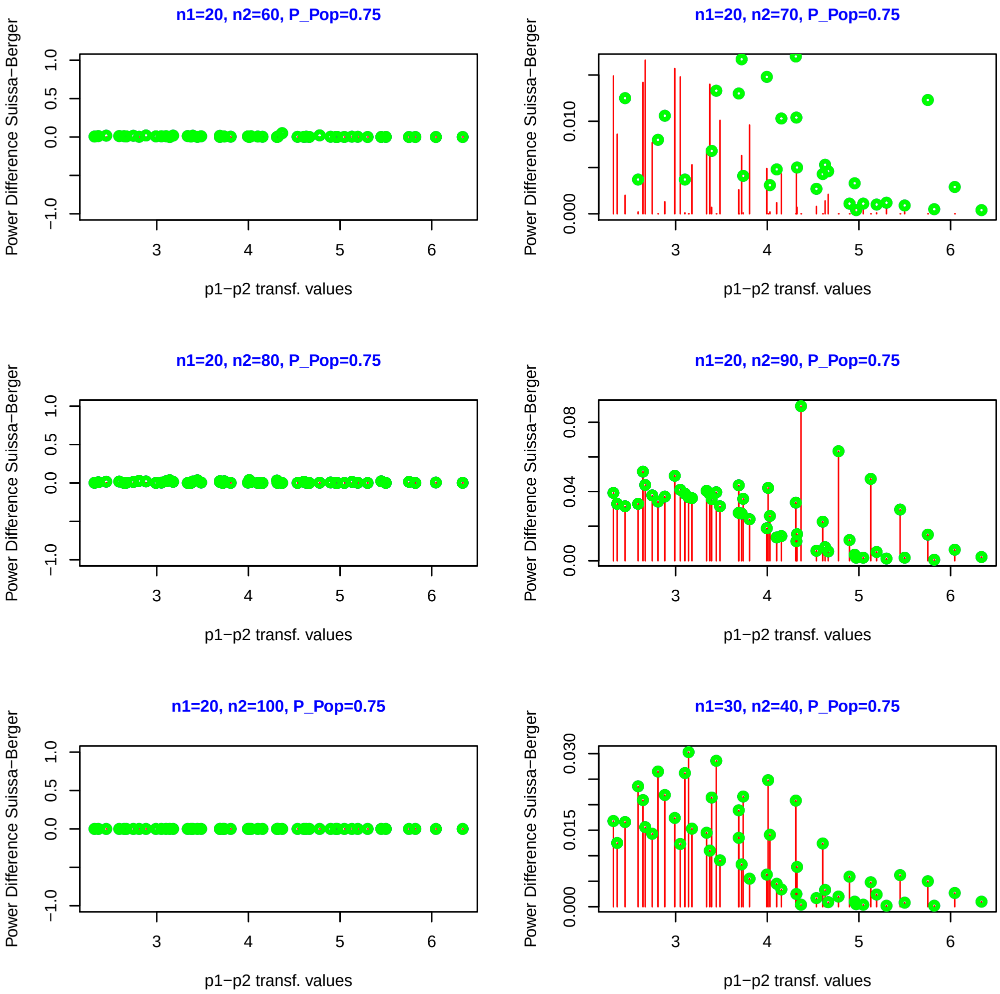

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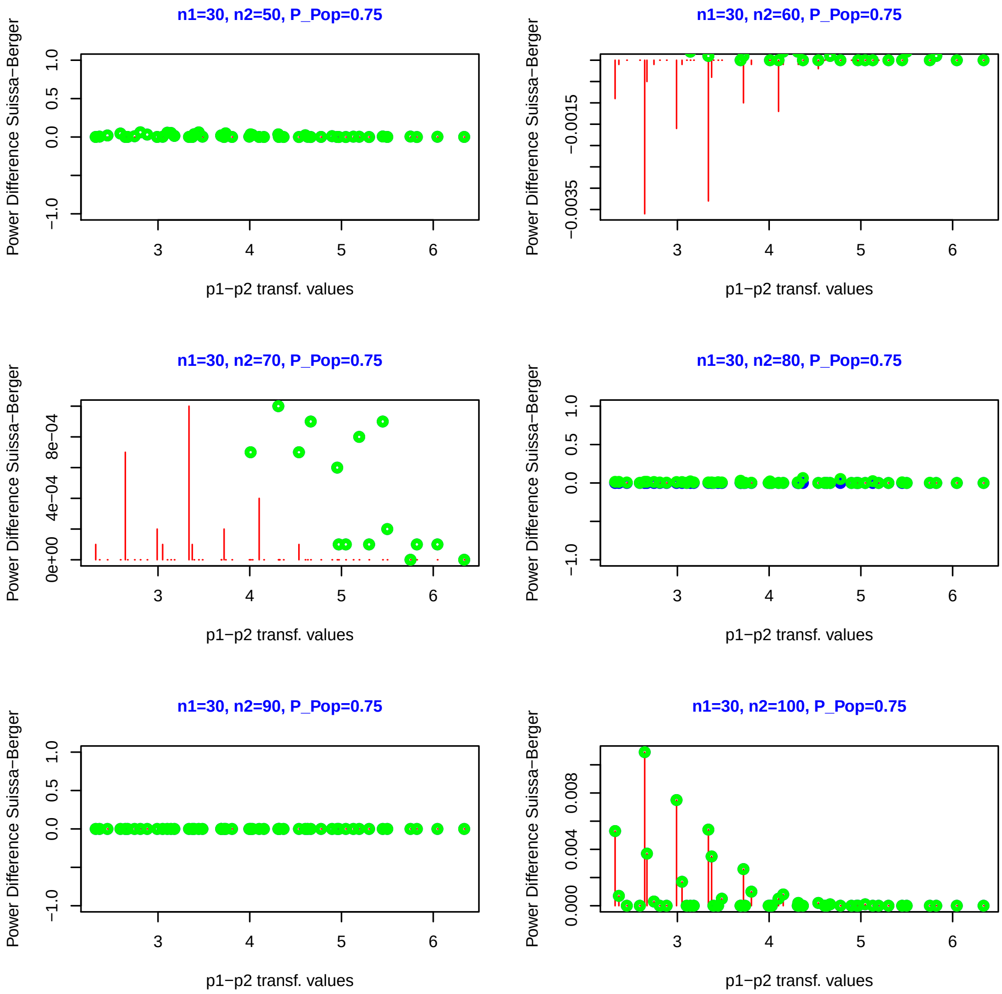

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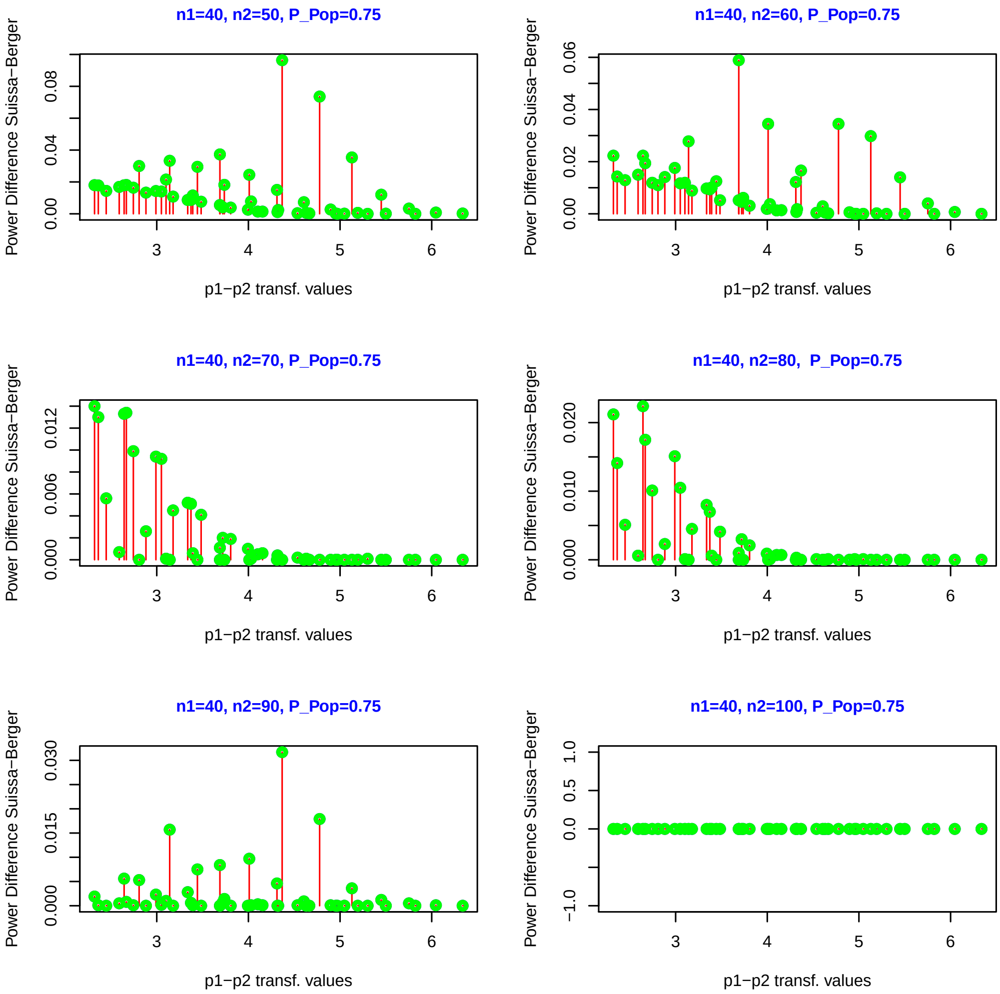

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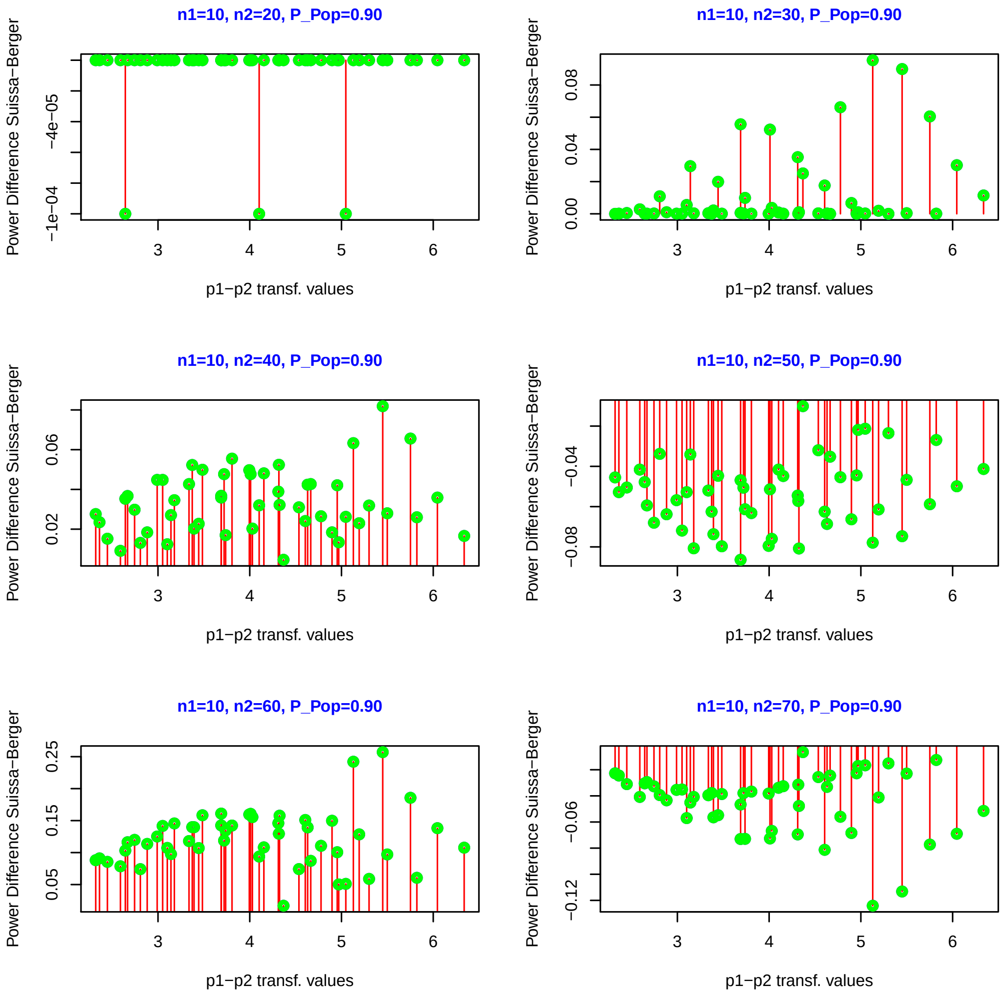

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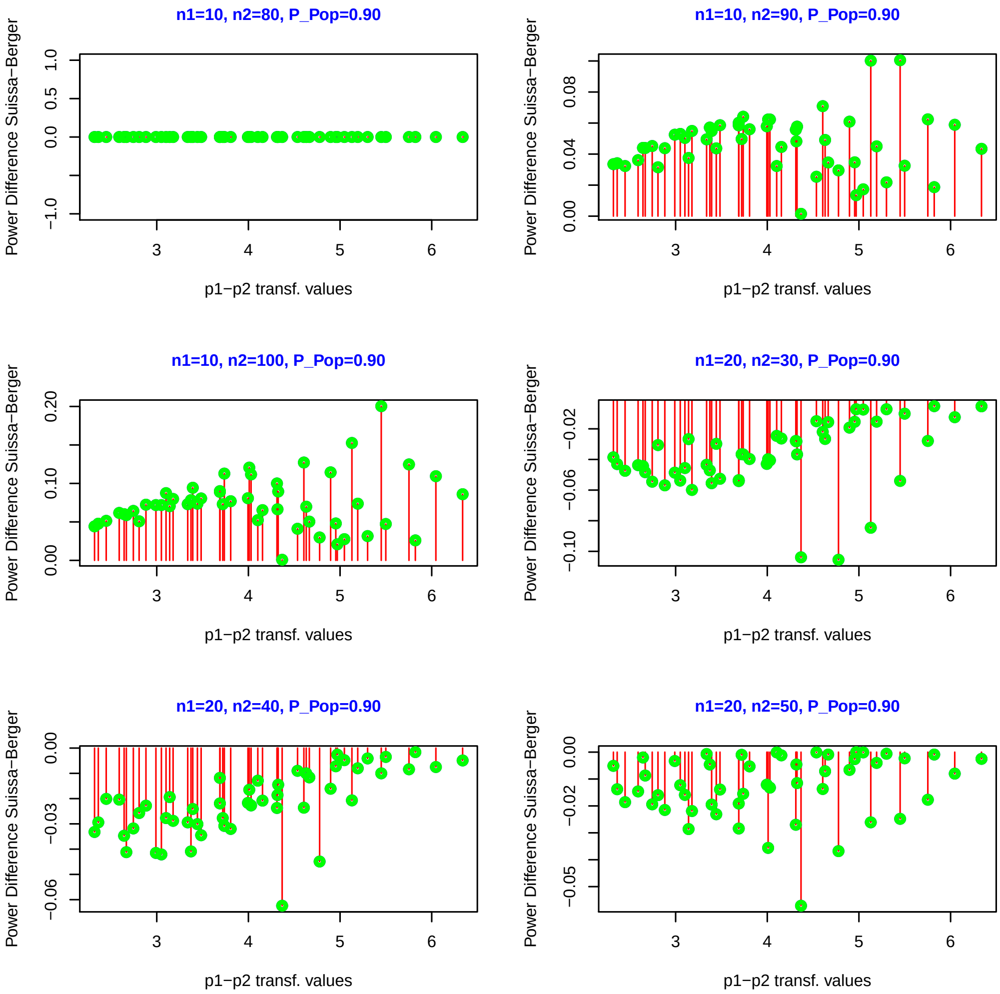

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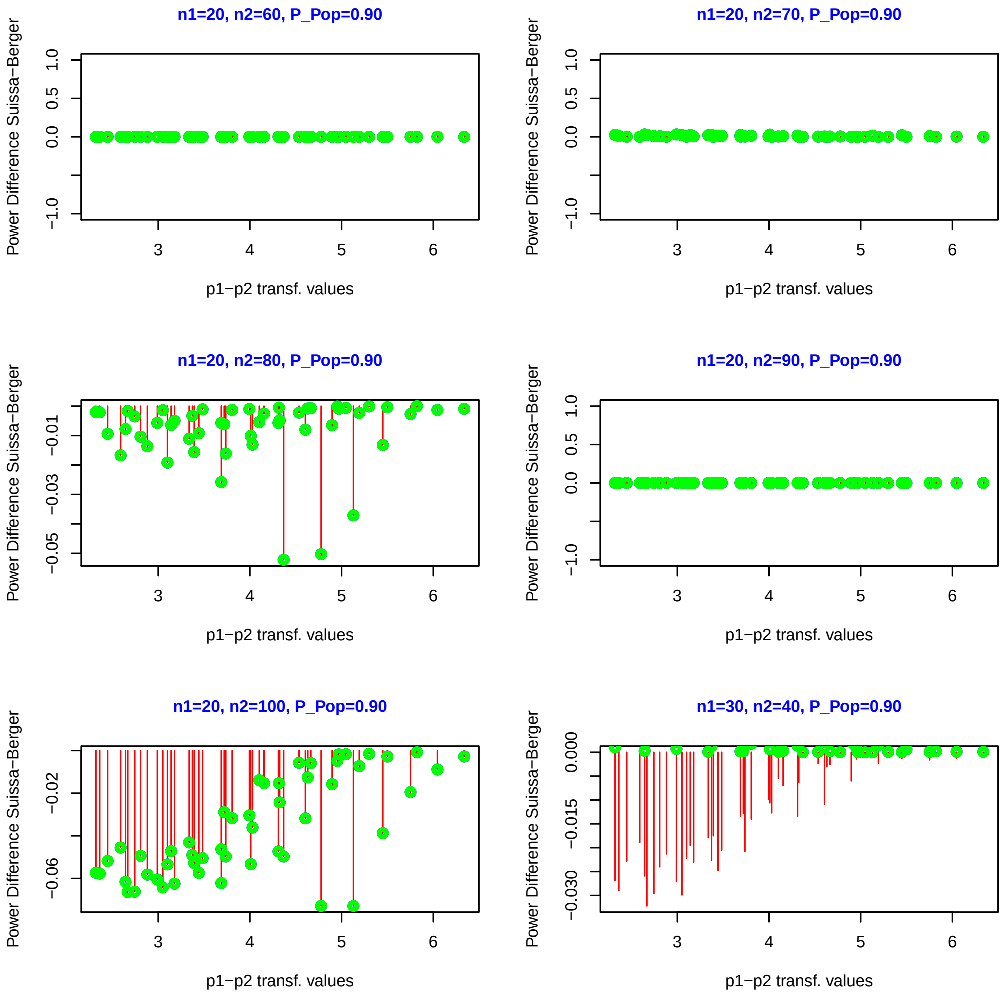

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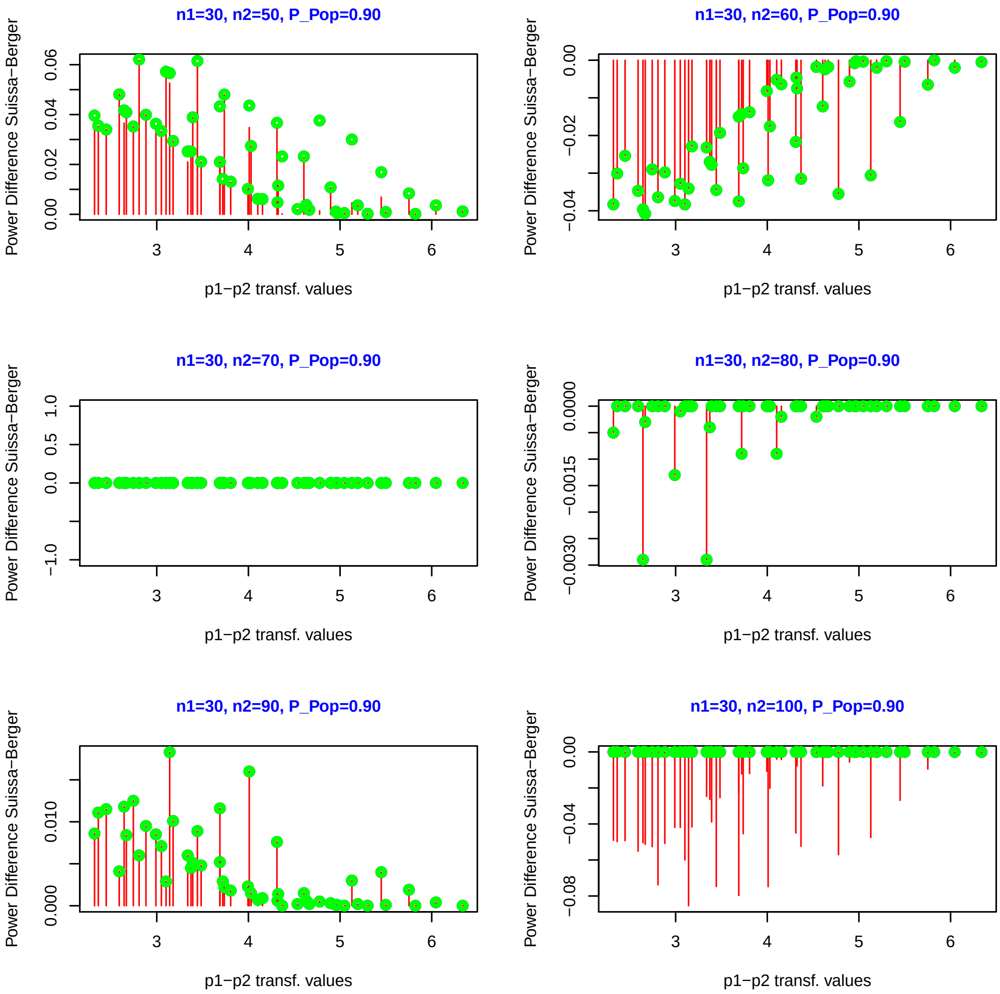

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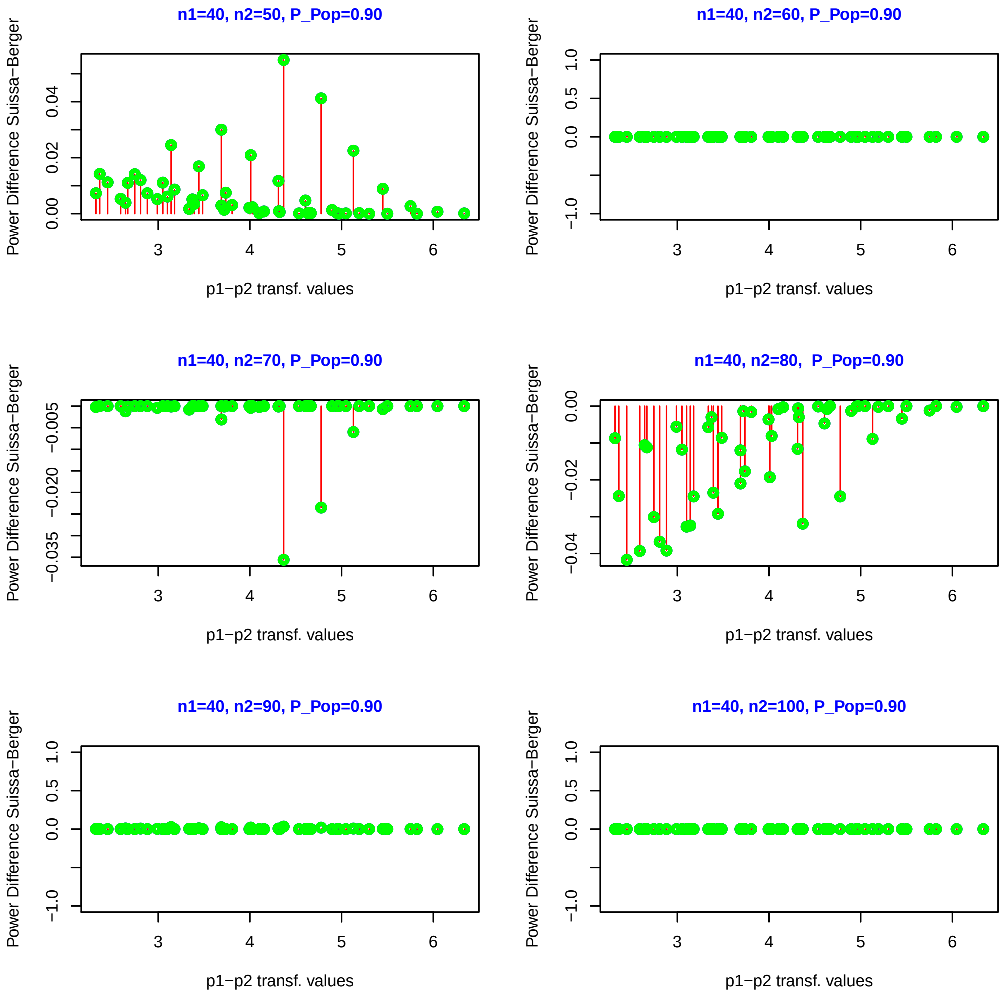

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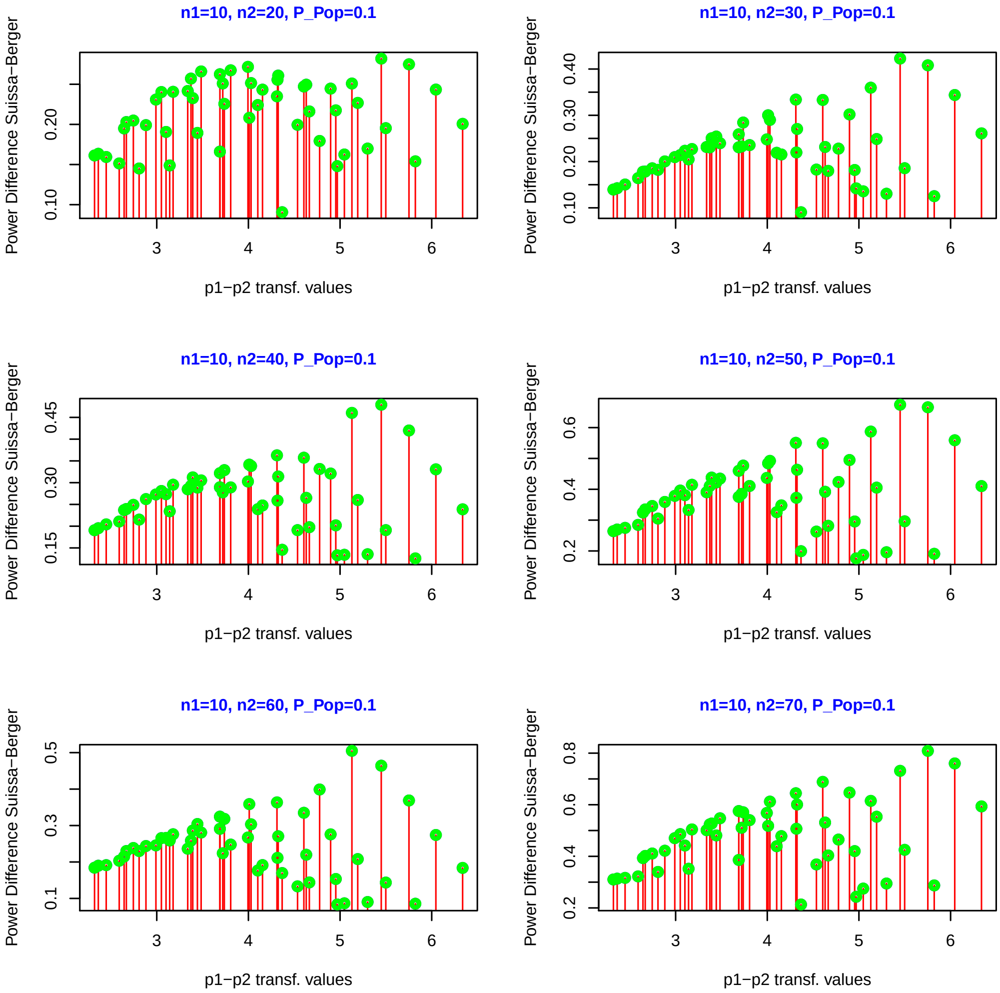
Figure C.20: Comparison of power between the Suissa pooled test and the Berger pooled test for different sample sizes, $\boldsymbol{\alpha}$= **0.025**.



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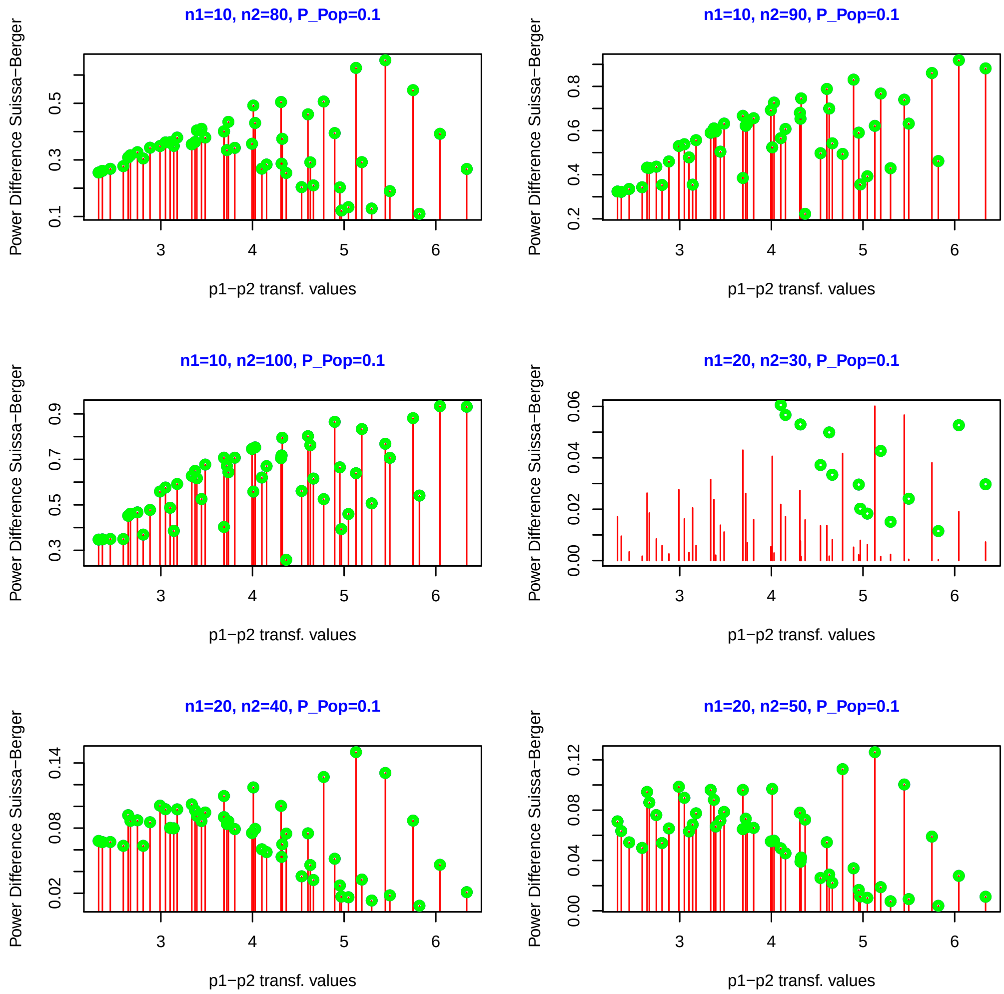

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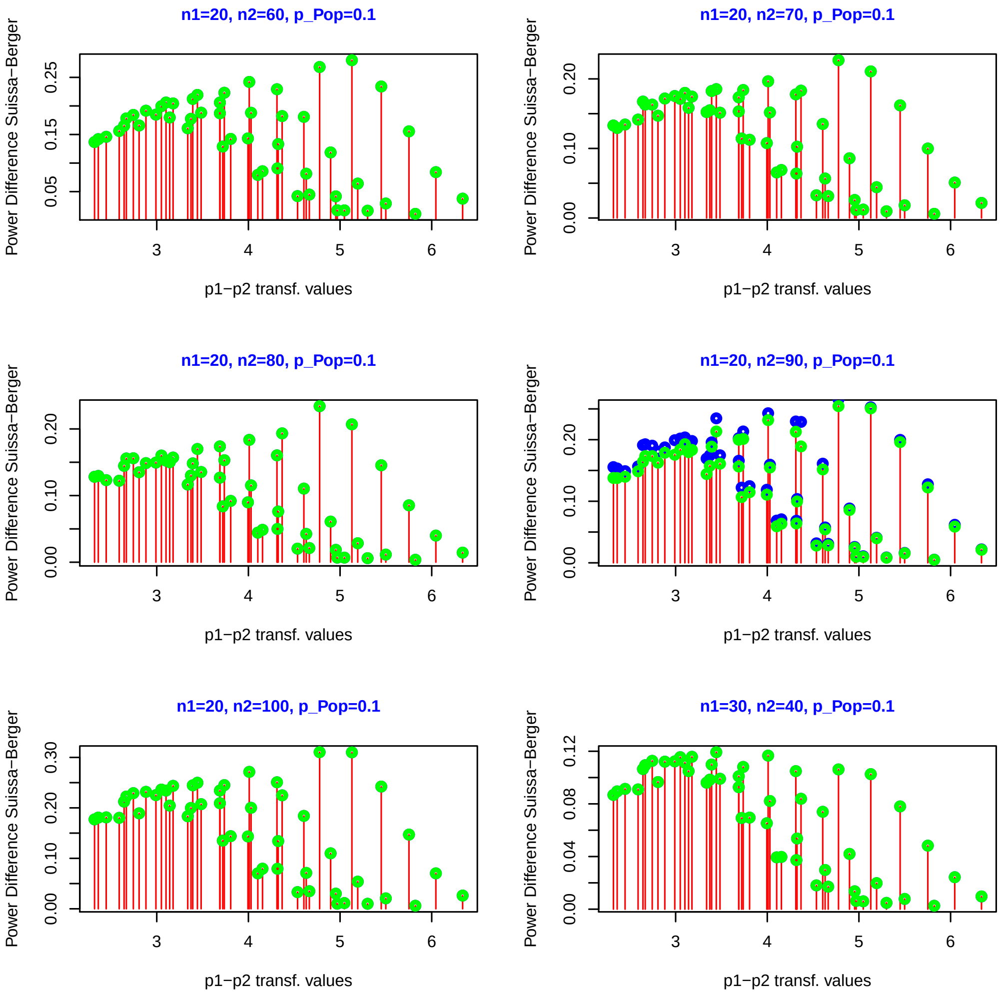

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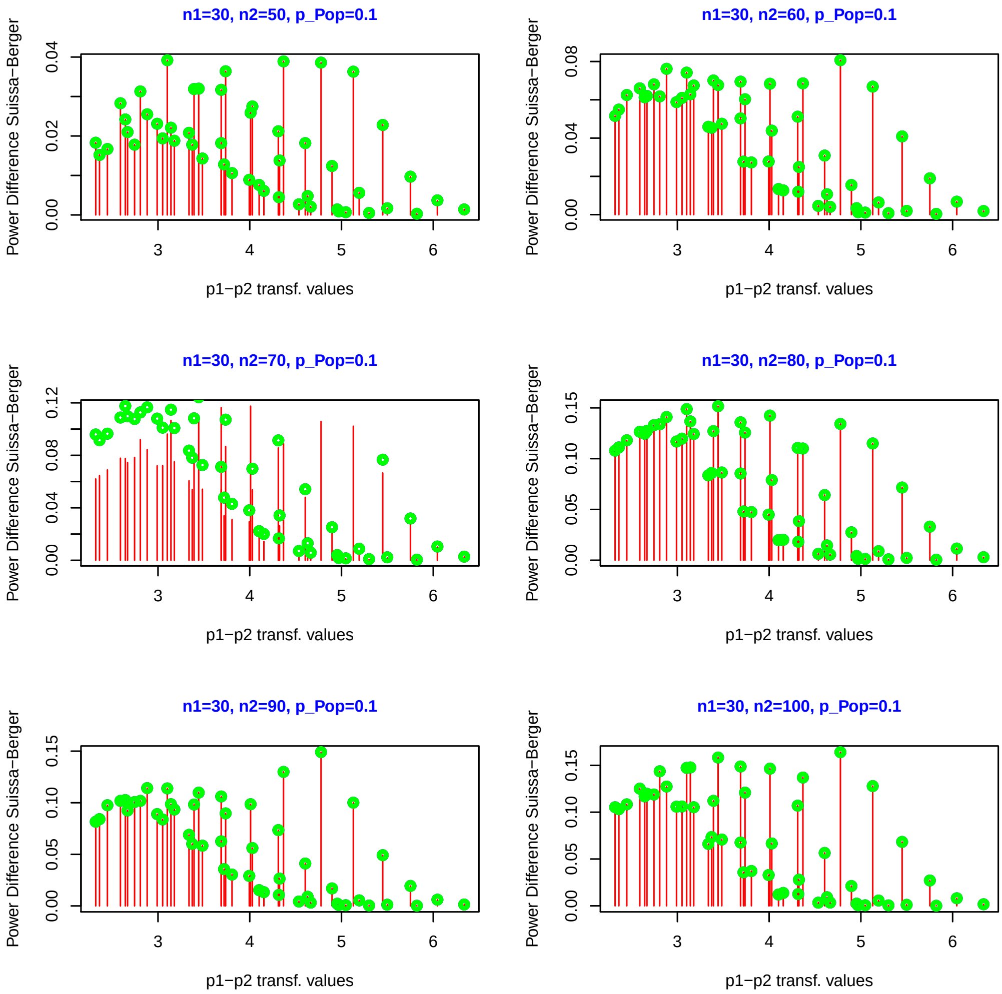

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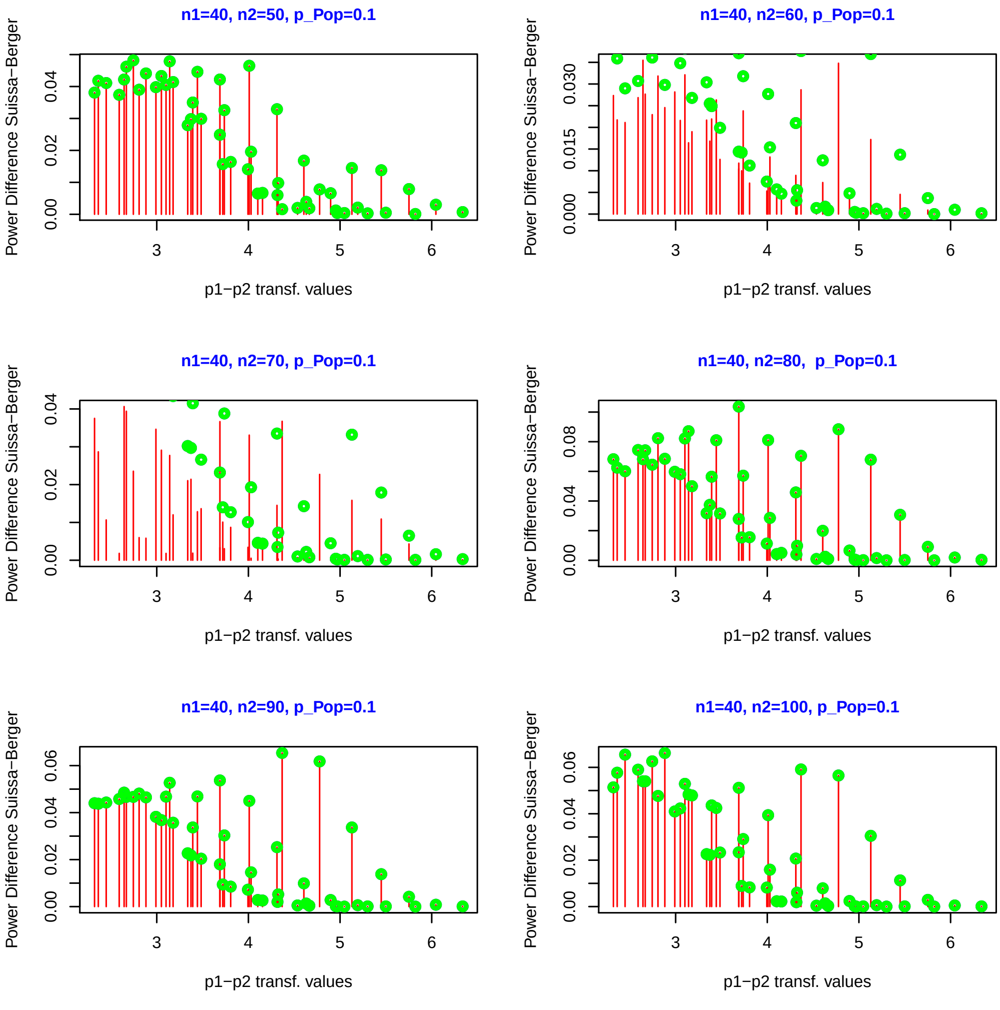

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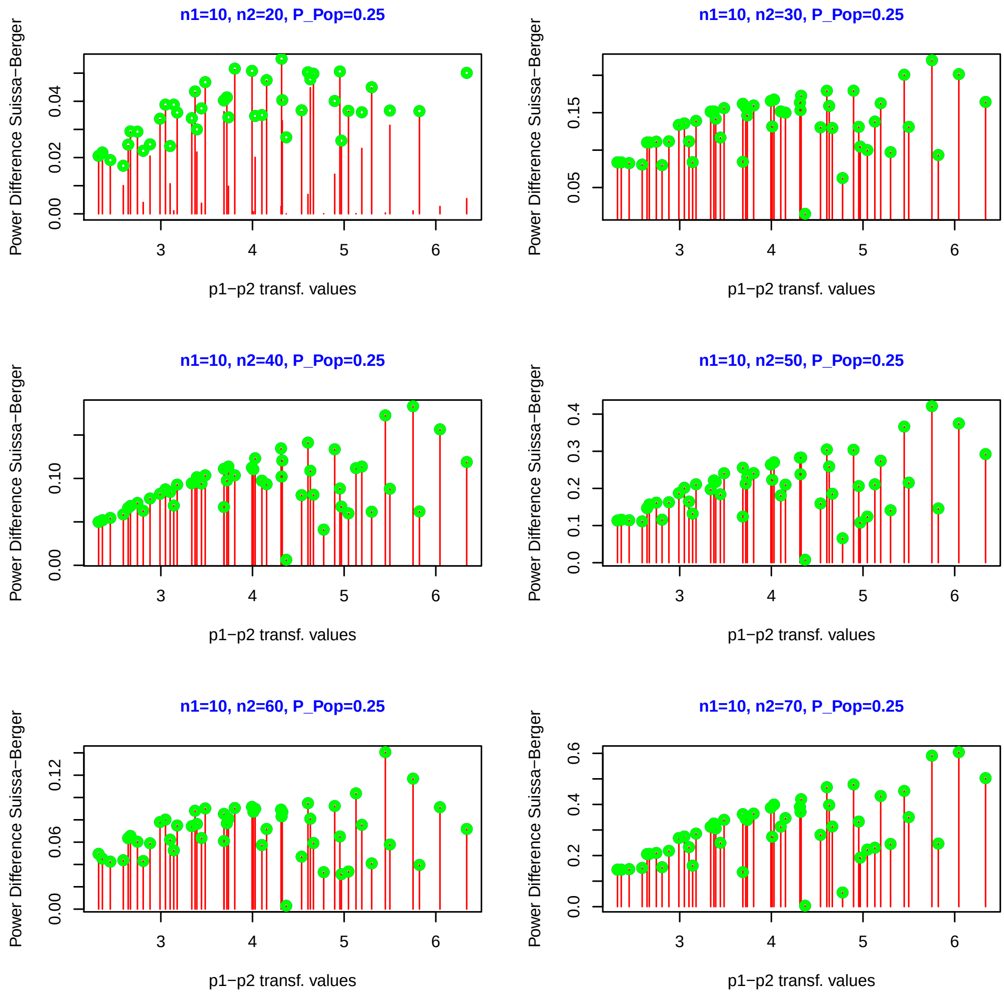

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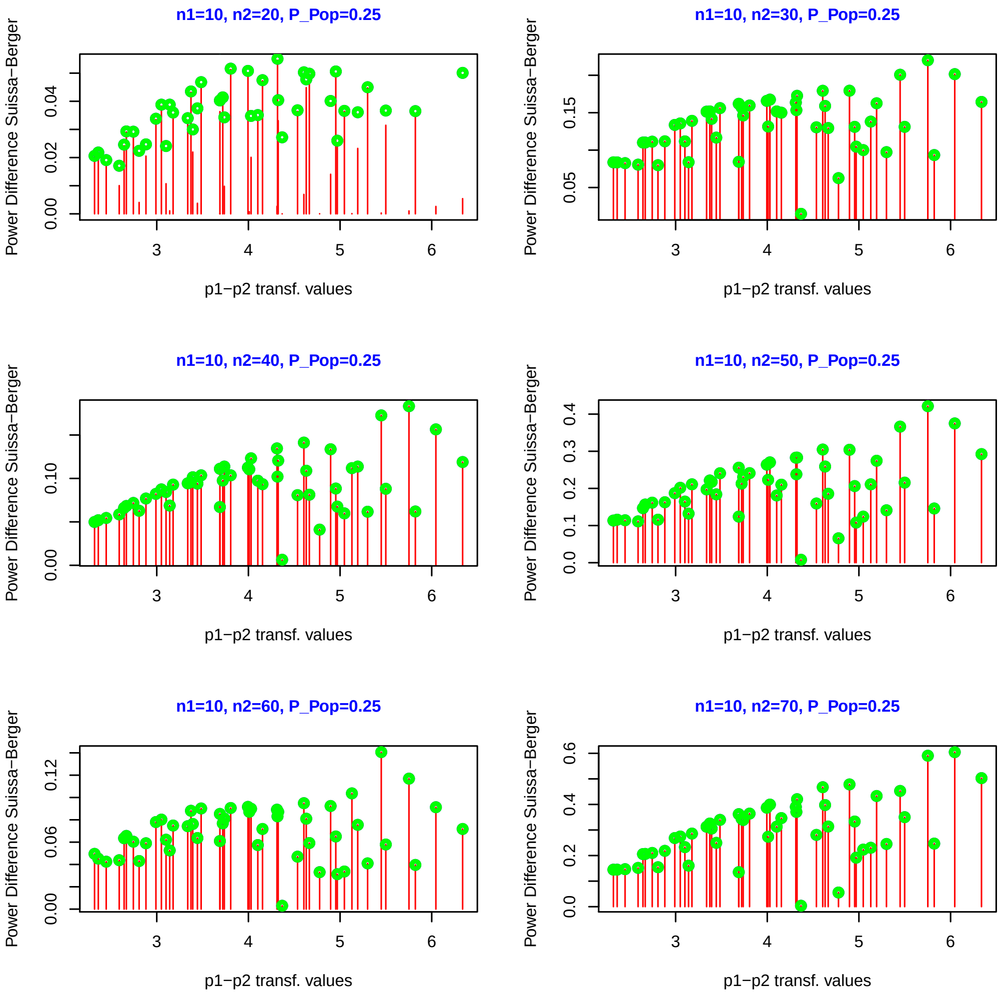

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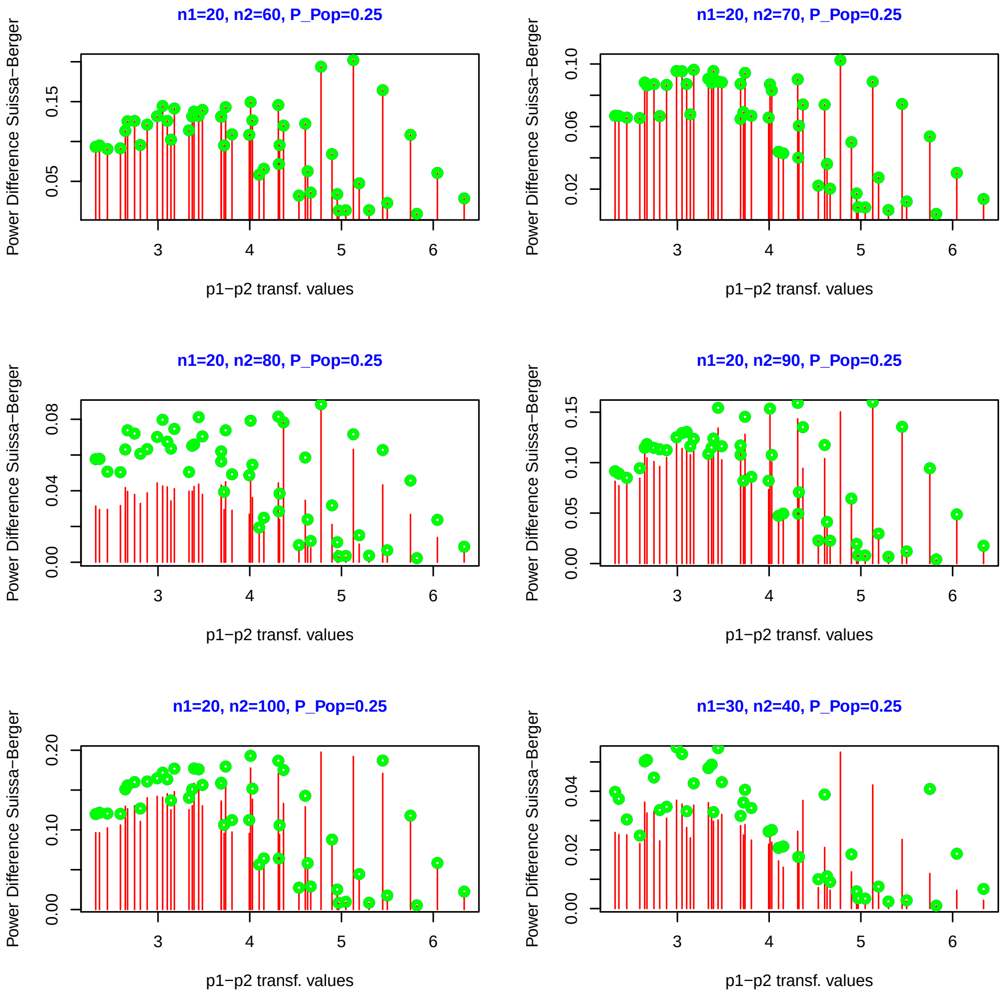

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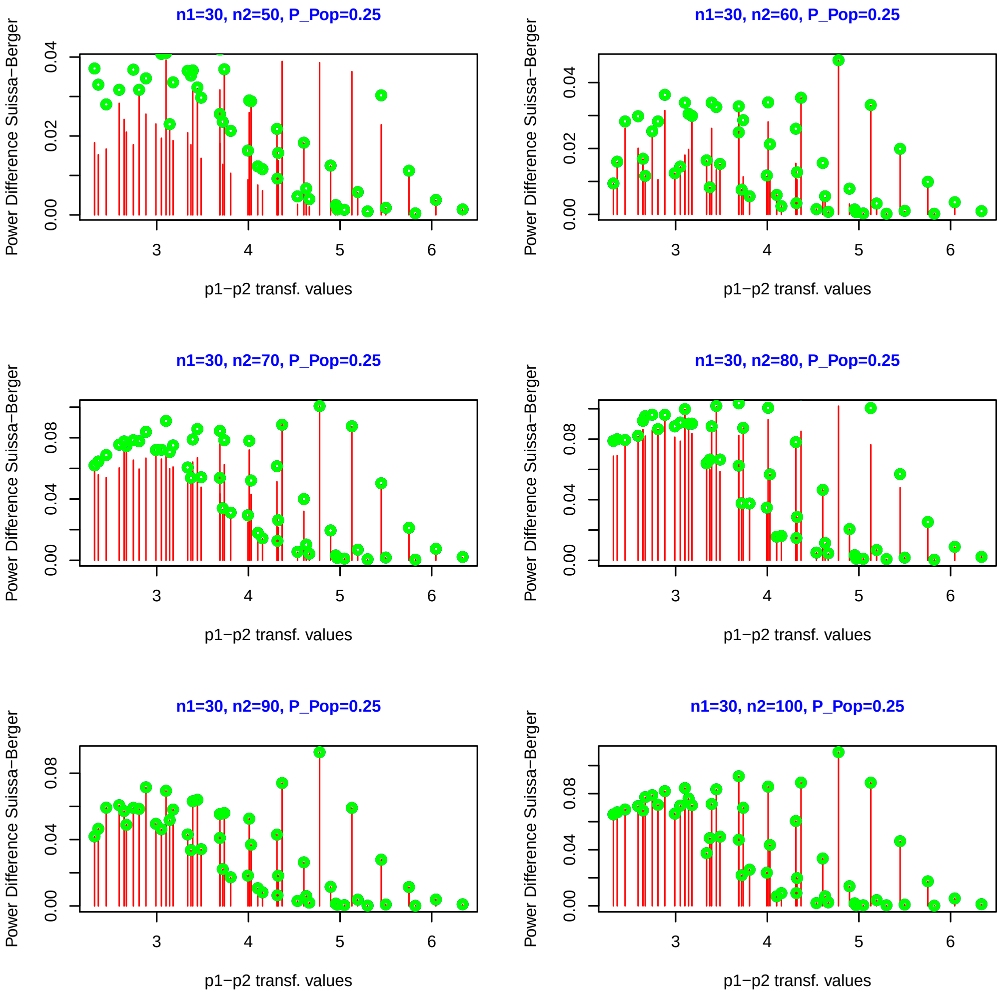

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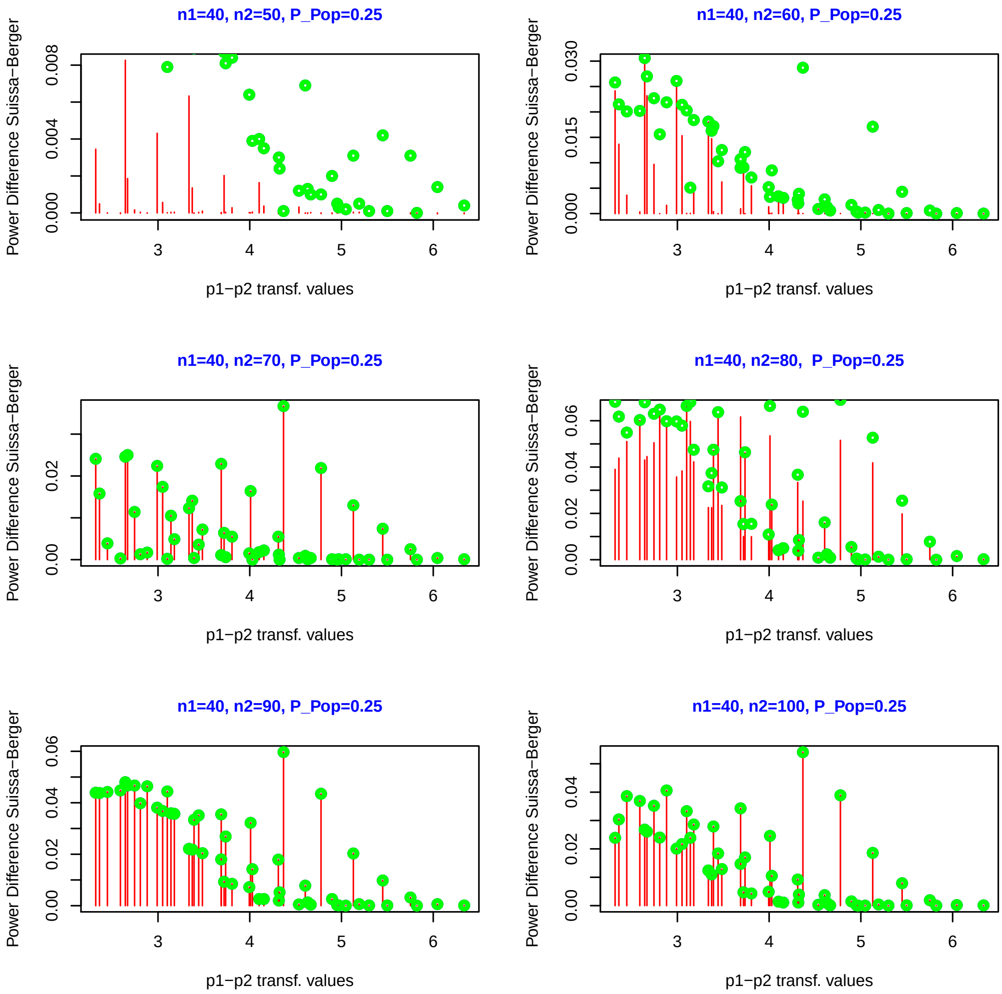

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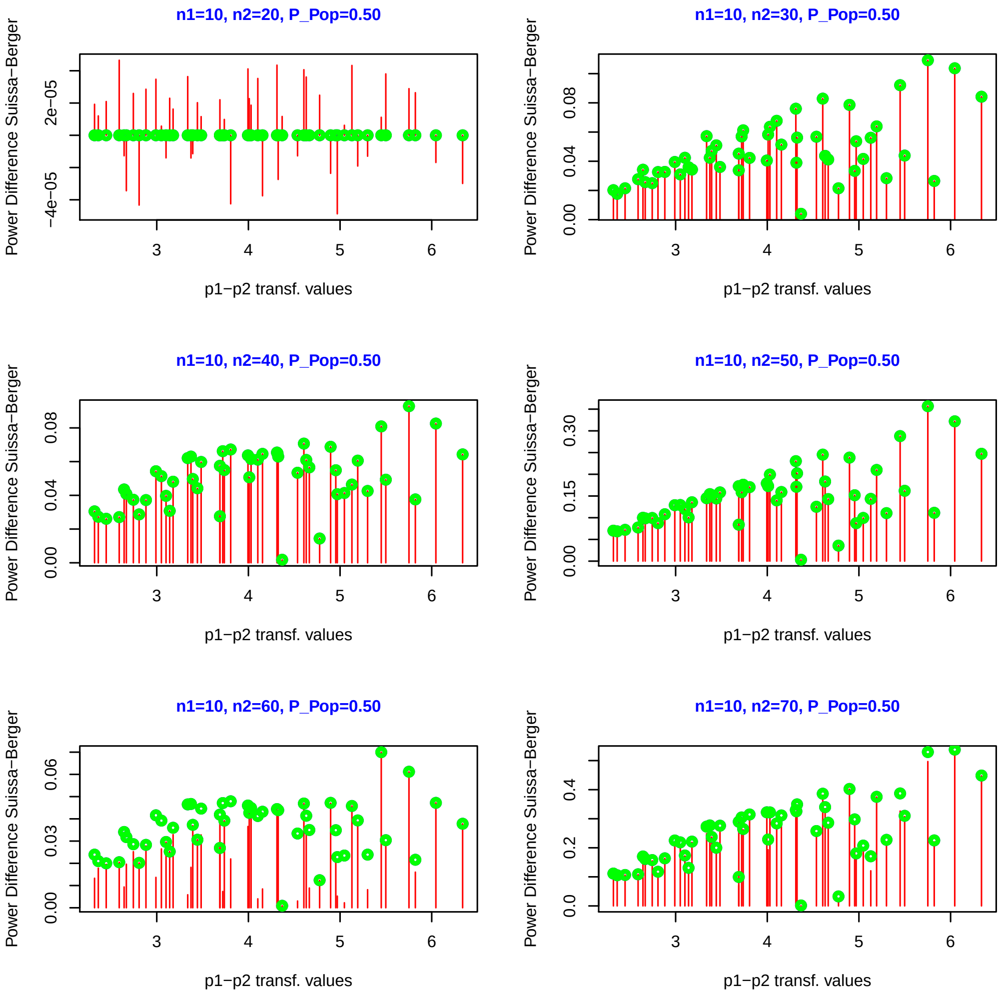

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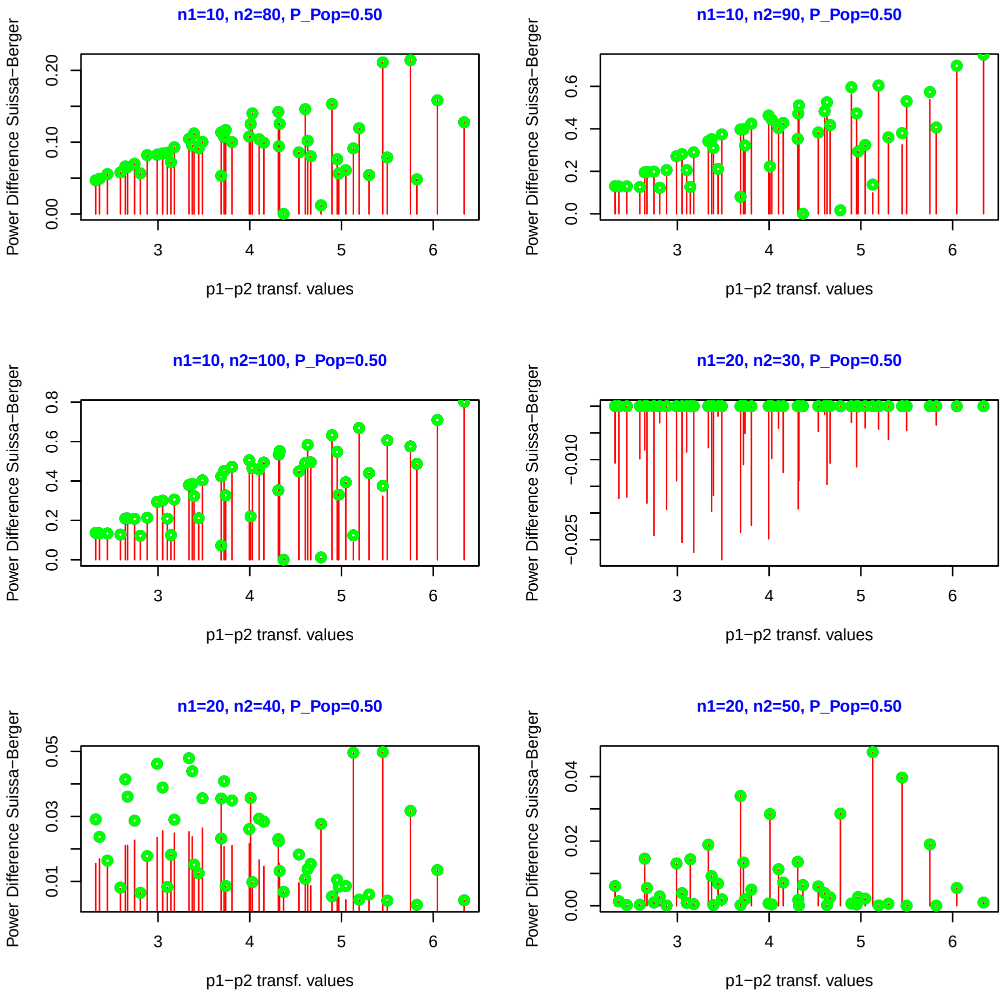

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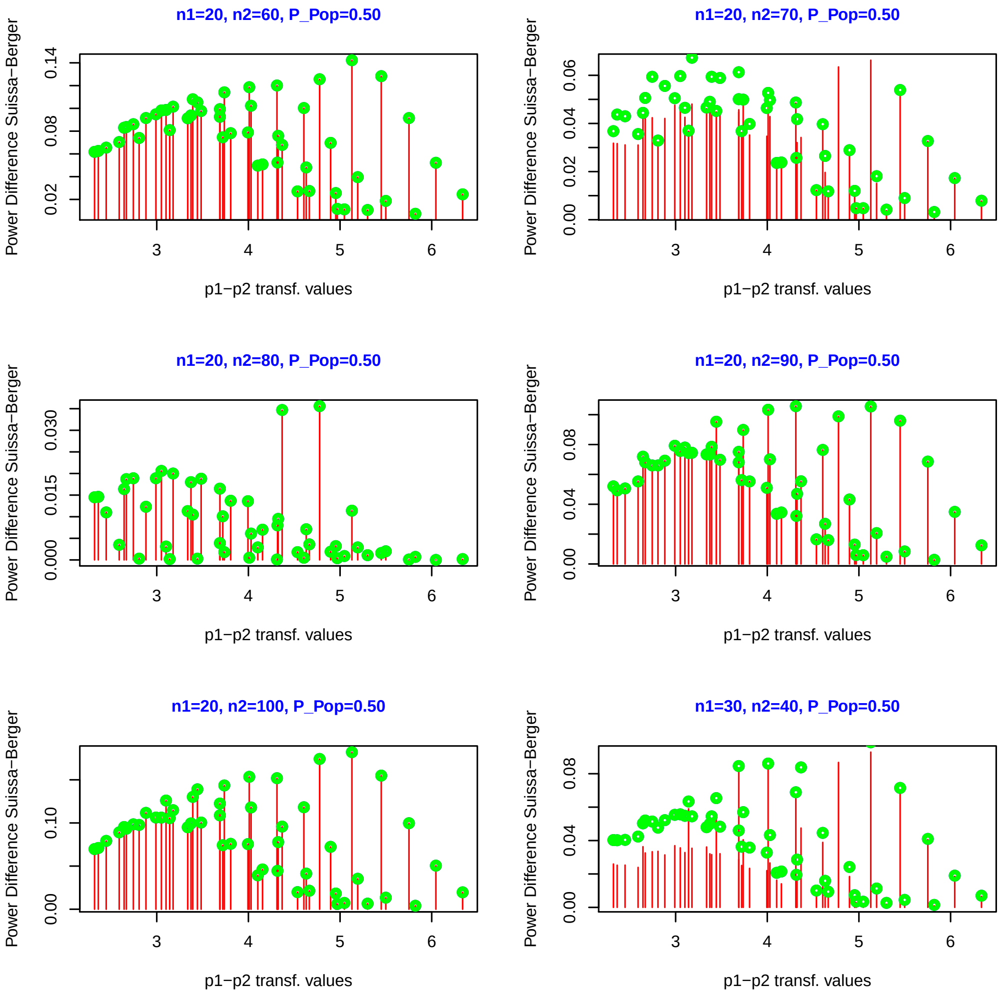

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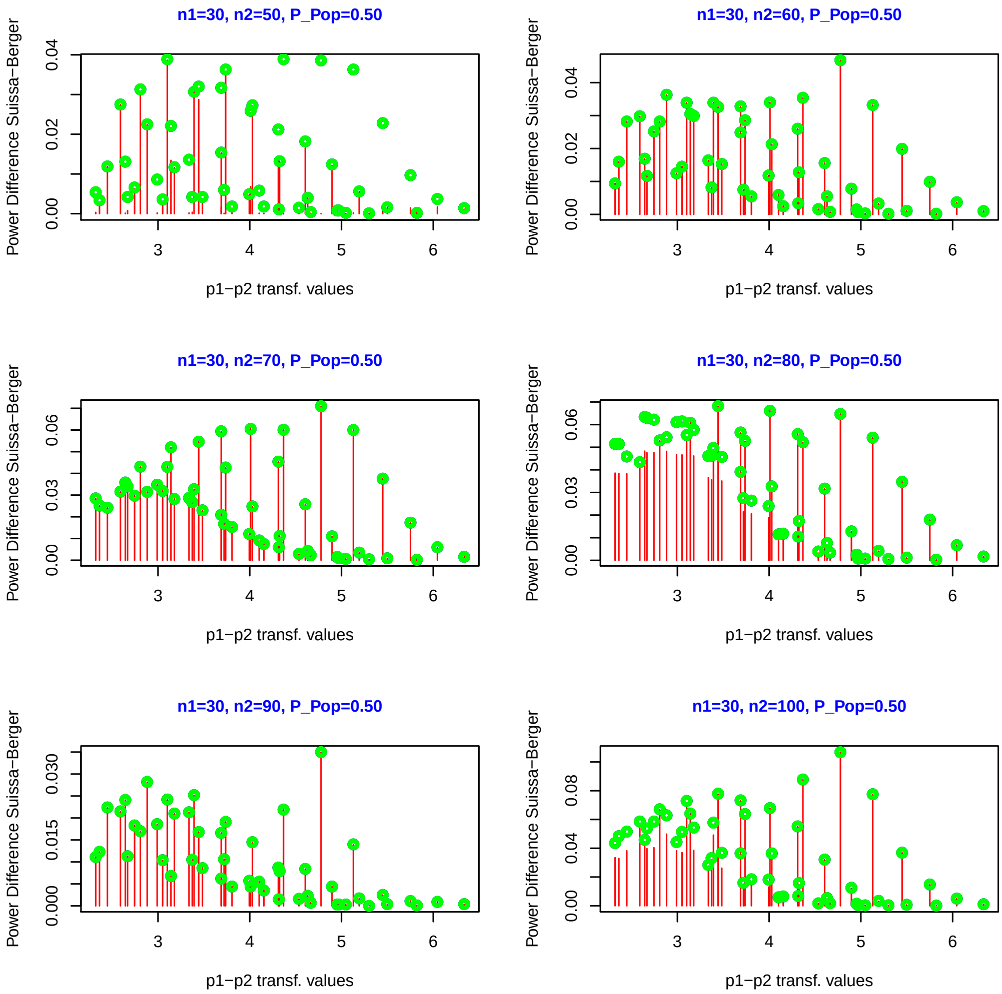

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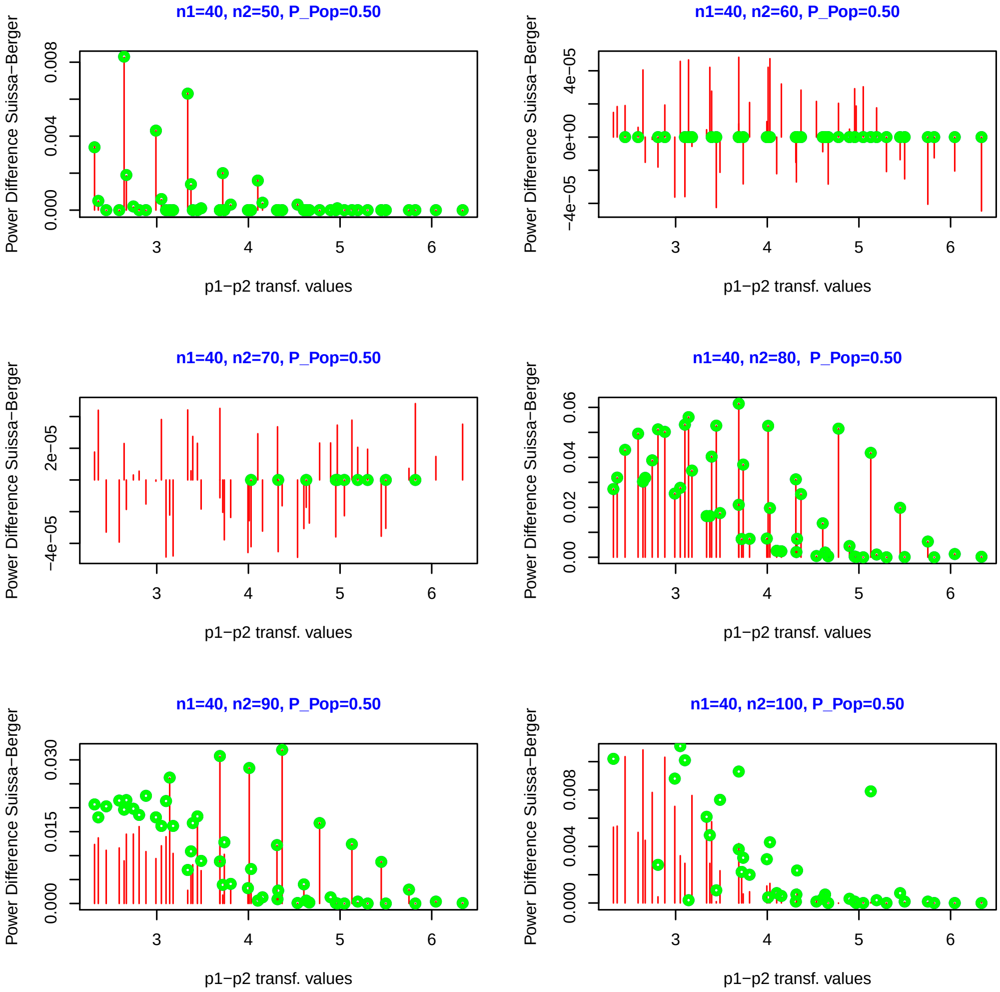

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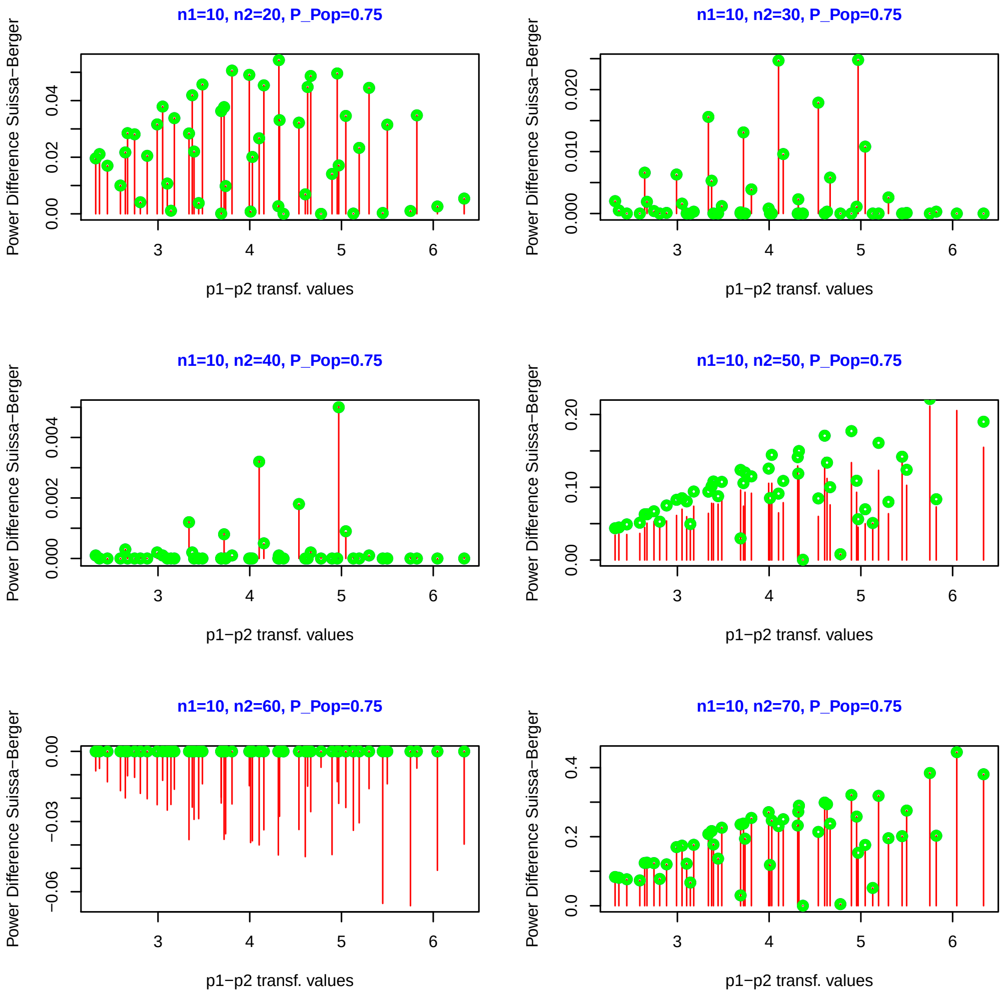

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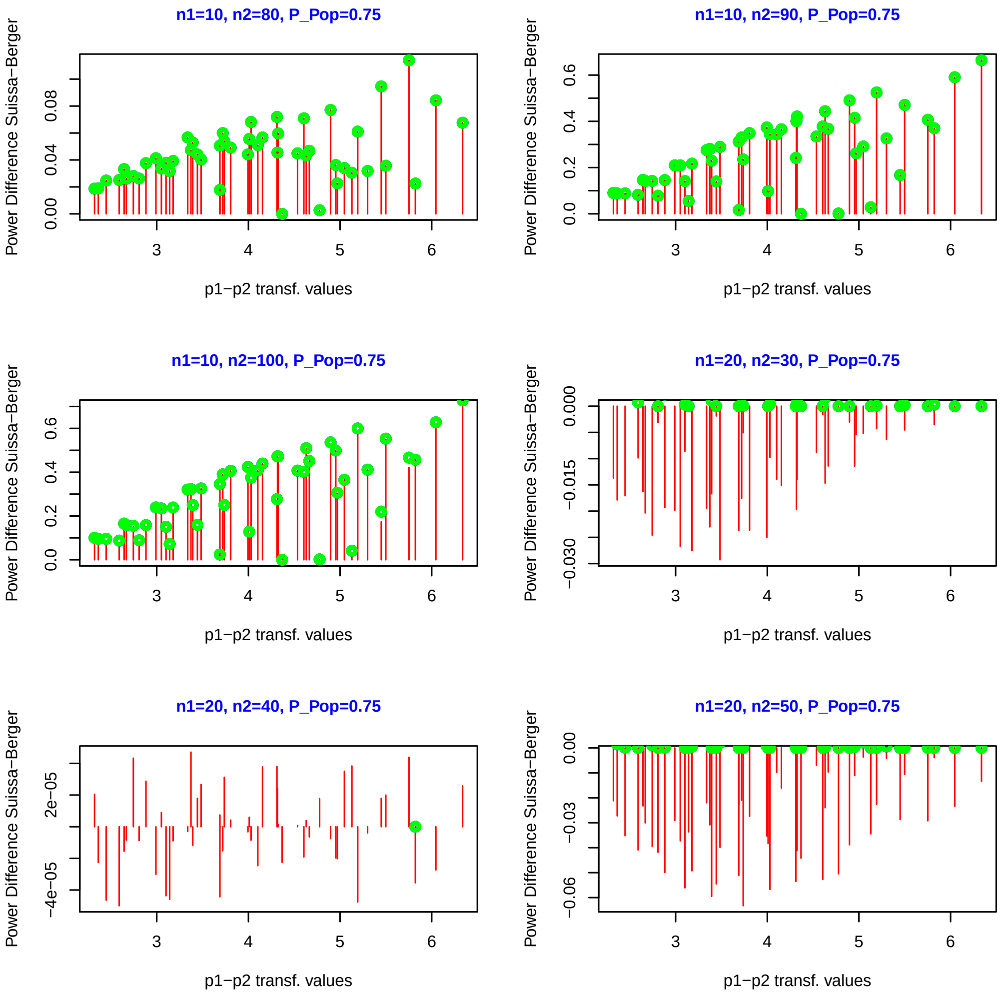

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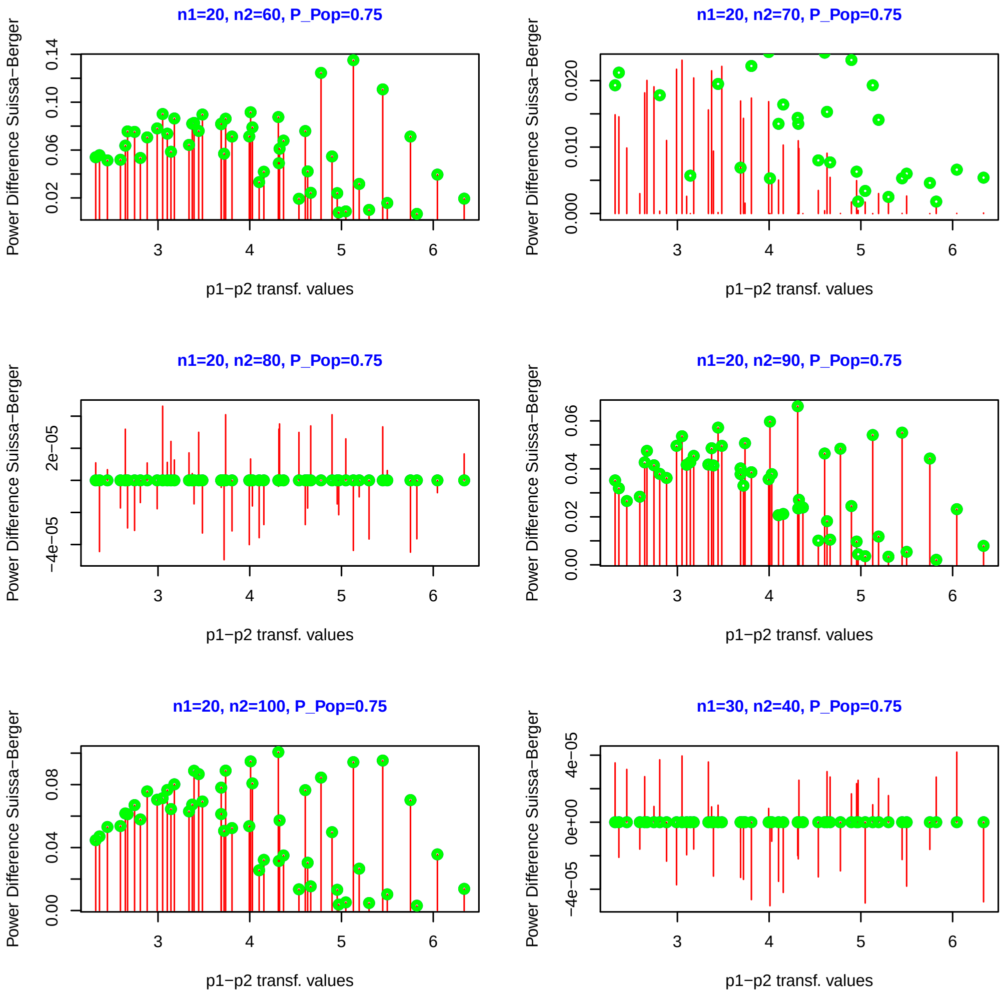

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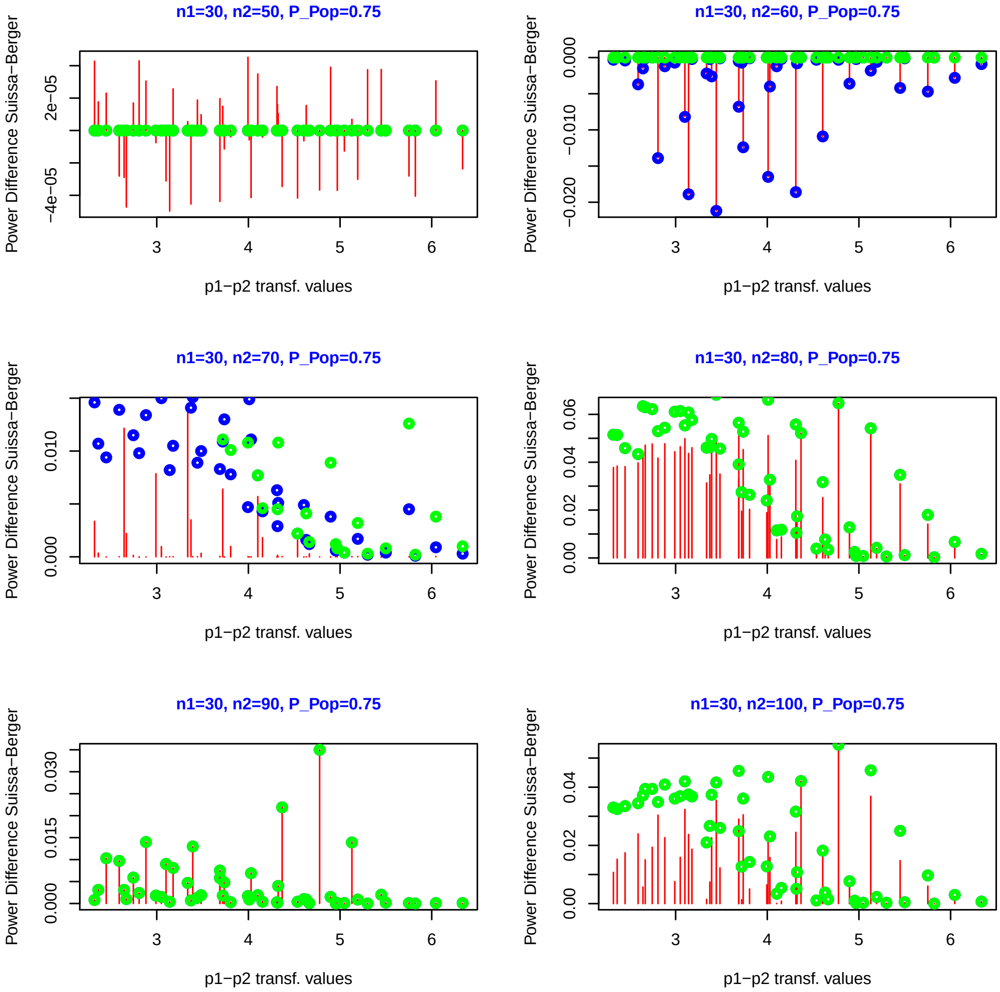

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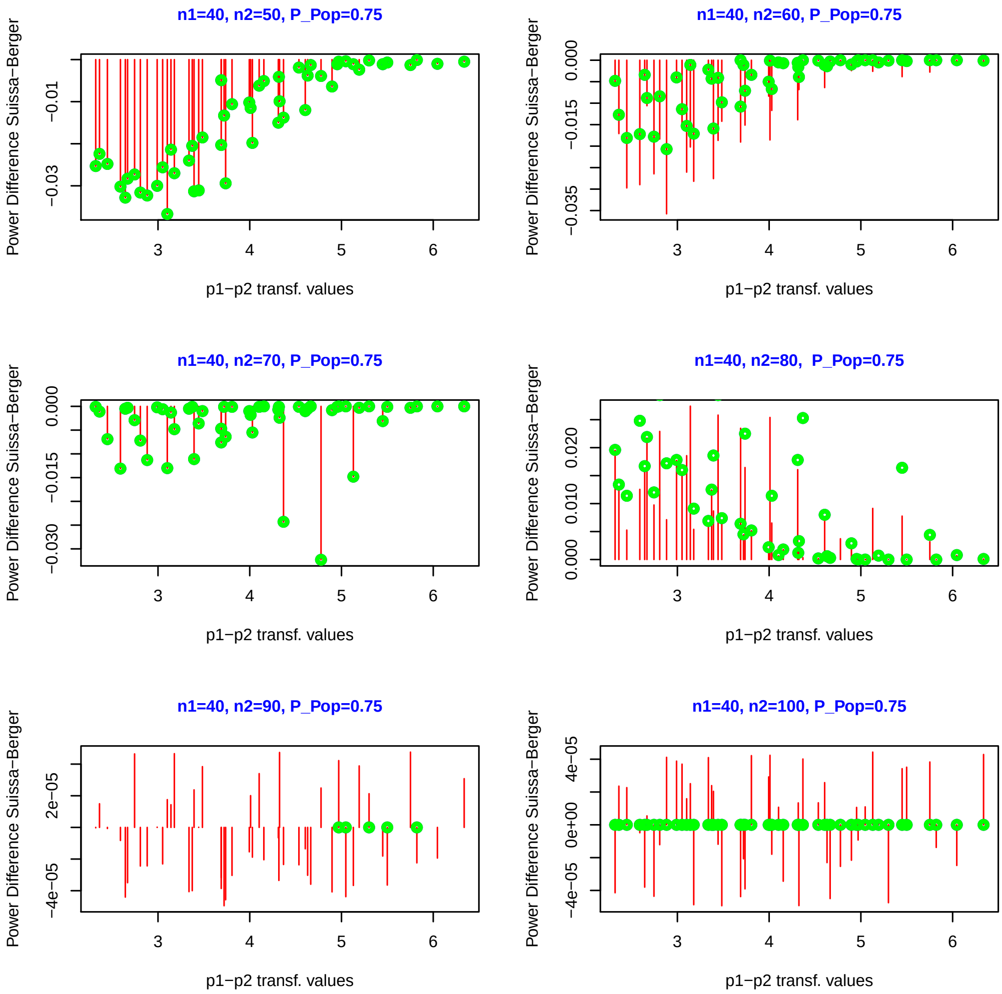

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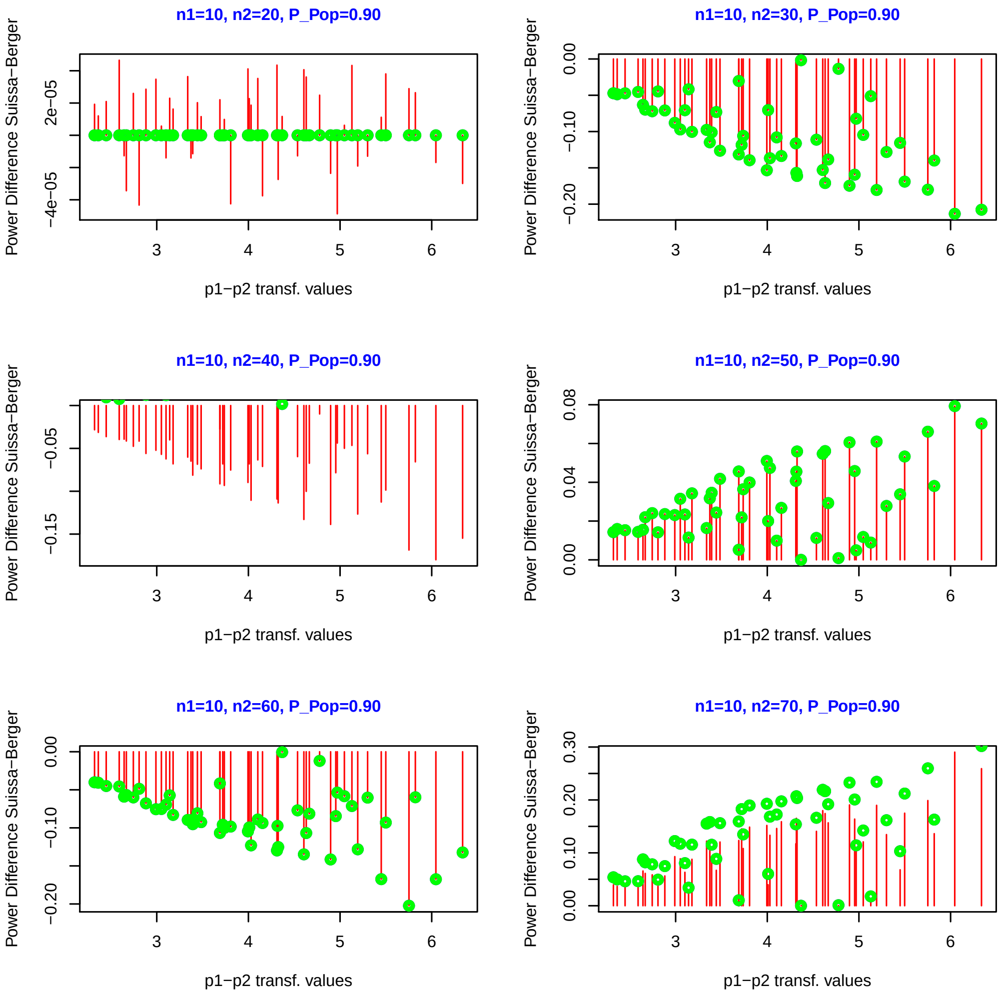

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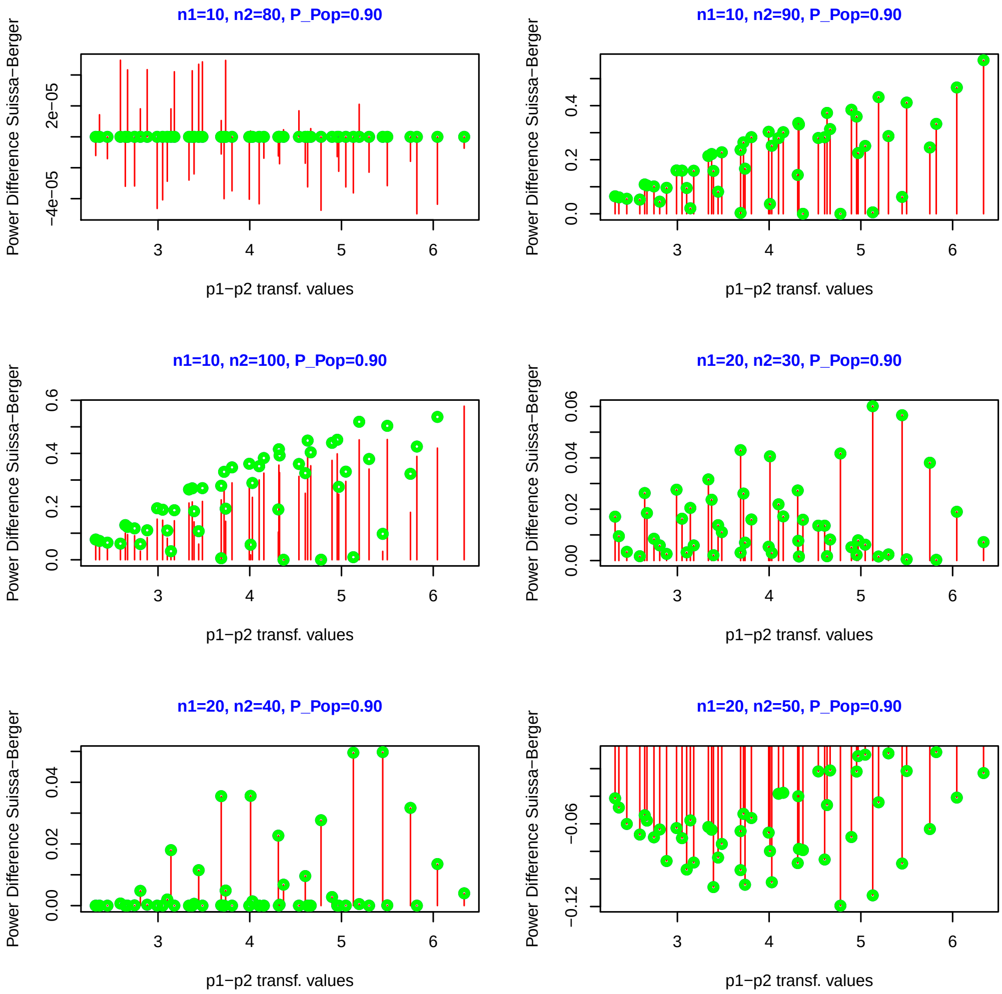

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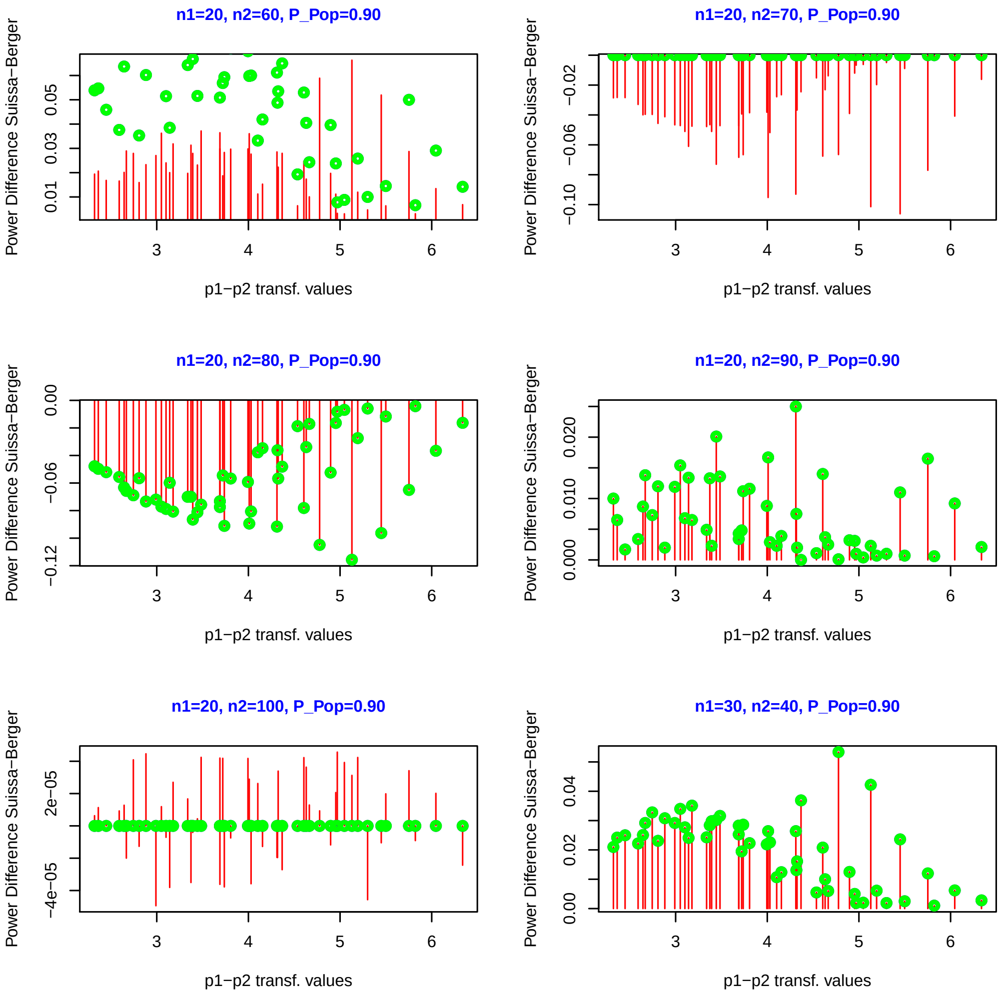

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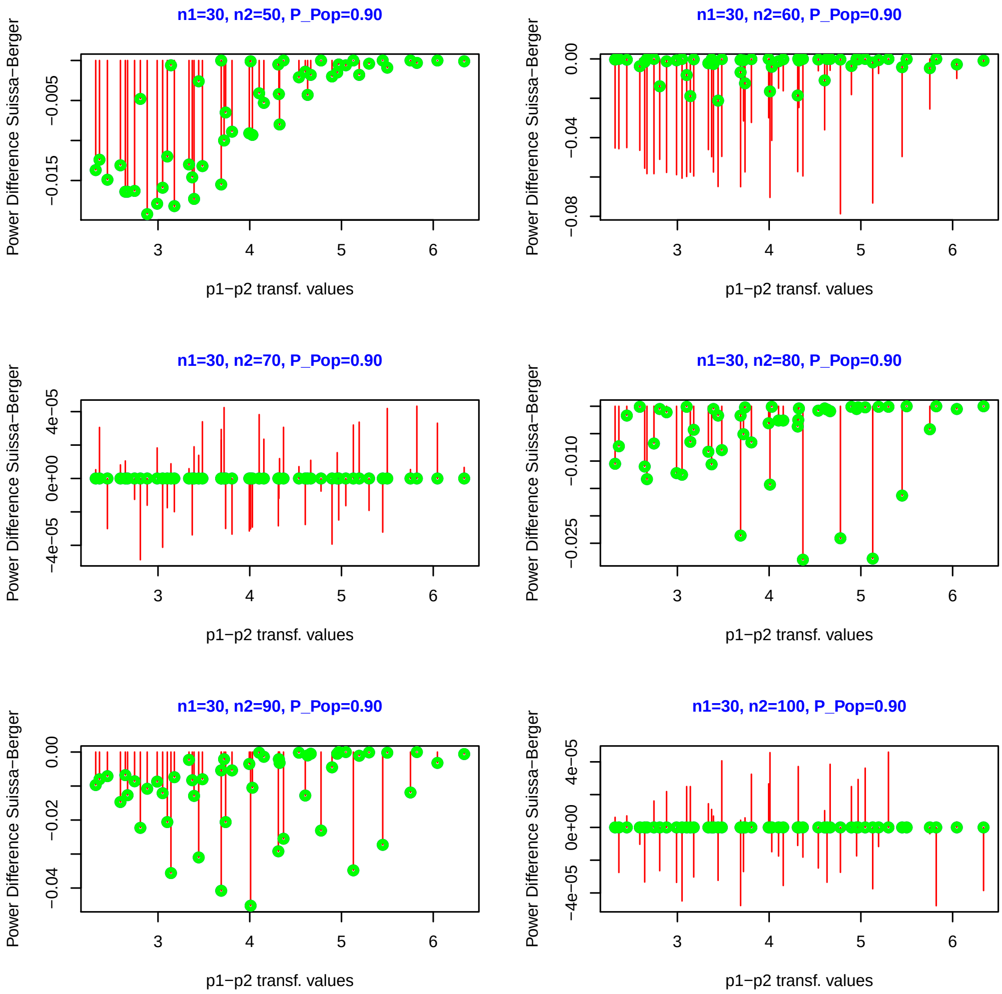

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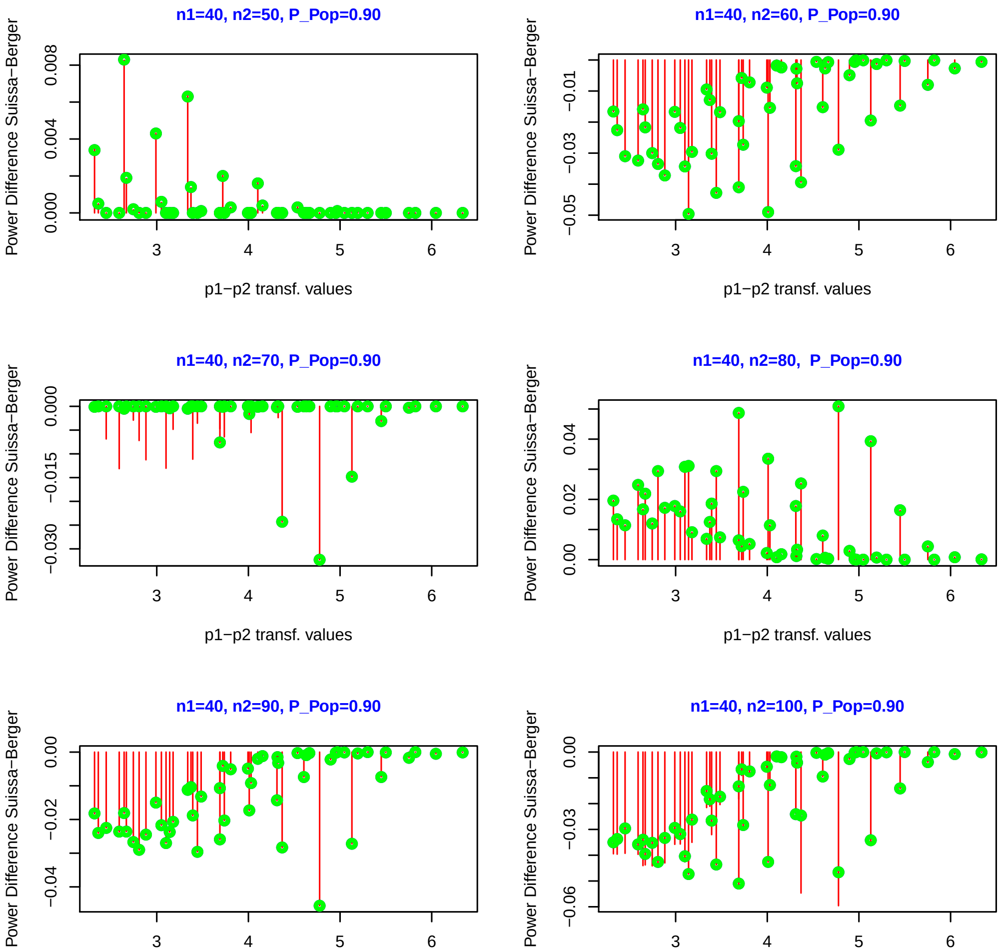

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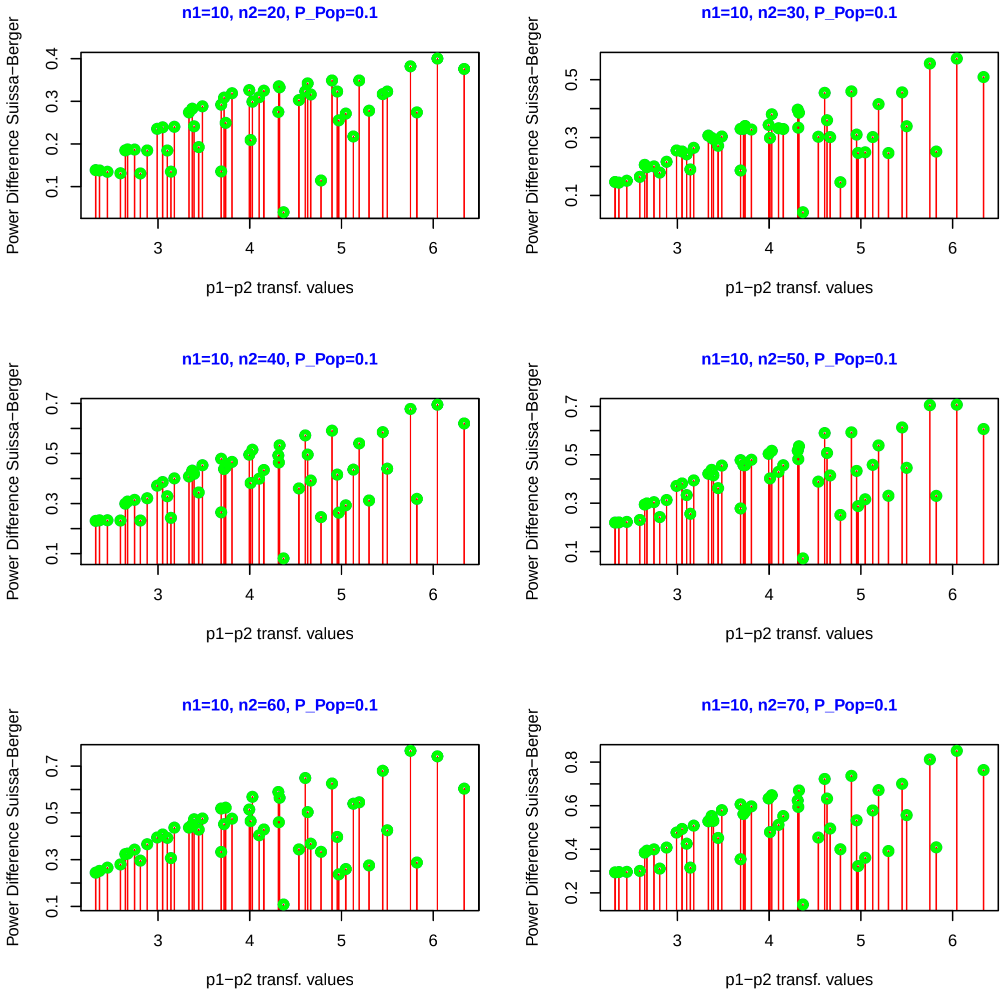
Figure C.21: Comparison of power between the Suissa pooled test and the Berger pooled test for different sample sizes, $\boldsymbol{\alpha}$= **0.01**.



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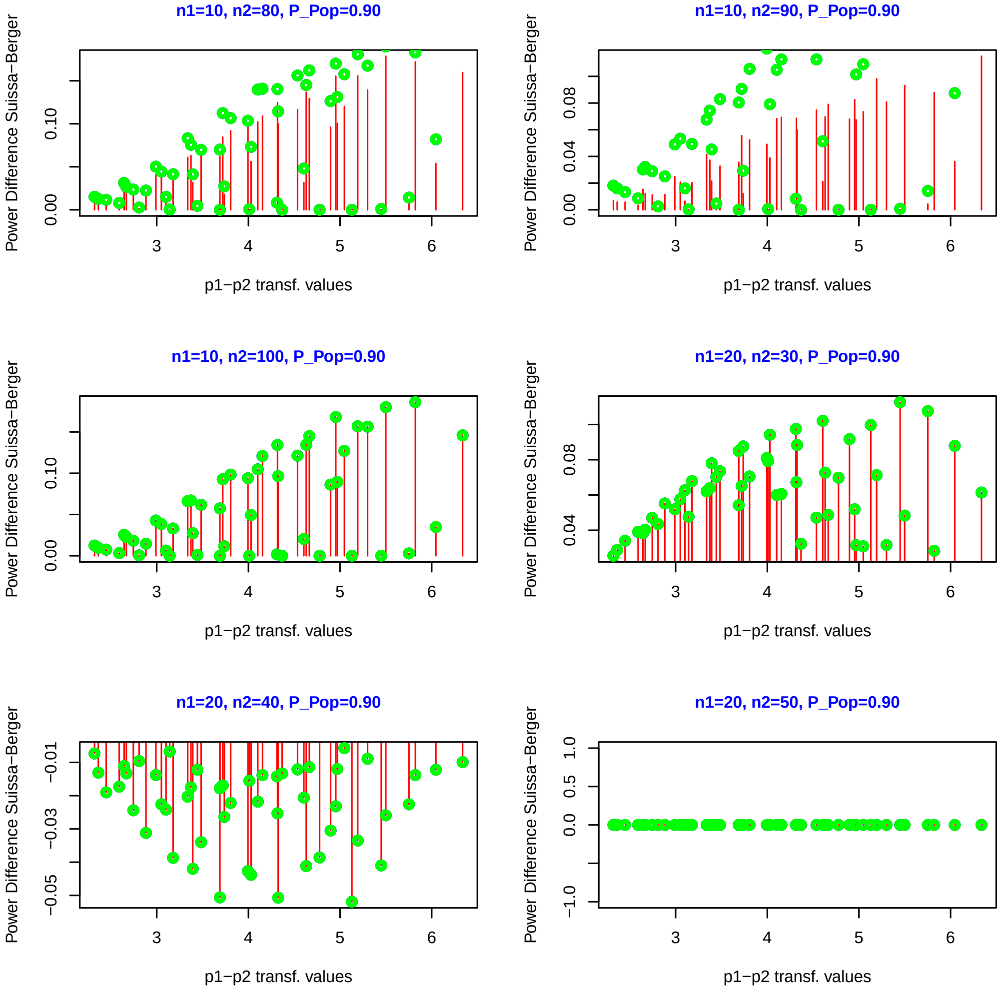

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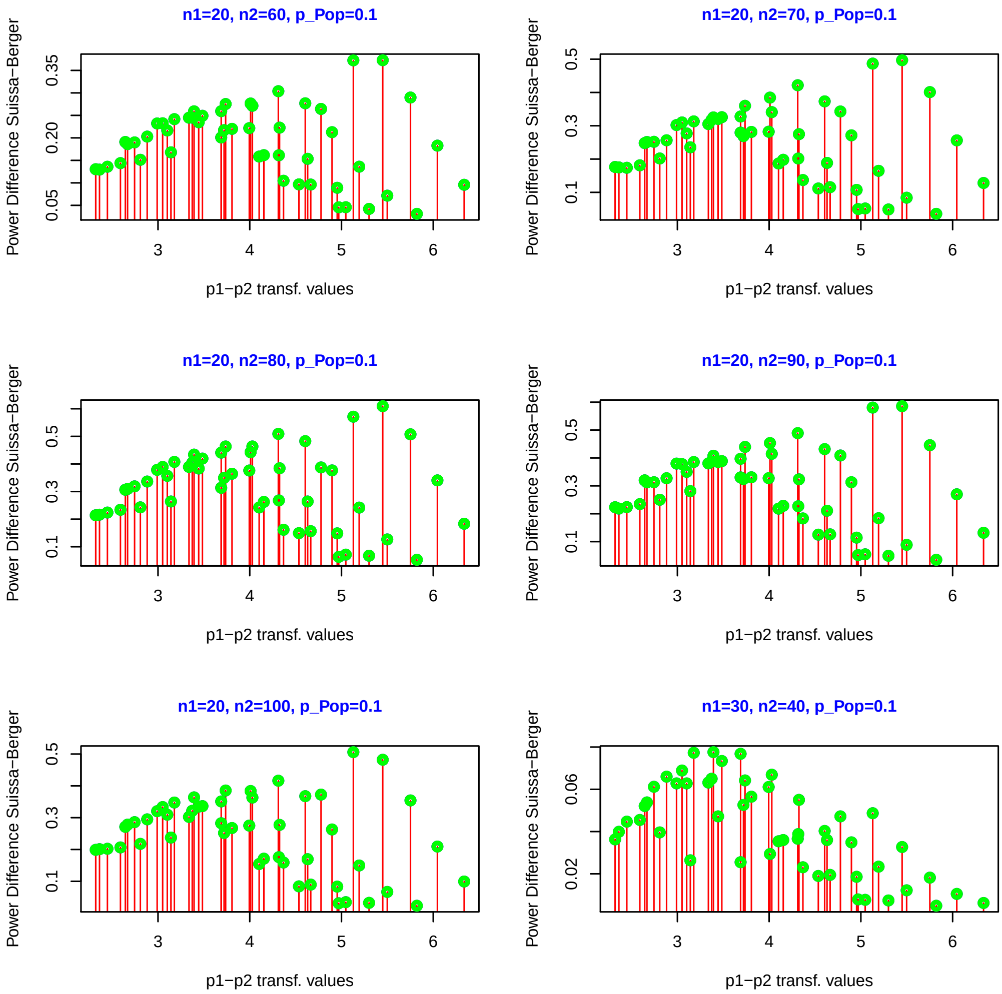

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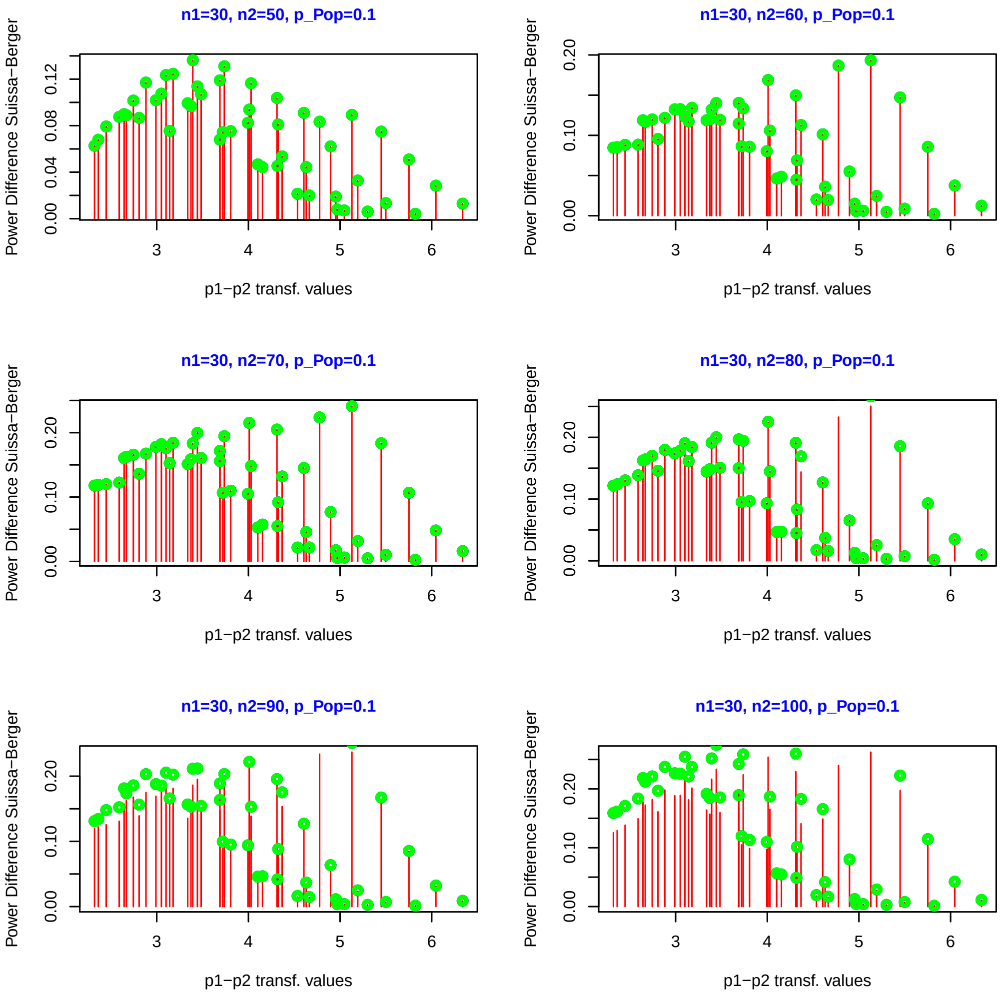

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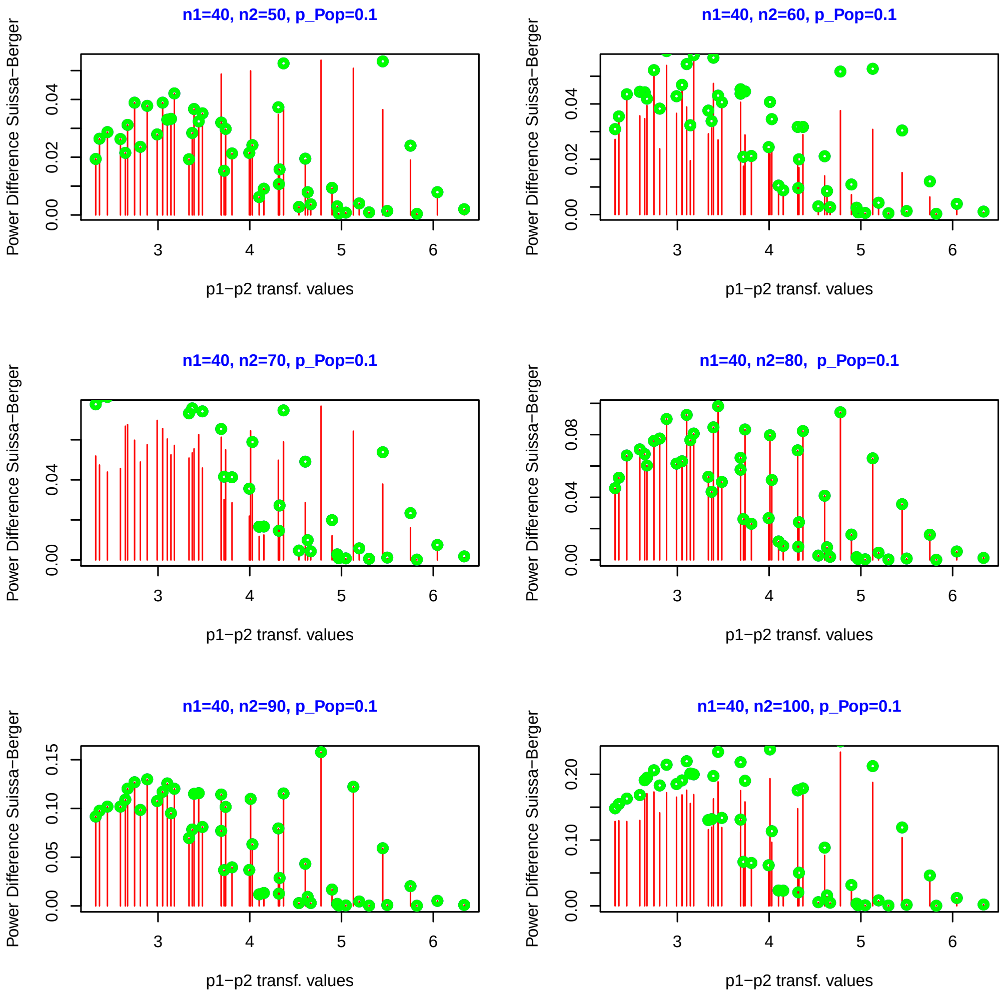

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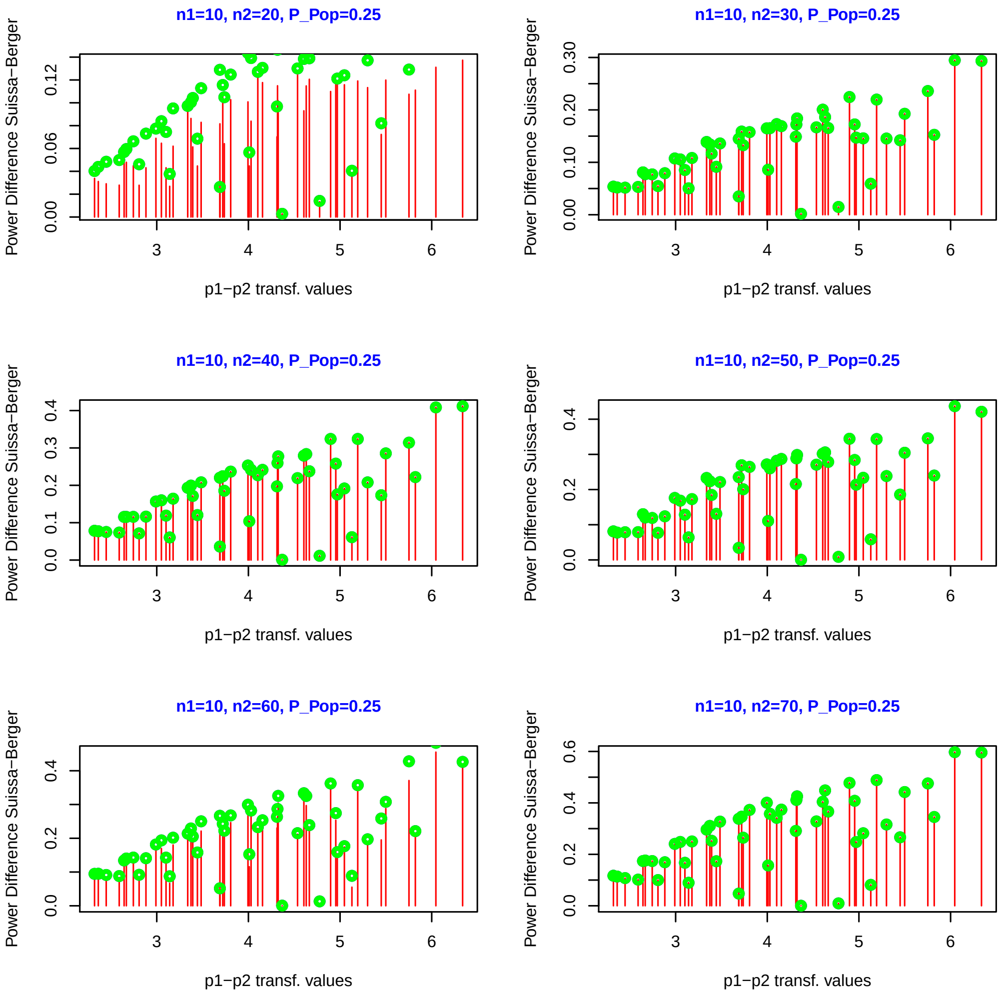

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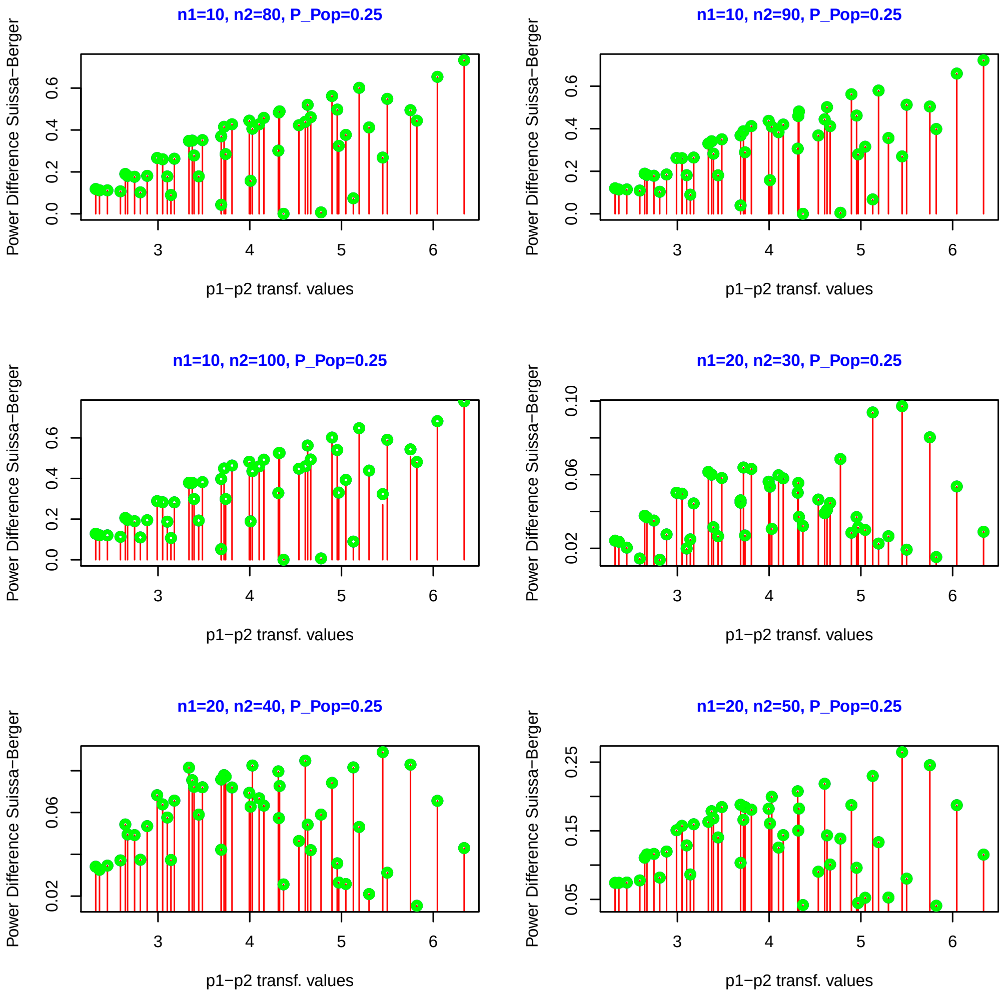

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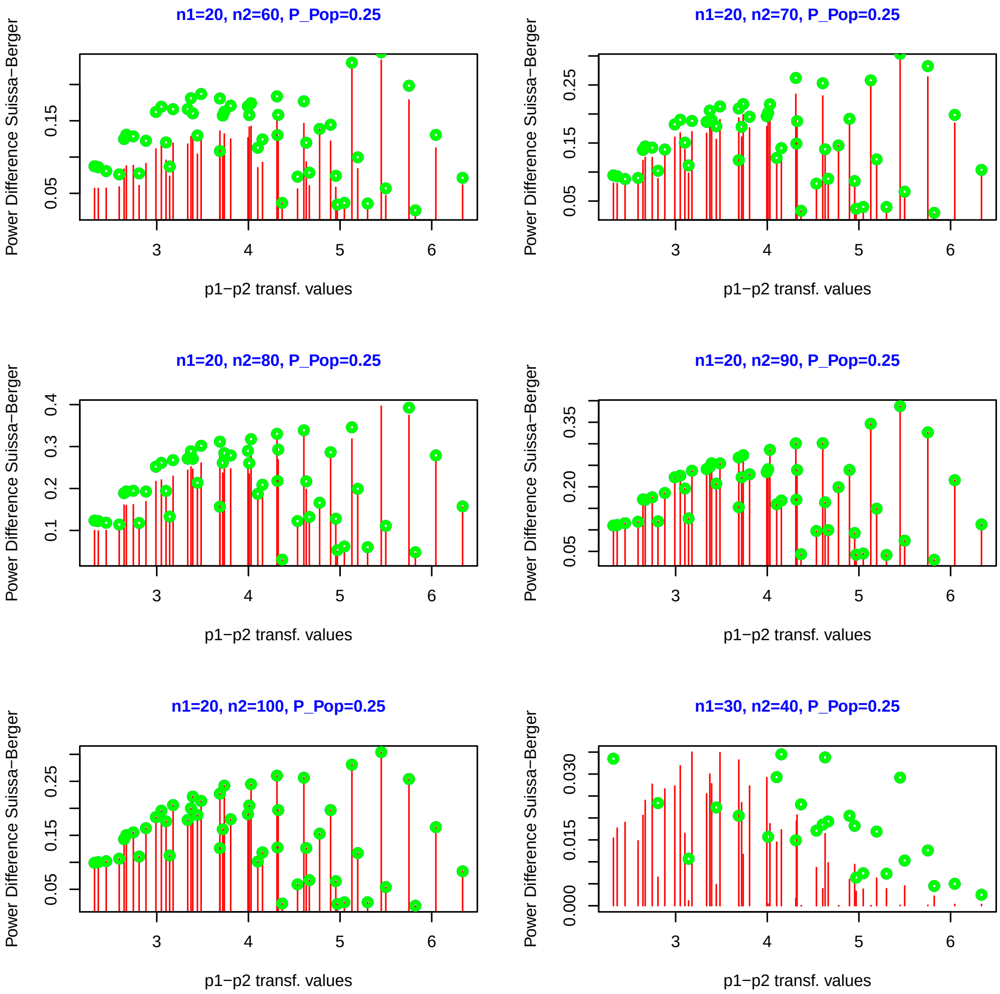

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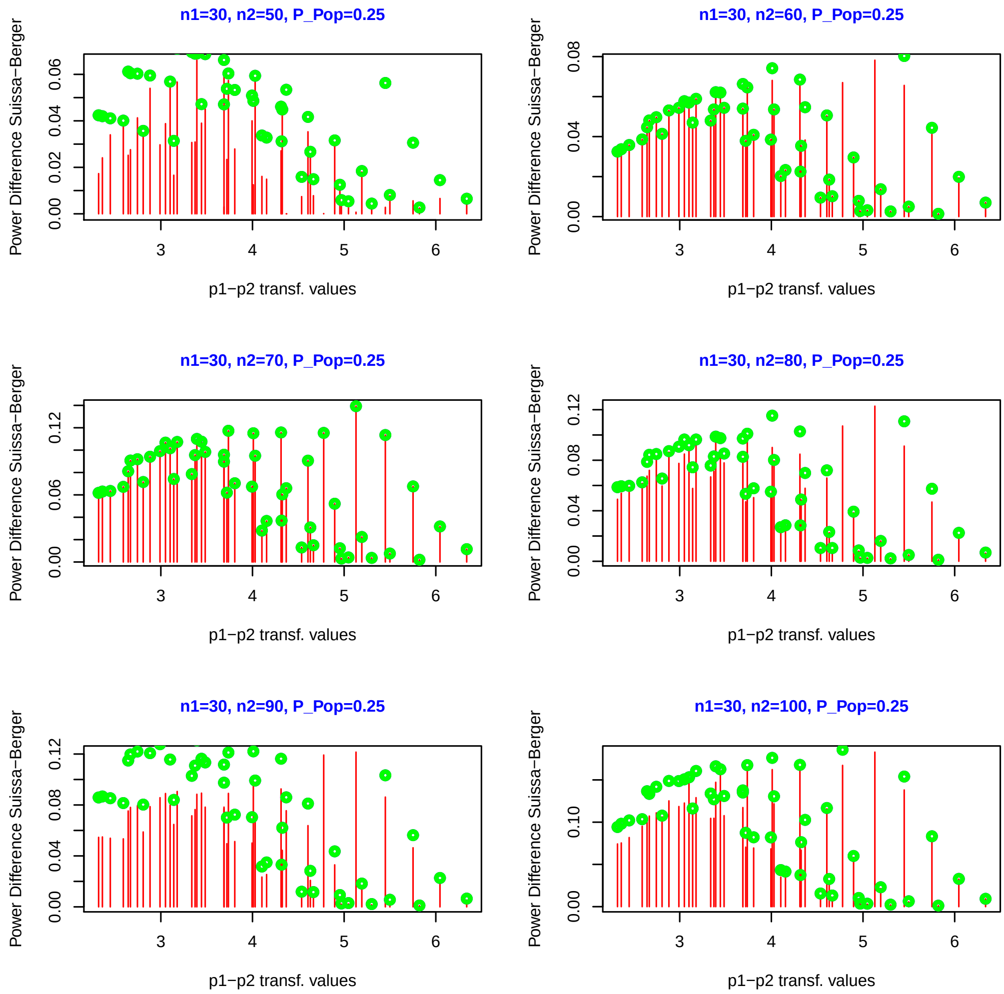

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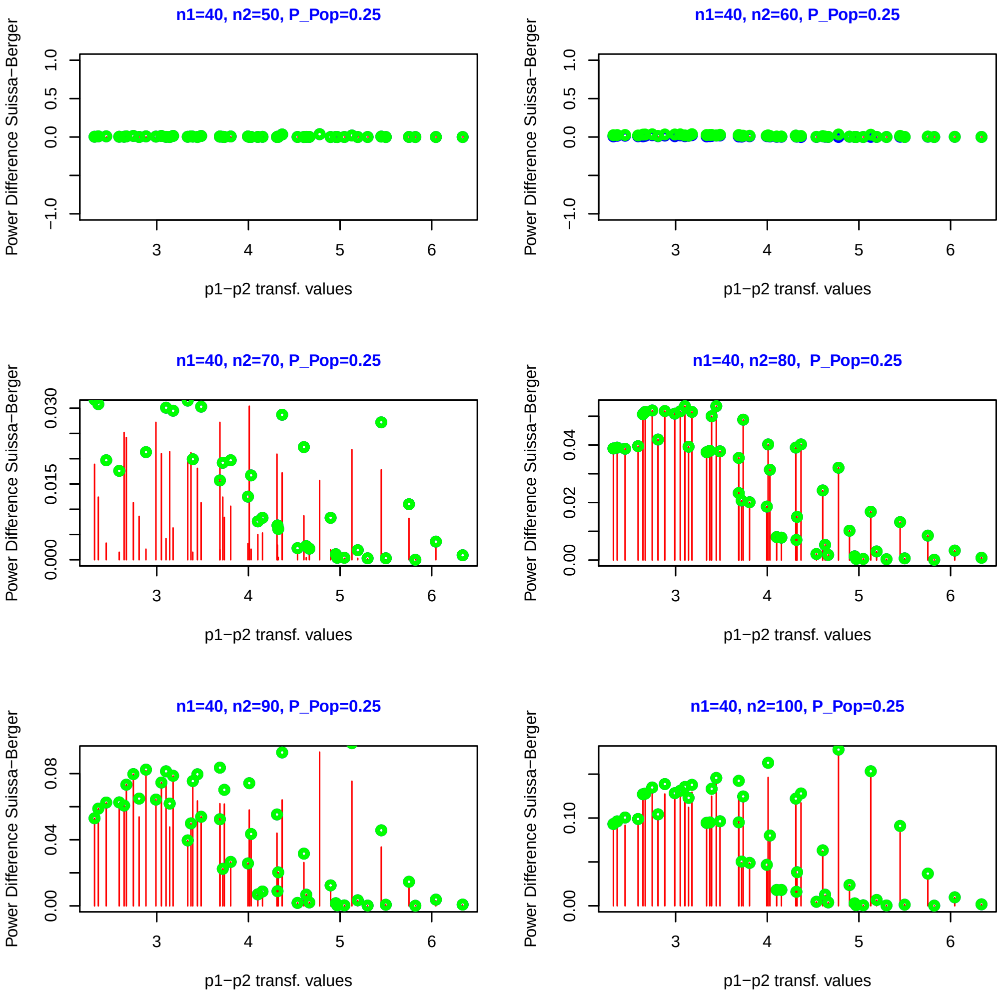

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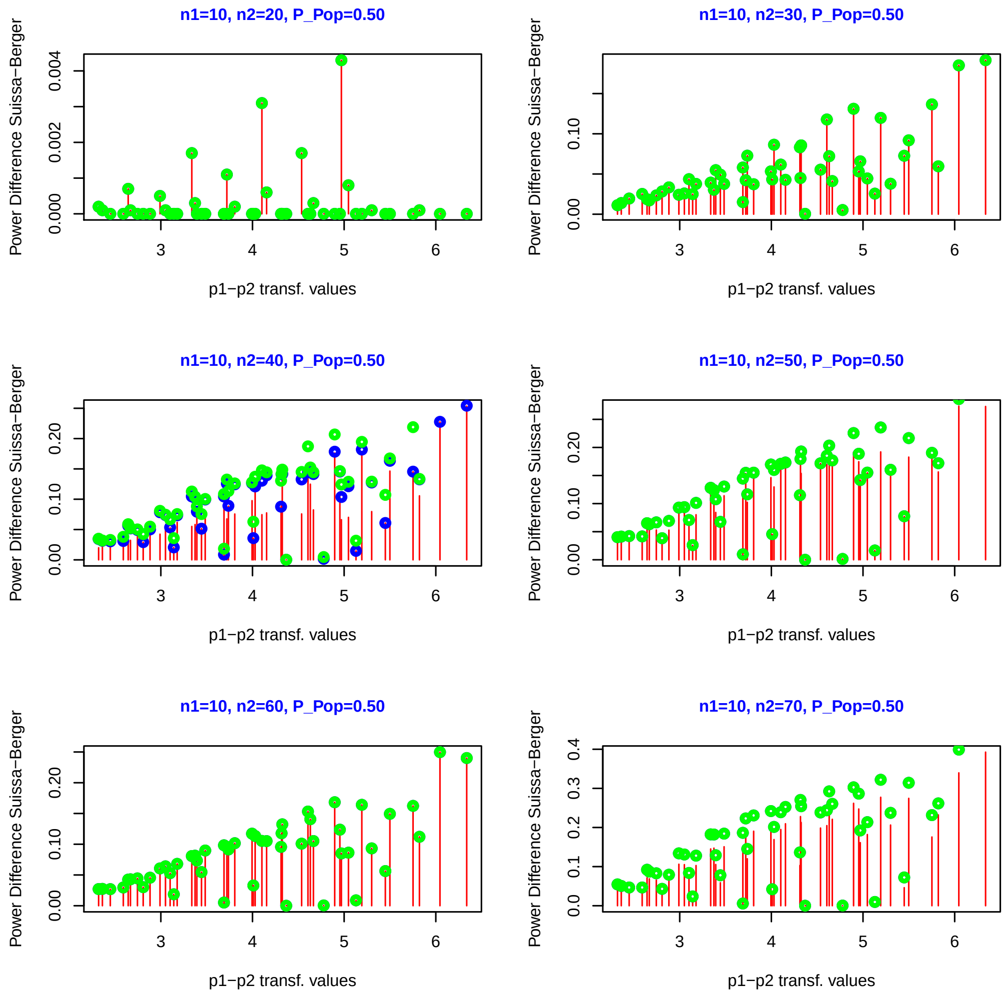

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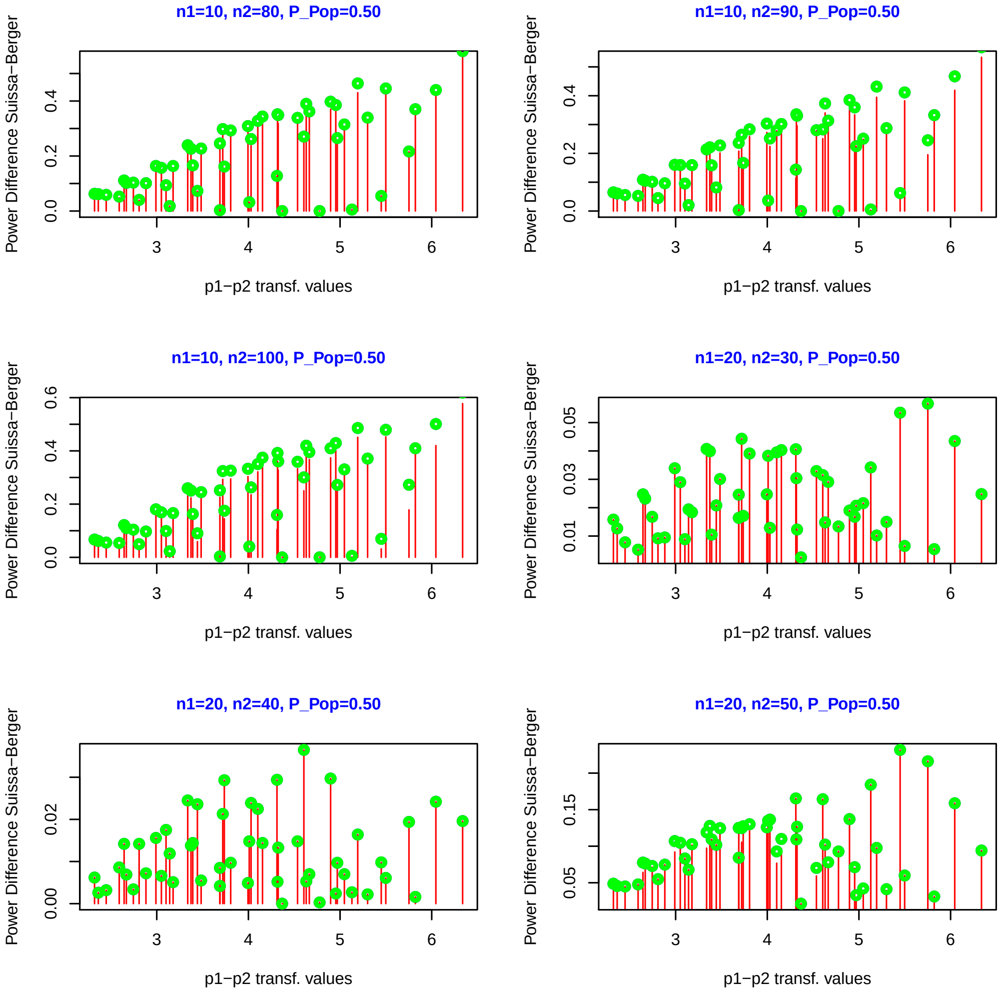

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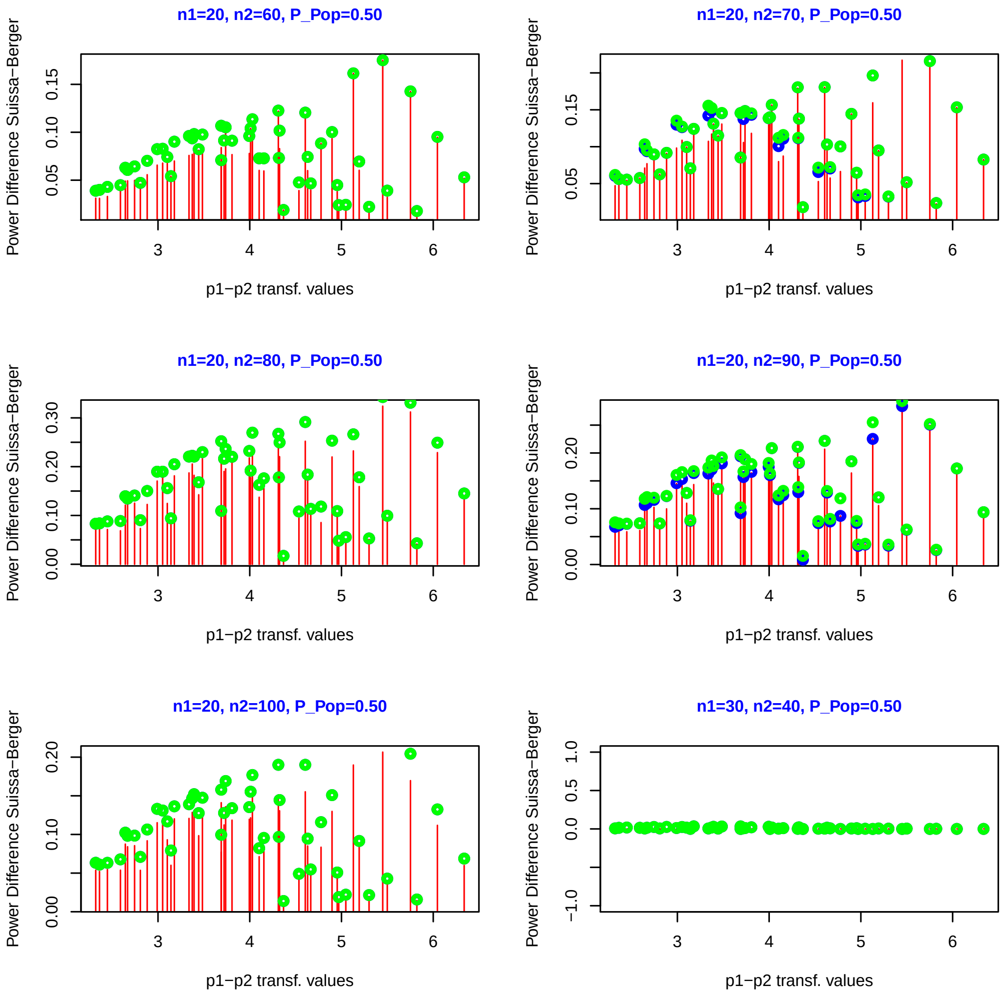

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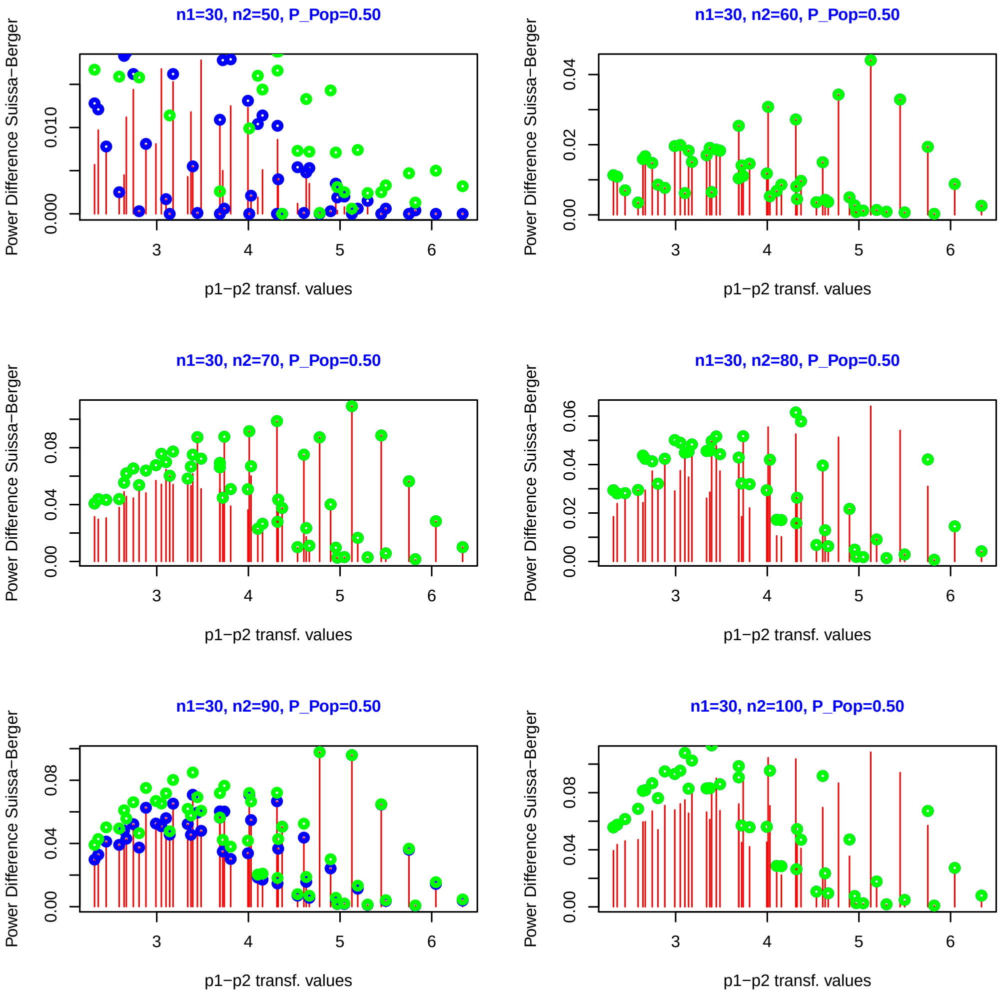

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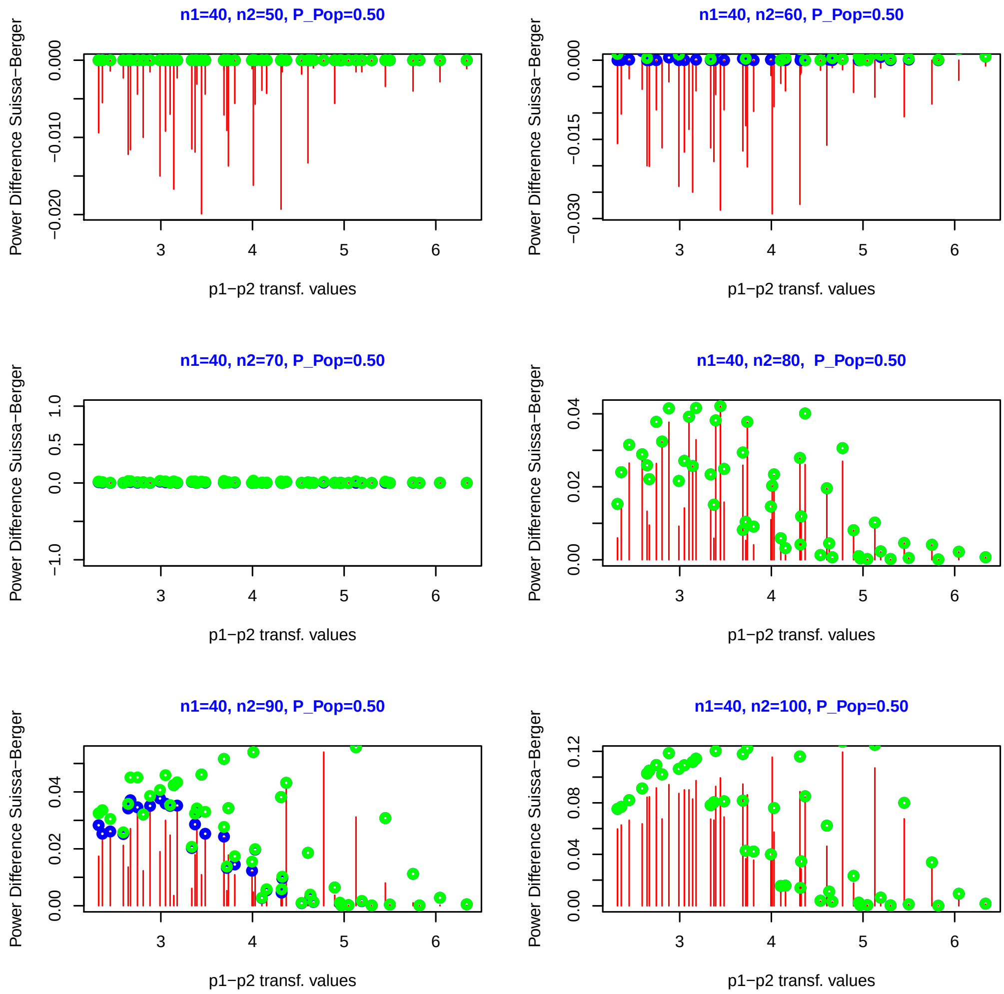

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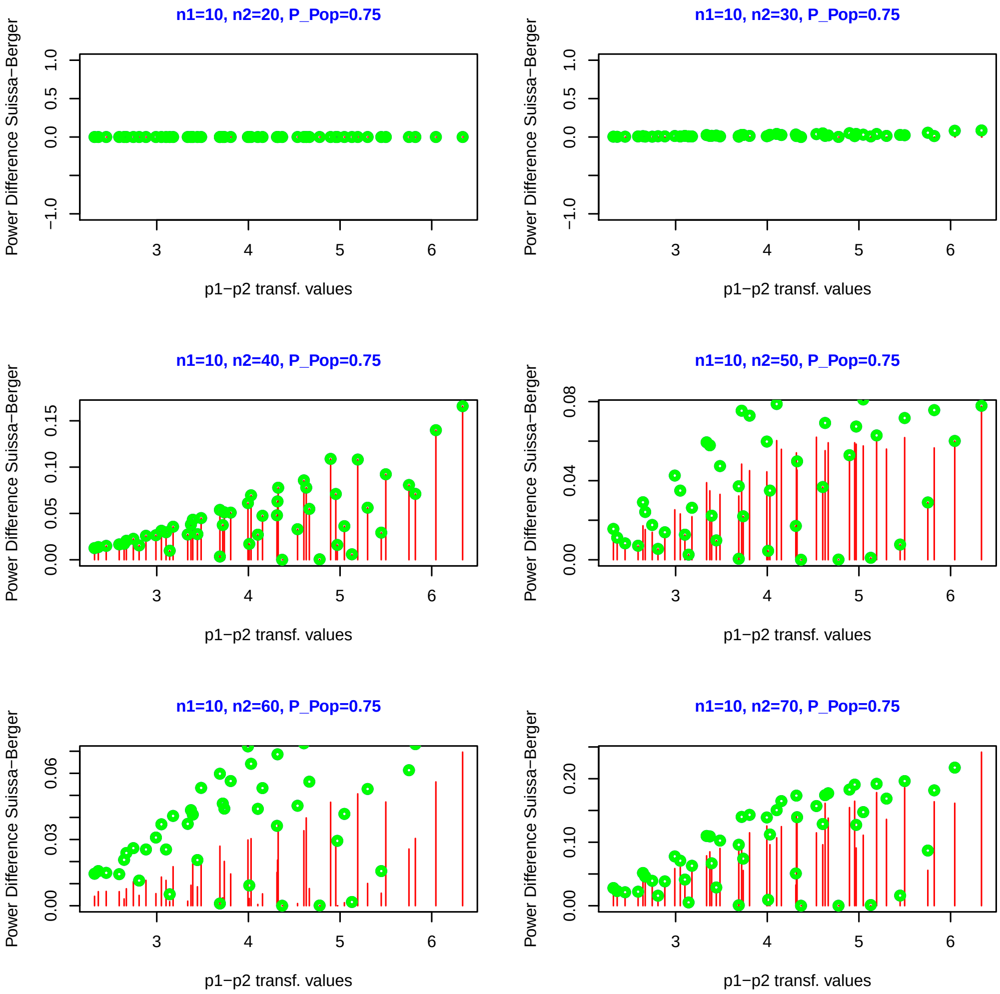

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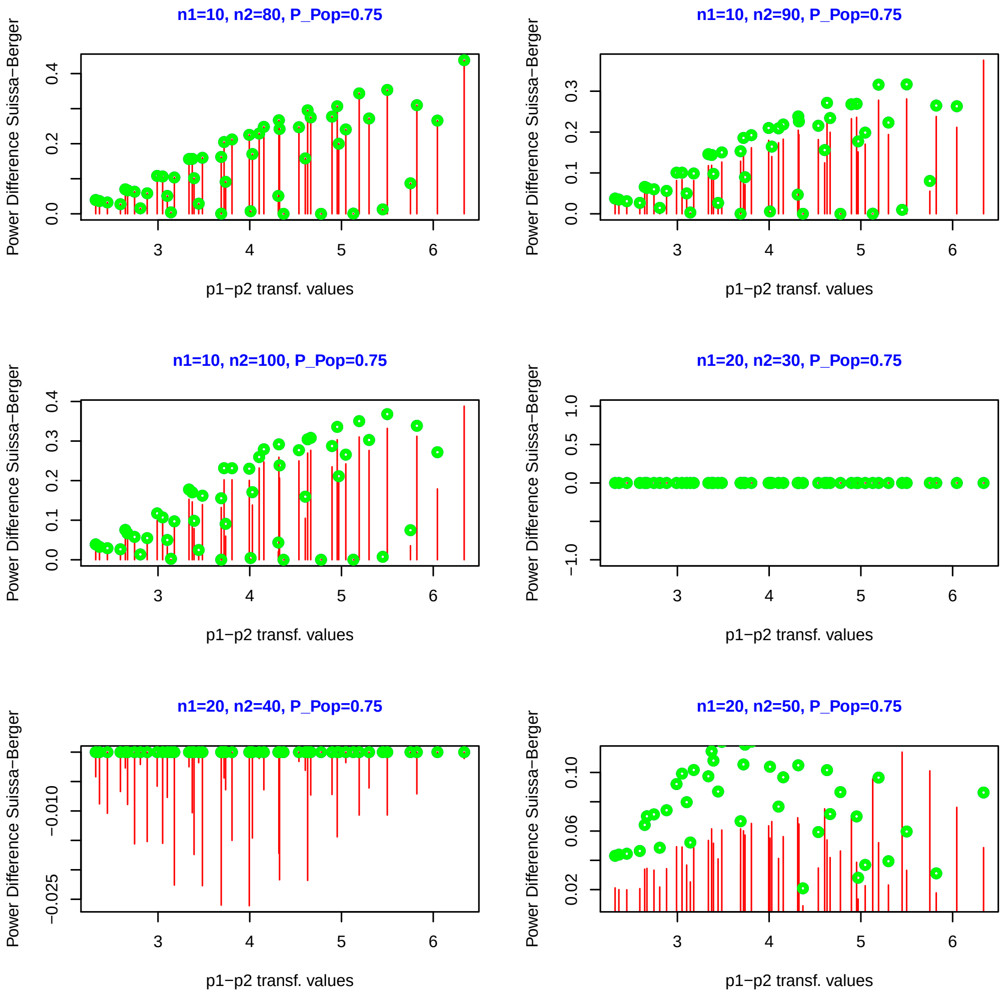

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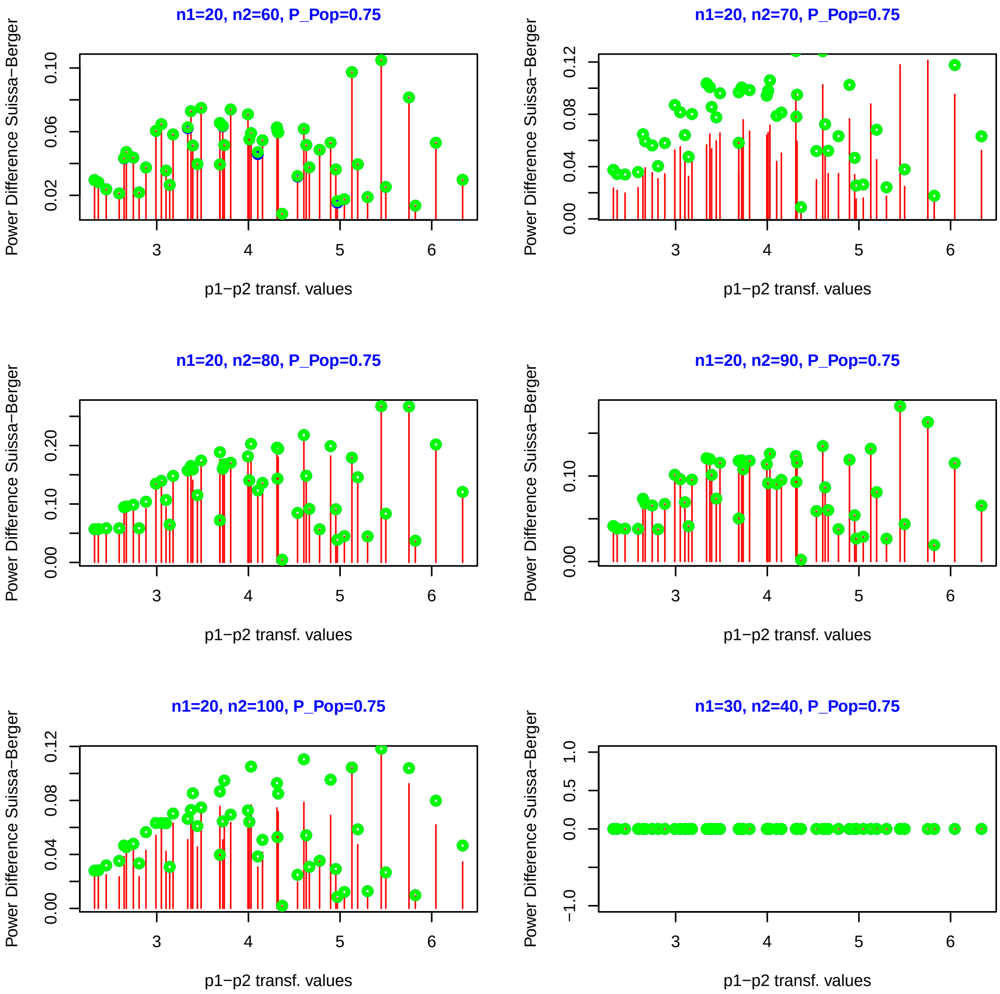

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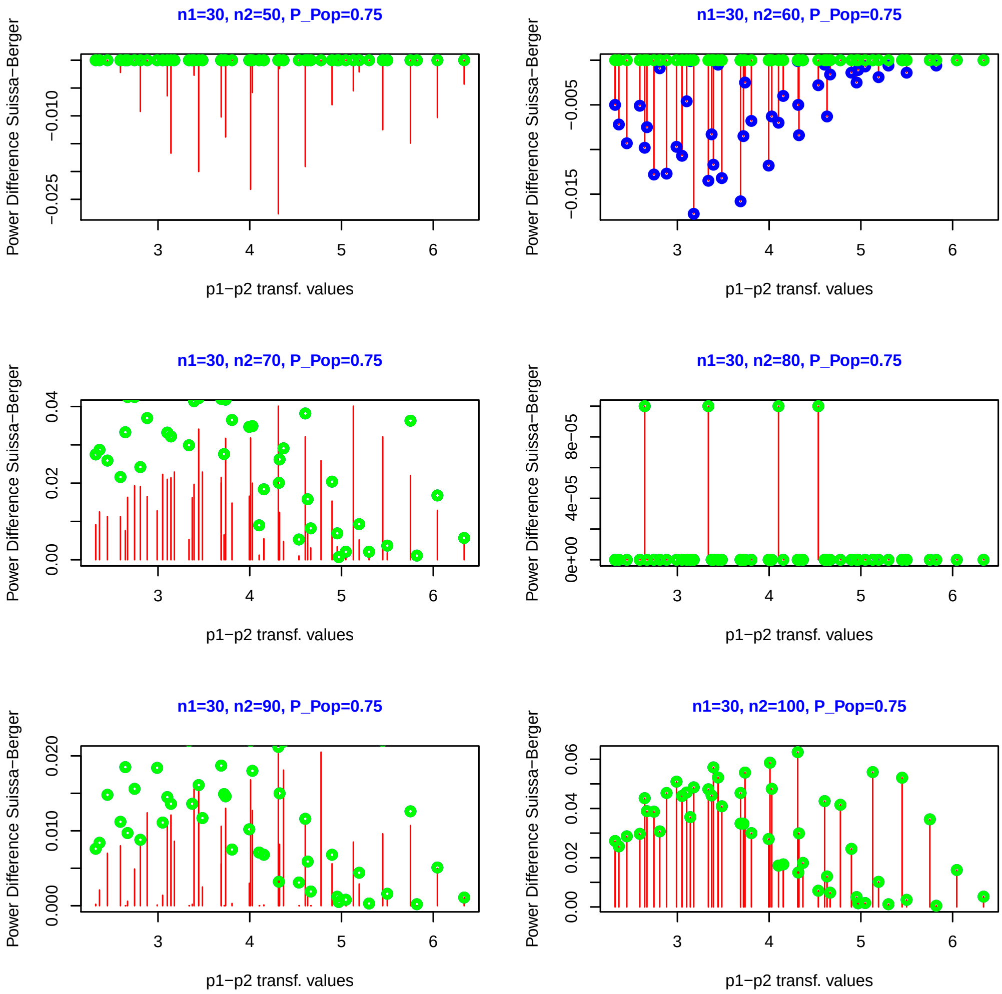

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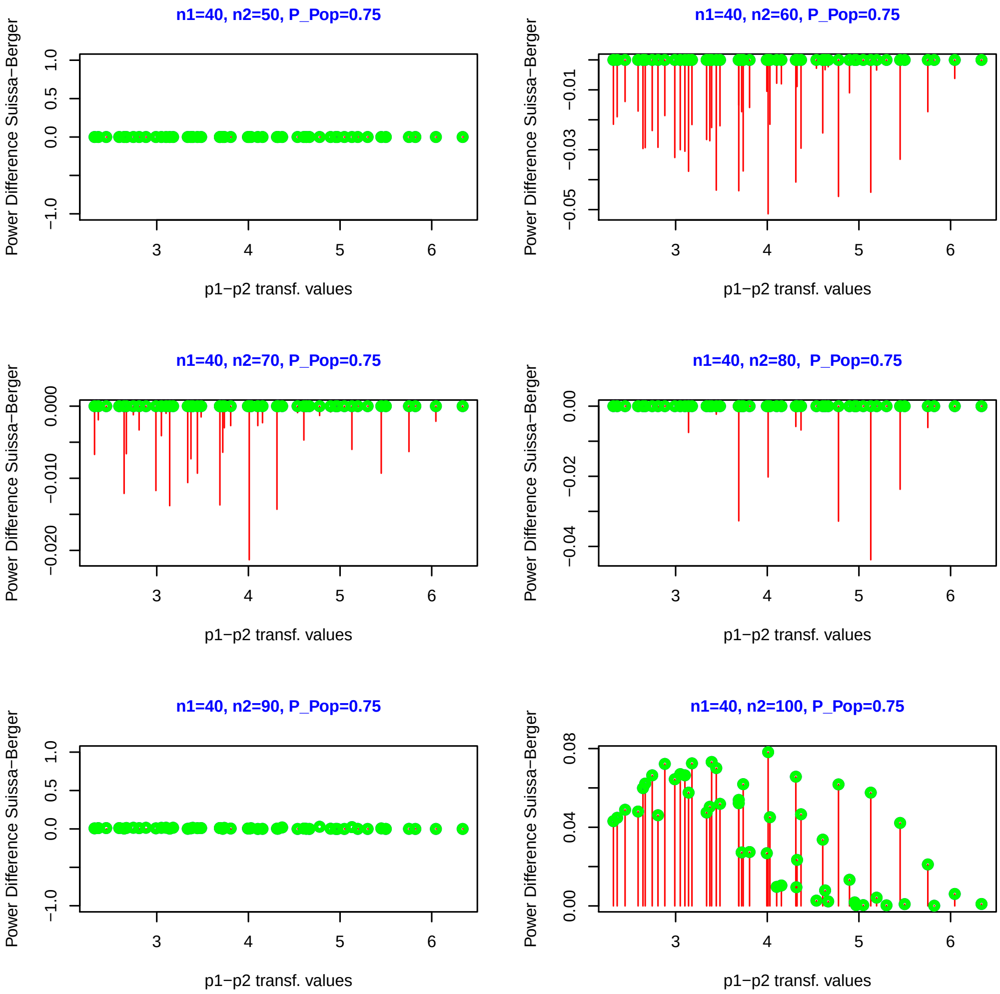

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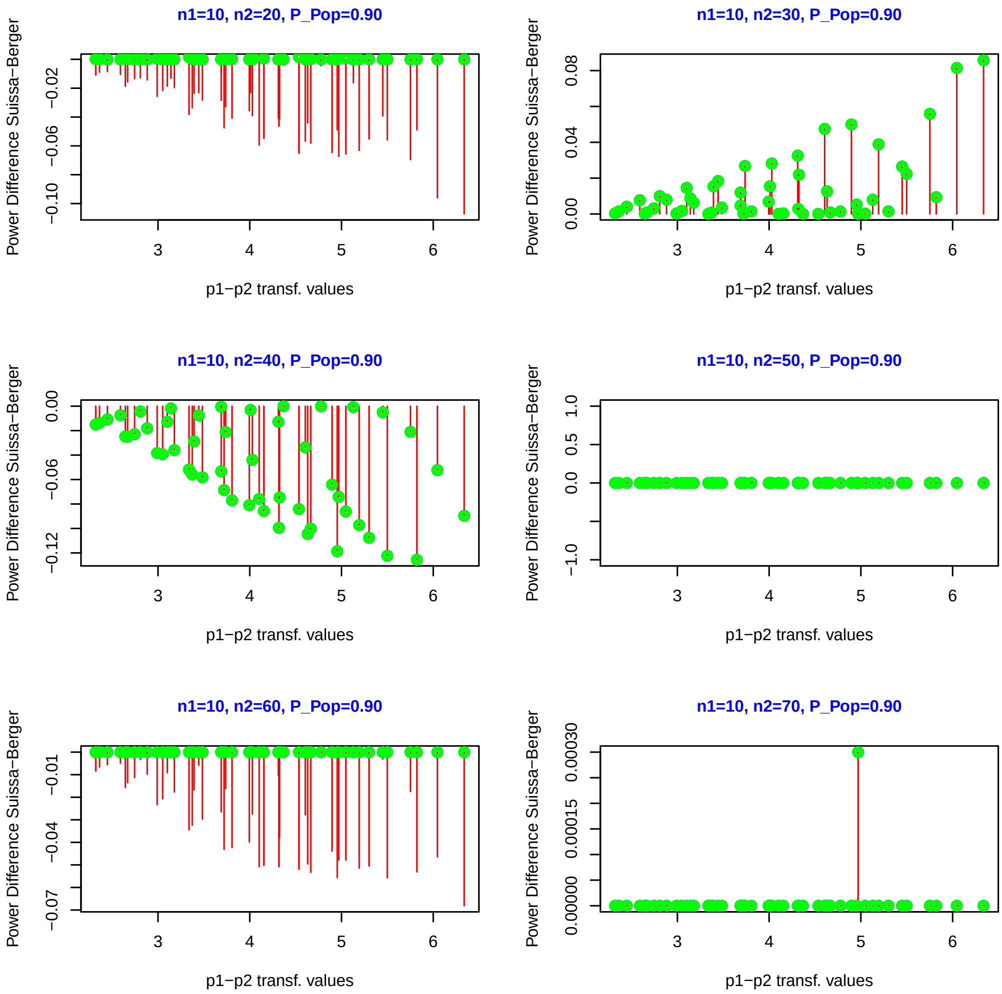

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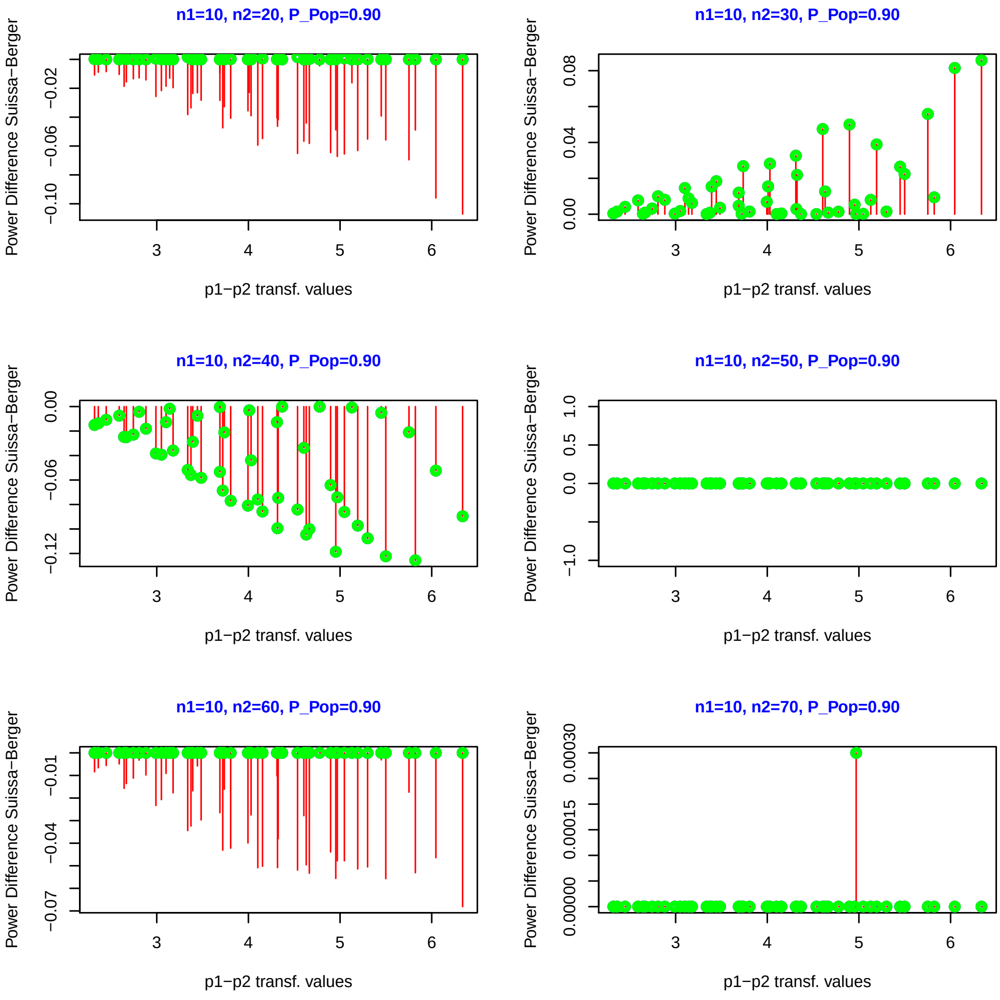

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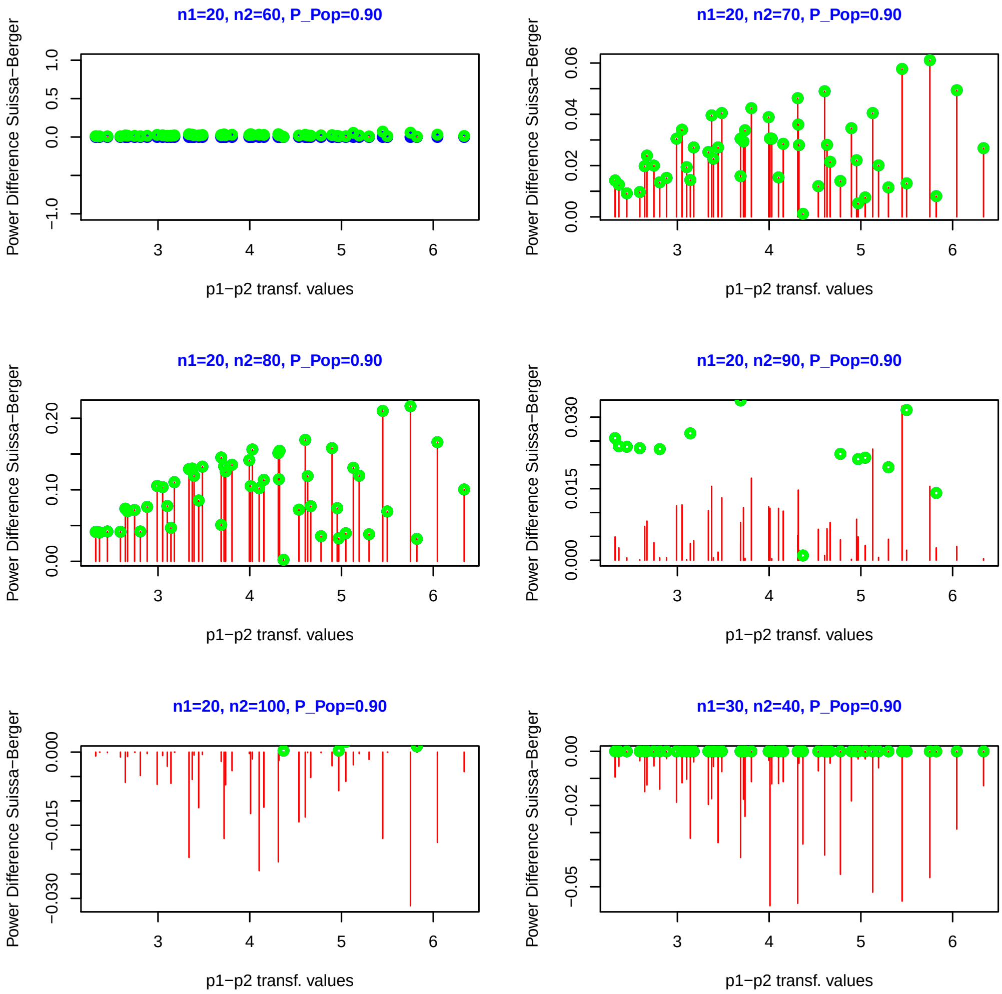
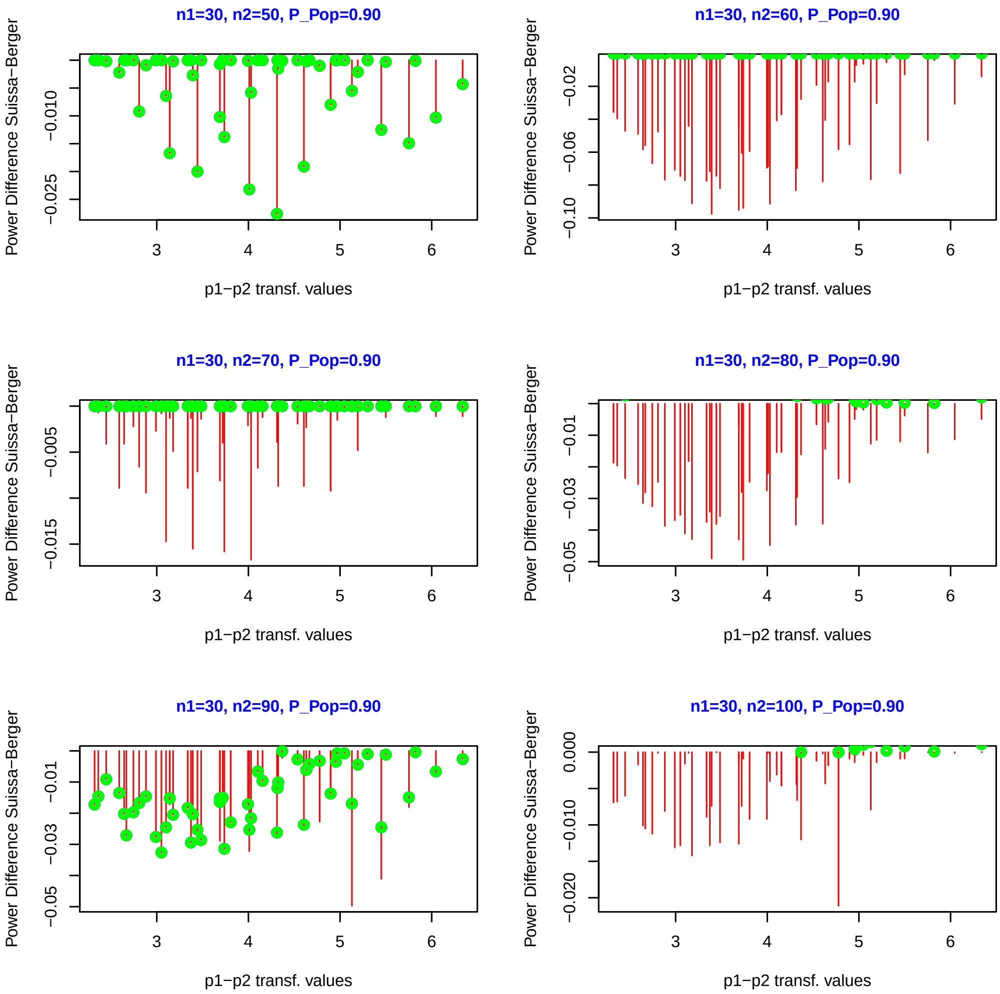


X-axis represents the values of the trasformed variable: $log((p_2 * (1 - p_1))/(p_1 * (1 - p_2))^2)$ whereas on the y-axis is indicated the power difference between the Berger pooled test ($\gamma = 0.001$) and the Suissa pooled test (red bars). Power difference between the Berger pooled test ($\gamma = 0.0001$) and the Suissa pooled test is represented by green dots whereas power difference between the Berger pooled test ($\gamma = 0.00001$) and the Suissa pooled test is represented by blue dots. In case the Berger pooled test ($\gamma = 0.0001$) and the Berger pooled test ($\gamma = 0.00001$) achieve the same level of power, only the green dots are drawn.



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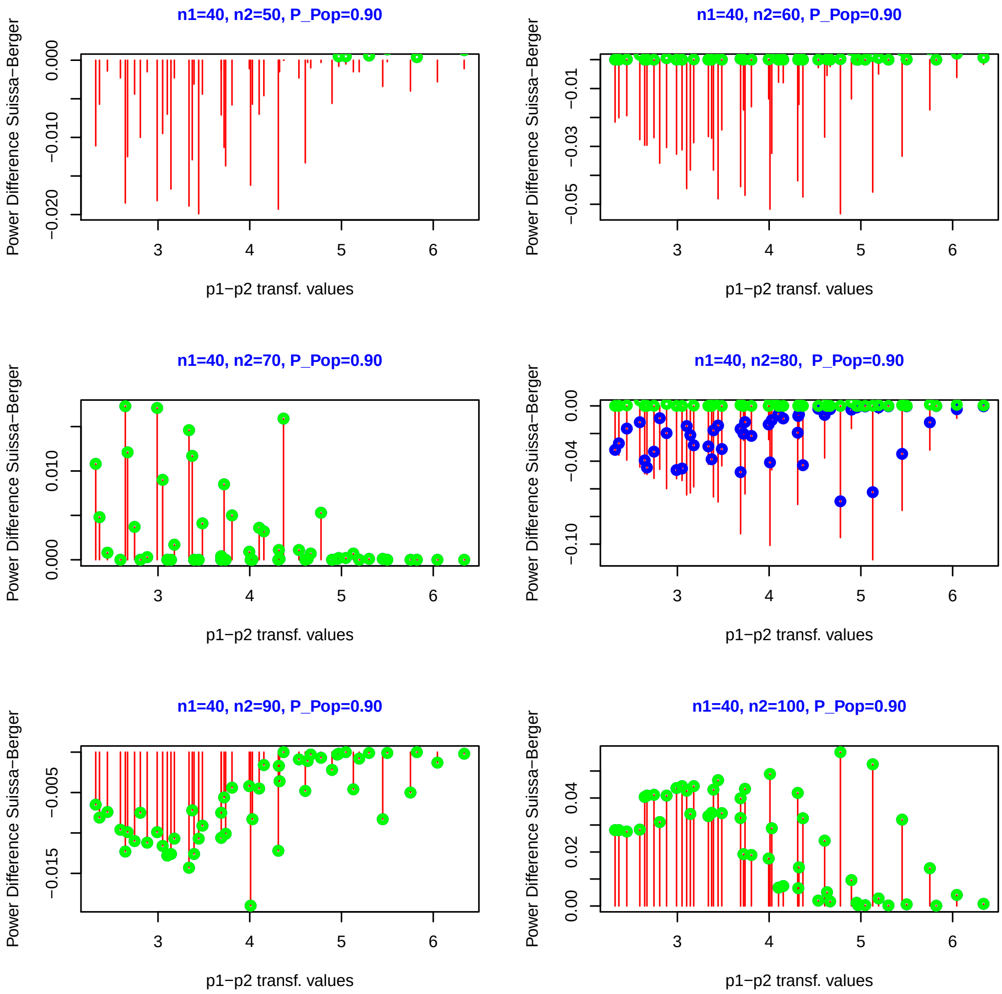

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