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NEIGHBOURHOOD EFFECTS ON PHYSICAL AND MENTAL HEALTH: EVIDENCE FROM ITALY

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But how many times can I walk away and wish "If only"
But how many times can I talk this way and wish "If only"
Keep on making the same mistake
Keep on aching the same heartbreak
I wish "If only"
But "If only"
Is a wish too late

The Cure – Cut Here

Dedicated to the loving memory of my Grandparents.

ABSTRACT

English: In the last 25 years, the literature has been figuring out how to answer the question, however outlined, on the independent effect that surrounding contexts, together with social contexts, have on individual health. There is no study that has been devoted to studying the link between places and health for the whole Italian territory. The present research wants to demonstrate the existence of the association between daily-living contexts and individual health in Italy. This work is a preliminary exploration of the phenomenon since no information is available for Italy yet.

ITA.LI survey collected data from 8,778 subjects belonging to 4,900 families living in 278 municipalities. Individual physical and mental health, measured through the SF-12, is the outcome considered in this study. Essentially, two dependent variables are analysed: one is the Physical Component Summary Scale Score (PCS), and the other one is the Mental Component Summary Scale Score (MCS). In studying the context, reference is made to both subjective measures (social cohesion and neighborhood disorder) and objective measures, both compositional (census data) and contextual (meteorological conditions). Moreover, together with individual characteristics, household-level deprivation is considered.

Multilevel analysis is implemented considering a three-level structure in which individuals are nested in families, which are nested in neighbourhoods. Four models are estimated: first a null model, second a random-intercepts model, third a random-slopes model, and finally a cross-level contextual model.

Evidence suggests the existence of neighbourhood effects in Italy, especially on mental health conditions. Compositional characteristics such as unemployment and the proportion of rented houses affect individual physical health, while contextual characteristics affect mental health. The subjective perception of social cohesion is essential only to mental health, while neighborhood disorder is related to both mental and physical health. Different results are found between regions and macro-areas.

Italian: Negli ultimi 25 anni, la letteratura ha cercato di capire come rispondere alla domanda, comunque posta, sull'effetto indipendente che i contesti circostanti, insieme ai contesti sociali, hanno sulla salute individuale. Non esiste uno studio che sia stato dedicato alla analisi del legame tra vicinato e salute per tutto il territorio italiano. Il presente studio vuole quindi dimostrare l'esistenza, in Italia, della associazione tra contesti di vita quotidiana e salute individuale. Questo lavoro è una esplorazione preliminare del fenomeno poiché non sono ancora disponibili informazioni per l'Italia.

L'indagine ITA.LI ha raccolto i dati di 8.778 soggetti appartenenti a 4.900 famiglie residenti in 278 comuni. La salute individuale fisica e mentale, misurata attraverso la SF-12, è l'aspetto che viene considerato in questo studio. In sostanza, vengono analizzate due variabili dipendenti: una è il *Physical Component Summary Scale Score (PCS)* e l'altra è il *Mental Component Summary Scale Score (MCS)*. Per lo studio del contesto si fa riferimento sia a misure soggettive (coesione sociale e disordine di vicinato) sia a misure oggettive, sia compositive (dati censuari) che contestuali (condizioni meteorologiche). Inoltre, insieme alle caratteristiche individuali, viene considerata la deprivazione a livello familiare.

L'analisi multilivello viene implementata considerando una struttura a tre livelli dove gli individui sono nidificati in famiglie, che sono nidificate in quartieri. Vengono stimati quattro modelli: primo un modello *null*, secondo un modello *random-intercepts*, terzo un modello *random-slopes* e infine un modello contestuale *cross-level*.

I risultati suggeriscono l'esistenza di un effetto di vicinato in Italia, in particolare sulle condizioni di salute mentale. Le caratteristiche compositive come la disoccupazione e la proporzione di case affittate influiscono sulla salute fisica individuale, mentre la caratteristica contestuale influisce sulla salute mentale. La percezione soggettiva della coesione sociale è importante solo per la salute mentale, mentre il disturbo di vicinato è legato sia alla salute mentale che fisica. Risultati diversi si riscontrano tra regioni e macroaree.

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Special thanks to Rinaldo, because you are always there, because you never give up on making me feel better, because they do not know what I have been through like you do, because it is always enough for me to look at you to know that everything is going to be great.

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ACRONYMS

CAPI Computer Assisted Personal Interviewing

CATI Computer Assisted Telephone Interviewing

CAWI Computer Assisted Web Interviewing

CES-D Center for Epidemiologic Studies Depression Scale

DSM-IV Diagnostic and Statistical Manual of Mental Disorders, fourth edition

EFA Exploratory Factor Analysis

ESDA Exploratory Spatial Data Analysis

FA Factor Analysis

GHQ-12 12-item General Health Questionnaire

GIS Geographic Information System

GPS Global Positioning System

HRQoL Health-Related Quality of Life

IRT Item Response Theory

ISTAT Istituto nazionale di statistica

ITA.LI Italian Lives - Survey on Life Courses in Italy

KMO Kayser-Meyer-Olkin

MCAR Missing Completely At Random

MCS Mental Component Summary Scale Score

ND Neighbourhood Disorder

PCA Principal Component Analysis

PCS Physical Component Summary Scale Score

SC Neighbourhood Social Cohesion

SF-12 12-item Short-Form Health Survey

SF-36 36-item Short Form Health Survey

SOM Self-Organising Map

SRQ-20 20-item Self-Reporting Questionnaire

1 INTRODUCTION

People's health is a public concern and it is in policy makers' interest to ensure good health to individuals. It is quite intuitive to think that the location where we live can have, in some way, an impact on our health (Kawachi and Berkman, 2003). Up to the 1990s, the study of health has been primarily focused on individual factors (e.g., biological factors, habits) as the determinant of the health status (Pickett and Pearl, 2001). Mainly, geography was taken into account to analyse health inequalities, or diseases transmission, across countries and places (Diez Roux, 2001). In the last 20/30 years, the literature has been figuring out how to answer the question, however outlined, on the independent effect that environmental contexts, together with social contexts, have on individual health. This idea of independence refers to the fact that local realities may have an impact on people's health that goes beyond individual genetic traits and probably even beyond individual lifestyles and motivations (Oakes et al., 2015). Indeed, for instance, the recent evidence shows that living in neighbourhoods that are deprived, considering deprivation from different points of view (such as material or social), has an adverse effect on individuals, jeopardising their life opportunities even going beyond their individual characteristics (Van Ham and Manley, 2009). The challenge is, thus, to assess what are the relevant context characteristics in the link between place and health, and how, through which mechanisms, and for which kind of individuals this relationship works.

The investigation of the effect that the context of living can exert on health is widespread and involves interdisciplinary approaches. Among the others, there are epidemiology, sociology (and social epidemiology in turn), and economics, the latter with particular reference to public policies. The idea that time, individuals, and places are three main epidemiological variables allows epidemiologists to use local data (such as demographic aspects, socioeconomic status, pollution, and health outcomes) and to allocate them within space. Since the surroundings where individuals live and act may affect their health, these spatial data are gaining more and more importance in epidemiology. Geographical analysis in epidemiology is a field dealing with spatial or even spatial-temporal data, which can be linked to the phenomenon of disease spread or population health-related risks (Pfeiffer et al., 2008). It is understood how, in epidemiology, social determinants and characteristics are considered as the background of the bio-medical mechanisms being at the center of the inquiry.

Instead, social epidemiology is distinguished from epidemiology by its peculiarity of directly investigating the social determinants in the distribution of health, diseases, and general well-being in the population (Krieger, 2001). In the social epidemiological neighbourhood effects literature (whose final intent is to find and weigh the independent role that the dynamic neighbourhood context plays on individual health - Oakes et al., 2015), the analysis of the impact of place on health is based on the local environment. This approach implies several notions (such as social cohesion and social capital, neighbourhood disorder, safety, and deprivation) as well as several types of valuable information for assessing them (e.g., census and administrative data, surveys on subjective perceptions). The finding that social capital varies from place to place has led interest in its study as it could have the potential to explain some geographical inequalities in health that had previously remained unknown (Mohan et al., 2005). Many studies which are interested in the place effect on health had based their analysis on the identification in the local social capital, however measured, as the factor that can affect health outcomes (Kawachi, Subramanian, and Kim, 2008). Several studies are also analysing the neighbourhood socioeconomic status as the context-related antecedent of health inequalities between areas and/or between individuals living in the same area (e.g., Carlsson et al., 2016; Diez-Roux et al., 1997; Jones and Duncan, 1995; Reijneveld and Schene, 1998). To date, on the one hand, what has been seen is that there are standard features in studies evaluating neighbourhood mechanisms that affect individual health. For example, concerning the studies carried out in the U.S.A., 70% of them used cross-sectional data; as a definition of the neighbourhood, almost all of the researches are based on a definition that coincides with the census limits; finally, as the context variable, more than 90% use non-spatial characteristics, such as poverty, as a determinant for health (Arcaya et al., 2016). On the other hand, the most recent trends that scholars have highlighted are a transition from cross-sectional studies to longitudinal studies and natural experiments; the dissemination of more sophisticated methodologies and the diffusion of ad hoc studies for the scrutiny of neighbourhood effects on health; more efficiency in the choice of context characteristics and in the outcomes to be analysed; a transition from ecological to multilevel to spatial studies; finally, the awareness that the complexity of the phenomenon must be adequately addressed (Duncan and Kawachi, 2018).

Unquestionably, the importance of assessing the way the relationship between context and health works is well-grounded for policy intervention (Strulik, 2008). Using Bambra et al.'s words, health is "political" for three reasons: first, health behaves like any other asset or resource in a neo-liberal economic system, since some social groups are healthier than others; second, health's social determinants are susceptible to public interventions and are dependent on political action/inaction; third, the right for health and well-being is/should be a fundamental condition of citizenship and a human right (Bambra, Fox, and Scott-Samuel, (2005).

It is as if all of these different approaches overlap in "place effect" studies. Here, health, which mainly has had a medical connotation, is now also an interest for society and public policies, which should analyse and take into account the independent effects of the local environment in order to implement the best interventions to promote and protect health. Indeed, to better detect how and when the relationship between health and local features takes place, Prior, Manley, and Sabel (2019) suggest that scholars should be engaged with both biological and sociological processes. Only in this way, new ground for health policy relevance can be detected.

For the moment, the present research has a more cautious ambition, namely that of establishing if neighbourhood effects exist and how they act on the Italian territory, leaving essential opportunities for future developments that seek to identify causal patterns as well. In doing so, the dissertation is structured as follows: the following two paragraphs of this chapter are going to deal with background and rationale (to give a clear statement of the research issues and final purposes, together with a brief examination of the context of the present research and its justification) and the conceptual framework (to give accurate description and consideration of the key concepts involved in the proposed research). Chapter 2 will be devoted to the literature review; in brief, I am going to analyse the literature dedicated to the study of the link between places and individual health outcomes, highlighting the most relevant developments and controversies, as well as, in the light of the purposes of this research, which health outcomes and which characteristics of the contexts of daily life (family and neighbourhood) are taken into account. Chapter 3 will explain the research design, the unit of analysis, and the sampling procedure; I will present the variables to be introduced in the regressions, as well as the multilevel model specification. Chapter 4 is devoted to the method; I will state how the variables are built and explain the models I will use to answer my research questions. Chapter 5 gives a view of the exploratory data analysis; both descriptive statistics and Exploratory Spatial Data Analysis (ESDA) will be presented. In Chapter 6 we find the results of the analysis which concern physical and mental health outcomes at the national level and also the analysis carried out on the Italian regions taken individually. Finally, with the last Chapter 7 I will conclude the dissertation by providing a discussion of the findings, exposing the main limitations of the research and its potential future developments.

1.1 BACKGROUND AND RATIONALE

In the extensive literature that is interested in the study of the social determinants of health (i.e., the conditions in which individuals are born, grow up, educate, work, interact with each other and age), it is clear that the neighbourhood individuals belong to represents one of the contexts in which they spend a large part of their lives (Duncan and Kawachi, 2018). Paraphrasing Oakes et al. (2015), the social epidemiological neighbourhood effects studies' final intent is to find and weigh the independent role that the dynamic neighbourhood context plays on the health of residents. In this respect, the importance of studying the role the context has on the health of the population in a territory as Italy, where actions concerning health protection are also taken decentrally at a regional level, may sound of a great necessity. Firstly, it should be clear to Italian policymakers if neighbourhood effects exist and how they evolve throughout the Italian territory; the social and public interest for population health calls for health policies of more and more rigor also taking into account such aspects. This work is a preliminary exploration of the phenomenon since no information is available for Italy yet. No study has been devoted to investigating the meaning of the place of living for health for the whole Italian territory. There are only a few studies focused on specific Italian cities, such as Turin (Marinacci et al., 2004; Petrelli et al., 2006), Rome (Michelozzi et al., 1999), Taranto (Gianicolo, Mangia, and Cervino, 2016), and Brindisi (Belli et al., 2004), who analysed the effects of the characteristics of life contexts on health outcomes such as mortality (both general and due to specific causes like cancer, overdose or respiratory diseases) and the occurrence of certain conditions such as heart diseases.

Understanding neighbourhood effects as the influence on individual's attitudes and behaviours due to the interaction with others in the neighbourhood and with the neighbourhood environment, this project aims to provide a descriptive analysis of the phenomenon of neighbourhood effects on health throughout the Italian territory. The novelty of the study is the possibility, thanks to the sampling design that was implemented for carrying out the survey, to introduce, together with individual-level characteristics, also family-level characteristics so that a three-level multilevel model can be implemented, allowing to account for individual-, family-, and neighbourhood-level factors. The importance of being able to also take into account nesting at the family level lies in the fact that, as suggested by Kawachi and Berkman (2003), it is necessary to recognize and study all the contexts proper to individual life, collecting different forms of information. It should be done in order to consider more competently all the relevant factors (not only the geographical one) for the health of the individual. Hence, there arises the need to use multilevel techniques since: first, the observations that have been collected are correlated or clustered along spatial (neighbourhood) and non-spatial (household) dimensions; second, the exerting mechanisms on health are thought to be simultaneously in action at more than one level; and third, there is driving interest in being able to more clearly analyse variability and heterogeneity at the different levels, going beyond the mere focus on average associations (Blakely and Subramanian, 2006).

Therefore, by means of a three-level multilevel model, the following questions tried to find answers: is health associated with perceived neighbourhood disorder and perceived neighbourhood social cohesion? Does household deprivation affect individual health? After taking all individuals' and households' characteristics into consideration, are there still significant health variations across neighbourhoods? Does the between-neighbourhood variation vary differently for different household deprivation groups? After having taken into consideration individuals' and households' characteristics, nationally, what role do exogenous contextual and compositional factors play in population health? To what extent do exogenous neighbourhoods characteristics account for the variation between neighbourhoods for the different groups of individuals? Finally, are these relationships between contexts and individual health the same throughout the territory? Are there differences between regions and macro-regions?

Thus, the aim is not only to analyse differences between individuals but also between contexts. The research wants to assess whether neighbourhood effects on health exist and how they evolve throughout the Italian territory. For instance, the overall impact of a contextual feature on health could be harmful; nevertheless, for specific individuals, the relationship could be positive, or still negative but with a greater magnitude, or it may not exist at all: a specific neighbourhood characteristic (such as the level of unemployment) may have more relevance in the association with individual health for deprived families, or older people, or unemployed people, than for other categories of the population. Furthermore, suppose it is true that a characteristic of the context at the national level has a significant effect on individual health. In that case, it may not be true for some regions or macro-areas of the territory, as well as neighbourhood variation in health may be present in some regions only.

In this respect, the identification of more vulnerable neighbourhoods plays an essential role for social epidemiological research and health policies future planning (Schüle, Gabriel, and Bolte, 2017). This research is an exploratory analysis of the phenomenon that aspires to demonstrate the existence of such association between context-related characteristics and individual health in Italy, analysing whether, where, and for whom neighbourhood effects exist and affect health. The purpose is to provide a picture of the territory that can first help public policies to understand whether this juxtaposition exists and how it works. Second, it calls for future research analysing causal patterns of the relationship between neighbourhoods and individual health. With these objectives, this research will involve individuals that have been interviewed throughout the Italian territory starting from the summer of 2019 to December 2020 through data from Italian Lives (ITA.LI) - Survey on Life Courses in Italy survey.

ITA.LI is an important longitudinal survey developed by the Department of Sociology and Social Research of the University of Milano-Bicocca and funded by the Ministry of Education University and Research.

1.2 CONCEPTUAL FRAMEWORK

At the base of the conceptual framework of valuable reference for this research, there are mainly two macro concepts of interest: the neighbourhood (or preferably, the context) and health indeed. Various implications and different details are then cascaded from these. As already anticipated, and also confirmed by Subramanian, Duncan, and Kelvyn (2003), the potential of the most recent multilevel techniques allows researchers to take simultaneously into consideration different contextual levels, which are significant for the determination of health. In this sense, the literature distinguishes between the neighbourhood, understood as a delimited (objectively or subjectively) geographical area, and other communities, understood as groupings of people united by the same antecedents or purposes, such as the workgroup, school, or family (O'Campo and Caughy, 2006). In this research, the relevant contexts that will be considered are two, i.e., the household context and the neighbourhood context.

The conception of the neighbourhood is understood both as the unit around individuals' home (Duncan et al., 2013), and as the place where individual lives, acts, and communicates, both with the environment and the society (Duncan and Kawachi, 2018). In this sense, a geographical delimitation of the place may not exist, but it may be necessary in order to define the range of action of a potential policy. Therefore, in some cases, an objective imposition of a geographical delimitation (e.g., census block) may not coincide with the perception that the subject has of her/his neighbourhood. At the same time, in studying the effects of the place of living on health, having objective geographical limits certainly helps to organize the data and the relevant information about the objective characteristics of the neighbourhood. That is to say, the neighbourhood can be understood both as a geographical unit and as a group of local individuals that share trust, customs, habits, and beliefs. Thus defined, the neighbourhood can be characterized through different features, physical, economic, social, as well as through the interactions and bonds between the subjects. These different categories of aspects can be broadly identified through two types of resources: for the former, mainly an objective source of measure (e.g., census or administrative data), while for the latter a subjective source (e.g., individual perception) (O'Campo and Caughy, 2006). Using Weden, Carpiano, and Robert (2008)'s words, the subjective impressions in measuring the aspects of the area refer to *"individual-level assessment of a resident's neighbourhood"*. In contrast, the objective measures are all those *"area-level indicators that can be characterized independently of a resident's own perception"*. Basically, it is true that the perception that the subject has of the place in which she/he lives undoubtedly has an impact on health (think for example of the perception that one has about security or crime that influences the level of stress, with consequences on well-being) (Lorenc et al., 2012). Thus, it is necessary to keep also these aspects into consideration when running the analysis, even if it is not possible to attribute to them an objective geographical limitation. However, in the same way, it is true that objective measures of the characteristics of the neighbourhood also have an impact on health (think of the direct effect that pollution has on the human body - Anderson, Thundiyil, and Stolbach, 2012). Those are therefore equally relevant when studying the effect of the place of living on health, even if an attribution "from above" of the administrative geographical delimitation may not coincide with the actual range of action of the individual. Thus, both objective and subjective neighbourhood-characteristics are needed (Kawachi and Berkman, 2003). Moreover, to take into consideration the characteristics of the local place, in some cases, the same measure can be obtained either objectively (e.g., using administrative data) or, otherwise, the subjective perception of individuals can be used. In this sense, let us consider an example of a measure on pollution: some studies rely on objective data on measures such as the level of particulate air pollution (Jerrett et al., 2001), while others base their analysis on individual perceptions by asking people if they believe that their neighbourhood is actually characterized by high or low levels of pollution (Ziersch et al., 2005). In this research, census data will be used to identify the objective characteristics of the neighbourhood and, therefore, the neighbourhood is understood as a bounded geographical unit, specifically the census block. With regard to the last available census, in 2011, Italy was partitioned into approximately 350,000 census blocks, each including nearly 200/250 families. Moreover, as will be explained later, subjective perceptions of neighbourhood disorder and social cohesion will also be considered.

The neighbourhood effects, understood as the independent economic, social, and environmental effect (Van Ham and Manley, 2012), has become a relevant concept in recent decades. Its importance has led it to be also considered by policymakers in the actions to be planned to control the social determinants of health. In particular, the empirical contributions of the last 20 years or so in the study of neighbourhood effects have allowed an even better understanding and increasing interest in the field. As illustrated by Subramanian (2004), three main contributions are worthy of consideration: first, the role, independent of individual characteristics, of neighbourhood features was found to be significant for many public health outcomes; second, these outcomes were associated with a multitude of context-level characteristics; third, the majority of studies rely on the use of multilevel techniques (suitable for modeling variation and nested data) to study neighbourhood effects. Thus, the understanding of neighbourhood effects as the influence on individual attitudes, habits, and behaviours due to interaction with others in the neighbourhood and with the neighbourhood environment, emphasizes the possibility of intervening to improve individual and public well-being and health, also going beyond a direct intervention on the individual, but acting at the higher level of contexts (Oakes et al., 2015). However, some shortcomings are also to be considered in this field, e.g., the identification of true causal effect (Van Ham and Manley, 2009), which derives from the fact that most studies limited the results of a correlation between individual health and the characteristics of the place where they live. Therefore, it is necessary to analyse these effects in order to have an ever greater understanding and to explore new solutions for possible future developments, which also allow defining the existence of a causal relationship between the individual health outcomes and the neighbourhood (Van Ham et al., 2012). In the present research, reference is made to the term "neighbourhood effects" intended as an association (not with a causal perspective) between the characteristics of the contexts in which individuals undertake their lives and individual health.

A place-level characteristic which is widely used when studying the neighbourhood is deprivation, understood as a situation of poverty and of lack of the potential to satisfy inhabitants' needs, whose deficiencies can be perceived in all types of resources, rather than financial needs only (Guillaume et al., 2016). Once again, there are both objective and subjective measures through which this aspect can be analysed. In fact, in some studies, researchers resort to objective measures, usually obtained from censuses, such as the percentage of illiterate individuals, the percentage of unemployed, or the percentage of people living in rented houses (Stafford and Marmot, 2003). Instead, other scholars rely on subjective measures of neighbourhood deprivation, for example, asking individuals about the presence of vandalism, cleanliness, or safety (Godhwani et al., 2019).

Social cohesion, which together with informal social control forms the broader concept of collective efficiency (Sampson, 1991), is a dimension that has been much analysed in the literature. According to Kawachi, Berkman, et al. (2000), moreover, social cohesion reflects two other dimensions of society, namely the absence of hidden social conflicts and the presence of strong ties (both between individuals and between individuals and the neighbourhood). To this extent, all these concepts are likely to overlap also with the concept of social capital, as understood by Kawachi, Subramanian, and Almeida-Filho (2002). It is described as the set of all resources available to individuals and society, which can be both psycho-social (such as support, reciprocity, or trust) and also be considered in a tangible form (such as loans or information sharing). The importance of social cohesion, as an indicator of attachment to and satisfaction with the neighbourhood and the other inhabitants (Kuipers et al., 2012), is thus seen in its consideration also in the study of neighbourhood effects on health. The reason is that, in neighbourhoods with high levels of social cohesion, people are expected to have better health because they would be more friendly and available to each other, they would like and trust each other, they would feel they belong their neighbourhood and feel more secure in it (Aminzadeh et al., 2013).

Subjective perceptions, as a measure of the characteristics of the context, were also taken into consideration to address more material aspects such as the presence of vandalism or graffiti and dirt (Ettema and Schekkerman, 2016; Franzini et al., 2005). In addition, perceptions about security and crime within the neighbourhood were also considered (Baum et al., 2009; Chan, Schwanen, and Banister, 2021). Using a broader concept of neighbourhood problems, (Feldman and Steptoe, 2004; Steptoe and Feldman, 2001) considered different dimensions to be captured with the subjects' impressions, such as safety, cleanliness and noise, vandalism, disturbance and perceived danger after dark. In some cases, the set of items considered above has been examined to represent the concept of social disorder in the neighbourhood. As intended by Ross and Mirowsky (1999), social disorder is observed in all the signs indicating a lack of social control that involve people. In particular, physical disorder, such as vandalism and noise, and social disorder, such as perceived crime and the presence of disreputable persons, also indicates that social control has failed. Thus, in this research, together with the subjective measure of social cohesion, reference will be made to the general concept of neighbourhood disorder. The latter, like in Burdette and Hill (2008)'s analysis, is captured with the aspect of material disorder (noise, dirt, and pollution) and the aspect of safety (presence of disreputable individuals, vandalism, and fear in the street during night).

Finally, the household context will also be taken into consideration in this research. Within this sphere, several aspects can be taken into account in their effect on the health of individuals. Poverty and deprivation are the most examined. The importance is in assessing poverty measures not only using monetary aspects (usually income). Thus, as Whelan and Maître (2012) say, the focus should be on a conception of poverty that indicates the family's inability, due to a lack of resources, to participate in everyday experiences in an at least decent way. In this sense, it can be seen that, on the one hand, there are material and structural aspects to be considered at the household level. On the other hand, there are financial aspects (which can both directly highlight monetary aspects and indicate the family's inability to afford certain expenses and experiences). A dimension that is often considered is that of material deprivation, which is measured by the presence (or lack of) of certain goods such as durables (Montgomery and Hewett, 2005). Then, there are all those aspects concerning the house, its structural conditions, and domestic crowding (Howden-Chapman, 2004). In addition to these material aspects, the household situation can also be analysed with reference to its ability to afford certain expenses (such as going on a one week-vacation once a year, eating meat or fish three times a week) (Gordon et al., 2000), and its financial condition (such as the burden of family expenses, and making ends meet), also defined as economic strain by Whelan et al. (2001).

Different studies analysing the link between health and context rely on different conceptions of health, on different ways to measure it, and to assess neighbourhood effect on health. Mainly, the literature have studied neighbourhood effects and their impact on: physical health, taking into consideration both diseases like diabetes or hypertension, and aspects like physical functioning and limitations (Kivimäki et al., 2018; Rocha et al., 2017); mental health, usually captured with questions administered in validated scales such as SF-36 and GHQ-12 (Rocha et al., 2017; Weimann et al., 2015); general health, and health-related behaviours such as alcohol consumption or access to health care services (Kuipers et al., 2012; Ngamini Ngui et al., 2012); and mortality (Marinacci et al., 2004; Petrelli et al., 2006). In the analysis of the effects that the context where individuals live has on their health, we see how many aspects of the latter can be studied. Moreover, the choice of which aspects of the health one wants to study also influences which characteristics of the neighbourhood to focus on. For example, studying how the context affects the potential access to health services undoubtedly requires a measure about the density of or the distance from such services. In contrast, studies on the effect of green areas on well-being may need very different information. In this research, the health outcomes that will be analysed are individual physical and mental health, measured through the SF-12 (12-Item Short-Form Health Survey). The SF-12 is the shorter version of the most popular generic measure of patients' outcomes, the 36-Item Short-Form Health Survey (SF-36), which covers eight dimensions of health status: physical functioning, role limitations due to physical health problems, bodily pain, social functioning, general mental health, role limitations due to emotional problems, vitality, and general health perception (Ware Jr and Sherbourne, 1992).

2 LITERATURE REVIEW

The relevant literature interested in the connection between place and health is very far-reaching and includes several fields that overlap in concepts, range of action, and techniques. The most crucial purpose of this field is to give evidence, tangibility, and clearness of the relationship between individual health outcomes and everything in the surroundings (such as the environment, other individuals, the relationships between them). A general framework is given to explain how the present research can be inserted in the broad literature of the social epidemiological neighbourhood effects. The main concepts and limitations of the studies are illustrated. In the end, relevance is given to aspects (such as health outcomes, household, and context characteristics) that have been analysed in the neighbourhood effects on health literature.

2.1 SPATIAL STUDIES AND NEIGHBOURHOOD EFFECTS

In the last decades, researchers are increasing their interest in studying different facets of the relationship between context and health, such as the identification of determinants of spatial inequalities in health, the relevance of particular places and spaces such as neighbourhoods, features, and functions of therapeutic landscapes, the impact of different health experiences on the construction of places, and contextualised analyses of policy reactions (Fleuret and Atkinson, 2007).

In the last 20 years, researchers have been interested in inspecting the independent effect that local contexts (like neighbourhoods), jointly with social contexts, have on individual health, evaluating how it works and what it involves. The idea of independent effect is based on the assumption that the neighbourhood and its own characteristics can influence health, regardless of the bio-genetic characteristics of the individuals and also regardless of their habits and preferences (Oakes et al., 2015). A similar assumption derives from the distinction between compositional and contextual factors. Researchers tried to demonstrate, on the one hand, whether the context (characteristics of the place where people live) has an explanatory function after population composition (characteristics of the people living in that place) has been taken into account. On the other hand, they tried to demonstrate how much of the geographical variation the context can explain. However, as stated by Macintyre, Ellaway, and Cummins (2002), this distinction is not clear enough in the literature, leading to contradictory evidence in the extent and magnitude of "place effects" on health because of different conceptualisations, in particular in whether specific contextual or individuals' features are seen as "confounding" or "intervening" variables. Moreover, the collective explanation (Macintyre, 1997) for geographical variation in health should also be considered: together with compositional explanation (attention is on the characteristics of individuals living in specific areas) and contextual explanation (attention is on environmental-related physical and social features), collective explanations should be given due consideration since it provides relevance to the socio-cultural sphere of local communities: it *"[...] emphasises the importance of shared norms, traditions, values, and interests, and thus adds an anthropological perspective to the socioeconomic, psychological, and epidemiological perspectives often used to examine area effects on health"* (Macintyre, Ellaway, and Cummins, 2002).

The study of the relationship between the local context and people's health is comprehensive, it involves different disciplines, and sometimes requires interdisciplinary approaches. Health geography takes health into account with the idea that the whole is more than merely the sum of its parts, embracing space and society, and conceptualising the functions of neighbourhood and geography in health, illnesses, and health habits (Dummer, 2008). Its primary emphasis is on spatial relations and spatial patterns where health, which mainly has had a medical connotation, is now also an interest of society and public policies. Therefore, policymakers should take advantage of these studies about the independent effects of the local context to implement the best interventions to promote and protect health.

Social epidemiology, which is another discipline that is interested in the context-health association, arises within an intersection between the fields of medicine (physiology and psychosomatic, social, and preventive medicine) as well as those of medical sociology, health psychology, and epidemiology itself (Berkman and Kawachi, 2014). In this framework, social epidemiology is defined by Krieger (2001) as a branch of epidemiology that promises to explicitly scrutinise social determinants ("social environment") of communities distributions of health, diseases, and wellbeing, rather than merely dealing with those determinants as background to biomedical phenomena. The idea behind it is that the way situations of disadvantage and advantage are distributed along the population is in turn reflected in the distribution of diseases and health in that same population. Thus, social epidemiology is concerned with defining which socio-cultural factors influence health and its distribution in the society, as well as defining the underlying processes and mechanisms that influence the health of individuals and the population (Honjo, 2004). The socio-cultural aspects are not the only ones to be examined, but also the socio-environmental ones (focus is on exposure rather than on specific illnesses) must be considered in their effects on physical and mental health conditions (Berkman and Kawachi, 2014). In general, this also refers to the "population perspective", according to which the individual risk of being affected by diseases or having her/his well-being threatened is not independent of the risk of the entire population in which she/he lives (Rose, Khaw, and Marmot, 2008).

The presence of different aspects and levels (individual and context primarily) through which individual health can be influenced has given rise to the need to develop and adopt statistical techniques that allow different levels of analysis to be simultaneously taken into account (Diez-Roux, 1998). In this sense, thus, the importance of multilevel approaches (also defined as contextual or hierarchical approaches) for social epidemiology is noticeable. As Krieger (2001) explains, these techniques can help in assessing whether the health of individuals is exposed to both individual and family components, as well as to population or local characteristics. Therefore, due consideration must also be given to the concept of the neighbourhood effect - understood as the independent effect of the local and social environment on inhabitants' life chances regardless of their own individual characteristics (Van Ham et al., 2012). The ability to model situations characterised by complex heterogeneity such as those analysed in the social epidemiology represents the strength of hierarchical models, thanks to which it may be possible to analyse neighbourhood effects with a causal perspective (Subramanian, 2004). Using Oakes et al. (2015)'s words, the social epidemiological neighbourhood effects studies' ambition is to find and weigh the independent role that the dynamic neighbourhood context plays on the health of residents.

Therefore, within this discourse, what mainly emerges is that social epidemiology also considers all those concepts that are at the limit of its sphere of interest. This is to say that the conceptual limits of this field are not linear and clear-cut (Berkman and Kawachi, 2014). The joint application of so different (sometimes overlapping) branches of knowledge and researches investigating context-health liaison has led, in recent years, to the need to put into an organic form the picture that is emerging in the literature. For this reason, many literature reviews try to organise health geographer scholars' researches. For instance, while Arcaya et al. (2016) take into account empirical studies that examine associations between neighbourhood environment (both objectively and subjectively assessed) and health outcomes, Schüle and Bolte (2015) consider both socioeconomic neighbourhood characteristics and objective factors of the built environment as playing an essential role for health and health-related behaviours.

The need to investigate how neighbourhood-level attributes can affect the relationship between place and health has brought extensive literature (both qualitative and quantitative) into the field. Researchers have conceptualised a wide range of neighbourhood characteristics, including area-level poverty, public spaces, walkability, air pollution, social cohesion, and crime, among the others, as drivers of an equally broad range of individual health outcomes (Arcaya et al., 2016). In this plethora of studies, we can identify some context-related factors that have emerged as relevant in the impact on health. Those are:

- Social capital
- Neighbourhood Socioeconomic Status
- Neighbourhood deprivation and disorder
- (Potential) Access to health care services
- Green places and therapeutic landscapes

First, as the neighbourhood is the principal territory of analysis in neighbourhood effects studies, neighbourhoods' characteristics are thus under investigation. Neighbourhoods are considered as important features when studying individuals since they are the places where individuals live, spend time, and social relationships occur (Murdoch, 2006). Indeed, social mechanisms at a neighbourhood level have received consideration from scholars, with researchers emphasising the role of social capital over a range of health issues (Aminzadeh et al., 2013). As Kawachi, Subramanian, and Kim (2008) noticed, there is not a unique definition of the concept of social capital. Indeed, it can also be conceived at different levels (individual level, neighbourhood level, as well as at broader levels of spatial aggregation like regions or countries); hence, there is not a single way to measure it. Among the aspects that have been considered to assess social capital, we can see how different choices have been made: for instance, Ziersch et al. (2005) took into account neighbourhood connections, neighbourhood trust, reciprocity, neighbourhood safety, and local civic action; Kuipers et al. (2012) selected nine items to measure social cohesion (like the attachment to the neighbourhood and the level of solidarity); Aminzadeh et al. (2013) dealt with social cohesion, facilities, physical disintegration, membership in community organisations, residential stability.

Second, to synthesise the neighbourhood Socioeconomic Status (nSES) Fang et al. (2015) built a composite index based on the following measures: the percentage of households receiving interest, dividend or net rental income, the percentage of adults with high school degree, the percentage of adults with a college degree, and the percentage of individuals in management and professional occupations. While social capital and nSES are measures derived from individual-level information (both objective and subjective, see Section 2.1.2), characteristics of the built environment are generally collected at the neighbourhood level directly. For instance, Kurka et al. (2015) took into consideration neighbourhood walkability, transit access, aesthetics, crime and traffic safety, pedestrian infrastructure, and recreation/park access.

Third, further aspects which are considered as relevant at the neighbourhood level are also neighbourhood disorder and neighbourhood deprivation. For instances, Kuipers et al. (2012) took into consideration eight measures, such as vandalism, noise, security and dirt, to represent neighbourhood-level disorder. Rocha et al. (2017) classified neighbourhood socioeconomic deprivation classes based on measures such as: percentage of retired individuals, percentage of families with a person aged 15 years or less, aging index, illiteracy, percentage of subjects with higher education, percentage of subjects with lower occupation, unemployment rate, mean expenditure on housing, attractiveness, and proportion of buildings with reparation needs. While not referring to social capital, nor to nSES, (Ngamini Ngui et al., 2012) take into consideration some features linked to them: proportion of recent immigrants, socioeconomic deprivation index (measured through six items such as unemployment and percentage of people with less than secondary education), percentage of single-parent families, mean household income, and residential stability. Finally, also measures on pollution are taken into account. For instance, Ziersch et al. (2005) considered individuals' perceptions of the level of noise in the neighbourhood and how dirt the neighbourhood was; instead, Richardson et al. (2013) accounted for objective measures of air pollution, noise pollution, and the traffic environment to build an index of multiple environmental deprivation.

What can be observed is that some characteristics are included in different concepts by different studies. Just to give an example, while Kuipers et al. (2012) considered security (being afraid to be bothered or robbed in this neighbourhood) to represent neighbourhood disorder, Ziersch et al. (2005) considered neighbourhood safety (a rating of the neighbourhood as a safe place to walk around at night) as a measure for social capital.

Fourth, access to, or in some cases, potential access to, services is of well-established interest. Of primary importance are the characteristics of the users, and then the hindrances that they cope with when accessing services; what is inspected are, for example, distances between facilities and individuals' homes, and the environment configuration of where these services are placed. Early studies were focused on the access to primary health care (e.g., GP) and hospitals. Emphasising the difference between access and potential access, Bissonnette et al. (2012) take into account the supply of health care resources, measured as the distribution of health care facilities in a specific neighbourhood (physician-to-population proportion), as a measure of equity. Additionally, they consider aspatial characteristics such as access to physicians who accept new patients and physicians providing services in foreign languages. As pointed out by Rosenberg (2014), more recent studies tend to analyse access to health services (such as hospices, pediatric care, mental health services) other than to primary health care or hospitals.

Fifth, a theme that has become increasingly prevalent since the 2000s concerns the natural environment (or green spaces), particularly in urbanised areas, and its health benefits. For instance, many studies have employed the notion of "therapeutic landscape" to describe how some places are implicated in processes of healing or health improvement, emphasising the role of active lived experience and the imbrication in the natural environment (Bell, Wheeler, and Phoenix, 2017; Conradson, 2005; Finlay et al., 2015). Moreover, it has been found that unfairly distributed green spaces may even intensify environmental health inequalities in an urban context. In this respect, the identification of more exposed neighbourhoods plays an important role in epidemiological research and health policies planning (Schüle, Gabriel, and Bolte, 2017).

2.1.1 *Geographical boundaries, and other issues*

As in all fields of study, there are some pitfalls, limits, and challenges also in the research on neighbourhood effects. Among others, as far as the present research is concerned, the following controversies will be discussed:

- Social self-selection
- Contextual and compositional effects
- Psychosocial and material mechanisms
- Subjective and objective measures
- The choice of the spatial unit

The problem with social selection lies in the fact that the different preferences that individuals have about where to live may reflect spatial variations in health outcomes. That is to say, the selection process underlying residential mobility leading to choose a neighbourhood instead of another may not be independent of the outcome under consideration (Lina and Van Ham, 2012). For example, the poorest individuals would tend to move in high deprived neighbourhoods, characterised by the presence of cheaper housing (Kawachi and Berkman, 2003). In this sense, as suggested by Lina and Van Ham (2012), residential mobility must become an integral part of the research and of the conceptual framework of reference in the understanding of neighbourhood effects. For example, one solution to social self-selection can be the implementation of instrumental variables. However, scholars found both the fading of the neighbourhood effects and the intensification of these effects after implementing the instrumental variables approach (Blume and Durlauf, 2006). In any case, research may also be necessary for defining the existence of benefits coming from the choices regarding residential mobility (Kawachi and Berkman, 2003).

The distinction between contextual and compositional effects (and features) has been widely discussed and addressed in the social epidemiological neighbourhood effects literature (Duncan, Jones, and Moon, 1998; Honjo, 2004; Kawachi and Berkman, 2003; Krieger, 2001; Oakes et al., 2015). The local characteristics taken into consideration to study the effects on health outcomes can derive either from an individual measure or from a measure that cannot be reduced to the inhabitants but is specific to the context. For example, the neighbourhood proportion of unemployed people is based on each individual employment status, while the presence of services or the level of atmospheric pollution cannot be attributed to the singular inhabitant. Years ago, this dichotomy generated problems since traditional techniques only worked on one level, so there were two possible choices (Duncan, Jones, and Moon, 1998). On the one hand, the possibility was that of aggregating all the individual characteristics at the area level, with the awareness, however, that a relationship observed at the highest level of the neighbourhood was not necessarily also proper to the lowest individual level (ecological fallacy) (Macintyre and Ellaway, 2003). On the other hand, the choice was to analyse only the individual level, with the risk of not taking into account the characteristics of the context and of committing the so-called atomistic fallacy (Blakely and Subramanian, 2006). The latter choice was very diffused last century, also because of a debated disciplinary focus on individual-risk factors (Pickett and Pearl, 2001). Thanks to the introduction of multilevel models and exogenous variables (Honjo, 2004), it is therefore possible to simultaneously take into account all the levels that potentially have an effect on individual health. This possibility is essential in these studies, because *"people make places and places make people"* (Macintyre and Ellaway, 2003), there is therefore no dichotomy between compositional and contextual, but these two elements must go hand in hand (Oakes et al., 2015).

Several scholars have been interested in either psychosocial or material explanations in defining which mechanisms underlying neighborhood effects affect health outcomes. As stated by Kawachi and Berkman (2003), both processes can occur, more than one can be involved for each health outcome, and they may also be intertwined with each other. That is, on the one hand, the material deprivation of an area (such as the presence of graffiti, abandoned buildings) can lead to an increase in crime or its perception. On the other hand, the presence of crime may generate a dislocation of public and commercial services.

As will be disclosed in more detail in the next paragraph (Section 2.1.2), the measures used to describe the context can be both objective (e.g., deriving from census or administrative data) or subjective (derived from the perception of individuals who live in the area of interest). What must be here considered is that it has been seen as subjective perception usually has less variation than objective measures (Macintyre and Ellaway, 2003). This may depend on the fact that a psychological adjustment occurs in individuals. As explained by Sen (1992), there is a protective mechanism that leads individuals to level their aspirations downward (subjects struggle to admit that they live in deprived and dangerous areas), leading subjective measures to be potentially misleading. However, it should be considered that subjective measures may be better adequate in explaining some behaviours; for instance, the perception of crime is much more explanatory than the objective occurrence of crimes (Kawachi and Berkman, 2003). Therefore, as concluded for the (controversial) dichotomy of compositional and contextual factors, also in this case, in measuring neighbourhood effects, one measure cannot disregard the other; both perceptions and objective data should be taken into consideration.

The choice of the unit of analysis one wants to consider when conducting neighbourhood-level research is of primary importance. The necessity to properly choose the neighbourhoods' boundaries is related to the modified areal unit problem (MAUP) (Openshaw, 1983). This problem occurs when dissimilarities in empirical conclusions result from the choice of different neighbourhood-level units. In details, the MAUP basically involves two elements: the "zoning (or aggregation) effect" and the "scale effect". The latter is linked to the fact that the choice of the boundaries of the neighbourhood affects the empirical result. Depending on the inclusion and exclusion of data that a different boundary's choice may produce, neighbourhood effects may also change from positive to negative. That is, the scale effect generates different empirical results by altering the denominator within the dataset (Amrhein, 1995). In other words, to give an example, if the units characterised by high values in the variable of interest are spatially grouped in areas separately from the units with low values, even if the total mean remains the same, much of the variability in the variable of interest is hidden by the spatial grouping. The zoning effect, instead, relates to the fact that, based on the spatial aggregation strategy (for example, if it were decided to use the Italian localities as a spatial unit instead of the Italian census blocks), the size or shape of the spatial unit of measure may change. In this sense, it has been demonstrated that more often than not, evidence is more marked for more vast units (Flowerdew, Manley, and Sabel, 2008).

The majority of the researches uses census based units or other administrative units (e.g., census blocks) to delimit the neighbourhood (Aminzadeh et al., 2013; Ivory et al., 2015; Rocha et al., 2017) while other studies consider specified distances (e.g., the distance between home and sport facilities) (Halonen et al., 2015; Lee and Moudon, 2008) or resident-defined boundaries (Korbin and Coulton, 1997). However, the choice of pre-definite units (such as administrative census units) may lead to wrong measures. Although they provide readily available data, they may not correctly reflect residents' perceptions or the actual areas of activity of the individuals under study (Bissonnette et al., 2012). By that way, in evaluating the role of spatial and aspatial factors in the availability and potential accessibility of health care services, Bissonnette et al. (2012) considered what is called natural or meaningful neighbourhood units. According to this notion, a neighbourhood is going to be identified in that specific area that better represents the area of the local life of individuals since it spatially contains the correct configuration of social and physical features the inhabitants are in interaction with (Ross, Tremblay, and Graham, 2004). According to Galster (2001), *"[...] neighbourhood is the bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses"*. In this sense, he emphasised that we should think of a neighbourhood as a homogeneous area with respect to many different features, such as with respect to structural characteristics of the residential and non-residential buildings, infrastructure, demographic composition, class status characteristics, environmental aspects, proximity factors, social-interactive elements, and sentimental characteristics. At the base of these choices, there is also the distinction between the neighbourhood and other forms of community as proposed by Kawachi and Berkman (2003), which suggest the importance of recognising and studying all the contexts (living, working, educational) proper to individual life, collecting different forms of information. In the investigation of the role that area-level features have on health, Pickett and Pearl (2001) argue that some aspects have to be taken into consideration and maybe even improved: qualitative information can help in the delineation of theorised causal channels needed to provide more clear-cut definitions and measurements of attributes at the neighbourhood level; data and information investigating relevant aspects in real neighbourhood needs should be regularly collected and combined with available data on individuals health outcomes; neighbourhoods' definitions should, thus, reflect the actual area of activity more accurately. Accordingly, the most recent studies rely on global positioning system technology (GPS) to define the subjects' area of action (Duncan and Kawachi, 2018). The use of GPS allows gathering two distinct kinds of information: first of all, information on the movements of individuals (when and where they travel), and second, information on their journeys through the environment and their range of action. According to how long the period of time under scrutiny is, the data collected can be plenteous and informative about the areas in which individuals act. To cite one of the latest studies, Chaix et al. (2016) relied on GPS to study the presence of an association between built environments and walking, where each individuals' trip over the seven days of study was observed, and the characteristics of the places of departure and arrival were taken into consideration to understand which were those factors that could favor or hinder the choice of walking.

2.1.2 *Measuring Context*

In studies investigating how the context influences individuals, their lives, the relationships between them, and their behaviours, the importance of choosing the context-related characteristics to be taken into consideration is always under scrutiny. Generally, two broad sub-categories can be distinguished when referring to the measures that are given due attention when assessing the context of residence: objective measures and subjective measures. Mainly, among the objective measures, researchers rely on various resources: census data, administrative data, environmental data, and the systematic observation of the context. Since the objective measures are generally attributed to a specific spatial unit (e.g., census block), the opportunity to introduce such objective measures relies on the possibility to define a spatial location of the units under analysis (e.g., individuals). It must be feasible to associate the individual with her/his spatial unit of residence in order to define the characteristics of the context in which she/he lives.

Census data is one of the resources that are most often used when studying the environment in which individuals live. Censuses are carried out in the majority of countries; this allows all scholars to have the guarantee of having official and objective data covering a wide range of place-relevant aspects, allowing for the possibility to make comparisons both over time and between countries (Findlay, 2006). Among the most frequently analysed dimensions there are education, the labour market, the population composition by age, the composition of families, the condition of buildings and dwellings, the dynamism of the population, and wealth (Eastwood et al., 2013; Findlay, 2006; Gianicolo, Mangia, and Cervino, 2016; Ngamini Ngui et al., 2012; Rocha et al., 2017; Schüle, Gabriel, and Bolte, 2017; Van Ham et al., 2012). The availability of census data covering such a wide range of choices allows both to introduce the variables individually and, as it is often done, to create composite indices or to use other dimensionality reduction techniques to represent the context's characteristics. To analyse the relevance of living context on health, of great importance are those indexes that have been developed to assess the contexts socioeconomic status or deprivation. The most diffuse are: the underprivileged area score, where eight factors are generally included in the index, such as older people living alone, children under five years old, single-parent families, social class, unemployed, house overcrowding, individuals who changed house in the previous year, and households headed by someone born in the new Commonwealth or Pakistan (Jarman, 1983); the Townsend index, based on unemployment, lack of car and homeownership, and house overcrowding (Townsend, Phillimore, and Beattie, 1986); and the Carstairs index, based on four variables reflecting the material deprivation of an area, i.e., male unemployment, lack of car ownership, house overcrowding, and low social class (Carstairs, 1995).

Finally, among the most used techniques to reduce the dimensions of census data, the factor analysis and the principal component analysis have been adopted in the literature (Baum et al., 2009; Eastwood et al., 2013; Li and Chuang, 2009; Ngamini Ngui et al., 2012). In general, those techniques were adopted to measure disparate dimensions such as age structure, social cohesion, health behaviours, family structure and employment, socioeconomic deprivation, and residential stability.

Among the most widely used administrative data in the literature on social epidemiology, the researchers mainly adopt data on crime (e.g., crimes of violence, domestic housebreaking, vandalism, drug offenses, and minor assault) and service access (e.g., healthcare services, schools, and public recreational areas such as parks).

Concerning measures on crime, it was noted that murder is one of the most reliable measures, both because the police register it and because it does not undergo the reporting limitations occurring with other crimes, such as rape and assault (Sampson, Raudenbush, and Earls, 1997). In order to decide which crimes to take into consideration, which ones are more relevant in affecting the health of individuals, researchers need to refer to the theory that analyses the link between crime and the well-being of the inhabitants (O'Campo and Caughy, 2006). In addition to the relative perception of security that derives from the more or less high presence of crimes (Raudenbush, 2003), the importance of this objective measure lies in the fact that crime is also observed as an indicator of neighbourhood disadvantage (Gale et al., 2011). Therefore, crime and safety measures are involved in the link between context and health because they represent socio-cultural characteristics of the neighbourhood that act on individuals as chronic stressors (Shareck and Ellaway, 2011). In particular, the most violent crimes, such as murder or robbery, but also property crimes, such as burglary, are found to be consistently correlated with situations of deprivation (inequality in income levels) and low social capital. In addition, areas with high crime rates are also characterised by higher death rates (from all causes) than areas with milder crime rates (Kawachi, Kennedy, and Wilkinson, 1999).

With reference to administrative data, it has been defined that measuring potential access to services makes it possible to reflect the presence of equity (or discrimination) in accessing these services (Bissonnette et al., 2012). As Ziersch et al. (2005) say, the presence and availability of services within neighbourhoods has consequences on health both directly and indirectly. First of all, it may reflect the lack of or difficulty in using certain health-promoting services; moreover, services and public spaces are necessary for their role of fostering interactions between inhabitants (claimed to be beneficial for health).

The environmental data that are mostly taken into account as objective measures in the study of the implications of place of residence on health are data on pollution (Crouse, Ross, and Goldberg, 2009; Jerrett et al., 2005), green places (Schüle, Gabriel, and Bolte, 2017; Wolch, Byrne, and Newell, 2014), and meteorological conditions (Feddersen, Metcalfe, and Wooden, 2016; Lee et al., 2018)

The relevance of green spaces for health is mainly based on two mechanisms, one is psychological, and the other one is behavioural. The former is based on the fact that looking at and being in contact with nature and natural elements gives a restorative and relieving effect from stress, indicating that the aesthetic experience of nature matters in this mechanism. Besides, an aesthetically pleasing living environment may further improve well-being by strengthening feelings of satisfaction and attachment. The behavioural mechanism is based on the fact that green areas may have the ability to stimulate residents to undertake physical activities that are beneficial to health, such as walking or cycling, or choosing to take advantage of these activities to move from one place to another (instead of using other means of transport). Moreover, the same discourse made previously for public places applies. That is to say, even the green areas within the neighbourhood can be shared meeting locations, where social interactions can take place, which can strengthen social ties and therefore social cohesion (Groenewegen et al., 2006).

The mechanisms underlying the link between pollution and weather with health are many. In the first place, exposure to pollutants (such as airborne participate matter and ozone) is primarily and consistently associated with increased recurrence of, and mortality rates from, respiratory and cardiovascular diseases. The consequences of these exposures were observed both in short-term studies, which were based on daily variations in air pollution levels with health, and also in long-term studies, which followed cohorts of exposed individuals (Brunekreef and Holgate, 2002). Furthermore, prolonged exposure to temperatures that are excessively above or below the optimum directly affects the physical health of individuals, increasing the occurrence of and death from, again, cardiovascular and respiratory diseases (Huynen et al., 2001). The importance of meteorological conditions can be, thus, appreciated on two occasions: first of all, the meteorological conditions can alter pollution, especially the accumulation of air pollutants, which has a direct effect on the health of individuals (Battista and Lieto Vollaro, 2017; EEA, 2013). Additionally, the weather influences the mood of the exposed subjects, which in turn has an effect on individual mental health aspects such as anxiety and stress (Schwarz and Clore, 1983).

So far, what has been exposed concerns objective measures that are generally collected on a wide territorial basis (e.g., national or regional) and that serve disparate purposes. On the contrary, regarding the systematic observation of the context, these objective measures are collected ad hoc to accomplish the research. To grasp neighbourhood characteristics, scholars relied on different techniques such as videotapes recorded while driving through the neighbourhoods, instant assessment while driving or walking through the space unit, and, more recently, Google Street View (Caughy, O'Campo, and Patterson, 2001; Curtis et al., 2013; Laraia et al., 2006; Raudenbush and Sampson, 1999). Thanks to this type of resource, some of the observed dimensions are similar to those available from census data and administrative sources (e.g., neighbourhood disorder or deprivation, access to/presence of services and public spaces - included green areas). Plus, thanks to systematic observation, what can also be captured are the relationships and interactions between individuals. As stated by Brooks-Gunn et al. (2000), to overcome the limitations of census data, systematic social observation can access other aspects of neighbourhoods, such as networks and social control and, thus, it should be considered as well.

In this case, what must be taken into consideration, is that the timing of data collection can influence its quality: in fact, it is demonstrated that on the one hand, during the day, the observed phenomena (for example, those of socialisation) change in terms of intensity and characteristics of the subjects; on the other hand, these changes are also observed during the year (seasonality) (O'Campo and Caughy, 2006).

As well as for systematic observation, which allows capturing context dimensions that are not available by referring only to census data and administrative data, community survey can also be helpful, enabling, for example, to capture the subjective perception of the neighbourhood of residence. As a subjective measure, indeed, residents' perception is the most widely used. The concept of "collective efficiency", as defined by Sampson (1991), must be certainly mentioned. It is conceptualised as the *"linkages of mutual trust and the shared willingness to intervene for the common good"*. Collective efficiency is, thus, composed of two dimensions: social cohesion, or feeling of connection/integration, and informal social control, i.e., the feeling of awareness of neighbourhood problems and the willingness to intervene to solve them. Moreover, as stated by Kawachi, Berkman, et al. (2000), social capital (intended as all those attributes of social structure - e.g., trust, mutual support - which can be engaged as resources for individuals and enhance collective actions) constitutes a subset of the concept of social cohesion. The latter, furthermore, refers to two broader intertwined features of the society, i.e., the absence of latent social conflict and the presence of a strong social relationship. Similarly, in their work, Baum et al. (2009) considered subjectively perceived neighbourhood cohesion as a crucial feature of neighbourhood social capital.

In this frame of reference, the questions that are submitted to individuals to grasp neighbourhood-based impressions are the most disparate and try to capture one or both dimensions of collective efficiency broadly. Moreover, individuals' neighbourhood perception is also taken into consideration to measure other dimensions comparable with those detected with objective measures. In fact, the perception of crime or deprivation can also be investigated.

Residents' crime perception was taken into account by Lenzi et al. (2013) to describe the level of physical and social disorder in the neighbourhood. In particular, it was measured by employing a scale asking participants how much they agreed in describing their neighbourhood using some concepts of disorder such as crime, robberies, fighting, abandoned buildings, graffiti, and drug dealing. Perceived neighbourhood disorder, the focal predictor variable in Burdette and Hill's (2008) study, was measured through the administration of three questions: individuals were asked to rate their degree of agreement with the characterisation of the neighbourhood as noisy, dirty, and with presence of crime.

To evaluate the action of social capital on health, Kawachi, Subramanian, and Kim (2008) refer to the concept of perceived trust, which is measured both at the individual level (as the level of trust that each individual feels towards the other components of the community) and at the higher level of neighbourhoods (measured by aggregating the responses of individuals for each spatial unit, obtaining, thus, the proportion of subjects trusting their neighbors). As a measure of neighbourhood social capital, measures of neighbourhood cohesion and safety were assessed using individual perceptions by Baum et al. (2009): for example, to capture social cohesion, individuals were asked if they felt part of the neighbourhood, if the neighbors were willing to help each other, if the people in the neighbourhood were trustworthy. Instead, the perception of safety was assessed by measuring the degree of danger and safety individuals attributed to the neighbourhood. Another example is found in Aminzadeh et al. (2013). Social capital, in this case, was assessed with the implication of different indicators covering different aspects on the perception of the neighbourhood, namely social cohesion (in turn a combination itself of reciprocity, sense of community, and safety perception in the neighbourhood), neighbourhood facilities, physical deterioration, membership in community organizations, and residential stability.

Measures relating to safety and perceived crime were, thus, found to be relevant in explaining the link of neighbourhood perception with individual health and well-being. The importance of the subject's feelings related to these aspects, in fact, was even more consistent than the objective presence of crimes in the neighbourhood (which is hypothesised to affect stress levels) in explaining the health of the inhabitants (Vieno et al., 2016). For example, living in a neighbourhood where one fears for her/his own safety can be a threat to one's health and well-being because individuals may decide to limit their engagement in, and give up the possibilities of, activities (both social and physical) outside their home (Vieno et al., 2016); furthermore, these situations can threaten the sense of trust in the community by feeding negative feelings such as anger, aggression, helplessness and loss of control, with possible consequences also on mental health (Anderson, 1999; Stafford, Chandola, and Marmot, 2007). Similarly, individuals living in contexts with social disorder, and relative lack of social control, may have high levels of anxiety, depression, fear, distrust, and poor health (Ross and Mirowsky, 1999). Finally, as confirmed by other studies (Anderson, 1999; Pain, 1997; Whitley and Prince, 2005), living in places that are felt to be dangerous for one's safety also leads to losses in monetary terms: people may decide to move by taxi instead of by walking or by public transports, or spend money to secure their home, with the installation of alarms, for example. It can be ascertained, therefore, that the evidence confirms that social cohesion is an essential characteristic for ensuring the well-being of the community and that the presence of crime is the "mirror" of the quality of social ties and of the social environment in which individuals interact (Kawachi, Kennedy, and Wilkinson, 1999).

Analysing more generally the role of social capital and the mechanisms through which it acts on the health of individuals, among those explanations that are most peculiar in this link and that are generally taken into consideration by scholars, different distinctions must be considered, based on the conceptualisation of social capital: in fact, it can exert an influence on health at an individual level, and at a community level (school or work for example) (Kawachi, Subramanian, and Kim, 2008). At the individual level, the most relevant mechanisms are those of social influences (plays a role in regulating health behaviours), social commitment, and mutual exchanges of social support (enhance well-being buffering stress) (Kawachi, Subramanian, and Kim, 2008). The social cohesion that characterises a community can be thought to influence health through three main mechanisms. First, the mechanism of informal social control, intended as the capacity to regulate/prevent members' (deviant) health behaviours according to shared objectives. Second, the mechanism of collective socialization (the role of adults in shaping youth development, actions, and health outcomes). Third, the mechanism of collective efficiency, namely the awareness of resources and their use in responding to the shortage of services, and the ability of residents to act collectively to address neighbourhood-related physical hazards (Browning and Cagney, 2002; Coutts and Kawachi, 2006; Kawachi, Berkman, et al., 2000).

To conclude, we can say that there are some advantageous and some less advantageous aspects for both the objective and subjective measures used in the literature to analyse the context in which individuals are involved. Researches on subjective neighbourhood conditions and health found that neighbourhood context is associated with health. However, the most relevant weakness of subjective measures, such as subjective perception, is that the relationship between the perception of the context and individual health can be, in whole or in part, due to the same source of error. That is to say, a third variable can be present influencing both neighbourhood perception and health (Weden, Carpiano, and Robert, 2008). Another problem that may concern the data on the subjective perception of the neighbourhood is the consistency, or not, with the objective measures that affect those same characteristics (O'Campo and Caughy, 2006). Concerning objective measures, there are some dimensions and aspects that the census data cannot represent, such as the characteristics that most affect the social sphere and its organization and interactions (Brooks-Gunn et al., 2000). However, as already mentioned, some administrative data, such as those on crime, may be affected in their quality due to reporting biases (Sampson, Raudenbush, and Earls, 1997).

Furthermore, with regard to systematic observation, in addition to the timing that is implemented to observe the phenomena (different points in time either during the day or during the year), the different techniques that have been used to aggregate the results are also a source of problems (complications in comparing the results and different results based on the different aggregation choices are some of those problems) (O'Campo and Caughy, 2006). In general, it is crucial to define, regardless of whether objective or subjective (or both) measures are examined to analyse the neighbourhood, the role of these characteristics net of all the socioeconomic and demographic features of the subjects (Weden, Carpiano, and Robert, 2008).

2.2 DAILY-LIFE CONTEXTS

As seen before, the possibility of using hierarchical models makes it possible to simultaneously consider the influences on individual health also from the point of view of local characteristics. The latter, in particular, can be compositional (derived at an aggregate level from single individuals) or contextual (not down-inferable to the individual) (Krieger, 2001). In this perspective, moreover, the use of multilevel techniques becomes of primary importance to take into consideration the fact that the observations grouped in families and neighbourhoods are not independent of each other. Within each grouping (regardless of the level, family or spatial), individuals are more similar to each other than they are compared to individuals belonging to different groupings (Subramanian, Duncan, and Kelvyn, 2003). Thus, multilevel is necessary to take into account different layers (household and neighbourhood in this case) of individuals' lives that influence their health. The purpose for a three-level multilevel model to be carried out is to simultaneously account for all those three levels potentially having an effect on health.

2.2.1 *Household and Health*

Several studies have tried to investigate whether and how family deprivation and poverty (defined with different connotations) have an influence on individuals' health. Do household and neighbourhood living standards influence health? Using multivariate models, Montgomery and Hewett (2005) answered this question finding that household living standards (in terms of the ownership of consumer durables such as TV, car, radio, and housing quality items, i.e., sleeping rooms and finished floors) are closely associated with health. In particular, household standards of living affected three health measures: unmet need for modern ways of contraception, attendance of a qualified health care provider at childbirth, and children's height for age. Moreover, they showed that the least-protected (in terms of birth attendance) households were the poor ones living in poor neighbourhoods, and the best-protected were the non-poor households living in non-poor neighbourhoods.

Jessel, Sawyer, and Hernández (2019) reviewed the literature by studying the evidence that showed how chronic and acute household energy insecurity (a long-term issue that can arise from a consistent inability to afford or access adequate energy to meet household needs) directly and indirectly result in numerous adverse health conditions. For both adults and children, they found that household energy insecurity contributes to the worsening of health outcomes such as mental health issues, sleeping troubles, cardiovascular and respiratory issues, excess mortality in summer and winter, and acute hospitalization, among others.

With a focus on the eating habits of young people, which are known to have a long-term effect on individual health (primarily physical), with a longitudinal study Min, Xue, and Wang (2018) examined the association between family poverty and the risk of overweight in childhood in the United States. Defining poverty on the basis of household income (below, at, or above the federal poverty threshold during follow-ups), they found that, compared to children who never experienced poverty, children who experience poverty in their lifetime are more likely to have an adverse body mass index trajectory, along with unhealthy eating behaviours and a sedentary lifestyle.

Chung et al. (2018) goal is to examine the association between deprivation and both mental and physical health, going beyond the notion of poverty understood as a mere income-based economic dimension. In fact, to define deprivation conditions, the study is based on 21 items: four items were measures of social deprivation such as the possibility to celebrate special occasions or to have a meal out once a month, while seventeen items were measures of material deprivation such as food deprivation, clothing deprivation, medical care deprivation, and, household facilities and equipment among the others. On the other hand, individual health was measured through the 12-item Short-Form Health Survey version 2 (SF-12 v2) validated in the Hong Kong Chinese population. What they have shown is that deprivation, also understood as poverty related to non-monetary resources, can affect health, both physical and mental, beyond income poverty.

Likewise, many other studies have shown the importance of basing poverty measures not only on monetary aspects (usually income). As Whelan and Maître (2012) say, the focus should be a conception of poverty that indicates the family's inability to participate in everyday experiences in a at least decent way, due to a lack of resources. In this sense, in the literature, household deprivation is often studied through multi-dimensional arrangements which broadly include: the satisfaction of basic needs (such as food consumption, clothes, adequate home heating), affordability of social activities and leisure (such as holidays, inviting friends and relatives at home, participating in school trips or events that cost money), material deprivation (the ownership of durables such as car, telephone, or washing machine), housing conditions (structural problems, house overcrowding), financial conditions (arrears on mortgages or bills, capacity to face unexpected expenses, satisfaction with household's economic conditions) schooling (the highest achieved level of study), and health (assessed through self-reported health and/or the presence of a chronic illness) (Arcagni et al., 2019; Bárcena-Martín et al., 2017; Billi and Scotti, 2018; Boarini and d'Ercole, 2006; Bossert, Chakravarty, and D'Ambrosio, 2013; Ponthieux and Cottrell, 2001; Whelan et al., 2001; Whelan and Maître, 2013; Whelan, Nolan, and Maitre, 2008).

2.2.2 *Neighbourhood and Health*

Different studies evaluating the association between health and context rely both on different conceptions of health and on different ways to measure it, and on different ways to assess neighbourhood effects on health. The literature has mainly scrutinised the neighbourhood effect on physical health, mental health, general health, and health-related behaviours, like health-risk behaviours such as smoking or alcohol abuse.

Concerning physical health, Chaix et al. (2011) found that the neighbourhood socioeconomic status has a substantial impact on some health proxies such as on body mass index or waist circumference. They also demonstrated that individuals in neighbourhoods with low education are associated with increased blood pressure. Comparably, defining physical health-related quality of life (HRQoL) with four dimensions (physical functioning, limitations in usual role activities, bodily pain, and general health perception) Rocha et al. (2017) provide evidence that individuals living in more deprived neighbourhoods report worse physical HRQoL than those living in less deprived neighbourhoods. Likewise, through a cohort study in Finland where individuals had been followed up for over 30 years, Kivimäki et al. (2018) show that individuals constantly living in disadvantaged neighbourhoods had a higher probability of being obese, hypertensive, to have a fatty liver, and diabetes. Neighbourhood disadvantage was here based on a score derived from the proportion of adults with primary education, unemployment rate, and the proportion of people living in rented dwellings. Implementing a qualitative analysis through in-depth interviews, Finlay et al. (2015) affirm that green and blue spaces can have a significant impact on physical, mental, and social health for older adults.

Similarly, using a multilevel linear regression where the percentage of green and natural environment within a ward was related to the variation in minor psychiatric morbidity in England, Scotland, and Wales, Astell-Burt, Mitchell, and Hartig (2014) found out that this association presents gender-specific trajectories. In particular, men start experiencing a benefit from the green environment on minor psychiatric morbidity during early adulthood, where higher exposure to green spaces is linearly related to better mental health. By contrast, the association between green environment exposure and mental health was non-linear for women, since the most favourable health was reported among those with a medium level of green spaces exposure. Instead, contrarily to what found for physical HRQoL, Rocha et al. (2017) did not find neighbourhood clustering nor place effects on mental HRQoL (measured with four dimensions: vitality, the extent to which physical health or emotional problems interfere with normal social activities, limitations in usual role activities because of emotional problems, and general mental health understood as psychological distress and well-being). Mair, Roux, and Galea (2008) reviewed the literature in the UK, which included neighbourhood effects studies on mental health and depressive symptoms, mainly measured with CES-D scale (Center for Epidemiologic Studies Depression scale), DSM-IV criteria (Diagnostic and Statistical Manual of Mental Disorders), GHQ (General Health Questionnaire) and SF-36 (Mental health index of the Short Form Health Survey 36). They found that the studied neighbourhood characteristics were mainly compositional aspects, such as ethnic composition or residential stability, and social characteristics, such as social cohesion or the perception of crime and neighbourhood disorder. They concluded that the majority of the reviewed studies confirmed the existence of associations of neighbourhood characteristics with depression or depressive symptoms after controlling for individual-level characteristics.

Analysing psychological well-being, measured with the 12-item General Health Questionnaire (GHQ-12), Weimann et al. (2015) show that in neighbourhoods with a higher presence of green qualities, individuals were experienced better mental health. Furthermore, they found that the general health of individuals (assessed with two questions, one on physical and mental health and one on the health status in general) had a higher likelihood to feel better when exposed to more neighbourhood green qualities. Ruijsbroek et al. (2015) studied the effect of neighbourhood social safety (area crime and area insecurity feelings) on self-reported health (rating of the general health) and physical activity (weekly hours devoted to physical activity or sports). They demonstrated that living in areas with lower social safety is associated with poorer general health and physical inactivity. Moreover, they show that individuals experiencing increased feelings of insecurity reported even poorer health.

Keeping talking about physical activity, Ivory et al. (2015) studied its association with the built environment (street connectivity, neighbourhood destinations, and streetscape). They demonstrated causal evidence of an effect of the neighbourhood built environment on physical activity. In addition, they showed that the more an individual is exposed to the residential area, the more intense is the association with the area built environment. Similarly, Chaix et al. (2011) found that some environmental features such as the presence of services and the presence of green spaces were associated with walking activities (utilitarian and recreational walking). Other health-related behaviours that are inspected in the literature are health habits such as alcohol consumption and access to health care services. According to Kuipers et al. (2012), the neighbourhood-level disorder is associated with hazardous alcohol use (more than 14 alcohol units per week for women and more than 21 units for men). Precisely, they demonstrated that high neighbourhood disorder was associated with more hazardous alcohol use for female individuals but not for men. Moreover, they did not find a consistent association between hazardous alcohol use and social cohesion. The neighbourhood effects on the utilisation of health care services have been studied by Ngamini Ngui et al. (2012). They assert that neighbourhood characteristics have an impact on mental health service demand besides individual features. What they established is, indeed, that neighbourhood socioeconomic deprivation decreases the probability of accessing mental health services while residential stability increases the likelihood of health care utilization.

Another critical element of the environment in which individuals live that has been evaluated in relation to its effect on health is the weather (and atmospheric agents). Considering the weather (temperatures and wind speed are potentially relevant determinants) as an exogenous variable that can affect an individual's self-assessed health, Chadi (2017) found that an increase in the number of days with bad weather conditions has some, albeit mild, effects on the perceived health of individuals, and even a more relevant increase in working hours (especially for women). Furthermore, with a study carried out on college students, Yu et al. (2019) demonstrated that weather features (such as air quality of the day, visibility, and air pressure) highly contributed to, and can predict, future self-reported individuals' mood, stress, and health (assessed with self-reported daily evening well-being non-numeric scales).

Bos, Hoenders, and Jonge (2012) analysed the connection between mental health aspects (anxiety and energy) of male individuals in the Netherlands. In particular, selecting the weather station nearest to the patient's home, they tried to find out if men with recurrent anxiety disorder are influenced by some meteorological variables, i.e., vector-average wind direction, vector-average wind velocity, mean temperature, hours of sunlight, hours of precipitation, mean air pressure, mean relative humidity and mean cloud cover (conceived as eight categories). Among all these variables, they found that the wind direction was the only one related to the levels of patients' energy, i.e., energy levels were worsened by wind originating from the southeast. To assess if poverty can have a causal effect on the mental health (measured using the 20-item Self-Reporting Questionnaire, SRQ-20) of subjects in developing countries, Hanandita and Tampubolon (2014) implemented an analysis by inserting weather conditions as an instrumental variable (the amount of precipitation is correlated with crop production in mainly agriculture-dependent economies, thus it strongly determines individual income and consumption expenditure). They have confirmed that an anomaly in rainfall has a causal effect on individuals' mental health.

Focusing on substantive changes in life expectancy in USA, Deschênes and Greenstone (2011) aimed at developing estimates of the impact of temperature on mortality. By combining the estimated impacts of temperature on mortality with predicted changes in climate, they ascertained mortality estimates suggest an increase in the overall annual mortality rate ranging from 0.5% to 1.7% by the end of the century. Similarly, it has been found that extended periods of extreme heat, usually referred to as "heat waves", have been linked with substantial increases in mortality, and specific events have been recorded as public health disasters (Gasparrini and Armstrong, 2011). Especially, deaths from cerebrovascular and respiratory disease are those most concerned by very hot weather conditions (Rooney et al., 1998). Another similar evidence is found in the Huynen et al. (2001) study: the recurrence of high temperatures and temperatures above the optimal generates an increase in total mortality and in mortality from malignant neoplasm, cardiovascular, and respiratory diseases. Furthermore, again in the latter study, the researchers show that even sub-optimal temperatures are associated with an increase in total mortality and in mortality relative to the conditions mentioned above. In particular, being exposed to very cold temperatures may cause cardiovascular stress because of changes in vasoconstriction, blood pressure, as well as the increase of blood viscosity (occasionally leading to clots), in conjunction with red blood cells counts, plasma cholesterol, and plasma fibrinogen. Chadi (2017) stresses the importance of taking into account the weather and meteorological conditions starting a few weeks before the survey to better capture the effect it can have on individual health. This is because it has been demonstrated how, in addition to short-term effects that can derive from exposure to adverse weather, e.g., low temperatures or precipitation, there are also long-term effects that can be attributed to weather conditions which have an impact on the immune system and can, thus, threaten its resistance to infections (Group, 1997; Martens, 1998; Meng et al., 2013).

To assess the exposure to the weather variables, Lee et al. (2018) used the data available from the monitoring station closest to the participants. In particular, the maximum temperature (as the temperature indicator) and the dew point (for humidity) on the same day of symptom occurrence were used to study the effects on physical health. The participants were asked to keep a daily diary of the physical symptoms for about a month. In this setting, the weather was associated with various physical symptoms like headache, sneezing, and menstrual cramp, as well as agitation and anxiety. Moreover, women were found to be more sensitive to weather conditions in association with physical symptoms, notably higher humidity and lower temperature.

Schwarz and Clore (1983) studied the effects that weather conditions have on subjects' mood, considering the latter as an indirect channel between weather and the subjects' well-being. The researchers interviewed people on either sunny and warm, and rainy and cold days, and with different settings, they ran two distinct experiments. They found that, in both experiments, the weather influenced mood, and that, furthermore, the mood was influencing perceptions of well-being. Therefore, participants who were feeling a good mood stated to be usually more satisfied with their lives than participants in a bad mood. That is to say, being in advantageous or disadvantageous weather conditions influenced individuals' well-being. Nevertheless, this effect was not direct: it manifested itself only when atmospheric factors could influence the subjects' mood, and these moods could therefore be considered as reasonable proxies for the well-being of the participants.

To conclude, considering air pollution as an element that directly impacts health, some studies have shown how weather conditions (i.e., air temperature, solar radiation, wind direction, and velocity) can affect the concentration of gaseous pollutants in the air. Also in this case weather is seen as an indirect element, which is capable of influencing individuals' health (Battista and Lieto Vollaro, 2017). For instance, an increase in solar radiation and temperatures, as well as changes in the wind regime, precipitation, and alterations in the height of the pollutant mixing layers, result in an increase in the concentrations of these compounds (EEA, 2013).

3 RESEARCH DESIGN

As was pointed out in the introduction of this dissertation, neighbourhood effects on physical and mental health have never been studied in Italy, with some exceptions of studies focused on specific Italian cities (Belli et al., 2004; Gianicolo, Mangia, and Cervino, 2016; Marinacci et al., 2004; Michelozzi et al., 1999; Petrelli et al., 2006) who analysed the effects of the characteristics of life contexts on health outcomes such as mortality and the incidence of certain conditions such as heart diseases.

The present research aims to assess the existence of neighbourhood-level effects throughout Italy and if they affect individuals' health (measured through the SF-12 scale). The intention is to show how the place effect on health behaves in Italy: does the same effect occur throughout the whole territory? Are there differences between individuals with different characteristics? Are there differences in the neighbourhood effects throughout the Italian territory? The novelty of the study is the possibility, thanks to the sampling design, to introduce also family-level characteristics, together with individual- and neighbourhood-level characteristics. In this way, a three-level multilevel model can be implemented, allowing to account for micro-, meso-, and macro- factors.

In this chapter, the first section is devoted to the illustration of the survey and the unit of analysis; the second section focuses on the gathered data and on the variables implemented in the statistical investigation, paying attention to all the three levels of analysis; the third section deals with the georeferentiation of the data, which was essential to be able to implement a three-level multilevel model; finally, the fourth section is devoted to a brief introduction of the model and its specification which will be deepened in the next chapter.

3.1 UNIT OF ANALYSIS, POPULATION AND SAMPLE

This research uses data that has been collected throughout the Italian territory from the summer of 2019 to December 2020. Italian Lives (ITA.LI) - Survey on Life Courses in Italy is an essential longitudinal survey developed by the Department of Sociology and Social Research of the University of Milano-Bicocca and funded by the Ministry of Education University and Research for the period going from 2018 to 2022. This longitudinal project aims to realize at least three waves on the same subjects living in Italy. The waves are going to be carried out using CAPI (Computer Assisted Personal Interviewing), CATI (Computer Assisted Telephone Interviewing), and CAWI (Computer Assisted Web Interviewing) as surveying techniques.

The survey selected 280 Italian municipalities through a three-stage probability sampling system developed in conjunction with the Italian Institute of Statistics (ISTAT) in order to detect the sample unit. In order to identify the sample unit, a multi-stage stratified sampling design was implemented. For each randomly selected municipality, a sample of addresses was selected from the *Registro Base degli Individui* (an official register containing personal data and living addresses of individuals), with a probability that was proportional to the number of families living at each address. The total number of selected addresses was larger than the number defined by the theoretical sample design to allow the replacement of addresses that could not be examined or that were difficult to examine. At each selected address, then, a family was randomly selected.

A family was considered to be eligible if both of the following conditions were met:

- De facto residence: At least one member of the family usually lived in the house
- Legal residence: At least one member of the family had officially registered residence in the municipality

Within each eligible family, then, all 16 years old or older components were eligible and interviewed according to the following guideline:

- Families with one member: one member was interviewed
- Families with two members: two members were interviewed
- Families with three members or more: at least two members were interviewed

It could have happened that one eligible component of the family was not able to participate in the investigation because she/he was physically or mentally incapable, or she/he was not available during the entire duration of the survey. Only and exclusively in these two cases, it was possible to use a proxy interview. It consisted of an abbreviated version of the questionnaire to be administered to another member of the family that answered on behalf of the individual of interest. During the waves following the first one, all the subjects belonging to the original sample will be interviewed again in order to update their life courses (*update interviews*). In addition, new members of the original families and individuals who formed new families together with one or more members of the original families (*split off*) will become part of the survey. Therefore, all individuals who were interviewed in any previous waves will be part of the longitudinal sample.

On the occasion of the first wave, 8,967 eligible subjects belonging to 4,900 families of the original sample have been interviewed. The questionnaires allowed the reconstruction of subjects' life course (looking at their geographic or residential mobility, education, career, marriage or cohabitation, and the birth or adoption of children) starting from their birth until the time of the survey (*retrospective questionnaire*). Moreover, a broader analysis on some current aspects of individuals and families (such as health, quality of life, financial resources, debts and family support, internet access, and political participation) was carried out with the *prospective questionnaire*. Therefore, 278 municipalities were involved, 4,900 families were contacted, and within these, 8,778 individuals were administered the standard questionnaire (189 individuals were administered a proxy interview, those respondents were not considered in this research).

The neighbourhood of residence was established with the census block where individuals lived. In 2011, Italy was partitioned into approximately 350,000 census blocks, each one containing about 200/250 families. In Section 3.3 the procedures used to georeference the data will be expressed in more detail. Following the phase of data cleaning, which saw the elimination of subjects with non-response items in the variables of interest for this research (e.g., helpful information for the reconstruction of household deprivation variables was available for 4,789 households, corresponding to 8,554 individuals), 7,835 observations remained valid at the end.

3.2 DATA AND VARIABLES

Variables from Italian Lives - ITA.LI survey was taken into account to grasp individual characteristics, habits, subjective perceptions of the neighbourhoods of residence, and household characteristics. Moreover, data from ISTAT and E-OBS[1] (Cornes et al., 2018) were implemented to analyse exogenous compositional and contextual neighbourhood-level characteristics.

3.2.1 *Individual Health*

Individual physical and mental health, measured through the SF-12 (12-Item Short-Form Health Survey), is the dependent variable of this research. The SF-12 is the shorter version of the most popular generic measure of patients' outcomes, the 36-Item Short-Form Health Survey (SF-36), which covers eight dimensions of health status: physical functioning, role limitations due to physical health problems, bodily pain, social functioning, general mental health, role limitations due to emotional problems, vitality, and general health perception (Ware Jr and Sherbourne, 1992). Two summary measures can be obtained from the eight dimensions without loss of information, generating a measure concerning physical health

1 I acknowledge the E-OBS dataset and the data providers in the ECA&D project - https://www.ecad.eu)

(Physical Component Summary Scale Score - PCS) and another one concerning mental health (Mental Component Summary Scale Score - MCS) (Ware, Kosinski, and Keller, 2001). The decision to reduce the number of items from 36 to 12 has been made in order to reduce the room 36 questions required in a questionnaire and to reduce respondents' burden. It has been demonstrated that the 12-item sub-set of the original 36 items, which includes one or two items for each of the eight dimensions, can be a valid shorter version. Moreover, SF-12 produces the two summary scales PCS and MCS closely replicating those obtained through the original SF-36 (Jenkinson and Layte, 1997; Ware Jr, Kosinski, and Keller, 1996). Additionally, Gandek et al. (1998) validated the SF-12 for Italy, asserting that it provides good replications of the SF-36 summary measures. Thus, these measures can be reliably used on the data available from the ITA.LI survey.

In Table 1, the two summary measures and their respective items, which correspond to the questions asked to individuals who participated in the ITA.LI survey, are reported.

Table 1: 12-Item Short-Form Health Survey - Items

Summary measure	Items
Physical Component Summary Scale Score - PCS	General health (GH1) Moderate activities (PF02) Climb several flights (PF04) Accomplished less (RP2) Limited in kind (RP3) Pain-interfere (BP2)
Mental Component Summary Scale Score - MCS	Accomplished less (RE2) Not careful (RE3) Energy (VT2) Peaceful (MH3) Blue/sad (MH4) Social-time (SF2)

In details, the 6 items concerning the questions on physical health administered in the questionnaire were the following: General health (GH1) was the question about the self-perceived health asking whether the individuals' health is Excellent, Very good, Good, Fair, or Poor; Moderate activities (PF02) determined whether individuals' health limited them in performing moderate activities, such as moving a table, pushing a vacuum cleaner, bowling, or cycling (extremely, partially, or not at all); Climb several flights (PF04) asked individuals whether their health limited them in climbing several flights of stairs (a lot, partially, or not at all); Accomplished less (RP2) asked individuals whether they accomplished less than they would have liked with their work or other daily activities, as a result of their physical health (yes or no); Limited in kind (RP3) assessed whether individuals were limited in the kind of work or other activities, as a result of their physical health (yes or no); finally, Pain-interfere (BP2) determined how much pain interfered with individuals' everyday work, including both work outside the home and housework (not at all, a little bit, moderately, quite a bit, extremely).

Furthermore, the 6 items concerning the questions on mental health administered in the questionnaire were the following: Accomplished less (RE2) asked individuals whether they accomplished less than they would have liked with their work or other daily activities, as a result of emotional problems, such as feeling depressed or anxious (yes or no); Not careful (RE3) assessed whether individuals did work or other activities less carefully than usual, as a result of any emotional problems, such as feeling depressed or anxious (yes or no); Energy (VT2) asked individuals how much of the time during the previous 4 weeks they have had a lot of energy (none of the time, a little of the time, some of the time, a good bit of the time, most of the time, all of the time); Peaceful (MH3) asked individuals how much of the time during the previous 4 weeks they have felt calm and peaceful (none of the time, a little of the time, some of the time, a good bit of the time, most of the time, all of the time); Blue/sad (MH4) asked individuals how much of the time during the previous 4 weeks they have felt downhearted and blue (none of the time, a little of the time, some of the time, a good bit of the time, most of the time, all of the time); finally, Social-time (SF2) determines how much of the time physical health or emotional problems interfered with individuals' social activities, like visiting friends, relatives, etc. (all of the time, most of the time, some of the time, a little of the time, none of the time).

Essentially, two dependent variables were studied: one is the Physical Component Summary Scale Score (PCS), and the other one is the Mental Component Summary Scale Score (MCS). To compute those summary measures, procedures recommended by the developers (Ware, Kosinski, and Keller, 1995) were used, those are seen in detail in Section 4.1.1. First, all the variables considered had to have the same coding so that higher scores represented good health. Second, for each variable, dummy indicator variables were created for all but one response choice category. Therefore, out of 47 total response categories among the 12 items, 35 indicator variables were created. Third, the indicator variables were weighted. This step was implemented using coefficients from the general US population (Ware, Kosinski, and Keller, 1995) since Italian coefficients were not available and, however, it has been demonstrated that this procedure leads to reliable measures even for the Italian case (Gandek et al., 1998). Moreover, Gandek et al., 1998 recommended employing standard U.S.A. - derived scoring of the SF-12 summary measures, in order to be the data comparable and interpretable across countries in relation to standard benchmarks, i.e., scores with a mean of 50 and standard deviation of 10 in the U.S.A. general population. Calculation of PCS was then achieved by multiplying each indicator variable by its physical weight and by summing the 35 products. Accordingly, MCS was computed by multiplying each indicator variable by its mental weight and summing the 35 products. Finally, the sum of the products was added to the respective constant from the general U.S.A. population (Ware, Kosinski, and Keller, 1995). To sum up, two continuous variables, one concerning physical health (PCS) and one concerning mental health (MCS), were used as continuous dependent variables to assess the existence of neighbourhood-level effects throughout Italy and their relevance for individual health.

3.2.2 *Individual Characteristics*

Individual face-to-face interviews were carried out to collect, among the others, information on respondents' socio-demographic characteristics and lifestyles. Precisely, the following variables were introduced in the models at the individual level: gender (male, female), age classes (16-24, 25-34, 35-54, 55-64, and 65 or older), education level (illiterate, primary school, lower secondary school, upper secondary school, tertiary education and higher), employment status (employed, unemployed, homemaker, student, retired, unable to work), marital status (married or civil union, single, divorced or separated, widow/er), children (with, without), citizenship (foreign, Italian), and sleeping trouble (in the last four weeks, have you had difficulty falling asleep or suffered from insomnia? Not at all, a little, a lot).

Moreover, at the individual level, available subjective variables were taken into account from the ITA.LI questionnaire to cover two dimensions concerning the subjective perception on the neighbourhood of residence: neighbourhood social cohesion and neighbourhood disorder (Kuipers et al., 2012). The first dimension was based on the following 4 items, which considered the individuals' attachment to the neighbourhood, asking how much individuals agreed with the following statements:

- This neighbourhood is now part of me
- It would be hard to leave this neighbourhood
- This is an ideal neighbourhood for me
- I do not feel integrated into this neighbourhood

The second dimension was instead based on the following 5 items:

- Individuals' perception on the presence of pollution, dirt and other environmental issues caused by traffic or industries

- Individuals' perception on the presence of noise
- Individuals' perception on the presence of disreputable individuals
- Individuals' perception on the presence of vandalism
- Individuals' fear to be bothered or robbed in the neighbourhood during the night

Different methods and approaches can be undertaken to reduce the number of variables while preserving as much original information as possible. In this case, Exploratory Factor Analysis (EFA) helped in this direction and, as specified later (Section 4.1.2), two factors were introduced in the models: one factor for Neighbourhood Social Cohesion (SC) and one for Neighbourhood Disorder (ND).

3.2.3 *Household Deprivation*

The second level of nesting concerns household-level characteristics. At this level, household deprivation will be introduced in the model. In this case, the questions referring to the household were submitted only to one family member, identified as the head of the household. To compute the household deprivation, I made use of the eighteen items, available in Table 2, that were present in the questions administered in the ITA.LI questionnaire, which covers four different dimensions. Seven indicators are associated with Material Deprivation where the presence of the following goods was considered: mobile phone, colour TV, computer, washing machine, internet access, dishwasher, and car (the item concerning the refrigerator was also present but, since all the subjects replied they had one, it did not discriminate deprived families, so it was removed from the analysis). These indicators observed the presence of the good, and in case of its absence, they asked individuals whether they would have liked to have it, but it was not affordable, or if they did not have it for other reasons (e.g., do not want or need it). The dimension on Housing concerned the quality of housing; this dimension was measured by asking individuals: how much they were satisfied with their housing, whether the house was characterized by reduced living space, and by structural problems (e.g., roof to be repaired, lack of adequate heating, inadequate sanitation). The Affordability dimension observed if the family had the potential to manage some economic circumstances and to face some expenses such as: to afford a week of vacation per year away from home, to eat meat or fish or a vegetarian equivalent at least once every two days, to adequately heat the home, to cope with unforeseen expenses of an amount of around 800 €, and whether someone in the family has had to give up dental check-ups or treatment for economic reasons, even if they needed them.

Table 2: Household Deprivation - Items and Dimensions

Dimension	Indicators
Material Deprivation	Colour TV Mobile Telephone Car Washing machine Personal computer Dishwasher Internet access
Housing	Satisfaction for the house Reduced living space Structural problems
Affordability	Holiday Meat or fish or a vegetarian equivalent Adequately heat home Cope with unforeseen expenses Dental check-ups or treatment
Economic Condition	Satisfaction for the economic situation Burden family expenses Manage to make ends meet

The last dimension concerning the Economic Condition determined: how much the family was satisfied with its economic situation, whether the domestic expenses were a heavy, bearable, or negligible burden, and how the family managed to make ends meet (with difficulty or easily). It was decided not to introduce the financial information on household net monthly income in the analysis, as this variable had too many missing values (more than 50%) in the sample.

As will be explained in more detail in the next chapter (precisely, in Section 4.1.3), a Self-Organizing Map (SOM) was developed in order to introduce domestic deprivation in the analyses. Thanks to this technique, 10 household deprivation clusters, useful for descriptive statistics, were identified at first. Furthermore, in a second step, these 10 clusters were grouped into 4 definitive clusters that were introduced in the models.

3.2.4 *Neighbourhood Characteristics*

To analyse the context in which individuals live, together with individuals' subjective perception (at the individual level), also objective aspects (compositional characteristics from census and contextual characteristics such as adverse weather conditions) of the neighbourhoods (at the third level of the analysis) were taken into account. Both features are needed, objective and subjective measures (Kawachi and Berkman, 2003).

Individuals' neighbourhood of residence was established with the census block where individuals resided. Data from the 2011 Census at the census block level were available by ISTAT (Italian Institute of Statistics). The entire national territory had been divided into census sections, the minimum municipality surveying unit. Starting from the census block, it is possible to reconstruct, by sum, the upper-level geographical and administrative entities (inhabited areas, sub-municipal areas, electoral districts, and others). Each census section is completely contained within a single location. The municipal territory is exhaustively divided into census sections (ISTAT, 2015). In particular, from the 2011 census, data concerned aggregated (compositional) measures such as, among the others, illiteracy, unemployment, rented dwellings, single parents, household density, and age structure was available.

Moreover, data from E-OBS v23.1 (latest version available), with a resolution of 0.1 degrees (about 12 km), allowed the introduction in the analyses of a contextual variable that was exogenous to the individual. Briefly, each individual was located in the grid according to the proximity rule, and three main variables were considered in order to indicate unfavorable weather conditions: maximum temperature (°C), minimum temperature (°C), and precipitations (mm).

3.3 GEOREFERENTIATION

The geo-codification of all the addresses included in the sample was carried out using the software ArcGIS, starting from the file containing all the addresses the survey ITA.LI had reached. First, an automatic geocoding took place by applying the Word Geocoding Service ESRI as address locator. Out of 12,906 addresses, this phase automatically associated 12,655 addresses, while 251 were not because a perfect match could not be found, even though there were close match candidates. Out of these 251, 222 addresses were matched by choosing the proper address among the candidates suggested by the software; the other 29 addresses were, instead, matched manually by choosing the appropriate point directly on the map. Overall, 12,906 addresses were matched and associated to their own geographic coordinates (latitude and longitude), defined in degrees according to the World Geodetic System (WGS84) as the geographic coordinate system.

At this point, from the ISTAT website, two documents about the census that took place in 2011 were downloaded: one dataset with the identifier of the census blocks and the geographic coordinates (latitude and longitude) of their respective centroids, and one dataset containing the identifier of the census blocks and their respective information collected during the 2011 census (e.g., about education, unemployment, housing overcrowding). The first dataset was uploaded in ArcGIS in order to associate each ITA.LI address to the closest census block. After transforming each ISTAT census blocks' coordinates from meters to decimal degrees to obtain the same unit of measurement, the software was employed to get the association. In particular, Near Tool was implemented. Near tool - an instrument available with the software - calculates distance and additional proximity information between the input features (the file containing the ITA.LI survey addresses and their coordinates, in this case) and the closest feature in another layer or feature class (the ISTAT file containing the geographic coordinates of the centroids of the census blocks, in this case). Thus, after the software performed all the calculations, in the first file (the one presenting the ITA.LI address identifiers with their respective geographic coordinates), a column with the identifier of the closest census block's centroid and two columns with the census block's centroid geographic coordinates were added.

Thus, through the processes explained above, a dataset with the following information was obtained:

- Household address identifier
- Household address latitude
- Household address longitude
- Closest census block identifier
- Closest census block latitude
- Closest census block longitude

where each household address was associated with the census block with the closest centroid. Finally, it was possible to associate each address that the survey ITA.LI contacted with information at the census block level, which was collected during the census that took place in 2011. In other words, each individual in each family was associated with information relating to the census block closest to their dwelling.

3.4 MODEL SPECIFICATION

The aim of the research is to assess the existence of neighbourhood-level characteristics throughout Italy and if they affect individuals' health (physical and mental health measured through the SF-12 scale). Thus, the interest is not only in analysing differences between individuals but also in analysing variations across contexts. The novelty of the study is the possibility, thanks to the sampling design, to introduce, together with individual- and context-level characteristics, also family-level characteristics so that a multilevel model can be implemented, allowing to account for micro-, meso-, and macro-level factors. In other words, multilevel linear regression analysis was implemented considering a three-level hierarchical data structure in which individuals are nested within families, which are nested within neighbourhoods.

The rationale for distinguishing three levels of data hierarchy is that families living in the same neighbourhood tend to be more similar to each other than they are with respect to families from another neighbourhood. The reason for within-neighbourhood similarity could be the closeness of residences to some facilities or the shared environment. Moreover, individuals belonging to the same family are closer to each other than they are to individuals of a different family because of shared experiences, imitation, and genetic traits.

An example of the model that was implemented is explained below. The following model is a simplified model that considers one covariate for each of the three levels and where all the coefficients (intercepts and slopes) are random. Precisely, in equation (1) Y_{ijk} is the dependent variable for individual *i*'s health, nested within the *j* family, nested within the *k* neighbourhood. X_{ijk} represents the covariate at the individual level for individual *i*, nested within the *j* family, nested within the *k* neighbourhood.

$$Y_{ijk} = \alpha_{0jk} + \beta_{1jk}X_{ijk} + \epsilon_{ijk} \tag{1}$$

Equations (2) and (3) represent the second level (household level) specifications where Z_{jk} represents the covariate at the household level (i.e., household deprivation) for the *j* family, nested within the *k* neighbourhood. At this level, the intercept and slope from the previous level model can vary among the second-level units:

$$\alpha_{0jk} = \gamma_{00k} + \gamma_{01k}Z_{jk} + u_{0jk} \tag{2}$$

$$\beta_{1jk} = \gamma_{10k} + \gamma_{11k}Z_{jk} + u_{1jk} \tag{3}$$

Finally, Equations (4) and (5) represent the third level (neighbourhood level) specifications where W_k represents the covariate at the neighbourhood level for the *k* neighbourhood (census variables and adverse weather conditions). Here, the second-level intercepts and slopes can vary among level-3 units (neighbourhoods):

$$\gamma_{00k} = \gamma_{00} + \gamma_{01}W_k + r_{0k} \tag{4}$$

$$\gamma_{10k} = \gamma_{10} + \gamma_{11}W_k + r_{1k} \tag{5}$$

Using this base model, the idea was to follow the literature (Rocha et al., 2017; Subramanian, Kawachi, and Kennedy, 2001) where four categories of models were estimated: first a "null" multilevel model, second "random-intercepts" models, third a "random-coefficients" model, and fourth a "cross-level" contextual model. However, in order to adapt the models to the three levels that are here considered, some arrangements were implemented (Zhu, 2014).

4

METHOD

This chapter concerning the method is divided into two main sections. The first part is dedicated to illustrating the variables of interest and how they have been handled to obtain the definitive variables to be included in the models. The second part illustrates the models that have been implemented to study neighbourhood effects and the research questions they answer.

4.1 VARIABLES

Individuals' health (PCS and MCS), subjective perception of the neighbourhoods (social cohesion and disorder), household deprivation, objective compositional characteristics of the census blocks (proportions of low educated individuals, unemployed individuals, rented houses, single parents, average housing density, and young proportion), and objective contextual characteristic about adverse weather conditions are the variables that will be analysed in this section and whose definition is explained.

4.1.1 *Individual Health*

As already mentioned, the variables concerning the SF-12 (12-Item Short-Form Health Survey) available in Table 1 were implemented to analyse the neighbourhood effects on health. Specifically, two dependent variables have been studied: one was the Physical Component Summary Scale Score (PCS), and the other one was the Mental Component Summary Scale Score (MCS).

To compute those summary measures, the procedures recommended by the developers were carried out (Ware, Kosinski, and Keller, 1995). First, all the variables considered must have the same coding so that higher scores represent good health and lower scores bad health. Thus, three variables (GH1, BP2, and MH4) were reversed. Second, dummy indicator variables were created for all but one response choice category for each variable. Therefore, out of 47 total response categories among the twelve items, 35 indicator variables were generated. For each indicator, with *n* choice categories, *n-1* dummy variables - excluding the choice category indicating the best health situation - were created. For instance, the item PF02, about the presence of limitations in moderate activities, has three response choice categories: 1=yes, limited a lot; 2=Yes, limited a little; 3=No, not limited at all; in this case, no indicator variable was derived for the third response choice category. Third, the indicator variables were weighted. This step was implemented using coefficients from the general U.S.A. population (Ware, Kosinski, and Keller, 1995) since Italian coefficients are not available and, however, it has been demonstrated that this procedure leads to reliable measures even for the Italian case (Gandek et al., 1998). Calculation of PCS was achieved by multiplying each indicator variable by its physical weight and by summing the 35 products. Accordingly, MCS was computed by multiplying each indicator variable by its mental weight and by summing the 35 products. Finally, the sum of the products was added to the constant from the general U.S.A. population (Ware, Kosinski, and Keller, 1995). To sum up, two continuous variables, one concerning individuals' physical health (PCS) and one concerning individuals' mental health (MCS), were used as continuous dependent variables to assess the existence of neighbourhood-level effects throughout Italy and their impact on subjects' health.

Moreover, as suggested by Ware, Kosinski, and Keller (1995), some checks were performed. The correlation between PCS and MCS should be low (0.36 in this case); the items GH1, PF02, PF04, RP2, RP3, BP2 were checked to be higher correlated with PCS than with MCS; and, finally, the items RE2, RE3, VT2, MH3, MH4, SF2 were checked to be higher correlated with MCS than with PCS. Summary statistics for these two dependent variables are shown in the next section, in Table 8.

To conclude, since the reference paper confirming the weights of the American population are also suitable for Italy is not very recent (Gandek et al., 1998), some additional investigations were also performed by means of Item Response Theory (IRT), Factor Analysis (FA) and Principal Component Analysis (PCA). Both for the measure on physical health and the measure on mental health, the correlations between the results obtained with these alternative methods and the developers' method were very high. In particular, for the PCS the correlations were equal to 0.88, 0.97, and 0.97 (with IRT, FA, and PCA respectively) and for the MCS the correlations were equal to and 0.90, 0.91, and 0.94 (with IRT, FA, and PCA respectively), indicating that the method suggested by Ware, Kosinski, and Keller (1995) is reliable even for these data.

4.1.2 *Neighbourhood Subjective perception*

Following the literature (Baum et al., 2009; Greene et al., 2020; Hale et al., 2013; Hill, Burdette, and Hale, 2009; Liu et al., 2020; Poortinga, Dunstan, and Fone, 2007; Robinette, Boardman, and Crimmins, 2019; Ruijsbroek et al., 2015), different techniques can be implemented to compute the index on Neighbourhood Social Cohesion (SC) and the index on Neighbourhood disorder (ND). Here, Exploratory Factor Analysis (EFA) was preferred to Principal Component Analysis (PCA), since the latter works on the assumption that the observed data are perfectly reliable with the goal of maximising the explained variance of the correlation matrix. In this case, including the possibility that errors may be present in the matrix and assuming my goal was not to maximize the explained variance but, instead, to discover latent dimensions underneath the observed variables, Exploratory Factor Analysis was implemented.

Table 3: Neighbourhood Social Cohesion - Summary statistics

	Mean	S.D.	Min	Max
It is part of me	5.54	1.28	1.00	7.00
It is hard to leave	5.23	1.47	1.00	7.00
Ideal neighbourhood	5.24	1.39	1.00	7.00
Feeling integrated	5.23	1.68	1.00	7.00
N	**7835**			

As a first step, Cronbach's alpha was calculated as a measure of scale reliability. Cronbach's alpha is a measure of internal consistency, i.e., it indicates how closely associated a set of items (four items for social cohesion available in Table 3 and five items for neighbourhood disorder available in Table 4 in this case) are as a group (Cronbach, 1951). In this case, Cronbach's alpha is equal to 0.77, available in Table 5 showing high internal consistency for this group of items (values higher than 0.7 are considered as acceptable). Afterward, using the principal factor as a technique to decompose the variance, the analysis generated two eigenvalues higher than one, providing evidence that the scales in question were bi-dimensional.

Table 4: Neighbourhood Disorder - Summary statistics

	Mean	S.D.	Min	Max
Pollution	0.17	0.38	0.00	1.00
Noise	0.18	0.38	0.00	1.00
Danger	0.10	0.31	0.00	1.00
Vandalism	0.11	0.31	0.00	1.00
Fear to be Attacked	0.15	0.35	0.00	1.00
N	**7835**			

In Table 5, results of the factor analysis are shown. Orthogonal rotation was implemented to facilitate the interpretation of the two factors, leading to a more homogeneous variance distribution across the factors. It is noticeable that in relation to each factor, the relevant variables are those with values greater than 0.30, which helps define the over-representation of the variable in the reference factor. The value also represents the relative "weight", i.e., the importance of the variable in defining the factor compared to the other variables that make it up. The last column shows the value of the uniqueness of the variable with respect to the factors, relating to the percentage of variance that is not shared with the remaining variables in the factorial model. Lower values, therefore, imply a greater relevance of the variable in the factor model; vice versa, higher values indicate a scarce contribution of the variable in defining the identified factors.

Therefore, as it is also used in the literature (Burdette and Hill, 2008; Cramm, Van Dijk, and Nieboer, 2013; Eastwood et al., 2013; Li and Chuang, 2009), factor analysis was implemented to study the effects of neighbourhood characteristics on health. In particular, two factors will be introduced in the models, one for Neighbourhood Social Cohesion (Factor 1) and one for Neighbourhood Disorder (Factor 2).

Table 5: Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Uniqueness
Pollution		0.48	0.72
Noise		0.47	0.73
Danger		0.78	0.37
Vandalism		0.80	0.34
Fear to be Attacked		0.75	0.42
It is part of me	0.87		0.23
It is hard to leave	0.89		0.21
Ideal neighbourhood	0.87		0.21
Feeling integrated	0.40		0.81

blanks represent abs(loading)<0.3

Cronbach's alpha: 0.77

The goodness of fit was assessed with Kayser-Meyer-Olkin (Kaiser, 1974) and with Bartlett's test of sphericity. On the one hand, the former compares the magnitude of the observed correlation coefficients to the amount of the partial correlation coefficients; for the KMO measure, large values indicate that a factor analysis of the items of interest is a good solution. On the other hand, Bartlett's test null hypothesis is that the intercorrelation matrix comes from a population in which the variables are non-collinear and that the non-zero correlations in the sample matrix are due only to sampling error (Bartlett, 1950; De Lillo, 2007). With the available information, results (0.81 for KMO and p-value<0.00 for Bartlett's test) suggested data were adequate for the Exploratory Factor Analysis.

4.1.3 *Household Deprivation*

In order to introduce family deprivation in the models, as anticipated, eighteen items (available in Table 6) were taken into consideration.

Due to the presence of many missing values, some crucial variables should have been eliminated from the analyses. In particular, the variables in the Affordability dimension assessing if the family can afford a holiday a year (5% of observations with missing values), if they can eat meat or substitutes at least two or three times a week (almost 3% of observations with missing values), and if they have the possibility of facing unexpected expenses of € 800 (7% of observations with missing values), and the question concerning the Economic Condition dimension on the difficulty of making ends meet would have been removed (nearly 2% of observations with missing values). However, this would have generated some limitations: first of all, the multidimensional structure would have been undermined, and second, the SOM generated some clusters among the others without any associated observation; furthermore, by removing those four variables, Cronbach's alpha decreased from 0.76 to 0.65.

Another alternative was not to consider individuals with missing answers in the analyses. However, this was problematic for two reasons: first, the lost observations would have been about 1,300; furthermore, it was assessed that the missing items were not random and that the individuals who did not answer those questions were significantly different from those who answered instead. First, Little's chi-squared test for the MCAR (Missing completely at random) was implemented (Little, 1988). If data are MCAR, it means that there is no relationship between the missingness of the data and any values. Those missing data points are a random subset of the data. There is nothing systematic going on that makes some data more likely to be missing than others. In doing so, it was seen that the non-responses were indeed not random in the present dataset. Moreover, some two-sample t-test using groups discriminating by those with missing answers and those without missings on the relevant variables (e.g., age, gender, employment status, marital status, education, having children, citizenship, and the dependent variables on physical and mental health) were evaluated. The results clearly showed that the two groups differed in most of these characteristics.

For these reasons, it was decided to use a method of imputation for the missing answers. Precisely some crucial variables that did not contain missing values (i.e., age, education, gender, citizenship, municipality of residence, number of household components, and the seven variables on material deprivation) were considered as predictors. Thus, new variables were generated of those that contained missings, now complete. With this method, a total of 662 observations were imputed.

Then, after this imputation process, I proceeded with the analysis and the derivation of the deprivation clusters. First, all variables were handled to have higher values to express higher deprivation. Seven variables indicating the presence of the following goods were considered: telephone (including mobile phone), colour TV, computer, washing machine, internet access, dishwasher, and a car. These indicators observed the presence of the good, and in case of its absence, they asked individuals whether they would have liked to have it, but it was not affordable, or if they did not have it for other reasons. Thus, only if the good was not affordable, the family (and its components by consequence) was marked as deprived of that item. On a scale from 0 to 10, satisfaction with the house was determined (where 0 was "very satisfied" and 10 "not satisfied at all"), then the presence of living space problems and structural problems was also evaluated. Again, on the basis of dummy variables, the possibility for the household to afford the following expenses was assessed: a week of vacation per year away from home, meat or fish or a vegetarian equivalent at least once every two days, to adequately heat the home, to cope with unforeseen expenses of an amount of around 800 €, and whether someone in the family has had to give up dental check-ups or treatment for economic reasons. Finally, satisfaction with the financial situation of the family was evaluated on a scale from 0 to 10 (where 0 was "very satisfied" and 10 "not satisfied at all"), whether the domestic expenses were a heavy (= 3), bearable (= 2), or negligible (= 1) burden, and how the family managed to make ends meet (with difficulty = 6 or easily = 1).

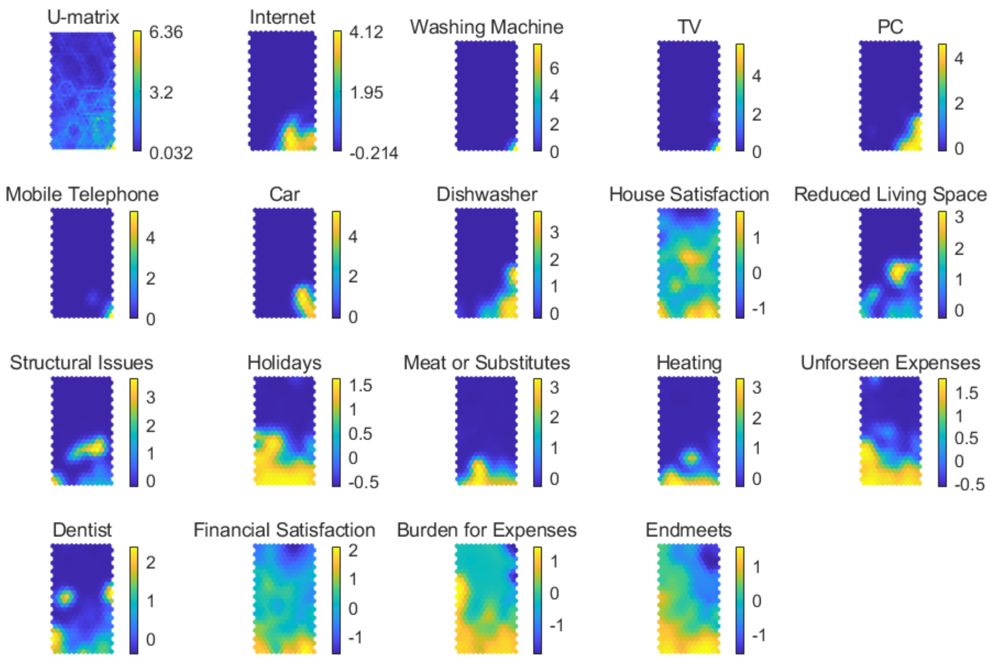
Table 6: Items on Household Deprivation - Summary statistics

Dimension		Mean	S.D.	Min	Max
Material deprivation	Internet	0.04	0.19	0	1
	Washing machine	0.00	0.04	0	1
	TV	0.00	0.03	0	1
	PC	0.04	0.19	0	1
	Mobile phone	0.00	0.04	0	1
	Car	0.03	0.16	0	1
	Dishwasher	0.06	0.23	0	1
Housing	House satisfaction	3.05	1.48	0	10
	Reduced living space	0.09	0.28	0	1
	Structural issues	0.06	0.23	0	1
Affordability	Holidays	0.27	0.44	0	1
	Meat or substitutes	0.07	0.26	0	1
	Heating	0.07	0.25	0	1
	Unforseen expenses	0.22	0.41	0	1
	Dentist	0.14	0.35	0	1
Economic condition	Financial satisfaction	4.02	1.76	0	10
	Burden for expenses	2.16	0.58	1	3
	Endmeets	3.74	1.12	1	6
	N	**7835**			

The goal of introducing household deprivation in the analyses was to propose an innovative analytical tool by which to represent the multidimensionality involved in the elements illustrated before. Following researches already conducted in other European countries (Whelan et al., 2010; Pisati et al., 2010; Lucchini and Assi, 2013; Ponthieux and Cottrell, 2001), the aim was to develop Self-Organizing Maps (SOMs) applied to the above set of indicators on deprivation. By means of this technique, the intention was to identify a certain number of clusters of individuals characterised by different forms of household deprivation, preserving as much as possible of the information contained in the wide range of the chosen indicators.

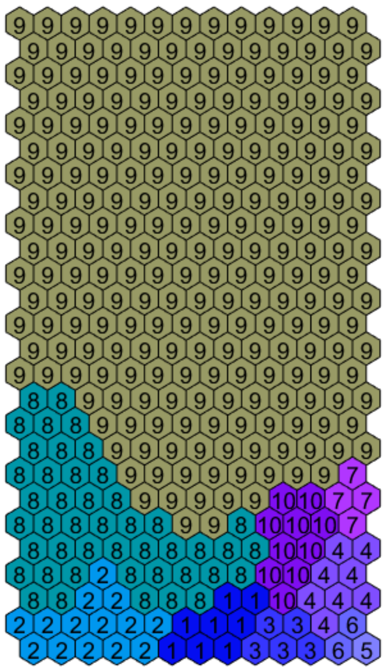
In the SOM algorithm, the elements of the input vectors were automatically associated with the nodes of a regularly ordered lattice (a map size with dimensions 26x13, in this case). The elements were then spatially ordered on the lattice so that elements with similar characteristics (according to the features that describe the data) were associated with adjacent nodes in the grid. This global organization constitutes a sort of similarity diagram of observations and allows one to get an idea of the topographic relationships existing in the data. Self-Organizing Maps can, in fact, be considered a dimensionality-reduction technique that maintains the topology (the geometric properties that are conserved under continuous deformations) of the original vector space of the data.

Figure 1: Household Deprivation - U-Matrix and Component Planes



Starting from those eighteen items, each input-vector element was allocated to its final best matching unit at the end of the development process. As it can be seen in Figure 1, two kinds of data are available as results of the algorithm in the first instance. First, the U-matrix is obtained by coloring the map according to the Euclidean distance between adjacent elements; this view is very convenient for understanding the trend of the data clustering. Dark colors (blue), in fact, represent very close elements in the space of the input data, and lighter colors (yellow) indicate nodes that are separated by more space: groups of elements of dark color can be viewed as clusters, while the lighter areas can be considered as the boundaries between those clusters. Second, by coloring the elements according to the value of the dataset variables, the component planes can be obtained. This view is really useful for understanding the probability distribution of the variables; furthermore, by analysing the colored maps with different variables, it is possible to have an insight into the inter-dependencies between variables. In this case, higher values indicate higher deprivation, thus, yellow areas are those that are characterized by attracting observations that present a more severe deprivation. What arises is, thus, the presence of an area of advantage coinciding with the upper part of the map and an area of deprivation coinciding, instead, with the lower part. Peculiarly, the southeast part of the map identifies what concerns variables in material deprivation and housing dimensions, and the south-southwest part of the map identifies the variables dealing with affordability and economic condition dimensions. Note how the presence of dishwashers, TVs, and mobile phones sharply discriminate the most south-eastern area, which is identified as that of the severest deprivation.

Figure 2: Household Deprivation - Clustering of the SOM units



Additionally, to give substantive meaning to the map and to be able to introduce information on household deprivation into the analyses, it was necessary to aggregate the micro-clusters within macro-clusters. In particular, a subdivision of 10 clusters (which offers a justifiable compromise between detail and parsimony) was chosen. The 10 clusters of SOM units were thus projected on a two-dimensional space; results are available in Figure 2. The size of each cluster indicates its prevalence; moreover, the Euclidean distance existing between clusters on the map approximately mimics their Euclidean distance in the data space. As can be seen, the clusters that are located in the lower part of the map are those characterized by the presence of higher household deprivation; specifically, the most deprived clusters (6 and 5) are located in the lower-right area of the map.

In order to introduce the useful information concerning household deprivation in the analysis and in the statistical models, it was chosen to reduce the number of clusters to 4, always on the basis of the similarity between the elements, according to the following logic: cluster 1 will be the least deprived cluster (9); in cluster 2, some clusters presenting a few elements of deprivation but experiencing a favorable condition compared to the others will be grouped (7, 8, and 10); in cluster 3, there will be clusters that present deprivation in several items and with greater severity but which individually still have a fair condition in different dimensions, especially as regards the dimension of material deprivation (1, 2, 3); in conclusion, in cluster 4, clusters that report the highest degree of household deprivation in the different dimensions will be grouped (4, 5, and 6). In the next chapter (Section 5.1.3), a description for each cluster relating to the deviations around the total average levels and their position compared to the other clusters of the eighteen items illustrated above will be provided.

4.1.4 *Compositional characteristics*

On the one hand, to analyse neighbourhood deprivation effects on the outcomes of interest, various methods have been analysed in the literature which mainly try to reduce the number of variables. Using census data, different techniques have been implemented to build an index for neighbourhood deprivation. Principal Component Analysis (PCA) and Factor Analysis (FA) have been largely used (Ngamini Ngui et al., 2012; Michelozzi et al., 1999). Indexes have also been extensively implemented: among the others, the Townsend index (Townsend, Phillimore, and Beattie, 1986), the underprivileged area score (Jarman, 1983), and the Carstairs index (Carstairs, 1995) are noteworthy.

On the other hand, following the literature handling with Italian census data (Caranci et al., 2010; Gianicolo, Mangia, and Cervino, 2016; Marinacci et al., 2004; Petrelli et al., 2006; Rosano et al., 2020), a neighbourhood deprivation index could be computed based on individual conditions of deprivation (compositional characteristics), among the others: low educational level (primary school or illiterate), unemployment, rented dwellings (or non-owned dwellings, that is, rented or other entitlement different from rent and ownership), single-parent households, and household overcrowding. In the literature, the index is computed by cumulating the Italian standardised scores of each of these conditions at the neighbourhood level. According to quintiles, the scores are then restricted into five categories, where the higher the belonging quintiles, the higher the deprivation in the census block.

The most problematic aspect of these data is the lack of an up-to-date census (Noble et al., 2006). In fact, the accessible data date back to the last census, which took place in 2011. Nevertheless, the available data showed a very low Cronbach's alpha (around 0.2) on these six items. In addition, the implementation of a factor analysis did not generate any factor with an eigenvalue greater than 1, suggesting to prefer different strategies. This proves that techniques for dimensionality reduction were not so appropriate to apply to these data. Furthermore, as suggested by (Rosano et al., 2020), the variable concerning education can be influenced by the structure of the population: in the original low-education measure, on the one hand, the youngest subjects (less than ten years old) who cannot have yet obtained a primary school certificate are included; on the other hand, older subjects are also included who, due to generational effects, generally have lower educational qualifications. Therefore, it was decided to consider the age group 15-60 years old to compute the proportion of individuals with low education (primary education or less) in the census block. Moreover, it was chosen to introduce in the analyses also the proportion of young individuals (15 years old or younger) in order to take into account the population age structure. This is because other variables (such as the proportion of single parents) can be influenced by the presence of many (or few) young individuals (e.g., the higher the number of young people in the neighbourhood, the more likely there are those with only one parent among them).

Therefore, within the following analyses, six items on the census block level will be introduced separately: the proportion of low educated individuals (with primary school education or less), the proportion of unemployed and looking for first job individuals, the proportion of rented dwellings, the proportion of single-parent households, the average house density (dwellers per 100 square meters), and the proportion of young individuals (younger than 15 years).

4.1.5 *Contextual characteristic*

In studying the effects that the context in which individuals live may have on their health, it is important to also take into consideration additional exogenous variables which, in this sense, are not under the influence of the individuals. It is widely recognized weather can affect health (both physical and mental). Weather conditions, such as number of good weather conditions, sunlight, rainfall, wind direction and speed, humidity, and temperature are demonstrated to influence mood (Cunningham, 1979; Harmatz et al., 2000; Keller et al., 2005; Noble et al., 2006), life satisfaction and well-being (Connolly, 2013; Feddersen, Metcalfe, and Wooden, 2016; Maddison and Rehdanz, 2011), mental health (An et al., 2016; Bos, Hoenders, and Jonge, 2012; Ding, Berry, and Bennett, 2016), and the occurrence or the worsening of physical symptoms (Lee et al., 2018; Yang et al., 2015). However, looking at the last outcome, what emerges from the literature are different and conflicting conclusions. What appears to be certain is that for patients who are more sensitive to weather conditions and who believe their pain is actually affected by the weather, even if the causes are not certain, the effect is visible (Quick, 1997).

In this health-weather relationship, the contrary is not valid: the individual cannot influence the weather (at least not directly and in the short term). Climate change indeed stems from humans and their habits; still, a single individual has no power in the short term to drastically influence, for example, the level of humidity or the amount of precipitation on a given day.

Therefore, introducing this exogenous variable allows having a potent tool to analyse the effect of the living neighbourhood on individuals' health. Thus, according to the literature, the weather was introduced as a covariate perturbing health. Data were obtained from the observational grid dataset: E-OBS v23.1 (latest version available), with a resolution of 0.1 degrees (about 12 km). Based on this spatial grid, each individual was located on the space according to proximity rule, as well as done for the connection of dwellings to census blocks. In other words, the available data concerning weather involved the whole Italian territory with a resolution of 12 km, by and large. Therefore, the country was partitioned into a grid where each cell contained the data necessary for the analysis. In this way, the cell (together with its weather information) containing the address where the interview took place was assigned to each dwelling and, accordingly, to each family and individual.

What was introduced in the model is a variable recording the number of days with unfavorable weather conditions that occurred in the 35 days before the interview. Three main variables were here considered in order to indicate unfavorable weather conditions: maximum temperature (°C), minimum temperature (°C), and precipitations (mm). The logic by which the weather conditions were not observed only on the day of the interview lies in two reasons: on the one hand, the weather does not have an immediate effect on health, its impact takes time to accumulate, and a particular phenomenon on a specific day takes time to manifest itself; on the other hand, the weather can influence the responses of individuals on the day of the interview but not the actual health (Chadi, 2017). In other words, *ceteris paribus*, two individuals that are identical for all characteristics could report two different levels of health just because one was interviewed on a rainy day while the other one was interviewed on a sunny day. It thus makes sense to use a time window of several weeks to capture a concentrated impact of weather conditions (Deschênes and Greenstone, 2011).

In this case, thanks to the available data, it was possible for each individual to know how many days with adverse weather conditions occurred on the day of her/his interview and during the previous 35 days. In particular, a solution was chosen for which a day was marked as characterised by unfavorable weather conditions if it had a minimum temperature lower than 10 degrees centigrade, or a maximum temperature higher than 28 degrees centigrade and with the presence of precipitation of at least 5 millimeters.

4.2 MODEL - OVERVIEW OF THE ANALYSIS

As specified earlier, the interest of the research is to understand how and through which ways the context where the individual is immersed can have an effect on her/his health. In this sense, the daily living circumstances of the individual can be analysed from two points of view, the family context, and the geographical/environmental context. The first level of analysis is, therefore, the individual, with her/his health and her/his characteristics, habits, and beliefs (including the subjective perception of the neighbourhood - Section 4.1.2); the second level is the household, characterised by a specific level of deprivation (Section 4.1.3); at the third level, we find the context, analysed both through compositional census data (Section 4.1.4), and by contextual adverse weather conditions (Section 4.1.5).

Implementing a multi-stage stratified sampling design requires a hierarchical multilevel model to be carried out for the analyses of relationships. Ignoring the hierarchical structure of the data would mean losing the ability to make simultaneous inferences on more than one population, where each population taken into consideration is, in this case, a meaningful sociological entity (individuals, families, and neighbourhoods). In the researches where the sampling design leads to nested data, it is known that the grouped observations are not independent of each other. Because of this, their errors are correlated, and the models to be introduced should account for that. By contrast, it is also known that observations belonging to different groups are mathematically independent of each other. As such, the rationale for distinguishing three levels of data hierarchy is that it can be assumed that families living in the same neighbourhood tend to be more similar to each other than they are with respect to families from another neighbourhood; moreover, it can be presumed individuals belonging to the same family are closer to each other than they are to individuals belonging to a different family.

The advantage of using the multilevel model lies mainly in three factors: first, the estimated parameters take into account the hierarchy of the data collected; second, it allows to simultaneously analyse different levels (mean, variance and covariance); third, the specified model allows the relationships between variables to change across different levels of analysis. In other words, the relationship between the covariates and the dependent variable can be positive within the first level (within the household). Instead, it can simultaneously be negative between neighbourhoods, that is, at the higher level.

Therefore, by means of three-level multilevel models, the following questions tried to find answers:

- Nationally, how is health associated with perceived neighbourhood disorder, perceived neighbourhood social cohesion, and individuals' socio-demographic characteristics?
- Nationally, how does household deprivation affect health?
- After having taken into account all of the individuals', and households' characteristics, are still there significant variations in health between neighbourhoods?
- If the differences between neighbourhoods are not an artifact of variation arising from specific types of people living in specific places, does the between-neighbourhood variation vary differently for different household deprivation groups?
- After having taken into consideration individuals' and households' characteristics, nationally, what role do exogenous contextual and compositional factors play in influencing health?
- To what extent do exogenous neighbourhoods characteristics, such as adverse weather conditions or unemployment proportion, account for the variation between neighbourhoods for the different groups of individuals?
- Are these relationships between contexts and individual health the same throughout the territory, or are there differences between regions and macro-regions?

What can be expected is that the context-related conditions in which individuals live can have an effect on their health. In particular, living in neighbourhoods perceived as poorly cohesive and/or with significant disorder settings can lead to poorer health (Kuipers et al., 2012; Ruijsbroek et al., 2015), as well as compositional neighbourhood features can (e.g., living in neighbourhoods characterised by low education, high unemployment or high rental rate may jeopardize the health of individuals) (Rocha et al., 2017; Ross, Tremblay, and Graham, 2004; Stafford and Marmot, 2003). Furthermore, the conditions of deprivation of the family in which one lives are expected to have a correlation with the health of the subjects; the more the family is deprived, the more the family members will suffer from poor health (Boarini and d'Ercole, 2006; Chung et al., 2018; Eibner and Evans, 2005). Moreover, it is expected that even exogenous contextual characteristics, not controllable by the individual, such as weather conditions, may have a correlation with health (Bos, Hoenders, and Jonge, 2012; Feddersen, Metcalfe, and Wooden, 2016; Lee et al., 2018; Noble et al., 2006). Specifically, individuals who live in contexts characterized by the manifestation of many days with unfavorable weather conditions can present poor health.

Therefore, in order to assess the existence of neighbourhood-level effects throughout Italy and their impact on subjects' health, the analyses were carried out with the following procedures:

- *Model 1*: An empty model (or null model), without the introduction of any covariate. This model will allow calculating the intra-class correlation, which in this context gives the proportion of the total variation at the neighbourhood level, household level, and the residual individual level: how similar families within neighbourhoods are on the outcome, and also, how similar individuals within households are on the outcome
- *Model 2*: A random intercept model with the introduction of the individual-level variables, i.e., the subjective perception of neighbourhood social cohesion and neighbourhood disorder, and the individuals' socio-demographic characteristics (gender, age, education level, employment status, marital status, children, citizenship, and sleeping troubles)
- *Model 3*: A random intercept model as the previous one, in which family-level variables have been introduced, i.e., the household deprivation clusters
- *Model 4*: A model as the previous one, but with the extension of household deprivation being allowed to vary between neighbourhoods. In this way, neighbourhood-level differences in the relationship between health and household deprivation were given due consideration (random slopes model)
- *Model 5*: A random slopes model as the previous one, where the neighbourhood-level variables (the compositional and contextual characteristics of the context in which individuals live) have been inserted, i.e., the proportions of low educated individuals, unemployed individuals, rented houses, single-parent households, average house density, the proportion of young individuals, and the number of days with adverse weather conditions. This model will be proposed both nationally and by analysing region by region
- *Model 6*: Finally, a cross-level model was run as the previous one, but in this case, the significant exogenous variables were made to

interact with the individual characteristics and with the household characteristics; the extent to which the neighbourhood characteristics accounted for variation between-neighbourhood for the different groups were then ascertained.

5 EXPLORATORY DATA ANALYSIS

In this chapter, attention is devoted to describing the variables of interest, their statistical distributions, their spatial distributions, and how distinct subgroups of the population are characterised differently. Descriptive statistic (Section 5.1) is relevant in this work because by simply presenting raw data, it would be hard to visualize what the data are showing, especially in this case where there is a lot of it. Moreover, in the second paragraph of this chapter (Section 5.2), some spatial analyses are proposed, allowing us to understand better where and what is occurring throughout the Italian territory.

5.1 DESCRIPTIVE STATISTICS

As anticipated, the following descriptive statistics facilitate presenting the data in a more significant way, which favors a more straightforward interpretation of the data under scrutiny. Individuals' socio-demographic characteristics, individuals' health, individuals' perception of neighbourhood disorder and social cohesion, clusters on household deprivation, and objective neighbourhood characteristics are the aspects that will be investigated.

5.1.1 *Individual Characteristics*

In this section, it is possible to learn about the structure of the final sample regarding the main characteristics of the subjects (e.g., gender, age, education) introduced in the models at the first level of analysis (individual level).

Looking at Table 7 we can see that the final sample (7,835 individuals) is composed of 53.96% of females and 46.04% of males. The age structure follows the following distribution: 8.91% of individuals are between 16 years old and 24 years old; 12.90% of subjects are in the range of 25-34 years old; 33.87% of the sample is between 35 and 54 years old; 16.98% of individuals are between 55 years old and 64 years old; while the remaining individuals (27.34%) are aged 65 or more. The majority of the individuals (44.37%) have an upper secondary education, while 12.25% have a tertiary education or higher. A small portion of the sample is illiterate (1.95%), 10.43% has a primary education, and 31.00% has a lower secondary education. Considering the employment status, the percentage of unemployed individuals is 6.59% (including those looking for the first job), while employed individuals are about 47.94%. The remaining sample comprises retired people (23.65%), homemakers (13.87%), and unable to work individuals (0.78%), while the percentage of students is 7.17%. As regards the marital status, the majority of the sample (54.52%) is married or joined in a civil union, 30.56% declares to be single, 6.46% is divorced or separated. At the same time, 8.46% of the subjects are widows or widowers. In the sample, the majority of the individuals (62.45%) have children, while the remainder has no children (37.55%).

Table 7: Covariates - Summary statistics

Variables	Frequency	Percentage
Gender		
Male	3607	46.04%
Female	4228	53.96%
Age		
16-24	698	8.91%
25-34	1011	12.90%
35-54	2654	33.87%
55-64	1330	16.98%
65 and older	2142	27.34%
Education		
Illiterate	153	1.95%
Primary	817	10.43%
Lower Secondary	2429	31.00%
Upper Secondary	3476	44.37%
Tertiary and Higher	960	12.25%
Employment status		
Employed	3756	47.94%
Unemployed or looking for first job	516	6.59%
Homemaker	1087	13.87%
Student	562	7.17%
Retired	1853	23.65%
Unabe to work	61	0.78%
Marital status		
Married or Civil Union	4272	54.52%
Single	2394	30.56%
Divorced or Separated	506	6.46%
Widow/er	663	8.46%
Children		
No	2942	37.55%
Yes	4893	62.45%
Citizenship		
Italian	7558	96.46%
Foreign	277	3.54%
Insomnia issues		
Not at all	4849	61.89%
A little	2542	32.44%
A lot	444	5.67%
N	**7835**	

Besides, the share of Italian citizens is preponderant compared to the share of foreign citizens (96.46% and 3.54% accordingly). Finally, individuals without sleep troubles are 61.89% of the sample, 32.44% of the sample affirms to have minor insomnia issues, while 5.67% declares to have many sleeping troubles.

5.1.2 *Individual Health*

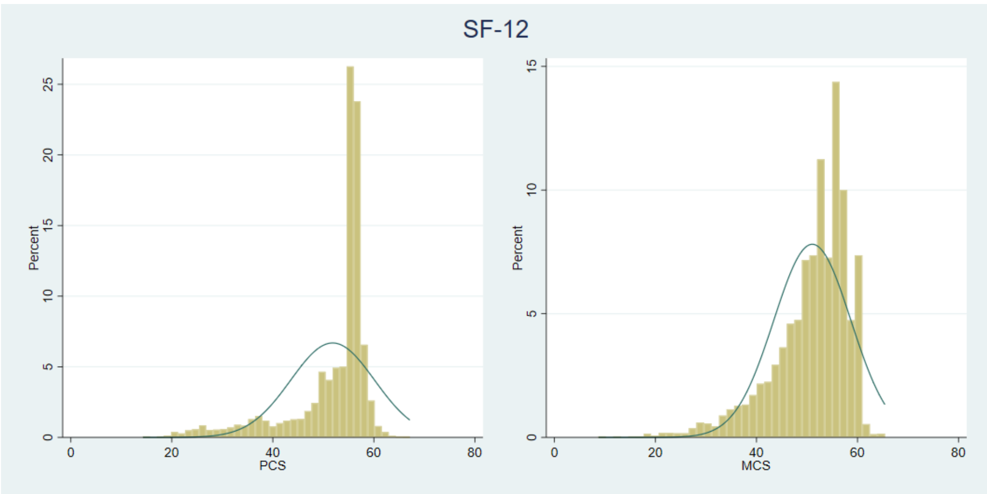
In Table 8 and Figure 3 some basic feature of the two SF-12 component score, PCS and MCS, can be understood. As regards the PCS, as mentioned in the previous chapter, the variable follows a distribution with a mean of 51.84 and a standard deviation of 8.30. What can be added is that the distribution has heavier tails than a standard normal distribution (with zero mean and unit variance) and that it is left-skewed (negative skewness).

Table 8: SF-12 - Summary statistics for PCS and MCS

	Mean	S.D.	Min	Max
PCS	51.84	8.30	14.26	67.13
MCS	51.06	7.63	8.68	65.43
N	**7835**			

The same can be seen for what concerns the MCS, even if, with respect to the PCS, the mental component score has a distribution that is closer to the one of a standard normal (less left-skewed and less leptokurtic), following a distribution with mean 51.06 and standard deviation 7.63.

Figure 3: Histograms for PCS and MCS



Moving forward to Table 9, what can be noticed is how the two dependent variables of this study are differently distributed for different subgroups of the population. Looking at the gender, both for PCS and MCS, male individuals have higher scores (52.42 and 51.79 respectively) than females (51.35 and 50.43 respectively), on average. Looking at the results for age groups it can be seen that both physical health and mental health tend to deteriorate with advancing age. In fact, the age group that on average reports the best health conditions is the youngest age group (56.57 for PCS and 53.25 for MCS), while the age group characterised by the worst health condition is that of individuals aged 65 and older (45.25 for PCS and 49.00 for MCS).

Table 9: SF-12 - Scores by Subgroups

	PCS		MCS		
	Mean	S.D.	Mean	S.D.	N
Gender					
Male	52.42	7.70	51.79	7.35	3607
Female	51.35	8.76	50.43	7.81	4228
Age					
16-24	56.57	2.69	53.25	6.26	698
25-34	56.10	3.12	53.12	6.47	1011
35-54	54.34	5.16	51.77	7.12	2645
55-64	51.74	7.27	50.22	7.69	1330
65 and older	45.25	10.60	49.00	8.49	2142
Education					
Illiterate	37.17	11.59	44.78	10.12	153
Primary	44.22	10.97	47.55	8.44	817
Lower Secondary	51.74	8.04	50.92	7.72	2429
Upper Secondary	53.66	6.23	51.89	7.03	3476
Tertiary and Higher	54.33	5.73	52.35	6.91	960
Employment status					
Employed	54.53	4.78	52.46	6.42	3756
Unemployed or looking for first job	54.65	6.54	48.73	9.05	516
Homemaker	49.57	9.59	49.32	8.05	1087
Student	56.58	2.40	53.30	6.52	562
Retired	46.01	10.25	49.48	8.48	1853
Unabe to work	36.24	10.95	42.54	10.72	61
Marital status					
Married or Civil Union	51.54	7.90	51.40	7.20	4272
Single	54.62	6.13	51.86	7.41	2394
Divorced or Separated	53.35	6.39	49.82	7.95	506
Widow/er	42.55	11.39	46.88	9.27	663
Children					
No	53.82	6.89	51.64	7.44	2942
Yes	50.65	8.84	50.70	7.72	4893
Citizenship					
Italian	51.74	8.37	51.03	7.65	7558
Foreign	54.66	5.65	51.75	6.98	277
Insomnia issues					
Not at all	54.49	5.23	53.47	5.64	4849
A little	48.47	9.44	48.41	7.70	2542
A lot	42.20	13.19	39.85	10.58	444
Household deprivation - clusters					
1	52.32	7.66	51.85	6.96	6033
2	50.58	9.51	49.30	8.48	1185
3	49.48	10.66	47.24	9.44	472
4	49.75	11.52	44.82	10.78	145

Furthermore, the table shows how the higher the education, the higher the health, both physical and mental, on average. Indeed, the most educated individuals (with tertiary education or higher) show on average the highest score both for PCS (54.33) and MCS (52.35), while illiterate individuals report the worst PCS (37.17) and MCS (44.78). Considering the employment status, we see that students have, on average, the highest physical health score (56.58). In contrast, individuals suffering from the poorest physical health are, as predictable, those that are unable to work (36.24). The physical component score is similar for individuals that are employed (54.53) and unemployed (54.65), while on average, retired individuals and homemakers suffer worse physical health (46.01 and 49.57 correspondingly); mental component score, instead, behaves a bit differently among different employment status groups. Employed individuals and students are those who report the best mental health (52.46 and 53.30 respectively) while the unemployed, homemakers, and retired individuals have on average lower mental health (48.73, 49.32, and 49.48 correspondingly); however, the individuals who are worse off are, also in this case, those that are unable to work (42.54). About the marital status, the widows and widowers are those reporting on average the lowest PCS (42.55) and MCS (46.88). Concerning mental health, divorced individuals report a higher score on average (49.82) than widows and widowers, while single individuals and married individuals present the highest (and similar) scores (51.86 and 51.40 accordingly). About physical health, instead, single individuals are those reporting, on average, the best condition with a physical component score equal to 54.62, followed by divorced (53.35) and married individuals (51.54). On average, if the individual has children, she/he shows worse physical and mental health (50.65 and 50.70 respectively), compared to individuals without children (53.82 for PCS and 51.64 for MCS). Moreover, on average, foreign individuals report higher physical health (54.66) and mental health (51.75) than individuals with Italian citizenship (51.74 and 51.03 correspondingly). Concerning sleeping troubles, individuals with insomnia issues report the lowest physical and mental scores (42.20 and 39.85), versus 54.49 for PCS and 53.47 for MCS of those individuals claiming to have no insomnia issues. Finally, looking at the clusters on household deprivation, the mental component score is the highest (indicating better mental health) for least deprived families (the first cluster reports an average score equal to 51.85). Moreover, it seems to decrease as far as household deprivation increases, with the second and the third clusters being worse off (49.30 and 47.24 respectively). Instead, the fourth cluster presents the worst values in MCS (44.82) among the four groups. On the contrary, for the physical component score, the reasoning seems to be different: the cluster reporting, on average, the better PCS is again the first one (52.32), followed by the second cluster with an average measure of 50.58. Then, the third and fourth clusters present the worst scores, but those are very similar (49.48 and 49.75 respectively) and very close to the second cluster. This, perhaps, could mean that family deprivation may have a more noticeable and sharper impact on mental health than on physical health.

5.1.3 *Household Deprivation*

After having carried out the SOM and having grouped the clusters concerning household deprivation as indicated in the previous chapter, in Figure 4 the mean for each household deprivation item used for the analyses is reported, moreover, the table reveals how household deprivation items combine across the four clusters indicating the average score obtained in each item. In the interpretation of the table, it should be remembered that the higher the score, the higher the deprivation.

Figure 4: Clusters of Household Deprivation - Mean values

	Clusters				
	1	2	3	4	**Total Mean**
Internet	0.00	0.06	0.29	0.69	**0.04**
Washing machine	0.00	0.00	0.00	0.08	**0.00**
TV	0.00	0.00	0.00	0.05	**0.00**
PC	0.00	0.05	0.23	0.96	**0.04**
Mobile phone	0.00	0.00	0.00	0.10	**0.00**
Car	0.00	0.07	0.02	0.72	**0.03**
Dishwasher	0.02	0.07	0.28	0.91	**0.06**
House satisfaction	2.87	3.31	4.57	4.50	**3.06**
Reduced living space	0.05	0.15	0.37	0.25	**0.09**
Structural issues	0.03	0.02	0.41	0.20	**0.06**
Holidays	0.10	0.75	0.97	0.90	**0.27**
Meat or substitutes	0.00	0.15	0.66	0.40	**0.07**
Heating	0.01	0.05	0.76	0.37	**0.07**
Unforseen expenses	0.03	0.86	0.94	0.83	**0.22**
Dentist	0.07	0.29	0.53	0.51	**0.14**
Financial satisfaction	3.57	5.06	6.45	6.60	**4.02**
Burden for expenses	2.01	2.57	2.75	2.78	**2.16**
Endmeets	3.40	4.70	5.33	5.21	**3.75**
N	6051	1193	476	146	

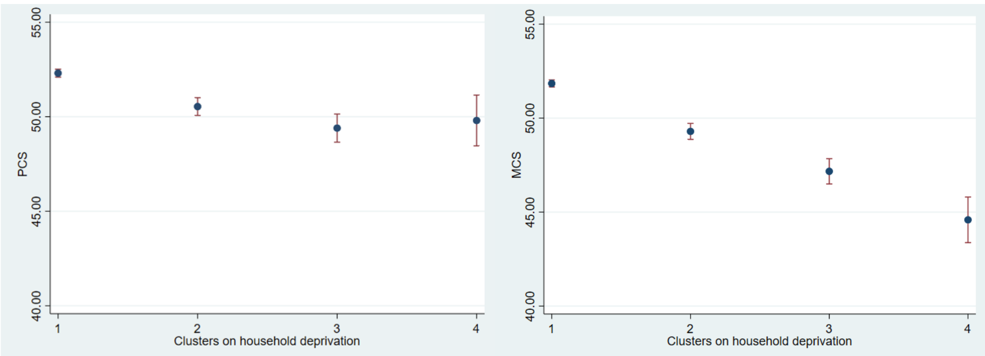
Cluster 1: It includes 77.00% of the observations. It is identified, comparatively, by the best scores in all the items related to the four dimensions.

Cluster 2: It contains 15.12% of the observations. It is characterised by quite a good situation in the dimension regarding the material deprivation even if some items are above the mean (i.e., internet, PC, car, and dishwasher) but remains acceptable; slightly worse conditions (with the majority of items presenting average scores above the total mean) are visible in the remaining three dimensions.

Cluster 3: It comprises 6.02% of the observations. With respect to the previous cluster, it is identified by similar scores in the material deprivation (i.e., see scores for internet, PC, car, and dishwasher). However, it reports the worst values in all the items concerning the housing dimension and the affordability dimension, and the highest score in the variable indicating the difficulty the family manages to make ends meet.

Cluster 4: It includes 1.85% of the observations. It is identified by the worst situation in the dimension about material deprivation, showing all the items above the mean. In the housing dimension, the three items also present values above the mean. Additionally, the circumstances are pretty inadequate also in the dimensions concerning affordability and economic conditions. In particular, in the latter, two items out of three (financial satisfaction and burden of expenses) report the worst scores among the four clusters on household deprivation.

Figure 5: Plot estimates with confidence limits (95%) for PCS and MCS by Household Deprivation Clusters



What can also be interesting is to see, in Figure 5, how physical component score and mental component score differ across the clusters on household deprivation. For the PCS, what is evident is that the first cluster is the one with the best physical health situation. In contrast, the remaining clusters seem to be slightly worse off, but, among each other, they overlap, suggesting that they experience a similar condition as regards physical health and confirming what was already said as regard the Table 9. The results on the mental component score are of a more straightforward interpretation: the higher the household deprivation, the worse the mental health. In particular, the first cluster shows the best mental score while the fourth cluster experiences the worst health condition. Note that all the clusters do not overlap each other, suggesting that the four clusters have a different situation each.

5.1.4 *Neighbourhood Subjective Perception*

In this paragraph, some basic features of the two factors about the neighbourhood's subjective perception (Neighbourhood Disorder and Social Cohesion) can be understood.

Table 10: Neighbourhood Disorder and Social Cohesion - Summary statistics

	Mean	S.D.	Min	Max
Neighbourhood Disorder	0.00	0.91	-1.00	3.33
Neighbourhood Social Cohesion	0.00	0.94	-3.39	1.62
N	**7835**			

Taking into consideration that, for what concerns the neighbourhood disorder, the higher the value, the worse the situation, while for what concerns the social cohesion, the higher the value, the better the situation, in Table 11 we can see how the two factors are differently distributed for different subgroups of the population. Looking at the gender, what can be noticed is that the two subgroups present the same average score (0 for both) for the social cohesion dimension. At the same time, for the neighbourhood disorder factor, males report an average score that is slightly better than the one for females (-0.01 and 0.01 respectively). Examining the results for age groups, the neighbourhood disorder factor is quite similar across the different subgroups. However, it can be noticed that the youngest age groups (16-24 and 25-34) are those reporting the lowest average scores (-0.03 and -0.01 accordingly), while the oldest age groups (55-64 and 65 and older) are those reporting the worst scores (0.01 for both). Nevertheless, it can be seen that concerning social cohesion, the two oldest age groups are characterised by a comfortable social cohesion within the neighbourhood (0.06 and 0.28 correspondingly). On the contrary, the two youngest age groups are those that, on average, live in the worst condition (-0.23 for individuals aged 16-24 and -0.22 for individuals aged 25-34). Besides, the table shows that, on average, illiterate individuals and individuals with primary education live in neighbourhoods with a high level of disorder (0.11 and 0.05, respectively). Individuals with lower secondary education and tertiary education live on average in slightly better neighbourhoods (0 and -0.01 respectively). Furthermore, on average, individuals with upper secondary education report the lowest level of disorder in the neighbourhood (-0.02). On the contrary, regarding social cohesion, education seems to follow a different path. Individuals living in the best conditions are, on average, those how are illiterate or with primary education (0.16 and 0.22 correspondingly), while the most educated individuals, with upper secondary education and tertiary education or higher, show on average the lowest scores in the factor on social cohesion (-0.04 and -0.16 accordingly).

Table 11: ND and SC - Scores by Subgroups

	Neighbourhood Disorder		Neighbourhood Social Cohesion		
	Mean	S.D.	Mean	S.D.	N
Gender					
Male	-0.01	0.90	0.00	0.94	3607
Female	0.01	0.94	0.00	0.95	4228
Age					
16-24	-0.03	0.90	-0.23	1.01	698
25-34	-0.01	0.95	-0.22	0.97	1011
35-54	0.00	0.93	-0.11	0.96	2645
55-64	0.01	0.91	0.06	0.91	1330
65 and older	0.01	0.86	0.28	0.82	2142
Education					
Illiterate	0.11	0.98	0.16	0.98	153
Primary	0.05	0.91	0.22	0.85	817
Lower Secondary	0.00	0.92	0.04	0.96	2429
Upper Secondary	-0.02	0.90	-0.04	0.93	3476
Tertiary and Higher	-0.01	0.90	-0.16	0.98	960
Employment status					
Employed	-0.02	0.90	-0.08	0.94	3756
Unemployed or looking for first job	0.13	1.07	-0.30	1.02	516
Homemaker	0.11	1.00	0.06	0.93	1087
Student	-0.08	0.82	-0.18	1.02	562
Retired	-0.03	0.82	0.28	0.83	1853
Unabe to work	0.12	0.98	0.00	1.13	61
Marital status					
Married or Civil Union	0.00	0.90	0.09	0.90	4272
Single	-0.01	0.93	-0.19	0.98	2394
Divorced or Separated	-0.04	0.86	-0.15	0.99	506
Widow/er	0.02	0.90	0.23	0.90	663
Children					
No	0.00	0.93	-0.13	0.97	2942
Yes	0.00	0.89	0.08	0.92	4893
Citizenship					
Italian	0.00	0.90	0.02	0.94	7558
Foreign	0.08	1.01	-0.50	0.92	277
Insomnia issues					
Not at all	-0.06	0.84	0.02	0.95	4849
A little	0.06	0.99	-0.02	0.90	2542
A lot	0.25	1.09	-0.09	1.10	444
Household deprivation - clusters					
1	-0.06	0.84	0.07	0.91	6033
2	0.09	1.00	-0.13	0.95	1185
3	0.37	1.19	-0.37	1.15	472
4	0.38	1.25	-0.49	1.04	145

Considering the employment status, both for neighbourhood disorder and social cohesion, unemployed individuals are, on average, those living in the worst conditions (0.13 for ND and -0.30 for SC). Although with different values, employed individuals, students, and retired subjects generally report an acceptable condition for what concerns the neighbourhood disorder (-0.02, -0.08, and -0.03, respectively). On the contrary, homemakers and unable to work individuals are characterised, on average, by high scores (very close to the unemployed individuals' scores) in the neighbourhood disorder dimension (0.11 and 0.12 accordingly). As regards the social cohesion factor, retired individuals are those reporting the average best condition (0.28), homemakers and unable to work individuals are characterised, on average, by quite decent scores (0.06 and 0 correspondingly), while employed subjects and students live in an uncomfortable condition, on average(-0.08 and -0.18 respectively). Regarding marital status, widows and widowers are those reporting, on average, the best score in the social cohesion factor (0.23), while concerning neighbourhood disorder, they report the highest value (0.02), corresponding to an unfavorable situation. Single individuals experience a neighbourhood disorder near to the general population's mean (-0.01). However, they report the worst conditions for what regards social cohesion in the neighbourhood (-0.19). Married subjects are characterised by the second best score in the dimension concerning neighbourhood social cohesion (0.09) and an average neighbourhood disorder situation. Finally, divorced and separated individuals are those living in neighbourhoods with the lowest level of disorder (-0.04) but with the second worst level of social cohesion (-0.15). The subgroups differing for having or not children do not diverge in the average score in the neighbourhood disorder factor (0 for both). However, it can be noticed that if the individual has children, on average, she/he lives in a better neighbourhood considering the level of social cohesion (0.08) compared to individuals without children (-0.13). Moreover, on average, foreign individuals report worse neighbourhood conditions (0.08 for neighbourhood disorder and -0.50 for social cohesion) than individuals with Italian citizenship (0 and 0.02 accordingly). Concerning insomnia, individuals with sleeping troubles report on average the most wanting conditions (0.25 for ND and -0.09 for SC) versus -0.06 for ND and 0.02 for SC of those individuals claiming to have no insomnia issues. Finally, the neighbourhood disorder is lower (indicating optimal conditions in the neighbourhood) for less deprived families - first cluster (-0.06) - and seems to increase as far as the household deprivation increases (clusters 3 and 4 are those with the highest neighbourhood disorder, i.e., 0.37 and 0.38). Correspondingly, for the social cohesion factor, the reasoning seems to be the same, the higher the deprivation in the family, the worst the social cohesion in the neighbourhood: the families belonging to the least deprived cluster are those living in neighbourhoods with the highest average social cohesion (0.07), while, the fourth cluster is, again, the one characterised by worst condition (-0.49).

5.1.5 *Compositional and Contextual Characteristics*

In this paragraph, I will briefly analyse the census data concerning the objective characteristics of the neighbourhoods (understood as census blocks). In the next paragraph (Section 5.2), proper spatial data analysis will be arranged for the entire Italian territory; however, since files with boundaries of administrative units for statistical purposes are available for municipalities as the smallest spatial unit from ISTAT, the proposed maps will handle aggregated measures at the municipality level.

Table 12: Neighbourhood's Objective Characteristics - Summary statistics

	Italian Neighbourhoods (ISTAT)				ITA.LI Neighbourhoods			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Low Education	0.15	0.07	0.00	1.00	0.15	0.05	0.00	1.00
Unemployment	0.11	0.12	0.00	1.00	0.12	0.09	0.00	1.00
Rented Houses	0.15	0.18	0.00	1.00	0.20	0.17	0.00	1.00
Single Parents	0.08	0.08	0.00	1.00	0.10	0.06	0.00	1.00
House Density	2.46	1.12	0.11	257.89	2.57	0.52	0.48	5.88
Young Individuals	0.13	0.08	0.00	1.00	0.13	0.05	0.00	0.50
N	**366928**				**3537**			

Table 12 is divided into two parts. The first one shows the mean and standard deviation for the variables of interest considering the whole Italian territory (366,928 census blocks). The second one shows the same features but refers to the neighbourhoods involved in the survey (3,537 census blocks). Compared to the total sample that considers all the neighbourhoods on the Italian territory, in the final sample, the neighbourhoods with a high percentage of low educated individuals, unemployed individuals, and young individuals are somewhat well represented in the sample (the means are almost the same). Regarding the remaining characteristics, instead, neighbourhoods with a high percentage of rented houses, a high percentage of single-parent households, and high household overcrowding are slightly over-represented in the final sample.

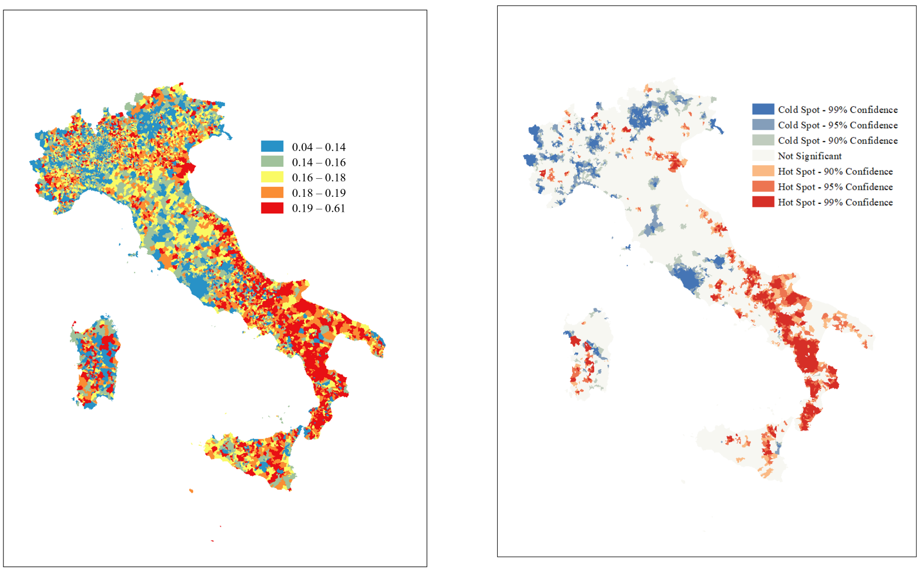
5.2 EXPLORATORY SPATIAL DATA ANALYSIS

As specified in the previous paragraph (Section 5.1.5), maps for census variables are proposed on a municipality level. On the contrary, maps concerning dependent variables, household deprivation, and subjective perception of the neighbourhood will handle aggregated measures at the regional level since the data do not allow a more fine-grained level of spatial analysis. The same is true for weather data; thus, maps about adverse weather conditions are also proposed on a regional level.

5.2.1 *Census Data*

For each census variable, two kinds of visual evidence are available: first, a choropleth map on quintiles on the municipalities mean is proposed; second, since spatial trends in the former kind of map are highly subjective (changing the classification scheme - for example, from quintiles to equal intervals and the number of class to 10 intervals instead of 5 - may make patterns disappear), in order to understand if there are clusters in the country that are statistically significant, a hot spot analysis is presented. In particular, hot spots (statistically significant clusters of high values) and cold spots (statistically significant clusters of low values) are shown in red and blue respectively, with different shades for different levels of significance (99%, 95%, and 90%).

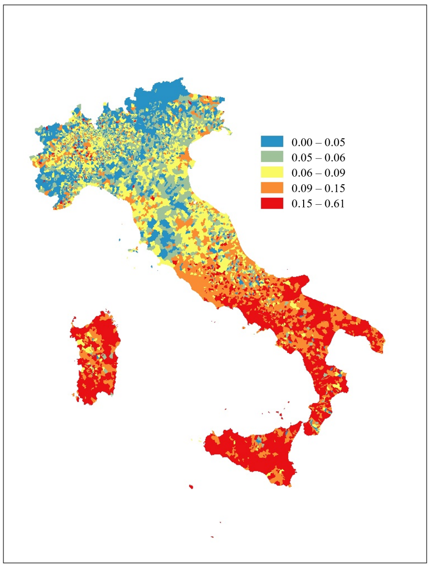
In Figure 6 the proportion of low educated individuals in the age 15-60 is analysed. At first glance, in the choropleth map, we can see on the one hand broad areas characterised by a high presence of low educated individuals (see areas near the Romagna riviera, near the coasts of the Marche, Abruzzo and Molise, Campania, Basilicata, Calabria, and the northern part of Puglia). On the other hand, different zones present meager existence of low educated individuals (in the north of Italy, e.g., in Trentino Alto Adige, near Milan, in Valle d'Aosta, in the mountainous areas of Piedmont; and in the center of Italy, e.g., in Emilia Romagna, in Tuscany, near Rome, and all along the northernmost part of the Apennines). As anticipated, clearer patterns are visible in Figure 6b, confirming what was deduced from the choropleth map. Moreover, distinct hot and cold spots are also visible in the territories of Sardinia and Sicily.



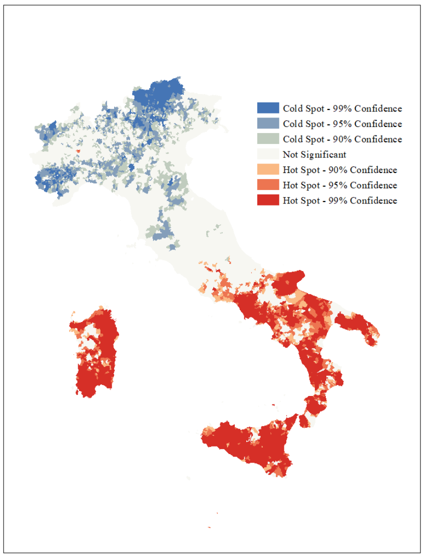
(a) Choropleth Map: Municipality mean (b) Hot Spot Analysis

Figure 6: Low Education - Choropleth Map and Hot Spot Analysis

In Figure 7 the proportion of unemployed individuals is inspected. A clear pattern seems to emerge from the choropleth map: the north of Italy is typified by a low presence of unemployed subjects. At the same time, the south of the territory shows a high incidence of unemployed individuals. This distinction is confirmed with the hot spot analysis, which shows significant hot spots in the southern regions, isles included, and significant cold spots in the north (especially see Bolzano, Trent, Valle d'Aosta, and western Piedmont).



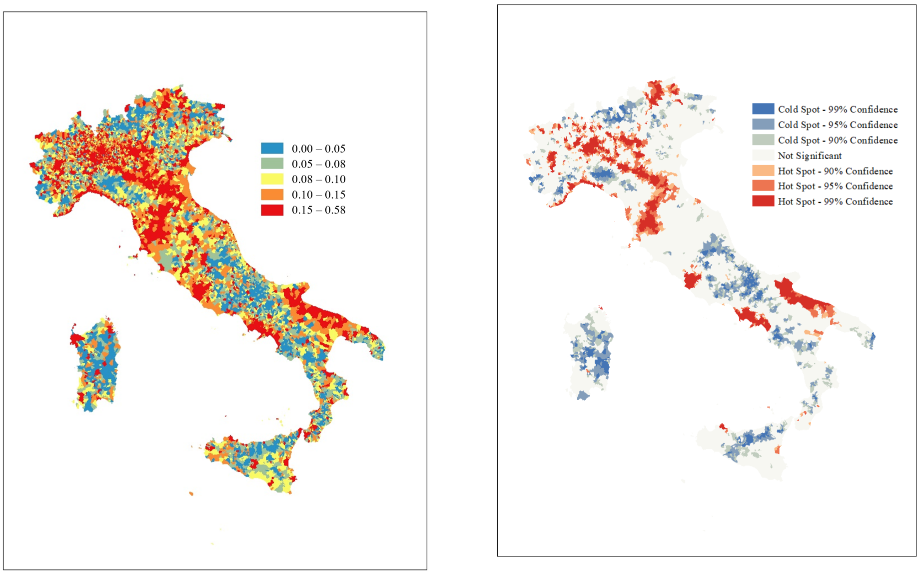
(a) Choropleth Map: Municipality mean



(b) Hot Spot Analysis

Figure 7: Unemployed Individuals - Choropleth Map and Hot Spot Analysis

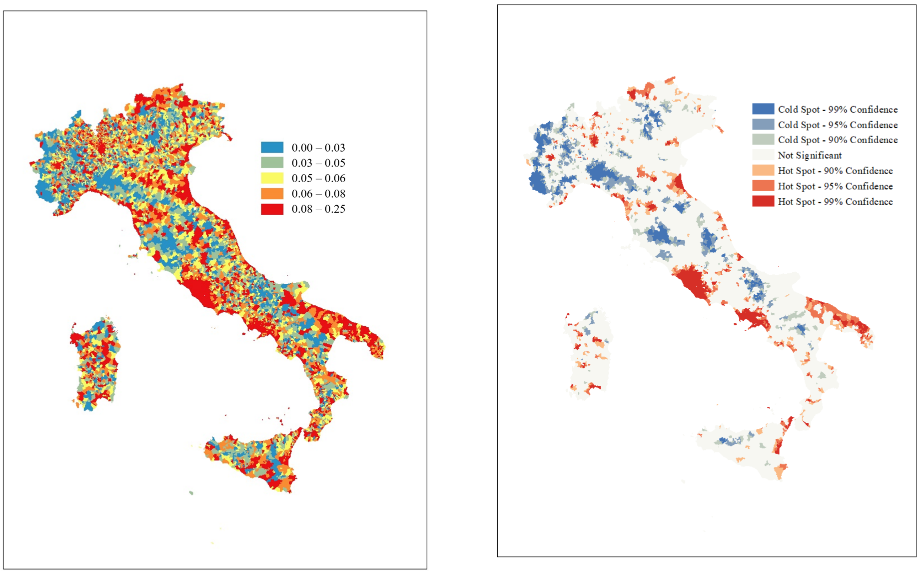
Concerning the proportion of rented houses in the municipalities, Figure 8a shows its spatial distribution. In particular, it is possible to notice many municipalities with high values in Puglia, in Naples and surroundings, in Rome, in the north-west of Sardinia, on the Ligurian coast, in the north of Tuscany, in Lombardy, and Emilia-Romagna. A low presence of rented houses is visible in Sardinia and in the center-south of the territory: south Marche, Abruzzo, Molise, Calabria, and in the south of Campania. In Figure 8b hot spots are clearly visible in the north of Puglia, in Naples and surroundings, in Rome, on the Ligurian coast, in the north of Tuscany, and in the main province centers of Piedmont, Lombardy, and Emilia-Romagna. Cold spots are instead consolidated in Sardinia, in the north of Sicily, in the south of Lazio, Campania, and Marche, the mountainous fields between Emilia-Romagna and Liguria, and some smaller spots in Piedmont, in the north of Lombardy, in Veneto and Friuli-Venezia Giulia.



(a) Choropleth Map: Municipality mean

(b) Hot Spot Analysis

Figure 8: Rented Houses - Choropleth Map and Hot Spot Analysis



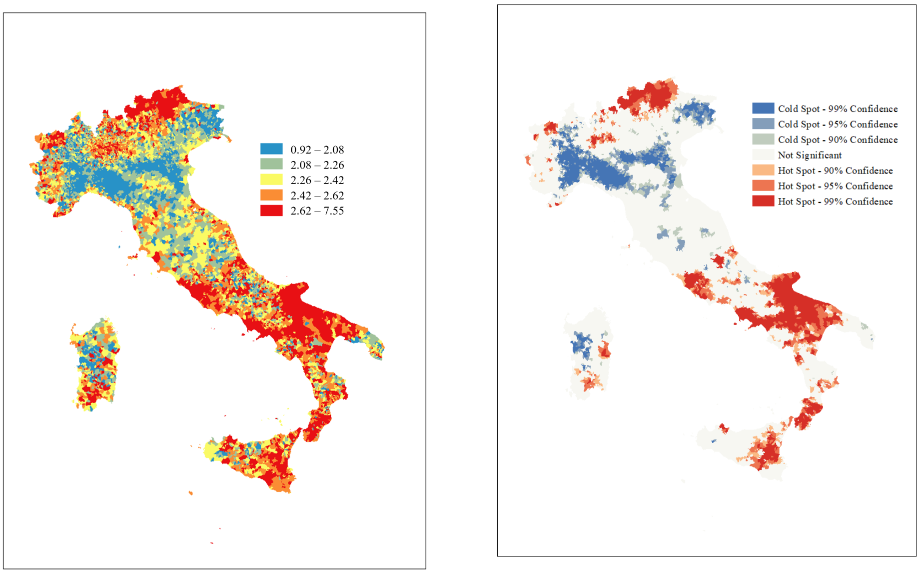
(a) Choropleth Map: Municipality mean

(b) Hot Spot Analysis

Figure 9: Single Parents - Choropleth Map and Hot Spot Analysis

Evidence about the proportion of single-parent households are available in Figure 9a and Figure 9b. Positive clustering is scattered throughout the Italian territory. Again, as for the proportion of rented houses, municipalities near Rome and Naples are characterised by high values. Moreover, significant positive clustering is visible also in Puglia, on the Romagna coast, in Tuscany (the northern coast and around Florence), and between Modena and Bologna. Also, municipalities around Turin, Genoa, Milan, and Padua appear to be hot spots. Contrariwise, cold spots are located in the center (see municipalities around Siena, Arezzo and Perugia and the mountainous areas of Marche, Abruzzo, and Molise) and in the north-west of Italy mainly (e.g., see the mountainous fields between Emilia-Romagna and Liguria, western Piedmont, Valle d'Aosta, northern Veneto, and Trento).

To conclude the paragraph on the census variables, let us analyse the spatial distribution of housing overcrowding. Looking at the choropleth map (Figure 10a), it seems evident the presence of municipalities characterised by high values in particular in the center-south of the Italian territory, in the isles, and in the north, in the areas of Trentino Alto Adige, in Lombardy, in Valle d'Aosta, and in western Piedmont.



(a) Choropleth Map: Municipality mean

(b) Hot Spot Analysis

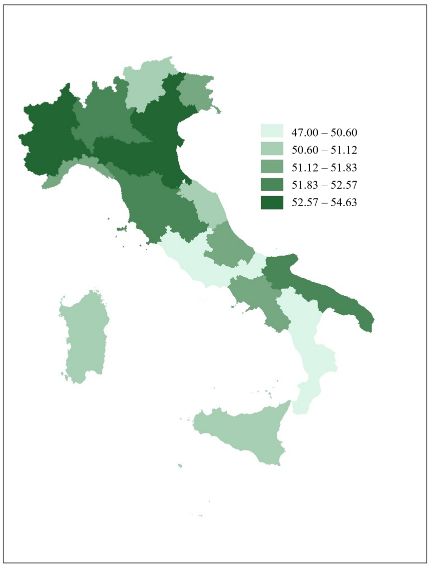
Figure 10: Housing Overcrowding - Choropleth Map and Hot Spot Analysis

Furthermore, large areas with the presence of low housing overcrowding are shown above all in northern Italy: in the Po Valley, in Piedmont, in the mountainous territory between Emilia-Romagna and Liguria, and in Friuli-Venezia Giulia. The hot spot analysis confirms the conclusions made at first glance. Moreover, in Sardinia, both hot and cold spots can be found.

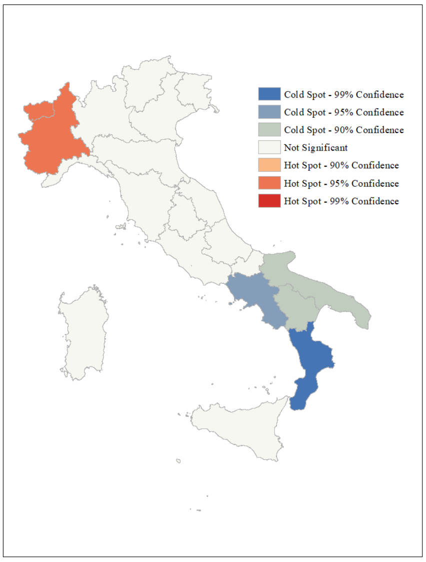
5.2.2 *Individual Health*

As in the last paragraph, to analyse the spatial distribution of the two dependent variables, two types of investigations are proposed: choropleth maps (with quintiles as classification scheme) and hot spot analysis. In this case, as anticipated, the level of analysis is the regional level. Therefore, from a purely mathematical point of view, the power of a hot spot analysis may not be enough and it may lead to unsubstantial results. Nevertheless, it can be helpful for the reader to fully grasp the spatial distribution of the phenomena and to appreciate the existing differences between the Italian regions.

Looking at Figure 11a it is possible to see Valle d'Aosta, Piedmont, Veneto, and Emilia-Romagna are the regions belonging to the highest quintile. On the contrary, in lowest quintile we find Lazio, Molise, and Calabria. In general, the north of Italy is characterised by regions with mid to high physical health conditions on average. In contrast, the south is characterised by regions with mid to low physical health on average. The Figure 11b confirms the presence of a cold spot in the south (between Puglia, Basilicata, Campania, and Calabria) and a hot spot in the northwest of the Italian territory (between Piedmont and Valle d'Aosta).



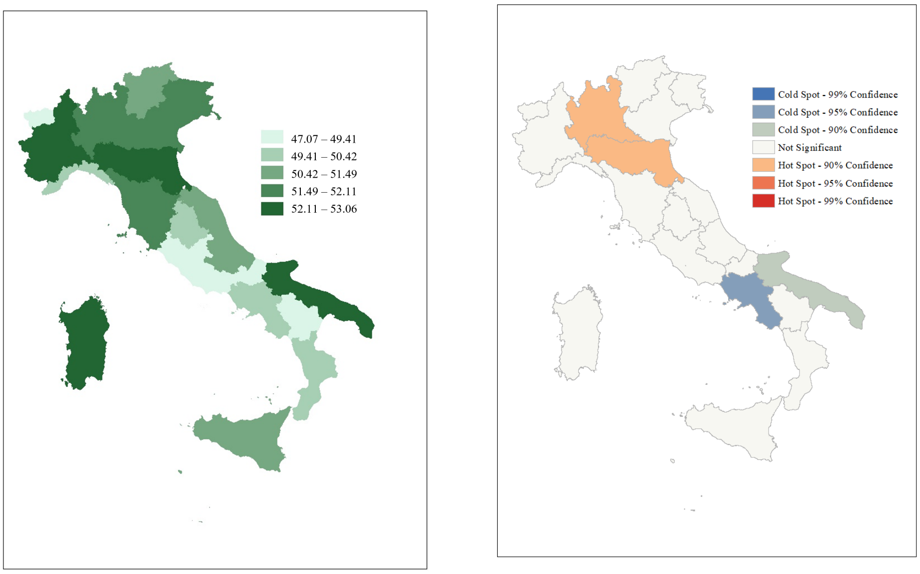
(a) Regional Mean: Quintiles



(b) Hot Spot Analysis

Figure 11: Physical Component Summary Scale Score - Choropleth Map and Hot Spot Analysis

Considering the mental health score, what is evident at first glance from Figure 12a, is that there does not seem to be a clear pattern as to what happens for physical health. Regions belonging to the best quintile are found both in the north (Piedmont and Emilia-Romagna) and in the south and isles (Puglia and Sardinia). The same happens for regions belonging to the worst quintile (Valle d'Aosta in the north, Lazio in the center, and Molise and Basilicata in the south). Indeed, what emerges from the hot spot analysis is a hot spot in the north but not very statistically significant (between Emilia-Romagna and Lombardy). The same is true for a cold spot in the south (between Campania and Puglia).



(a) Regional Mean: Quintiles

(b) Hot Spot Analysis

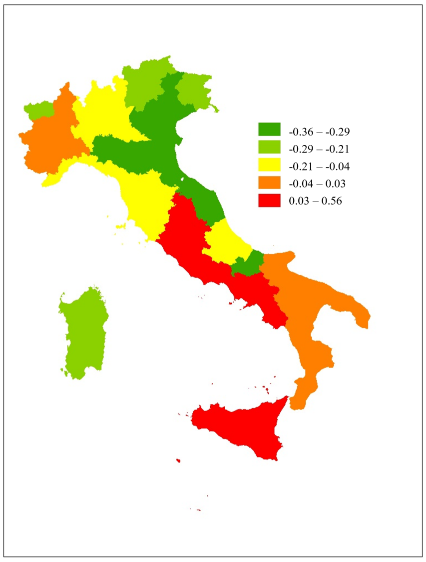
Figure 12: Mental Component Summary Scale Score - Choropleth Map and Hot Spot Analysis

5.2.3 *Neighbourhood Subjective Perception*

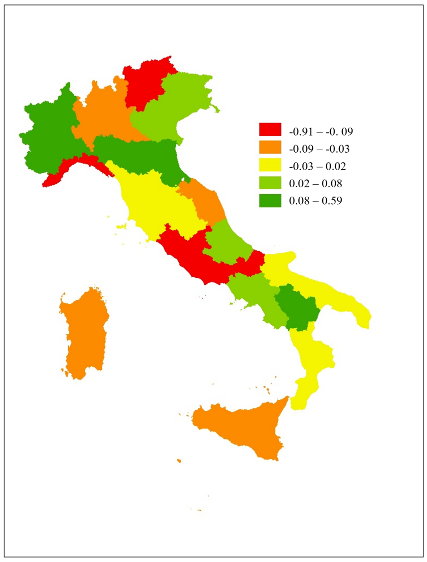
The analyses regarding the subjective perception of the neighbourhood only propose choropleth maps (with quintiles as the classification scheme). That is because, in this case, the hot spot analysis did not produce any significant results, indicating that as regards the neighbourhood disorder and the neighbourhood social cohesion, there is no clustering pattern at the regional level on the Italian territory.

Looking at Figure 13a we can see that the south is characterised by regions in the worst quintiles with high levels of neighbourhood disorder (exception is Sardinia, belonging to the second quintile), while the north in general shows regions included in the best quintiles (exception is Piedmont, belonging to the fourth quintile). The regions belonging to the intermediate group are Lombardy, Lazio, and Abruzzo.

The choropleth map on social cohesion shows a different picture, where there does not seem to be a geographical pattern on the Italian territory. There are, in fact, regions with an excellent situation both in the north and in the south. The same goes for the regions with a worse situation. On the one hand, in the best quintile, we see Valle d'Aosta, Piedmont, Emilia-Romagna, and Basilicata regions. On the other hand, regions inserted in the worst quintile are Trentino Alto Adige, Liguria, Lazio and Molise.



(a) Regional Mean: Quintiles on Neighbourhood Disorder

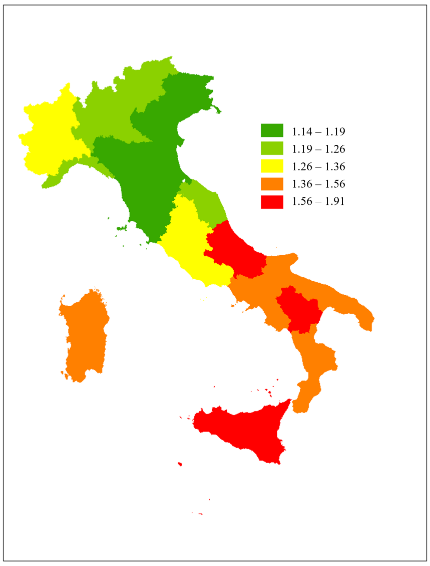


(b) Regional Mean: Quintiles on Neighbourhood Social Cohesion

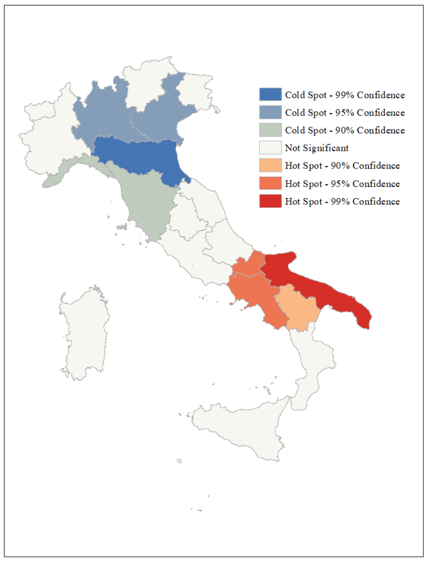
Figure 13: Neighbourhood Subjective Perception - Choropleth Maps for Social Cohesion and Neighbourhood Disorder

5.2.4 *Household Deprivation*

For the analysis of the spatial distribution of the clusters on household deprivation, two types of investigations are proposed too:



(a) Regional Mean: Quintiles



(b) Hot Spot Analysis

Figure 14: Household Deprivation - Choropleth Map and Hot Spot Analysis

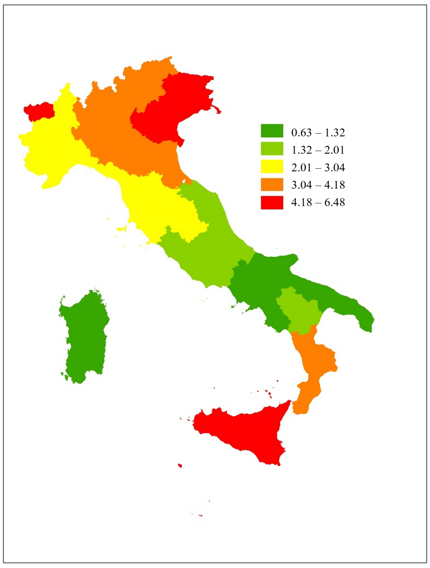
choropleth maps (again with quintiles as classification scheme) and hot spot analysis. Even in this case, the region is the level of analysis.

The choropleth map in (Figure 14a) immediately reveals the presence of a gap between the north and south of the country, where the regions belonging to the best quintiles are located in the center-north of Italy, while the regions belonging to the worst quintiles are located in the south of Italy. This pattern is confirmed in the hot spot analysis (Figure 14b): a positive and significant clustering (indicating high household deprivation) is shown in the southern regions. In contrast, a negative and significant clustering (which indicates a lower average prevalence of deprived households) is evident in the northern regions.

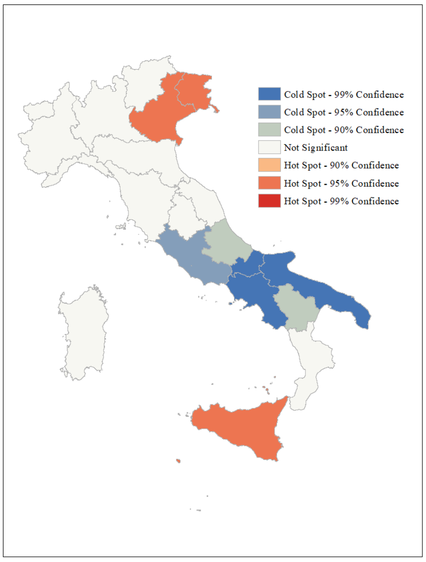
5.2.5 *Adverse Weather Conditions*

To conclude this chapter on descriptive analysis, let us analyse the spatial distribution of unfavorable weather conditions in Figure 15. For the analysis of the spatial distribution of the clusters on household deprivation, two types of investigations are also proposed: choropleth maps (again with quintiles as classification scheme) and hot spot analysis. Even in this case, the level of analysis is the regional level.

What seems to be evident in the choropleth map is that the central-southern regions (except for Calabria and Sicily) belong to the quintiles with the most favorable scores. In contrast, in the north of Italy, most regions belong to the quintiles with the worst situation (Valle d'Aosta, Veneto, and Friuli-Venezia Giulia).



(a) Regional Mean: Quintiles



(b) Hotspot Analysis

Figure 15: Adverse Weather Conditions - Choropleth Map and Hot Spot Analysis

This arrangement is proved to be significant with the hot spot analysis in Figure 15b. A clear and significant cold spot is delineated in the regions in the center-south of Italy. Finally, the regions which are further north-east and the regions which are further south generate two hot spots about the number of days with adverse weather conditions. Intuitively, this can be caused by two different phenomena: in the north, the cold and the high frequency of precipitations, while in the south, the presence of many days with high temperatures.

6 RESULTS

As anticipated in the chapter dedicated to the method (Section 4.2), mainly four types of models will be proposed for each of the two dependent variables: an empty model, random intercepts models, random slopes models, and a cross-level model. The first part of the chapter will be dedicated to the analysis of the results obtained on physical health. The second part will focus on the analysis of the results for what concerns the study of mental health. Finally, the last part is devoted to the regional heterogeneous effects analysis.

6.1 PHYSICAL COMPONENT SUMMARY SCALE SCORE

As a first step, the unconditional means or empty model (Model 1) is run, and the proportion of variance in PCS scores at each level, i.e., between individuals, between families, and between neighbourhoods, is quantified in Table 13. The average PCS score is 51.68, with the following variance estimates: 47.15 at level-1, 17.38 at level-2, and 5.34 at level-3. Hence, much of the variation in PCS scores occurs between individuals (67.5%) and between families (24.9%). The between-neighbourhood variance is much lower (7.6%); however, it is statistically significant, suggesting the existence of differences in physical health between neighbourhoods.

Table 13: PCS - Empty Model

	Model 1	
	Coeff.	Std. Err.
Fixed Part		
Constant	51.68***	(0.11)
Random Part		
var(Constant level-3)	5.34***	(1.34)
var(Constant level-2)	17.38***	(1.80)
var(Residual)	47.15***	(1.22)
ICC level-3 (%)	7.65	
ICC level-2 (%)	32.52	
N	7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The same conclusion can be reached by looking at the intra-class correlation. The ICC is a measure of the degree to which individuals share everyday experiences due to their living in the same neighbourhood and household. In this case, the ICC is greater than zero at the two highest levels (7.65 at the census block level, 32.52 at the household level), then there is a case for applying random intercepts and random slopes models. Accordingly, the analysis proceeds with the following models, shown in Table 14, which represent two different random intercepts multilevel models. In these models, the between-families and between-contexts variation are computed after allowing for, and conditional on, chosen individual and domestic characteristics that can be seen in the fixed part results.

Table 14: PCS - Random Intercepts Models

	Model 2		Model 3	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	48.94***	(0.72)	49.67***	(0.72)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.02	(0.08)	-0.04	(0.08)
Neighbourhood Disorder	-0.28***	(0.08)	-0.22**	(0.08)
Gender				
Female	0.08	(0.15)	0.05	(0.15)
Age				
25-34	-0.26	(0.41)	-0.24	(0.40)
35-54	-1.23**	(0.42)	-1.26**	(0.42)
55-64	-2.73***	(0.45)	-2.81***	(0.45)
65 and older	-5.95***	(0.51)	-6.10***	(0.51)
Education				
Primary	5.52***	(0.56)	5.24***	(0.56)
Lower Secondary	7.91***	(0.55)	7.50***	(0.55)
Upper Secondary	8.24***	(0.56)	7.65***	(0.56)
Tertiary and Higher	8.53***	(0.59)	7.84***	(0.59)
Employment status				
Unemployed or looking for first job	0.30	(0.31)	0.73*	(0.31)
Homemaker	-1.06***	(0.26)	-0.95***	(0.26)
Student	0.32	(0.43)	0.26	(0.43)
Retired	-1.52***	(0.30)	-1.54***	(0.30)
Unabe to work	-13.04***	(0.82)	-12.91***	(0.82)
Marital status				
Single	-0.20	(0.25)	-0.12	(0.25)
Divorced	0.98**	(0.30)	1.14***	(0.30)
Widow/er	-2.77***	(0.30)	-2.68***	(0.30)
Children				
Yes	0.14	(0.22)	0.18	(0.22)
Chitizenship				
Foreign	0.54	(0.41)	0.99*	(0.42)
Insomnia issues				
A little	-3.56***	(0.17)	-3.51***	(0.16)
A lot	-8.69***	(0.32)	-8.57***	(0.32)
Household Deprivation				
Cluster 2			-0.98***	(0.22)
Cluster 3			-1.84***	(0.34)
Cluster 4			-2.12***	(0.59)
Random Part				
var(Constant level-3)	0.85	(0.64)	0.68	(0.63)
var(Constant level-2)	6.32***	(0.97)	6.34***	(0.96)
var(Residual)	32.69***	(0.82)	32.57***	(0.81)
N	7835		7835	

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

First of all, in Model 2, the neighbourhood subjective perception (neighbourhood social cohesion and neighbourhood disorder) and the individuals' socio-demographic characteristics (gender, age, education, employment status, marital status, having children, citizenship, and sleep troubles) are included. Results indicate that the intercept, i.e., the average physical component score (PCS), is 48.94. The change in physical health as neighbourhood disorder in the census block increases is negative and statistically significant (-0.28). At the same time, the perceived social cohesion in the context does not seem to be associated with the individuals' physical health. What is noticeable is that the age seems to be relevant in affecting physical condition: the youngest age groups (16-24 and 25-34) are similar, while older groups are more and more experiencing worse physical health (i.e., with respect to young individuals, subjects aged 65 or older have a 5.95 lower PCS). Individuals with higher education report better physical health: with respect to illiterate subjects, individuals with primary education have a 5.52 higher PCS, individuals with lower secondary education have a score that is 7.91 higher, subjects with upper secondary education have a PCS that is 8.24 higher, and individuals with tertiary or higher education have a physical component score that is 8.53 higher. Compared to employed subjects, homemakers, retired and unable to work individuals are experiencing worse physical health, reporting, respectively, a PCS that is lower of about 1.06, 1.52, and 13.04. With respect to married individuals, single individuals experience the same health (the coefficient is not significant), while divorced subjects have a 0.98 higher PCS, and widows and widowers have a physical component score that is lower by about 2.77. To conclude, having sleep troubles seems to decrease the individuals' physical health: compared to individuals without insomnia issues, subjects with a bit of and many sleeping troubles have a physical component score of 3.56 and 8.69 lower, respectively. Looking at the random components, we see statistically significant variance in physical component scores at the between-individual (32.69) and between-household (6.32) levels.

In Model 3, again in Table 14, clusters on household deprivation are introduced. Results indicate that the intercept, i.e., the average physical component score, is 49.67. The results observed in the individual characteristics are similar to those of the previous model, with the difference that by introducing the variables on family deprivation, the coefficients of unemployed individuals and individuals with foreign citizenship also become significant. In this sense, we can add that, compared to those who have a job, the unemployed have higher physical health of about half a point (0.73), and compared to those who have Italian citizenship, those with foreign citizenship have a higher PCS of almost one point (0.99). Considering the household deprivation, it is clear that PCS change is negative and statistically significant as deprivation increases. In particular, with respect to the reference group (the least deprived), the remaining clusters show statistically significant lower physical health (-0.98 for cluster 2, -1.84 for cluster 3, and -2.12 for cluster 4), *ceteris paribus*.

Table 15: PCS - Random Slopes Models

	Model 4		Model 5	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	49.39***	(0.73)	49.91***	(0.87)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	-0.04	(0.08)	-0.04	(0.08)
Neighbourhood Disorder	-0.19*	(0.08)	-0.18*	(0.09)
Gender				
Female	0.07	(0.15)	0.06	(0.15)
Age				
25-34	-0.31	(0.40)	-0.32	(0.40)
35-54	-1.23**	(0.42)	-1.23**	(0.42)
55-64	-2.74***	(0.45)	-2.72***	(0.45)
65 and older	-5.97***	(0.51)	-5.96***	(0.51)
Education				
Primary	5.46***	(0.57)	5.43***	(0.57)
Lower Secondary	7.74***	(0.57)	7.70***	(0.57)
Upper Secondary	7.88***	(0.57)	7.85***	(0.58)
Tertiary and Higher	8.12***	(0.61)	8.11***	(0.61)
Employment status				
Unemployed or looking for first job	0.61	(0.32)	0.67*	(0.32)
Homemaker	-0.94***	(0.26)	-0.86***	(0.26)
Student	0.26	(0.43)	0.29	(0.43)
Retired	-1.51***	(0.30)	-1.52***	(0.30)
Unabe to work	-13.18***	(0.82)	-13.10***	(0.82)
Marital status				
Single	-0.10	(0.25)	-0.09	(0.25)
Divorced	1.21***	(0.30)	1.17***	(0.30)
Widow/er	-2.62***	(0.29)	-2.64***	(0.29)
Children				
Yes	0.15	(0.22)	0.19	(0.22)
Chitizenship				
Foreign	0.94*	(0.44)	0.87*	(0.44)
Insomnia issues				
A little	-3.52***	(0.16)	-3.55***	(0.16)
A lot	-8.67***	(0.32)	-8.68***	(0.32)
Household Deprivation				
Cluster 2	-1.01***	(0.25)	-0.95***	(0.25)
Cluster 3	-1.92***	(0.42)	-1.85***	(0.42)
Cluster 4	-2.16**	(0.79)	-2.11**	(0.79)
Exogenous neighbourhood characteristics				
Low Education			1.05	(1.62)
Unemployment			-2.71**	(0.97)
Rented Houses			1.12*	(0.52)
Single Parents			-1.72	(1.42)
House Density			-0.04	(0.19)
Young Individuals			-1.59	(1.70)
Adverse Weather Conditions (days)			-0.03	(0.02)
Random Part				
var(Household deprivation 2 at level-3)	8.14***	(1.92)	8.21***	(1.91)
var(Household deprivation 3 at level-3)	18.22***	(4.02)	18.63***	(4.04)
var(Household deprivation 4 at level-3)	26.09***	(8.03)	26.32***	(8.05)
var(Constant level-3)	0.46	(0.61)	0.34	(0.61)
var(Constant level-2)	4.30***	(0.93)	4.31***	(0.93)
var(Residual)	32.17***	(0.80)	32.17***	(0.80)
N	7835		7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Looking at the random components, we see again statistically significant variance in physical component scores at the between-subject (32.57) and between-household (6.34) levels; no variance is detected between neighbourhoods, instead.

The next step is the random slopes model (Table 15), where the effect of household deprivation on physical health is allowed to vary at the third level. The importance of allowing relevant variables to vary at the neighbourhood level lies in the fact that it is possible to understand how the neighbourhood of residence can have different effects based on different characteristics of individuals. In other words, although significant differences are seen to be present between neighbourhoods, it was assumed, so far, that such differences apply to all individuals in the same way. However, this could be a wrong assumption. For instance, individuals in highly deprived families, while reporting poorer health, on average, may show more considerable variation, depending on their neighbourhood of residence, compared to those living in less deprived families. Thus, while neighbourhood matters for both household deprivation groups, it may matter relatively more for the most deprived families. What can be seen in Model 4 is that, overall, the results in the fixed part are similar to those presented in the previous model. Analysing the random part, instead, we see that there is variance at the third level between families, the variance of household deprivation at the third level is statistically significant for all the clusters, and it appears to increase as far as the deprivation increases. The variance at the third level for the second cluster is equal to 8.14, the variance at the third level for the third cluster is equal to 18.22, while the variance at the third level for the fourth cluster is equal 26.09. It means that, on the one hand, nationally, the most deprived families suffer from poorer physical health than the least deprived ones (fixed coefficients). Furthermore, on the other hand, the neighborhood where families live has importance in exerting this effect of deprivation on health (random coefficients). However, the covariances (results were removed from the table for a matter of space) between the constant term at the third level and the household deprivation clusters at the third level appeared to be not statistically significant, implying that, apparently, the effect that household deprivation has on physical health across the neighbourhoods does not follow a sharp direction. There is no relationship between intercepts and slopes; it is not true that the higher the intercept, the higher the slope, nor that the higher the intercept, the lower the slope.

In model 5, the variables characterizing the context where individuals live are introduced (i.e., proportions of low educated individuals, unemployed individuals, rented houses, single-parent households, young individuals, average house crowding, and adverse weather conditions). Introducing exogenous variables allows having a potent tool to analyse the effect of the living neighbourhood on individuals' health. Looking at the objective contextual characteristics, thus, it is noticeable that the amount of unemployed individuals in the census block appears to be negative and significant, with a large coefficient (-2.71), indicating that the reduction in PCS is negative as the context-related portion of unemployed individuals increases. Moreover, the percentage of rented houses in the census block seems to be associated with an increase in the physical health of individuals, with a significant coefficient of 1.12. The reason for this effect, different from what one might expect, lies in the fact that it is not possible to discriminate between those who live in a rented house because they do not have the economic possibilities to buy a house and those who live in rented houses because they are living a momentary situation (e.g., off-site students, workers who have just found a new job and had to move closer). Seen in this way, it would seem that objective compositional characteristics play a more critical role in affecting physical health than individuals' subjective perception of the context.

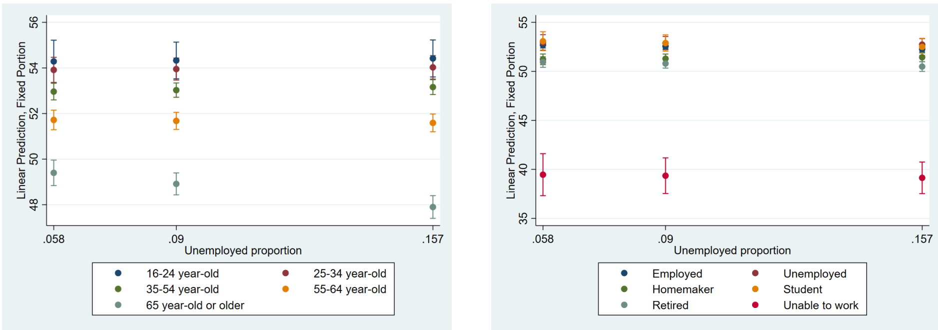
The final step of the examination about physical health is the introduction in the model of interactions between the significant third-level context-related characteristics with first-level and second-level variables in the fixed part. With the cross-level interaction, it is possible to assess to what extent an exogenous context aspect accounts for the variation between neighbourhoods for the different groups of individuals. That is to say, the overall effect of the percentage of rented houses in the neighbourhood is positive; however, for some individuals, it can be negative. Similarly, the overall negative effect of the percentage of unemployed individuals in the census block is negative, and introducing interactions may reveal that the effect is more considerable for some groups with respect to others. The results, shown in Table 16, show that for the individual characteristics that are here considered, the oldest individuals are those suffering the most from a higher unemployment in the neighbourhood. That is, overall, with respect to a young individual aged 16-24, a 65 years old or older individual reports a lower PCS of about 4.07 and moreover, she/he is further worse off in neighbourhoods with higher unemployment, an increase of 0.01 in the amount of unemployed individuals will lower physical health by an additional 15.55. Contrariwise, a higher presence of unemployed people in the neighbourhood has a protective effect for homemakers compared to the reference category. Overall, compared to employed individuals, homemakers have a lower PCS (-1.76); however, in neighbourhoods with an increase of 0.01 in the proportion of unemployment, the effect on physical health is positive (5.87), cutting out the overall negative effect, making homemakers feel physically better than working individuals of about 4.11 in PCS.

Table 16: PCS - Unemployment Cross-Level Model

	Model 6	
	Coeff.	Std. Err.
Fixed Part		
Constant	50.38***	(1.35)
Subjective neighbourhood perception		
Neighbourhood Social Cohesion	0.11	(0.13)
Neighbourhood Social Cohesion x Unemployment	-1.12	(0.82)
Neighbourhood Disorder	-0.23	(0.14)
Neighbourhood Disorder x Unemployment	0.27	(0.80)
Gender		
Female	0.25	(0.24)
Female x Unemployment	-1.92	(1.77)
Age		
25-34	-0.32	(0.68)
35-54	-1.36	(0.70)
55-64	-2.45**	(0.75)
65 and older	-4.07***	(0.86)
25-34 x Unemployment	-0.44	(4.40)
35-54 x Unemployment	0.60	(4.53)
55-64 x Unemployment	-2.47	(4.93)
65 and older x Unemployment	-15.55**	(5.71)
Education		
Primary	4.35***	(1.03)
Lower Secondary	6.84***	(1.01)
Upper Secondary	7.14***	(1.03)
Tertiary and Higher	8.09***	(1.08)
Primary x Unemployment	6.17	(5.62)
Lower Secondary x Unemployment	3.63	(5.53)
Upper Secondary x Unemployment	3.01	(5.74)
Tertiary and Higher x Unemployment	-3.31	(6.25)
Employment status		
Unemployed or looking for first job	0.52	(0.55)
Homemaker	-1.76***	(0.43)
Student	0.43	(0.71)
Retired	-1.71***	(0.50)
Unabe to work	-13.19***	(1.50)
Unemployed or looking for first job x Unemployment	-0.05	(3.21)
Homemaker x Unemployment	5.87*	(2.69)
Student x Unemployment	-1.44	(4.81)
Retired x Unemployment	-0.79	(3.36)
Unabe to work x Unemployment	0.58	(8.86)
Marital status		
Single	0.15	(0.42)
Divorced	1.06*	(0.50)
Widow/er	-2.28***	(0.49)
Single x Unemployment	-1.79	(3.22)
Divorced x Unemployment	1.32	(3.67)
Widow/er x Unemployment	-3.00	(3.40)
Children		
Yes	0.31	(0.37)
Yes x Unemployment	-0.94	(2.89)
Chitizenship		
Foreign	0.58	(0.77)
Foreign x Unemployment	3.77	(6.32)
Insomnia issues		
A little	-3.81***	(0.27)
A lot	-8.95***	(0.53)
A little x Unemployment	2.69	(1.89)
A lot x Unemployment	2.93	(3.32)
Household Deprivation		
Cluster 2	-1.21**	(0.41)
Cluster 3	-2.61***	(0.79)
Cluster 4	-1.83	(1.32)
Cluster 2 x Unemployment	2.16	(2.51)
Cluster 3 x Unemployment	4.98	(4.21)
Cluster 4 x Unemployment	-1.82	(6.92)
Exogenous neighbourhood characteristics		
Low Education	0.89	(1.62)
Unemployment	-1.11	(7.75)
Rented Houses	0.95	(0.52)
Single Parents	-1.18	(1.42)
House Density	-0.13	(0.19)
Young Individuals	-1.72	(1.69)
Adverse Weather Conditions (days)	-0.03	(0.02)
Random Part		
var(Household deprivation 2 at level-3)	8.96***	(1.94)
var(Household deprivation 3 at level-3)	17.69***	(3.94)
var(Household deprivation 4 at level-3)	26.03***	(7.98)
var(Constant level-3)	0.16	(0.59)
var(Constant level-2)	4.26***	(0.92)
var(Residual)	31.91***	(0.79)
N	7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The following graphs show the post-estimate margins of the main significant results also present in tabular form. The contextual variable that has been put into interaction with the first level variables is reported on the abscissa axis. To be precise, the results for the first, second, and third quartiles are reported. On the ordinate axis, there is the dependent variable. Therefore, with this type of graph, it is possible to illustrate the predicted margin of change in health as the proportion of rented houses (Figure 16) or unemployed people (Figure 17) in the neighborhood changes for different groups of individuals.



(a) Predictive Margins of Age with 95% CIs

(b) Predictive Margins of Employment Status with 95% CIs

Figure 16: Unemployed Individuals - Linear prediction after estimation

The results for different age categories and different occupational statuses as the proportion of unemployed individuals changes in the context are shown in Figure 16. The first graph shows that old individuals are worse off than the young as the number of unemployed grows. This is clearly seen in the last quartile, where the predicted value for the older age group drops significantly, moving further away from the values of the younger age groups. Similar to what has been seen for homemakers in the previous table, the physical health of employed and homemakers is different where the unemployment proportion in the neighborhood is low. However, as this proportion rises (see in particular the third quartile), the predicted value of the PCS for homemakers grows and approaches that of the employed group.

Let us now look at the cross-level model concerning the proportion of rented houses in the neighbourhood. Considering the effect that the percentage of the rented house in the neighbourhood has on physical health, it can be seen that in the cross-level model (Table 17), the national effect is positive and equal to 18.46. This means that, at the national level, individuals who live in a neighbourhood with a higher percentage of rented homes are physically better off. Looking at the coefficients for what concerns education, it is noted how, overall, individuals with higher education have a higher PCS compared to the illiterate.

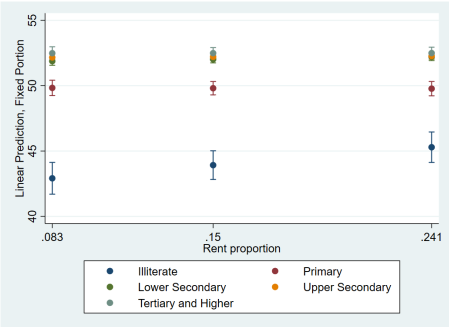
Table 17: PCS - Rented dwellings Cross-Level Model

	Model 7	
	Coeff.	Std. Err.
Fixed Part		
Constant	46.77***	(1.16)
Subjective neighbourhood perception		
Neighbourhood Social Cohesion	-0.04	(0.12)
Neighbourhood Social Cohesion x Rent	-0.05	(0.51)
Neighbourhood Disorder	-0.12	(0.13)
Neighbourhood Disorder x Rent	-0.22	(0.44)
Gender		
Female	0.09	(0.23)
Female x Rent	-0.16	(0.96)
Age		
25-34	0.19	(0.63)
35-54	-0.65	(0.64)
55-64	-1.71*	(0.69)
65 and older	-5.07***	(0.78)
25-34 x Rent	-2.47	(2.44)
35-54 x Rent	-2.71	(2.48)
55-64 x Rent	-5.15	(2.70)
65 and older x Rent	-4.11	(3.16)
Education		
Primary	8.20***	(0.79)
Lower Secondary	10.04***	(0.78)
Upper Secondary	10.44***	(0.80)
Tertiary and Higher	10.82***	(0.86)
Primary x Rent	-15.42***	(3.24)
Lower Secondary x Rent	-12.97***	(3.10)
Upper Secondary x Rent	-14.36***	(3.21)
Tertiary and Higher x Rent	-14.98***	(3.46)
Employment status		
Unemployed or looking for first job	0.75	(0.47)
Homemaker	-1.65***	(0.39)
Student	0.85	(0.67)
Retired	-1.38**	(0.45)
Unabe to work	-11.47***	(1.53)
Unemployed or looking for first job x Rent	-0.21	(1.76)
Homemaker x Rent	4.33**	(1.66)
Student x Rent	-2.68	(2.68)
Retired x Rent	-1.03	(1.98)
Unabe to work x Rent	-11.95	(8.72)
Marital status		
Single	-0.03	(0.39)
Divorced	1.03*	(0.47)
Widow/er	-1.61***	(0.44)
Single x Rent	-0.21	(1.57)
Divorced x Rent	0.56	(1.81)
Widow/er x Rent	-5.27**	(1.83)
Children		
Yes	0.16	(0.34)
Yes x Rent	0.17	(1.34)
Chitizenship		
Foreign	0.86	(0.69)
Foreign x Rent	-0.26	(2.45)
Insomnia issues		
A little	-3.79***	(0.25)
A lot	-9.00***	(0.52)
A little x Rent	1.26	(1.04)
A lot x Rent	1.49	(2.14)
Household Deprivation		
Cluster 2	-0.93*	(0.38)
Cluster 3	-1.15	(0.62)
Cluster 4	-1.35	(1.20)
Cluster 2 x Rent	-0.06	(1.56)
Cluster 3 x Rent	-3.23	(2.10)
Cluster 4 x Rent	-3.15	(3.60)
Exogenous neighbourhood characteristics		
Low Education	0.91	(1.63)
Unemployment	-2.93**	(0.98)
Rented Houses	18.46***	(4.21)
Single Parents	-1.91	(1.43)
House Density	-0.05	(0.19)
Young Individuals	-1.47	(1.70)
Adverse Weather Conditions (days)	-0.03	(0.02)
Random Part		
var(Household deprivation 2 at level-3)	8.99***	(1.98)
var(Household deprivation 3 at level-3)	19.44***	(4.14)
var(Household deprivation 4 at level-3)	27.28***	(8.28)
var(Constant level-3)	0.36	(0.61)
var(Constant level-2)	4.49***	(0.92)
var(Residual)	31.59***	(0.79)
N	7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

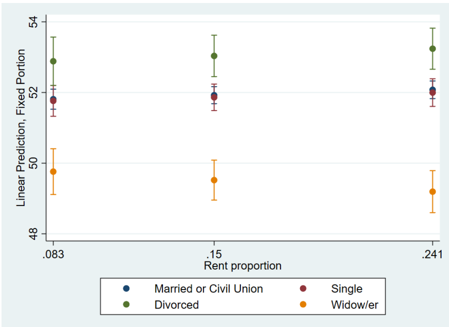
However, they suffer quite a lot from the increase in the proportion of rented dwellings within the census block. In fact, the positive effect that the proportion of rented dwellings has on physical health is lower for more educated individuals. Nevertheless, in the end, educated individuals report higher physical health than illiterate people, i.e., tertiary-educated individuals have a 10.82 higher PCS with respect to illiterate individuals, overall, and the total effect of a higher percentage of rented dwellings is equal to 18.46 - 14.98 for tertiary-educated individuals, making highest educated individuals having a higher PCS of an additional 3.48 compared to illiterate individuals. Similar to what happens with the increase of unemployed individuals in the neighbourhood, the effect on homemakers seems to be the same with the increase of rented houses in the neighbourhood. In fact, overall, homemakers are physically worse off (-1.65) compared to employed individuals, but the increase in rented dwellings more than balances what is negative (4.33), making homemakers feel better than employed individuals. To conclude, widow/er individuals are also negatively affected by the increase of rented houses within the neighbourhood. In particular, overall, widow/ers have a lower PCS (-1.61) compared to married individuals. In addition, an increment in the percentage of rented dwellings results in an even worse effect on the health of widow/ers compared to married individuals (-5.27).

The results for different education level, employment statuses, and marital statuses as the proportion of rented houses changes in the neighbourhood are also shown in Figure 17. The first graph shows that illiterate individuals are overall worse off than the more educated. However, illiterate people benefit from an increase of rented houses in the neighborhood, reducing the distance in the outcome with the most educated individuals. Therefore, this result explains the negative signs observed in the table above. As the proportion increases, the differential in physical health between the illiterate and the more educated individuals gradually decreases. This is clearly seen in the last quartile, where the predicted value for the illiterate group increases significantly, approaching the predicted values of individuals with higher education. Similar to what has been seen for homemakers in the previous table, the graph shows that the predicted values for the first two quartiles differ from those of the reference category (employed individuals), i.e., blue and green plots do not overlap. Instead, we see that in the last quartile, where the proportion of rented dwelling is increasing, the predicted values of employed individuals and homemakers overlap. The finding suggests that the general difference between the health of the former and the health of the latter vanishes as the proportion of houses rented in the neighborhood increases. The last graph (Figure 17c) clearly shows the health trend of widowed individuals. In general, they suffer from the worst health compared to all other individuals. Furthermore, an increase in rented homes in the neighborhood worsens their health even more, while the health of married, single, and divorced individuals appears to improve slightly, although the confidence intervals continue to overlap as the proportion increases.



(a) Predictive Margins of Education with 95% CIs

(b) Predictive Margins of Employment Status with 95% CIs



(c) Predictive Margins of Marital Status with 95% CIs

Figure 17: Rented Houses - Linear prediction after estimation

6.2 MENTAL COMPONENT SUMMARY SCALE SCORE

As a first step, replicating what was done for the PCS, the unconditional means or empty model (Model 1) is run, and the proportion of variance in MCS scores at each level, i.e., between individuals, between families, and between neighbourhoods, is quantified (Table 18). The average MCS score is 50.89, with the following variance estimates: 31.82 at level-1, 13.44 at level-2, and 13.92 at level-3. Hence, also in this case, much of the variation in MCS scores occurs between individuals (53.8%). The remaining unexplained variance is split at the two higher levels: between-families (22.7%) and between-neighbourhoods (23.5%) levels. It is evident that the variance at the highest level is much higher for mental health than it was for physical health; moreover, it is statistically significant, suggesting the existence of differences in mental health between neighbourhoods. The same conclusion is possible by looking at the intra-class correlation. In this case, the ICC is greater than zero at the two highest levels (23.52 at the census block level, 46.23 at the household level) then, there is a case for applying random intercepts and random slopes models.

Table 18: MCS - Empty Model

	Model 1	
	Coeff.	Std. Err.
Fixed Part		
Constant	50.89***	(0.11)
Random Part		
var(Constant level-3)	13.92***	(1.52)
var(Constant level-2)	13.44***	(1.52)
var(Residual)	31.82***	(0.80)
ICC level-3 (%)	23.52	
ICC level-2 (%)	46.23	
N	7853	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Accordingly, the analysis proceeds with the following models, shown in Table 19, which represent two different random intercepts multilevel models. In these models, the between-families and between-contexts variation are computed after allowing for, and conditional on, chosen individuals (Model 2) and household (Model 3) characteristics that can be seen in the fixed part results. First of all, in Model 2, the neighbourhood subjective perception (neighbourhood social cohesion and neighbourhood disorder) and the individuals' socio-demographic characteristics (gender, age, education, employment status, marital status, having children, citizenship, and sleep trouble) are included. Results indicate that the intercept, i.e., the average mental component score (MCS), is 53.40. The change in mental health as neighbourhood disorder in the census block increases is negative and statistically significant (-0.72); moreover, neighbourhood social cohesion does have importance for mental health, showing that the higher the social cohesion, the better the individuals' mental condition. Females are affected by slightly worse mental health than males, with a significant coefficient of -0.34. What is noticeable is that the age seems to be relevant in affecting the mental condition: the youngest age group (16-24) is the one experiencing the highest MCS, while older groups are more and more suffering worse mental health. Unlike what happens for physical health, however, the group that seems to be characterised by the worst mental health is that between the ages of 55 and 64 (i.e., with respect to young individuals, subjects aged 55-64 have a 2.90 lower MCS). Individuals with higher education report good mental health: with respect to illiterate subjects, individuals with primary education have a 1.39 higher MCS, individuals with lower secondary education have a score that is 2.43 higher, subjects with upper secondary education have a 2.86 higher MCS, while individuals with tertiary or higher education have a mental component score that is 3.34 higher. Compared to employed subjects, homemakers, unemployed, and unable to work individuals are experiencing worse mental health, reporting, respectively, an MCS that is lower of about 0.85, 2.45, and 5.67. Note how, with respect to the results regarding the PCS (which saw the unemployed subjects feel as good as the workers, or even better after the introduction of household deprivation clusters), the situation changes for mental health: i.e., an unemployed individual reports, *ceteris paribus*, about 2.5 points worse mental health score compared to an employed individual.

Table 19: MCS - Random Intercepts Models

	Model 2		Model 3	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	53.40***	(0.72)	54.51***	(0.72)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.99***	(0.08)	0.88***	(0.08)
Neighbourhood Disorder	-0.72***	(0.09)	-0.62***	(0.09)
Gender				
Female	-0.34*	(0.14)	-0.38**	(0.14)
Age				
25-34	-0.79*	(0.40)	-0.72	(0.40)
35-54	-1.90***	(0.41)	-1.91***	(0.41)
55-64	-2.90***	(0.45)	-2.98***	(0.44)
65 and older	-2.60***	(0.51)	-2.78***	(0.51)
Education				
Primary	1.39*	(0.56)	0.97	(0.55)
Lower Secondary	2.43***	(0.55)	1.80***	(0.55)
Upper Secondary	2.86***	(0.56)	1.95***	(0.56)
Tertiary and Higher	3.34***	(0.59)	2.29***	(0.59)
Employment status				
Unemployed or looking for first job	-2.45***	(0.30)	-1.88***	(0.30)
Homemaker	-0.85***	(0.25)	-0.72**	(0.25)
Student	-0.67	(0.42)	-0.76	(0.41)
Retired	-0.56	(0.30)	-0.59*	(0.29)
Unabe to work	-5.67***	(0.81)	-5.48***	(0.80)
Marital status				
Single	-0.81**	(0.26)	-0.67*	(0.26)
Divorced	-1.16***	(0.30)	-0.92**	(0.30)
Widow/er	-1.39***	(0.30)	-1.27***	(0.30)
Children				
Yes	0.00	(0.23)	0.07	(0.23)
Chitizenship				
Foreign	-0.01	(0.43)	0.85*	(0.43)
Insomnia issues				
A little	-3.80***	(0.17)	-3.73***	(0.16)
A lot	-11.00***	(0.32)	-10.84***	(0.32)
Household Deprivation				
Cluster 2			-1.35***	(0.24)
Cluster 3			-2.82***	(0.36)
Cluster 4			-5.23***	(0.61)
Random Part				
var(Constant level-3)	7.89***	(1.02)	7.87***	(0.99)
var(Constant level-2)	6.85***	(1.08)	6.38***	(1.05)
var(Residual)	27.29***	(0.69)	27.02***	(0.67)
N	7853		7853	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

With respect to married subjects, single people, divorced, and widow/ers are all worse off, reporting a lower MCS of about 0.81, 1.16, and 1.39 points, respectively. To conclude, having sleeping troubles seems to decrease the individuals' mental health: compared to individuals without insomnia issues, subjects with a few and many sleeping troubles have a mental component score that is 3.80 and 11.00 points lower accordingly. Looking at the random components, we see there is statistically significant variance in mental component scores at the between-individual (27.29), between-household (6.85), and between-neighbourhood (7.89) levels.

In Model 3, again in Table 19, clusters on household deprivation are introduced. Results indicate that the intercept (i.e., the average mental component score) is 54.51. The results observed in the individual characteristics are similar to those of the previous model, with the difference that by introducing the variables on family deprivation, the coefficients of individuals with foreign citizenship also become significant. In this sense, we can add that subjects with foreign citizenship have a higher MCS of less than one point (0.85) compared to those with Italian citizenship. Considering the household deprivation, it is clear that the change in MCS as deprivation increases is negative and statistically significant. In particular, with respect to the reference group (the least deprived), the remaining clusters show statistically significant lower mental health (-1.35 for cluster 2, -2.82 for cluster 3, and -5.23 for cluster 4). Looking at the random components, we see there is again statistically significant variance in mental component scores at the between-subject (27.02), between-household (6.38), and between-context (7.87) levels.

The next step is the random slopes model (Table 20), where the effect of household deprivation on mental health is allowed to vary at the third level. What can be seen in Model 4 is that, overall, the results in the fixed part are similar to the one presented in the previous models. Analysing the random part, instead, we see that there is variance at the third level between families, the variance of household deprivation at the third level is statistically significant for all the clusters, and it appears to increase as far as the deprivation increases. The variance at the third level of the second cluster is equal to 8.26, the variance at the third level of the third cluster is equal to 15.10, while the variance at the third level of the fourth cluster is equal to 24.95. It means that, on the one hand, nationally, the most deprived families suffer from poorer mental health than the least deprived ones (fixed coefficients). Furthermore, on the other hand, the neighborhood where families live has importance in exerting this effect of deprivation on health (random coefficients). However, the covariances (results were removed from the table for a matter of space) between the constant term at the third level and the household deprivation clusters at the third level appeared to be not statistically significant, implying that, apparently, the effect that household deprivation has on mental health across the neighbourhoods does not follow a sharp direction. There is no relationship between intercepts and slopes; it is not true that the higher the intercept, the higher the slope, nor that the higher the intercept, the lower the slope.

Table 20: MCS - Random Slopes Model

	Model 4		Model 5	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	54.42***	(0.73)	54.16***	(0.90)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.90***	(0.08)	0.91***	(0.08)
Neighbourhood Disorder	-0.61***	(0.09)	-0.64***	(0.09)
Gender				
Female	-0.36*	(0.14)	-0.35*	(0.14)
Age				
25-34	-0.73	(0.40)	-0.74	(0.40)
35-54	-1.86***	(0.41)	-1.86***	(0.41)
55-64	-2.94***	(0.44)	-2.93***	(0.44)
65 and older	-2.74***	(0.51)	-2.70***	(0.51)
Education				
Primary	1.01	(0.56)	1.06	(0.56)
Lower Secondary	1.86***	(0.56)	1.91***	(0.56)
Upper Secondary	2.01***	(0.57)	2.08***	(0.57)
Tertiary and Higher	2.32***	(0.60)	2.39***	(0.60)
Employment status				
Unemployed or looking for first job	-1.80***	(0.31)	-1.82***	(0.31)
Homemaker	-0.79**	(0.25)	-0.83**	(0.25)
Student	-0.75	(0.41)	-0.74	(0.41)
Retired	-0.57	(0.29)	-0.58*	(0.29)
Unabe to work	-5.61***	(0.81)	-5.63***	(0.81)
Marital status				
Single	-0.70**	(0.26)	-0.68**	(0.26)
Divorced	-0.93**	(0.30)	-0.93**	(0.30)
Widow/er	-1.27***	(0.30)	-1.28***	(0.30)
Children				
Yes	0.05	(0.23)	0.05	(0.23)
Chitizenship				
Foreign	0.80	(0.45)	0.86	(0.45)
Insomnia issues				
A little	-3.68***	(0.16)	-3.68***	(0.16)
A lot	-10.71***	(0.32)	-10.73***	(0.32)
Household Deprivation				
Cluster 2	-1.37***	(0.26)	-1.40***	(0.26)
Cluster 3	-2.84***	(0.42)	-2.92***	(0.42)
Cluster 4	-5.31***	(0.80)	-5.41***	(0.80)
Exogenous neighbourhood characteristics				
Low Education			1.51	(1.83)
Unemployment			0.90	(1.08)
Rented Houses			0.61	(0.58)
Single Parents			-0.53	(1.59)
House Density			0.04	(0.21)
Young Individuals			-1.00	(1.91)
Adverse Weather Conditions (days)			-0.06**	(0.02)
Random Part				
var(Household deprivation 2 at level-3)	8.26***	(2.11)	8.13***	(2.10)
var(Household deprivation 3 at level-3)	15.10***	(3.91)	15.30***	(3.94)
var(Household deprivation 4 at level-3)	24.95***	(8.50)	25.16***	(8.53)
var(Constant level-3)	7.27***	(0.96)	7.24***	(0.95)
var(Constant level-2)	4.66***	(1.01)	4.61***	(1.01)
var(Residual)	26.80***	(0.66)	26.79***	(0.66)
N	7853		7853	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In model 5 (Table 20), the variables characterising the context where individuals live are introduced (i.e., proportions on low educated individuals, unemployed individuals, rented houses, single parents, young individuals, average house crowding, and adverse weather conditions). Introducing exogenous variables allows having a very powerful tool to analyse the effect of the living neighbourhood on individuals' health. Looking at the compositional characteristics, thus, unlike what has been seen for physical health, we see the socio-demographic characteristics of the context in which the subjects live do not seem to have importance for mental health. On the other hand, what seems to be relevant is the contextual feature concerning the weather conditions. Indeed, with a significant coefficient equal to -0.06, it can be said that an increase of 10 days with adverse conditions that occurred in the previous month is associated with a decrease in the mental health of about half a point (0.6). This result is ultimately consistent with what emerges from the literature, which shows how the exogenous variable on the meteorological conditions affects the mental health of individuals.

The final step of the examination about mental health is the introduction in the model of interactions between the significant third-level context-related characteristics with first-level and second-level variables in the fixed part. With the cross-level interaction, it is possible to assess to what extent an exogenous context aspect accounts for the variation between neighbourhoods for the different groups of individuals. That is to say, the overall effect of the days of weather conditions in the neighbourhood is negative, and introducing interactions may reveal that the effect is more considerable for some groups with respect to others. In this case, the results (which are available in the Appendix A for space reasons) shown in Table 30, demonstrate that for the individual characteristics that are here considered, all the individuals are affected by weather conditions in the same ways, being all the interactions not significant.

6.3 REGIONAL HETEROGENEITY

In this last section, we will briefly look at the results by analysing one region at a time. For a matter of space, only the results for four regions are proposed here, i.e., one for each Italian macro-area, those with the highest number of observations: Lombardy for the northwest, Veneto for the north-east, Lazio for central Italy, and Campania for the south and islands. The results for all regions are instead proposed in the Appendix A (from Table 31 to Table 35 for results on PCS, and from Table 36 to Table 40 for results on MCS).

As can be seen at first glance, concerning physical health (Table 21), the variance at the third level for the four regions under analysis is zero (or not estimated at all), suggesting that there are no unobserved context-related characteristics that have an effect on individual health (the same that also happened at the national level).

Table 21: PCS - Random Slopes

	Lombardy		Veneto		Lazio		Campania	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	53.61***	(2.76)	52.62***	(2.67)	55.77***	(2.91)	48.20***	(3.24)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	0.09	(0.22)	0.01	(0.24)	0.45	(0.30)	0.00	(0.27)
Neighbourhood Disorder	-0.24	(0.26)	0.14	(0.34)	-0.25	(0.19)	-0.23	(0.26)
Gender								
Female	0.39	(0.40)	0.59	(0.34)	-0.11	(0.51)	0.35	(0.61)
Age								
25-34	-0.75	(1.15)	0.08	(0.97)	-0.51	(1.29)	-0.13	(1.32)
35-54	-1.78	(1.14)	0.30	(1.00)	-2.57	(1.32)	-0.77	(1.45)
55-64	-3.54**	(1.22)	-0.61	(1.09)	-3.88**	(1.46)	-3.98*	(1.57)
65 and older	-4.83***	(1.43)	-2.97*	(1.21)	-7.81***	(1.68)	-7.88***	(1.74)
Education								
Primary	-2.21	(1.94)	-1.06	(2.07)	-0.97	(2.12)	4.75**	(1.68)
Lower Secondary	2.35	(1.93)	2.30	(2.03)	0.11	(2.03)	5.35**	(1.64)
Upper Secondary	2.90	(1.94)	2.04	(2.05)	0.23	(2.07)	5.26**	(1.71)
Tertiary and Higher	3.24	(2.02)	3.10	(2.12)	0.51	(2.14)	5.42**	(1.83)
Employment status								
Unemployed or looking for first job	-2.00	(1.02)	0.88	(1.14)	0.99	(0.93)	0.38	(0.92)
Homemaker	-0.48	(0.79)	-0.47	(0.66)	-1.97*	(0.85)	-1.59	(0.84)
Student	0.33	(1.25)	0.37	(0.99)	-0.23	(1.40)	-0.37	(1.40)
Retired	-1.86*	(0.86)	-0.48	(0.68)	-5.83***	(1.12)	-1.42	(1.00)
Unabe to work	-16.88***	(4.08)	-8.96***	(1.99)	-19.12***	(2.66)	-16.42***	(2.74)
Marital status								
Single	0.26	(0.65)	0.38	(0.59)	-0.33	(0.71)	-0.48	(1.32)
Divorced	1.51*	(0.72)	0.64	(0.69)	1.03	(0.93)	-0.53	(1.35)
Widow/er	-2.34**	(0.76)	-4.19***	(0.73)	-2.66*	(1.17)	-4.43***	(1.07)
Children								
Yes	0.06	(0.57)	-0.33	(0.50)	0.58	(0.59)	0.08	(1.16)
Chitizenship								
Foreign	1.14	(1.04)	1.89	(1.10)	1.44	(0.95)	4.34	(3.89)
Insomnia issues								
A little	-3.19***	(0.45)	-3.51***	(0.38)	-2.76***	(0.51)	-2.21***	(0.62)
A lot	-6.87***	(0.93)	-10.18***	(1.02)	-9.89***	(1.03)	-7.15***	(1.05)
Household Deprivation								
Cluster 2	-0.44	(0.68)	-3.13**	(0.96)	-1.55*	(0.70)	-0.92	(0.72)
Cluster 3	-0.15	(1.86)	0.09	(1.62)	-5.91***	(1.41)	-2.75*	(1.24)
Cluster 4	-2.14	(2.30)	-2.99	(2.47)	-2.92	(1.96)	-2.84	(2.28)
Exogenous neighbourhood characteristics								
Low Education	2.85	(5.21)	-6.94	(4.43)	0.85	(6.38)	-1.45	(8.70)
Unemployment	0.75	(6.03)	-0.66	(3.93)	-0.71	(3.41)	-2.87	(3.96)
Rented Houses	0.57	(1.40)	-1.18	(1.43)	2.28	(1.48)	-4.13	(2.34)
Single Parents	8.23	(5.25)	3.99	(3.11)	1.37	(3.43)	5.06	(6.19)
House Density	0.42	(0.59)	0.45	(0.58)	0.83	(0.62)	1.48*	(0.63)
Young Individuals	-7.44	(5.08)	5.84	(4.16)	-5.55	(5.19)	3.16	(6.11)
Adverse Weather Conditions (days)	-0.10*	(0.05)	0.00	(0.05)	0.00	(0.12)	0.42	(0.24)
Random Part								
var(Household deprivation 2 at level-3)	0.00	(.)	19.60***	(7.69)	0.00***	(0.00)	3.11	(5.43)
var(Household deprivation 3 at level-3)	47.25	(.)	12.64**	(12.12)	7.23	(12.32)	24.02***	(12.15)
var(Household deprivation 4 at level-3)	30.69	(.)	0.00	(0.00)	10.96	(17.65)	34.68***	(28.59)
var(Constant level-3)	0.00	(.)	0.15	(1.33)	0.00	(0.00)	0.00***	(0.00)
var(Constant level-2)	4.40	(.)	2.71	(1.89)	1.1	(2.03)	1.33	(3.18)
var(Residual)	35.62	(.)	15.71***	(1.42)	37.00***	(2.74)	37.94***	(3.52)
N	1160		706		761		690	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

By referring, instead, to the tables in the Appendix A, we see that for two southern regions, this variance is significant and quite large. For Basilicata, which has few observations, and for Sicily, the neighbourhood effects seem to be essential for individual health. Sicily and Basilicata, which we recall (referring to the results on spatial data analysis proposed in Section 5.2) are among the regions characterised by a high proportion of unemployed individuals and a high average house crowding in the neighbourhoods.

Table 22: MCS - Random Slopes

	Lombardy		Veneto		Lazio		Campania	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	55.02***	(2.61)	51.01***	(2.97)	56.56***	(3.31)	55.50***	(3.13)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	1.02***	(0.20)	0.84**	(0.27)	1.12***	(0.34)	0.48	(0.26)
Neighbourhood Disorder	-0.43	(0.25)	-1.20**	(0.37)	-0.53*	(0.22)	-0.30	(0.25)
Gender								
Female	-0.61	(0.35)	-0.02	(0.37)	-0.59	(0.49)	-0.18	(0.57)
Age								
25-34	-2.08	(1.06)	0.75	(1.05)	-0.49	(1.34)	-2.70*	(1.23)
35-54	-3.76***	(1.05)	0.38	(1.08)	-1.34	(1.38)	-4.91***	(1.36)
55-64	-5.17***	(1.13)	-0.26	(1.19)	-1.03	(1.53)	-5.91***	(1.49)
65 and older	-4.66***	(1.33)	-1.06	(1.33)	-1.87	(1.79)	-6.01***	(1.65)
Education								
Primary	-1.18	(1.75)	0.45	(2.19)	-2.49	(2.32)	1.55	(1.59)
Lower Secondary	1.03	(1.74)	0.95	(2.16)	-1.68	(2.26)	1.68	(1.55)
Upper Secondary	1.37	(1.76)	1.72	(2.18)	-1.89	(2.31)	2.15	(1.62)
Tertiary and Higher	1.36	(1.83)	3.43	(2.26)	-1.28	(2.38)	3.28	(1.74)
Employment status								
Unemployed or looking for first job	-2.82**	(0.91)	-2.46*	(1.24)	-1.00	(0.98)	-1.68	(0.87)
Homemaker	-1.82*	(0.72)	0.22	(0.72)	-1.01	(0.87)	-0.36	(0.79)
Student	-1.54	(1.14)	1.09	(1.07)	-0.42	(1.43)	-0.25	(1.31)
Retired	0.65	(0.78)	0.91	(0.73)	-2.06	(1.15)	-1.71	(0.94)
Unabe to work	-1.20	(3.59)	-2.21	(2.20)	-3.36	(2.65)	-9.82***	(2.54)
Marital status								
Single	-1.32*	(0.62)	0.71	(0.66)	-1.68*	(0.83)	-1.15	(1.27)
Divorced	-1.05	(0.67)	-0.79	(0.75)	-1.73	(0.99)	-2.20	(1.27)
Widow/er	-1.34	(0.72)	-1.56*	(0.79)	-0.77	(1.30)	0.51	(1.01)
Children								
Yes	0.57	(0.54)	0.81	(0.55)	-0.65	(0.70)	-0.05	(1.12)
Chitizenship								
Foreign	2.31*	(1.01)	0.06	(1.18)	3.06**	(1.12)	0.55	(3.84)
Insomnia issues								
A little	-3.03***	(0.42)	-2.19***	(0.43)	-2.99***	(0.54)	-3.45***	(0.58)
A lot	-9.27***	(0.87)	-11.29***	(1.12)	-9.13***	(1.09)	-12.43***	(1.00)
Household Deprivation								
Cluster 2	-2.71***	(0.76)	-1.81*	(0.80)	-1.95*	(0.96)	-1.11	(0.73)
Cluster 3	-2.61*	(1.15)	-3.73*	(1.84)	-3.77*	(1.49)	-2.77*	(1.25)
Cluster 4	-7.24***	(1.58)	0.63	(2.83)	-6.48*	(2.59)	-5.56**	(1.85)
Exogenous neighbourhood characteristics								
Low Education	5.57	(5.39)	-8.19	(5.33)	7.41	(8.33)	1.23	(8.44)
Unemployment	1.55	(6.12)	9.26*	(4.21)	-2.32	(4.47)	-2.71	(3.83)
Rented Houses	0.53	(1.40)	-0.18	(1.66)	2.59	(1.86)	-0.82	(2.26)
Single Parents	-2.61	(5.49)	-3.81	(3.68)	-0.78	(4.39)	0.37	(6.02)
House Density	0.74	(0.61)	1.34	(0.71)	-0.5	(0.79)	0.44	(0.61)
Young Individuals	-2.63	(5.22)	-13.43**	(5.02)	7.94	(6.60)	4.58	(5.94)
Adverse Weather Conditions (days)	-0.05	(0.05)	-0.06	(0.06)	0.07	(0.14)	0.19	(0.23)
Random Part								
var(Household deprivation 2 at level-3)	11.09***	(6.31)	4.31	(5.29)	15.00***	(10.02)	6.10*	(4.38)
var(Household deprivation 3 at level-3)	0.46	(8.46)	15.53**	(14.27)	0.00	(0.00)	28.02***	(13.01)
var(Household deprivation 4 at level-3)	0.00*	(0.00)	0.00	(.)	32.96***	(30.77)	17.26**	(16.28)
var(Constant level-3)	5.79***	(1.73)	6.25***	(2.22)	14.46***	(5.71)	0.00***	(0.00)
var(Constant level-2)	3.47*	(2.05)	0.27	(2.44)	2.72	(5.62)	2.32	(2.47)
var(Residual)	26.09***	(1.77)	17.73***	(1.62)	29.02***	(2.28)	32.16***	(2.66)
N	1160		706		761		690	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

They are also among the regions belonging to the lowest quintiles for physical health, while they belong to the highest quintiles for neighbourhood disorder and family deprivation. The results concerning the fixed part (Table 31 to Table 35), on the other hand, seem to be more or less, with some exceptions, in line with the national ones. It should be noted, for example, that among the compositional characteristics, the increase in the average house density in the neighbourhood has a positive effect on physical health in Campania. As for the weather, an increase in the number of days with unfavorable weather conditions has a negative effect on physical health in Lombardy. In most regions, however, the exogenous variables seem not relevant in the link with individual physical conditions. Nevertheless, some contradictory results are seen in Tuscany and Marche, where the increase in adverse weather conditions and average house density, respectively, are associated with higher PCS. To be noted is the offbeat result in Basilicata, which shows a positive correlation between the increase in low educated individuals in the neighbourhood and physical health.

Turning to table Table 22 relating to mental health, it is possible to see that the variance at the neighbourhood level remains significant and substantial for most of the regions (Lombardy, Veneto, and Lazio). However, also referring to the tables in the appendix, all the regions of southern Italy and the islands do not show the presence of neighbourhood effects on mental health, as well as the central regions (excluding Lazio), Trentino Alto Adige, Liguria, and Valle d'Aosta, while all the others do. For what concerns the fixed part, also in this case, the results are similar to those obtained at the national level. To be noticed is the non-significance of all the exogenous variables in the northwest and center of Italy, except for Umbria, showing a positive association of mental health with the increase of the average house density in the census block. Similarly, other counter-intuitive effects are present. For example, the increase in compositional unemployment is associated with better mental health, while an increase in the portion of young people is linked to a decline in mental health in Veneto. The same happens in Molise. A positive association is also found for mental health with the increase of single-parent households proportion in Friuli-Venezia Giulia as well as in Puglia.

7 CONCLUSIONS

The following paragraphs are devoted to discussing the results, which provide hypotheses to be verified in future studies, to explain the main findings. In consideration of future developments, the paragraph dedicated to the research's main limitations is also noteworthy. Finally, this thesis's main contributions and implications will be underlined in the last paragraph.

7.1 DISCUSSION

The main goal of the current study was to contribute to the analysis of the neighbourhood effects for the whole Italian territory, determining the existence of the association between places and individual health. The most prominent finding to emerge from this study is that considering the whole national territory, neighbourhood effects (understood as neighbourhood variation in health) are much more significant for mental health compared to physical health. The latter shows very low variance at the neighbourhood level, that is, the variance in individual physical health is mainly due to differences between individuals and between families.

Nevertheless, we have seen compositional and contextual characteristics are essential for physical health, the former (proportion of unemployed individuals and rented houses), and for mental health, the latter (unfavorable weather conditions). In accordance with the present results, previous studies have demonstrated the existence of this strong relationship between context-related (compositional) features and individual physical health outcomes. For example, Rocha et al. (2017) brought evidence that neighbourhood deprivation (based on measures such as illiteracy and unemployment rate, among the others) is linked to worse physical HRQoL (Health-Related Quality of Life). Furthermore, neighbourhood deprivation (based on a score derived from the proportion of adults with primary education, unemployment rate, and the proportion of people living in rented dwellings) has also been associated with unhealthy physical conditions such as obesity, hypertension, fatty liver, and diabetes (Kivimäki et al., 2018). Consistent with the literature, this research also found weather (contextual variable) to be relevant for mental health. On the one hand, wind and its direction, for instance, have been seen to affect anxiety and energy levels in individuals (Bos, Hoenders, and Jonge, 2012). On the other hand, moreover, weather conditions indirectly affect health through the influence on mood, which consequently influences some aspects of mental symptoms such as anxiety and stress levels (Schwarz and Clore, 1983).

What has been observed, thus, is that for individual mental health, the contextual feature seems to be more critical than the compositional features of the neighbourhood. However, in contrast to earlier findings, no evidence of weather effect on physical health was detected. For example, Lee et al. (2018) had seen that the weather (temperature and humidity) affects physical symptoms, including headache and sneezing. Moreover, women were found to be more sensitive to weather conditions (particularly higher humidity and lower temperature) in association with physical symptoms. Furthermore, it has been shown that prolonged exposure to temperatures that are too high or too low directly affects individual physical health, increasing the incidence of cardiovascular and respiratory illnesses (Huynen et al., 2001). This effect, however, was found in Lombardy, showing a one-point drop in PCS as a result of a 10-day increase in bad weather. The lack of evidence of compositional variables' effects on mental conditions is, on the one hand, consistent with some evidence from the existing literature: Rocha et al. (2017) did not find neighbourhood clustering nor place effects on mental HRQoL. On the other hand, this finding is contrary to previous studies which have suggested that both compositional (e.g., economic disadvantage index, from census) and contextual (e.g., neighbourhood walkability) characteristics are essential for mental health conditions, such as depressive symptoms (Mair, Roux, and Galea, 2008). If not nationally, at the regional level, there were associations between mental health and some compositional characteristics of the place, for example in Veneto, Friuli-Venezia Giulia, and Molise with the percentage of young individuals, in Sardinia and Friuli-Venezia Giulia with the percentage of single-parent households, and in Emilia-Romagna and Umbria with house crowding.

Moreover, considering the results concerning subjective neighbourhood perception at the national level, the findings of this research support the literature's primary pieces of evidence. In general, it has been found that individuals living in places characterised by disorders, low collective efficiency, and low social capital have worse physical health than those who live in better neighbourhoods. For example, Ruijsbroek et al. (2015) saw that living in low-safe areas is associated with poorer general health and with physical inactivity. Moreover, the association between neighbourhood disorder and some poor health habits such as alcohol abuse (Kuipers et al., 2012), and bad health outcomes such as obesity risk (Burdette and Hill, 2008) have been observed. However, the findings of the current study, which do not detect any association between social cohesion and physical health nationally, do not support the existing evidence exerting that social cohesion were found to be positively associated with physical activity (Yip, Sarma, and Wilk, 2016). As well, the findings do not match with previous researches according to which social cohesion is a significant positive predictor of both mental and physical health, with, also, increasing mediation effect over time for physical health (Kress et al., 2020). However, it is true that in some Italian regions, such as Molise and Valle d'Aosta, this relationship between social cohesion and physical health has been noted. Moreover, a counter-intuitive link in Friuli-Venezia Giulia and Emilia-Romagna is observed: those regions present a negative association between social cohesion and PCS.

As for the results on mental health outcomes, however, they support previous research into this area which links social cohesion and neighbourhood disorder to mental health conditions. Mair, Roux, and Galea (2008) have stated that, in neighbourhood studies, also the individual perception on context-related aspects (such as social cohesion or the perception of crime and neighbourhood disorder) is essential for mental health. They confirmed the existence of associations of perceived neighbourhood characteristics with depression or depressive symptoms after controlling for individual-level characteristics. Similarly, it was found that individuals living in contexts with social disorder and relative lack of social control report high levels of anxiety, depression, fear, distrust, and poor health (Ross and Mirowsky, 1999). The social cohesion that characterises a community can be thought to have the possibility of influencing health through the mechanisms of informal social control (capacity to regulate/prevent members' (deviant) health behaviours according to shared objectives), collective socialization (role of adults in shaping youth development, actions, and health outcomes), and, mostly, collective efficiency (awareness of resources and their use in responding to the shortage of services, and the ability of residents to act collectively to address neighbourhood-related physical hazards) (Browning and Cagney, 2002; Coutts and Kawachi, 2006; Kawachi, Berkman, et al., 2000). It can be ascertained, therefore, coherent with Kawachi, Kennedy, and Wilkinson's (1999) conclusions, that this evidence confirms that social cohesion is an essential characteristic for ensuring the well-being of the community.

Nationally, an unexpected association was detected between the percentage of rented houses (introduced as a measure of deprivation) and physical health: the higher the percentage in the neighbourhood, the better the individual physical conditions. What can be stated is that a high percentage of rented dwellings may not necessarily mean deprivation. From this measure, it is not possible to discriminate against those who live in rented houses and do not own the house because they cannot afford it and those who have a changing life, which leads them to change their residence often. Think of the university neighbourhoods, for example. The proportion of rented houses can also reflect the dynamism of a neighbourhood, a young neighbourhood, where students and newly hired move. Since correlation does not mean causation, one explanation could also be that the people who make the neighbourhood so changing by continuing to move are primarily young people with a decent level of health. Hypothetically, high dynamism may perhaps indicate less social cohesion and social control because people barely know each other, with consequences on safety feelings and stressors (Shareck and Ellaway, 2011). Therefore, on the one hand, the high percentage of rented houses can be used to represent deprivation when the people who live there rent houses because they do not have the economic means to own one. On the other hand, the high percentage of rented houses may indicate a dynamic context. Nevertheless, neighbourhood poverty has been found to be associated with a good health habit, namely the likelihood of walking. In particular, in areas with a higher percentage of people living in rented houses, it is more likely to walk, perhaps due to the neighbourhood structure: higher density encourages walking (Ross and Mirowsky, 2001).

Continuing to analyse the results obtained on the association between physical health and compositional characteristics, the percentage of unemployed in the neighbourhood is also linked to worse individual health, as expected (Van Lenthe et al., 2005). What has also been observed is that both for the percentage of unemployed and for the percentage of rented houses in the neighbourhood, these characteristics have different relevance for some groups of the population. For what concerns unemployment proportion in the neighbourhood, the association is more intense for older people (for whom the effect is negative) and homemakers (for whom the effect is positive). For what concerns the proportion of rented houses, instead, the importance is more substantial for educated individuals and widow/er (for whom the positive effect is hindered), and homemakers (for whom the positive effect is enhanced). As found by Chung et al. (2018), older people are most affected by neighbourhood deprivation, partly because they presumably spend more time in their neighbourhoods. However, this explanation does not hold for more educated individuals, who are not observed to spend more time in the neighbourhood, nor does for homemakers, who are also expected to be more in touch with the neighbourhood but are here showing a more significant benefit from this deprivation feature. On the contrary, however, it appears that the meteorological conditions have the same relevance for all the subgroups here analysed.

The results relating to family deprivation are also interesting. They show that, at a national level, individuals belonging to less wealthy families have a worse health condition (both physical and mental) than individuals belonging to more wealthy families. Thus, these results are in agreement with Chung et al.'s (2018), Min, Xue, and Wang's (2018), and Montgomery and Hewett's (2005) findings which showed a negative association of household poverty and deprivation (also based on non-monetary measures) with individual health. Furthermore, it has been seen that the most deprived families at the neighbourhood level show a higher variance in health conditions, i.e., they have a higher heterogeneity in health outcomes compared to less deprived families. Thus, while context matters for all deprivation groups, it matters relatively more for the high-deprivation groups. On the other hand, the covariances between the slopes in the deprivation clusters and the intercept at the neighbourhood level are not significant, indicating that there is no clear relationship between the two: it is not accurate nor that the higher the intercept, the higher the slope, nor that the higher the intercept, the lower the slope. In other words, whatever the cluster of household deprivation, it is not correct nor that the higher the health in the neighbourhood, the higher the variability in the health outcome, nor that the higher the health in the neighbourhood, the lower the variability in the health outcome. However, what is true is that across the neighbourhoods, more deprived families are highly heterogeneous in physical and mental health outcomes.

Another aim of this study was to investigate the regional heterogeneity on the neighbourhood effects. Contrary to national results, at the regional level, some things change for the PCS for two southern regions. Indeed, the unexplained variance at the third level in Basilicata and Sicily appears to be significant. Apparently, neighbourhood effects are there for physical health in those two regions, asking for future in-depth analyses. For mental health, on the other hand, the southern regions and most of the regions of central Italy do not show neighbourhood effects, revealing very low variance at the neighbourhood level, that is, the variance in individual mental health is mainly due to differences between individuals or between families.

Furthermore, among the results obtained at the regional level, some unexpected results are noteworthy and require further detailed analysis. First of all, it appears that the higher the single-parent households proportion (introduced as a measure of neighbourhood deprivation), the higher the mental health in Puglia and Friuli-Venezia Giulia. However, correlation is not causation. This result may be due to the fact that single parents may tend to move where contexts are better-off, with strong social cohesion and lower disorders, with a consequent positive effect on mental health conditions. As suggested by Weiss's (1979), single parents frequent move with the attempt to *"create a better fit between the family's new circumstances, its housing, and the neighbourhood environment"*, often choosing locations that are near to relatives or friends. Another unanticipated finding is that in some regions, the higher the average house density in the neighbourhood, the higher the individual health. This appears to be true in Umbria (which belongs to the second lower quintile in MCS - Figure 12) for mental health, and in Campania and Marche (which belong to the medium and second lower quintiles in PCS respectively - Figure 11) for physical health. A counter-intuitive result is found in weather effects on physical health in Tuscany, where a 10-day increase in bad weather conditions results in a two-point increase in PCS. It may be that the construction of the variable on weather conditions that was built at the national level may not be suitable at the regional level. For example, it can be expected that in regions characterised by more rainy days, an increase in days with precipitation may be less significant than in regions with lower rainfall. A variable that also considers the regional baseline regarding temperatures and precipitations could be more appropriate. Finally, another result that is somewhat out of place at the regional level is the association between mental health and the proportion of young people in the census block: it seems that the higher the young proportion, the lower mental health in Veneto and Molise. One may think that a high presence of young people could be associated with a higher occurrence of crime and lower safety in the neighbourhood, with a consequent increase in stressors and lower perceived safety generating negative repercussions on mental symptoms (Lorenc et al., 2012). This may support Leventhal, Dupéré, and Brooks-Gunn's (2009) argument that in local areas characterised by cohesive and supportive connections between neighbours, young people are less likely to develop deviant behaviours related to crime and delinquency, with respect to neighbourhoods characterised by less cohesive and supportive relationships. This may be true in Molise, where social cohesion is relatively low on average; however, this mechanism does not hold in Veneto, where social cohesion is instead high on average (Figure 13b).

7.2 RESEARCH LIMITATIONS

The present research, which has the humble aim of ascertaining the existence of a link between the contexts in which individuals live and interact and their health, certainly has some limits to which due importance must be given. First of all, a study on the causal effects of the living contexts on health outcomes will absolutely be a necessary future development in order to address policies better. One of the primary limits of the majority of the multilevel studies analysing the connection between context exposure and individual health is indeed the use of cross-sectional data; this can be a problem since context exposure should not be considered as a single point in time measure; there is a plausible time lag between exposure and health outcomes (Blakely and Subramanian, 2006). In this sense, two possible solutions are available. First, the analysis of a sub-sample of individuals could be studied, that is, only the stable individuals. In this case, however, it would be necessary to understand how many years of stability in a place are needed to consider that it is that neighbourhood that acts on health and not the previous one. Furthermore, stable individuals may be statistically different from dynamic individuals, leading to carrying out the analysis on an unrepresentative sub-sample. Therefore, a more suitable solution is to introduce a longitudinal view of the phenomenon as widely discussed in the literature. On the one hand, the use of cross-sectional data does not give the possibility to carry out analyses on the causality of the effects. The longitudinal data, on the other hand, allows capturing the concatenation of events over time in order to establish causal mechanisms (Bernelius and Kauppinen, 2012), allowing, in this case, to analyse the development of neighbourhood effects and individual health over time. The use of longitudinal data is an essential breakthrough in studying neighbourhood effects. By introducing the temporal dimension, it could be possible to unmistakably model the directions of causality in the link between neighbourhood-related characteristics and individual-level outcomes (Van Ham et al., 2012). Accordingly, for instance, with the continuation of the ITA.LI survey, it will be possible to introduce a new level in the analysis (namely, that of time, including in the models repeated occasions nested within the subjects); the possibility of introducing the successive waves of the ITA.LI survey into these analyses is thus entrusted to future research.

Second, in connection with what has been said on the contextual exposure issue, the residential selection is a problem that should not be underestimated. According to this, the role of residential preferences should be taken into account in analysing variations in health. For example, poor people may choose to move to more deprived neighbourhoods because of the availability of cheap and affordable housing (Kawachi and Berkman, 2003). The use of longitudinal data can also be helpful in this situation to eliminate the possibility of reverse causality (Blakely and Subramanian, 2006). However, what is interesting is also to understand if there are, and in what direction they act, the consequences of choosing the place to live. This can also be established with cross-sectional data, as done in the present research. It is true, in fact, that individuals select themselves in the places where they want to live, based on various hindrances and opportunities. In this sense, *"separating the impact of personal factors affecting choice of neighbourhood from the effects of neighbourhood requires great ingenuity and work on the part of the researcher"* (Cheshire, 2012).

Third, data were collected both before and after the COVID-19 outbreak. The mechanisms underlying the relationships that we have seen exist between the exogenous characteristics, and the perception of the neighbourhood may have been different during the months of the lockdown and the period before it. This is true because when a community has to face a crisis that suddenly changes its everyday life, the determinants of social behaviour that are affected can be several and can be affected simultaneously (Elcheroth and Drury, 2020). One might think that the characteristics of the external context, such as weather conditions or neighbourhood disorder, during a "stay at home" policy may not have much importance for individual health, being people at home most of the time. However, what has been found is that during the months of the lockdown, the effects that neighbourhood stressors, such as neighbourhood disorder, have had on individuals' mental health symptoms were become more robust compared to the previous months (Teo et al., 2021).

It is also true that emergency conditions that are lived as a shared experience may help to enhance social cohesion, to maintain strong bonds (or even strengthen them), and to strengthen mechanisms of mutual aid and solidarity (Drury et al., 2016), with beneficial consequences on health. Contrariwise, the tension of living in an unfamiliar situation such as the COVID-19 pandemic, and the annexed rules of distancing, may have led to a deterioration of social cohesion with the increase of conflicts between people (stigmatization, ethnic discrimination) (Borkowska and Laurence, 2021). In this case, one could think of a before-after model to not neglect this aspect. In any case, the present study did not want to evolve into an analysis focused on the pandemic but instead wanted to take a broader look at a theme that is still little explored in Italian literature. For the purposes of this thesis, the analyses were repeated, also introducing in the models the COVID-19 outbreak as a control (Appendix A). What emerges is that the results do not undergo substantial changes. Therefore, as anticipated, there remains room for future research allowing us to make the most of the opportunity of such an exogenous shock.

Fourth, the importance of using both compositional (derived at an aggregate level from single individuals) and contextual features (attention is on environmental-related physical and social features) has been widely emphasized in the first part of this research. In this case, the introduction in the analyses of a single contextual variable (adverse weather) is limiting in the study of the independent roles that the dynamic neighbourhood contexts may have on individual health. For this reason, additional exogenous variables (preferably capturing contextual characteristics such as pollution, presence of/distance from services, facilities or green places, building conditions) should be introduced in future research.

Fifth, another limit is the remoteness of census data (which are the only contextual data available for the entire Italian territory with a fine grain like that of the census cell), although even other studies in this field used census data from many years before. Rocha et al. (2017) built the classification of neighbourhoods (least, medium and most deprived) using the 2001 census data; Ngamini Ngui et al. (2012) considered five variables from the 2006 census, while in the Schüle, Gabriel, and Bolte (2017)'s analysis eight socioeconomic neighbourhood variables aggregated on administrative neighbourhood districts were available for the years 2011–2013. Therefore, the availability of more recent census data in the coming years will certainly be an opportunity to update the analyses.

Another shortcoming of this study is the lack of sampling weights (the inverse probabilities of selection for each individual) that allow rearranging the sample, providing more accurate population estimates for the main parameters of interest. Within the research team, work was still being carried out on constructing a sophisticated weight system; it is expected that these will be available for future developments.

Finally, the definition of contextual units can be considered a limit even if, to date, there is still no evidence that witnesses whether it is better to use geographical limits imposed "from above" (such as the census blocks or the construction of an artificial ray of action) or subjective perceptions of individuals. Some might say that it is better to have objective and fixed limits of the neighbourhood because, in this way, the organization of information is more composite and unambiguous; however, MAUP should be adequately addressed (Duncan et al., 2013). Others might argue that letting the subject define her/his actions' limits has more power in determining the effects of context on health. Thus, the best and most informative solution is to use both objective and subjective neighbourhood characteristics (Kawachi and Berkman, 2003). Referring to this research, one might think, for example, that the lack of unexplained variance at the neighbourhood level for physical health could result from misleading neighbourhood boundaries; that is to say, the identification of the neighbourhood with the census block does not fit. A possible solution is that of repeating the analyses using another geographical unit. As confirmed by Coulton (2012), it would be necessary to have spatial definition methods based on the information of the inhabitants that allow an appropriate circumscription of the boundaries of the neighbourhood to which they belong. For example, she suggests using Geographic Information System (GIS) tools to define the geographical unit in a more informative and efficient way for the planning of research and public policies. Similarly, the use of Global Positioning System technology (GPS) can also be helpful for defining the range of action of individuals and their movements (Duncan and Kawachi, 2018). More complex and precise techniques also provide for a multi-stage process based first on a geographical analysis of the census blocks (e.g., analysing land use and census data) and then, on a systematic observation of the contexts, ensuring the possibility of taking into account a wide range of factors used in defining the boundaries of the neighbourhood (Weiss et al., 2007).

7.3 CONCLUDING REMARKS

The main findings, in response to the research questions expressed before, allow to formulate the following conclusions: in Italy, neighbourhood effects are stronger for mental health than for physical health; neighbourhood social cohesion and disorder have been seen to be relevant to individual health; household deprivation is associated with worse both mental and physical individual health; the between-neighbourhood variation varies differently for different household deprivation groups, being more deprived families more variable; the exogenous characteristics are also relevant, in particular, compositional features were more important for physical health, while the contextual feature on weather conditions were found to be more relevant for mental health; in particular, the latter impacts on different groups of individuals in the same way, contrary to what happens with compositional characteristics in the neighbourhood, i.e for what concerns unemployment the association is more intense for older people (for whom the effect is negative), and homemakers (for whom the effect is positive), while for what concerns the proportion of rented houses the importance is more substantial for educated individuals and widow/er (for whom the positive effect is hindered), and homemakers (for whom the positive effect is enhanced); finally, differences between regions were found, especially the presence of neighbourhood effects for physical health in two regions of southern Italy (Basilicata and Sicily) and, on the contrary, the absence of these effects on mental health in all southern regions, in the islands, in most of the central regions (except Lazio), as well as in Trentino Alto Adige, Liguria and Valle d'Aosta.

It is quite tricky, and perhaps presumptuous, to try to find mechanisms underlying the associations between the compositional components at the census level and health since the former relates to a very distant survey; moreover, since the present research has illustrative purposes of the phenomenon, the contribution of more detailed future studies is called for, with the aim to illustrate causal relationships and interpretations of these underlying mechanisms, as well as to confirm or reject the hypotheses concerning the main findings expressed in the first paragraph of this chapter. The crucial aspect will be to verify what is the causal effect of the neighbourhood context, independent of the characteristics of the inhabitants, and to be able to exploit this evidence in view of an improvement in the individual health; we need to give certainty about the magnitude, mechanisms, and changeability of these effects, how large they are, how they operate and how they can be implemented to improve public health (Oakes, 2004). In this sense, this research is essential because it made it possible to answer the original questions, which had never been asked for the Italian territory, and because it gives space to new causal questions. As confirmed by Lupton and Kneale (2012), in fact, the researches that use cross-sectional data are necessary to describe the phenomenon of interest, just as they are helpful for establishing the presence of primary evidence for the first steps of exploratory research. As already mentioned, however, the structure of these data must be abandoned when the goal is to make causal inferences in favor of data that allow, for example, to guarantee the correct timing of the association between exposure (to everyday contexts) and the outcome (individual health).

These findings are, thus, a starting point to take a chance from in order to enrich the analyses and thus to be able to introduce new contextual characteristics, the temporal dimension, the possibility of deepening therefore also the investigation on the regional heterogeneity of the effects, with the aim of providing a causal framework of the association between places and health which can help policymakers to program policies that are as suitable as possible for the area of interest.

A APPENDIX

Table 23: PCS - Random Intercepts Models after controlling for COVID-19 outbreak

	Model 2A		Model 3A	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	48.84***	(0.72)	49.58***	(0.72)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.01	(0.08)	-0.05	(0.08)
Neighbourhood Disorder	-0.28***	(0.08)	-0.22**	(0.08)
Gender				
Female	0.08	(0.15)	0.05	(0.15)
Age				
25-34	-0.25	(0.41)	-0.24	(0.40)
35-54	-1.20**	(0.42)	-1.23**	(0.42)
55-64	-2.69***	(0.45)	-2.77***	(0.45)
65 and older	-5.93***	(0.51)	-6.08***	(0.51)
Education				
Primary	5.50***	(0.56)	5.23***	(0.56)
Lower Secondary	7.86***	(0.55)	7.46***	(0.55)
Upper Secondary	8.19***	(0.56)	7.61***	(0.56)
Tertiary and Higher	8.49***	(0.59)	7.81***	(0.59)
Employment status				
Unemployed or looking for first job	0.30	(0.31)	0.72*	(0.31)
Homemaker	-1.04***	(0.26)	-0.94***	(0.26)
Student	0.32	(0.43)	0.26	(0.43)
Retired	-1.50***	(0.30)	-1.53***	(0.30)
Unabe to work	-13.06***	(0.82)	-12.92***	(0.82)
Marital status				
Single	-0.20	(0.25)	-0.12	(0.25)
Divorced	0.99**	(0.30)	1.15***	(0.30)
Widow/er	-2.76***	(0.30)	-2.67***	(0.30)
Children				
Yes	0.14	(0.22)	0,0125	(0.22)
Chitizenship				
Foreign	0.56	(0.41)	0.99*	(0.42)
Insomnia issues				
A little	-3.58***	(0.17)	-3.53***	(0.17)
A lot	-8.69***	(0.32)	-8.57***	(0.32)
Household Deprivation				
Cluster 2			-0.97***	(0.22)
Cluster 3			-1.84***	(0.34)
Cluster 4			-2.10***	(0.59)
Pandemic Outbreak				
After	0.36*	(0.17)	0.34*	(0.17)
Random Part				
var(Constant level-3)	0.88	(0.64)	0.71	(0.63)
var(Constant level-2)	6.28***	(0.97)	6.29***	(0.96)
var(Residual)	32.67***	(0.82)	32.56***	(0.81)
N	7835		7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: PCS - Random Slopes Models after controlling for COVID-19 outbreak

	Model 4A		Model 5A	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	49.31***	(0.73)	49.83***	(0.87)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	-0.05	(0.08)	-0.05	(0.08)
Neighbourhood Disorder	-0.19*	(0.08)	-0.18*	(0.09)
Gender				
Female	0.06	(0.15)	0.05	(0.15)
Age				
25-34	-0.31	(0.40)	-0.32	(0.40)
35-54	-1.21**	(0.42)	-1.21**	(0.42)
55-64	-2.71***	(0.45)	-2.70***	(0.45)
65 and older	-5.95***	(0.51)	-5.95***	(0.51)
Education				
Primary	5.45***	(0.57)	5.42***	(0.57)
Lower Secondary	7.71***	(0.57)	7.68***	(0.57)
Upper Secondary	7.85***	(0.57)	7.82***	(0.58)
Tertiary and Higher	8.10***	(0.61)	8.09***	(0.61)
Employment status				
Unemployed or looking for first job	0.61	(0.32)	0.67*	(0.32)
Homemaker	-0.92***	(0.26)	-0.84**	(0.26)
Student	0.26	(0.43)	0.29	(0.43)
Retired	-1.49***	(0.30)	-1.50***	(0.30)
Unabe to work	-13.19***	(0.82)	-13.11***	(0.82)
Marital status				
Single	-0.10	(0.25)	-0.09	(0.25)
Divorced	1.21***	(0.30)	1.18***	(0.30)
Widow/er	-2.62***	(0.29)	-2.64***	(0.29)
Children				
Yes	0.14	(0.22)	0.18	(0.22)
Chitizenship				
Foreign	0.95*	(0.44)	0.88*	(0.44)
Insomnia issues				
A little	-3.53***	(0.16)	-3.56***	(0.16)
A lot	-8.67***	(0.32)	-8.68***	(0.32)
Household Deprivation				
Cluster 2	-1.00***	(0.25)	-0.94***	(0.25)
Cluster 3	-1.91***	(0.42)	-1.84***	(0.42)
Cluster 4	-2.15**	(0.79)	-2.10**	(0.79)
Exogenous neighbourhood characteristics				
Low Education			1.09	(1.62)
Unemployment			-2.71**	(0.97)
Rented Houses			1.10*	(0.52)
Single Parents			-1.63	(1.43)
House Density			-0.04	(0.19)
Young Individuals			-1.57	(1.70)
Adverse Weather Conditions (days)			-0.03	(0.02)
Pandemic Outbreak				
After	0.28	(0.16)	0.24	(0.16)
Random Part				
var(Household deprivation 2 at level-3)	8.19***	(1.92)	8.26***	(1.91)
var(Household deprivation 3 at level-3)	17.97***	(4.00)	18.40***	(4.03)
var(Household deprivation 4 at level-3)	25.71***	(7.99)	25.98***	(8.01)
var(Constant level-3)	0.49	(0.61)	0.36	(0.61)
var(Constant level-2)	4.27***	(0.93)	4.29***	(0.93)
var(Residual)	32.16***	(0.80)	32.16***	(0.80)
N	7835		7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: PCS - Unemployment Cross-Level Model after controlling for COVID-19 outbreak

	Model 6A	
	Coeff.	Std. Err.
Fixed Part		
Constant	50.28***	(1.35)
Subjective neighbourhood perception		
Neighbourhood Social Cohesion	0.10	(0.13)
Neighbourhood Social Cohesion x Unemployment	-1.10	(0.82)
Neighbourhood Disorder	-0.23	(0.14)
Neighbourhood Disorder x Unemployment	0.26	(0.80)
Gender		
Female	0.25	(0.24)
Female x Unemployment	-1.92	(1.77)
Age		
25-34	-0.32	(0.68)
35-54	-1.33	(0.70)
55-64	-2.43**	(0.75)
65 and older	-4.06***	(0.86)
25-34 x Unemployment	-0.40	(4.40)
35-54 x Unemployment	0.49	(4.53)
55-64 x Unemployment	-2.51	(4.93)
65 and older x Unemployment	-15.57**	(5.71)
Education		
Primary	4.35***	(1.03)
Lower Secondary	6.82***	(1.01)
Upper Secondary	7.12***	(1.03)
Tertiary and Higher	8.07***	(1.08)
Primary x Unemployment	6.08	(5.62)
Lower Secondary x Unemployment	3.58	(5.53)
Upper Secondary x Unemployment	2.99	(5.74)
Tertiary and Higher x Unemployment	-3.29	(6.25)
Employment status		
Unemployed or looking for first job	0.51	(0.55)
Homemaker	-1.74***	(0.43)
Student	0.42	(0.71)
Retired	-1.69***	(0.50)
Unabe to work	-13.21***	(1.50)
Unemployed or looking for first job x Unemployment	0.02	(3.21)
Homemaker x Unemployment	5.85*	(2.69)
Student x Unemployment	-1.44	(4.81)
Retired x Unemployment	-0.82	(3.36)
Unabe to work x Unemployment	0.65	(8.86)
Marital status		
Single	0.16	(0.42)
Divorced	1.06*	(0.50)
Widow/er	-2.28***	(0.49)
Single x Unemployment	-1.85	(3.22)
Divorced x Unemployment	1.29	(3.67)
Widow/er x Unemployment	-3.06	(3.40)
Children		
Yes	0.31	(0.37)
Yes x Unemployment	-0.96	(2.89)
Chitizenship		
Foreign	0.57	(0.77)
Foreign x Unemployment	3.82	(6.32)
Insomnia issues		
A little	-3.83***	(0.27)
A lot	-8.95***	(0.53)
A little x Unemployment	2.72	(1.89)
A lot x Unemployment	2.96	(3.31)
Household Deprivation		
Cluster 2	-1.21**	(0.41)
Cluster 3	-2.59***	(0.79)
Cluster 4	-1.81	(1.32)
Cluster 2 x Unemployment	2.17	(2.51)
Cluster 3 x Unemployment	4.91	(4.21)
Cluster 4 x Unemployment	-1.85	(6.90)
Exogenous neighbourhood characteristics		
Low Education	0.93	(1.62)
Unemployment	-1.00	(7.75)
Rented Houses	0.93	(0.52)
Single Parents	-1.09	(1.42)
House Density	-0.13	(0.19)
Young Individuals	-1.70	(1.69)
Adverse Weather Conditions (days)	-0.03	(0.02)
Pandemic Outbreak		
After	0.23	(0.16)
Random Part		
var(Household deprivation 2 at level-3)	9.01***	(1.94)
var(Household deprivation 3 at level-3)	17.49***	(3.93)
var(Household deprivation 4 at level-3)	25.74***	(7.94)
var(Constant level-3)	0.19	(0.60)
var(Constant level-2)	4.23***	(0.92)
var(Residual)	31.90***	(0.79)
N	7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: PCS - Rented dwellings Cross-Level Model after controlling for COVID-19 outbreak

	Model 7A	
	Coeff.	Std. Err.
Fixed Part		
Constant	46.66***	(1.16)
Subjective neighbourhood perception		
Neighbourhood Social Cohesion	-0.05	(0.12)
Neighbourhood Social Cohesion x Rent	-0.03	(0.51)
Neighbourhood Disorder	-0.12	(0.13)
Neighbourhood Disorder x Rent	-0.22	(0.44)
Gender		
Female	0.08	(0.23)
Female x Rent	-0.16	(0.96)
Age		
25-34	0.20	(0.63)
35-54	-0.62	(0.64)
55-64	-1.67*	(0.69)
65 and older	-5.05***	(0.78)
25-34 x Rent	-2.54	(2.44)
35-54 x Rent	-2.76	(2.48)
55-64 x Rent	-5.20	(2.70)
65 and older x Rent	-4.17	(3.16)
Education		
Primary	8.19***	(0.79)
Lower Secondary	10.02***	(0.78)
Upper Secondary	10.42***	(0.80)
Tertiary and Higher	10.80***	(0.86)
Primary x Rent	-15.41***	(3.24)
Lower Secondary x Rent	-12.98***	(3.10)
Upper Secondary x Rent	-14.37***	(3.20)
Tertiary and Higher x Rent	-15.01***	(3.46)
Employment status		
Unemployed or looking for first job	0.75	(0.47)
Homemaker	-1.64***	(0.39)
Student	0.87	(0.67)
Retired	-1.36**	(0.45)
Unabe to work	-11.50***	(1.53)
Unemployed or looking for first job x Rent	-0.21	(1.76)
Homemaker x Rent	4.31**	(1.66)
Student x Rent	-2.77	(2.68)
Retired x Rent	-1.05	(1.98)
Unabe to work x Rent	-11.72	(8.72)
Marital status		
Single	-0.02	(0.39)
Divorced	1.03*	(0.47)
Widow/er	-1.61***	(0.44)
Single x Rent	-0.22	(1.57)
Divorced x Rent	0.55	(1.81)
Widow/er x Rent	-5.27**	(1.83)
Children		
Yes	0.16	(0.34)
Yes x Rent	0.14	(1.34)
Chitizenship		
Foreign	0.86	(0.69)
Foreign x Rent	-0.25	(2.45)
Insomnia issues		
A little	-3.80***	(0.25)
A lot	-8.98***	(0.52)
A little x Rent	1.25	(1.04)
A lot x Rent	1.40	(2.14)
Household Deprivation		
Cluster 2	-0.92*	(0.38)
Cluster 3	-1.15	(0.62)
Cluster 4	-1.31	(1.20)
Cluster 2 x Rent	-0.08	(1.56)
Cluster 3 x Rent	-3.22	(2.10)
Cluster 4 x Rent	-3.24	(3.59)
Exogenous neighbourhood characteristics		
Low Education	0.96	(1.63)
Unemployment	-2.93**	(0.98)
Rented Houses	18.54***	(4.21)
Single Parents	-1.82	(1.43)
House Density	-0.05	(0.19)
Young Individuals	-1.46	(1.70)
Adverse Weather Conditions (days)	-0.03	(0.02)
Pandemic Outbreak		
After	0.25	(0.16)
Random Part		
var(Household deprivation 2 at level-3)	9.05***	(1.98)
var(Household deprivation 3 at level-3)	19.18***	(4.11)
var(Household deprivation 4 at level-3)	26.93***	(8.24)
var(Constant level-3)	0.38	(0.61)
var(Constant level-2)	4.47***	(0.92)
var(Residual)	31.59***	(0.79)
N	7835	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 27: MCS - Weather Cross-Level Model

	Model 6	
	Coeff.	Std. Err.
Fixed Part		
Constant	54.50***	(1.01)
Subjective neighbourhood perception		
Neighbourhood Social Cohesion	0.95***	(0.10)
Neighbourhood Social Cohesion x Weather	-0.01	(0.02)
Neighbourhood Disorder	-0.61***	(0.11)
Neighbourhood Disorder x Weather	-0.02	(0.02)
Gender		
Female	-0.39*	(0.18)
Female x Weather	0.01	(0.03)
Age		
25-34	-0.76	(0.48)
35-54	-1.85***	(0.49)
55-64	-2.70***	(0.54)
65 and older	-2.51***	(0.61)
25-34 x Weather	0.00	(0.09)
35-54 x Weather	-0.01	(0.09)
55-64 x Weather	-0.08	(0.10)
65 and older	-0.06	(0.11)
Education		
Primary	1.19	(0.66)
Lower Secondary	1.75**	(0.65)
Upper Secondary	1.81**	(0.67)
Tertiary and Higher	1.96**	(0.71)
Primary x Weather	-0.05	(0.13)
Lower Secondary x Weather	0.05	(0.13)
Upper Secondary x Weather	0.09	(0.13)
Tertiary and Higher x Weather	0.15	(0.14)
Employment status		
Unemployed or looking for first job	-1.61***	(0.36)
Homemaker	-0.80**	(0.30)
Student	-0.51	(0.51)
Retired	-0.94**	(0.36)
Unabe to work	-6.56***	(1.09)
Unemployed or looking for first job x Weather	-0.07	(0.06)
Homemaker x Weather	-0.00	(0.06)
Student x Weather	-0.08	(0.09)
Retired x Weather	0.12	(0.07)
Unabe to work x Weather	0.36	(0.29)
Marital status		
Single	-0.82*	(0.32)
Divorced	-1.20**	(0.39)
Widow/er	-1.21***	(0.36)
Single x Weather	0.04	(0.06)
Divorced x Weather	0.09	(0.08)
Widow/er x Weather	-0.02	(0.07)
Children		
Yes	-0.07	(0.28)
Yes x Weather	0.03	(0.05)
Chitizenship		
Foreign	0.75	(0.60)
Foreign x Weather	0.03	(0.10)
Insomnia issues		
A little	-3.71***	(0.20)
A lot	-10.96***	(0.39)
A little x Weather	0.01	(0.04)
A lot x Weather	0.10	(0.09)
Household Deprivation		
Cluster 2	-1.48***	(0.31)
Cluster 3	-3.23***	(0.48)
Cluster 4	-4.98***	(0.94)
Cluster 2 x Weather	0.03	(0.06)
Cluster 3 x Weather	0.10	(0.08)
Cluster 4 x Weather	-0.16	(0.17)
Exogenous neighbourhood characteristics		
Low Education	1.63	(1.83)
Unemployment	0.86	(1.09)
Rented Houses	0.58	(0.58)
Single Parents	-0.54	(1.59)
House Density	0.04	(0.21)
Young Individuals	-1.00	(1.91)
Adverse Weather Conditions (days)	-0.17	(0.17)
Random Part		
var(Household deprivation 2 at level-3)	8.16***	(2.10)
var(Household deprivation 3 at level-3)	14.89***	(3.92)
var(Household deprivation 4 at level-3)	24.16***	(8.45)
var(Constant level-3)	7.23***	(0.95)
var(Constant level-2)	4.58***	(1.01)
var(Residual)	26.72***	(0.66)
N	7853	

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 28: MCS - Random Intercepts Models after controlling for COVID-19 outbreak

	Model 2A		Model 3A	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	53.31***	(0.72)	54.43***	(0.72)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.98***	(0.08)	0.88***	(0.08)
Neighbourhood Disorder	-0.72***	(0.09)	-0.62***	(0.09)
Gender				
Female	-0.34*	(0.14)	-0.38**	(0.14)
Age				
25-34	-0.79*	(0.40)	-0.72	(0.40)
35-54	-1.88***	(0.41)	-1.89***	(0.41)
55-64	-2.87***	(0.45)	-2.96***	(0.44)
65 and older	-2.59***	(0.51)	-2.76***	(0.51)
Education				
Primary	1.38*	(0.56)	0.96	(0.55)
Lower Secondary	2.40***	(0.55)	1.78**	(0.55)
Upper Secondary	2.82***	(0.56)	1.92***	(0.56)
Tertiary and Higher	3.32***	(0.59)	2.27***	(0.59)
Employment status				
Unemployed or looking for first job	-2.46***	(0.30)	-1.88***	(0.30)
Homemaker	-0.84***	(0.25)	-0.71**	(0.25)
Student	-0.67	(0.42)	-0.77	(0.41)
Retired	-0.55	(0.30)	-0.58*	(0.29)
Unabe to work	-5.69***	(0.81)	-5.49***	(0.80)
Marital status				
Single	-0.81**	(0.26)	-0.66*	(0.26)
Divorced	-1.16***	(0.30)	-0.92**	(0.30)
Widow/er	-1.39***	(0.30)	-1.27***	(0.30)
Children				
Yes	0.00	(0.23)	0.07	(0.23)
Chitizenship				
Foreign	0.00	(0.43)	0.85*	(0.43)
Insomnia issues				
A little	-3.81***	(0.17)	-3.75***	(0.16)
A lot	-11.00***	(0.32)	-10.84***	(0.32)
Household Deprivation				
Cluster 2			-1.34***	(0.24)
Cluster 3			-2.82***	(0.36)
Cluster 4			-5.22***	(0.61)
Pandemic Outbreak				
After	0.33	(0.19)	0.29	(0.18)
Random Part				
var(Constant level-3)	7.93***	(1.02)	7.91***	(0.99)
var(Constant level-2)	6.78***	(1.08)	6.31***	(1.05)
var(Residual)	27.30***	(0.69)	27.03***	(0.67)
N	7853		7853	

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 29: MCS - Random Slopes Models after controlling for COVID-19 outbreak

	Model 4A		Model 5A	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	54.33***	(0.73)	54.08***	(0.90)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.89***	(0.08)	0.90***	(0.08)
Neighbourhood Disorder	-0.61***	(0.09)	-0.64***	(0.09)
Gender				
Female	-0.36*	(0.14)	-0.35*	(0.14)
Age				
25-34	-0.73	(0.40)	-0.74	(0.40)
35-54	-1.84***	(0.41)	-1.84***	(0.41)
55-64	-2.92***	(0.44)	-2.92***	(0.44)
65 and older	-2.73***	(0.51)	-2.69***	(0.51)
Education				
Primary	1.00	(0.56)	1.05	(0.56)
Lower Secondary	1.84**	(0.56)	1.89***	(0.56)
Upper Secondary	1.98***	(0.57)	2.06***	(0.57)
Tertiary and Higher	2.30***	(0.60)	2.38***	(0.60)
Employment status				
Unemployed or looking for first job	-1.81***	(0.31)	-1.83***	(0.31)
Homemaker	-0.78**	(0.25)	-0.82**	(0.25)
Student	-0.75	(0.41)	-0.74	(0.41)
Retired	-0.56	(0.29)	-0.57	(0.29)
Unabe to work	-5.62***	(0.81)	-5.64***	(0.81)
Marital status				
Single	-0.69**	(0.26)	-0.68**	(0.26)
Divorced	-0.93**	(0.30)	-0.92**	(0.30)
Widow/er	-1.27***	(0.30)	-1.28***	(0.30)
Children				
Yes	0.05	(0.22)	0.05	(0.23)
Chitizenship				
Foreign	0.80	(0.45)	0.87	(0.45)
Insomnia issues				
A little	-3.70***	(0.16)	-3.69***	(0.16)
A lot	-10.71***	(0.32)	-10.73***	(0.32)
Household Deprivation				
Cluster 2	-1.37***	(0.26)	-1.40***	(0.26)
Cluster 3	-2.84***	(0.42)	-2.92***	(0.42)
Cluster 4	-5.30***	(0.80)	-5.40***	(0.80)
Exogenous neighbourhood characteristics				
Low Education			1.54	(1.83)
Unemployment			0.90	(1.08)
Rented Houses			0.58	(0.58)
Single Parents			-0.44	(1.59)
House Density			0.04	(0.21)
Young Individuals			-0.98	(1.91)
Adverse Weather Conditions (days)			-0.06**	(0.02)
Pandemic Outbreak				
After	0.29	(0.18)	0.23	(0.18)
Random Part				
var(Household deprivation 2 at level-3)	8.31***	(2.11)	8.17***	(2.10)
var(Household deprivation 3 at level-3)	14.89***	(3.89)	15.11***	(3.92)
var(Household deprivation 4 at level-3)	25.20***	(8.53)	25.38***	(8.57)
var(Constant level-3)	7.32***	(0.96)	7.28***	(0.95)
var(Constant level-2)	4.59***	(1.01)	4.56***	(1.01)
var(Residual)	26.81***	(0.66)	26.80***	(0.66)
N	7853		7853	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 30: MCS - Weather Cross-Level Model after controlling for COVID-19 outbreak

	Model 6A	
	Coeff.	Std. Err.
Fixed Part		
Constant	54.41***	(1.01)
Subjective neighbourhood perception		
Neighbourhood Social Cohesion	0.94***	(0.10)
Neighbourhood Social Cohesion x Weather	-0.01	(0.02)
Neighbourhood Disorder	-0.61***	(0.11)
Neighbourhood Disorder x Weather	-0.02	(0.02)
Gender		
Female	-0.39*	(0.18)
Female x Weather	0.01	(0.03)
Age		
25-34	-0.76	(0.48)
35-54	-1.83***	(0.49)
55-64	-2.68***	(0.54)
65 and older	-2.49***	(0.61)
25-34 x Weather	0.01	(0.09)
35-54 x Weather	-0.01	(0.09)
55-64 x Weather	-0.08	(0.10)
65 and older	-0.06	(0.11)
Education		
Primary	1.18	(0.66)
Lower Secondary	1.72**	(0.65)
Upper Secondary	1.78**	(0.67)
Tertiary and Higher	1.93**	(0.71)
Primary x Weather	-0.05	(0.13)
Lower Secondary x Weather	0.05	(0.13)
Upper Secondary x Weather	0.09	(0.13)
Tertiary and Higher x Weather	0.15	(0.14)
Employment status		
Unemployed or looking for first job	-1.61***	(0.36)
Homemaker	-0.79**	(0.30)
Student	-0.51	(0.51)
Retired	-0.94**	(0.36)
Unabe to work	-6.57***	(1.09)
Unemployed or looking for first job x Weather	-0.07	(0.06)
Homemaker x Weather	-0.00	(0.06)
Student x Weather	-0.08	(0.09)
Retired x Weather	0.12	(0.07)
Unabe to work x Weather	0.36	(0.29)
Marital status		
Single	-0.83*	(0.32)
Divorced	-1.20**	(0.39)
Widow/er	-1.21***	(0.36)
Single x Weather	0.04	(0.06)
Divorced x Weather	0.09	(0.08)
Widow/er x Weather	-0.02	(0.07)
Children		
Yes	-0.07	(0.28)
Yes x Weather	0.03	(0.05)
Chitizenship		
Foreign	0.74	(0.60)
Foreign x Weather	0.03	(0.10)
Insomnia issues		
A little	-3.73***	(0.20)
A lot	-10.96***	(0.39)
A little x Weather	0.02	(0.04)
A lot x Weather	0.11	(0.09)
Household Deprivation		
Cluster 2	-1.47***	(0.31)
Cluster 3	-3.22***	(0.48)
Cluster 4	-4.95***	(0.94)
Cluster 2 x Weather	0.03	(0.06)
Cluster 3 x Weather	0.10	(0.08)
Cluster 4 x Weather	-0.17	(0.17)
Exogenous neighbourhood characteristics		
Low Education	1.67	(1.83)
Unemployment	0.86	(1.09)
Rented Houses	0.55	(0.58)
Single Parents	-0.44	(1.59)
House Density	0.04	(0.21)
Young Individuals	-0.98	(1.91)
Adverse Weather Conditions (days)	-0.17	(0.17)
Pandemic Outbreak		
After	0.28	(0.18)
Random Part		
var(Household deprivation 2 at level-3)	8.21***	(2.11)
var(Household deprivation 3 at level-3)	14.67***	(3.90)
var(Household deprivation 4 at level-3)	24.38***	(8.48)
var(Constant level-3)	7.28***	(0.95)
var(Constant level-2)	4.51***	(1.01)
var(Residual)	26.73***	(0.66)
N	7853	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 31: PCS - Random Slopes: North-West Regions

	Piedmont		Valle d'Aosta		Lombardy		Liguria	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	49.11***	(3.15)	51.23***	(9.61)	53.61***	(2.76)	53.43***	(3.03)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	0.14	(0.31)	3.06***	(0.67)	0.09	(0.22)	0.09	(0.39)
Neighbourhood Disorder	0.04	(0.27)	-6.51***	(1.07)	-0.24	(0.26)	1.06*	(0.47)
Gender								
Female	0.41	(0.50)	0.92*	(0.38)	0.39	(0.40)	-0.54	(0.59)
Age								
25-34	-0.69	(1.34)	8.71***	(2.27)	-0.75	(1.15)	-0.71	(1.68)
35-54	-2.17	(1.41)	7.66**	(2.39)	-1.78	(1.14)	-0.8	(1.88)
55-64	-4.74**	(1.51)	8.70***	(2.18)	-3.54**	(1.22)	-0.01	(1.87)
65 and older	-5.43**	(1.80)	8.66***	(2.48)	-4.83***	(1.43)	-6.86**	(2.15)
Education								
Primary	13.00***	(2.11)	-0.46	(3.53)	-2.21	(1.94)	0.00	(.)
Lower Secondary	13.22***	(2.06)	1.03	(3.63)	2.35	(1.93)	3.33**	(1.07)
Upper Secondary	13.84***	(2.07)	0.37	(3.71)	2.90	(1.94)	3.66***	(1.03)
Tertiary and Higher	12.13***	(2.20)	-3.51	(3.78)	3.24	(2.02)	5.28***	(1.27)
Employment status								
Unemployed or looking for first job	0.55	(1.21)	4.13**	(1.45)	-2.00	(1.02)	1.27	(1.82)
Homemaker	-1.99	(1.04)	-2.34**	(0.75)	-0.48	(0.79)	0.30	(1.26)
Student	-2.01	(1.47)	3.29	(2.09)	0.33	(1.25)	-0.27	(1.61)
Retired	-1.89	(1.13)	1.34	(0.94)	-1.86*	(0.86)	3.68**	(1.37)
Unabe to work	0.30	(6.44)	-14.80***	(1.56)	-16.88***	(4.08)	-12.31**	(3.77)
Marital status								
Single	-0.21	(0.81)	-2.46*	(1.24)	0.26	(0.65)	1.89*	(0.96)
Divorced	1.91	(1.09)	1.80	(1.16)	1.51*	(0.72)	2.52*	(1.08)
Widow/er	-1.81	(1.11)	0.15	(1.27)	-2.34**	(0.76)	-1.77	(1.06)
Children								
Yes	0.06	(0.66)	-6.61***	(1.39)	0.06	(0.57)	0.06	(0.79)
Chitizenship								
Foreign	-0.34	(1.33)	-0.54	(3.04)	1.14	(1.04)	1.56	(1.81)
Insomnia issues								
A little	-4.45***	(0.63)	-1.38	(0.93)	-3.19***	(0.45)	-5.13***	(0.78)
A lot	-8.56***	(1.10)			-6.87***	(0.93)	-20.97***	(1.42)
Household Deprivation								
Cluster 2	0.67	(0.86)	5.14	(2.92)	-0.44	(0.68)	-1.76	(1.06)
Cluster 3	-3.42**	(1.29)	11.93*	(5.62)	-0.15	(1.86)	3.56	(5.57)
Cluster 4	-3.41	(4.43)	-1.73	(5.55)	-2.14	(2.30)	-9.14	(6.76)
Exogenous neighbourhood characteristics								
Low Education	-5.43	(5.91)	-3.07	(17.47)	2.85	(5.21)	-19.59	(11.75)
Unemployment	-3.14	(4.13)	44.93	(27.67)	0.75	(6.03)	-18.28	(10.03)
Rented Houses	-0.18	(2.16)	-2.68	(4.99)	0.57	(1.40)	3.23	(2.84)
Single Parents	-5.98	(6.99)	-11.13	(23.33)	8.23	(5.25)	-2.71	(7.91)
House Density	-0.61	(0.74)	-2.62	(2.86)	0.42	(0.59)	0.94	(0.89)
Young Individuals	-9.36	(6.94)	14.58	(17.63)	-7.44	(5.08)	0.01	(8.77)
Adverse Weather Conditions (days)	0.15	(0.11)	0.01	(0.30)	-0.10*	(0.05)	0.04	(0.11)
Random Part								
var(Household deprivation 2 at level-3)	0.00	(0.00)	0.00	(.)	0.00	(.)	5.77	(9.20)
var(Household deprivation 3 at level-3)	9.19	(10.46)	19.81	(.)	47.25	(.)	165.64***	(105.68)
var(Household deprivation 4 at level-3)	64.09***	(65.42)	0.00	(.)	30.69	(.)	75.88***	(91.30)
var(Constant level-3)	0.10	(1.87)	0.05	(.)	0.00	(.)	0.00***	(0.00)
var(Constant level-2)	5.18**	(3.21)	18.88	(.)	4.40	(.)	0.00***	(0.00)
var(Residual)	30.07***	(2.67)	0.91	(.)	35.62	(.)	15.12***	(1.91)
N	626		75		1160		239	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: PCS - Random Slopes: North-East Regions

	Trentino Alto Adige		Veneto		Friuli-Venezia Giulia		Emilia-Romagna	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	54.79***	(7.20)	52.62***	(2.67)	58.72***	(4.40)	52.16***	(3.37)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	-0.30	(0.57)	0.01	(0.24)	-1.26*	(0.51)	-0.57**	(0.21)
Neighbourhood Disorder	0.51	(0.64)	0.14	(0.34)	0.87	(0.56)	-0.16	(0.36)
Gender								
Female	0.26	(0.74)	0.59	(0.34)	0.55	(0.64)	-0.24	(0.35)
Age								
25-34	-0.71	(3.27)	0.08	(0.97)	1.25	(2.36)	0.45	(1.21)
35-54	-1.71	(3.59)	0.30	(1.00)	0.41	(2.52)	-0.85	(1.24)
55-64	-6.03	(3.73)	-0.61	(1.09)	-0.43	(2.65)	-1.58	(1.32)
65 and older	-5.15	(4.04)	-2.97*	(1.21)	-1.97	(2.83)	-4.54**	(1.53)
Education								
Primary	0.61	(6.14)	-1.06	(2.07)	0.00	(.)	5.86	(3.06)
Lower Secondary	2.30	(5.96)	2.30	(2.03)	-0.19	(1.44)	4.55	(2.89)
Upper Secondary	1.30	(6.03)	2.04	(2.05)	0.44	(1.51)	4.32	(2.90)
Tertiary and Higher	4.86	(6.12)	3.10	(2.12)	-2.09	(1.87)	5.43	(2.95)
Employment status								
Unemployed or looking for first job	-1.67	(5.24)	0.88	(1.14)	-5.65*	(2.32)	0.72	(1.11)
Homemaker	-4.70**	(1.78)	-0.47	(0.66)	-2.53	(1.52)	-1.47	(0.88)
Student	3.13	(3.36)	0.37	(0.99)	-0.08	(2.30)	0.33	(1.25)
Retired	-4.83**	(1.67)	-0.48	(0.68)	-3.34*	(1.42)	-3.42***	(0.95)
Unabe to work	-19.29**	(6.62)	-8.96***	(1.99)			-26.30***	(4.02)
Marital status								
Single	-0.74	(1.63)	0.38	(0.59)	0.55	(1.17)	0.47	(0.56)
Divorced	3.33	(2.19)	0.64	(0.69)	-0.45	(1.58)	0.77	(0.70)
Widow/er	-1.80	(2.00)	-4.19***	(0.73)	-5.62***	(1.53)	-3.73***	(0.81)
Children								
Yes	2.88*	(1.39)	-0.33	(0.50)	1.46	(1.02)	1.13*	(0.52)
Chitizenship								
Foreign	0.12	(2.86)	1.89	(1.10)	-0.34	(2.20)	-0.29	(1.32)
Insomnia issues								
A little	-5.22***	(0.88)	-3.51***	(0.38)	-6.89***	(0.81)	-1.26**	(0.41)
A lot	-9.89***	(2.19)	-10.18***	(1.02)	-0.39	(4.53)	-6.28***	(0.87)
Household Deprivation								
Cluster 2	-2.94*	(1.31)	-3.13**	(0.96)	-3.22	(1.67)	-1.10	(1.04)
Cluster 3	-21.45***	(3.98)	0.09	(1.62)	2.25	(3.29)	-5.93*	(2.96)
Cluster 4	2.93	(5.43)	-2.99	(2.47)			-1.14	(1.44)
Exogenous neighbourhood characteristics								
Low Education	-34.47*	(13.74)	-6.94	(4.43)	5.50	(7.26)	-2.74	(3.06)
Unemployment	2.57	(17.47)	-0.66	(3.93)	-18.24	(9.72)	-0.51	(2.92)
Rented Houses	-0.31	(3.44)	-1.18	(1.43)	0.96	(2.46)	-0.63	(1.22)
Single Parents	8.21	(6.89)	3.99	(3.11)	6.12	(9.29)	-0.11	(4.05)
House Density	0.22	(1.17)	0.45	(0.58)	-1.35	(1.23)	-0.04	(0.50)
Young Individuals	21.11*	(10.70)	5.84	(4.16)	4.53	(9.06)	4.44	(3.93)
Adverse Weather Conditions (days)	-0.07	(0.11)	0	(0.05)	-0.09	(0.09)	-0.08	(0.06)
Random Part								
var(Household deprivation 2 at level-3)	0.00	(.)	19.60***	(7.69)	29.99	(.)	10.93**	(7.99)
var(Household deprivation 3 at level-3)	0.00	(.)	12.64**	(12.12)	(0.00)	(.)	21.64*	(28.23)
var(Household deprivation 4 at level-3)	0.00	(.)	0.00	(0.00)			0.00*	(0.00)
var(Constant level-3)	0.00	(.)	0.15	(1.33)	(0.00)	(.)	0.00	(0.00)
var(Constant level-2)	7.38	(.)	2.71	(1.89)	4.09	(.)	1.32	(1.03)
var(Residual)	19.22	(.)	15.71***	(1.42)	14.06	(.)	14.00***	(1.27)
N	201		706		203		555	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 33: PCS - Random Slopes: Center Regions

	Tuscany		Marche		Umbria		Lazio	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	52.10***	(2.84)	37.07***	(6.45)	41.31***	(7.47)	55.77***	(2.91)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	0.12	(0.26)	-0.62	(0.45)	-0.05	(0.65)	0.45	(0.30)
Neighbourhood Disorder	-0.46	(0.40)	-0.68	(0.80)	0.35	(0.61)	-0.25	(0.19)
Gender								
Female	-0.87	(0.49)	-0.23	(0.80)	-1.37	(1.12)	-0.11	(0.51)
Age								
25-34	-1.84	(1.15)	-1.75	(2.74)	-1.13	(3.00)	-0.51	(1.29)
35-54	-1.47	(1.18)	-3.16	(2.90)	-0.81	(2.94)	-2.57	(1.32)
55-64	-2.11	(1.30)	-3.57	(3.04)	2.40	(3.19)	-3.88**	(1.46)
65 and older	-3.04	(1.57)	-6.63*	(3.31)	-1.93	(3.75)	-7.81***	(1.68)
Education								
Primary	4.68*	(1.91)	15.30***	(4.16)	8.13	(5.16)	-0.97	(2.12)
Lower Secondary	6.21***	(1.89)	17.92***	(4.24)	11.60*	(4.98)	0.11	(2.03)
Upper Secondary	6.96***	(1.92)	17.49***	(4.23)	12.15*	(5.14)	0.23	(2.07)
Tertiary and Higher	7.05***	(2.05)	18.58***	(4.31)	14.44**	(5.23)	0.51	(2.14)
Employment status								
Unemployed or looking for first job	2.00	(1.04)	-1.81	(4.18)	-3.01	(2.51)	0.99	(0.93)
Homemaker	1.29	(0.99)	-0.10	(1.67)	-1.71	(2.27)	-1.97*	(0.85)
Student	0.65	(1.22)	0.72	(2.58)	-3.15	(2.87)	-0.23	(1.40)
Retired	-2.02	(1.05)	-2.71	(1.56)	-2.17	(2.20)	-5.83***	(1.12)
Unabe to work	1.99	(4.95)	-15.06**	(5.77)	-29.49***	(4.59)	-19.12***	(2.66)
Marital status								
Single	-0.31	(0.74)	-1.41	(1.50)	3.42	(2.56)	-0.33	(0.71)
Divorced	0.49	(0.97)	0.58	(2.16)	3.73	(2.16)	1.03	(0.93)
Widow/er	-3.85***	(0.90)	-2.42	(1.59)	-6.54*	(2.93)	-2.66*	(1.17)
Children								
Yes	-0.41	(0.67)	-1.17	(1.21)	-1.81	(2.17)	0.58	(0.59)
Chitizenship								
Foreign	3.42	(1.82)	-0.17	(2.25)	3.82	(2.59)	1.44	(0.95)
Insomnia issues								
A little	-3.43***	(0.55)	-3.80***	(0.99)	-3.55**	(1.38)	-2.76***	(0.51)
A lot	-6.23***	(1.05)	-4.38	(2.25)	-3.24	(3.14)	-9.89***	(1.03)
Household Deprivation								
Cluster 2	-1.51	(0.96)	-2.89	(1.82)	1.22	(2.42)	-1.55*	(0.70)
Cluster 3	2.12	(4.07)	-0.78	(2.74)	-2.35	(2.16)	-5.91***	(1.41)
Cluster 4	0.55	(5.04)	-1.66	(3.18)	-3.35	(3.85)	-2.92	(1.96)
Exogenous neighbourhood characteristics								
Low Education	3.48	(6.37)	-3.43	(9.73)	-0.89	(18.21)	0.85	(6.38)
Unemployment	-4.40	(5.79)	-13.01	(7.70)	-13.69	(10.70)	-0.71	(3.41)
Rented Houses	-1.16	(2.12)	0.89	(4.05)	2.11	(5.33)	2.28	(1.48)
Single Parents	-4.31	(5.35)	2.06	(7.43)	-6.57	(16.03)	1.37	(3.43)
House Density	-0.60	(0.72)	2.96*	(1.25)	2.27	(2.00)	0.83	(0.62)
Young Individuals	5.78	(6.00)	-5.23	(9.93)	5.52	(16.29)	-5.55	(5.19)
Adverse Weather Conditions (days)	0.21*	(0.10)	-0.46	(0.30)	-0.32	(0.26)	0.00	(0.12)
Random Part								
var(Household deprivation 2 at level-3)	10.82	(.)	7.93	(13.04)	0.00	(.)	0.00***	(0.00)
var(Household deprivation 3 at level-3)	0.00	(.)	0.00	(0.00)	0.00	(.)	7.23	(12.32)
var(Household deprivation 4 at level-3)	0.00	(.)	0.00	(0.00)	0.00	(.)	10.96	(17.65)
var(Constant level-3)	0.00	(.)	1.76	(2.15)	0.00	(.)	0.00	(0.00)
var(Constant level-2)	4.27	(.)	0.00***	(0.00)	0.00	(.)	1.10	(2.03)
var(Residual)	18.94	(.)	28.47***	(3.28)	28.09	(.)	37.00***	(2.74)
N	458		241		124		761	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 34: PCS - Random Slopes: South Regions

	Abruzzo		Molise		Campania		Puglia		Basilicata		Calabria	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part												
Constant	40.58***	(6.39)	88.94***	(10.21)	48.20***	(3.24)	47.16***	(2.90)	52.05***	(13.92)	49.53***	(5.81)
Subjective neighbourhood perception												
Neighbourhood Social Cohesion	0.51	(0.45)	2.27*	(1.04)	0.00	(0.27)	-0.13	(0.27)	0.16	(0.57)	-0.69	(0.48)
Neighbourhood Disorder	-2.47**	(0.80)	-3.48	(2.01)	-0.23	(0.26)	-0.55	(0.29)	-0.33	(0.63)	0.74	(0.52)
Gender												
Female	0.76	(1.26)	2.59	(1.51)	0.35	(0.61)	0.99	(0.59)	1.57	(1.26)	-1.73	(1.00)
Age												
25-34	0.28	(3.21)	-2.94	(3.88)	-0.13	(1.32)	-0.32	(1.28)	1.78	(4.50)	-0.26	(3.29)
35-54	-0.16	(3.11)	-11.21**	(3.90)	-0.77	(1.45)	-0.42	(1.33)	0.57	(4.61)	-0.62	(3.54)
55-64	-1.09	(3.37)	-12.91**	(4.42)	-3.98*	(1.57)	-1.19	(1.45)	-2.95	(4.60)	-1.29	(3.67)
65 and older	-2.75	(3.74)	-20.75***	(4.96)	-7.88***	(1.74)	-8.96***	(1.67)	-8.29	(4.99)	-7.23	(3.92)
Education												
Primary	6.96*	(3.16)	12.06***	(3.24)	4.75**	(1.68)	4.89***	(1.48)	17.52***	(2.22)	13.36***	(2.86)
Lower Secondary	14.31***	(2.94)	18.77***	(3.62)	5.35**	(1.64)	7.27***	(1.46)	14.45***	(2.80)	14.74***	(2.73)
Upper Secondary	13.92***	(3.02)	22.36***	(3.79)	5.26**	(1.71)	7.17***	(1.48)	15.05***	(2.63)	14.79***	(2.72)
Tertiary and Higher	14.01***	(3.35)	22.83***	(4.65)	5.42**	(1.83)	7.70***	(1.68)	16.01***	(2.99)	13.96***	(2.94)
Employment status												
Unemployed or looking for first job	0.34	(2.74)	-0.04	(3.24)	0.38	(0.92)	2.19*	(1.02)	-2.3	(2.19)	2.27	(1.51)
Homemaker	-3.56*	(1.71)	-0.71	(3.30)	-1.59	(0.84)	-0.34	(0.79)	-1.32	(1.55)	-0.92	(1.47)
Student	-0.87	(3.56)	0.05	(5.57)	-0.37	(1.40)	1.61	(1.40)	3.78	(6.00)	3.81	(3.12)
Retired	-4.70*	(2.05)	0.36	(3.39)	-1.42	(1.00)	-0.03	(1.04)	7.18***	(1.47)	-1.33	(1.81)
Unabe to work	-10.17***	(2.54)	-3.01	(7.03)	-16.42***	(2.74)	-16.11***	(2.61)	-3.44	(3.73)	-18.04***	(3.22)
Marital status												
Single	-0.01	(1.90)	1.02	(3.09)	-0.48	(1.32)	-1.10	(0.96)	-8.12*	(3.59)	-0.44	(2.02)
Divorced	-0.28	(3.32)	1.91	(4.10)	-0.53	(1.35)	1.00	(1.14)	-41.04***	(6.66)	-0.40	(2.48)
Widow/er	-1.42	(1.89)	6.99*	(3.07)	-4.43***	(1.07)	-5.24***	(1.02)	-7.49**	(2.28)	-2.21	(1.76)
Children												
Yes	0.66	(1.93)	5.55	(2.97)	0.08	(1.16)	0.84	(0.84)	-8.68**	(3.04)	-0.40	(1.92)
Chitizenship												
Foreign	-2.68	(2.46)	-2.13	(4.69)	4.34	(3.89)	4.21	(4.13)	5.10	(3.45)	2.87	(3.38)
Insomnia issues												
A little	-3.19*	(1.29)	-10.98***	(2.42)	-2.21***	(0.62)	-3.20***	(0.61)	-4.43**	(1.53)	-1.27	(1.03)
A lot	-7.90**	(2.94)	-10.28**	(3.21)	-7.15***	(1.05)	-8.48***	(1.18)	1.38	(2.32)	-8.51***	(1.91)
Household Deprivation												
Cluster 2	-1.48	(1.30)	-0.49	(2.84)	-0.92	(0.72)	0.41	(0.76)	4.10	(3.75)	-1.92	(1.13)
Cluster 3	1.90	(1.76)	-0.57	(2.31)	-2.75*	(1.24)	-1.06	(0.77)	-4.73	(3.44)	0.31	(1.85)
Cluster 4	-1.84	(7.90)	12.45**	(4.72)	-2.84	(2.28)	-2.36	(3.66)	0.84	(2.89)	-6.65*	(3.19)
Exogenous neighbourhood characteristics												
Low Education	15.18	(12.47)	-12.73	(22.47)	-1.45	(8.70)	2.60	(6.32)	70.45*	(31.40)	9.78	(11.62)
Unemployment	-9.33	(9.59)	-45.20*	(19.21)	-2.87	(3.96)	1.71	(4.13)	-41.09	(24.99)	-6.37	(5.90)
Rented Houses	10.83	(6.22)	9.15	(14.03)	-4.13	(2.34)	-0.71	(2.18)	30.61	(15.73)	2.25	(3.64)
Single Parents	-21.90	(13.52)	68.33*	(34.33)	5.06	(6.19)	4.59	(5.76)	-32.08	(36.51)	0.65	(4.65)
House Density	-0.13	(1.65)	-20.20***	(5.58)	1.48*	(0.63)	0.09	(0.61)	-8.28	(4.50)	-3.36*	(1.32)
Young Individuals	15.26	(15.02)	40.89	(28.99)	3.16	(6.11)	4.69	(5.72)	50.36	(42.68)	-1.01	(10.64)
Adverse Weather Conditions (days)	-0.02	(0.17)	0.48	(0.37)	0.42	(0.24)	-0.28	(0.36)	0.20	(0.39)	0.00	(0.07)
Random Part												
var(Household deprivation 2 at level-3)	0.00	(.)	0.00	(.)	3.10	(5.43)	9.03	(.)	73.91***	(48.07)	0.00	(.)
var(Household deprivation 3 at level-3)	0.00	(.)	0.00	(.)	24.02***	(12.15)	0.00	(.)	0.00	(.)	0.00	(.)
var(Household deprivation 4 at level-3)	138.92	(.)	0.00	(.)	34.68***	(28.59)	41.32	(.)	0.00	(0.00)	0.00	(.)
var(Constant level-3)	0.00	(.)	0.00	(.)	0.00***	(0.00)	0.00	(.)	64.37***	(18.19)	0.00	(.)
var(Constant level-2)	0.00	(.)	0.00	(.)	1.33	(3.18)	0.00	(.)	0.00	(0.00)	2.61	(.)
var(Residual)	38.57	(.)	21.65	(.)	37.94***	(3.52)	28.03	(.)	6.94***	(1.66)	40.21	(.)
N	175		68		690		513		87		261	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 35: PCS - Random Slopes: Isles

	Sicily		Sardinia	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	51.16***	(3.43)	34.81***	(6.58)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	-0.36	(0.44)	0.31	(0.57)
Neighbourhood Disorder	0.53	(0.38)	0.09	(1.13)
Gender				
Female	0.17	(0.76)	-1.83	(1.15)
Age				
25-34	0.07	(1.72)	1.85	(3.46)
35-54	-0.37	(1.70)	2.21	(3.60)
55-64	-1.19	(1.86)	0.54	(3.83)
65 and older	-6.05**	(2.14)	-1.58	(4.26)
Education				
Primary	3.56	(1.93)	14.44***	(3.48)
Lower Secondary	5.89**	(1.97)	17.94***	(3.68)
Upper Secondary	6.99***	(2.06)	18.60***	(3.78)
Tertiary and Higher	6.03**	(2.31)	19.40***	(3.98)
Employment status				
Unemployed or looking for first job	2.21*	(1.11)	-1.48	(1.78)
Homemaker	-0.54	(1.05)	-0.57	(1.86)
Student	2.29	(1.91)	3.00	(3.43)
Retired	-2.36	(1.33)	-4.94*	(2.09)
Unabe to work	-8.71**	(3.15)	-9.99*	(4.36)
Marital status				
Single	0.02	(1.30)	3.51	(2.60)
Divorced	1.75	(1.43)	2.78	(2.36)
Widow/er	-3.21*	(1.31)	6.94***	(2.08)
Children				
Yes	0.28	(1.11)	2.60	(2.39)
Chitizenship				
Foreign	1.29	(2.45)		
Insomnia issues				
A little	-3.92***	(0.76)	-0.15	(1.23)
A lot	-6.96***	(1.34)	-8.81***	(1.68)
Household Deprivation				
Cluster 2	-0.47	(1.01)	0.12	(1.25)
Cluster 3	-0.90	(1.02)	-3.59	(3.33)
Cluster 4	1.01	(3.05)	2.05	(4.24)
Exogenous neighbourhood characteristics				
Low Education	4.15	(8.00)	-7.00	(12.46)
Unemployment	-1.25	(4.34)	2.55	(7.78)
Rented Houses	-5.02	(3.33)	5.84	(6.01)
Single Parents	-2.72	(8.69)	-26.64	(14.69)
House Density	-0.40	(1.00)	0.42	(1.74)
Young Individuals	0.33	(9.08)	-8.13	(15.04)
Adverse Weather Conditions (days)	-0.06	(0.04)	0.57	(0.52)
Random Part				
var(Household deprivation 2 at level-3)	12.53***	(9.22)	0.00	(.)
var(Household deprivation 3 at level-3)	0.84	(7.67)	11.78	(.)
var(Household deprivation 4 at level-3)	27.36**	(30.24)	0.00	(.)
var(Constant level-3)	7.23***	(3.44)	0.00	(.)
var(Constant level-2)	0.00***	(0.00)	6.10	(.)
var(Residual)	34.92***	(3.59)	48.91	(.)
N	450		242	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 36: MCS - Random Slopes: North-West Regions

	Piedmont		Valle d'Aosta		Lombardy		Liguria	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	48.69***	(3.10)	69.06***	(12.19)	55.02***	(2.61)	51.86***	(3.34)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	0.72*	(0.30)	-1.35	(1.79)	1.02***	(0.20)	0.81	(0.42)
Neighbourhood Disorder	-1.07***	(0.28)	2.85*	(1.20)	-0.43	(0.25)	1.03*	(0.48)
Gender								
Female	-0.07	(0.43)	-1.12	(1.31)	-0.61	(0.35)	0.01	(0.53)
Age								
25-34	-1.39	(1.21)	-6.62	(5.90)	-2.08	(1.06)	0.82	(1.67)
35-54	-2.26	(1.29)	-8.79	(6.10)	-3.76***	(1.05)	-1.02	(1.85)
55-64	-2.63	(1.40)	-12.36*	(5.99)	-5.17***	(1.13)	-1.50	(1.88)
65 and older	-3.22	(1.65)	-11.02	(6.74)	-4.66***	(1.33)	-1.40	(2.12)
Education								
Primary	4.74*	(2.00)	-2.02	(4.58)	-1.18	(1.75)	0.00	(.)
Lower Secondary	6.37**	(1.95)	-4.04	(4.96)	1.03	(1.74)	1.35	(1.04)
Upper Secondary	6.23**	(1.96)	-3.79	(5.41)	1.37	(1.76)	1.75	(1.08)
Tertiary and Higher	7.14***	(2.07)	-4.13	(5.78)	1.36	(1.83)	0.94	(1.33)
Employment status								
Unemployed or looking for first job	-1.46	(1.12)	-3.10	(3.85)	-2.82**	(0.91)	-4.17*	(1.67)
Homemaker	-2.32*	(0.94)	-0.28	(2.38)	-1.82*	(0.72)	-0.46	(1.19)
Student	0.12	(1.32)	-6.78	(6.29)	-1.54	(1.14)	-0.52	(1.61)
Retired	-0.42	(1.02)	-2.40	(2.60)	0.65	(0.78)	-1.29	(1.33)
Unabe to work	-4.99	(5.87)	-11.94*	(5.01)	-1.20	(3.59)	6.71*	(3.23)
Marital status								
Single	-1.17	(0.79)	-0.84	(2.57)	-1.32*	(0.62)	0.10	(1.07)
Divorced	-0.14	(1.01)	-1.74	(3.38)	-1.05	(0.67)	-0.02	(1.12)
Widow/er	-0.87	(1.03)	1.74	(2.02)	-1.34	(0.72)	0.38	(1.12)
Children								
Yes	0.75	(0.66)	3.67	(2.20)	0.57	(0.54)	0.45	(0.89)
Chitizenship								
Foreign	1.96	(1.38)	-3.11	(2.44)	2.31*	(1.01)	-0.52	(1.91)
Insomnia issues								
A little	-3.01***	(0.58)	-14.30***	(2.50)	-3.03***	(0.42)	-3.55***	(0.81)
A lot	-12.95***	(1.07)			-9.27***	(0.87)	-10.64***	(1.36)
Household Deprivation								
Cluster 2	-2.08	(1.13)	1.64	(2.70)	-2.71***	(0.76)	-1.74	(1.29)
Cluster 3	-0.88	(1.48)	-10.77*	(4.26)	-2.61*	(1.15)	-9.57***	(2.26)
Cluster 4	-7.81*	(3.77)	1.67	(5.64)	-7.24***	(1.58)	-9.48**	(3.20)
Exogenous neighbourhood characteristics								
Low Education	9.01	(6.77)	-1.46	(16.58)	5.57	(5.39)	-26.95	(14.27)
Unemployment	2.55	(4.35)	-47.48	(24.23)	1.55	(6.12)	13.69	(11.91)
Rented Houses	0.02	(2.36)	-5.67	(4.60)	0.53	(1.40)	-2.53	(3.34)
Single Parents	-10.05	(8.07)	13.97	(19.14)	-2.61	(5.49)	16.37	(9.40)
House Density	0.10	(0.85)	0.11	(2.51)	0.74	(0.61)	0.74	(1.10)
Young Individuals	3.97	(7.81)	-8.05	(14.27)	-2.63	(5.22)	8.23	(10.44)
Adverse Weather Conditions (days)	-0.02	(0.11)	-0.21	(0.24)	-0.05	(0.05)	-0.07	(0.14)
Random Part								
var(Household deprivation 2 at level-3)	23.94***	(10.47)	0.00	(.)	11.09***	(6.31)	10.28**	(8.46)
var(Household deprivation 3 at level-3)	24.43***	(15.66)	0.00	(.)	0.46	(8.46)	7.79	(16.81)
var(Household deprivation 4 at level-3)	40.08**	(45.81)	0.00	(.)	0.00*	(0.00)	0.66	(19.75)
var(Constant level-3)	7.41***	(2.21)	0.00	(.)	5.79***	(1.73)	0.00	(0.00)
var(Constant level-2)	3.41*	(1.92)	0.00	(.)	3.47*	(2.05)	7.64***	(2.66)
var(Residual)	20.85***	(1.75)	17.74	(.)	26.09***	(1.77)	10.04***	(1.78)
N	626		75		1160		239	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 37: MCS - Random Slopes: North-East Regions

	Trentino Alto Adige		Veneto		Friuli-Venezia Giulia		Emilia-Romagna	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	62.73***	(6.56)	51.01***	(2.97)	49.73***	(8.78)	60.67***	(4.52)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	1.19*	(0.53)	0.84**	(0.27)	-0.64	(0.43)	1.01***	(0.29)
Neighbourhood Disorder	-0.88	(0.59)	-1.20**	(0.37)	0.17	(0.48)	0.43	(0.48)
Gender								
Female	0.21	(0.71)	-0.02	(0.37)	0.76	(0.52)	-0.86*	(0.40)
Age								
25-34	-2.40	(3.11)	0.75	(1.05)	1.57	(1.91)	-1.71	(1.43)
35-54	-2.67	(3.39)	0.38	(1.08)	1.05	(2.05)	-2.55	(1.46)
55-64	-2.96	(3.52)	-0.26	(1.19)	-0.60	(2.16)	-5.34***	(1.58)
65 and older	-3.49	(3.79)	-1.06	(1.33)	-1.86	(2.31)	-5.38**	(1.91)
Education								
Primary	-7.49	(5.50)	0.45	(2.19)	0.00	(.)	-0.80	(4.11)
Lower Secondary	-9.65	(5.32)	0.95	(2.16)	-0.81	(1.12)	-0.48	(3.88)
Upper Secondary	-9.36	(5.41)	1.72	(2.18)	-0.68	(1.18)	-0.62	(3.89)
Tertiary and Higher	-7.24	(5.52)	3.43	(2.26)	-0.71	(1.47)	-0.77	(3.94)
Employment status								
Unemployed or looking for first job	-7.61	(4.87)	-2.46*	(1.24)	-11.21***	(1.91)	-3.30*	(1.29)
Homemaker	0.20	(1.67)	0.22	(0.72)	-3.88**	(1.23)	-1.87	(1.02)
Student	-0.46	(3.17)	1.09	(1.07)	0.29	(1.85)	-1.03	(1.47)
Retired	-2.59	(1.56)	0.91	(0.73)	-0.41	(1.15)	-0.05	(1.24)
Unabe to work	-13.07*	(6.56)	-2.21	(2.20)			-11.37*	(5.54)
Marital status								
Single	-0.84	(1.47)	0.71	(0.66)	-1.35	(0.98)	-1.34	(0.77)
Divorced	3.51	(2.02)	-0.79	(0.75)	-3.69**	(1.29)	0.29	(0.90)
Widow/er	0.78	(1.83)	-1.56*	(0.79)	2.53*	(1.23)	-3.37**	(1.08)
Children								
Yes	0.86	(1.22)	0.81	(0.55)	-0.78	(0.83)	-0.85	(0.71)
Chitizenship								
Foreign	-6.28*	(2.62)	0.06	(1.18)	-0.80	(1.84)	0.31	(1.88)
Insomnia issues								
A little	-5.52***	(0.80)	-2.19***	(0.43)	-3.99***	(0.68)	-2.35***	(0.52)
A lot	-16.11***	(2.06)	-11.29***	(1.12)	-8.72*	(3.76)	-9.17***	(1.06)
Household Deprivation								
Cluster 2	-1.4	(1.13)	-1.81*	(0.80)	-3.18*	(1.28)	-4.02***	(1.14)
Cluster 3	-17.57***	(4.43)	-3.73*	(1.84)	-1.42	(2.82)	-6.39*	(2.62)
Cluster 4	5.95	(4.96)	0.63	(2.83)		(7.03)	-0.97	(2.10)
Exogenous neighbourhood characteristics								
Low Education	1.71	(12.13)	-8.19	(5.33)	4.97	(9.76)	5.72	(4.15)
Unemployment	3.75	(14.98)	9.26*	(4.21)	-11.81	(2.47)	1.99	(4.28)
Rented Houses	1.55	(3.01)	-0.18	(1.66)	1.28	(8.54)	4.03*	(1.83)
Single Parents	1.22	(6.08)	-3.81	(3.68)	20.08*	(1.15)	-6.12	(6.23)
House Density	0.98	(1.02)	1.34	(0.71)	0.90	(8.45)	-1.61*	(0.76)
Young Individuals	0.16	(9.42)	-13.43**	(5.02)	16.82*	(0.08)	8.87	(6.05)
Adverse Weather Conditions (days)	-0.04	(0.10)	-0.06	(0.06)	0.02	(3.81)	-0.03	(0.09)
Random Part								
var(Household deprivation 2 at level-3)	0.00	(0.00)	4.31	(5.29)	13.92***	(0.00)	1.59	(8.00)
var(Household deprivation 3 at level-3)	14.23	(34.70)	15.53**	(14.27)	0.00	(2.55)	0.00	(.)
var(Household deprivation 4 at level-3)	0.00	(0.00)	0.00	(.)			0.00	(0.00)
var(Constant level-3)	3.07	(5.01)	6.25***	(2.22)	5.51***	(0.00)	5.33**	(3.05)
var(Constant level-2)	0.00***	(0.00)	0.27	(2.44)	0.00***	(1.44)	9.68***	(3.20)
var(Residual)	19.17***	(9.15)	17.73***	(1.62)	8.99***		14.07***	(1.43)
N	201		706		203		555	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 38: MCS - Random Slopes: Center Regions

	Tuscany		Marche		Umbria		Lazio	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part								
Constant	56.30***	(3.59)	59.37***	(5.93)	47.77***	(9.28)	56.56***	(3.31)
Subjective neighbourhood perception								
Neighbourhood Social Cohesion	0.47	(0.31)	0.6	(0.41)	2.35**	(0.81)	1.12***	(0.34)
Neighbourhood Disorder	0.06	(0.48)	0.27	(0.71)	-2.11**	(0.75)	-0.53*	(0.22)
Gender								
Female	-1.82***	(0.53)	1.24	(0.71)	-5.31***	(1.39)	-0.59	(0.49)
Age								
25-34	-0.16	(1.27)	-0.48	(2.50)	0.82	(3.72)	-0.49	(1.34)
35-54	-0.56	(1.33)	-2.13	(2.64)	-3.15	(3.69)	-1.34	(1.38)
55-64	-2.86	(1.50)	-2.16	(2.75)	-1.72	(4.02)	-1.03	(1.53)
65 and older	-1.08	(1.82)	-0.66	(3.00)	-1.75	(4.68)	-1.87	(1.79)
Education								
Primary	-0.20	(2.20)	-1.56	(3.69)	-0.73	(6.37)	-2.49	(2.32)
Lower Secondary	-1.7	(2.23)	-2.90	(3.77)	-1.91	(6.14)	-1.68	(2.26)
Upper Secondary	-1.77	(2.27)	-2.83	(3.76)	0.82	(6.34)	-1.89	(2.31)
Tertiary and Higher	-1.2	(2.43)	-2.67	(3.82)	0.15	(6.45)	-1.28	(2.38)
Employment status								
Unemployed or looking for first job	-1.52	(1.11)	4.68	(3.70)	4.10	(3.11)	-1.00	(0.98)
Homemaker	0.96	(1.09)	-1.44	(1.49)	1.02	(2.79)	-1.01	(0.87)
Student	-0.71	(1.35)	-0.40	(2.32)	2.49	(3.61)	-0.42	(1.43)
Retired	0.72	(1.19)	-2.40	(1.39)	-3.21	(2.71)	-2.06	(1.15)
Unabe to work	2.78	(5.62)	-15.15**	(5.09)	-6.64	(5.66)	-3.36	(2.65)
Marital status								
Single	-1.19	(0.92)	0.45	(1.37)	0.35	(3.25)	-1.68*	(0.83)
Divorced	-2.19	(1.12)	-2.43	(2.03)	-2.67	(2.66)	-1.73	(0.99)
Widow/er	-4.03***	(1.07)	-3.77**	(1.44)	1.47	(3.61)	-0.77	(1.30)
Children								
Yes	-0.21	(0.83)	-0.38	(1.11)	1.72	(2.71)	-0.65	(0.70)
Chitizenship								
Foreign	-1.11	(2.10)	4.66*	(2.35)	-2.91	(3.20)	3.06**	(1.12)
Insomnia issues								
A little	-3.58***	(0.65)	-3.42***	(0.90)	-1.50	(1.70)	-2.99***	(0.54)
A lot	-12.04***	(1.20)	-9.13***	(2.07)	4.43	(3.88)	-9.13***	(1.09)
Household Deprivation								
Cluster 2	0.79	(1.01)	-7.03**	(2.71)	2.58	(2.98)	-1.95*	(0.96)
Cluster 3	-12.25*	(5.61)	1.48	(3.48)	1.69	(2.66)	-3.77*	(1.49)
Cluster 4	-10.26	(5.30)	-3.12	(2.99)	5.33	(5.10)	-6.48*	(2.59)
Exogenous neighbourhood characteristics								
Low Education	-2.92	(8.79)	-17.23	(9.44)	-13.19	(22.47)	7.41	(8.33)
Unemployment	-6.38	(7.79)	1.29	(7.63)	-7.19	(13.19)	-2.32	(4.47)
Rented Houses	1.25	(2.86)	-1.49	(3.96)	-0.69	(6.56)	2.59	(1.86)
Single Parents	-1.12	(7.19)	-2.27	(7.07)	-2.52	(19.77)	-0.78	(4.39)
House Density	0.89	(0.99)	0.65	(1.18)	4.92*	(2.46)	-0.5	(0.79)
Young Individuals	-0.39	(8.24)	0.23	(9.37)	-0.40	(20.07)	7.94	(6.60)
Adverse Weather Conditions (days)	0.05	(0.13)	-0.33	(0.27)	-0.60	(0.32)	0.07	(0.14)
Random Part								
var(Household deprivation 2 at level-3)	0.00	(.)	65.75***	(38.93)	0.00	(.)	15.00***	(10.02)
var(Household deprivation 3 at level-3)	0.00	(.)	15.45	(43.84)	0.00	(.)	0.00	(0.00)
var(Household deprivation 4 at level-3)	0.00	(.)	0.00	(0.00)	13.35	(.)	32.96***	(30.77)
var(Constant level-3)	17.33	(.)	2.55	(2.71)	0.00	(.)	14.46***	(5.71)
var(Constant level-2)	0.00	(.)	0.00	(0.00)	0.00	(.)	2.72	(5.62)
var(Residual)	19.77	(.)	21.32***	(3.15)	42.57	(.)	29.02***	(2.28)
N	458		124		241		761	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 39: MCS - Random Slopes: South Regions

	Abruzzo		Molise		Campania		Puglia		Basilicata		Calabria	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part												
Constant	42.26***	(6.57)	32.28**	(10.27)	55.50***	(3.13)	54.40***	(2.96)	48.21***	(10.90)	51.57***	(5.80)
Subjective neighbourhood perception												
Neighbourhood Social Cohesion	0.75	(0.46)	0.13	(1.03)	0.48	(0.26)	1.26***	(0.27)	1.11	(0.62)	1.90***	(0.49)
Neighbourhood Disorder	-1.86*	(0.82)	1.83	(1.90)	-0.30	(0.25)	-1.70***	(0.30)	0.44	(0.69)	-0.29	(0.52)
Gender												
Female	-1.39	(1.28)	0.92	(1.32)	-0.18	(0.57)	-0.44	(0.59)	-0.12	(1.32)	-1.06	(0.96)
Age												
25-34	-1.31	(3.30)	3.93	(3.34)	-2.70*	(1.23)	-0.89	(1.28)	7.75	(5.09)	3.47	(3.14)
35-54	1.47	(3.19)	1.67	(3.38)	-4.91***	(1.36)	-1.79	(1.33)	5.63	(5.26)	4.60	(3.40)
55-64	0.87	(3.47)	0.40	(3.87)	-5.91***	(1.49)	-2.02	(1.46)	0.81	(5.13)	3.92	(3.54)
65 and older	3.87	(3.84)	-5.97	(4.47)	-6.01***	(1.65)	-2.98	(1.68)	0.44	(5.42)	5.21	(3.81)
Education												
Primary	7.94*	(3.22)	2.83	(2.77)	1.55	(1.59)	2.57	(1.50)	2.62	(2.59)	3.61	(2.84)
Lower Secondary	5.83	(3.02)	3.18	(3.19)	1.68	(1.55)	4.23**	(1.50)	1.61	(2.95)	2.93	(2.69)
Upper Secondary	7.17*	(3.10)	2.31	(3.44)	2.15	(1.62)	2.97	(1.52)	6.21*	(2.85)	2.85	(2.68)
Tertiary and Higher	9.56**	(3.44)	1.42	(4.12)	3.28	(1.74)	3.71*	(1.71)	2.81	(3.19)	2.05	(2.89)
Employment status												
Unemployed or looking for first job	-0.82	(2.80)	-0.01	(2.96)	-1.68	(0.87)	-1.51	(1.03)	0.72	(2.33)	-1.83	(1.48)
Homemaker	-0.33	(1.74)	-5.27	(2.80)	-0.36	(0.79)	0.77	(0.79)	-4.29**	(1.57)	-1.57	(1.44)
Student	-2.08	(3.65)	-4.33	(4.33)	-0.25	(1.31)	-0.38	(1.40)	9.14	(6.96)	2.14	(2.99)
Retired	-4.40*	(2.06)	3.67	(2.73)	-1.71	(0.94)	0.44	(1.03)	-0.21	(1.68)	-2.52	(1.75)
Unabe to work	-5.27*	(2.60)	-24.30***	(6.29)	-9.82***	(2.54)	-12.78***	(2.58)	-9.10*	(4.44)	-6.95*	(3.13)
Marital status												
Single	-2.89	(1.95)	4.12	(2.79)	-1.15	(1.27)	0.84	(0.97)	-5.12	(3.33)	-3.47	(2.02)
Divorced	-2.39	(3.11)	3.08	(3.70)	-2.20	(1.27)	-2.67*	(1.15)	-2.44	(6.66)	-4.42	(2.44)
Widow/er	-0.11	(1.94)	5.50	(2.94)	0.51	(1.01)	-3.36***	(1.02)	-2.31	(2.38)	-2.48	(1.73)
Children												
Yes	-2.62	(1.98)	0.13	(2.76)	-0.05	(1.12)	0.56	(0.85)	-4.34	(2.83)	-4.47*	(1.93)
Chitizenship												
Foreign	1.45	(2.51)	3.37	(4.42)	0.55	(3.84)	-1.61	(4.07)	-2.51	(3.25)	-0.62	(3.33)
Insomnia issues												
A little	-8.03***	(1.31)	-0.02	(2.22)	-3.45***	(0.58)	-6.18***	(0.62)	-2.73	(1.59)	-3.03**	(1.00)
A lot	-14.97***	(3.02)	-10.27***	(2.80)	-12.43***	(1.00)	-12.94***	(1.18)	-9.51***	(2.42)	-12.91***	(1.90)
Household Deprivation												
Cluster 2	1.32	(1.33)	-2.16	(3.57)	-1.11	(0.73)	-0.67	(0.75)	2.57	(1.83)	-0.20	(1.14)
Cluster 3	-1.40	(1.81)	-1.54	(2.13)	-2.77*	(1.25)	-2.33**	(0.86)	-1.27	(2.65)	-7.54*	(3.13)
Cluster 4	-1.75	(3.48)	-0.30	(4.54)	-5.56**	(1.85)	-5.65*	(2.23)	-6.35*	(3.13)	-1.04	(3.15)
Exogenous neighbourhood characteristics												
Low Education	-3.37	(12.81)	42.6	(23.06)	1.23	(8.44)	-1.33	(6.59)	26.87	(21.25)	-6.53	(12.33)
Unemployment	16.85	(9.86)	30.69	(20.10)	-2.71	(3.83)	-8.84*	(4.26)	-4.12	(17.09)	-5.11	(6.16)
Rented Houses	4.12	(6.37)	6.50	(13.60)	-0.82	(2.26)	-0.35	(2.28)	8.22	(10.93)	3.21	(3.73)
Single Parents	22.39	(13.89)	-43.63	(39.35)	0.37	(6.02)	13.38*	(6.03)	-26.41	(24.84)	-0.14	(4.88)
House Density	1.88	(1.70)	5.91	(5.90)	0.44	(0.61)	0.14	(0.63)	0.84	(3.14)	1.11	(1.38)
Young Individuals	-11.27	(15.43)	-89.86**	(31.44)	4.58	(5.94)	-6.84	(5.90)	-20.57	(30.14)	-12.59	(11.10)
Adverse Weather Conditions (days)	-0.12	(0.18)	0.57	(0.37)	0.19	(0.23)	-0.51	(0.37)	-0.36	(0.37)	-0.01	(0.07)
Random Part												
var(Household deprivation 2 at level-3)	0.00	(.)	29.42	(.)	6.10*	(4.38)	7.58**	(5.37)	0.00	(.)	0.00	(.)
var(Household deprivation 3 at level-3)	0.00	(.)	0.00	(.)	28.02***	(13.01)	4.72	(5.79)	0.00	(.)	52.99	(.)
var(Household deprivation 4 at level-3)	0.00	(.)	0.00	(.)	17.26**	(16.28)	0.00	(0.00)	0.00	(.)	0.00	(.)
var(Constant level-3)	0.00	(.)	0.00	(.)	0.00***	(0.00)	1.36	(2.01)	24.38	(.)	2.75	(.)
var(Constant level-2)	0.00	(.)	5.86	(.)	2.32	(2.47)	0.00***	(0.00)	0.00	(.)	3.51	(.)
var(Residual)	40.82	(.)	11.63	(.)	32.16***	(2.66)	26.31***	(2.43)	10.8	(.)	34.29	(.)
N	175		68		690		513		87		261	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 40: MCS - Random Slopes: Isles

	Sicily		Sardinia	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Fixed Part				
Constant	64.96***	(3.64)	65.49***	(5.81)
Subjective neighbourhood perception				
Neighbourhood Social Cohesion	0.92*	(0.46)	0.62	(0.49)
Neighbourhood Disorder	-0.73	(0.41)	0.33	(1.01)
Gender				
Female	-1.26	(0.77)	0.06	(0.95)
Age				
25-34	-0.62	(1.79)	-4.81	(2.92)
35-54	-3.29	(1.76)	-5.23	(3.03)
55-64	-6.35**	(1.95)	-6.85*	(3.22)
65 and older	-5.72*	(2.26)	-8.12*	(3.57)
Education				
Primary	-3.61	(2.02)	0.72	(2.86)
Lower Secondary	-1.58	(2.10)	0.53	(3.07)
Upper Secondary	-0.89	(2.19)	0.47	(3.15)
Tertiary and Higher	0.64	(2.45)	-1.69	(3.32)
Employment status				
Unemployed or looking for first job	-2.31*	(1.16)	-4.61**	(1.46)
Homemaker	0.95	(1.08)	-3.56*	(1.54)
Student	-2.63	(1.98)	-6.81*	(2.89)
Retired	-0.15	(1.38)	-1.69	(1.76)
Unabe to work	-1.07	(3.20)	-1.64	(3.58)
Marital status				
Single	-2.01	(1.43)	-0.81	(2.23)
Divorced	2.34	(1.52)	-1.59	(2.05)
Widow/er	-5.17***	(1.41)	-0.25	(1.74)
Children				
Yes	-1.23	(1.24)	-0.65	(2.02)
Chitizenship				
Foreign	3.12	(2.76)		
Insomnia issues				
A little	-4.09***	(0.79)	-3.92***	(1.02)
A lot	-8.04***	(1.42)	-6.59***	(1.40)
Household Deprivation				
Cluster 2	0.46	(1.10)	0.33	(1.02)
Cluster 3	-1.57	(1.17)	-2.48	(3.41)
Cluster 4	-11.46**	(3.67)	-2.68	(3.52)
Exogenous neighbourhood characteristics				
Low Education	-8.19	(8.86)	1.17	(12.63)
Unemployment	4.01	(4.87)	-12.7	(7.69)
Rented Houses	-2.32	(3.70)	-5.41	(5.47)
Single Parents	-5.20	(9.73)	-26.68*	(13.45)
House Density	-0.65	(1.11)	1.12	(1.68)
Young Individuals	-0.23	(10.06)	5.73	(13.93)
Adverse Weather Conditions (days)	-0.10**	(0.04)	0.26	(0.48)
Random Part				
var(Household deprivation 2 at level-3)	8.54	(.)	0.00	(.)
var(Household deprivation 3 at level-3)	0.00	(.)	29.88	(.)
var(Household deprivation 4 at level-3)	43.99	(.)	0.00	(.)
var(Constant level-3)	0.00	(.)	8.6	(.)
var(Constant level-2)	17.79	(.)	0.00	(.)
var(Residual)	32.45	(.)	32.59	(.)
N	450		242	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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