**UNIVERSITY OF MILANO-BICOCCA**

Department of Economics, Management and Statistics (DEMS)

Ph.D program: Ph.D in Economics, DEFAP-Bicocca
Cycle: XXXI

**Thesis Title : Essays on Dynamics of Inequality In Undernutrition, and Impact of Social Protection Program On Nutrition and Educational Attainment In Ethiopia**

Surname: Negasi

Name: Mengesha Yayo

Matricola / Registration number: 811395
Tutor: Prof. Matteo Manera

Supervisor: Prof. Mariapia Mendola

Coordinator: Prof. Matteo Manera

**ACADEMIC YEAR : 2017/18**

## Dedication

Though I am not lucky to have her alive and see my success, I would like to dedicate this accomplishment to my beloved Mother, Belaynesh Kebede Tefera who sacrificed her entire life to educate her children.

## Acknowledgment

*Let me take a moment of praise to the Almighty GOD for solving all the obstacles I faced, sending miracles and bringing me up to this point in my life. Glory to His Mother Holy Virgin Mary who has been a shed all the way here. I thank the Holy Angels, Holy Fathers and Holy Martyrs for helping me with my problems.*

*Next, I would like to thank the Department of Economics, Management and Statistics (DEMS), University of Milano-Bicocca, and Catholic University of Milan for granting me the scholarship and giving me the opportunity to pursue my PhD. Doctoral school of University of Milano-Bicocca and DEFAP administrative staffs also deserve special thanks for their kind assistance during my stay in Milan.*

*I would like to express my sincere gratitude to my supervisor, Prof. Mariapia Mendola for all her patience and solid advice in the course of this dissertation which contribute a lot to the quality of this thesis. My special thank also goes to Prof. Matteo Manera, Cordinator of Ph.D program (DEFAP) at University of Milano-Bicocca, and Prof. Gianluca Femminis, Director of DEFAP at Catholic University of Milan for their generous support and advise which enabled me to accomplish the study properly. I also thank Prof, Massimiliano Bratti and Prof. Flaviana Palmisano for their valuable comments and suggestions. Their advice has helped me to improve the dissertation a lot. I also extend gratitude to various offices in Ethiopia such as Ministry of Agriculture (Food Security Directorate), Ministry of Health, Ministry of Finance and Economic Cooperation, Central Statistical Agency, Ministry of Education, Disaster Prevention and Preparedness Commission (DPPC) for the information and material support they provided me which made me capable to perform this dissertation accordingly.*

*I would like to provide my paramount thanks to my family, friends and colleagues who have continued to support and encourage me over the last few years which was the pillar of my strength for the completion of this work. A special appreciation goes to my Mother Belaynesh Kebede. Her kindness, love, strength and commitment to educate her children alone has been source of inspiration, courage, and the core to my academic career. I am also particularly thankful to my beloved friends Getachew Yirga Belete (Wemenew), Mulugeta Ayehu Asnake (Mule- Grand Dige), Belete Hailu Demissie (Bele- Great Dige), and Nika Bekiri for their special involvement in my life, rentless follow up, support, inspiring me, strongly stand beside me in the difficult time of my life. I love you so much. I would like also forward my gratitude to my Ethiopian Ph.D colleagues in Milan as you sit beside me, especially while I lost my beloved mother in the mid of my study. It was the hardest time of my life.*

Mengesha Yayo Negasi

Milan, Italy

# Contents

**Essays on Dynamics of Inequality In Undernutrition, and Impact of Social Protection Program on Nutrition and Educational Attainment In Ethiopia**

**Summary**

Child malnutrition continues to be the leading public health problem in developing countries. Undernutrition among children is a critical problem because its effects are long lasting and go beyond childhood. It has both short- and long-term consequences (Glewwe, 2007; Abuya, 2012). Ethiopia has the second highest rate of malnutrition in Sub-Saharan Africa (SSA). The country faces the four major forms of malnutrition: acute and chronic malnutrition, iron deficiency anaemia, vitamin A deficiency, and iodine deficiency disorder (UNICEF, 2017). Although Ethiopia has already achieved a remarkable progress in reducing under-five mortality in the last decades, undernutrition among children is still a common problem in this country. Undernutrition can best be described in the country as a long-term year-round phenomenon due to chronic inadequacies in food combined with high levels of illness in under-five children. Thus, socioeconomic inequalities in health outcomes have been of focus in academia and policy spheres for a while now. Most of the existing empirical evidences on inequalities in child health outcomes are using cross -sectional such as DHS data and various national survey. However, the growing number of countries with longitudinal data sets comprising socioeconomic and health related information has stimulated the development and refinement of different approaches to the measurement of health inequalities. It implies that we need more sophisticated approaches to monitor inequalities and design appropriate policy interventions because longitudinal measures are required to determine the incidence and effectiveness of interventions designed to tackle such health inequalities in the population.

In the first chapter of this thesis, we thus provide a more policy-relevant measure of inequality taking a longitudinal perspective to analyze dynamics of child undernutrition inequalities in Ethiopia, focusing only on children under five age. We use three round of household panel survey ( 2011/12, 2013/14 and 2015/16) from the Ethiopia Socioeconomic Survey (ESS) collected by the World Bank in collaboration with the country's Central Statistical Agency (CSA) as Living Standards Measurement Study, LSMS. For measuring the static and dynamic socioeconomic status (SES) related- child malnutrition inequalities, we employ different methods, starting from simple measurement like absolute and relative inequalities from rate differences and rate ratios to multiple measures of inequalities, using concentration indices and various alternative extensions. For dynamics of inequalities in child undernutrition, we use both Jones and Lopez (2004), and Allanson et al. (2010) approach to compute both health-related SES

mobility indices and SES-related health mobility indices. Estimation of concentration index and inference is via-regression approach using user-written stata command conindex developed by O'Donnell et.al (2016). For our decomposition results, we employ both random and fixed effect estimator. Batteries of sensitivity analyses are then conducted for robustness of our results. The key results of this study show that inequality in undernutrition varies while we use different socioeconomic status (SES) indicators (such as wealth index and consumption), i.e relatively higher inequality is observed in case of consumption as SES ranking variable. Results on inequality using spatial aspect signify that significant difference in inequality of undernutrition is shown across regions. In terms of dynamics inequality, persistence of inequality in undernutrition-stunting is seen. Our inequality results are robust to different measurement scale, inequality aversion parameters/distributional sensitivity parameters, symmetric concentration index or 'sensitivity to extremity. Those results are also standardized for age and gender. Results on decomposition of inequalities show that the major contributors are wealth index, consumption and mother's education. Those imply that in both socioeconomic status ranking variables, the bulk of inequality in malnutrition is caused by inequality in socioeconomic status in which it disfavors the poor in both cases. This calls for enhancing the policy measures that narrow socioeconomic gaps between groups in the population and targeting on early childhood intervention and nutrition sensitive.

Since nutrition is the best indicator of quality of human capital of a country, fighting for chronic malnutrition is recognized as the foundations of social and economic development. However, addressing those children health related problems in Africa have been thus a serious challenge given its uneven distribution. As a remedy, social protection measures are increasingly seen as an indispensable policy tool for African governments to tackle poverty and socioeconomic related health outcome disparity. Hence, the second chapter of this thesis focus on impact of social protection program on nutrition and educational attainment. Social protection programs, which include cash transfers and social support services, are increasingly implemented as a key policy tool for reducing poverty and increasing the accumulation of human capital in developing regions, including Africa. In 2005, the Ethiopian Government launched its social protections program, which is one of the largest in the region. The Productive Safety Nets Programme (PSNP) was introduced by joint efforts of the Government of Ethiopia and international donors through a multi-trust fund managed by the World Bank (Ministry of Agriculture and Natural Resource, 2015). The overall goal of the program is to provide a long-term solution to the chronically food insecure households found in poor regions in Ethiopia, which is the second country with the highest rate of malnutrition in Sub Saharan Africa. Malnutrition and starvation have devastating impact on children, adults and especially on pregnant women.

They also have severe and far-reaching socio-economic impacts, in terms of low human capital, productivity and well-being (World Bank, 2010).

The PSNP was first targeted to five major regions in Ethiopia, while later on it scaled up to the rest of the country. This program included both cash-for-work, cash-for-food as well as other welfare (assistance) measures. As of 2005, the PSNP was designed to address food insecurity by providing transfers to over 5.5 million targeted beneficiaries throughout the country. The programme has completed three phases now and it is currently under its fourth phase to last until 2020. To date PSNP reached over 10 million rolling rural poor and vulnerable beneficiaries, hence being the second largest safety net programme in Africa, after South Africa. The question of whether social protection programs, by reducing poverty through transfers, improve nutrition, food security and human capital accumulation, especially of children, is a long lasting concern for both development economists and policy makers (Hanna and Olken, 2008; World Bank 2010).

For our empirical analysis, from Ethiopian Demographic Household Survey (DHS) various rounds, we use a large individual-level data set on native-born males and females from all over the country to construct a panel data of cohorts by birth year and birthplace. Hence, we build a year-of-birth-varying indicator of childhood exposure to the program, i.e. our 'treatment dummy', which we then interact with program intensity indicators at the regional level. Our research design combines differences in program intensity across regions with differences across cohorts induced by the timing of the program. In our difference-in-difference estimation strategy, identification comes both from individual's spatial variation and time variation in the year of birth, while controlling for systematic variation across regions and cohorts through fixed effects. Indeed, being born after the program and in areas with higher intensity treatment implies more benefits from exposure to the program. A similar strategy has been used to estimate the effect of school quantity on (returns to) education in Indonesia (Duflo, 2001) and the effect of big health improvement programs such as malaria eradication on labor productivity in North ans South America (Bleakely, 2010).

Our findings show that exposure to the PSNP led to an increase in both Heigh-for-age Z-scores (HAZ) and primary educational attainment as measures by years of schooling. On average, one extra million Birr PSNP budget (about 35,000USD) allocated per 1000 children in birth regions increases child height-for-age Z-score by 0.1. As a result, an increase in the intensity of the program increase completed years of primary schooling by about 0.7. Results, which are robust to different ways in measuring program intensity and different estimation sample, seem to be increasing with the time of exposure (i.e. measured by year of birth and age). The estimation of fully flexible models in years of birth or age ensures the non-violation of common trend assumptions. Moreover, results of some placebo tests performed using only pre-program cohorts suggests that results can be interpreted as causal.

**Dymanics of Inequality In Child Undernutrition In Ethiopia**

**(CHAPTER ONE)**

**This version:** ***March 2019***

Mengesha Yayo Negasi *

Ph.D in Economics, DEFAP

University of Milano-Bicocca, Italy

*Ph.D student (DEPAF) at University of Milano-Bicocca. Email: ymanga28@gmail.com

## Abstract

Although Ethiopia has already achieved a remarkable progress in reducing under-five mortality in the last decades, undernutrition among children is still a common problem in this country. Socioeconomic inequalities in health outcomes in Ethiopia have been thus of focus in academia and policy spheres for a while now. This study provides new evidence on child undernutrition inequalities in Ethiopia using longitudinal perspective. Using three round of household panel survey, we use concentration index (associated curve), different mobility index approaches for measuring inequalities and its dynamics, and decomposition method to identify contributing factors. In all concentration index computing approaches and Socioeconomic Status (SES) ranking variables, the concentration indices are significant with negative value. This implies that in either of short-run or long-run inequality estimates, the burden of unequal distribution of undernutrition remains on the poor with significant difference across regions. While employing different SES ranking variables, the difference in the concentration indices is only found significant in case of Height-for-age Z-score (HAZ). Using standard method, for example, in HAZ, -0.040 and -0.070 of concentration index (CI) for wealth index and consumption are scored respectively. It signifies that relatively higher inequality is measured using consumption as ranking variable. With respect to dynamics of inequalities, results on mobility indices computed based on Allanson et al. (2010) approach show that inequality remain stable (persistence of inequality) in Height-for- age Z-score, and reduction of inequality in Weight-for-age Z-score while in case of Weight-for- height Z-score, there is no clear trend over subsequent waves. Our inequality results are robust to different measurement scale, inequality aversion parameters/distributional sensitivity parameters, and sensitivity to extremity. Results on decomposition of inequalities show that the major contributors are wealth index, consumption and mother's education. Those imply that in both socioeconomic status ranking variables, the bulk of inequality in malnutrition is caused by inequality in socioeconomic status in which it disfavors the poor. This calls for enhancing the policy measures that narrow socioeconomic gaps between groups in the population and targeting on early childhood intervention and nutrition sensitive.



JEL codes: F22; I15; O15
Keywords: Child, undernutrition, dynamics of inequalities, Ethiopia

# 1 Dynamics Of Inequality In Child Undernutrition In Ethiopia

## 1.1 Introduction

Child malnutrition continues to be the leading public health problem in developing countries. Globally, there were 165 million stunted, 99 million underweight, and 51 million wasting children by year 2012. It killed 3.1 million under-five children every year (Black, 2013). Undernutrition among children is a critical problem because its effects are long lasting and go beyond childhood. It has both short and long term consequences (Glewwe, 2007; Abuya, 2012). Ethiopia has the second highest rate of malnutrition in Sub-Saharan Africa (SSA). The country faces the four major forms of malnutrition: acute and chronic malnutrition, iron deficiency anaemia, vitamin A deficiency, and iodine deficiency disorder (UNICEF, 2017).

Although Ethiopia has already achieved a remarkable progress in reducing under-five mortality in the last decades, undernutrition among children is still a common problem in this country. Undernutrition can best be described in the country as a long term year round phenomenon due to chronic inadequacies in food combined with high levels of illness in under-five children. It is the underlying cause of 57% of child deaths (CSA, 2011). Thus, socioeconomic inequalities in health outcomes have been of focus in academia and policy spheres for a while now. The vast empirical literature in the area, however, is mixed and context-specific. Many recent papers pursue a cross-country path, documenting widening inequalities in some countries and improvements in others. For example, Wagtaff (2014), based on demographic household survey (DHS) data from 64 developing countries, find that the poor are more likely to face health risks, including child undernutrition and mortality, and less likely to receive key health services. They conclude that health outcomes are pro-rich while health interventions such as vaccinations are pro-poor.

Studies from low income countries reveal similar mixed conclusions (e.g. Baros et al., 2010; Quentin, 2014; McKinnon, 2014). After reviewing vast literature and data from nearly 100 low and middle income countries, Baros et al. (2010) find that poor children and their mothers lag well behind the better-off in terms of mortality and under nutrition. In contrast, they note that poor children are less obese and more adequately breastfed than their rich counter parts. Very recently, McKinnon (2014) analyze wealth-related and educational inequalities in neonatal mortality (NMR) for 24 low- and middle-income countries and find substantial heterogeneity in both magnitude and direction of NMR inequalities between countries. They note that while inequalities declined in most of the countries, pro-rich inequalities increased in a few countries, including Ethiopia. Quentin (2014) compare inequalities in child mortality and their trends across 10 major African cities including the Ethiopian capital, Addis Ababa. Using Demographic Health Survey (DHS) data by computing both absolute (difference and Erreyger's index) and relative inequality (rate ratio and concentration index) measures, they reveal significant inequalities in four of the 10 cities including Addis Ababa in the most recent survey.

The multi-country studies highlighted earlier and many others can provide useful insight into inequalities in child health outcomes. However, for an in-depth scrutiny of the issue, a country-level study would offer more as it takes into account the specific contexts of the country under investigation. To this end, there are various reasons why Ethiopia could be an interesting case study on inequalities in child health outcomes. Firstly, the government of Ethiopia over the past decade and half has enacted various strategies and plans in the health sector to expand health infrastructure (UNICEF, 2015). Nonetheless, the country has not yet met all the international benchmarks established by the WHO for various indicators in addition to issues related quality of health services. Secondly, Ethiopia has been a focus of many in relation to its commitments to achieve child health-related Millennium Development Goals (MDGs). Although Ethiopia has already achieved a remarkable progress in reducing under-five mortality in the last decades, undernutrition among children is still a common problem in this country. This indicates that further efforts using a more policy-relevant measure of inequality taking a longitudinal perspective (dynamics aspect) are still required to reverse the situation. Lastly, there are various household- and child-level surveys in Ethiopia. In addition to the traditional Demographic and Health Survey (DHS), there are Young Lives Survey and the Ethiopia Socioeconomic Survey (ESS). Launched by the World Bank and the country's Central Statistical Agency (CSA) in 2011, the ESS contains selected child health outcome indicators and is superior to the DHS in terms of containing consumption expenditure and providing panel data (of three rounds in 2011/12, 2013/14 and 2015/16). Given those facts, conducting study on inequality of health outcome using different welfare indicators and longitudinal aspect is relevant to get updated evidences for formulating appropriate and timely policy.

In fact, there are few previous studies that explore child health outcome inequalities in Ethiopia such as Ambel et al., 2015; Alemu et al., 2016; Haile et al., 2016 ; Derek, 2014; Misgan et al., 2016; Asfaw et al., 2015; Zewdie and Abebaw, 2013. Estimates from a World Bank (2012) fact sheet on health equity and financial protection on the country show progress over the 2000-2011 periods on a host of child health indicators such as stunting, underweight, diarrhea, fever, etc. However, these DHS-based estimates reveal increased pro-poor inequalities over time. A recent study that is of high relevance to our case is Ambel et al. (2015). They analyze child (and maternal) health inequalities using DHS data from 2000 to 2014. Very recently, Alemu et al. (2016) provide a spatial analysis of all standard indicators of undernutrition and identify hotspot locations in the country. Haile et al. (2016) do the same but only for stunting and identify the determinants of inequality using multi-level regression.

Most of the aforementioned empirical evidences on inequalities in child health outcomes are using cross -sectional such as DHS data and various national survey. However, previous DHS-based studies have been constrained by the lack of expenditure data. In a predominantly rural society such as Ethiopia, measuring household economic status by a stock variable i.e. wealth index is questionable while analyzing such issues as inequalities in child undernutrition. It is fact that aggregate consumption may well be a better indicator of household welfare than the DHS wealth index because it may not respond quickly to shocks. Again, this implies that the choice of welfare indicator can have a large and significant impact on measured socioeconomic inequalities in a health variable. Moreover, the growing number of countries with longitudinal[1] data sets comprising socioeconomic and health related information has stimulated the development and refinement of different approaches to the measurement of health inequalities. It implies that we need more sophisticated approaches to monitor inequalities and design appropriate policy interventions because longitudinal measures are required to determine the incidence and effectiveness of interventions designed to tackle such health inequalities in the population[2]. Nonetheless, analyzing inequalities in child health outcome using alternative welfare indicators such as consumption and panel estimation[3] is not common or limited in many

[1]Socioeconomic determinants for health outcome are either interrelated or longitudinal in nature.

[2]Chronic inequalities might call for policies to tackle the structural problems that trap some individuals in deprivation and ill-health while transitory episodes might demand measures such as improvements in access to and delivery of acute health services or temporary welfare assistance. Thus, further work towards a comprehensive framework for modeling and evaluating the impact of specific policies and interventions on health inequalities is required to provide a consistent basis for resource allocation and welfare policies.

[3]Little attention has focused on measuring health mobility or whether the health of the poor is improving relative to the rich over time. This is an important issue since significant income-related inequalities in health have persisted, and even increased, in countries over the last decade in spite of considerable improvements in average health status (Doorslaer and Koolman, 2004). However, measures that do not exploit the advantages of "real" longitudinal data (i.e., that do not follow individuals over time) are unable to distinguish transitory inequalities (short episodes of ill-health and poverty) from ongoing structural socioeconomic and health-related deprivation. In particular, "dynamic" measures allow one to distinguish between transitory and chronic health inequalities and to characterize processes of inequality change.

studies, especially in Ethiopia.

In this paper, we thus provide a more policy-relevant measure of inequality taking a longitudinal perspective to analyze dynamics of child undernutrition inequalities in Ethiopia, focusing only on children under five age. This study differs from the previous literature (with specific to Ethiopia's case) in that it uses a flow measure – consumption expenditure (data with good-quality nationally-representative household consumption surveys from the World Bank's Living Standards Measurement Study, LSMS), missing in DHS – to investigate inequalities in child undernutrition while still supplementing it with wealth index. It also examines spatial aspect of inequalities in child malnutrition such as across regions and rural-urban. Besides, unlike previous studies, the current study employs panel data trend analysis on the inequalities from similar children tracked by the three rounds of the ESS from 2011 to 2016. Moreover, to address the short-run and long-run situation of inequality, analysis on dynamics of inequalities in child malnutrition over time using different approaches for mobility indices is considered. We also use decomposition approach in order to identify the contributing factors to the prevailed inequality.

The key results of this study show that inequality in undernutrition varies while we use different socioeconomic status (SES) indicators (such as wealth index and consumption), i.e relatively higher inequality is observed in case of consumption as SES ranking variable. Results on inequality using spatial aspect signify that significant difference in inequality of undernutrition is shown across regions. In terms of dynamics inequality, persistence of inequality in undernutrition-stunting is seen. Our inequality results are robust to different measurement scale, inequality aversion parameters/distributional sensitivity parameters, symmetric concentration index or 'sensitivity to extremity.Those results are also standardized for age and gender.

The rest of the study is organized as follows: In section two, we present comprehensive literature review on inequality in child health outcome. Section three covers a brief discussion of methods, data sources and variables measurement. Section four provides results and analyses on inequalities in child malnutrition, dynamics of socioeconomic related inequality using mobility indices, decomposition of inequality to major contributing factors and different robustness of results. Last section puts some concluding remarks.

## 1.2 Literature Review

To have better understanding on the dynamic relationship or interaction between socioeconomic and other factors, and health outcomes, it is noteworthy to adopt multidimensional conceptual framework. One of such a framework is developed by Wagstaff (2002) in which it states that health outcomes are subject to different factors such as household and communities, health service and systems, supply side factors and policies which have multidimensional or dynamic nature. There are also alternative frameworks that can be used to describe the complex range of factors that influence child nutrition. One that is widely cited is the United Nations Children's Fund (UNICEF) framework for improving child nutrition, which was developed a couple of years ago. As of Thomson et al. (2014), at the core of this framework, there are a number of direct determinants of nutrition, called 'immediate' causes, followed by a further group called 'underlying' causes and, at the periphery, a group of 'basic' causes. Basic causes include political, ideological, economic, environmental, resource and technology factors. The UNICEF framework describes 'short-route' interventions that address the immediate causes and 'long-route' interventions that address underlying and basic causes.

There are dozens of empirical findings applied to assess health outcome, particularly the inequality of child health outcome. Basically, they vary in methods/approaches, and data type. Some use cross-sectional while others though limited and at macro level, apply panel data approach. They also differ in following either bi-variate-descriptive approach or multivariate-causal analysis. However, some very relevant works are covered here.

One of the debating on health outcome inequalities is on the approach applied to measure inequality. In this regard, Wagstaff et al. (1991) offer a critical appraisal of the various methods employed to date to measure inequalities in health. However, they suggest that that only two of these--the slope index of inequality and the concentration index-are likely to present an accurate picture of socioeconomic inequalities in health. Kakwani et al. (1997) also contribute on inequality measurement by looking at standardizing using demographic factors (like age and sex) play a vital role on socioeconomic inequality analysis in health.

Jones and Lobez (2004) presents a method for the measurement of changes in health inequality and income-related health inequality over time in a population. However, Allanson et al. (2010) elucidate the nature of the Jones and Lopez Nicholas (2004) index of "health-related income mobility" and explains the negative values of the index that have been reported in all the empirical applications to date. They further question the value of their index to health policymakers and proposes an alternative index of "income-related health mobility" that measures whether the pattern of health changes is biased in favour of those with initially high or low incomes. They illustrate their work by investigating mobility in the General Health Questionnaire measure of psychological well-being over the first nine waves of the British Household Panel Survey from 1991 to 1999.

Specifically, with regard to malnutrition inequalities, although many surveys of children have been conducted since the 1970s, lack of comparability between them has made it difficult to monitor trends in child malnutrition. To this end, DeOnis (2000) demonstrates that analysis of cross sectional data from 241 nationally representative surveys in a standard way to produce comparable results of low height-for-age (stunting). He then documents that despite an overall decrease of stunting in developing countries, child malnutrition still remains a major public health problem in these countries. In some countries, rates of stunting are rising, while in many others they remain disturbingly high. Moreover, using decomposition method, Wagstaff et al. (2003) show that inequalities in height-for-age in Vietnam in 1993 and 1998 are largely accounted for by inequalities in consumption and in unobserved commune-level influences. They add that rising inequalities are largely accounted for by increases in average consumption and its protective effect, and rising inequality and general improvements at the commune level. Although it seems superior in using consumption rather than wealth index for ranking household position based on their socioeconomic status, this study is still subject to the usual caveats regarding the causal interpretation of cross-sectional results and also unable to see the long-run inequality situation. Using cross sectional data sets available from the Demographic and Health Surveys (DHS) of 15 countries in sub-Saharan Africa (SSA), Fotso (2006) also notes that though socioeconomic inequalities in stunting do exist in both urban and rural areas across countries in SSA, they are significantly larger in urban areas.

Many recent papers also follow a cross-country path, documenting widening inequalities in some countries and improvements in others (see, for instance, Baros et al., 2010; McKinnon et al., 2014; Wagstaff et al., 2014, and Bredenkamp et al., 2014). For example, using original data from 131 demographic health surveys and 48 multiple indicator cluster surveys from 1990 to 2011, Bredenkamp et al. (2014) examine trends in socioeconomic inequalities in stunting and underweight, as well as the relationship between changes in prevalence and changes in inequality, in 80 countries. Then, they infer that reductions in the prevalence of undernutrition have generally been accompanied by neither widening nor narrowing inequalities. It rather indicates that the picture is one of a strong persistence of existing inequalities. Baros et al. (2010) and McKinnon et al. (2014) also demonstrate similar results. However, to see such kind of dynamics of inequality, panel data is more appropriate than one time snapshot data. Other empirical works from developing countries show similar mixed conclusions.

Only few previous studies explore child health outcome inequalities in Ethiopia. Using cross sectional data from the 2000, 2005 and 2011 Ethiopian Demographic and Health Surveys, Skaftun et al. (2014) compute concentration index and a geographic Gini index to measure inequality. Then, they report that significant pro-rich inequalities were found for all indicators except treatment for suspected pneumonia in 2011. The socioeconomic inequalities seem to increase from 2000 to 2011 for under-five and neonatal deaths, whereas they are stable or decreasing for the other indicators. More importantly, Ambel et al. (2015) analyze trends in child (and maternal) health inequalities by household wealth status, mothers' education, and place of residence in Ethiopia. Using cross sectional DHS data from 2000 to 2014, they compute concentration indices (CIs) in three undernutrition indicators (stunting, wasting and underweight) and show that widening pro-rich inequality. Trend-wise, they report that inequalities more than doubled for all undernutrition indicators over the survey periods. These findings show the issue of inequality in child health outcomes should be a concern of research and policy in Ethiopia.

In summary, the existing literature on the area under this study differs in many ways, even those findings are mixed. They are subject to number of critics. Previous DHS-based studies have been constrained by the lack of expenditure data. In a predominantly rural society such as developing countries, particularly Ethiopia, measuring household economic status by a stock variable i.e. wealth index is questionable[4] while analyzing such issues as inequalities in child undernutrition. This is due to the fact that the choice of welfare indicator might have a large and significant impact on measured socioeconomic inequalities in a health variable which it depends on the variable examined. In terms of data type also, all employ a cross-sectional data for specific context. However, for those who are interest looking at long-run inequality compare to short-run one and policy formulation, rely on cross-sectional evidence is not warranted. It is true that the determination of health is essentially a dynamic process; health today reflects experiences of the past. Hence, applying longitudinal data is superior.

Thus, to the best of our knowledge, this study is different from the previous literature in particular to Ethiopia, in that it uses a flow measure – consumption expenditure, missing in DHS to investigate trend and magnitude of inequalities in child undernutrition while still supplementing it with wealth index. Moreover, unlike previous studies which use DHS and other data sets, the current study provides a panel data trend analysis on the inequalities from similar children tracked by the three rounds of the Ethiopia Socioeconomic Survey (ESS) from 2011 to 2016. Then, for dynamics of inequalities in child undernutrition, we employ different

[4] The justification behind this is that in developing countries, formal employment is less common, many households have multiple and continually changing sources of income, and home production is more widespread. In these contexts, it is generally far easier to measure consumption than income.

mobility index computing approaches, and there by see whether the cross-sectional (short-run) evidences on inequality overestimate or underestimate the long-run inequality picture. In the second paper (chapter), we devote merely on impact of social protection program on child nutrition and educational attainment.

## 1.3 Method and Data

### 1.3.1 Data

Data for this study comes from the Ethiopia Socioeconomic Survey (ESS) collected jointly by the Central Statistical Agency (CSA) of Ethiopia and the World Bank as part of the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA). It is a longitudinal survey with three waves (2011/12, 2013/14 and 2015/16). The ESS[5] sample is a two-stage probability sample. It employs a stratified, two-stage design where the regions of Ethiopia serve as the strata. The first stage of sampling entails selecting enumeration areas (i.e. the primary sampling units) using simple random sampling (SRS) from the sample of the Agriculture Sample Survey (AgSS) enumeration areas (EAs). The AgSS EAs were selected based on probability proportional to size of population (PPS). The sample design of the first wave provides representative estimates at the national level for rural-area and small-town households while subsequent waves include large towns and cities. The samples are also regionally representative for the major regions of the country (Oromia, Amhara, Tigray, and SNNP) as well as Addis Ababa since the second wave. The second stage of sampling is the selection of households to be interviewed in each EA.

The surveys provide household-level data on a range of issues such as consumption expenditure, assets, food security shocks, copying strategies, non-farm enterprises, credit etc. Very importantly, individual-level data are available on socioeconomic, demographics, education, health and time use (labor and leisure). Moreover, as traditional in LSMS surveys, community-level data on a host of issues such as health infrastructure as well as market price data from two nearest local markets are collected. Finally, data are obtained from 3,969, 5,262 and 4954 households in the first, second and third waves respectively. However, the sample for health

[5]ESS began as ERSS (Ethiopia Rural Socioeconomic Survey) in 2011/12. The first wave of data collection in 2011/12 included only rural and small town areas.The survey name dropped the word “Rural” in the second wave of data collection when the sample was expanded to include all urban areas.The urban supplement was done in such a way to ensure that the ESS data can provide nationally representative estimates.

variable data is restricted to children under the age of 5 in this study.

**Health outcome variable**

Our health outcome interest is malnutrition using anthropometric indicator. Theoretically, the body of a child responds to malnutrition in two ways that can be measured by anthropometric survey. First, a reduction in growth over the long-term results in low height-for-age or stunting. Second, a short-term response to inadequate food intakes is assessed by weight relative to height (wasting). The combination of short-term and long-term food shortage and growth disturbances produces low weight-for-age (underweight) (ONIS, 2000). Survey data often contain measures of weight and height, in particular for children. Weight and height do not indicate malnutrition directly. Besides age and sex, they are affected by many intervening factors other than nutrient intake, in particular genetic variation. However, even in the presence of such natural variation, it is possible to use physical measurements to assess the adequacy of diet and growth, in particular in infants and children. This is done by comparing indicators with the distribution of the same indicator for a "healthy" reference group and identifying "extreme" or "abnormal" departures from this distribution (World Health Organization, 1995).

Irrespective of what particular reference data are used, anthropometric indices are constructed by comparing relevant measures with those of comparable individuals (in regard to age and sex) in the reference populations. There are three ways of expressing these comparisons: Z-score (standard deviation score), percent of median and percentile. However, the preferred and most common way of expressing anthropometric indices is in the form of z-scores. This approach has a number of advantages over others. Primarily, z-scores can be used to estimate summary statistics (e.g., mean and standard deviation) for the population or subpopulations. This cannot be meaningfully done with percentiles. Moreover, at the extreme of the distribution, large changes in height or weight are not necessarily reflected in changes in percentile values. The percent of median is deficient relative to the z-score in that it expresses deviation from the reference median without standardizing for the variability in the reference population. More specifically, Z-score for an individual $i$ is calculated using equation 1.1:

$$Z - scorei = \left(\frac{X_i - X_r}{\delta_r}\right) \tag{1.1}$$

where $X_i$ is an observed value for $i^{th}$ child in a target population; $X_r$ is a median of the reference population ; and $\delta_r$ is a standard deviation(SD) of the reference population.

Thus, the health outcome variables used in this study are the three anthropometric indicators

(Height-for-age Z-score (HAZ), Weight-for-Height Z-score (WHZ), and Weight-for-Age Z-score (WAZ). We first compute those anthropometric indicators from age, height/length and weight data following the WHO (2006) child growth standards. We then state stunting, wasting and underweight levels for children aged less than 5 years as shown in Table 1.1.

**Table 1.1:** ***List and description of child undernutrition indicators***

| ***Indicator*** | ***Description*** |
|---|---|
| Stunted | If child's height-for-age z-score is less -2 standard deviations (SD) from the international median (WHO, 2006) healthy reference group |
| Wasted | If child's weight-for-height z-score is less -2 standard deviations (SD) from the international median (WHO, 2006) healthy reference group |
| Under-weighted | If child's weight-for-age z-score is less -2 standard deviations (SD) from the international median (WHO, 2006) healthy reference group |

**Other variables**

Those are used as explanatory variables for regression -based decomposition analysis as well as socioeconomic (SES) ranking variables in computing SES - related health inequalities. Broadly, they can be grouped as child level characteristics, household and community level characteristics. The child level characteristic includes child's age, age square, gender, and illness. Under household level, wealth index, consumption expenditure, mother's education, toilet facilities[6] and household sizes are considered. At community level, health facilities, access to safe drink water and spatial dimension such as household's place of residence in the form of rural –urban or regions. Detail on each variable definition and measurement are given in ***Table (1.2).*** However, among those household socioeconomic characteristics, wealth index and consumption expenditure are chosen as socioeconomic (SES) ranking variables for household position in measuring inequalities. Let's see below in detail how those values are constructed:

***Wealth index*** : Households were asked whether they owned from a list of asset items (such as farm implements, furniture and kitchenware, entertainment and communication equipment, electronic item personal items etc) or not [7]. It also considers various indicators of housing condition of household such as walls, roof, and floor of the main dwelling; type of kitchen, cooking

[6]Categorized based on WHO standard given for toilet type . It includes Flush toilet -private , Flush toilet-shared, Pit latreen- private ventilated , Pit lantreen-shared ventilated , Pit lantreen-private -ventilated, Pit lantreen-shared not ventilated , Bucket, Field / forest/ and Others.

[7]Included 35 asset items such as Kerosene stove, Butane Gas Stove, Electric Stove, Blanket/Gabi, Mattress and /or Bed, Wrist watch/clock, Fixed line telephone, Mobile telephone, Radio/ radio and tape/ tape, Television, CD/ VCD/ DVD / Video Deck, Satellite Dish, Sofa set, Bicycle, Motorcycle, Cart (hand pushed),

and bathing facilities.Then, following the standard approach of assessing economic status of the household, the study uses household asset and housing conditions to compute wealth index using principal component analysis (PCA) while sampling weight is taken in to account. Unlike Demographic Household Survey (DHS) and other data sets' wealth index which is constructed from urban-based social and economic amenities and may be measuring more of urban/city condition instead of inclusive socioeconomic status, this study uses Ethiopian Socioeconomic Survey (ESS) data which also includes rural based socioeconomic asset indicators.

***Consumption***[8]: The surveys include questions on expenditure on food and non-food items, food security, shocks, and coping mechanisms. The total consumption expenditure (available from the survey) is constructed from food consumption, non food consumption and education expenditure. Initially, a common reference period is established for all items, and values are imputed in cases in which they are not available (converted to a uniform reference period—for example, a year). Then, it follows three steps in constructing a consumption-based living standards measure: (a) construct an aggregate of different components of consumption, (b) make adjustments for cost of living differences, and (c) make adjustments for household size and composition. Household size and a measure of adult-equivalency[9] are constructed based on scale factors such as categorizing age in to different ranges(13 age categories) for both male and female by allocating different weights for each categories. In addition, it uses a regional price index (for 10 regions), based on the index created by the Ministry of Finance and Economic Development (MoFED) in their Household Consumption Expenditure (HCE) 2010/2011, 2013/14 and 2015/16 reports. Nominal and real per adult equivalent consumption were then calculated, and real consumption was re-scaled to have the same overall mean value as nominal consumption. The calculated per capita amounts winsorised at the $97^{th}$ percentile for non-zero consumption for each item (for details, see LSMS annual report of each wave, guideline for constructing aggregate consumption). In this study, we also group the households into quintiles based on the wealth index and consumption adjusted by sample weights for

Cart (animal drawn), Sewing machine, Weaving equipment, Mitad-Electric, Mitad-power saving (modern), Refridgerator, Private car, Jewels (Gold and silver), Wardrobe, Shelf for storing goods, Biogas stove (pit), Water storage pit, Mofer and Kember, Sickle (Machid), Axe (Gejera), Pick Axe (Geso), Plough (traditional), Plough (modern) and Water Pump

[8]In all surveys, consumption and expenditure information was collected on a limited number of items. The consumption and expenditure information was collected within the household questionnaire during the third visit to the household in both surveys; this occurred between January and March 2012 for ESS1 and between February and April 2014 for ESS2. Information was collected for 25 food items consumed over the last 7 days2, 11 basic household goods (matches, batteries soap, etc.) over the past month, and 12 other expenditures (men's clothing, linens, etc.) over the past 12 months.

[9]Bases on Dercon and Krishnan (1998)1 proposed equivalences on nutritional (caloric) requirements of different ages for both men and women.

nationally representative inferences.

**Table 1.2:** ***Description and measurement of variables used used in analysis***

| *Variables* | *Definition/Description* | *Measurement /type* |
|---|---|---|
| | ***Anthropometrics indicators*** | |
| HAZ-score | The length/height(in meters) of children 0 months to 59 months of age | Height –for –age Z-score |
| WHZ-score | The weigh( in kilogram) and height of children 0 months to 59 months of age | Weight –for-height Z-score |
| WAZ-score | The weight (in kilogram) children of 0 months to 59 months of age | Weight –for age Z-score |
| | ***Demographic characteristics at individual level*** | |
| Age | Age of child | Continuous, in months |
| Age-square | Child age square | Continuous, in months |
| Gender | Sex of child | Dummy; 1 if male, 0 otherwise |
| Child illness incidence | Whether the child has had diarrhea in the last two weeks leading up to the interview | Dummy; 1 if yes, 0 otherwise |
| | ***Socioeconomic characteristics at household level*** | |
| Wealth index | How many of each of the following items does the household own? (housing condition) | Continuous, index computed based on PCA |
| Consumption | Household's real annual consumption (food and non food total expenditure) per adult equivalent | Continuous, annual real total per adult equivalent |
| Mother's education | What is/was biological mother's highest educational level completed? | Categorical, level of certificate completed |
| Household size | Total number of family members | Numbers, continuous |
| Household size under age 5 | Number of under 5 age household members | Numbers, continuous |
| Toilet facility | What type of toilet facilities does the household use? | Categorical, types of toilet facilities |
| | ***Community level characteristics*** | |
| Health care services | Is there any health post in the surrounding community | Dummy ;1 if yes, 0 otherwise |
| Water availability | Is there water service in the community | Dummy ;1 if yes, 0 otherwise |
| Place of residence | Household residence place (urban-rural, region) | Dummy ; 1 if rural 0 if urban or regional dummies |

### 1.3.2 Method

#### 1.3.2.1 Measures of inequality in child undernutrition

The study aims to examine the child undernutrition inequalities in socioeconomic status and spatial dimensions. For socioeconomic inequalities in child health, we use consumption expenditure and wealth index as alternative welfare measures and see the gap between the worse off (bottom 60 %) and the better off (top 40 %) as well as between the poorest ($1^{st}$ quintile) and the richest ($5^{th}$ quintile). And for the spatial dimension, inequalities are traced between rural and urban children as well as among those in various regions of the country. We also compute absolute and relative inequalities from rate differences and rate ratios.

When there are only two subgroups to compare, difference and ratio are the most straightforward ways to measure absolute and relative inequality. However, the differences and ratios between different groups do not consider inequalities by the whole population. Hence, concentration curves are used to illustrate the trend of the socioeconomic and spatial inequalities in child undernutrition over time. The concentration curve plots the cumulative proportion of the population ranked by a measure of socioeconomic status (such as an index of household wealth and consumption) against the cumulative proportion of the health measure (undernutrition indicators). If concentration curve lies above the diagonal (45 degree line of equality ), it is interpreted as child malnutrition is disproportionately concentrated among the poor and the reverse is true while it lies below line of equality. We also conduct tests of dominance between concentration curves following the procedures in O'Donnell et al. (2008).

Since a concentration curve does not give a measure of the magnitude of inequality that can be compared conveniently across many time periods, countries, regions, or whatever groups may be chosen for comparison, we examine inequalities using concentration index (Kakwani et al., 1997; O'Donnell et al., 2008) and with possible extension. The concentration index is defined as twice the area between the concentration curve and the line of equality (the 45-degree line). It provides a summary measure of socioeconomic related health inequality, i.e. a measure of the extent to which the concentration curve diverges from the diagonal. The convention is that the index takes a negative value when the curve lies above the line of equality, indicating disproportionate concentration of the health variable among the poor, and a positive value when it lies below the line of equality. However, when there is no socioeconomic-related inequality, the concentration index becomes zero.

In this study, with availability of panel data, we follow dynamic approach to measure inequality in health rather than a static one used in cross sectional data. The basic nationality behind is that longitudinal data are more relevant for policy making analysis. The cross sectional data, static approach is often used to compare inequality at two different points in time while the panel, dynamic approach is essentially useful when interest lies in the long –run rather short-run inequality (which can be the case for, e.g., policy makers). As Jones and Lopez (2004) proved theoretically, looking at a different point in time using short-run concentration index (CI) does not give a complete picture rather in panel, we are able to follow each individual in every year and have thus a complete picture of their relative evolution.

To this end, there are various ways of expressing the concentration index (CI) algebraically. For the measurement of inequality at one point in time, we use the concentration index (CI) stated in equation 1.2, that is mostly used in the literature for its convenience. It is derived by ranking the population by a measure of socioeconomic status (SES) and then comparing the cumulative proportion of health with the cumulative proportion of the population ranked by SES.

$$CI_t = \frac{2}{N\bar{y_t}} \sum_{i=1}^{N} (y_{it} - \bar{y_t}) \left(R_i^t - \frac{1}{2}\right) = \frac{2}{\overline{y_t}} cov\left(y_{it}, R_i^t\right) \tag{1.2}$$

where $y_{it}$ represents the health level of individual $i$ in period $t$, and $R_i^t$ denotes the relative fractional rank of $i^{th}$ individual in the distribution of SES in period $t$; $N$ is the sample size at period t. $\bar{y_t} = \frac{\sum_{i=1}^{N} y_{it}}{N}$ is the mean health of the sample in the period $t$.

Equation 1.2 shows that the value of concentration index is equal to the co-variance between individual health ($y_i$) and the individual's rank ($R_i^t$), scaled by the mean of heath in the population ($\bar{y_i}$). Then, to ensure the concentration index ranges between -1 and +1, the whole expression is multiplied by 2. Alternatively, it can be defined as a measure of the degree of association of between an individuals' level of health and their relative position in the SES distribution. The negative and positive sign of concentration index tells us that health outcome is concentrated among poor and rich people respectively. It is important to highlight that a value of concentration index (CI) is equal to zero does not mean an absence of inequality, but an absence of socioeconomic gradient in the distribution, i.e. an absence of inequality associated with socioeconomic characteristics.

However, Jones and Lopez (2004) illustrate that cross sectional concentration index (CIs) can lead to wrong conclusions when trying to measure socioeconomic-related health inequality in the long run as these do not take into account the possibility that people may change in socioeconomic rank. As such, they derive a formula to measure inequality in the long run, which is similar to the cross-sectional CI. They find that the CI for the distribution of average health after $T$ periods can be written as the difference between two terms: the weighted sum of the CIs for each of the sub periods ($term1$) minus a residual which is the difference between period specific SES ($R_i^t$) and ranks for average specific socioeconomic status (SES) over all periods ($R_i^T$) and their relationship to health over time ($term2$) as stated below in equation 1.3.

$$CI^T = \underbrace{\sum_i w_t CI^t}_{Term1} \underbrace{- \frac{2}{NT\overline{y}^T} \sum_i \sum_i \left(y_{it} - \overline{y}^t\right) \left(R_i^t - R_i^T\right)}_{Term2} \tag{1.3}$$

where $\bar{\bar{y}} = \frac{\sum_i \sum_i y_{it}}{NT}$ is the over all average health status/population/ in $T$ periods; $\sum \frac{\bar{y}_t}{T} = \overline{y}^T$ is the average health of the individual over the T periods , $\bar{y}^t = \frac{\sum_i y_{it}}{N}$ is the mean of health of individual in each $t$ period , $w_t = \frac{\bar{y}_t}{T\bar{\bar{y}}^T}$ can be seen as the share of total health in each period ; and $CI^T$ is defined as long-run $CI$ and $CI^t$ is short-run $CI$ of each health variable under consideration in period $t$.

Our inequality results and analyses rely on the nature of health outcome interest and ranking variables we choose, measurement scale, types of inequality indices, ethical consideration, estimation approaches. One can classifies variables as unbounded and bounded based on their characteristics. Bounded variables- Variables with a finite upper limit, such as years in school, a (health) utility index or any-binary indicator. However, unbounded variables are variables with infinite upper limit. For instance, bounded variables can be represented either as attainments or as shortfalls from the upper limit. Erreygers (2009a) introduced the 'mirror' property that requires that the magnitude of measured inequality represented by the absolute value of an index should not depend on whether the index is computed over attainments or shortfalls. The standard concentration index does not satisfy this condition: and hence inequality in attainments do not mirror inequality in shortfalls (Erreygers, 2009a). Moreover, inequality orderings based on the standard concentration index might depend on whether one uses shortfalls or attainments. One must choose between satisfaction of the mirror condition and satisfaction of relative inequality invariance. The generalized concentration index satisfies the mirror condition. However, the value of this index is not invariant to permissible transformations of ratio-scaled and cardinal variables. Erreygers (2009a) proposed a modification of the generalized concentration index that corrects this deficiency. This index ranges between $-1$ and $+1$. Wagstaff (2005) stated that the range of the standard concentration index depends on the mean of the bounded variable and suggested rescaling the standard concentration index to ensure that it always lies in the range $[-1, 1]$. This index satisfies the mirror condition and so cannot be in line with the relative invariance criterion. Unlike for unbounded variables, the precise scaling of bounded variables does not affect the value of any rank-dependent inequality index provided that the bounding is taken into account.

As of O'Donnell et al. (2016), in bivariate inequality measurement, an ordinal scale is sufficient for the variable that is used for the ranking of individuals. Rank-dependent indices can then be deployed to quantify inequality in variables measured at three levels: Fixed:- the measurement scale is unique with zero corresponding to a situation of complete absence e.g. number of visits to a hospital within a given period. Ratio:- the measurement scale is unique up to a proportional scaling factor with the zero point corresponding to a situation of complete absence e.g. life expectancy that could be measured in years, months etc. Cardinal:- the scale is such that differences between values are meaningful but ratios are not and the zero point is fixed arbitrarily e.g. temperature in Celsius or Fahrenheit, a (health) utility index. For variables on a fixed scale, the standard and generalized concentration indices quantify inequality in the attribute of fundamental interest. Both are appropriate, with the choice between them depending on whether one is concerned about relative or absolute inequality. Changing the proportionality factor of a ratio-scaled variable will affect the value of the generalized concentration index, but not that of the standard concentration index. The generalized concentration index should therefore be used with ratio-scaled data only when the variables compared in an inequality ordering are subject to the same scaling factor.

The magnitude and sign of concentration index depends on the method used to compute the required index. These results also affect the inequality analysis. When the variable of interest has an infinite upper bound on a fixed scale, the main normative choice is between absolute and relative invariance. Matters are more complicated when the measurement scale is not unique. Applying the generalized concentration index to a ratio or cardinal variable requires one to accept that the inequality ordering may depend on the scaling adopted. This can be avoided for the relative inequality invariance criterion if one replaces the standard concentration index with the modified one. When the variable has a finite upper bound, one should first choose between relative inequality invariance and the mirror condition. If one prioritizes the relative invariance criterion (in attainments or shortfalls), then the standard concentration index or its modified version can be used. When priority is given to the mirror condition, one faces a choice between the Erreygers index, which focuses on absolute differences, and the Wagstaff index, which mixes concern for relative inequalities in attainments and relative inequalities in shortfalls (O'Donnell et al., 2016).

With respect to ethical response to inequality, we can consider extended concentration index: 'sensitivity to poverty'. This approach makes it possible to vary the weight put on those at the top relative to those at the bottom of the distribution of the ranking variable. It is refered as 'sensitivity to poverty' as it allows more (or less) weight to be placed on the poorest individuals when income is used as the ranking variable. The second approach is symmetric concentration index: 'sensitivity to extremity'. It allows more (or less) weight to be placed on the extremes of the ranking distribution (e.g. the very rich and very poor) vis-a-vis those in the middle. This approach is termed as 'sensitivity to extremity'. The choice between the symmetric and extended indices is normative. The symmetric index gives equal weight (but with an opposite sign) to individuals that are equally far apart from the pivotal individual with median rank, while the extended index prioritizes the lower regions of the ranking (income) distribution. Applied to income-related health inequality, the symmetric index is increasingly sensitive to a change that raises the health of a richer individual and reduces that of a poorer individual by an equal magnitude the further those individuals are from the pivotal individual. In contrast, the extended concentration index will be increasingly sensitive the closer is the location of such a 'health transfer' to the bottom of the income distribution. Erreygers et al. (2012) argue that the symmetric index is more concerned about the association between income and health, while the extended concentration index puts priority on the income distribution, and only then analyzes health differences within the prioritized region of the income distribution (O'Donnell et al., 2016).

In our case, for standard and generalized concentration index (CI), the health variable (the dependent variable) is negative of Z-score which is continuous and unbounded variables while in case of Erreygers and Wagstaff, it is binary which is bounded variables taking a value either 1 if stunted, wasted and underweighted or 0 if not undernutitioned. The concentration index can be computed easily in stata software either using covariance method or regression-based method. Accordingly, this study adopts the user-written stata command conindex developed by O'Donnell et.al. (2016). The user written Stata command conindex, which calculates rank-dependent inequality indices while offering a great deal of flexibility in taking account of measurement scale and alternative attitudes to inequality. Estimation and inference is via a regression approach that can allow for sampling design, misspecification and grouped data, as well as testing for differences in inequality across populations. An advantage of this approach is that Stata readily allows for sampling weights, as well as robust and clustered standard errors. Moreover, with repeated cross-section or panel data, one can use the command to compare inequality across periods. Furthermore, conindex has comparative advantage of estimating a battery of concentration indices which allows the analyst to select an index that is appropriate given the measurement properties of the variable of interest and is consistent with their normative principles concerning inequality.

#### 1.3.2.2 Mobility index and dynamics of inequality in child undernutrition

Since this study prefers to use longitudinal data, its other basic concern is examining the measurement of malnutrition inequality with variation of socioeconomic status (SES) variables over time (SES related health inequality mobility). In this regard, even if individuals do not experience health changes, long-run SES- related inequality can be greater or less than that obtained with snapshot cross-sectional estimates, as long as the patterns of SES mobility are systematically related to health. Averaging the short-run measures of inequality will then tend to underestimate or overestimate the long-run picture. However, in situations where SES-related inequality tends to fade either solely due to health mobility or solely due to SES mobility, the mobility index would be zero. In these cases, the information obtained from the series of cross sectional concentration indices would be sufficient to capture the dynamics of interest. Hence, it is useful to measure how much the longitudinal perspective alters the picture that would emerge from a series of cross sections, in the same spirit as Shorrocks' (1978) index of income mobility. With same notational representation used above for computing long-run CI, Jones and Lopez (2004) put mobility index ($M^T$) for any SES variables by:

$$M^T = 1 - \frac{CI^T}{\sum\limits_t w_t CI^t} = \frac{2}{N \sum\limits_t \bar{y}^t CI^t} \left( \sum_i \sum_t \left( y_{it} - \bar{y}^t \right) \left( R_i^t - R_i^T \right) \right) \tag{1.4}$$

Here, mobility index would be different from zero if the following two conditions hold: i) The SES rank of individuals is sensitive to the length of the time window over which measurement is taken, i.e. there is SES mobility, as defined by Shorrocks (1978)[10]. ii) These changes in SES

[10]There is complete immobility when the relative incomes of all individuals remain constant over time.However, as income profiles deviate further from this extreme, income mobility increases. If incomes are not "completely immobile", inequality tends to decline as the length of the measurement period increases(Shorrocks', 1978).

rank are associated with systematic differences in health variable considered. If mobility index is negative in sign, it implies that short-run concentration index(cross sectional) underestimates long-run one(longitudinal data) while it is positive, it shows that short-run CI overestimate long-run one.

Jones and Lopez (2004) provide an index that measures the difference between short run and long run income-related health inequality and suggest that it can be interpreted as an index of health-related income mobility. Nonetheless, as of Allanson et al. (2010), it is questionable whether this index is more appropriate to health policy makers other than to illustrate that income-related health inequalities may be slightly more important than might be inferred from cross-sectional estimates. Moreover, they note that, initially, health policy-makers are more likely to be interested in income-related health changes, less so in health-related income changes, especially since a large amount of health-related income changes are likely to be unavoidable. Jones and Lopez (2004) measure is equal zero if there is no income mobility "regardless of whether there is health mobility". Conversely, the measure may not equal zero even if "there are no health changes". Second, the index provided by Jones and Lopez (2004) is symmetric in the sense that the value of the index is invariant to the ordering of the years. Yet, policy makers may want to distinguish between equalizing and disequalising income changes since these have diametrically opposed implications for the level of income-related health inequality over time. Finally, the value of the Jones and Lopez (2004) index is likely to be little more than a reflection of the unimodal shape of the income distribution and the strength of the association between income and health in the long run compared to the short run.

As a remedy for these shortcomings, Allanson et al. (2010) propose an alternative approach based on the simple observation that any change in income-related health inequality over time must arise from some combination of changes in health outcomes and income ranks. By decomposing the change in between two periods, they provide an index of income-related health mobility that captures the effect on short run income-related health inequality of differences in relative health changes between individuals with different initial levels of income. Thus, the measure addresses the question of whether the pattern of health changes is biased in favour of those with initially high or low incomes, providing a natural counterpart to measures of income-related health inequality that address the issue of whether those with better health tend to be the rich or poor. In addition, like Jones and Lopez (2004), they also obtain a health-related income mobility index that captures the effect of the reshuffling of individuals within the income distribution on cross-sectional socioeconomic inequalities in health. Accordingly, in this study, we adopt Allanson et al. (2010) approach to decompose the change in the short run concentration index ($CI$) between any initial or start period $s$ and any final period $f$ into two part:

$$CI^f - CI^s = \frac{2}{\overline{y}^f} cov\left(y_{if}, R_{if}\right) - \frac{2}{\overline{y}^s} cov\left(y_{is}, R_{is}\right); s, f = 1, ....T; s \leq f$$

$$= \left(\frac{2}{\overline{y}^f} cov\left(y_{if}, R_{if}\right) - \frac{2}{\overline{y}^f} cov\left(y_{if}, R_{is}\right)\right) + \left(\frac{2}{\overline{y}^f} cov\left(y_{if}, R_{is}\right) - \frac{2}{\overline{y}^s} cov\left(y_{is}, R_{is}\right)\right)$$

$$= \left(CI^{ff} - CI^{fs}\right) + \left(CI^{fs} - CI^{ss}\right) = M^R - M^H \tag{1.5}$$

where $y_{is}$ and $R_{is,}$are health and relative fractional rank of individual at starting period. Similarly, $y_{if}$ and $R_{if}$ denote health and relative fractional rank of individual at final period. $\overline{y}^f$ and $\overline{y}^s$ represent mean of health at final and starting period respectively. $CI^{ss}$ and $CI^{ff}$ are the $CI$'$s$ in periods starting ( $s$ ) and final ($f$ ) respectively, and $CI^{fs}$ is the $CI$ obtained when health outcomes in the final period are ranked by income in the initial period.

In equation 1.5, the mobility index, $M^H = CI^{fs} - CI^{ss}$ provides a measure of income-related health mobility, which captures the effect of differences in relative health changes between individuals with different initial levels of income. $M^H$ is positive (negative) if health changes are progressive (regressive) in the sense that the poorest individuals either enjoy a larger (smaller) share of total health gains or suffer a smaller (larger) share of total health losses compared to their initial share of health, and equals zero if relative health changes are independent of income. $M^H$ in turn depends on the level of progressivity and scale of health changes.

However, the income-related health mobility index, $M^H$ is not exactly equal the change in income-related health inequality because it does not allow for the effect of changes in the ranking of individuals in the income distribution between the initial and final periods. This effect is captured by the health-related income mobility index, $M^R = CI^{ff} - CI^{fs}$. It may be negative since the concentration index of final period health outcomes ranked by initial income can exceed that ranked by final income. $M^R$ can be equal to zero, irrespective of the degree of reshuffling of individuals in the income distribution, if final period health is uncorrelated with changes in income rank (Allanson et al., 2010).

#### 1.3.2.3 *Decomposition of inequality in child undernutrition*

In this part of the study, we decompose the concentration index of each child undernutrition indicator in order to identify the major contributing factors to the inequality. Such decomposition method enables us to know what extent of inequality in child malnutrition is explained by inequalities in socioeconomic status such as education, health access to maternal and child health care, etc? Wagstaff, van Doorslaer, and Watanabe (2003) demonstrate that the health concentration index can be decomposed into the contributions of individual factors to income-related health inequality, in which each contribution is the product of the sensitivity of heath with respect to that factor (the elasticity) and the degree of income-related inequality in that factor (the respective concentration index).

To explain variations in a child's under-nutrition level, we adopt a standard household production-type anthropometric regression framework (Lavy et al., 1996; Thomas et al., 1996), in which negative of each child's arthropometric indicators (Z-score) is specified to be a linear function of a vector of child-level variables, a vector of household-level variables, and community level. We interpret our estimating equation as a reduced-form demand equation—rather than a production function.

Here, we focus on inequalities in all malnutrition indicators measured using the negative of the child's height-for-age z-score, weight-for-height z-score, and weight-for -age z-score respectively following the WHO (2006) child growth standard data. Like Wagstaff et al. (2003) and many others in the literature, we have two reasons for favoring the z-score over a binary variable indicating whether or not the child in question was undernutritioned or not. First, it conveys information on the depth of malnutrition rather than simply whether or not a child was malnourished. Second, it is amenable to linear regression analysis, which is favorable to our decomposition method. Since the equation used for decomposing the concentration index (CI) requires linearity of the underlying regression model, most of the decomposition result holds for a linear model of health outcomes. Moreover, we use the negative of the z-score to make our malnutrition variable easier to interpret. Rising of negative of the z-score indicates an increasing in malnutrition level. Accordingly, for our regression based -decomposition, we rely on malnutrition level rather than binary outcome as dependent variable.

Since this study employs longitudinal data, the specification of our model for decomposing socioeconomic related inequality in health could be simple pooled OLS model, random effect model and fixed effect model. Most studies in this topics use simple pooled linear model, estimating by ordinary least square (OLS) but it doesn't take in to account potential error components structure and dynamics. We then use both random and fixed effect to model and estimate the regression equation for decomposing inequality. We thus consider linear panel models[11] as it is indicated in equation 1.6.

$$Y_{ihct} = \beta_0 + \beta_1 \left(X_1\right)_{it} + \beta_2 \left(X_2\right)_{ht} + \beta_3 \left(X_3\right)_{ct} + \mu_{ithct} \tag{1.6}$$

where $Y_{ihct}$ indicates that malnutrition level of child $i$ in a household $h$, community $c$ and in time $t$. $X_1$, $X_2$ and $X_3$ are vector of child level, household level and community level explanatory variables respectively (for details on variable definition and measurement, see Table 1.2). While $\beta$ is a vector of regression coefficients which show the effect of X on Y; $\mu_{ihct} = \alpha_i + \varepsilon_{ihct}$, $\alpha_i$[12] is individual specific effect and $\varepsilon_{ihct}$ is idiosyncratic error term. A cluster- robust estimate for the variance co-variance matrix estimator (VCE) is then used to correct for error correlation over time for a given individual.

In decomposing concentration index (CI), we follow the formula proposed by Wagstaff et al. (2003) while linear panel data is taken in to account in this study. Then, the decomposed concentration index as stated in equation 1.7 shows that it is equal to the weighted sum of the concentration indices of the K –regressors:

$$CI^T = \sum_k \left( \frac{\beta_k \bar{X}_k}{\bar{y}^T} \right) CI_k^T + \frac{GC_\varepsilon^T}{\bar{y}^T} = \sum \eta_k CI_k^T + \frac{CC_\varepsilon^T}{\bar{y}^T} \tag{1.7}$$

where $CI^T$ is overall long-run $CI$ for health, $\bar{y}^T$ is the mean health over all periods, $\beta_k$ are coefficients obtained from regression of equation 1.6, $\bar{X}_k$ is the mean of the $k^{th}$regressor taken over all periods, $CI_k^T$ is the long-run $CI$ of the $k^{th}$ regressor and $GC_\varepsilon^T$ is long-run generalized

[11]With respect to interpretation of decomposition results, one should carefully realized that though decomposition methods are based on regression analyses, there are two possible cases: First ,If regressions are purely descriptive, they reveal the associations that characterize the health inequality.Then inequality is explained in a statistical sense but implications for policies to reduce inequality are limited. Second, if data allow identification of causal effects, the factors that generate the inequality are identified .Then, it is possible to draw conclusions about how policies would impact on inequality. Hence, estimation technique and model that fit for our purpose is selected with this context.

[12] Depending on our estimators choice, $\alpha_i$ can be random or non-random if it is randome effect or fixed effect estimator respectively.

concentration index for each error term[13] and $\left(\eta_k = \beta_k \frac{\bar{X_k}}{\bar{y}^T}\right)$ is elasticity of health variable under consideration with respect to the explanatory variables $(X_k)$.

Since the main objective of decomposition analysis is to offer an explanation of socioeconomic inequality of health by including the contributions of each explanatory variable to such inequality, the product of elasticity $(\eta_k)$ and concentration index of $k^{th}$ regressor $\left(CI_k^T\right)$ gives us the contribution of each explanatory variables in the variation of inequality in health variables.

#### 1.3.2.4 Blinder -Oaxaca Decomposition

It is common to raise why do gaps in health outcome exist between the poor and better-off in many countries despite health systems explicitly aimed at eliminating gap in health outcome? Hence, the Oaxaca-type decomposition (Oaxaca, 1973; O'Donnell et al., 2008) is employed to explain the difference between two groups. Such type of decomposition explains the gap in the means of an outcome variable between two groups (e.g., between the poor and the non-poor). The gap is decomposed into group differences in the magnitudes of the determinants of the outcome in question and group differences in the effects of these determinants. But, such method does not allow us to decompose inequalities in health outcome across the full distribution of SES variable, rather we simply restricted to analysis between the poor and the better-off. The decomposition equation we use to estimate the health outcome gap between two groups is given in equation 1.11. However, we take panel data rather than different cross sectional data for our estimate.

$$Y_{ihct} = \beta^R X_{ihct} + \varepsilon^R_{ihct} \longrightarrow if.............Rich \tag{1.8}$$

$$Y_{ihct} = \beta^P X_{ihct} + \varepsilon^P_{ihct} \longrightarrow if............Poor \tag{1.9}$$

$$\overline{Y_R} - \overline{Y_P} = \left(\overline{X}_R - \overline{X_P}\right)\beta^P + \left(\beta_R - \beta_P\right)\overline{X_R} \tag{1.10}$$

[13] The residual component—captured by the last term—reflects the income-related inequality in health that is not explained by systematic variation in the regressors such as by income, which should approach zero for a well-specified model.

$$\overline{Y_P} - \overline{Y_R} = \left(\overline{X_R} - \overline{X_P}\right)\beta^R + \left(\beta_R - \beta_P\right)\overline{X_R} \tag{1.11}$$

where $Y_{it}$ is individual child undernutrition level at time $t$, $X_{ihct}$ is vector of child, household and community level characteristics at time $t$. $\overline{Y}$ represents mean of individual child undernutrition level for each group and $\overline{X}$ represents vector of child, household and community level characteristics evaluated at mean for each groups and $\beta's$ also represents estimated coefficients including intercepts for poor and non-poor. So, the gap in $Y$ between the poor and the non-poor might come from differences in the coefficients ($\beta$) including intercepts (difference in effects), and differences in those determinants level ($X$). Estimates of the difference in the gap in mean outcomes can be obtained by substituting sample means of the $X$'$s$ and estimates of the parameters $\beta$'$s$ into equation 1.8. As it is stated in equation 1.12, the mean health outcome difference between the two considered gaps can be attributable to (i) differences in the $X$'$s$ (sometimes called the explained component); (ii) differences in the $\beta$'$s$ (sometimes called the unexplained component) and interaction effect (change in product of $X$ and $\beta$, $X\beta$).

$$\overline{y_R} - \overline{y_P} = \left(\overline{X}_R - \overline{X_P}\right)\beta^P - \left(\beta_R - \beta_P\right)\overline{X_R} + \left(\overline{X_R} - \overline{X_P}\right)\left(\beta_R - \beta_P\right) \tag{1.12}$$

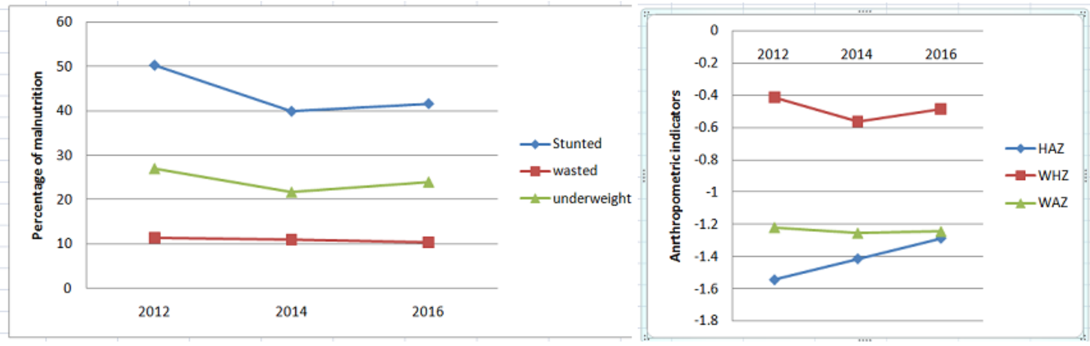
## 1.4 Results and Discussion

This part is basically devoted for result interpretation and analysis on inequalities in malnutrition based on different approach of measuring inequality and its dynamics. It also covers analysis on contribution of major factors for the inequalities prevalence using decomposition method.

### 1.4.1 Basic descriptive statistics

It is noteworthy to see first some basic descriptive statistics on major health and socioeconomic variables used in this study. Referring to Figure (1.1), from 2011/12 to 2015/16, one can observe that percentage of undernutritioned children in all indicators (on average) falls.

**Figure 1.1: Trend of malnutrition and Anthropometric indicators across wave**




As it is aforementioned, the final data used in this study is constructed from various individual, household and community level covered in all three survey waves. The health variable data is prepared from each individual child's age, sex, weight and height, using Zanthro ado –file with reference to WHO (2006) child growth standards. Finally, total of 11,061 individual observations from those three waves are considered for analysis. However, we use a balanced panel data with observations of 6087 individuals for measuring dynamic of inequalities over time using mobility indices. Then, outliers and normality tests are conducted for major socioeconomic variables (see, Figure 1.1).

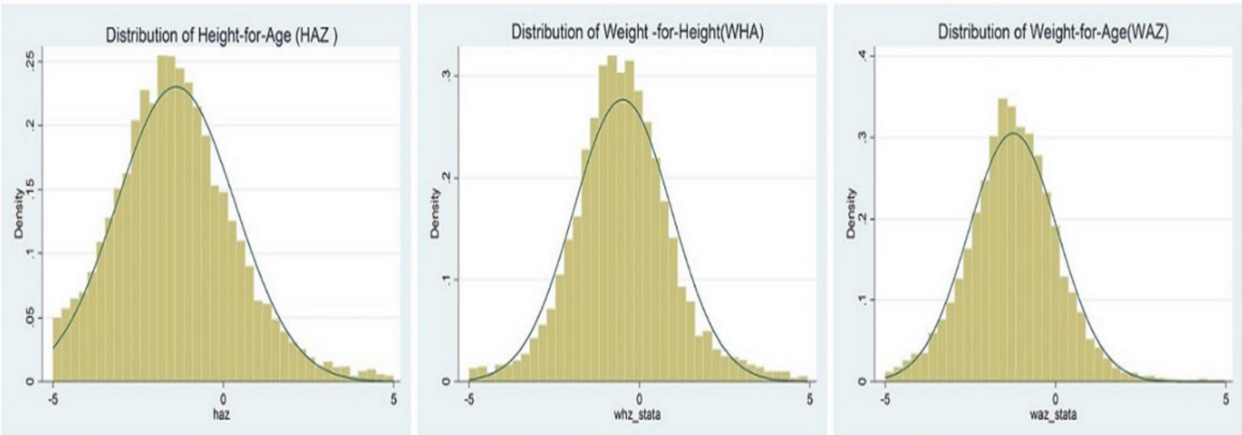
**Table 1.3: Summary statistics of variables used in regression for decomposition analysis**

| Variable | Obs | Mean | Std. Dev |
|---|---|---|---|
| Age_months | 11061 | 45.73339 | 27.44576 |
| Age square | 11061 | 2844.744 | 2829.643 |
| llness incidence | 10835 | .1728657 | .3781486 |
| Water_availability | 11049 | .4469679 | .2758621 |
| Toilet facility | 11056 | 6.342438 | 1.205653 |
| Health post | 10819 | 1.105093 | .3066873 |
| mother education | 10767 | .4592737 | .9098248 |
| Household size | 11061 | 6.23063 | 2.020077 |
| Household size under 5 age | 11061 | 1.504114 | .8234286 |
| HAZ | 9011 | -1.3873 | 1.73204 |
| WHZ | 8415 | -.49157 | 1.43958 |
| WAZ | 9784 | -1.24230 | 1.30505 |
| Wealth index | 11007 | -.7662025 | 1.444134 |
| Real consumption per capita (adult equivalent) | 10785 | 5278.117 | 4394.013 |

Figure (1.2) shows an overview of distribution of child malnutrition indicators by their Z-score. Similarly, Figure 1.1 (in appendix) signifies that the distribution of wealth index is more concentrated to the left with negative sign which indicates that most of the households are poor. It also apparently shows that real annual consumption per adult equivalent is skewed to the right for the clear reason that consumption can't be negative in values.

Basically, the analysis of anthropometric data is used for the identification of undernourishment in a population or sub-population. Accordingly, a first step is to look at the distribution of the z-scores and the overall prevalence of undernourishment. When compared with the distribution of z-scores in the reference population, this provides a first impression of different dimensions of nutritional status in the population.

**Figure 1.2:** Distribution of Anthropometric Indicators




Almost in all Z-scores (see, Figure 1.2 ), the distribution is skewed to the left which implies that many individuals are away from the median of the distribution. HAZ-score and WAZ-score are also positively correlated while HAZ and WHZ-score are negatively correlated.

### 1.4.2 Inequality in undernutrition

Before measuring inequality using complex approach, it is common to use simple approach which is helpful merely to look at the absolute mean difference of anthropometric score between to groups. In due respect, significant mean difference is exhibited between different groups considered in this analysis such as rural and small town, bottom 60 % and top 40 %, richest and poorest, male and female. This shows that the prevalence of malnutrition is disproportionately distributed across different groups.

**Table 1.4: Mean difference of anthropometric indicator between two groups**

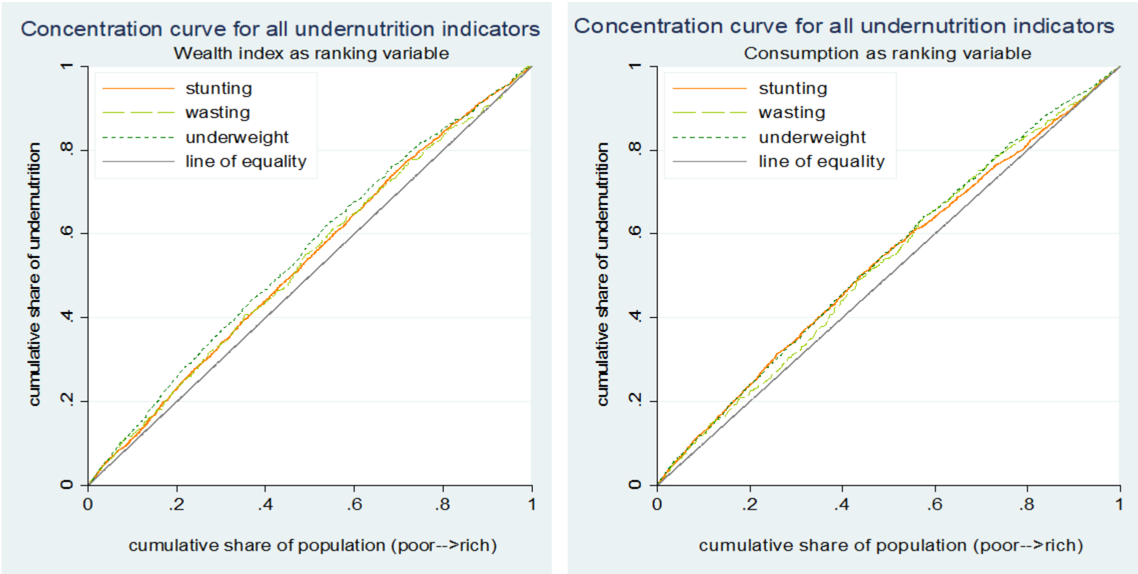
| Groups | HAZ | WHZ | WAZ |
|---|---|---|---|
| Small town | -1.1(.064) | -.33 (.057) | -.84 (.048) |
| Rural | -1.4( .018) | -.50 (.016) | -1.2 (.013) |
| Deference(Small town -Rural) | .30** (.070) | .16*** (.061) | .42*** (.051) |
| Male | -1.4(.025) | -.47 (.022) | -1.2 (.018) |
| Female | -1.3 (.026) | -.51 (.022) | -1.1 .(018) |
| Deference(Male -Female) | -.06*(.036) | .04(.031) | -.08*** (.026) |
| Wealth index | | | |
| Poorest($1^{st}$ quintile) | -1.5 (.062) | -.57 (.054) | -1.4 (.042) |
| Richest ( $5^{th}$quintile) | -1.1 (.079) | -.26 (.067) | -.86 (.058) |
| Difference ($1^{st}$-$5^{th}$) | -.44*** (.103) | -.31** (.089) | -.59*** (.072) |
| Non-poor( Top 40%) | -1.1(.031) | -.42 (.027) | -1.03 (.023) |
| Poor( Bottom 60%) | -1.4 (.022) | -.52 (.019) | -1.33 (.015) |
| Difference (40%-60%) | .30*** (.039) | .09*** (.033) | .29*** (.028) |
| Consumption | | | |
| Poorest($1^{st}$quintile) | -1.5 (.065) | -.61 (.056) | -1.4 (.045) |
| Richest ( $5^{th}$quintile) | -1.2 (.075) | -.27 (.064) | -.94 (.053) |
| Difference ($1^{st}$-$5^{th}$) | -.35** (.099) | -.34** (.085) | -.53*** (.069) |
| Non-poor(Top 40%) | -1.2 (.030) | -.45 (.026) | -1.1 (.021) |
| Poor( Bottom 60%) | -1.4 (.023) | -.51 (.019) | -1.3 (.016) |
| Difference (40%-60%) | .22*** (.038) | .06* (.032) | .20*** (.027) |

*Note :Significance level ***, ** and * is at 1% , 5% and 10% respectively and; Std. Errors are in parenthesis. Two-sample t test with equal variances ($H_o$: difference is zero ; $H_1$: difference is different from zero*

In terms of HAZ- malnutrition level, regions can be ranked from highest to lowest as Tigray, Amhara, SNNP, Oromia, and Other regions respectively while in WHZ- malnutrition level, it is as follows Tigray, Other regions, Amhara, Oromia, and SNNP respectively. Similarly, with WAZ- malnutrition level, it is given as Tigray, Amhara, Other regions, SNNP, and Oromia respectively( for details, see Table 1.1, in the appendix part).

Since pairwise comparisons ignore all other subgroups that are not being compared, it is common to employ multiple (complex) measures in the analysis of inequality. The most common and appropriate methods for measuring inequality magnitude and directions are thus concentration curves and index.

**Figure 1.3:** Concentration Curves of malnutrition Indicators




As it is illustrated in Figure (1.3), the concentration curves for each malnutrition indicators is located above the line of equality. These indicate that higher malnutrition level is disproportionately prevailed among the poor section of the population in both socioeconomic status (SES) ranking variables, i.e. pro- poor inequality in terms of malnutrition level.

While measuring inequality using concentrration index, estimation and inference is via a regression approach, user-written stata command conindex, developed by O'Donnell et al. (2016). This approach allows for addressing the issue of sampling design, misspecification and for testing for differences in inequalities across population or sub-populations. For standard and generalized concentration index (CI), the health variable is negative of Z-score which is continuous and unbounded variables while in case of Erreygers and Wagstaff, it is binary which is bounded variables (either 0 or 1).

**Table 1.5: Concentration indices (CI) of malnutrition prevalence by methods**: Ranking variables -wealth index and consumption

| Method/ | Standard CI | | | Generalized CI | | |
|---|---|---|---|---|---|---|
| Indicators | Wealth | Consumption | Difference (CIc-CIw) | Wealth | Consumption | Difference (CIc-CIw) |
| HAZ | -.040*** | -.070*** | -.024** | -.065*** | -.114*** | -.039** |
| | (.011) | (.012) | (.011) | (.019) | (.020) | (.017) |
| WHZ | -.028** | -.023*** | .000 | -.023** | -.019* | .000 |
| | (.012) | (.013) | (.012) | (.010) | (.011) | (.010) |
| WAZ | -.061*** | -.059*** | .002 | -.087*** | -.084*** | .004 |
| | (.010) | (.010) | (.009) | (.014) | (.015) | (.015) |
| | Erreygers normalized | | | Wagstaff normalized | | |
| | Wealth | Consumption | Difference (CIc-CIw) | Wealth | Consumption | Difference (CIc-CIw) |
| Stunting | -.093*** | -.111*** | -.054** | -.107*** | -.132*** | -.059** |
| | (.024) | (.025) | (.023) | (.028) | (.029) | (.025) |
| Wasting | -.028** | -.031*** | -.009 | -.083** | -.092*** | -.025 |
| | (.012) | (.012) | (.014) | (.036) | (.035) | (.037) |
| Underweight | -.132*** | -.108*** | .007 | -.172*** | -.140*** | .010 |
| | (.022) | (.021) | (.025) | (.029) | (.024) | (.032) |

*Note :Significance level ***, ** and * is at 1% , 5% and 10% respectively and; Std. Errors ( in parenthesis) are adjusted for each clusters in ea_id (enumeration areas or primary sampling units).*

As it is shown in Table 1.5, the concentration indices for each malnutrition indicators and socioeconomic status (SES) ranking variables vary across the methods employed for computing those indices. In all approaches and SES ranking variables, the concentration indices are significant with negative value which exhibit higher malnutrition in all indicators is disproportionately observed in poor part of the population. While employing different SES ranking variables, the difference in the concentration indices is only found significant in case of Height-for-age Z-score (HAZ). Using standard method, for example, in HAZ, -0.040 and -0.070 of concentration index (CI) for wealth index and consumption are scored respectively. It signifies that relatively higher inequality is measured using consumption as ranking variable.

Using Wagstaff method, for example, in stunting, -0.107 and -0.132 of concentration index

(CI) for wealth index and real annual total consumption per adult equivalence are observed respectively. With the same method, in terms of SES ranking variables altering, the highest CI and thus inequality, in each malnutrition indicators is relatively recorded in case of consumption. From these results, we can also infer that in all SES ranking variables, higher inequality of malnutrition is concentrated in poor part of the society.

**Table 1.6: Concentration indices of malnutrition prevalence by region:** Ranking variables -wealth index and consumption

| **Regions** | **Height-for-Age** | **(HAZ)** | **Weight-for-Height** | **(WHZ)** | **Weight-for-Age** | **(WAZ)** |
|---|---|---|---|---|---|---|
| | Wealth | Consumption | Wealth | Consumption | Wealth | Consumption |
| Tigray | -.029** | -.053** | -.001 | .021 | -.050*** | -.038* |
| | (.021) | (.022) | (.025) | (.042) | (.016) | -.017 |
| Amhara | -.036* | -.019* | -.069*** | -.036 | -.052** | -.017 |
| | (.023) | (.014) | (.025) | (.025) | (.021) | (.013) |
| Oromia | -.035** | -.039** | -.036* | -.028 | -.047*** | -.040** |
| | (.015) | (.016) | (.022) | (.021) | (.013) | (.016) |
| SNNP | -.054*** | -.057*** | -.010 | -.038 | -.057*** | -.067** |
| | (.010) | (.019) | (.020) | (.028) | (.013) | (.020) |
| Other | -.052** | -.017 | -.040 | .006 | -.053*** | -.015 |
| Regions | (.023) | (.023) | .028 | (.019) | (.016) | (.015) |
| Difference | 1% | 1% | 1% | 1% | 1% | 1% |

*Note : Significance level : ***, ** and * is at 1% , 5% and 10% respectively; and Std. Errors( in parenthesis) are adjusted for each clusters in ea_id(enumeration areas or primary sampling units).*

Another concern of this study is examining malnutrition inequalities using spatial dimensions and across other groups considered in this analysis. For each malnutrition indicators, concentration index (CI) is computed for each regions, male-female, rural-urban and then compares them to see the existence of significant difference between those groups considered. Thus, our results signify that significant inequality of malnutrition difference is shown across regions. We also recognize same result across lower administrative areas such as provinces (Zones), districts (Woredas) and Kebeles (lowest administrative units). For instance, in Height-for-Age Z-score (HAZ) with wealth index as ranking variable, the highest and lowest inequality of malnutrition is seen in SNNP (CI=-0.054) and Tigray (CI=-0.029) regions respectively. However, when real consumption per adult equivalence is taken in to account as ranking variable, the highest and lowest malnutrition inequality is observed in SNNP and Other regions respectively. As it is displayed in Table 1.6, in case of the other malnutrition indicators such as Weight-for-Height Z-score (WHZ) and Weight-for-Age Z-score (WAZ), analysis of inequality is different. In terms of sex-wise, except in consumption as ranking variable for WHZ and WAZ, the difference is insignificant. Similarly, inequality difference is almost insignificant while we consider rural-urban. In short, regardless of its significance, malnutrition inequality varies across considered groups in each indicator while we alter ranking socioeconomic status (SES) variables[14].

**Table 1.7: Concentration indices of malnutrition prevalence by sex and rural –small town:** Ranking variables -wealth index and consumption

| **Groups** | **Height-for-Age** | **(HAZ)** | **Weight-for-Height** | **(WHZ)** | **Weight-for-Age** | **(WAZ)** |
|---|---|---|---|---|---|---|
| | Wealth | Consumption | Wealth | Consumption | Wealth | Consumption |
| Male | -.044*** | -.051*** | -.041** | -.038** | -.061*** | -.051*** |
| | (.011) | (.012) | (.014) | (.015) | (.010) | (.011) |
| Female | –.049*** | -.044*** | -.021 | .018 | -.047*** | -.023* |
| | (.011) | (.011) | (.015) | (.016) | (.011) | (.012) |
| Difference | not sign | not sign | not sign | 5% | not sign | 5% |
| Small town | -.090** | -.002 | .024 | .009 | -.073* | -.026 |
| | (.034) | (.034) | (.052) | (.045) | (.044) | (.032) |
| Rural | -.043*** | -.048*** | -.031*** | -.019 | -.049*** | -.044*** |
| | (.009) | (.009) | (.012) | (.013) | (.009) | (.009) |
| Difference | not sign | 5% | not sign | no sign | no sign | no sign |

*Note : Significance level : ***, ** and * is at 1% , 5% and 10% respectively; and Std. Errors ( in parenthesis) are adjusted for each clusters in ea_id (enumeration areas or primary sampling units).*

### 1.4.3 Mobility indices and SES-related inequality in children undernutrition

The basic argument here is that taking on concentration index of each cross sectional data or weighted average of them hides the effect of time on inequality and fail to see dynamics of SES related inequality. It is either by the short-run concentration index (CI) underestimates or overestimates the long-run CI. This again leads to wrong inequality measurement inference. As

[14]We also compute concentration index while the health variable is binary outcome (stunted, wasted , and underweighted. The results are almost similar.

we can discern from Figure 1.4, there is apparent trends in short-run and long-run concentration indices in all undernutrtion indicators and SES ranking variables. This is a clear indication for existence of health -related SES mobility indices.

**Figure 1.4:** Trends in short-run and long-run concentration indices, and mobility indices


Results from Table (1.8) show us that in both malnutrition indicators and socioeconomic status (SES) ranking variables, the mobility indices are positive which implies that short-run (cross-sectional) CI overestimates the long-run (longitudinal data) CI. Hence, the results exhibit that the long-run SES related inequality in malnutrition declines while longitudinal data is considered, rather than using the weighted average of the cross sectional concentration indices. For example, in case of Height-for-age Z-score (HAZ) with wealth index as ranking variable, the mobility index is 0.54 and 0.63 for second and third wave respectively. It can be interpreted as the short-run measure overestimates long-run pro-poor inequality by 54 % and 63 % over respected waves for HAZ -malnutrition with wealth index as ranking variable.

**Table 1.8: Concentration and mobility indices for each undernutrition indicators**: Ranking variables -wealth index and consumption

| **Wave** | **Wealth** | | | **Consumption** | | |
|---|---|---|---|---|---|---|
| | $CI^t$ | $CI^T$ | $M^T$ | $CI^t$ | $CI^T$ | $M^T$ |
| **Height-for-Age Z-score** | | | | | | |
| 2011/12 | -.052 | -.052 | 0 | -.056 | -.056 | 0 |
| 2013/14 | -.080 | -.041 | .54 | -.058 | -.063 | .24 |
| 2015/16 | -.066 | -.040 | .63 | -.037 | -.070 | .25 |
| **Weight-for-Height Z-score** | | | | | | |
| 2011/12 | -.046 | -.046 | 0 | -.038 | -.038 | 0 |
| 2013/14 | -.046 | -.052 | .24 | -.018 | -.019 | .59 |
| 2015/16 | -.040 | -.028 | .65 | -.038 | -.023 | .61 |
| **Weight-for-Age Z-score** | | | | | | |
| 2011/12 | -.073 | -.073 | 0 | -.059 | -.059 | 0 |
| 2013/14 | -.072 | -.074 | .30 | -.055 | -.056 | .34 |
| 2015/16 | -.066 | -.061 | .52 | -.048 | -.059 | .41 |

*Note: $CI^t$ is CI at time t (each wave) or short-run CI and $CI^T$ is long-run CI (for longitudinal data). $M^T$ is mobility index for each wave. If $M^T$ >0, $CI^t$ overestimates $CI^T$ while $M^T$ <0, $CI^t$ underestimates $CI^T$; and $M^T$ =0 , no change in inequality.*

Similarly, for real annual consumption per adult equivalent as ranking variable, it makes long-run SES-related health inequality greater than what we could infer from the cross sectional measures or it declines by 24 % and 25 %, as reflected by the mobility index ($M^T$) of 0.24 and 0.25 in second and third wave respectively. These results and analyses strengthen our initial argument that examining SES related inequality using cross-sectional data masks the effect of dynamics on inequality over time (fails to see the correct long-run CI and thereby inequality). In general, Table 1.8 illustrates that the health-related income mobility index and shows that, by the last (third) wave, the short run measure over estimates long run inequality by around

63 % and 25 %, 65 % and 61 %, and 52 % and 41 % for HAZ, WHZ and WAZ respectively while wealth index and consumption are considered as ranking variable. Therefore, employing longitudinal perspective rather than weighted average of cross-sectional data is justifiable to see the dynamic of inequality in child malnutrition.

However, Allanson et al. (2010) question the value of the Jones and Lopez (2004) index to health policymakers and proposes an alternative index of "income-related health mobility", based on a decomposition of the change in the short run concentration index over time, that measures whether the pattern of health changes is biased in favour of those with initially high or low incomes.

**Table 1.9: SES-related health mobility and Health-related SES mobility index from Wave 1(2011/12), based on Allanson et al. (2010) approach**

| **SES ranking variable** | | **Wealth-** | **index** | | **Consum-** | **ption** |
|---|---|---|---|---|---|---|
| **Health indicator/Wave** | 2011/2012 | 2013/14 | 2015/16 | 2011/12 | 2013/14 | 2015/16 |
| **HAZ** | | | | | | |
| Average health ($\overline{y}$) | 1.83 | 1.64 | 1.43 | 1.83 | 1.64 | 1.43 |
| Concentration Index ($CI$) | -.043 | -.084 | -.062 | -.056 | -.072 | -.068 |
| Average health change ($\overline{\triangle y}$=$\overline{y}^f$-$\overline{y}^s$) | - | -.228 | -.457 | - | -.228 | -.457 |
| Concentration Index of health changes ($CI^{\triangle s}$) | - | .0743 | -.051 | - | -.013 | -.136 |
| Change in inequality ($CI^f - CI^s$) | - | -.041 | -.019 | - | -.016 | -.012 |
| SES-related health mobility ($M^H$) | - | -.023 | -.008 | - | -.008 | -.002 |
| Progressive Index ($P$=$CI^s - CI^{\triangle s}$) | - | -.117 | .008 | - | -.043 | .080 |
| Scale factor ($Q$=$\overline{\triangle y}/\overline{y}^f$ ) | - | -.139 | -.320 | - | -.139 | -.320 |
| Health-related SES mobility ($M^R$) | - | -.018 | -.011 | - | -.008 | -.014 |
| **WHZ** | | | | | | |
| Average health ($\overline{y}$) | .77 | .82 | .89 | .77 | .82 | .89 |
| Concentration Index ($CI$) | -.071 | -.036 | -.001 | -.043 | .002 | -.042 |
| Average health change ($\overline{\triangle y}$=$\overline{y}^f$-$\overline{y}^s$) | - | .016 | .102 | - | .016 | .102 |
| Concentration Index of health changes ($CI^{\triangle s}$) | - | -.203 | .299 | - | -.343 | .170 |
| Change in inequality ($CI^f - CI^s$) | - | .035 | .070 | - | .041 | .001 |
| SES-related health mobility ($M^H$) | - | .059 | .049 | - | .045 | .001 |
| Progressive Index ($P$=$CI^s - CI^{\triangle s}$) | - | .132 | -.37 | - | .39 | -.213 |
| Scale factor ($Q$=$\overline{\triangle y}/\overline{y}^f$ ) | - | .019 | .114 | - | .019 | .114 |
| Health-related SES mobility($M^R$) | | -.024 | .021 | - | 0 | 0 |
| **WAZ** | | | | | | |
| Average health ($\overline{y}$) | 1.35 | 1.40 | 1.42 | 1.35 | 1.40 | 1.42 |
| Concentration Index ($CI$) | -.080 | -.078 | -.051 | -.060 | -.055 | -.067 |
| Average health change ($\overline{\triangle y}$=$\overline{y}^f$-$\overline{y}^s$) | - | .025 | .052 | - | .025 | .052 |
| Concentration Index of health changes ($CI^{\triangle s}$) | - | .173 | .712 | - | -.168 | .467 |
| Change in inequality ($CI^f - CI^s$) | - | .002 | .029 | - | .005 | -.007 |
| SES-related health mobility ($M^H$) | - | .023 | .034 | - | .006 | .008 |
| Progressive Index ($P$=$CI^s - CI^{\triangle s}$) | - | -.253 | -.792 | - | .108 | -.527 |
| Scale factor ($Q$=$\overline{\triangle y}/\overline{y}^f$ ) | - | .017 | .036 | - | .017 | .036 |
| Health-related SES mobility ($M^R$) | - | -.021 | -.005 | - | -.001 | -.015 |

Note; $M^H$=$CI^{fs}$ -$CI^{ss}$. $CI^{ss}$ and $CI^{ff}$ are the CI's in periods $s$ and $f$ respectively, and $CI^{fs}$ is the CI obtained when health outcomes in the final period are ranked by SES in the initial period. $M^R$=$CI^{ff}$ -$CI^{fs}$. $CI^{ff}$ and $CI^{fs}$ are the CI's in periods $f$ , and $CI^{fs}$ CI obtained when health outcomes in the final period are ranked by SES in the initial period. $CI^{\triangle s}$ represents mean health change ranked by initial rank (the concentration coefficient of health changes ranked by initial period income).

Based on Allanson et al. (2010) approach, the decomposition of change in inequality (concentration index) between Wave 1 and each subsequent wave, as illustrated in Table (1.9) provides us both SES-related health mobility and health-related SES mobility indices. Sign of the index of SES-related health mobility, $M^H$ is both positive and negative for given time spans and each malnutrition indicator. When it is positive, it implies that differences in relative health changes experienced on average by individuals with different initial levels of SES had the effect of reducing socioeconomic inequalities in health. While, negative sign of $M^H$ has regressive effect which indicates that differences in relative health changes had the effect of rising socioeconomic inequalities in health. Put it differently, when decomposing the initial and final concentration indices, health changes are found to be biased against those in the lower (upper) end of the SES rankings as the SES-related health mobility index is negative (positive) respectively.

Similarly, the sign of health related SES mobility index, $M^R$ is mixed. Positive sign indicates that those who moved up the income ranking tended to be healthier in the final period compared to those who moved down. And the reverse is true while it bears negative sign. In other words, the positive/negative/ values on the health-related SES mobility index suggest that the healthy are more upward/downward/ mobile respectively.

Specifically, in case of HAZ, the sign of both SES related health mobility index ($M^H$) and health related SES mobility index ($M^R$ ) are negative in both wealth index and consumption. It implies that individuals face regressive effect ($M^H < 0$) from health change as well as progressive effect from SES ranking change ($M^R < 0$) and the counter balance effect leads to a cumulative effect of no change in inequality change. In other word, persistence of SES inequality in HAZ occurs in the long-run. This result doesn't confirm results we obtained from mobility indices computed based on Jones and Lopez (2004) approach. Similarly, results on WAZ show that $M^H$>0 and $M^R$<0. This indicates that individuals face progressive effect in both indices. Thus, it has a cumulative effect of reducing effect on inequality in the long-run which confirms results we obtain based on Jones and Lopez (2004) approach. However, for WHZ ( short -run indicator), there is no clear trend over subsequent waves to put any concluding remarks.

### 1.4.4 Decomposing inequality of undernutrition

Since the equation(1.6) used for decomposing the concentration index (CI) requires linearity of the underlying regression model, for our decomposition, we employ negative of each child Z-score as malnutrition level which is continuous variable against the relevant covariates[15]. We then use both random effect and fixed effect estimator to estimate the required coefficients for computing contribution of each factors. In Table 1.10 and 1.11, the coefficients are presented along with robust standard errors that are adjusted for clustering to enumeration areas (primary sampling units) due to the use of panel survey data. Decomposition results based on the alternative estimator, fixed effect is also attached at the appendix part, Table 1.2 and 2.19 [16].

[15]Alternatively, using binary outcomes as dependent variables(stunted, wasted and under-weighted option), we also estimate our regression model by OLS and pooled probit and results are more or less similar.

[16]Though specific results based on those alternative estimators are different from that of random effect, the contribution of socioeconomic factors to the observed inequalities in malnutrition is still dominant.

Table 1.10: Decomposition of child malnutrition inequality (CI): Ranking variable –Wealth index

| | HAZ | | | | WHZ | | | | WAZ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Regressors** ($k$) | $\beta_k$ | Elasti-city | CI | Contri-bution | $\beta_k$ | Elasti-city | CI | Contri-bution | $\beta_k$ | Elasti-city | CI | Contri-bution |
| Age | .006*(.002) | .17 | -.03 | -.01(.11) | -.014***(.002) | -.81 | -.03 | .02(-.72) | .007*** (.002) | .24 | -.03 | .01(.12) |
| Age-square | -.001*(.000) | -.18 | -.05 | .01(-.20) | -.000(.000) | .50 | -.05 | -.03(.82) | .000 (.000) | -.06 | -.05 | .00(-.05) |
| Sex | .077**(.035) | .02 | .02 | .00(-.01) | -.018(.025) | -.01 | .02 | -.00(.01) | .089***(.025) | .03 | .02 | .00(-.01) |
| Illness incidence | .103**(.040) | .01 | .05 | .00(-.01) | .107*** (.032) | .02 | .06 | .00(-.03) | .180***(.030) | .02 | .05 | .00(-.02) |
| Water availability | -.057(.055) | -.01 | .19 | -.00(.03) | .045 (.038) | .01 | .19 | .00(-07) | .008(.043) | .00 | .19 | .00(-.00) |
| Toilet type | -.002(-.016) | -.01 | -.02 | .00(-.00) | .034***(.013) | .26 | -.02 | -.01(.17) | .037***(.013) | .16 | -.02 | -.00(.07) |
| Health post | -.141** (.067) | -.09 | -.00 | .00(-.00) | .011 (.058) | .01 | .00 | 4.3(-.00) | -.078(.058) | -.06 | -.00 | .00(-.00) |
| Mother educ | - .110***(.022) | -.03 | .32 | -.01(.20) | -.024 (.015) | -.01 | .31 | -.00(.11) | -.074***(.018) | -.02 | .32 | -.01(.13) |
| Household size | -.016 (.010) | -.06 | .01 | -.00(.01) | .001 (.008) | .01 | .01 | .00(-.00) | -.006(.008) | -.03 | .01 | -.00(.00) |
| Household sizeU5 | -.039(.025) | -.03 | -.01 | .00(-.00) | -.001 (.018) | -00 | -.00 | 4.6(-.00) | -.049**(.020) | -.05 | -.00 | .00(-.00) |
| Rural-urban | yes | .02 | -.01 | -.00(.01) | yes | .13 | -.01 | -.00(.05) | yes | .16 | -.01 | -.00(.04) |
| Region variation | yes | | | -.003(.08) | yes | | | .00(.-12) | yes | | | -.00(.03) |
| **Wealth index** | - .045***(.016) | | | -.01(.30) | -.039***(.011) | | | -.03(.91) | -.045***(.013) | | | -.02(.30) |
| Quntile 1 | .158**(.068) | .02 | -.80 | -.02(.34) | .120*** (.045) | .03 | -.80 | -.02(.70) | .141***(.053) | .02 | -.80 | -.02(.30) |
| Quntile 2 | .111*(.064) | .01 | -.40 | -.01(.12) | .060 (.043) | .01 | -.39 | -.01(.17) | .059 (.045) | .01 | -.40 | -.00(.06) |
| Quntile 3 | .089 (.061) | .01 | .02 | .00(-.00) | .037 (.043) | .01 | .01 | .00(-.00) | .078* (.045) | .01 | .01 | .00(-.00) |
| Quntile 4 | .144** (.054) | .02 | .42 | .01(-.16) | -.013(.037) | -.00 | .41 | -.00(.04) | .054 (.041) | .01 | .41 | .00(-.06) |
| Residual | | | | -.022(.45) | | | | 004(-.13) | | | | -.021(.42) |
| Observation | 8,686 | | | | 8,132 | | | | 9,426 | | | |
| $R^2$ | 0.03 | | | | 0.046 | | | | 0.052 | | | |

Note: *Significance level : ***, ** and * is at 1% , 5% and 10% respectively; and Std. Errors ( in parenthesis) are adjusted for each clusters in ea_id (enumeration areas or primary sampling units).* Under each malnutrition indicators, in the contribution column, the figure in parenthesis represents the percentage contribution. Each figure is rounded to two digits only. Hence, point zero zero doesn't mean that it is actually zero, it is rather rounded value

Each column under each malnutrition indicators in Table (1.10) and (1.11) presents coefficients, elasticity of each regressor with respect to the health variable considered, concentration index of each regressor, contributions to the overall concentration index as well as percentages contribution of the overall concentration index which is given in parenthesis. Comparatively, our findings indicate that there is very limited contribution of the legitimate factor (such as age) in all malnutrition inequalities which signify that almost all are due to illegitimate factors such as wealth index, illness toilet facility etc. In Height-for-age Z-score (HAZ) and Weight-for-age Z-score (WAZ), wealth index and mother's education are the major contributors of socioeconomic related inequality in children undernutrition. For example, wealth index and mother's education contribute 30 % and 20 %, 91 %, and 11 % in case of HAZ and WAZ respectively while in Weight-for-Height Z-score (WHZ), the loin share is taken by wealth index (30 %) and toilet facility (17 %). Of course, the contribution of unexplained (residual) of the econometric model is higher for HAZ and WAZ. It accounts 45 %, 13 %, and 42 % of total contribution in case of HAZ, WHZ and WAZ respectively. The contribution of other factors such toilet facility is nil for HAZ while it is 17 % and 7 % for WHZ and WAZ respectively. Similarly, the contribution of sex, health facility and household size is almost zero in all malnutrition indicators. Illness incidence contributes 1 %, 3 %, and 2 % in case of HAZ, WHZ, and WAZ consecutively.

The contribution of mother education varies across malnutrition indicators. It is higher (20 %) in case of the long-run malnutrition indicator, low HAZ (stunting). Here, the possible reason could be due to the fact that effect of formal education is more pronounced on long-run than short -run indicator (Ambel et al., 2015). However, in case of short-run malnutrition indicator (low WHZ or wasting) and composite malnutrition indicator (low WAZ or underweight), mother education level accounts for 11 % and 13 % of the total contribution of observed inequalities in malnutrition respectively.

Table 1.11: Decomposition of child malnutrition inequality (CI): Ranking variable –Consumption

| | HAZ | | | | WHZ | | | | WAZ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Regressors** ($k$) | $\beta_k$ | Elasticity | CI | Contribution | $\beta_k$ | Elasticity | CI | Contribution | $\beta_k$ | Elasticity | CI | Contribution |
| Age | .006**(.003) | .19 | .01 | .00(-.02) | -.015***(.002) | -.82 | -.00 | .00(-.15) | .008***(.002) | .27 | .01 | .00(-.03) |
| Age-square | -.000(.000) | -18 | .01 | -.00(.04) | -.000(.000) | .53 | -.00 | -.00(.08) | -.000(.000) | -.07 | .01 | -.00(.02) |
| Sex | .080**(.035) | .02 | -.00 | -.00(.00) | -.016(.025) | -.01 | .00 | -.00(.00) | .091***(.026) | .03 | .00 | .00(-.00) |
| Illness incidence | .108***(0.041) | .01 | -.00 | -.00(.00) | .111***(.032) | .02 | .00 | .00(-.00) | .189***(.031) | .02 | -.01 | -.00(.00) |
| Water availability | -.072 (.056) | -.01 | .05 | -.00(.01) | .036 (.038) | .01 | .04 | .00(-.03) | -.003(.043) | -.00 | .04 | -.00(-.00) |
| Toilet type | .001(.017) | .00 | -.00 | -.00(.00) | .039***(.012) | .29 | -.00 | -.00(.05) | .040***(.013) | .18 | -.00 | -.00(.01) |
| Health post | -.137** (.067) | -.09 | .01 | -.00(.01) | .009(.061) | .01 | .01 | .00(.02) | -.083(.056) | -.06 | .01 | -.00(.01) |
| Mother educ | -.111*** (.021) | -.02 | .26 | -.01(.15) | -.027* (.016) | -.01 | .26 | -.00(.21) | -.074***(.017) | -.02 | .25 | -.01(.13) |
| Household size | -.024** (.010) | -.09 | -.03 | .00(-.06) | -.003(.008) | -.02 | -.03 | .00(-.05) | -.012(.008) | -.05 | -.03 | .00(-.04) |
| Household sizeU5 | -.032 (.025) | -.03 | -.01 | .00(-.01) | .001 (.019) | .00 | -.00 | -.00(.00) | -.045**(.020) | -.05 | -.01 | .00(-.01) |
| Rural-urban | yes | .04 | -.01 | -.00(.01) | yes | .15 | -.00 | -.00(.05) | yes | .17 | -.01 | -.00(.02) |
| Region variation | yes | | | -.01(.12) | yes | | | .00(-.27) | yes | | | -.00(.07) |
| **Consumption** | -.126***(.033) | | | -.02(.48) | -.029(.023) | | | -.01(.71) | -.099***(.024) | | | -.02(.49) |
| Quntile 1 | | .02 | -.80 | -.02(.36) | | .01 | -.80 | -.01(.54) | | .02 | -.80 | -.02(.42) |
| Quntile 2 | | .02 | -.40 | -.01(.13) | | .01 | -.40 | -.00(.24) | | .01 | -.40 | -.01(.13) |
| Quntile 3 | | .01 | .00 | .00(-.00) | | .02 | .01 | .00(-.02) | | .02 | .01 | .00(-00) |
| Quntile 4 | | .00 | .40 | .00(-.01) | | .00 | .41 | .00(-.05) | | .01 | .40 | .00(-.05) |
| Residual | | | | -.013(.28) | | | | -.006(.33) | | | | -.014(.31) |
| Observation | 8,505 | | | | 7,973 | | | | 9,229 | | | |
| $R^2$ | 0.039 | | | | 0.045 | | | | 0.052 | | | |

Note: *Significance level : ***, ** and * is at 1% , 5% and 10% respectively; and Std. Errors ( in parenthesis) are adjusted for each clusters in ea_id (enumeration areas or primary sampling units).* Under each malnutrition indicators, in the contribution column, the figure in parenthesis represents the percentage contribution. Each figure is rounded to two digits only. Hence, point zero zero doesn't mean that it is actually zero, it is rather rounded value

While we change our socioeconomic ranking variable from wealth index to real annual total consumption per adult equivalent, we observe different result. As in wealth index case, our results indicate that contribution of legitimate factor (such as age) is a very insignificant which signify that almost all is due to illegitimate factors such as consumption, illness toilet facility etc. In HAZ and WAZ, consumption and mother's education represent as the major contributors of socioeconomic related inequality in children undernutrition. For example, contribution of consumption and mother's education account for 48 % and 15 %, 71 % and 21 %, 42 %, and 13 % in case of HAZ, WHZ, and WAZ respectively. In a similar fashion, the contribution of other factors such as toilet facility, illness, sex, water availability and health facility is almost zero in all malnutrition indicators. Household size contributes 6 %, 5 %, and 4 % in case of HAZ, WHZ and WAZ consecutively. The contribution of unexplained (residual ) of the econometric model also accounts for 28 %, 33 %, and 31 % of total contribution in HAZ, WHZ and WAZ respectively.

**Table 1.12: Decomposition of child malnutrition inequality (CI): Over all contribution by related groups. Ranking variables -wealth index and consumption**

| **Categories** | **HAZ** | | **WHZ** | | **WAZ** | |
|---|---|---|---|---|---|---|
| | Wealth | Consumption | Wealth | Consumption | Wealth | Consumption |
| Wealth/consumption | -.01(.30) | -.02(.48) | -.03(.91) | -.01(.71) | -.02(.30) | -.02(.49) |
| Health -care | -.001(.02) | -.00(.02) | -.00(.07) | -.00(.02) | -.00(.05) | -.00(.02) |
| Family size | -.00(.01) | .00(-.07) | .00(-.00) | .00(-.05) | -.00(.00) | .00(-.05) |
| Mother educ | -.01(.20) | -.01(.15) | -.00(.12) | -.00(.21) | -.01(.13) | -.01(.13) |
| Time variant | -.02(.43) | -.03(.60) | -.04(1.2) | -.01(.82) | -.03(.56) | -.03(.57) |
| Regional variation | -.003(.08) | -.01(.12) | .00(.-12) | .00(-.27) | -.00(.03) | -.00(.07) |
| Rural-urban variation | -.00(.01) | -.00(.01) | -.00(.05) | -.00(.05) | -.00(.04) | -.00(.02 |
| Time invariant | -.003(.08) | -.01(.12) | .00(-.06) | .00(-.22) | -.00(.06) | -.00(.09) |
| Residual | -.022(.45) | -.013(.28) | 004(-.13) | -.006(.33) | -.021(.42) | -.014(.31) |

Note: under each malnutrition indicators, in the contribution column, the figure in parenthesis represents the percentage contribution. Each figure is rounded to two digits only. Hence, point zero zero doesn't mean that it is actually zero, it is rather rounded value.

In terms of related groups, the contributions of time variant factors (all socioeconomic variables) strongly dominate that of time invariant (fixed variables like place of residence). The contribution of regional variation in both wealth index and consumption is 8 % and 12 %, 12 % and 27 %, 3 % and 7 % for HAZ, WHZ and WAZ respectively. Similarly, rural-urban variation contributes 1 % and 1 %, 5 % and 5 %, 4 % and 2 % respectively. Though it varies from one malnutrition to other malnutrition indicator, the contribution of regional as well as rural-urban related variation to the inequality is thus smaller by large compared to socioeconomic related variation. These imply that in both socioeconomic status ranking variables, the bulk of inequality in malnutrition is caused by inequality in socioeconomic status in which it disfavors the poor in both cases.

Since our data is panel and well identified, we can also interpret our coefficients for causal inferences. In all undernutrition indicators and both SES ranking variables, age, sex, illness incidence are found statistically significant. Toilet type is only significant in case of HAZ and WAZ while health post availability is statistically significant (with expected sign) in HAZ. Number of under five children in household, and number of household members are also found as significant determinants of WAZ and HAZ respectively. Moreover, mother's education level, wealth index and consumption expenditure are found statistically significant (with expected sign) in both HAZ and WAZ only (see Table 1.10 and Table 1.11).

### 1.4.5 Decomposing poor–non-poor differences in child undernutrition

Before we estimate our decomposition equation, we first test null of no differences in mean dependent variables, covariates, and regression coefficients between the two groups while allowing sample weights and clustering. As result, we observe significant difference in all attributes to mean outcome difference for HAZ and WAZ while the results are insignificant for WHZ. In our estimation, we consider different cases like three-fold decomposition (endowments, coefficients and interactions), two-fold decomposition (with poor or non-poor coefficients as the reference) and two-fold decomposition with pooled coefficients as the reference (with group or with out group variable included in the pooled model). Coefficients, means and predictions for both poor, rich and pooled are also computed. Decomposition results that show how each covariates explain the non-poor-poor gap in undernutrition can be provided upon request.

**Table 1.13: Three fold decomposition of mean difference of child undernutrition between poor (bottom 60 %) and non-poor (top 40 %)**

| Variables /undernutrition levels | HAZ | WHZ | WAZ |
|---|---|---|---|
| **Overall differential** | | | |
| Mean prediction for Rich (R) | -1.21*** | -.429*** | -1.10*** |
| | (.060) | (.051) | (.050) |
| Mean prediction for Poor (P) | -1.52*** | -.530*** | -1.35*** |
| | (.056) | (.042) | (.041) |
| **Row Difference(R-P)** | .305*** | .100* | .249*** |
| | (.073) | (.059) | (.056) |
| due to Endowments(explained) =E | .265* | .039 | .313*** |
| | (.146) | (.118) | (.097) |
| due to Coefficients(unexplained) =C | .188* | .025 | .097 |
| | (.105) | (.079) | (.079) |
| due to Interactions (CE) | -.147 | .036 | -.162 |
| | (.167) | (.130) | (.113) |
| Observations(N) | 8686 | 8132 | 9426 |

*Note : Significance level : ***, ** and * is at 1% , 5% and 10% respectively and Std. Errors( in parenthesis) are adjusted for each clusters in ea_id(enumeration areas or primary sampling units)*

Our Blinder-Oaxaca decomposition analysis is conducted to decompose the poor - non-poor differences in child malnutrition outcomes into two components; one that is explained by differences in the level of the determinants (covariate effects), and another component that is explained by differences in the effect of the determinants on the child nutritional status (coefficient effects). Results show that the poor- non-poor gap in child malnutrition is significant in all indicators. The explained and unexplained(coefficient) effects are only significant in case of HAZ and WAZ however interaction effects are insignificant in all indicators. Our results also show that the explained (covariate) effect is dominant while the coefficients effects are relatively low in the all all malnutrition indicators. SES variables such as wealth index, consumption, and mother education inequality between poor and non-poor households explains most of the malnutrition gap between the two groups. Results are robust to the different decomposition weighting schemes.

**Table 1.14: Summary of decomposition results: Decomposition results of the poor-non-poor gap in malnutrition with different weighting schemes**

| D | 0 | 1 | 0.5 | .276 | * |
|---|---|---|---|---|---|
| **HAZ** | | | | | |
| Unexplained | 0.040 | 0.188 | 0.114 | 0.081 | 0.066 |
| Explained | 0.265 | 0.117 | 0.191 | 0.224 | 0.239 |
| % unexplained | 13.2 | 61.6 | 37.4 | 26.6 | 21.7 |
| % explained | 86.8 | 38.4 | 62.6 | 73.4 | 78.3 |
| **WHZ** | | | | | |
| Unexplained: | 0.061 | 0.025 | 0.043 | 0.051 | 0.027 |
| Explained | 0.039 | 0.075 | 0.057 | 0.049 | 0.074 |
| % unexplained | 61.0 | 25.1 | 43.1 | 51.1 | 26.7 |
| % explained | 39.0 | 74.9 | 56.9 | 48.9 | 73.3 |
| **WAZ** | | | | | |
| Unexplained | -0.065 | 0.098 | 0.016 | -0.020 | 0.026 |
| Explained | 0.314 | 0.152 | 0.233 | 0.269 | 0.223 |
| % unexplained | -26.0 | 39.2 | 6.6 | -8.0 | 10.3 |
| % explained | 126.0 | 60.8 | 93.4 | 108.0 | 89.7 |

Note: D in 4th column = relative frequency of high group , * reference: pooled model over both categories

### 1.4.6 Robustness of results

It is common and expected to conduct appropriate sensitivity analysis on results obtained to check their robustness either internally or externally.

While we conduct test of dominance of concentration curve against 45 degree line and Lorenz curve, we find that in all SES ranking variables and malnutrition indicators, concentration curve dominates 45 degree line and Lorenz curve at the default multiple comparison approach decision rule, 5 % significance level, 19 equally spaced quintiles points and rule mca (less strict option). Hence, our results confirm that the concentration curves in all SES ranking variables and malnutrition indicators dominate the 45- degree line and Lorenz curve (lies above). This implies that in all SES and malnutrition indicators, the concentration curve lies above the line of equality, i.e, pro-poor health outcome distribution. However, the results become non dominance of concentration curve over that of 45 degree line and Lorenz curve at the other option, 5 % significance level, 19 equally spaced quintile points and rule iup (more strict option). This reflects the fact that the two curves overlap toward the bottom of the SES variable distribution. Further tests on on dominance of concentration curve for stunting against wasting, stunting against underweight, and wasting against underweight are conducted. Differences between the cumulative shares of the health and living standards variables at each quintiles are also tested (detail results are available up on request).

**Table 1.15: Extended and Symmetric Concentration indices (CI) of malnutrition prevalence by methods**

| **Method** | **HAZ** | | **WHZ** | | **WAZ** | |
|---|---|---|---|---|---|---|
| $v$,$\beta$ parameters | 1.5 | 5 | 1.5 | 5 | 1.5 | 5 |
| **Ranking variable -Wealth index** | | | | | | |
| Extended CI($v$) | -.029 | -.094 | -.019 | -.068 | -.033 | -.112 |
| Symmetric CI($\beta$) | -.038 | -.073 | -.028 | -.043 | -.047 | -.076 |
| Generalized extended CI($v$) | -.327 | -.290 | -.107 | -.106 | -.310 | -.293 |
| Generalized symmetric CI($\beta$) | -.252 | -.486 | -.094 | -.144 | -.262 | -.425 |
| **Ranking variable -Consumption** | | | | | | |
| Extended CI($v$) | -.026 | -.120 | -.014 | -.022 | -.027 | -.101 |
| Symmetric CI($\beta$) | -.045 | -.060 | -.016 | -.034 | -.040 | -.065 |
| Generalized extended CI($v$) | -.297 | -.370 | -.082 | -.035 | -.256 | -.264 |
| Generalized symmetric CI($\beta$) | -.303 | -.399 | -.054 | -.114 | -.225 | -.366 |

*Note* :$V$= inequality risk aversion parameter, $\beta$ = degree of sensitivity to extremity or symmetric parameter. $V$=1.5⇒more weight to rich, $V$ =5⇒more weight to poor, $\beta$ =1.5 ⇒more to middle classes, and $\beta$ = 5⇒ more to extreme classes.

Although the concentration index is an appropriate method for measuring inequalities in the health sector, it has implicit in it a particular set of value judgments about aversion to inequality. Accordingly, we apply Wagstaff (2002) "extended" concentration index (sensitivity to poverty), which allows attitudes to inequality to be made explicit, and to see how measured inequality changes as the attitude to inequality changes. We thus find that inequality rises in all malnutrition indicators when we increase inequality aversion parameters/distributional sensitivity parameter[17]. This assures our results on malnutrition inequalities (with negative sigh of concentration index) are pro poor[18] irrespective of the inequality aversion parameters

[17] As inequality aversion parameters/distributional sensitivity parameter, the more weight is attached to health of poor individuals in the distribution and the weight attached to the health of people who are above the 55th percentile decreases.

[18] In terms of sign concentration index, results using standard concentration index with regular parameters are same as while we alter inequality aversion parameters above regular parameters. In both option, inequalities in malnutrition are pro-poor.

(for details, see Table 1.15).

We also apply the normalised concentration indices proposed by Wagstaff (2005) and Erreygers (2009a) by specifying the Wagstaff and Erreygers option while our health variable becomes binary outcome (stunting, wasting and underweight), for details, see Table (1.5). Our results on malnutrition inequalities are still same, i.e. pro-poor. We also test our results using another alternative of attitude to inequality, i.e. symmetric concentration index or 'sensitivity to extremity.

The choice between the symmetric and extended indices is normative. The symmetric index gives equal weight (but with an opposite sign) to individuals that are equally far apart from the pivotal individual with median rank, while the extended index prioritizes the lower regions of the ranking (income) distribution. Erreygers et al. (2012) argue that the symmetric index is more concerned about the association between income and health, while the extended concentration index puts priority on the income distribution, and only then analyzes health differences within the prioritized region of the income distribution (ODonnell, 2016).

To refine results, using decomposition method ( as indirect method), our results on inequality in malnutrition measured by respected concentration indices for all indicators and SES variables are standardized for age and gender, for details on the results, see Table (1.15)[19].

**Table 1.16: Standardized of CI and Decomposition of child malnutrition inequality-Over all inequality by related groups: Ranking variables -wealth index and consumption**

| Groups | HAZ | | WHZ | | WAZ | |
|---|---|---|---|---|---|---|
| | Wealth | Consumption | Wealth | Consumption | Wealth | Consumption |
| All SES inequality | -.045 | -.050 | -.033 | -.016 | -.054 | -.044 |
| Age-sex standardized CI | -.049 | -.047 | -.030 | -.018 | -.050 | -.045 |
| Legitimate inequality | .004 | -.0009 | -.003 | .001 | -.003 | .0007 |
| Illegitimate inequality | -.027 | -.034 | -.034 | -.011 | -.030 | -.031 |
| Residual | -.022 | -.013 | .004 | -.006 | -.021 | -.014 |

Note: under each malnutrition indicators, in the contribution column, the figure in parenthesis represents the percentage contribution

Most surveys used for analysis of health sector inequalities in developing countries have complex sample designs. Hence, in our all estimations, we consider appropriate sampling weights

[19] As such, by incorporating various confounding variables, all computed concentration indices are standardized using indirect methods (see O'Donnell et al. 2008 Chapter 8 for details)

to adjust the point estimates for difference in sample size and stratification, and thus for national representative inference. Robust standard errors are also adjusted for each cluster in enumeration areas ( primary sampling units).

With respect to external validation of our results, we try to see some previous studies findings that can be compared. One study that supports our findings in dynamics of inequality (not in sign) is by Jones and Lopez (2004) in which they demonstrate that over the long-run, represented by a period of 9 years, adverse mental health is more concentrated among the poor. In particular, individual dynamics increase the absolute value of the concentration index of health on income by 10 %. Similarly, for Australia, Samuel (2015) shows that socioeconomic related health inequalities have indeed increase over the given time period.

There are some evidence that concentration indices for health outcome are more sensitive to the living standards measure. In due respect, for 19 countries, Wagstaff and Watanabe (2003) test the sensitivity of the concentration index for child malnutrition to the use of household consumption and a wealth index as the living standards ranking variable. For each of underweight and stunting, the difference between the concentration indices is significant (10 %) for 6 of 19 comparisons. This suggests that in the majority of countries, child nutritional status is not strongly correlated with inconsistencies in the ranking of households by consumption and wealth. In a similar fashion, Lindelow (2006) demonstrates that substantial and significant differences between the concentration indices (CI) for a variety of health services in Mozambique using consumption and an asset index as the living standards measure. In the case of consumption, the concentration index indicates statistically significant inequality in favor of richer households for all services. He also notes that with households ranked by the asset index rather than consumption, the inequality is greater for all services except health center visits, for which the concentration index indicates inequality in utilization in favor of poorer households. Like our study, he argues that the choice of welfare indicator can have a large and significant impact on measured socioeconomic inequalities in a health variable which it depends on the variable examined.

Specifically, Ambel et al. (2015) is a similar work in Ethiopia to our study. Using recent four cross sectional surveys of Demographic and Health Surveys (DHS) implemented in 2000, 2005, 2011, and 2014, they investigates the dynamics of inequalities, employing concentration curves for different years. They find that substantial improvements in health outcomes and health services. Although there still exists a considerable gap between the rich and the poor, the study finds some reductions in inequalities of health services. However, our evidence is differ from it, in using longitudinal data and alternative welfare measures, consumption as measure of dynamics of inequality in child undernutrition.

## 1.5 Conclusion

In Ethiopia, undernutrition can best be described in the country as a long term year round phenomenon due to chronic inadequacies in food combined with high levels of illness in under-five children. Although Ethiopia has already achieved a remarkable progress in reducing under-five mortality in the last decades, undernutrition among children is still a common problem in this country. Thus, socioeconomic inequalities in health outcomes have been of focus in academia and policy spheres for a while now.This study provides new evidence on child undernutrition inequalities in Ethiopia using longitudinal perspective and look at the dynamics of inequality using mobility indices. In all concentration index computing approaches and SES ranking variables, the concentration indices are significant with negative value. This implies that in either of short-run or long-run inequality estimates, the burden of unequal distribution of undernutrition remains on the poor. While employing different SES ranking variables, the difference in the concentration indices is only found significant in case of Height-for-age Z-score (HAZ). Using standard method, for example, in HAZ, -0.040 and -0.070 of concentration index (CI) for wealth index and consumption are scored respectively. It signifies that relatively higher inequality is measured using consumption as ranking variable. This assures the argument of the choice of welfare indicator can have a large and significant impact on measured socioeconomic inequalities in a health variable which it depends on the variable examined. For spatial inequality in malnutrition, concentration index (CI) is also computed for each region and rural-urban. Thus, our results signify that significant difference in inequality of undernutrition is shown across regions while not significant in case of male -female and rural-urban. In this regard, our findings may be helpful in prioritizing resources to reduce inequality and in designing region specific suitable interventions to address such inequity issues. Our inequality results are robust to different measurement scale, inequality aversion parameters/distributional sensitivity parameters, symmetric concentration index or 'sensitivity to extremity, and normalization of concentration index.Those results are also standardized for age and gender.

Results on the health-related SES mobility indices computed using Jones and Lobez (2004) show that, by the last (third) wave, the short run measure overestimates long run inequality by around 63 % and 25 %, 65 % and 61 %, 52 % and 41 % for HAZ, WHZ and WAZ respectively while wealth index and consumption are considered as ranking variable. Put it differently, this reveals that dynamics decrease the absolute value of the concentration indices of child malnutrition by those given figures. However, results on mobility indices computed based on Allanson et al. (2010) approach show that in case of HAZ, the sign of both SES related health mobility index (MH) and health related SES mobility index (MR) are negative in both wealth index and consumption. It implies that individuals face regressive effect (MH $< 0$) from health change as well as progressive effect from SES ranking change (MR $< 0$) and the counter balance effect leads to a cumulative effect of no change in inequality change. In other word, persistence of SES inequality in HAZ occurs in the long-run. Similarly, results on WAZ show that MH $>0$ and MR$<0$. These indicate that individuals face progressive effect in both indices. Thus, it has a cumulative effect of reducing effect on inequality in the long-run which confirms results we obtain based on Jones and Lopez (2004) approach. While, for WHZ ( short -run indicator), there is no clear trend over subsequent waves to put any concluding remarks. Therefore, employing longitudinal perspective rather than weighted average of cross-sectional data is justifiable to see the dynamic of inequality in child malnutrition.

Our findings also indicate that there is very limited contribution of the legitimate factor (age) in all malnutrition inequalities which signify that almost all are due to illegitimate factors such as disparity in wealth index, consumption, illness, toilet facility etc. In Height-for-age Z-score (HAZ) and Weight-for-age Z-score (WAZ), wealth index and mother's education are the major contributors of socioeconomic related inequality in children undernutrition. While in Weight-for-Height Z-score (WHZ), the loin share is taken by wealth index (30 %) and toilet facility (17 %). While we change our socioeconomic ranking variable from wealth index to real annual total consumption per adult equivalent, our results indicate that contribution of legitimate factor is a very insignificant which signify that almost all is due to illegitimate factors such as consumption, illness toilet facility etc. In HAZ and WAZ, consumption and mother's education represent as the major contributors of socioeconomic related inequality in children undernutrition. Though it varies from one undernutrition to other malnutrition indicator, the contribution of regional as well as rural-urban related variation to the inequality is thus smaller by large compare to socioeconomic related variation. Those major contributors to the inequality (mother's education level, wealth index and consumption expenditure) are also found statistically significant (with expected sign). Results on Oaxaca decomposition shows that the explained and unexplained (coefficient) effects are only significant in case of HAZ and WAZ while interaction effects are insignificant in all indicators. Our results also show that the explained (covariate) effect is dominant while the coefficients effects are relatively low in the all all malnutrition indicators. SES variables such as wealth index, consumption, and mother education inequality between poor and non-poor households explains most of the malnutrition gap between the two groups. These imply that in both socioeconomic status ranking variables, the bulk of inequality in malnutrition is caused by inequality in socioeconomic status in which it disfavors the poor in both cases. This calls for enhancing the policy measures that narrow socioeconomic gaps between groups in the population and targeting on early childhood intervention and nutrition sensitive.

# Bibliography


- Abuya BA, Ciera JM, Kimani-Murage E. 2012. Effect of mother's education on child's nutritional status in the slums of Nairobi. BMC Pediatr. 2012;12:80.
- Africa Health Observatory, AFO. 2016. Ethiopia: Fact sheets of Health Statistics. World Health Organization.
- Alemu, Z.A., A.A. Ahmed, A.W. Yalew and B.S.Birhanu. 2016. Nonrandom distribution of child under-nutrition in Ethiopia: spatial analysis from the 2011 Ethiopia demographic and health survey, International Journal for Equity in Health, 15 (198).
- Allanson Paul, Ulf-G Gerdtham and Dennis Petrie. 2010. Longitudinal analysis of income-related health inequality. Dundee Discussion Working Paper No. 214, August, 2008 ISSN:1473-236X
- Ambel, A., C. Andrews, A. Bakilana, E. Foster, Q. Khan and H. Wang. 2015.Maternal and Child Health Inequalities in Ethiopia. Policy Research Working Paper 7508. The World Bank.
- Asfaw M, Wondaferash M Taha M , Dube L. 2015. Prevalence of under-nutrition and associated factors among children aged between six to fifty nine months in Bule Hora district, South Ethiopia.. BMC Public Health. 2015 Jan 31;15:41.
- Barros Fernando C, Cesar G Victora, Robert Scherpbier, and Davidson Gwatkin. 2010. Socioeconomic inequities in the health and nutrition of children in low/middle income countries. Rev Saúde Pública 2010;44(1):1-16
- Bredenkamp, Leander R Buisman and Ellen Van de Poel. 2014. Persistent inequalities in child undernutrition: evidence from 80 countries, from 1990 to today. International Journal of Epidemiology, 2014, 1328–1335.
- Black R. E. , C. G. Victora, S. P. Walker et al. 2013. Maternal and child undernutrition and overweight in low-income and middleincome countries, The Lancet, vol. 382, no. 9890, pp. 427–451, 2013.
- Central Statistical Authority (Ethiopia) and ORC Macro. 2011. Ethiopia Demographic and Health Survey 2011. Addis Ababa. Maryland: Ethiopia and Calverton.
- Deaton A. 2003. Health, inequality, and economic development, Journal of Economic Literature Vol. XLI March 2003) pp. 113–158 .
- Deaton A. 2008. Income, Health, and Well-Being around the World: Evidence from the Gallup World Poll, Journal of Economic Perspectives Vol. 22 No. 2 Spring 2008.

- Deaton A. 2013. The great escape: health , wealth, and the origins of inequality. Princeton University press, edition(2013).
- Derek Heady. 2014. An analysis of trends and determinants of child under-nutrition in Ethiopia, 2010-2011, ESS, IFPRI working paper 70.
- DeOnis, Edward A. Frongillo, & Monika Blo¨ssner. 2000. Is malnutrition declining? An analysis of changes in levels of child malnutrition since 1980 Mercedes de.Bulletin o f t h e World Health Organization, 2000, 78: 1222–1233.
- Erreygers, G. 2009a. Can a single indicator measure both attainment and shortfall inequality? Journal of Health Economics 28: 885–893.
- Erreygers, G., P. Clarke, and T. Van Ourti. 2012. "Mirror, mirror, on the wall, who in this land is fairest of all?"—Distributional sensitivity in the measurement of socioeconomic inequality of health. Journal of Health Economics 31: 257–270.
- Fotso Jean-Christophe. 2006. Child health inequities in developing countries: differences across urban and rural areas: International Journal for Equity in Health 2006 5:9
- Glewwe P, Miguel EA. 2007. the Impact of Child Health and Nutrition on education in less developed countries. Hand book of Development Economics. Volume 4. Oxford: Elsevier B.V; 2007. pp. 3561–3606.
- Hailie, D., M. Azage, T. Mola and R. Rainey. 2016. Exploring spatial variations and factors associated with childhood stunting in Ethiopia: spatial and multilevel analysis, BMC Paediatrics, 16(49).
- Jones, A.M., Lopez, A. 2004. Measurement and explanation of socioeconomic inequality in health with longitudinal data , Health Econ. 13, 1015-1030 (2004).
- Kakwani N., A. Wagstaff and E. van Doorslaer. 1997. Socioeconomic inequalities in health: measurement, computation and statistical inference. Journal of Econometrics, 77: 87–103.
- Lavy, Victor and Strauss, John and Thomas, Duncan & de Vreyer, Philippe. 1996. "Quality of health care, survival and health outcomes in Ghana," Journal of Health Economics, Elsevier, vol. 15(3), pages 333-357, June.
- Lindelow, M. 2006. "Sometimes More Equal Than Others: How Health Inequalities Depend upon the Choice of Welfare Indicator." Health Economics15(3): 263–80.
- McKinnon, B., S. Harper, J.S. Kaufman and Y. Bergevin. 2014. Socioeconomic inequality in neonatal mortality in countries of low and middle income: a multi-country analysis. The Lancet Global Health, 2(3): e165 - e173.
- Misgan Legesse Liben, Taye Abuhay, Yohannes Haile. 2016. Determinants of Child Malnutrition among Agro Pastorals in Northeastern Ethiopia: A Cross-Sectional Study. Health Science Journal ISSN 1791-809X. Vol.10 No.4:15.
- Pitt, M. M., & Rosenzweig, M. R. 1985. Health and Nutrient Consumption across and within Farm Households. The Review of Economic Statistics, 67(2), 212–223.

- O'Donnell O., E. van Doorslaer, A. Wagstaff A, and M. Lindelow. 2008. Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and their Implementation. Washington, DC: World Bank.
- O'Donnell Owen, O'Neill Stephen, Van Ourti Tom and Walsh Brendan. 2016. Conindex: Estimation of concentration indices.The Stata Journal(2016), 16, Number 1, pp. 112–138.
- Oaxaca, R. 1973. Male-Female Wage Differentials in Urban Labor Markets. International Economic Review 14: 693–709.
- Quentin, W., O. Abosede, J. Aka, P. Akweongo, K. Dinard, A. Ezeh and L. Sundmacher. 2014. Inequalities in child mortality in ten major African cities. BMC Medicine, 12: 95.
- Samuel.P. Q.Calaka. 2015. Dynamics of Socioeconomic -related health inequalities in Australia.A master thesis, Lund University.
- Shorrocks, A.1978. Income inequality and income mobility. Journal of Economic Theory 19, 376-393
- Skaftun EK, Ali M, Norheim. 2014. Understanding Inequalities in Child Health in Ethiopia: Health Achievements are Improving in the Period 2000–2011. PLoSONE9(8):e106460.
- Thomson Liz Comrie, Jess Davis, Andre Renzaho, Michael Toole. 2014. Addressing child undernutrition: evidence review , Published by the Office of Development Effectiveness, Australian Government Department of Foreign Affairs and Trade, Canberra.
- Thomas, D., Lavy, V., & Strauss, J. 1996. Public Policy and Anthropometrics Outcomes in the Côte D'Ivoire. Journal of Public Economics, 61(2), 155–192.
- Thomas, Duncan & Strauss, John, 1992. "Prices, infrastructure, household characteristics and child height," Journal of Development Economics, Elsevier, vol. 39(2), pages 301-331, October.
- United Nations Children's Fund, UNICEF. 2017. Child Malnutrition Estimates.
- United Nations Children's Fund, UNICEF .1990. Strategy For Improved Nutrition Of Children And Women In Developing Countries. A Unicef Policy Review, New York, N.Y., USA
- Wagstaff A., P.Pact and E. Doorslae. 1991.On The Measurement Of Inequalities In Health. Sm. Sci.Med. Vol. 33.No. 5, pp. 545.
- Wagstaff Adam. 2002. Theme Papers Poverty and health sector inequalities: Bulletin of the World Health Organization 2002;80:97-105.
- Wagstaff, A, van Doorslaer, E., Watanabe, N. 2003. On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in Vietnam, Journal of Econometrics, 112: 207-223.
- Wagstaff, A. 2005. The bounds of the concentration index when the variable of interest is binary, with an application to immunization inequality. Health Economics 14: 429– 432.

- Wagstaff Adam ,Caryn Bredenkamp, Leander R. Buisman. 2014. Progress Toward the Health MDGs: Are the Poor Being Left Behind? Word Bank Policy Research Working Paper 6894.
- Zewdie Tadiwos and Abebaw Degnet . 2013. Determinants of Child Malnutrition: Empirical Evidence from Kombolcha District of Eastern Hararghe Zone, Ethiopia. Quarterly Journal of International Agriculture 52 (2013), No. 4: 357-37.
- WHO. 2006. WHO Child Growth Standards: Length/height-for-age, weight-for-age, weight-for-length, weight-for-height and body mass index-for-age: Methods and development. Geneva: World Health Organization.
- World Bank. 2012. Health Equity and Financial Protection Data sheet - Ethiopia. Washington, D.C.: World Bank.
- Wooldridge Jeorey M. .2002. Econometric Analysis of Cross Section and Panel Data.The MIT Press Cambridge, Massachusetts London, England.


## *Appendix*

**Figure 1.1:** Socioeconomic ranking variables distribution by household (normalized )

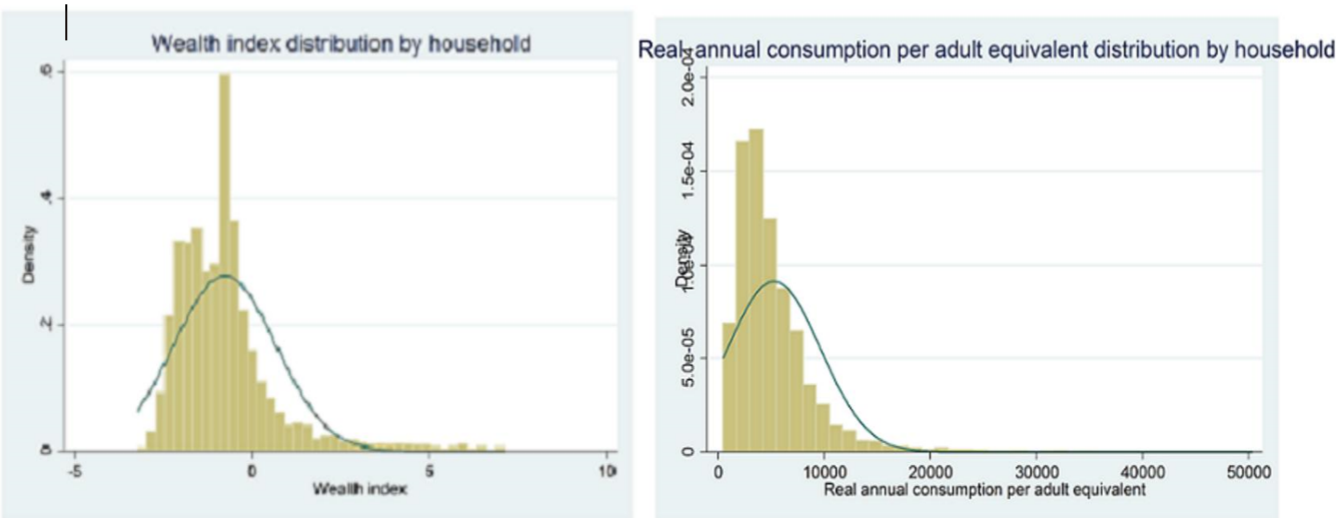


**Table 1.1: Prevalence of stunting, wasting and underweight by region and rural/urban**

| Groups | Stunting | Wasting | Underweight |
|---|---|---|---|
| **Rural -urban** | | | |
| Rural | 3,214 (30.90) | 1,007(9.68) | 2,479(23.83) |
| Small town | 183(22.56) | 58 (7.15) | 122(15.04) |
| **Regions** | | | |
| Tigray | 351(35) | 131(13.06) | 326 (32.50) |
| Amhara | 624(33.91) | 171 (9.29) | 449 (24.40) |
| Oromia | 637(26.91) | 181 (7.65) | 458 (19.35) |
| SNNP | 1,050(33.35) | 231(7.34) | 707(22.46) |
| Other Regions | 735(25.75) | 351(12.30) | 661(23.16) |

Note: All values in parentheses are in percentage. Others includes samples from Afar, Somalie, Gambelia, Benshangul Gumuz, Harari and Diredwa which are all together nationally representative.

**Table 1.2: Decomposition of child malnutrition inequality (CI) based on Fixed effect estimator: Ranking variable –Wealth index**

| | HAZ | | | | WHZ | | | | WAZ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Regressors ($k$)** | $\beta_k$ | Elasticity | CI | Contribution | $\beta_k$ | Elasticity | CI | Contribution | $\beta_k$ | Elasticity | CI | Contri-bution |
| Age | .006* (.003) | .17 | -.02 | -.01(.11) | -.015***(.003) | -.85 | -.03 | . 03(-.76) | .006*(.003) | .21 | -.03 | -.01(.11) |
| Age-square | -.000**(.000) | -.11 | -.05 | .01(-.12) | -.000*(.000) | .51 | -.05 | -.03(.83) | .000(.000) | .01 | -.05 | -.00(.01) |
| Sex | .433***(.114) | .13 | .02 | .00(-.06) | .131*(.076) | .08 | .02 | .00(-.05) | .327***(.081) | .12 | .02 | .00(-.04) |
| Illness incidence | .142**(.055) | .01 | .05 | .00(-.02) | .122***(.043) | .02 | .06 | .00(-.04) | .160***(.038) | .02 | .05 | .00(-.02) |
| Water availability | -.019(.067) | -.00 | .19 | -.00(.01) | .055(.049) | .02 | .19 | .00(-.09) | .025(.054) | .00 | .19 | .00(-.01) |
| Toilet type | .012(.023) | .05 | -.02 | -.00(.02) | .004(.018) | .03 | -.02 | -.00(.02) | .037**(.015) | .16 | -.02 | -.00(.07) |
| Health post | -.144* (.084) | -.09 | .00 | .00(-.00) | .006 (.076) | .01 | .00 | 2.5(-.00) | -.059(.070) | -.05 | -.00 | .00(-.00) |
| Mother educ | -.033(.058) | -.01 | .32 | -.00(.06) | -.033(.034) | -.02 | .31 | -.01(.16) | .004(.040) | .00 | .32 | .00(-.01) |
| Household size | -.042(.027) | -.16 | .01 | -.00(.03) | .031(.023) | .23 | .01 | .00(-.04) | .001(.018) | .01 | .01 | .00(-.00) |
| Household sizeU5 | -.037(.038) | -.03 | -.01 | .00(-.01) | -.023(.032) | -.04 | -.00 | .00(-.00) | -.096***(.026) | -.10 | -.00 | .00(-.00) |
| **Wealth index** | 0.114***(.033) | | | .05(-1.12) | -.028(.022) | | | -.02(.75) | .062***(.021) | | | 03(-.58) |
| Quntile 1 | | -.04 | -.78 | .04(-.80) | | .02 | -.80 | -.01(.53) | | -.03 | -.80 | .02(-.43) |
| Quntile 2 | | -.04 | -.40 | .02(-.38) | | .01 | -.40 | -.00(.07) | | .03 | -.40 | .01(-.23) |
| Quntile 3 | | -.02 | .02 | -.00(.01) | | .01 | .01 | .00(-.00) | | -.02 | .01 | -.00(.00) |
| Quntile 4 | | -01 | .41 | -.00(.06) | | -.01 | .41 | -.00(.15) | | -.01 | .42 | -.00(.08) |
| Residual | | | | -.094(2.07) | | | | -.007(.22) | | | | 08(1.7) |
| Observation | 8,686 | | | | 8,132 | | | | 9,426 | | | |
| $R^2$ | 0.025 | | | | 0.025 | | | | 0.040 | | | |

Note: under each malnutrition indicators, in the contribution column, the figure in parenthesis represents the percentage contribution. Each figure is rounded to two digits only. Hence, point zero zero doesn't mean that it is actually zero, it is rather rounded value

Table 1.3: Decomposition of child malnutrition inequality (CI) based on Fixed effect estimator : Ranking variable -Real annual total consumption per adult equivalent

| | **HAZ** | | | | **WHZ** | | | | **WAZ** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Regressors ($k$)** | $\beta_k$ | Elasticity | CI | Contribution | $\beta_k$ | Elasticity | CI | Contribution | $\beta_k$ | Elasticity | CI | Contribution |
| Age | .003(.003) | .08 | .01 | .00(-.01) | -.014(.003) | -.81 | -.00 | .00(-.15) | .005*(.002) | .17 | .01 | .00(-.02) |
| Age-square | -.000*(.000) | -.10 | .01 | -.00(.02) | -.000**(.000) | .53 | -.00 | -.00(.08) | .000(.000) | .00 | .01 | .00(-.00) |
| Sex | .453***(.115) | .14 | -.00 | -.00(.00) | .119(.080) | .07 | .00 | .00(-.01) | .332***(.079) | .12 | .00 | 3.7(-.00) |
| Illness incidence | .149***(.055) | .01 | -.00 | -.00(.00) | .129***(.043) | .02 | .00 | .00(-.00) | .163***(.038) | .02 | -.00 | -.01(-.00) |
| Water availability | -.029(.069) | -.00 | .05 | -.00(.00) | .052(.048) | .01 | .04 | .00(-.04) | .027(.057) | .00 | .04 | .00(-.00) |
| Toilet type | .004(.023) | .01 | -.00 | -.00(.00) | .010(.017) | .07 | -.00 | -.00(.01) | .036**(.016) | .16 | -.00 | -.00(.00) |
| Health post | -.163* (.090) | -.10 | .01 | -.00(.01) | .009(.080) | .01 | .01 | .00(-.00) | -.079(.075) | -.06 | .01 | -.00(.00) |
| Mother educ | -.015(.056) | -.00 | .26 | -.00(.02) | -.032(.034) | -.02 | .26 | -.00(.24) | -.000(.039) | -.00 | .26 | -5.2(.00) |
| Household size | -.047* (.028) | -.18 | -.03 | .01(-.12) | 0.031(.024) | .23 | -.03 | -.01(.47) | .007(.019) | .03 | -.03 | -.00(.02) |
| Household sizeU5 | -.028 (.040) | .01 | -.01 | .00(-.00) | -.020(0.34) | -.03 | -.01 | .00(-.01) | -.088***(.026) | -.09 | -.01 | .00(-.02) |
| **Consumption** | -.103**(.044) | | | -.02(.39) | .004(.029) | | | 00(-.15) | -.028(.031) | | | -.01(.11) |
| Quntile 1 | | .02 | -.80 | -.01(.30) | | -.01 | -.80 | .01(-.31) | | .01 | -.80 | -.00(.10) |
| Quntile 2 | | .01 | -.40 | -.00(.09) | | -.00 | -.40 | .00(-.06) | | -.00 | -.40 | .00(-.01) |
| Quntile 3 | | .01 | .00 | .00(-.00) | | .02 | .01 | .00(-.01) | | .01 | .01 | .00(-.00) |
| Quntile 4 | | .00 | .40 | .00(-.01) | | -.01 | .41 | -.008(.23) | | -.00 | .41 | -.00(.02) |
| Residual | | | | -.033(.69) | | | | -.01(.56) | | | | -.040(.89) |
| Observation | 8,505 | | | | 7,973 | | | | 9,229 | | | |
| $R^2$ | 0.018 | | | | 0.027 | | | | 0.037 | | | |

Note: under each malnutrition indicators, in the contribution column, the figure in parenthesis represents the percentage contribution. Each figure is rounded to two digits only. Hence, point zero zero doesn't mean that it is actually zero, it is rather rounded value.

## Nutritional and Schooling Impact of a Cash Transfer Program in Ethiopia:

## A Retrospective Analysis of Childhood Exposure

## (CHAPTER TWO)

**This version: March 2019**

Mengesha Yayo Negasi *

Ph.D in Economics, DEFAP

University of Milano-Bicocca, Italy

Mariapia Mendola†

University of Milano-Bicocca, Italy

*Ph.D student (DEPAF) at University of Milano-Bicocca. Email: ymanga28@gmail.com
*Ph.D student (DEPAF) at University of Milano-Bicocca. Email: ymanga28@gmail.com
†Professor at Department of Economics, Università di Milano Bicocca. Email: mariapia.mendola@unimib.it

## Abstract

The rate of malnutrition among under-five children in the Ethiopia is among the highest in the world and Sub-Saharan Africa. Malnutrition and deprivation have devastating direct effects on children and pregnant women as well as indirect socio-economic impacts. Since 2005 the Government of Ethiopia has been implementing a large-scale social protection program throughout the country, with the aim to improve nutrition and food security, decrease poverty and, thereby, enhance human capital accumulation. This paper investigates the direct impact of this program on long-term anthropometric measures of nutritional status and the indirect effects on educational attainment. Our research design combines differences in program intensity across regions with differences across cohorts induced by the timing of the program. Difference-in-difference estimates suggest that early childhood exposure to the program leads to better nutritional status and hence higher human capital accumulation. Results are robust to different measures of program intensity, estimation samples, empirical models and some placebo tests.

JEL codes: J15; D85; C45
Keywords: Cash Transfers, Social Protection, Nutrition, Primary Education, Ethiopia

# 2 Nutritional and Schooling Impact of a Cash Transfer Program in Ethiopia: A Retrospective Analysis of Childhood Exposure

## 2.1 Introduction

Social protection programs, which include cash transfers and social support services, are increasingly implemented as a key policy tool for reducing poverty and increasing the accumulation of human capital in developing regions, including Africa. In 2005, the Ethiopian Government launched its social protections program, which is one of the largest in the region. The Productive Safety Nets Programme (PSNP) was introduced by joint efforts of the Government of Ethiopia and international donors through a multi-trust fund managed by the World Bank (Ministry of Agriculture and Natural Resource, 2015). The overall goal of the program is to provide a long-term solution to the chronically food insecure households found in poor regions in Ethiopia, which is the second country with the highest rate of malnutrition in Sub Saharan Africa. Malnutrition and starvation have devastating impact on children, adults and especially on pregnant women. They also have severe and far-reaching socio-economic impacts, in terms of low human capital, productivity and well-being (World Bank, 2010).

The PSNP was first targeted to five major regions in Ethiopia, while later on it scaled up to the rest of the country. This program included both cash-for-work, cash-for-food as well as other welfare (assistance) measures. As of 2005, the PSNP was designed to address food insecurity by providing transfers to over 5.5 million targeted beneficiaries throughout the country. The programme has completed three phases now and it is currently under its fourth phase to last until 2020. To date PSNP reached over 10 million rolling rural poor and vulnerable beneficiaries, hence being the second largest safety net programme in Africa, after South Africa. The question of whether social protection programs, by reducing poverty through transfers, improve nutrition, food security and human capital accumulation, especially of children, is a long lasting concern for both development economists and policy makers (Hanna and Olken, 2008; World Bank 2010).

While the fact that the program started due to external support from the World Bank reduces endogeneity issues, a major methodological problem when carrying out an impact assessment is that the allocation of the program (and of beneficiaries) is not random across geographical areas. The bias in estimates that treat policy intervention as exogenous is likely to be significant in developing countries. Areas more intensively treated than other may have some (observable and unobservable) characteristics that may be correlated with final individual outcomes. Moreover, if more affluent regions are able to allocate higher local financing to the social protection program or to target more households, then comparing individuals living in 'treated' vs 'untreated' areas will deliver upward biased results. Likewise, in a more centralized system, governments may allocate more fundings to poorer regions (as it is the case in Ethiopia), where nutrition and schooling may be particular lacking, so that in this case the estimation bias would be downward. In the absence of a policy experiment, which is difficult to develop when the program is nation-wide, a possible source of exogenous (natural) variation comes from targeted interventions. In particular, our identification strategy relies on the fact that the exposure to the nation-wide program varied by region of birth and date of birth. By gathering data from official governmental sources, we show that there is substantial variation in program intensity across Ethiopian regions, due to the government effort to allocate more social protection fundings to regions where initial food security was low. Moreover, we leverage variation in individual's age at the time of the program kick-off and focus on the first two years of a child's life as primary setting for the program impact. Those who where young enough (i.e. the first two years window) to be in regions when the program started are expected be better off in terms of health and nutrition than older individuals in all regions, but these difference should be larger in regions that were more heavily targeted from the program. This is so as children who are undernourished during childhood are at high risk for impaired cognitive development, which adversely affect school achievement and individual productivity (Victora et al., 2008). According to the medical literature, nutrition at a very early age, i.e. in utero and by age 2, has long-lasting effects on child height and indeed on adult health (Barker, 1990; Scrimshaw, 1997). The possibility to catch-up skeletal growth after an episode of low growth in infancy is limited, while most stunting[1] and catch-up occurs between 6 and 24 months of age.[2]

Our impact evaluation exploits the combination of variation in year and region of birth, which is as good as random, to employ a difference-in-difference strategy. Hence, we estimate the impact of PSNP exposure on child nutrition, as measured by a long-term antrophometric indicator of

[1]Stunting reflects a failure to receive adequate food intake over a long period of time, and is, therefore, a measure of chronic malnutrition.

[2]Stunting after 24 months of age generally reflects the interaction of nutrition and infection at earlier ages (Martorell and Habicht,1986).

nutritional status, i.e. Height-for-age Z-score (HAZ). An additional goal of our analysis is to identify the effect that childhood exposure to PSNP has on subsequent school attendance and achievement. While direct effects of social protection programs on both adults and children can be partially measured with higher earnings from cash(-for-work) and higher school attendance/achievement respectively, little is known about effects that persist from better nutrition early in life, such as school achievement and attainment (e.g. years of schooling). Hence, we estimate the shift in the relationship between educational attainment and program intensity that coincides with childhood exposure to the PSNP intensity in the first 1000 days in life. As pointed out by several scholars, understanding the drivers of impact assessments is a necessary condition to inform policy (Deaton, 2010).

For our empirical analysis, we use a large individual-level data set on native-born males and females from all over the country to construct a panel data of cohorts by birth year and birthplace. Hence, we build a year-of-birth-varying indicator of childhood exposure to the program, i.e. our 'treatment dummy', which we then interact with program intensity indicators at the regional level. In our difference-in-difference estimation strategy, identification comes both from individual's spatial variation and time variation in the year of birth, while controlling for systematic variation across regions and cohorts through fixed effects. Indeed, being born after the program and in areas with higher intensity treatment implies more benefits from exposure to the program. A similar strategy has been used to estimate the effect of school quantity on (returns to) education in Indonesia (Duflo, 2001) and the effect of big health improvement programs such as malaria eradication on labor productivity in North ans South America (Bleakely, 2010).

Our findings show that exposure to the PSNP led to an increase in both Heigh-for-age Z-scores (HAZ) and primary educational attainment as measures by years of schooling. On average, one extra million Birr PSNP budget (about 35,000USD) allocated per 1000 children in birth regions increases child height-for-age Z-score by 0.1. As a result, an increase in the intensity of the program increase completed years of primary schooling by about 0.7. Results, which are robust to different ways in measuring program intensity and different estimation sample, seem to be increasing with the time of exposure (i.e. measured by year of birth and age). The estimation of fully flexible models in years of birth or age ensures the non-violation of common trend assumptions. Moreover, results of some placebo tests performed using only pre-program cohorts suggests that results can be interpreted as causal.

The remainder of the paper is organized as follows. Section 2.2 provides a description of the Productive Safety net Program (PSNP) as well as the research design of the study. In Section

2.3, we report a review of the related literature in economics. Section 2.4 describes the data sources used in the empirical analysis while Section 2.5 illustrates the econometric model and identification strategy. In Section 2.6, we present the results ad discussion. Finally, Section 2.9 concludes.

## 2.2 The program

The Productive Safety Net Program (PSNP) is a development-oriented large scale social protection program. In Ethiopia, it was started in 2005, aiming at improving food security and stabilizing asset levels. The PSNP contains a mix of public works employment and unconditional cash and food transfers. It is a well-targeted program, even though several years passed before payment levels reached the intended amounts. It was introduced by joint efforts of the Government of Ethiopia and donors in an attempt to provide a long-term solution to the chronically food insecure households found in poor regions of the country. It aims at covering more than 263 woredas (districts) and 1.6 million households in five major regions in Ethiopia (which correspond to roughly 10 million individuals), namely Tigray, Amhara, Oromiya, Somali and SNNP . However, later it extended to cover other regions such as Afar, Dire dawa, and Harari (Bethelhem et al., 2014). While the program builds on the experiences of the earlier emergency relief program, it has distinct characteristics in its long-term nature. It provides a predictable amount of transfers (cash or food) for a predictable period of time (at least five years) (Bethelhem et al., 2014). Able-bodied adults are required to work five days per month in community infrastructure development in return for food (mainly wheat and cooking oil) or cash. Elderly, disabled, sick or mentally challenged individuals, pregnant and best-feeding women, and orphaned teenagers receive free food or cash without a work requirement. The former is the public work (food-for-work or cash-for-work) component and the latter is the direct support component.

The PSNP kicked-off as a food "safety net" that would provide food or cash for food insecure households during the "hungry" seasons of the year in exchange for public works through the Ministry of Agriculture. Although it began as a household food security program it has, for all practical purposes, evolved into a broader package of social protection, now comprising four components: social protection, livelihoods, disaster risk management, and nutrition and climate resilience/green economy. During its following up stages, the program was made more nutrition-sensitive through the incorporation of additional nutrition provisions, "soft conditionality" exemptions from physical labor for pregnant and breast-feeding women with a child under 1 and for mothers with a severely malnourished child under 5. These mothers are provided with "temporary transition to direct support" (i.e., cash or food). Instead of participating in public works, they engage in community based nutrition activities, such as social and behavioral change communication and growth monitoring and promotion sessions. A process of "co-responsibility" helps ensure their participation in these activities.

A new phase of PSNP (PSNP4) began in 2015, with the objective of supporting the transition towards a social protection system. PSNP4 will achieve this by ensuring that poor and vulnerable households benefit from an essential suite of services, including safety net transfers, livelihood interventions, key health and nutrition services, community assets constructed through public works and support to households up to, during and beyond safety net graduation. By mainstreaming nutrition throughout the programme implementation, PSNP4 will address some determinants of malnutrition, including maternal and child health, vaccinations, infant and young child feeding practices, dietary diversity, women empowerment and water, sanitation, and hygiene. Demand for health services will further be promoted through the introduction of soft conditionalities within the PSNP, which are linked to the health-seeking behaviour of temporary direct support clients. Under the PSNP4 umbrella, an Integrated Nutrition and Social Cash Transfer (IN-SCT) pilot is ongoing, enabling the trial of an integrated system of social cash transfers and the promotion of linkages with basic social services. The Urban Food Security and Job Creation Strategy and Programme has been gradually implemented starting from 2016, and is supported by an Urban Productive Safety Net Programme (UPSNP) (UNICEF/ETHIOPIA, 2016). Recognizing of the fact that social programs in Ethiopia have not been given in harmonized way, Ethiopia launched its National Social Protection Policy (NSPP) in 2014. The policy introduces the concept of a 'sustainable social protection system'. Various strategies and programmes are underway to support the implementation of the NSPP, but often these are still implemented in a fragmented manner (UNICEF/ETHIOPIA, 2016).

### 2.2.1 Research Design

The PSNP was launched due to donor's support and international aid, which are substantially external factors that are uncorrelated with cross-regional heterogeneity. This reduces concerns about potential policy endogeneity and reverse causality in its impact assessment. Moreover, different regions across the country have different intensity of the program, which we can measure with both budget allocation and targeted beneficiaries. Finally, the timing of the program roll-out induces variation in childhood nutrition that has a clear pattern across year-of-birth cohorts. Cohorts that were already 'old' enough before the PSNP started, could not have an early-life exposure to better nutrition. Thus, we compare cohorts based on (i) the program intensity in their place of birth and (ii) their year of birth relative to the PSNP kick-off. The kick-off of the PSNP combined with cross-area differences in program intensity form the core of our research design. Since the analysis considers the effect of childhood exposure to the program on later-life outcomes, it is useful to characterize the 'exposure rule' as Bleakly (2010). The program started in 2005 and the treatment or exposure assignment is defined by year of birth. In our impact assessment, we use early childhood as being the cut-off for the treatment effect, being the first 2 years of life particularly important for child development. Hence, children born more than 2 years before the program are considered as 'untreated'.[3]

A child born in 2003 or before cannot benefit from the PSNP program, launched in 2005, in his key early months of life. A child born later, instead, is fully exposed to the treatment early in life so that s/he is considered as treated. In particular those born between 2003 and 2004 are only partially treated while those born between 2004 and 2005 are fully exposed also while in utero (see the empirical section for more details on identification). Moreover, most of a person's human-capital and physiological development happens in childhood (Bleakley, 2010). On both human-capital side and physiological side, being exposed to improved food security, and accumulation of asset during childhood period might mean that the individual is more robust as an adult, with concomitant increases in educational achievement. Thus, we argue that an intervention, such as social protection program, aiming to improve food security and reduce poverty is expected to have indirect influence on socioeconomic outcomes such as educational attainment. We further assess the impact of early childhood exposure to the program on years of schooling of individuals aged 13 years or more. Normally, Ethiopian children start primary schooling at age of 7 and are supposed to complete this cycle 7 years later [4]. Yet, while primary enrollment is about 90% of 7 years old Ethiopians, only half of them complete the entire educational cycle. The differential incidence of the program implementation

[3] By postulating uniform effects of malnutrition per years of childhood exposure, the formula for exposure is *max(min(2, k-(y-2)),0)/2*, where $k$ is the year of birth and $y$ is a starting year (see Bleakly, 2010).

[4] There are three years of pre-primary school in Ethiopia, which has an official entry age of 4 and is referred to as Kindergarten. Primary school has an official entry age of 7 and ends at age of 14 (a duration of eight grades). At the end of the cycle, students sit for a national examination that results in the Grade 8 Completion Certificate. Secondary school is divided into two cycles: lower secondary (length of program 2 years, and age ranges from 15 to 16) and upper secondary (length of program 2 years, and age ranges from 17 to 18).

across regions joint with the use of non-exposed children as comparison group, combine to form the research design of our analysis.

## 2.3 Review of the literature

Ethiopia is the second country with the highest rate of malnutrition in Sub Saharan Africa, facing the four major forms of malnutrition, i.e. growth failure malnutrition, acute malnutrition or wasting, chronic malnutrition or stunting and micro-nutrient malnutrition (Dube et al, 2017). Child malnutrition is one of the many challenges that pose a threat to economic growth in developing countries, as it undermines educational attainment, lowers non-cognitive skills, leads to low labor productivity during adulthood and ultimately boosts inter-generational poverty (World Bank, 2010; Save the Children, 2012). Since nutrition is an indicator of the quality of human capital of a country, addressing chronic malnutrition is recognized as key for socioeconomic development. Cash transfers and social protection programs have been targeted to reduce poverty and improve standards of living across a variety of developing settings and intervention designs (Batagli et al., 2018). In many of the poor and targeted regions, children typically make up the highest share of local poorest people because of high fertility rates, inequality and deep-seated privation in low-income settings. Poverty in childhood has been shown to impact on children's physical, cognitive and social development, potentially placing them on a lifelong trajectory of low education, low productivity and perpetuating inter-generational cycles of poverty (e.g. Cunha F, Heckman, 2008; Dahl and Lochner, 2012).

Global evidence shows that social protection can support, directly or indirectly, the realization of children's rights in a number of ways, for example by enabling children and their families to access health care, early childhood nutrition, and primary and secondary education programmes. However, the evidence relating to effectiveness of these programmes on child wellbeing is significantly plagued by different empirical approaches and methodological issues (Ravallion, 2009; Deaton, 2010). Moreover, both programs and findings (and contexts) are mixed by their own nature. Seminal and influential work by Kremer & Miguel (2004) use a randomized control and data collected from primary schools in Kenya to show that deworming programs reduce child school absenteeism by 25%. They did not find an improvement in academic attainment, but they did find that deworming substantially improved health and school participation among untreated children in both treatment schools and neighbouring schools, via spillover effects. In the absence of a randomized control trial, Duflo (2001) leverages exogenous natural variation in combination with statistical modeling strategy to evaluate the impact of a large School Construction Program in Indonesia. By combining differences across regions in the number of new schools with difference across cohorts induced by the timing of the program, she finds that exogenous school supply lead to a significant increase in education and earnings of program exposed children. Similarly, Bleakly (2010) use early-life exposure to large malaria eradication programs in different countries to show that cohorts born after eradication have higher income as adults than the preceding generation. These cross-cohort changes coincided with childhood exposure to the campaigns rather than to pre-existing trends. Cutler et al. (2010), Cecilia et al. (2017), and Mark et al. (1993) use similar identification strategies to examine the influence of social program on different socioeconomic outcomes.

Other related works include Ponce and Bedi (2010), which use a regression discontinuity strategy to identify the impact of a cash transfer program (the Bono de Desarrollo Humano) in Ecuador on student's cognitive achievements, and come out with no impact of the program on test scores. While analyzing the impact of the Indonesian Social Safety Net health card program on public health care demand, Pradhan et al. (2007) also find that most of the benefits go to the non-poor, even though distribution of the health cards was pro-poor. Conversely, Antonio et al. (2005) note that Colombia's subsidized insurance program greatly increased medical care utilization among the country's poor and uninsured. By using variation in ownership of water provision across time and space as a result of a large privatization program in Argentina, Galiani et al.(2003) find that child mortality falls by 8 percent upon the program, and the impact is larger in the poorest areas.

Prior empirical works on impact of social protection programs in Ethiopia also show diversified and mixed results. For instance, using nationally representative data, Yamano et al. (2005) find that while harvest failure leads to child growth faltering, food aid affected child growth positively and offset the negative effects of shocks in communities that received food aid. Similarly, Yablonski and Woldehanna (2008) note that different social protection programmes in Ethiopia have had unexpected impacts on girls' and boys' participation in school, and in paid and unpaid work. Gilligan et al. (2009) also find little evidence of improvements in consumption among targeted households. Using a longer time-period of evaluation, Berhane et al. (2014) find improvements in food security for households that received PSNP for more than four years. Bethelhem et al. (2014), taking one region in Ethiopia, also demonstrate that the PSNP is providing positive short-term nutritional benefits for children, especially in those households that can leverage underemployed female labor. Furthermore, using Young Lives data, Porter and Goyal (2016) find a significant positive medium-term impact of the PSNP on the nutrition of children aged 5 to 15 years.

## 2.4 Data sources and descriptive statistics

This study uses repeated cross-sectional data from three rounds (2005, 2011, 2016) of the Ethiopian Demographic Household Survey (EDHS) to build synthetic cohorts of exposed vs non-exposed individuals to the PSNP. The EDHS is a large nationally--representative repeated household survey collected by the Central Statistics Agency of Ethiopia in collaboration with the United States Agency for International Development (USAID), the World Bank LSMS group and the United Nations Children's Fund (UNICEF).[5] The EDHS include standard individual demographics and socio-economic characteristics, including anthropometric measures on both children (0-5 years of age) and adults (15 years of age and above) as well as educational attainment of all individuals. Our outcome of interest is child nutrition as measured by the anthropometrics indicator Height-for-Age Z-scores (HAZ). This is constructed for any age by standardizing height measurement to a reference group of well-nourished children using the recent WHO (2006) standard child growth reference data.[6] The second outcome interest is primary education attainment, which we measure with numbers of completed years of primary schooling of individuals 13 or older.

Importantly, EDHS include the indicator of each respondent's region of birth in Ethiopia, which we match with regional level data on the intensity of PSNP.[7] Hence, we use administrative data

[5] In all rounds, the EDHS sample is stratified and selected in two stages. In the first stage, Enumeration Areas (EAs) are selected with probability proportional to the EA size and with independent selection in each sampling stratum. EA is a geographic area that covers an average of 181 households. In the second stage, a fixed number of households per cluster are selected with an equal probability systematic selection from the newly created household listing.

[6] Z-score is the deviation of an individual's value from the median value of the global reference population, divided by the standard deviation of the global reference population (the global reference population is a population with a distribution of heights, weights, ages, or related measures that is considered normal by international standards). The Z-score indicates where one observation lies in reference to the global population. A Z-score of $-2$ or less (that is, equal to or smaller than two standard deviations below the median of the global reference population) is considered very low. The World Health Organization recommends the use of Z-scores, because they are the most age-independent method of presenting indexes. Hence, if height-for-age z-score is less -2, child is considered as stunt (WHO, 2006).

[7] The use of region of birth instead of residence as matching unit directly address the potential problem of selective internal migration. By using this information, though, our analysis resambles an intention-to-treat design.

at regional level from 2005 to 2016 to measure (ii) the amount of PSNP resources allocated to each region and (ii) the number of household beneficiaries.[8] We further use administrative data, as well as aggregated EDHS survey data, to measure other time-varying factors at regional-level that may influence child nutrition and development such as health-related infrastructure, health facilities/coverage (including immunization/vaccination coverage), child and maternal health service coverage (antenatal, and postnatal care delivery), improved water and sanitation coverage, aggregate primary school attendance, enrollment ratio, school drop rate, number of primary and secondary schools, public expenditure in education (for details, see Appendix I).

Our estimation sample consists of males and females in the EDHS data sets, born between 1992 and 2016 in different regions in Ethiopia. The date and region of birth jointly determine an individual degree of exposure to the PSNP treatment. A child born in 2003 or before was 2 or older in 2005, when the PSNP was launched. Hence, this child did not benefit from the program in his key 1000 days of of life. A child born in 2003 or later, instead, was partially or fully exposed to the treatment early in life so that s/he is considered as treated. In particular, those born between 2003 and 2004 are partially treated (so that considering them as treated may bias results downward). Exposure in utero, instead, could lead those born between 2004 and 2005 from partially to fully benefit from the program, such that the treated group may be measured with some minor error (which would still bias our results downward). To sum up, in our benchmark specifications we consider children 2 or older in 2005 as non-exposed to the program while for children born after 2003, the treatment effect is expected to be positive (possibly increasing with age, i.e. higher exposure).

When analysing the nutritional impact, we focus on individuals of any age with years of birth ranging from 1992 to 2016. When assessing the impact of the program on educational attainment instead, we restrict this same sample to individuals of 13 years of age or older, which ensures that youngest individuals in the sample are close to complete primary school (first and second cycle) in 2016. The official primary school entrance age is 7 in Ethiopia and the system is structured in two primary school cycles, lasting 4 years each, but we are forced to use 7 rather than 8 years due to the last available survey year that is 2016.[9] In a robustness

[8]These data has been gathered by one of the author in Ethiopia by visiting different institutional bodies including the Ministry of Agriculture, Ministry of Health, Ministry of Economic and Development Cooperation, Central Statistical Agency (CSA), National Emergency Relief and Preparedness Commission, and Regional State's Agricultural Bureaus.

[9] The oldest individuals in the sample (those born in 1992) are 13 years of age in 2005, i.e. our first survey year (and 24 years old in 2016, our last survey year). The youngest instead (those born in 2003) are 13 years old in 2016. Given the program treatment cut-off (2003) and our last survey year available (2016), we are forced to include children 13 years of age – instead of 14 – or older in our sample.

check, we include children 11 or older (i.e. we enlarge our estimation sample), where 11 is when children are supposed to finish the first cycle of primary school in Ethiopia (when we do this, we measure years of first-cycle primary schooling as our outcome variable).

Using this large cross-section of males and females born between 1992 and 2016 from the different survey years of EDHS, we therefore link each individual's antrophometric and educational indicators with regional level data on budget allocation and PSNP beneficiaries between 2005 and 2016 in her/his region of birth. Analogously, we do the same for other regional level control variables (for detailed description, see Appendix I).

### 2.4.1 Descriptive statistics

Table 2.1 reports the program intensity across regions, both in terms of average budget and number of beneficiaries. With respect to PSNP budget allocating, the average budget between 2005 and 2016 is 241,7 million Birr (which corresponds to about 8.5 million USD), but a lot of variation emerges across regions. The highest and lowest program intensity is recorded in Amhara (708.14 million Birr) and Harari (5.58 million Birr) regions respectively. Moreover, number of beneficiary households also vary across regions. We further report descriptive statistics on different emergency relief aid programs across regions, which do not present strong systematic correlation with PSNP intensity.

In Table 2.2 we report descriptive figures of stunting, as a measure of chronic malnutrition, across regions and time in Ethiopia. While average height-for-age Z-score is -1.25 in our sample, stunting is defined as a height that is more than 2 standard deviations below the World Health Organization (WHO) child growth standard median (WHO, 2006). Although there is a falling tendency in malnutrition in all regions over time, there is still high prevalence of child malnutrition in the country that also varies across regions. Many regions still record a prevalence of stunting greater than 40%, that is when stunting is considered as a severe public health problem in a community.

As far as education is concerned, primary school in Ethiopia has an official entry age of 7 and ends with either Grade 5 (first cycle) or Grade 8 (second cycle) at age of 14. Table 2.3 report different educational indicators gathered from the Ministry of Education for primary schooling between 2005 and 2016. While enrollment rates have been growing over time, drop-out rates and repetition rates are still as high as 10 percent as far as primary education is concerned.

**Table 2.1:** PSNP intensity and Emergency relief aid across regions in Ethiopia (average between 2005 and 2016)

| Region | PSNP | | Emergency relief aid | |
|---|---|---|---|---|
| | PSNP- budget (in million Birr) | PSNP- beneficiary (household n. in '000' ) | Aid-food (in ' 000' metric tons) | Aid- beneficiary (household n. in '000') |
| Tigray | 292.91 | 1246.27 | 55.85 | 459.83 |
| Amhara | 708.14 | 2145.81 | 93.92 | 730.05 |
| Afar | 28.00 | 480.40 | 14.48 | 121.17 |
| Oromia | 365.84 | 1349.65 | 107.28 | 943.29 |
| Somali | 39.81 | 698.16 | 116.34 | 1015.25 |
| SNNPR | 483.24 | 1210.12 | 32.99 | 280.89 |
| Harari | 5.58 | 15.94 | 28.69 | 199.03 |
| Dire Dawa | 6.54 | 52.20 | 24.67 | 174.25 |

Source: Ministry of Agriculture, and National Emergency Relief and Preparedness Commission, Ethiopia

Actually, educational records in our survey sample are slightly lower that official statistics. The average number of years of primary education in our sample is about 4.5 (about 10 percent of the whole sample report zero years of schooling) and this is in line with official UNESCO statistics for Ethiopia recording 32% of children of official primary school ages are out of school, more concentrated among boys and the poorest children.[10]

**Table 2.2:** Prevalence of malnutrition (stunting) by region and year

| Region/Year | 2000 | 2005 | 2011 | 2016 |
|---|---|---|---|---|
| Tigray | 55.3 | 41 | 51.4 | 39.3 |
| Amhara | 57 | 57 | 52 | 46.3 |
| Afar | 47.6 | 41 | 50.2 | 41.1 |
| Oromia | 47.2 | 41 | 41.4 | 36.5 |
| SNNP | 46.4 | 45 | 33 | 27.4 |
| Somali | 55.4 | 52 | 44.1 | 38.6 |
| Harari | 37.3 | 39 | 29.8 | 32 |
| Dire -Dawa | 30.5 | 31 | 36.3 | 40.2 |
| Ben-Gumuz | 41.3 | 40 | 48.6 | 42.7 |
| Gambella | 37 | 29 | 27.3 | 23.5 |
| AddisAbaba | 26.8 | 18 | 22 | 14.6 |
| National | 58 | 52 | 44.4 | 38.4 |

Source : Ethiopian Demographic Household Survey (EDHS) of various rounds ( 2000-2016)

[10]https://www.epdc.org/sites/default/files/documents/EPDC%20NEP_Ethiopia.pdf

**Table 2.3:** Primary Education indicators (grades 1-8)

| Indicators in % /Year | 2005/06 | | | 2013/14 | | | 2015/16 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Boys | Girls | Total | Boys | Girls | Total | Boys | Girls | Total |
| General Enrollment Rate (GER) | 98.6 | 83.9 | 91.3 | 105 | 98 | 101.2 | 102 | 93 | 97.5 |
| Net Enrollment Rate (NER) | 81.7 | 73.2 | 77.5 | 95 | 90 | 92.5 | 95 | 91 | 93 |
| Drop-out rate | 12.6 | 12.1 | 12.4 | 11 | 11 | 11 | 10 | 10 | 10 |
| Repetition rate | 6.4 | 5.7 | 6.1 | 9 | 8 | 8.5 | 7 | 7 | 10 |

Source: Ministry of Education, Ethiopia (2005-2015)

## 2.5 Empirical model and identification strategy

The empirical strategy exploits two source of variation, namely time variation coming from the individual age at the beginning of the program and cross-sectional variation arising from asymmetric regional coverage as well as intensity of the PSNP program. In a difference-in-difference framework, then, nutritional and educational outcomes of exposed *vs* non-exposed individuals in their childhood are compared across regions with different intensity of the treatment. The introduction of year of birth and region fixed effects controls for all time-invariant differences of both cohorts and regions. The identification strategy relies on the absence of any other shock occurred around early childhood of individuals (happening at the same time of the PSNP program launching) and correlated with the budget allocation and number of program beneficiaries across regions. The latter identification concern is addressed by controlling for region-specific factors that may bias the estimates, such as access to health and education facilities as well as aggregated health and human capital indicators.

Hence, we hypothesize that nutritional status of children who were very young enough to be in age of 0 to 2 years old when the program started will be higher than the nutritional status of old children with an age above 2 years in all regions[11], but the difference should be larger in the regions more intensively treated (i.e. which received more resources or covered a larger number of households). Put it differently, nutritional status of children who were exposed to the program in early childhood (i.e. the critical period during which the intervention is believed to have more nutritional impact) would be higher owing to the program intervention[12]

[11] From the medical literature, we considered that the program (PSNP) provides a significant boost to child growth while the child is exposed to the program within the first 1000 days.

[12]The nutrition literature also has a clear focus on the importance of the first 1000 days of life (from conception to age 24 months) (Victora et al., 2010).

Most of a person's human-capital and physiological development happens in childhood (Bleakley, 2010). On both human-capital side and physiological side, being exposed to improved food security, and accumulation of asset during childhood period might mean that the individual is more robust as an adult, with concomitant increases in educational achievement. Thus, an intervention (such as social protection program) aiming at reducing both malnutrition and poverty is expected to have *indirect* influence on socioeconomic outcomes such as educational achievement.

We start by estimating the equation that follows:

$$y_{ijk} = \alpha_0 + \alpha_j + \alpha_k + \gamma_1 \left(PSNP_j * Young_i\right) + \gamma_2 \left(X_j * Young_i\right) + \varepsilon_{ijk} \tag{2.1}$$

Where $y_{ijk}$ is the individual outcome, i.e. height-for-age Z-score and completed years of primary schooling, for the individual $i$ born in region $j$ and cohort $k$. While $\alpha_0$ is a constant, $\alpha_k$ is a cohort of birth fixed effect, capturing the effects of time-invariant unobservable characteristics specific to the cohort and $\alpha_j$ is birth place fixed effect (the main effects of the area-of-birth and exposure controls are therefore absorbed by these fixed effects).[13] $Young_i$ is the 'treatment dummy' indicating whether the individual belong to the 'young' cohort (i.e. born after 2003), $PSNP_j$ denotes the intensity of the program (PSNP) in the region of birth $j$, and $X_{jk}$ is a vector of region-specific time-variant variables (controls) including human capital and health service coverage in 2000s. $PSNP_j * Young_i$, represents the variable of interest, i.e. the interaction effect of program intensity and childhood exposure. $\varepsilon_{ijk}$ is the error term.

Results from Equation 2.1 relies on the identification assumption that there is no omitted time-varying and region specific effects correlated with the program by cohort. Our parameter interest, $\gamma_1$ captures the differential impact of the PSNP on our interest outcomes considered in this study. Put it differently, the exogenous variable is the interaction of the treatment status with the intensity of the program in region of birth. A similar strategy has been used by Duflo (2001) and Bleakely (2010).

The identification assumption would be violated if other regional-specific programs were correlated with the allocation of the PSNP efforts. Thus, we present specifications that control

[13] Cohort effects reflect secular trends that lead to different positions of age profiles for different cohorts. They typically embody a number of unobserved effects, including cohort size effects, generational differences in attitudes and cohort-specific government policies.

for the interactions of a vector of regional-specific variables, including the allocation of water and sanitation facilities, aggregate health status and school enrollment rate, with the cohort dummy.

Following Duflo (2001), we can test the identification assumption by exploiting the availability of more than two pre- and post-periods, which allow us to estimate estimate cohort-by-cohort contrasts through a more flexible nutrition specification. We start with the nutrition specification as follows:

$$y_{ijk} = \alpha_0 + \alpha_j + \alpha_k + \gamma_1 \sum_{t}^{t+5} (PSNP_j * Birthyear_{it}) + \gamma_2 \sum_{t}^{t+5} (X_j * Birthyear_{it}) + \varepsilon_{ijk} \quad (2.2)$$

where every thing is defined as above, with the exception that the treatment effect is identified in each cohort ($Birthyear_i$ ) going from 2001 (with $t$=2001 being the reference category) to 2005. Equation 2.2 does not impose a parametric assumption on the pre-treatment dynamics such that is allows for a test of the null hypothesis of no pre-treatment trends (i.e. since individuals born before 2003 are not exposed to the program, we expect no systematic difference across cohorts before 2003). Moreover, it also allows for checking the dynamics of the treatment effect in that we can test whether the effect is different across the post-treatment periods.

Similarly, we run the following regression for the education equation:

$$y_{ijk} = \alpha_0 + \alpha_j + \alpha_k + \gamma_1 \sum_{l=1}^{13} (PSNP_j * Age_{il}) + \gamma_2 \sum_{t}^{t+13} (X_j * Birthyear_{it}) + \varepsilon_{ijk} \quad (2.3)$$

Where $y_{ijk}$ is the individual outcome, i.e. completed years of primary schooling, for the individual $i$ born in region $j$ and cohort $k$. $Age_{il}$ is the age of individuals in 2005, with $l \in [1, 13]$ (13 being the reference category), and $Birthyear_i$ is individual's birth year. Here, while using the interaction between program intensity and age of individuals in 2005, we test the time dimension of exposure to the program with 13 age dummies (for being 1 to 13 in 2005). Each coefficient of interest, $\gamma_1$, can be interpreted as an estimate of the impact of the program on a given cohort.

## 2.6 Results

### 2.6.1 Mean difference by cohort and program intensity level in region of birth

Prior to presenting the main regression results, we start with some descriptive result which are preliminary and informative to our difference-in-difference estimation results. We assume that the average impact of the program on nutritional status of children who were very young enough (exposed) to be in age of 0 to 2 years old when the program was started should be higher than the nutritional status of old children with an age of above 2 years in all regions but the difference should be larger in the regions that received more PSNP resource. Table 2.14 provides us a mean difference-in-difference by cohort and program intensity by region of birth. The mean difference-in-difference in both height-for-age z-score and years of schooling estimates suggest that the difference by cohort and program intensity in region of birth is found positive as per our hypothesis. Hence, this unconditional simple descriptive analysis show the existence of difference in our outcome interest due to variation in program intensity across regions. However, individual's nutrition as well as education achievement are the outcome of interaction of several factors, we thus need to add careful multivariate analysis to study the causal effect of Productive Safety Net Program (PSNP) on these outcomes.

**Table 2.4:** Difference-in-Difference using mean difference by cohort and PSNP intensity level

| Variable | Height-for-Age-Z-score | | | Years of schooling | | |
|---|---|---|---|---|---|---|
| | PSNP intensity | | | PSNP intensity | | |
| Cohort/PSNP | High | Low | Diff | High | Low | Diff |
| Exposed | -1.34 | -1.66 | 0.32 | 4.85 | 4.34 | 0.51 |
| | (0.01) | (0.02) | (0.01) | (0.04) | (0.03) | (0.07) |
| Non-exposed | -2.12 | -2.05 | -0.07 | 4.26 | 4.55 | -0.29 |
| | (0.05) | (0.06) | (0.04) | (0.07) | (0.06) | (0.03) |
| Diff-in-Diff | 0.78 | 0.38 | 0.40 | 0.59 | 0.20 | 0.80 |
| estimates | (0.05) | (0.06) | (0.05) | (0.08) | (0.07) | (0.09) |

Note: PSNP is program intensity in region of birth

### 2.6.2 Regression result

This section presents the results of the effects of the PSNP on nutrition and education, following the empirical strategy outlined above and using two indicators of treatment intensity. Table

2.5 reports results by estimating Equation 2.1 on heigh-for-age Z-score. While column (1) and (2) report results using the whole sample (i.e. comparing children born in different cohorts between 1992 and 2016), in column (3) and (4) we only focus on children between 0 and 5 years old observed in the survey year 2005 (i.e. we compare young kids born right before and after 2003). Results point to a positive and statistically significant effect of PSNP on Z-score. One extra million Birr PSNP budget (about 35,000USD) allocated per 1000 children in birth regions increases child height-for-age Z-score by 0.07 to 0.13 in the full sample target. The effect is bigger in magnitude when we consider only the sample of young kids born right before and after the program (2005 DHS survey). Analogously, an increase in the number of beneficiary households by 1000 (per 1000 children) increase Z-score by 0.1 to 0.6. The magnitude of the impact across different indicators of PSNP intensity is not so different in both estimation samples considered.

Here, it might be interesting to raise question on the magnitude of program effect which is bigger on sample from kids of 2005 survey year. The possible justification can be sample size difference, time variation effect (survey year), other interventions effect with passage of time. In case of estimation sample from 2005 survey, we only considered kids under five only for both treated and control groups but in full estimation sample, children above five are included in control groups[14]. In addition to social protection program (in the form of PSNP or humanitarian emergency relief aid), our health out come interest might be affected by other health related programs such as community based nutrition program implemented in the country since 2008. Such programs and other interventions introduced after 2005 might lower the effect of PSNP on nutrition of children in full estimation sample.

The other issuse that might be concerned in such kind of analysis is on the magnitude of the effects with respect to other interventions or the same type of interventions which have a similar goal evaluated in the literature. This might be helpful for external validation of the result of the study. Although there is scaricity of emprical literature on nutritional effect of the social protection program with same strategy, it might be possible to compare our study's results with other prior studies employed similar identification strategy to evaluate education and other labor outcomes. One relevant work to our study is Duflo's (2001) study on school construction in Indonesia and its impact on education and wages. She suggests that the construction of primary

[14]In full sample estimation :- treated groups are those born in 2004 and after from all rounds. Controls :- those born between 1992 to 2003. However, in sample estimation from 2005 survey only, treated groups are those born in 2004 and after while cotrols are those born between 2000 to 2003 only - those born between 1992 to 1999 are not included as in full sample cases becuase the 2005 DHS survey only collected antropometric information for childern under five years.

schools led to an increase in education and earnings. Children ages 2 to 6 in 1974 received 0.12 to 0.19 more years of education for each school constructed per 1000 children in their region of birth. Using variations in schooling generated by this policy as instrumental variables for the impact of education on wages generates estimates of economic returns on education ranging from 6.8 percent to 10.6 percent. Bleakley (2010) also demonstrates that cohorts born after eradication had higher income as adults than the preceding generation. Jere R et al (2009) used different indentification strategy however they evaluated similar intervention to investigate how the Mexican conditional cash transfer program differentially affected younger and older children within this age range and examines whether the early nutritional intervention led to improvements in subsequent educational performance. Their empirical findings show positive program impacts on reducing ages at entering school for the younger children as well as on accumulated grades of schooling after 5.5 years of benefits for older children, with estimates implying a 1 percent reduction in the age of entry to primary and an increase in grades of schooling completed to date of about 8 to 9 percent.

**Table 2.5:** PSNP effect on Height-for-Age Z-score

| Estimation sample: | Full sample | | Kids 0-5 (2005 survey) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| PSNP budget*young | 0.077** | 0.135* | 0.515** | 1.13*** |
| | (0.031) | (0.069) | (0.190) | (0.343) |
| PSNP beneficiary households number *young | 0.101** | 0.673** | 0.480** | 0.840*** |
| | (0.049) | (0.321) | (0.177) | (0.254) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes |
| Health extension program coverage*young | no | yes | no | yes |
| Emergency humanitarian aid*young | no | yes | no | yes |
| Observations (N) | 25,304 | 25,304 | 2,841 | 2,841 |
| $R^2$ | 0.1765 | 0.1765 | 0.1097 | 0.1097 |

Note : This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1 and 2) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Similarly, we employ Equation 2.1 to examine program impact on years of primary schooling. In Table2.6, we report results while using a sample of individuals who have potentially completed all cycle of primary education (13 years of age or older, in columns 1-2) and while using those who have finished the first cycle only (11 years of age or older) (columns 3 and 4). Results exhibit a positive and statistically significant effect in all specifications and estimation samples.The magnitude of program effect coefficients across the estimation sample is almost the same. One extra million Birr PSNP budget allocated per 1000 children in birth region increases years of primary schooling by about 0.7 (results are similar across estimation samples). Similarly, an increase in 1000 household beneficiaries (for 1000 children) increases years of schooling by 1.2 to 1.4. These are sizable effects provided that the average years of schooling in our sample is about 3. Overall, it is noteworthy that results are robust across both different measures of PSNP intensity and estimation sample. Moreover, controlling for extra region-specific programs, such as emergency humanitarian aid, make the PSNP impact estimation higher, suggesting that the estimates are not biased upward by mean reversion or omitted programs. [15]

**Table 2.6:** PSNP Effect on Years of Primary Schooling

| Estimation sample: | Age>=13 | | Age>=11 | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| PSNP budget*young | 0.641*** | 0.727*** | 0.620*** | 0.701*** |
| | (0.137) | (0.159) | (0.102) | (0.116) |
| PSNP beneficiary households number | 1.41*** | 1.41*** | 1.22 *** | 1.23*** |
| *young | (0.341) | (0.335) | (0.244) | (0.240) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Enrollment rate in primary school*young | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes |
| Emergency humanitarian aid *young | no | yes | no | yes |
| Observations (N) | 7,487 | 7,487 | 9,724 | 9,724 |
| $R^2$ | 0.0744 | 0.0748 | 0.1806 | 0.1811 |

Note This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[15] In Appendix II we report two sensitivity checks wheile using different years as treatment cut-offs.

### 2.6.3 Program impact by gender

The PSNP is primarily designed to ensure that both male and female benefit equally from the programme, i.e. ensuring gender equity. Here, we report estimates of the program impact by gender, since unequal resource allocation is very common in most developing countries, including Ethiopia. Using Equation2.1 above, we thus run regressions within sub-sample of males and females respectively. Results on height-for-age are reported in Table 2.7 and show that PSNP has a significant impact on males' Z-score while we consider the full sample. Yet, the impact is mostly significant for both males and females if sample from 2005 DHS round only is taken into account.

We run the same impact estimation equation on schooling and results reported in Table 2.8 show a significant positive effect on both females and males. Yet, the magnitude of the effect is slightly higher for males across all specifications and sample. We interpret these results as evidence of a tendency to favor males against females upon having extra resources to invest in child human capital.

Our results ensure that investment on children might be favoured to boys than girls. In this regard, Kabeer (2008) noted that inequalities on the distribution of food, health care, access to property etc between household members due to norms and customs. Moreover, women may be systematically different from men in their preferences for types of expenditure or the welfare of particular family members. In Ethiopia, data from the early 2000's suggest male households have greater consumption expenditure capacity, in terms of per capita food energy consumption (Lampiettyt, J. and Stalker, L. 2000). Hence, the effect of interventions on outcomes is subject to households's decision on investment in each gender of individuals.

**Table 2.7:** PSNP effect on Height-for-Age Z-score by gender

| Estimation sample: | Full sample | | | | Kids 0-5 (2005 survey) | | | |
|---|---|---|---|---|---|---|---|---|
| | Male | | Female | | Male | | Female | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PSNP budget*young | 0.129*** | 0.206** | -0.016 | 0.081 | 0.629** | 0.993** | 0.318 | 1.150** |
| | (0.044) | (0.089) | (0.088) | (0.035) | (0.273) | (0.474) | (0.454) | (0.248) |
| PSNP beneficiary households number | 0.128* | 0.963** | -0.023 | 0.379 | 0.585** | 0.736** | 0.296 | 0.853** |
| *young | (0.413) | (0.070) | (0.409) | (0.056) | (0.352) | (0.254) | (0.336) | (0.231) |
| Cohort FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Regional controls: | | | | | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Health extension program coverage*young | no | yes | no | yes | no | yes | no | yes |
| Emergency humanitarian aid*young | no | yes | no | yes | no | yes | no | yes |
| Observations (N) | 12,264 | 12,264 | 13,040 | 13,040 | 1,442 | 1,442 | 1,399 | 1,399 |
| $R^2$ | 0.333 | 0.333 | 0.117 | 0.117 | 0.123 | 0.123 | 0.109 | 0.109 |

Note : This table reports diff-in-diff estimates of Equation 2.1 by gender. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1-4) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 2.8:** PSNP Effect on Years of Primary Schooling by gender

| Estimation sample: | Age>=13 | | | | Age>=11 | | | |
|---|---|---|---|---|---|---|---|---|
| | Male | | Female | | Male | | Female | |
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| PSNP budget*young | 0.619*** | 0.720*** | 0.621*** | 0.692*** | 0.683*** | 0.781*** | 0.530*** | 0.593*** |
| | (0.222) | (0.190) | (0.200) | (0.172) | (0.156) | (0.135) | (0.157) | (0.137) |
| PSNP beneficiary households number *young | 1.620*** | 1.619*** | 1.136** | 1.143** | 1.451*** | 1.461*** | 0.955*** | 0.966*** |
| | (0.443) | (0.453) | (0.443) | (0.450) | (0.305) | (0.309) | (0.317) | (0.323) |
| Cohort FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Regional controls: | | | | | | | | |
| Enrollment in primary school*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes | yes | yes | yes | yes |
| Emergency humanitarian aid *young | no | yes | no | yes | no | yes | no | yes |
| Observations (N) | 3,895 | 3,895 | 3,592 | 3,592 | 5,085 | 5,085 | 4,639 | 4,639 |
| $R^2$ | 0.098 | 0.098 | 0.064 | 0.064 | 0.196 | 0.196 | 0.176 | 0.176 |

Note This table reports diff-in-diff estimates of Equation 2.1 by gender. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

### 2.6.4 Program impact by gender of household head

The PSNP is designed to respond to the unique needs, interests and capabilities of men and women to ensure that they benefit equally from the programme, i.e. ensuring gender equity[16]. This is done by promoting the participation of both men and women in PSNP decision-making structures and responding to women's responsibility for both productive and reproductive work and the differential access of female-headed households to resources. The basic argument for this analysis is hence the effect of a program might be depend on the owner of resource /generator of income/, who receive the cash (women or men), gender of household head (female or male), who is decision maker on resource utilization, intra-household resource allocation in general. In Table 2.9and 2.10, we illustrate the effect of PSNP on both nutrition and years of schooling by gender of household head.

In any of program intensity and estimation sample, we found mixed results on Height-for-Age Z-score. For full estimation sample, the program is significant in female-head household while it is significant for male-headed if 2005 survey (estimation sample) is only considered. The effect of the program on years of schooling is significant for both cohorts from male and female - headed household. However, the magnitude of the effect is higher in case of female-headed household in all program intensity. This might suggest that the program had more differential effect if it targets beneficiaries from female-headed household. The literture noted that for a variety of reasons, women may be systematically different from men in their preferences for types of expenditure or the welfare of particular family members. For example, if women are more likely to be primary caregivers, they may be more likely to have knowledge and preferences about the types of expenditure that may increase child well-being. Women may be more likely to be the target of child health education programmes, and may thus be best positioned to make decisions about spending related to child health. In the second case, there is increasing evidence that women and men may have different preferences. Much discussion has centered on whether women tend to have more altruistic preferences (see for instance Phipps and Burton, 1998; Dooley et al., 2005; and Lundberg and Pollak, 1996) , or whether men and women may tend to favour household members of the same sex (Quisumbing, 1994). People argue that targeting women for cash transfers is based on the assumption that women prioritize the needs of children unlike men and can generally be relied upon to spend the money they are given in accordance with children's needs.

In Table 2.3 and Table 2.4 (see Appendix part), we also present results on effect of the program

[16]Gender equity is one of the eight principles that have guided PSNP implementation to date

effect by household's socioeconomic status, measured by wealth index (quintiles). The effect of the program on height-for-age z-score is significant for poorest and middle quintiles. In case of years of schooling, for those cohorts aged 13 years or above, it is rather significant for the poorest and poor quintiles. Those results might be informative for the programer, i.e. whether the program is pro-poor as it is intended primarily.

**Table 2.9:** PSNP effect on Height-for-Age Z-score by by gender of household head

| Estimation sample: | Full sample | | | | Kids 0-5 (2005 survey) | | | |
|---|---|---|---|---|---|---|---|---|
| Household head | Male-headed | | Female-headed | | Male-headed | | Female-headed | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PSNP budget*young | 0.068* | 0.114 | 0.132** | 0.377** | 0.542*** | 1.281*** | 0.499 | 0.983 |
| | (0.036) | (0.075) | (0.064) | (0.178) | (0.208) | (0.374) | (0.481) | (0.838) |
| PSNP beneficiary households number | 0.093* | 0.531 | 0.132 | 1.759** | 0.505*** | 0.950*** | 0.465 | 0.729 |
| *young | (0.056) | (0.348) | (0.102) | (0.467) | (0.193) | (0.278) | (0.448) | (0.621) |
| Cohort FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Regional controls: | | | | | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Health extension program coverage*young | no | yes | no | yes | no | yes | no | yes |
| Emergency humanitarian aid*young | no | yes | no | yes | no | yes | no | yes |
| Observations (N) | 20,506 | 20,506 | 4,798 | 4,798 | 2,474 | 2,474 | 367 | 367 |
| $R^2$ | 0.173 | 0.173 | 0.205 | 0.205 | 0.118 | 0.118 | 0.082 | 0.082 |

Note : This table reports diff-in-diff estimates of Equation 1 by gender. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1-4) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.10:** PSNP Effect on Years of Primary Schooling by gender of household head

| Estimation sample: | Age>=13 | | | | Age>=11 | | | |
|---|---|---|---|---|---|---|---|---|
| Household heaed | Male-headed | | Female-headed | | Male-headed | | Female-headed | |
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| PSNP budget*young | 0.643*** | 0.720*** | 0.773** | 0.858** | 0.612*** | 0.67*** | 0.708*** | 0.762*** |
| | (0.139) | (0.162) | (0.362) | (0.392) | (0.099) | (0.112) | (0.232) | (0.270) |
| PSNP beneficiary households number *young | 1.426*** | 1.439*** | 1.438** | 1.418** | 1.292*** | 1.303*** | 1.035** | 1.047** |
| | (0.376) | (0.369) | (0.632) | (0.613) | (0.258) | (0.254) | (0.449) | (0.442) |
| Cohort FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Regional controls: | | | | | | | | |
| Enrollment in primary school*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes | yes | yes | yes | yes |
| Emergency humanitarian aid *young | no | yes | no | yes | no | yes | no | yes |
| Observations (N) | 5,848 | 5,848 | 1,639 | 1,639 | 7,563 | 7,563 | 2,161 | 2,161 |
| $R^2$ | 0.078 | 0.078 | 0.076 | 0.077 | 0.177 | 0.178 | 0.208 | 0.209 |

Note This table reports diff-in-diff estimates of Equation 2.1 by gender. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

## 2.7 Generalized results and identification tests

In order to give a causal interpretation to the effect of the PSNP program, regions with different intensity of the treatment must have similar pre-program trend in the outcome variables. We test this hypothesis by estimating fully flexible models for each cohort as expressed in Equation 2.2 and2.3 above. Results of the flexible impact estimates on height-for-age Z-scores, while using the 2005 survey round (i.e. kids born right before and after the program) are reported in Table 2.11. In both specifications (column 1 and 2), the coefficient associated with the pre-treatment years (i.e. those born before 2003) are small and non significantly different from zero. Conversely, there is a positive and significant effect in the post-treatment years of birth. Remarkably, the size and significance of the coefficient slightly decreases with age, which seems to suggest that fully exposure to the treatment (both in utero and in the first year of life) is fundamentally important for child nutritional outcomes. Table 2.12 reports fully flexible impact estimates on years of primary schooling. Here, again, coefficient associates with kids not exposed to the program (i.e. those too old in 2005 to be exposed, that is older than 2 years old in 2005) are small and not statistically significant. The impact of the program on years of primary schooling is significantly only for kids exposed to the program, i.e. those 1 or 2 years old in 2005 (who are 12 or 13 years old in 2016). Remarkably, the size of the impact is similar across the two years of exposure we can exploit.

**Table 2.11:** Fully flexible impact estimates on Height-for-Age Z-score

| | Kids 0-5 (2005 survey) | |
|---|---|---|
| | (1) | (2) |
| PSNP budget*2005 | 0.396* | 0.312* |
| | (0.219) | (0.184) |
| PSNP budget*2004 | 0.527** | 0.506*** |
| | (0.244) | (0.213) |
| PSNP budget*2003 | -0.062 | -0.080 |
| | (0.187) | (0.206) |
| PSNP budget*2002 | 0.218 | 0.166 |
| | (0.216) | (0.201) |
| Cohort FE | yes | yes |
| Birth place FE | yes | yes |
| Regional controls: | | |
| Child related health service coverage*year of birth | yes | yes |
| Improved water use coverage*year of birth | yes | yes |
| Mother related health service coverage*year of birth | no | yes |
| Observations (N) | 2,841 | 2,841 |
| $R^2$ | 0.111 | 0.112 |

Note : This table reports diff-in-diff estimates of Equation 2.2. Outcome variable is individual's height-for-age z-score. The estimation sample include kids born between 2005 and 2005 observed drawn from survey year 2005. Coefficients of interest are interaction terms between year of birth and the amount of PSNP resource allocated (in million Birr) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inference. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.12:** Fully flexible impact estimates on Years of Primary Schooling

| | *Age in 2005* | Age >=13 (1) | (2) |
|---|---|---|---|
| PSNP budget*age | *1* | 0.613*** | 0.551*** |
| | | (0.122) | (0.112) |
| PSNP budget*age | *2* | 0.574*** | 0.478*** |
| | | (0.131) | (0.155) |
| PSNP budget*age | *3* | 0.239 | 0.100 |
| | | (0.151]) | (0.176) |
| PSNP budget*age | *4* | 0.218 | 0.062 |
| | | (0.149) | (0.185) |
| PSNP budget*age | *5* | -0.187 | -0.361* |
| | | (0.170) | (0.205) |
| PSNP budget*age | *6* | -0.163 | -0.330 |
| | | (0.211) | (0.245) |
| PSNP budget*age | *7* | -0.073 | -0.231 |
| | | (0.158) | (0.193) |
| PSNP budget*age | *8* | -0.244 | -0.477 |
| | | (0.273) | (0.317) |
| PSNP budget*age | *9* | -0.118 | -0.320 |
| | | (0.170) | (0.213) |
| PSNP budget*age | *10* | -0.393 | -0.580* |
| | | (0.263) | (0.303) |
| PSNP budget*age | *11* | -0.391 | -0.633** |
| | | (0.240) | (0.283) |
| PSNP budget*age | *12* | -0.046 | -0.243 |
| | | (0.288) | (0.336) |
| Cohort FE | | yes | yes |
| Birth place FE | | yes | yes |
| Regional controls: | | | |
| Total enrollment in primary school*year of birth | | yes | yes |
| Improved water use coverage *year of birth | | yes | yes |
| Emergency humanitarian aid * year of birth | | no | yes |
| Observation (N) | | 8,524 | 8,524 |
| $R^2$ | | 0.141 | 0.142 |

Note This table reports diff-in-diff estimates of Equation 2.3. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

As an extra robustness, we test the identification assumption by exploiting the multiple control groups formed by the successive cohorts that are not exposed to the program. Hence, in Table 2.13, we report results of Equation 2.1 on height-for-age Z-score while comparing two sub-samples of untreated children. In other words, we run a 'control experiment' by using as young cohorts those born between 2000 and 2003, and as older cohorts those born between 1992 and 1999. Results show a difference-in-difference coefficient close to zero (this table is comparable with Table 2.5 above). We run a similar 'control experiment' on years of schooling and in this case, we compare those born between 1980 and 1987 to born between 1971 and 1979. Both these groups are non-exposed to the program (and are old-enough to have potentially finished primary education). Results in Table 2.14 show again that the difference-in-difference results are not significantly different from zero (to be compared with Table 2.6 above).

**Table 2.13:** PSNP effect on Height-for-Age Z-score: Control Experiment

| Estimation sample: | Full sample | | Kids 0-5 (2005 survey) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| PSNP budget*young | -0.047 | -0.060 | 0.015 | 0.000 |
| | (0.038) | (0.039) | (0.140) | (0.000) |
| PSNP beneficiary households number *young | -0.107* | -0.098 | 0.014 | 0.000 |
| | (0.056) | (0.059) | (0.131) | (0.000) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes |
| Health extension program coverage*young | no | yes | no | yes |
| Emergency humanitarian aid*young | no | yes | no | yes |
| Observations (N) | 25,304 | 25,304 | 2,841 | 2,841 |
| $R^2$ | 0.1765 | 0.1765 | 0.1097 | 0.1097 |

Note : This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's height-for-age z-score. The estimation sample include two groups of children born before 2003. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.14:** PSNP Effect on Years of Primary Schooling: Control Experiment

| Estimation sample: | Age>=13 | |
|---|---|---|
| | (1) | (2) |
| PSNP budget*young | 0.158 | 0.111 |
| | (0.138) | (0.134) |
| PSNP beneficiary households number *young | 0.588 | 0.592 |
| | (0.465) | (0.451) |
| Cohort FE | yes | yes |
| Birth place FE | yes | yes |
| Regional controls: | | |
| Enrollment rate in primary school*young | yes | yes |
| Improved water use coverage *young | yes | yes |
| Emergency humanitarian aid *young | no | yes |
| Observations (N) | 7,487 | 7,487 |
| $R^2$ | 0.0744 | 0.0748 |

Note: This table illustrates diff-in-diff estimates of Equation 2.1. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

## 2.8 Further robustness of results and discussion

According to PSNP principle, when possible, cash should be the primary form of transfer,i.e cash first principle. This assists with the stimulation of markets – since people spend their cash in local markets – and the move away from food aid. Food transfers are provided at times and places when food is not available in the market, or where market prices for food are very high. This protects PSNP clients from food shortages and asset depletion[17]. Although the proportion of transfer in kind/food/ form is very small, it might be useful to compare the effect of the program in cash form with that of kind/food/ transfer. This could be quite helpful for the programer to see which way of safety net transfer brings better differential effects. In Table2.15 and Table2.16, we then illustrate the effect of PSNP in kind/food/ in comparison to PSNP in cash. Unlike to that of PSNP-cash per 1000 children results, while the program intensity is PSNP-kind (food) per 1000 children, our resuls show that we have insignificant program effect on both height-for-age z-score and years of schooling.

[17]A transfer is appropriate if it meets the needs of households: cash is provided in settings where markets function well, while food is provided in areas where there is no food to purchase or food prices are extremely high. An appropriate transfer also has the same value whether it is provided in cash or food.

Here, the difference in effect of the program between the two types of trasfers (in cash vs. in kind/food) is a bit debatable in the literature. The first view is that if individuals are utility maximizers and care about their children, effect with cash trasfer might be higher as we found in this study. However, others argue that transfer in kind form may be superior if individuals allocate money in the "wrong" way ("paternalistic" approach, e.g. if fathers use the money for their own consumption such as drinking). In such a case, giving food might be more appropriate than cash to fight child undernutrition. The possible reasons for our results might be due to the fact that proportion of kind transfer is very small (almost more than 85% of total transfer is in cash). Though the program started in 2005, kind transfer started in 2006 and from 2007 to 2014, no kind/food trasfer was given in Harari, Diredawa, Somali, and Afar. Even in those regions recieved kind tranfser (Tigray, Amhara, Oromia and SNNP), the amount was very small as compare to that of cash trasfer. (Ministry of Agriculture and Natural Resource, 2015). Moreveover, kind trasfers are given in the form of mainly wheat, maize and cooking oil. These products are directly consumed by adults and children- not specific food items that can be consumed only by children ( i.e, share of consumption might not be proportional to have desired effect on nutrition of choldren). Of course, if mother consumed it, it may have indirect effect on children's nutrition, through breast feeding practices but mostly mothers have less consumption level due to the fact in lage family size household, mothers give proriety to other children.

In the literature, there is mixed results. John et al. (2013 ) assess the relative impacts of receiving cash versus food transfers using a randomized design in Niger. They find that households randomized to receive a food basket experienced larger, positive impact on measures of food consumption and diet quality than those receiving the cash transfer. Cash transfers have known advantages relative to food transfers with respect to timeliness of delivery (Gentilini 2007; Lentz et al forthcoming). The other potential benefits and drawbacks of each form of transfer, across a range of criteria, depend on the context and objectives of the program (Upton and Lentz 2011). It is widely supposed that--as predicted by economic theory--recipients would prefer to receive cash; provided that cash transfers integrate the transaction costs involved in obtaining a comparable food transfer, recipients can better meet their diverse needs with a cash transfer. However, there is little rigorous evidence on the comparative impacts of cash and food transfers on food security and food related outcomes. Of course, there are numerous emprical works on the effect of cash transfers. However, Hidrobo et al (2012) aruge that comparisons of these impacts is subject to differences in program design, the magnitude of the transfer, and the frequency of the transfer.

**Table 2.15:** PSNP effect on Height-for-Age Z-score: Cash vs Food transfer

| Estimation sample: | Full sample | |
|---|---|---|
| | (1) | (2) |
| PSNP cash *young | 0.116** | 0.173* |
| | (0.057) | (0.102) |
| PSNP kind/food/*young | -0.081 | -0.246 |
| | (0.116) | (0.228) |
| Cohort FE | yes | yes |
| Birth place FE | yes | yes |
| Regional controls: | | |
| Child/mother health service coverage * young | yes | yes |
| Improved water use coverage*young | yes | yes |
| Health extension program coverage*young | no | yes |
| Emergency humanitarian aid*young | no | yes |
| Observations (N) | 25,304 | 25,304 |
| $R^2$ | 0.1765 | 0.1765 |

Note : This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1 and 2) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP kind/food/ (thousand metric ton) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.16:** PSNP Effect on Years of Primary Schooling: Cash vs Food transfer

| Estimation sample: | Age>=13 | | Age>=11 | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| PSNP -cash*young | 0.673*** | 0.713*** | 0.668*** | 0.743*** |
| | (0.163) | (0.178) | (0.124) | (0.134) |
| PSNP kind/food/*young | 0.030 | 0.067 | -0.303 | -0.271 |
| | (0.353) | (0.355) | (0.265) | (0.264) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Enrollment rate in primary school*young | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes |
| Emergency humanitarian aid *young | no | yes | no | yes |
| Observations (N) | 7,487 | 7,487 | 9,724 | 9,724 |
| $R^2$ | 0.0744 | 0.0748 | 0.1806 | 0.1811 |

Note This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP kind/food/ (thousand metric ton) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

The effect of the program might differ based on the definition and measurement of the program intensity we considered. It is fact that the average nutrition or educational attainment in the child population depends on how inclusive is the program i.e. program coverage (i.e. the extensive margin) and how intense is the program per treated person (the intensive margin). Hence, using equation 2.1, we run an estimation for each total PSNP budget spent per 1000 child (including the untreated) which captures both margins, program coverage and program intensity (i.e. average PSNP budget per treated). This enables us to disentangle the two effects. Table 2.17 and 2.18 shows results on effect of PSNP budget/kind/ allocated per treated or beneficiaries in comparison with program intensity per 1000 children population.

The effect of program intensity per treated (beneficiaries) is significant in both height-for-age z-score and years of schooling but the magnitude of effect for height-for-age z-score is higher in case of program intensity per treated compared to that of program intensity (in budget) per 1000 children population, i.e. effects from intensive margin is gretaer than that of extensive margin.

**Table 2.17:** PSNP effect per beneficiaries on Height-for-Age Z-score: Program intensity per 1000 children population Vs program intensity per treated (beneficiaries)

| Estimation sample: | Full sample | | Kids 0-5 (2005 survey) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| PSNP- budget*young | 0.077** | 0.135* | 0.515** | 1.13*** |
| | (0.031) | (0.069) | (0.190) | (0.343) |
| PSNP beneficiary households number *young | 0.101** | 0.673** | 0.480** | 0.840*** |
| | (0.049) | (0.321) | (0.177) | (0.254) |
| PSNP- budget per beneficiaries*young | 0.336*** | 0.543* | 0.140* | 1.597*** |
| | (0.086) | (0.316) | (0.075) | (0.371) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes |
| Health extension program coverage*young | no | yes | no | yes |
| Emergency humanitarian aid*young | no | yes | no | yes |
| Observations (N) | 25,304 | 25,304 | 2,841 | 2,841 |
| $R^2$ | 0.1765 | 0.1765 | 0.1097 | 0.1097 |

Note : This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1 and 2) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.18:** PSNP Effect per beneficiaries on Years of Primary Schooling: Program intensity per 1000 children population Vs program intensity per treated (beneficiaries)

| Estimation sample: | Age>=13 | | Age>=11 | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| PSNP budget*young | 0.641*** | 0.727*** | 0.620*** | 0.701*** |
| | (0.137) | (0.159) | (0.102) | (0.116) |
| PSNP beneficiary households number *young | 1.41*** | 1.41*** | 1.22 *** | 1.23*** |
| | (0.341) | (0.335) | (0.244) | (0.240) |
| PSNP- budget per beneficiaries*young | 0.428*** | 0.453*** | 0.454*** | 0.395*** |
| | (0.103) | (0.104) | (0.080) | (0.080) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Enrollment rate in primary school*young | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes |
| Emergency humanitarian aid *young | no | yes | no | yes |
| Observations (N) | 7,487 | 7,487 | 9,724 | 9,724 |
| $R^2$ | 0.0744 | 0.0748 | 0.1806 | 0.1811 |

Note This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

Basically, our aforementioned analysis on the program effect lies on the assumption of linearity. However, the effects might be non-linear after certain level of program intensity we considered. Hence, it is noteworthy to have an idea of the two effects because such analysis of the program effect is very relevant for policy makers/programmers/. This might be addressed using two effects cases (such as including doubling of program intensity as second program effect regressor ). As we can see from Table 2.19 and 2.20, compared to program coefficients using program intensity, the estimates using square of program intensity are by far smaller and insignificant in both height-for-age z-score and years of schooling. This suggest that program effect might fall and become insginificant after it reaches certain optimal level.

**Table 2.19:** PSNP effect on Height-for-Age Z-score

| Estimation sample: | Full sample | | Kids 0-5 (2005 survey) | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| PSNP- budget*young | 0.297** | 0.804*** | 0.414*** | 0.642*** |
| | (0.138) | (0.183) | (0.133) | (0.186) |
| (PSNP budget)$^2$ *young | -0.039 | -0.152 | -0.000 | -0.000 |
| | (0.027) | (0.036) | (0.000) | (0.000) |
| PSNP budget per beneficiary * young | 0.310*** | 0.310*** | 0.394** | 1.549** |
| | (0.082) | (0.082) | (0.189) | (0.749) |
| (PSNP budget)$^2$ per beneficiary * young | 0.000 | 0.000 | -0.000** | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes |
| Health extension program coverage*young | no | yes | no | yes |
| Emergency humanitarian aid*young | no | yes | no | yes |
| Observations (N) | 25,304 | 25,304 | 2,841 | 2,841 |
| $R^2$ | 0.1765 | 0.1765 | 0.105 | 0.110 |

Note : This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1 and 2) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** $p<0.01$, ** $p<0.05$, * $p<0.1$

**Table 2.20:** PSNP Effect on Years of Primary Schooling

| Estimation sample: | Age>=13 | | Age>=11 | |
|---|---|---|---|---|
| | (1) | (2) | (1) | (2) |
| PSNP budget*young | 0.482* | 0.669*** | 0.682*** | 0.875*** |
| | (0.291) | (0.316) | (0.222) | (0.242) |
| (PSNP budget)$^2$ * young | 0.038 | 0.013 | -0.014 | -0.039 |
| | (0.056) | (0.055) | (0.041) | (0.041) |
| PSNP budget per beneficiary * young | 0.541*** | 0.330** | 0.376*** | 0.375*** |
| | (0.154) | (0.167) | (0.110) | (0.115) |
| (PSNP budget)$^2$ per beneficiary * young | -0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Cohort FE | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes |
| Regional controls: | | | | |
| Enrollment rate in primary school*young | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes |
| Emergency humanitarian aid *young | no | yes | no | yes |
| Observations (N) | 7,487 | 7,487 | 9,724 | 9,724 |
| $R^2$ | 0.0744 | 0.0748 | 0.1806 | 0.1811 |

Note This table reports diff-in-diff estimates of Equation 1. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table 2.6 and 2.7, Table 2.15 and Table 2.16, we compare program impact by considering alternative measurement of program intensity, i.e, PSNP budget (cash), PSNP-kind (food) PSNP beneficiary household. However, we find significant program effect in both height-for-age z-score and schooling years although the program intensity measurement is altered. The other sensitivity analysis we considered is that examining our result while other social protection program such as emergency relief aid given to each region of birth. Here, both emergency relief aid (food in metric ton) and emergency relief aid beneficiary household are considered as other social protection program. As it is illustrated from Table 2.6 to 2.7, results on both outcome interest remain positive and significant. Furthermore, in addition to social protection program (in the form of PSNP or humanitarian emergency relief aid), our health out come interest might be affected by other health related programs such as community based nutrition program implemented in the country since 2008. It is thus noteworthy to net out the effect of PSNP from the effect of those related interventions which directly affect nutritional status of children. However, we argue that we can capture it by including health extension program[18] coverage as proxy for community based nutrition related health program in our regression.

The other basic issue in program evaluation is the mechanism of transmissions. Positive outcomes of social transfer programmes on children's welfare outcomes depend on the particular context and issues that children face in each country (UNICEF 2015b). Hence, it is valuable to demonstrate not only the existence of program impact on outcome interest, but also shed light on potential path way of impact. As Deaton (2010) argues, uncovering the factors that explain why an impact exists is a necessary task to inform policy. Nevertheless, since DHS is not primarily collected for program impact evaluation, it lacks information on how the transfer is allocated, household's consumption expenditure, and intra-household resource allocation in general. Analysis using those information would have been used as further evidence on mechanism of effect channel. However, with the absence of those information, we fail to incorporate results on channel of effect in such ways. Of course, beside to safety net transfer, the PSNP program component includes enhanced access to complementary to livelihood services (the form of skills training, behavioral change in health caring, business planning, savings promotion, credit facilitation, and, where appropriate, employment linkage, offer a livelihood transfer/grant for the purchase of productive assets). This could be one way of guiding beneficiaries to allocate the transfer cash or food in line with the intended objectives. Moreover, cost-benefit analysis of the program is not covered in this study, i.e. beyond the scope of the study.

## 2.9 Conclusion

By using exogenous variation provided by the combination of year and region of birth, this paper studies the direct and indirect effects of a large-scale social protection program implemented in Ethiopia since 2005. The introduction of the reform has been supported by international donors, led by the World Bank. According with the budgeting and roll-out of the program, there is variation across regions in the share of resources and beneficiaries devoted to the program. This cross-sectional variation provides differences in program intensity across regions, which we combine with differences in exposure to the program across cohorts induced by the individual year of birth. In line with the medical literature, we postulate that the two first years of life are a critical setting for the impact of the program on nutritional and long-term

[18] Other possible argument is that the included health related control variables can be a proxy for capturing the effect on our health out come interest because these interventions are being carried out at health posts, in communities, at other health facilities and through health development armies.

anthropometric outcomes and, thereby, on human capital accumulation. Hence, we employ a difference-in-difference strategy in our empirical analysis and the exogenous treatment variable is the interaction of the year of birth with the intensity of the program in the region of birth. We find that exposure to the PSNP led to an increase in both Heigh-for-Age Z-scores (HAZ) and primary educational attainment as measures by years of schooling. On average, one extra million Birr PSNP budget (about 35,000USD) allocated per 1000 children in birth regions increases child height-for-age Z-score by 0.1. As a result, an increase in the intensity of the program increase completed years of primary schooling by about 0.7. Results are are robust to different ways in measuring program intensity and different estimation sample. The estimation of fully flexible models in years of birth or age ensures the non-violation of common trend assumptions. Moreover, they point to increasing effects with the time of exposure (i.e. measure by year of birth and age). Our results are also robust to the inclusion of important regional-level controls which could lead to omitted variable bias. We finally show that changes between cohorts in both height-for-age and primary education are not systematically different in low- and high-program intensity regions before the program started.

Our findings show that in Ethiopia an unusually large government-administrated social protection program, which includes both cash-transfer and social assistance, has been effective in increasing both nutritional status and educational outcomes. While we can measure the impact on the quantity of education (measured by years of primary schooling), we have no information to dig deeper into the impact on the quality of that. However, positive results on the combination of both nutrition and years of schooling of individuals exposed to the program early in life is evidence in favor of an increase in human capital of future adults, which is a key input for productivity and well-being, having both private and social positive returns. Impact evaluations are usually of specific interventions in a specific context. It remains possible that these results cannot be generalized to different contexts. Yet, they contribute to provide systematic and causal evidence on the effectiveness of national and international efforts to reduce poverty and deprivation in Ethiopia, which is a country with one of the highest prevalence of (child) malnutrition and stunting in the world.

# Bibliography


- Angrist J. (1990) . Lifetime Earnings and the Vietnam Era Lottery Draft, American Economic Review, 80, 313-336.
- Angrist J and Lang D Oreopulus P. 2008. Incentives and Services for college Achievement: Evidence from a randomized trial "American Economic Journal Applied.
- Angrist J and Lavy V. 2009. The Effects of High Stakes High School Achievement Awards: Evidence from a Randomized Trial American Economic Review 99(4), September 2009.
- Bastagli, F., Hagen-Kanzer, J., Harman, L. and Barca, V. 2018. The Impact of Cash Transfers: A Review of the Evidence from Low- and Middle-income Countries, Journal of Social Policy, forthcoming.
- Barker,D. J. P. 1990. The Fetal and Infant Origins of Adult Disease. British Medical Journal 301(6761):1111.
- Behrman Jere R., Susan W. Parker , Petra E. Todd. 2009. Schooling Impacts of Conditional Cash Transfers on Young Children: Evidence from Mexico. Economic Development and Cultural Change(Chicago Journals), Vol. 57, No. 3 (April 2009), pp. 439-477.
- Berhane Guush, John Hoddinott, and Neha Kumar. 2017. The impact of Ethiopia's Productive Safety Net Programme on the nutritional status of children: 2008–2012. IFPRI-ESSP Working paper 99.
- Bethelhem L. Debela, Gerald Shively and Stein T. Holden. 2014. Does Ethiopia's Productive Safety Net Program Improve Child Nutrition? Centre for Land Tenure Studies Working Paper 01/14.
- Bleakley Hoyt. 2010. Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure, American Economic Journal: Applied Economics 2 (April 2010): 1–45
- Card, David; Krueger, Alan B. 1994. Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. American Economic Review 84 (4): 772–793.
- Cecilia Machado, V. Pinho Neto, and Christiane Szerman. 2017. Youth Responses to Cash Transfers: Evidence from Brazil .
- Cunha F, Heckman JJ (2008) Formulating, identifying and estimating the technology of cognitive and non-cognitive skill formation. J Hum Resour 43(4):738–782

- Cutler, David, Winnie Fung, Michael Kremer, Monica Singhal, and Tom Vogl. 2010. Early-life Malaria Exposure and Adult Outcomes: Evidence from Malaria Eradication in India.American Economic Journal: Applied Economics 2 (April 2010): 72–94 http://www.aeaweb.org
- Dahl GB, Lochner L. 2012. The impact of family income on child achievement: evidence from the earned income tax credit. Am Econ Rev 102(5):1927–1956
- Deaton A. 2010. Instruments, Randomization, and Learning about Development: Journal of Economic Literature Vol. 48 (June 2010): 424–455.
- Dercon Stefan and Sanchez Alan. 2013. Height in mid childhood and psychosocial competencies in late childhood: evidence from four developing countries. Human Biology, vol 11, issue 4, December 2013. DOL: 10.1016/j.ehb.2013.04.001.
- Dooley M, Lipman E, Stewart J .2005. Exploring the good mother hypothesis: do child outcomes vary with the mother's share of income? Canadian Public Policy 31(2): 123-143.
- Duflo, E. 2000. Child Health and Household Resources in South Africa: Evidence from the Old Age Pension Program. The American Economic Review, 90(2): 393–398.
- Duflo E .2001. "Schooling and labor market consequences of school construction in Indonesia: Evidence from an Unusual Policy Experiment", American Economic Review, 91(4), 785-813.
- Duflo, E. 2003. Grandmothers and Granddaughters: Old-Age Pensions and Intra household Allocation in South Africa. World Bank Economic Review, Oxford University Press, 17(1): 1-25.
- Duflo E., Dupas P., and Kremer M. 2014. Education, HIV, and Early Fertility: Experimental evidence from Kenya NBER Working Paper Series 20784.
- Galiani S., Gertler P., and Schargrodsky E. 2005. Water for Life: The Impact of the Privatization of Water Services on Child Mortality. Journal of Political Economy, Vol. 113, No. 1 (February 2005), pp. 83-120.
- Gertler Paul 2004. Do Conditional Cash Transfers Improve Child Health? Evidence from Progresa's Control Randomized Experiment. The American Economic Review, Vol. 94, No. 2, pp. 336-341.
- Gentilini, U. 2007. Cash and Food Transfers: A Primer. Occasional Papers No. 18. World Food Programme.
- Hanna, R. and Olken, B. (2018). Universal Basic Incomes vs. Targeted Transfers: Anti-Poverty Programs in Developing Countries with Rema Hanna. Journal of Economic Perspectives 32 (4), pp. 201-226..
- Hidrobo, M., J. Hoddinott, A. Peterman, A. Margolies, and V. Moreira. 2012. Cash, Food, or Vouchers? Evidence from a Randomized Experiment in Northern Ecuador. Mimeo. International Food Policy Research Institute.
- Jalana Jyotsna and Ravallion Martin. 2003. Does piped water reduce diarrhea for children in rural India? Journal of Econometrics 112 (2003) 153–173.

- Jere R. Behrman, Susan W. Parker, and Petra E. Todd. 2009. Schooling Impacts of Conditional Cash Transfers on Young Children: Evidence from Mexico. Econ Dev Cult Change. 2009 April ; 57(3): 439–477.
- John Hoddinott, Susanna Sandström, and Joanna Upton. 2013. The impact of cash and food transfers: Evidence from a randomized intervention in Niger. Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013.
- Jutting Johannes. 2004. Do Community-based Health Insurance Schemes Improve Poor People's Access to Health Care? Evidence From Rural Senegal. World Development Vol. 32, No. 2, pp. 273–288, 2004 2003 Elsevier Ltd.
- Kabeer, N. 2008. Mainstreaming Gender and Social Protection in the Informal Economy, London: Commonwealth Secretariat.
- Kabeer, Naila and Waddington, Hugh .2015. Economic impacts of conditional cash transfer programmes: a systematic review and meta-analysis. Journal of Development Effectiveness, 7 (3). pp. 290-303. ISSN 1943-9342.
- Lentz, E.C., S. Passarelli, and C.B. Barrett, (forthcoming). The Timeliness and Cost Effectiveness of the Local and Regional Procurement of Food Aid. World Development.
- Lampietti, J. and L. Stalker .2000. Consumption Expenditure and Female Poverty: A review of the Evidence. World Bank Working Paper Series No. 11.
- Lundberg S, PollakRA .1996. Bargaining and distribution in marriage. The Journal of Economic Perspectives 10 (4): 139-158.
- Mark M. Pitt, Mark R. Rosenzweig, and Donna M. Gibbons.1993. The Determinants and Consequences of the Placement of Government Programs in Indonesia. The World Bank Economic Review T, VOL. 7, NO. 3: 319-348.
- Miguel Edward and Kremer Michael. 2004. Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities. Econometrica, Vol. 72, No. 1 (Jan., 2004), pp. 159-217.
- Ministry of Education, Ethiopia. 2009. Education Statistics Annual Abstract (2007-2008), Education Sector Development Program Planning and Policy Analysis Department, Addis Ababa, Ethiopia
- Ministry of Education, Ethiopia. 2015. Education Sector Development Programme V (ESDP V) 2015/16 - 2019/20 . Programme Action Plan, Addis Ababa.
- Ministry of Agriculture and Natural Resource, Ethiopia. 2015. Productive Safety Net Programs (PSNP IV) Annual Work Plan and Budget for 2015/16. Rural Job Opportunity Creation and Food Security Sector Food Security Coordination Directorate.
- Phipps SA, Burton PS .1998. What's Mine is Yours? The Influence of Male and Female Incomes on Patterns of Household Expenditure. Economica 65: 599–613.

- Ponce Juan and Bedi Arjun S. 2010.The impact of a cash transfer program on cognitive achievement: The Bono de Desarrollo Humano of Ecuador.Economics of Education Review 29 (2010) 116–125.
- Porter, C. and R. Goyal. 2016. Social Protection for All Ages? Impacts of Ethiopia's Productive Safety Net Program on Child Nutrition. Social Science & Medicine, 159: 92–99.
- Quisumbing AR .1994. Intergenerational transfers in Philippine rice villages: gender differences in traditional inheritance customs. Journal of Development Economics 43(2): 167-195.
- Ravallion M. 2001.The Mystery of the vanishing benefits: An introduction to impact evaluation .The World Bank economic review , vol. 15, no.1 115-140.
- Ravallion M. 2009. Evaluation in the Practice of Development. The World Bank Research Observer, vol. 24, no. 1.24:29–53. Oxford University Press on behalf of the International Bank for Reconstruction and Development / the Word Bank.
- Save the Children. 2012. A Life free from hunger: Tackling child malnutrition. Save the Children, London, UK.
- Scrimshaw, Nevin S. 1997. The Relation between Fetal Malnutrition and Chronic Disease in Later Life. British Medical Journal 315:825-26.
- Smith, L.C., F. Khan, T.R. Frankenberger and A. Wadud. 2013. Admissible Evidence in the Court of Development Evaluation? The Impact of Care's Shouhardo Project on Child Stunting in Bangladesh. World Development, 41(1): 196–216.
- Smith J and Todd (2001) Reconciling conflicting evidence on the performance of propensity score matching methods. American Economic Review.
- UNICEF/ETHIOPIA. 2016. Ethiopia Social Protection: Access of the poor and vulnerable to basic services good practices: Linking safety net clients with complementary social services.
- Victora, CG; Adair, L, Fall, C, Hallal, PC, Martorell, R, Richter, L, Sachdev, HS, Maternal and Child Undernutrition Study, Group. "Maternal and child undernutrition: consequences for adult health and human capital". Lancet. 371 (2008): 340–57.
- Upton, J. and E. Lentz .2011. Expanding the Food Assistance Toolbox. Chapter 5 in Barrett, C.B., A. Binder and J. Steets (Eds). Uniting on Food Assistance: The Case for Transatlantic Policy Convergence. London: Routledge.
- World Bank. 2010. What Can We Learn from Nutrition Impact Evaluations? Lessons from a Review of Interventions to Reduce Child Malnutrition in Developing Countries. The World Bank, Washington, D.C.

## Appendix I

***A. Control variables for Nutrition***

- Full immunization coverage (child health service): proportion of surviving infants who receive all doses of infant antigens before their first birthday. The Infant Antigens are: BCG, Pentavalent (DPT-HepB, Hib), doses 1 -3; OPV, doses 1—3; and Measles.
- Maternal Health service indicators coverage: It includes antenatal, delivery and postnatal care. In addition, this section also encompasses the health care dimensions of family planning.
- Postnatal care (PNC) coverage: proportion of women who seek care, at least once during postpartum (42 days after delivery), from a skilled health attendant, including Health extension workers, for reasons relating to post-partum.
- Antenatal care (ANC) coverage: proportion of pregnant women attended, at least once during the current pregnancy, by a health professional, for reasons related to pregnancy. It is also defined as percentage of women who utilized antenatal care provided by skilled birth attendance for reasons related to pregnancy at least once during pregnancy as a percentage of live births in a given time period
- Number of health Facilities: the total number of health facilities (Hospitals, Health clinics, and Health posts) disaggregated by type and ownership while health facility over population coverage includes ratio of number of hospital, health center, and health post to the corresponding population.
- Primary health care coverage: Proportion of population living within 2 hours walking distance. It is a proxy indicator of equity in service access, estimated that a Health post covers 5,000 persons and Health center 25,000 persons, and minus the population covered by Health post.
- Functional facility to population ratio: reflects the number of persons served by each facility, by facility type.
- Potential health service coverage: The population covered in percentage based on the existing health centres and health stations in catchment's area.
- Health service coverage and Utilization: Health system indicators include: Outpatient (OPD) attendance per capita: average number of outpatient visits (including first and repeat visits) per person per year.

- Health infrastructure (Potential health service coverage ):-The population covered in percentage based on the existing health centres and health posts in catchments' area.
- Health Extension Program (HEP) is an innovative community-based strategy to deliver preventive and promotive services and selected high impact curative interventions at community level. It brings community participation through creation of awareness, behavioural change, and community organization and mobilization. It also improves the utilization of health services by bridging the gap between the community and health facilities through the deployment of Health Extension Workers (HEW). The main objective is to improve access to essential health services provided at village and household levels, contributing to the improvement of the health status of the families, with their full participation, using local technologies and the skill and wisdom of the communities. In this context, with the aim to promote community mobilization and adoption of healthy lifestyles, a major initiative undertaken by the Ethiopian Government is the implementation of the Health Development Arm (HDA).

***B. Control variables for Education outcome***

- Total enrollment rate : The ratio of total children who enrolled in current year to total school age children
- Net Enrollment Rate (NER) is the best measuring organized on-time school participation and is a more refined indicator of school and enrollment coverage in terms of explaining the proportion of puplis enrolled from the official age group. NER is calculated by dividing the number of properly aged primary students ( for Ethiopia ages 7-14) by the number of children of school ageing (7-14). NER is usually lower than the GER since it excludes over-aged and under-aged pupils.
- Water and sanitation coverage : Percentage of population using any improved source of drink water and an improved sanitation, not shared facility

**Table 2.1:** PSNP effect on Height-for-Age Z-score: Different treatment cut-offs

| | Kids 0-5 (2005 survey) | |
|---|---|---|
| | (1) | (2) |
| PSNP budget*young(2005) | 0.267*** | 0.321*** |
| | (0.068) | (0.091) |
| PSNP budget*young(2004) | 0.189** | 0.245*** |
| | (0.083) | (0.106) |
| PSNP budget*young(2002) | 0.119 | 0.039 |
| | (0.076) | (0.095) |
| PSNP budget*young(2001) | 0.131 | 0.087 |
| | (0.083) | (0.101) |
| Cohort FE | yes | yes |
| Birth place FE | yes | yes |
| Regional controls: | | |
| Child and mother related health service coverage*year of birth | yes | yes |
| Improved water use coverage*year of birth | no | yes |
| Observations (N) | 2,841 | 2,841 |
| $R^2$ | 0.1063 | 0.1086 |

Note : This table illustrates diff-in-diff estimates of Equation 2.1 with different treatment cut-offs (each line report the result of a different regression). Outcome variable is individual's height-for-age z-score. The estimation sample include kids born between 2001 and 2005 observed in survey year 2005. Coefficients of interest are interaction terms between year of birth and the amount of PSNP resource allocated (in million Birr) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inference. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.2:** PSNP Effect on Years of Primary Schooling: Different treatment cut-offs

| | | Age>=13 | |
|---|---|---|---|
| | *Age in 2005* | (1) | (2) |
| PSNP budget*age in 2005 | *1* | 0.209** | 0.198* |
| | | (0.084) | (0.112) |
| PSNP budget*age in 2005 | *2* | 0.200*** | 0.198* |
| | | (0.043) | (0.056) |
| PSNP budget*age in 2005 | *3* | 0.030 | -0.012 |
| | | (0.040) | (0.045) |
| PSNP budget*age in 2005 | *4* | 0.042 | 0.043 |
| | | (0.028) | (0.036) |
| PSNP budget*age in 2005 | *5* | -0.001 | -0.019 |
| | | (0.025) | (0.029) |
| PSNP budget*age in 2005 | *6* | 0.036 | 0.043 |
| | | (0.025) | (0.029) |
| PSNP budget*age in 2005 | *7* | -0.004 | -0.003 |
| | | (0.020) | (0.027) |
| PSNP budget*age in 2005 | *8* | -0.001 | -0.016 |
| | | (0.028) | (0.040) |
| PSNP budget*age in 2005 | *9* | 0.028* | 0.030 |
| | | (0.015) | (0.020) |
| PSNP budget*age in 2005 | *10* | -.0006 | 0.010 |
| | | (0.022) | (0.026) |
| PSNP budget*age in 2005 | *11* | -0.0007 | -0.002 |
| | | (0.016) | (0.022) |
| PSNP budget*age in 2005 | *12* | -0.007 | -0.008 |
| | | (0.018) | (0.022) |
| PSNP budget*age in 2005 | *13* | 0.008 | 0.003 |
| | | (0.017) | (0.021) |
| Cohort FE | | yes | yes |
| Birth place FE | | yes | yes |
| Regional controls: | | | |
| Total enrollment in primary school*year of birth | | yes | yes |
| Improved water use coverage *year of birth | | yes | yes |
| Emergency humanitarian aid * year of birth | | no | yes |
| Observation (N) | | 1,344 | 1,344 |
| $R^2$ | | 0.0551 | 0.0551 |

Note This table illustrates diff-in-diff estimates of Equation 2.1 with different treatment cut-offs (each line report the result of a different regression). Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.3:** PSNP effect on Height-for-Age Z-score by Socioeconomic Status (SES)/Wealth index

| Estimation sample: | Full sample | | | | Kids 0-5 (2005 survey) | | | |
|---|---|---|---|---|---|---|---|---|
| SES/Wealth index/Wealth index by quintiles | Poorest/Q1/ | Poor/Q2/ | Middle /Q3/ | Rich/Q4/ | Poorest/Q1/ | Poor/Q2/ | Middle /Q3/ | Rich/Q4/ |
| PSNP- budget*young | 1.045*** | 0.554 | 0.875* | -0.002 | 1.167* | 0.736 | 2.149*** | 0.000 |
| | (0.471) | (0.689) | (0.475 | (1.148) | (0.636) | (0.785) | (0.687) | ( 0.000) |
| Cohort FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Regional controls: | | | | | | | | |
| Child/mother health service coverage * young | yes | yes | yes | yes | yes | yes | yes | yes |
| Improved water use coverage*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Health extension program coverage*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Emergency humanitarian aid*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Observations (N) | 5,952 | 3,468 | 2,983 | 2,643 | 891 | 610 | 581 | 546 |
| $R^2$ | 0.125 | 0.127 | 0.148 | 0.139 | 0.121 | 0.086 | 0.173 | 0.166 |

Note : This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's height-for-age z-score. In the full sample regressions (columns 1 and 2) all DHS rounds (2005, 2011 and 2016 ) are included. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1

**Table 2.4:** PSNP Effect per beneficiaries on Years of Primary Schooling by Socioeconomic Status (SES)/Wealth index

| Estimation sample: | Age>=13 | | | | Age>=11 | | | |
|---|---|---|---|---|---|---|---|---|
| SES/Wealth index/Wealth index by quintiles | Poorest/Q1/ | Poor/Q2/ | Middle /Q3/ | Rich/Q4/ | Poorest/Q1/ | Poor/Q2/ | Middle /Q3/ | Rich/Q4/ |
| PSNP- budget*young | 0.759** | 0.586* | 0.461 | 0.766** | 0.694*** | 0.602*** | 0.556** | 0.843*** |
| | (0.320) | (0.353) | (0.296) | (0.272) | (0.255) | (0.213) | (0.219) | (0.187) |
| Cohort FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Birth place FE | yes | yes | yes | yes | yes | yes | yes | yes |
| Regional controls: | | | | | | | | |
| Enrollment rate in primary school*young | yes | yes | yes | yes | yes | yes | yes | yes |
| Improved water use coverage *young | yes | yes | yes | yes | yes | yes | yes | yes |
| Emergency humanitarian aid *young | yes | yes | yes | yes | no | yes | yes | yes |
| Observations (N) | 1,791 | 1,243 | 1,338 | 1,421 | 2,413 | 1,653 | 1,697 | 1,851 |
| $R^2$ | 0.104 | 0.096 | 0.102 | 0.088 | 0.176 | 0.191 | 0.198 | 0.210 |

Note This table reports diff-in-diff estimates of Equation 2.1. Outcome variable is individual's completed years of primary schooling. Coefficients of interest are interaction terms between treatment dummy and the amount of PSNP resource allocated (in million Birr) or PSNP beneficiary household (thousand) per 1000 children in the region of birth. All specifications include region of birth, year of birth dummies. Among region-specific controls, child/mother health service coverage includes immunization, antenatal, and postnatal service coverage, wile emergency-humanitarian aid includes both number of beneficiaries and amount of food (in metric tons) distributed across regions. In all regression, we consider sampling weight for national inferences. Standard errors are in parentheses are clustered at enumeration areas. Significance level as *** p<0.01, ** p<0.05, * p<0.1