Dymanics of Inequality In Child Undernutrition In Ethiopia

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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
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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

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[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

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.

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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.

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 mea-

sures 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

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[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.

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 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

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[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.

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 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:

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

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 δ_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,

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[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.

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 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

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[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), 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.

as nominal consumption. The calculated per capita amounts winsorised at the 97th 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 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 (1st quintile) and the richest (5th 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.

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

where y_{it} represents the health level of individual i in period t, and R_i^t denotes the relative fractional rank of ith 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 $\overline{\overline{y}} = \frac{\sum_i \sum_i y_{it}}{NT}$ is the over all average health status/population/ in T periods; $\sum \frac{\overline{y}_t}{T} = \overline{y}^T$ is the average health of the individual over the T periods , $\overline{y}^t = \frac{\sum_i y_{it}}{N}$ is the mean of health of individual in each t period , $w_t = \frac{\overline{y}_t}{T\overline{\overline{y}}^T}$ 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:

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

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

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[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.

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

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 β is a vector of regression coefficients which show the effect of X on Y; $\mu_{ihct} = \alpha_i + \varepsilon_{ihct}$, α_i[12] is individual specific effect and ε_{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:

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

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

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[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, α_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 (η_k) and concentration index of kth 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.

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

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

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

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[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 (β) 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 β'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 β's (sometimes called the unexplained component) and interaction effect (change in product of X and β, $X\beta$).

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

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
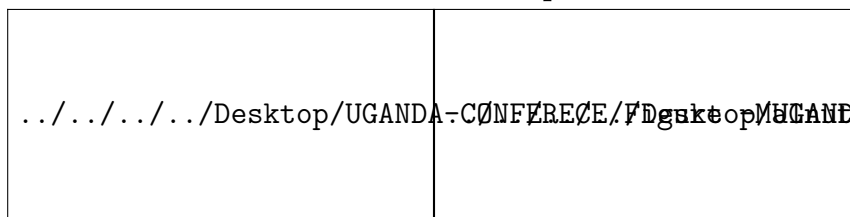
As it is aforementioned, the final data used in this study is constructed from various individual, household and community level covered in all three survey waves. The health variable data is prepared from each individual child's age, sex, weight and height, using Zanthro ado –file with reference to 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

../../../../Desktop/UGANDA-CONFERECE/Fig6-7-8.PNG
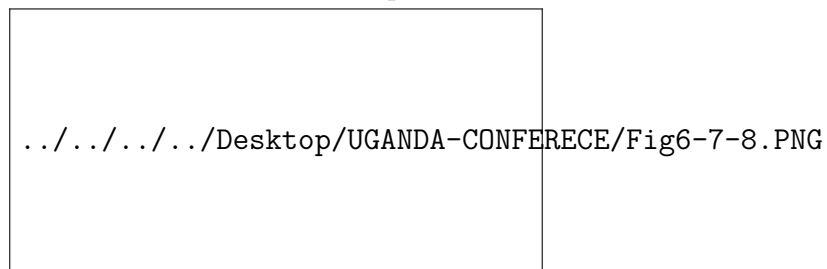
Almost in all Z-scores (see, Figure 1.2), the distribution is skewed to the left which implies that many individuals are away from the median of the distribution. HAZ-score and WAZ-score are also positively correlated while HAZ and WHZ-score are negatively correlated.

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(1st quintile)	-1.5 (.062)	-.57 (.054)	-1.4 (.042)
Richest (5thquintile)	-1.1 (.079)	-.26 (.067)	-.86 (.058)
Difference (1st-5th)	-.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(1stquintile)	-1.5 (.065)	-.61 (.056)	-1.4 (.045)
Richest (5thquintile)	-1.2 (.075)	-.27 (.064)	-.94 (.053)
Difference (1st-5th)	-.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
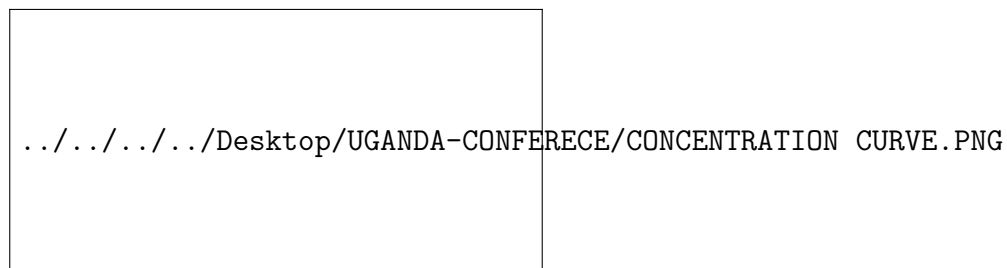
As it is illustrated in Figure (1.3), the concentration curves for each malnutrition indicators is located above the line of equality. These indicate that higher malnutrition level is disproportionately prevailed among the poor section of the population in both socioeconomic status (SES) ranking variables, 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

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

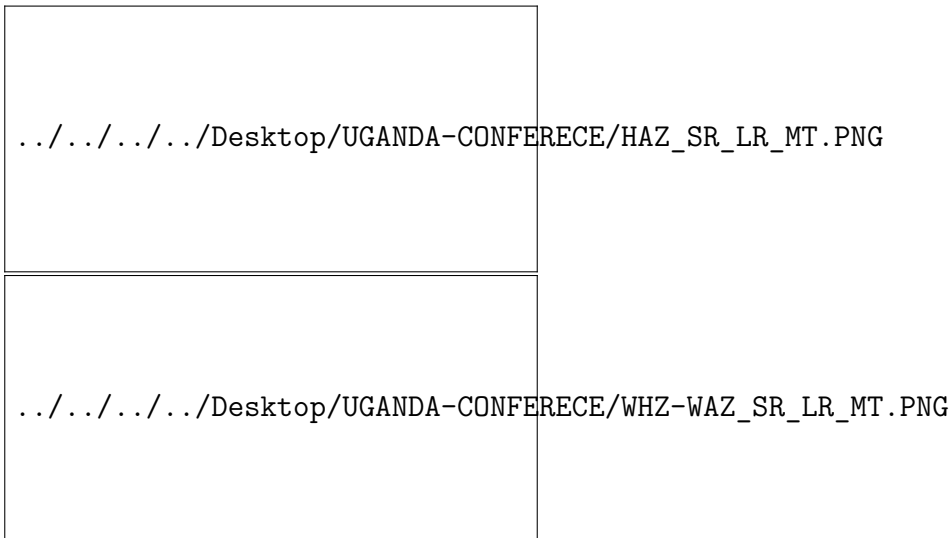| Groups	Height-for-Age	(HAZ)	Weight-for-Height	(WHZ)	Weight-for-Age	(WAZ)
	Wealth	Consumption	Wealth	Consumption	Wealth	Consumption
Male	-.044***	-.051***	-.041**	-.038**	-.061***	-.051***
	(.011)	(.012)	(.014)	(.015)	(.010)	(.011)
Female	–.049***	-.044***	-.021	.018	-.047***	-.023*
	(.011)	(.011)	(.015)	(.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).*

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

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 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

../../../../Desktop/UGANDA-CONFERECE/HAZ_SR_LR_MT.PNG

../../../../Desktop/UGANDA-CONFERECE/WHZ-WAZ_SR_LR_MT.PNG

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

../../../../Desktop/UGANDA-CONFERECE/Table-9.PNG
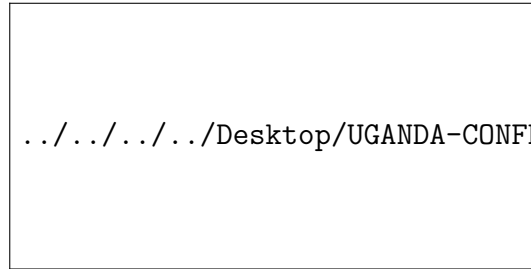
Based on Allanson et al. (2010) approach, the decomposition of change in inequality (concentration index) between Wave 1 and each subsequent wave, as illustrated in Table (1.9) provides us both SES-related health mobility and health-related SES mobility indices. Sign of the index of SES-related health 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 1.3 [16].

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[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

Regressors (k)	HAZ				WHZ				WAZ			
	β_k	Elasticity	CI	Contribution	β_k	Elasticity	CI	Contribution	β_k	Elasticity	CI	Contribution
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

Regressors (k)	HAZ β_k	HAZ Elasticity	HAZ CI	HAZ Contribution	WHZ β_k	WHZ Elasticity	WHZ CI	WHZ Contribution	WAZ β_k	WAZ Elasticity	WAZ CI	WAZ 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			
R²	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,β 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(β)	-.038	-.073	-.028	-.043	-.047	-.076
Generalized extended CI(v)	-.327	-.290	-.107	-.106	-.310	-.293
Generalized symmetric CI(β)	-.252	-.486	-.094	-.144	-.262	-.425
Ranking variable -Consumption						
Extended CI(v)	-.026	-.120	-.014	-.022	-.027	-.101
Symmetric CI(β)	-.045	-.060	-.016	-.034	-.040	-.065
Generalized extended CI(v)	-.297	-.370	-.082	-.035	-.256	-.264
Generalized symmetric CI(β)	-.303	-.399	-.054	-.114	-.225	-.366

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

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[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.

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

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../../../../Desktop/UGANDA-CONFERECE/Figure-5-wealth-consumption
```
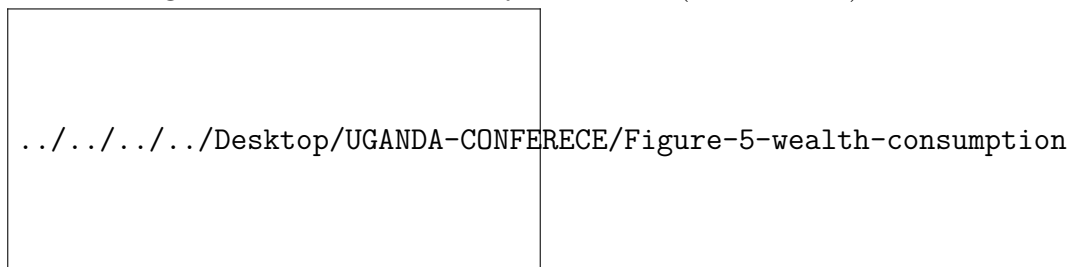
Table 1.1: Prevalence of stunting, wasting and underweight by region and rural/urban

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

Regressors (k)	HAZ β_k	Elasticity	CI	Contribution	WHZ β_k	Elasticity	CI	Contribution	WAZ β_k	Elasticity	CI	Contribution
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

Regressors (k)	HAZ				WHZ				WAZ			
	β_k	Elasticity	CI	Contribution	β_k	Elasticity	CI	Contribution	β_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)	.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.