Robust monitoring of child nutritional status in Ethiopia

A microdata analysis on child nutritional status in Ethiopia for 2005, 2011, and 2016

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

Abstract

This thesis analyses the full distribution of (socio-economic-related) nutritional status of children under the age of 5 between 2005, 2011, and 2016 in Ethiopia. Summary measures, like mean height deficit and the rate of stunting, provide an incomplete picture. I primarily use the height-for-age z-scores, an indicator for chronic undernutrition. The welfare foundations for evaluating full distributions of child nutritional status are explained using first- and second-order stochastic dominance. Furthermore, measurement of (socio-economic-related) health inequality is performed using (generalised) Lorenz and concentration curves and dominance, (generalised) Gini and concentration indices, and a wealth indicator. In conclusion, I find that Ethiopia is improving its child nutritional status between 2005, 2011, and 2016. Solely relying on the trend in the indicator used in Sustainable Development Goal 2 – the rate of child stunting – is consistent with the conclusions about improved nutritional status among children in the more robust comparison I perform. However, the Gini indices and (generalised) concentration indices are contradictory to the conclusions from the dominance tests, showing that improvements in nutrition between years are susceptible to the measures chosen.

Key Words: Child nutritional status, Height-for-Age z-score, Height deficit, Rate of stunting, First-order stochastic dominance, Second-order stochastic dominance, Health inequality, Lorenz curves, Generalised Lorenz curves, Gini index, Generalised Gini index, Socio-economic-related health inequality, Concentration curves, Generalised concentration curves, Concentration index, Generalised concentration index.

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Introduction

In general, poorer people are also less healthy (WHO, 2020a). A reason for this might be the association between undernutrition and poverty. On the one hand, poverty leads to undernutrition by increasing the risk of food uncertainty. On the other hand, undernutrition induces poverty conditions (Siddiqui, Salam, Lassi & Das, 2020). Therefore, policy interventions that improve nutrition can lead to better health and economic growth (WHO, 1997).

In 2000, most of the world's countries committed to eight Millennium Development Goals (MDG) set up by the United Nations, that needed to be achieved by 2015. These MDGs focused on combatting poverty, hunger, and disease, with child and maternal health centred (WHO, 2018). Succeeding the MDGs, in 2015, the world adopted 17 Sustainable Development Goals (SDGs) that need to be reached by 2030. In particular, SDG 2 and 3 are relevant to this paper. SDG 2 is no hunger by 2030 and is monitored through indicators of nutritional status, which includes the prevalence of childhood stunting and wasting (UN, 2020a). Undernutrition is still a prominent problem as stunting (low height for age) declines too slowly and wasting (low weight for height) puts too many young children at risk of death (WHO, 2020b). Moreover, poor investment in child nutrition is associated with a higher risk of death from diseases and forming a serious obstacle in achieving SDG 3 (UN, 2020b). SDG 3 is ensuring healthy lives and well-being globally and is indicated mostly by (under 5) death rates (UN, 2020c). Improving results in SDG 2 is expected to be followed by improvements in SDG 3.

In 2019, over 25% of all children under 5 that are wasted, and over 40% of all children under 5 that are stunted, are living in Africa (WHO, 2020b). In the past 20 years, upper-middle-income countries reduced their stunting prevalence by more than 67%, while low-income and lower-middle-income countries only achieved a reduction of less than 30% (WHO, 2020b). Even more striking, Sub-Saharan Africa has reported the least progress in protecting their children from stunting (Smith & Haddad, 2015). Moreover, wasting rates remain high in Africa too. Up to 12.7 million children under 5 are wasted, of which 3.5 million are severely wasted. Stunting and wasting can have lifetime and even intergenerational disastrous effects (WHO, 2020b).

The Ethiopia Demographic and Health Survey (EDHS) (Central Statistical Agency Ethiopia & Macro, 2006) reported that, in 2005, 47% of children under age 5 in Ethiopia are moderately or severely stunted, and this percentage declined to 44% in 2011 (Ethiopia Central Statistical Agency & ICF International, 2012). However, undernutrition remains a significant concern in Ethiopia for policymakers, as 38% (5.8 million children under 5) are still suffering from stunting in 2016 (Central Statistical Agency Ethiopia and ICF, 2017 ; USAID, 2019).

The proportion of children under 5 that are stunted – two standard deviations below the median height of a well-nourished child of the same age and sex – is only one aspect of the distribution of nutritional status. The problem is that this summary measure gives an incomplete picture of a child's nutritional status (Perumal, Bassani & Roth, 2018). The proportion of stunted children could go down, while the proportion of severely stunted children – three standard deviations below the median height of a well-nourished child of the same age and sex – could go up. Moreover, the mean height deficit (relative to a well-nourished child of the same age and sex) and percentage of stunted children do not say anything about inequality in nutritional status. A mean can arise from all children having the same height or from some being very tall and others being very short. Big differences in height can be worrisome, as this could indicate that policies are not targeted well. In relation to this, we can be particularly concerned about inequality since, for a given mean, greater inequality implies more children with very poor nutrition that is associated with disease, poverty, and poor cognition. To understand whether the distribution of nutritional status is improving, we need a way where changes in both the mean and a measure of inequality are addressed.

This research aims to make a robust comparison of child nutritional status in Ethiopia for 2005, 2011, and 2016 based on absolute and relative inequality measures of nutritional status. These comparisons are sensitive to both the mean level of nutritional status and inequality in its distribution. I assume that we prefer children on average to be better nourished and equally distributed among the population. The main research question is:

Has child nutritional status in Ethiopia improved between 2005, 2011, and 2016?

The key part in answering this question is to establish if not only the mean level of nutrition has improved or the proportion of the population that is stunting has decreased, but also if inequality has decreased.

I will answer this question with the following sub-questions:

1: In Ethiopia, has the mean level of child nutritional status improved, and the rate of stunting decreased between 2005, 2011, and 2016?

2: In Ethiopia, has the full distribution of child nutritional status improved between 2005, 2011, and 2016?

3: In Ethiopia, has the full distribution of socio-economic-related child nutritional status improved between 2005, 2011, and 2016?

This study computes a robust comparison using full distributions of child nutritional status and dominance tests to identify if child nutrition improved between 2005, 2011, and 2016 in Ethiopia. I assess the performance of child nutritional status in Ethiopia, and address whether relying solely on the trend in the indicator used in SDG 2 – the rate of child stunting – is consistent with the conclusions about improved nutritional status among children in the more robust comparison I perform. This could lead to conclusions about whether the monitoring being undertaken for SDG 2 could provide false conclusions about changes in nutritional status among children.

This thesis consists of the following parts. I start with the Theory section where I explain the measurement of child nutritional status, welfare foundations for evaluating full distributions of child nutrition, and measurement of (socio-economic-related) health inequality. In the Methods section, I describe the data, dominance tests, and implementation of inequality measures. In the Results section I provide summary statistics, first- and second-order stochastic dominance tests, and (socio-economic-related) health inequality results. Finally, the Discussion section summarises the findings and highlights some limitations of this thesis and provide future research recommendations.

Theory

In this section, I start with the measurement of child nutritional status. There are multiple ways to do this, but I focus on the height-for-age z-score. After this, the welfare foundations for evaluating full distributions of child nutritional status are explained by introducing first- and second-order stochastic dominance, and generalised Lorenz curves and dominance. The next part is about the measurement of health inequality, which is done using (generalised) Lorenz curves and dominance, and (generalised) Gini indices. The last part of this section is measurement of socioeconomic-related health inequality, which is related to (generalised) concentration curves and dominance, and (generalised) concentration indices.

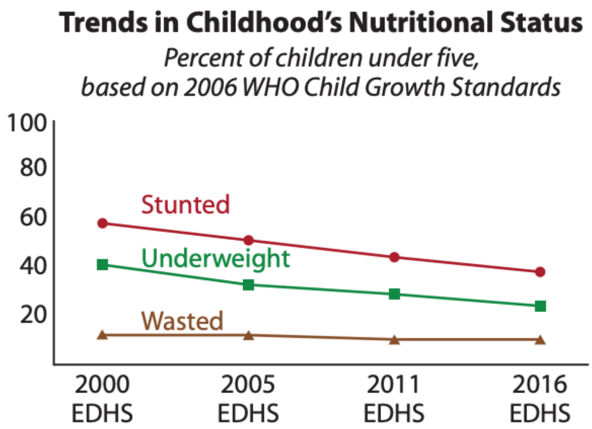
Measurement of child nutritional status

Child nutritional status can be measured using the height-for-age z-score (HAZ). To allow for comparison in the level of nutrition between 2005, 2011, and 2016 in Ethiopia, I calculate summary measures that depend on the prevalence of child stunting (percentage of children with HAZ -2 or lower) and mean height deficit (HAZ below 0). HAZ can be calculated with the following formula:

$$h_i = \frac{height_i - median_i}{stddev_i}$$

With $height_i$ is the height of child i, $median_i$ is the median height of a child of the same sex and age in a well-nourished reference population, and $stddev_i$ is the standard deviation of the height of a child of the same sex and age in a well-nourished reference population. The World Health Organization (WHO) developed this reference group as the Child Growth Standard (CGS) by constructing a length-for-age (birth to 2 years) and height-for-age (2 to 5 years) standard using six countries from the WHO Multicentre Growth Reference Study (MGRS) and adjust for the average difference between recumbent length and standing height (WHO, 2006; De Onis, Garza, Victora, Onyango, Frongillo & Martines, 2004). Low HAZ is an indicator of chronic undernutrition. If the HAZ is lower than 0, a child has a height deficit. If the HAZ is lower or equal to -2, a child is considered stunted. If the HAZ is lower or equal to -3, a child is considered severely stunted (WHO, 1997).

Alternative measures of child nutritional status are weight-for-height z-scores (WHZ) and weight-for-age z-scores (WAZ). Both can be calculated in the same way as HAZ. Low WHZ is an indicator of acute undernutrition (WHO, 1997). Low WAZ is an indicator for both chronic and acute undernutrition, which makes it hard to interpret as children are stunted, wasted, or both (WHO, 2020a). In this paper, I will focus on the HAZ measure, as SDG 2 indicators rely on stunting, which is the preferred measure of malnutrition for monitoring global health targets (Smith & Haddad, 2015). In addition, stunting is more prevalent in Ethiopia, compared with other measures of child nutritional status (Central Statistical Agency Ethiopia, 2017).

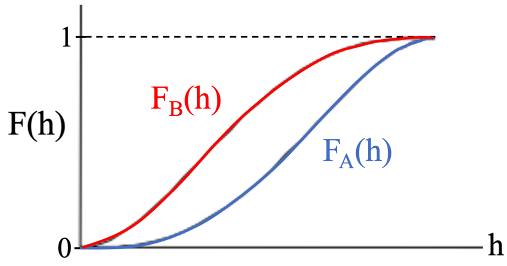


Welfare foundations for evaluating full distributions of child nutritional status

To do a robust comparison of the full distribution of child nutritional status dominance tests can be used. Dominance tests allow for minimal restrictions on social preferences compared to summary indices (O'Donnell, Van Doorslaer, Wagstaff & Lindelow, 2007). A distinction can be made between first-order stochastic dominance (FOSD) and second-order stochastic dominance (SOSD). FOSD involves comparing positions of cumulative distribution functions (CDF), while SOSD involves comparing both position and shape of CDF. Generalised Lorenz curves can be used for a dominance test that is equivalent to SOSD (Davidson, 2006).

A CDF for HAZ (h) in year A is labelled as $F_A(h)$ and a CDF for HAZ (h) in year B is labelled as $F_B(h)$. This is graphically shown in figure 1.

Figure 1



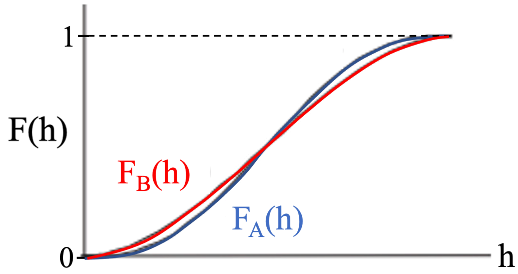
If for all (∀) HAZ levels, F_A(h) is below or equal to F_B(h) and there exists (∃) a HAZ where F_A(h) is below F_B(h), then the distribution in year A stochastically dominates at first order the distribution in year B. In other words, F_A(h) FOSD F_B(h) if there is at least one HAZ level in the distribution where there is a smaller proportion of short children in A compared to B, and there is no HAZ level at which there is a smaller proportion of short children in B. Mathematically this is defined as follows:

$$F_A(h) >_{FOSD} F_B(h) \ if \ \forall h_j = \{h_1, h_2, \dots, h_k\}, F_A(h_j) \leq F_B(h_j) \ and \ \exists h_j, F_A(h_j) < F_B(h_j)$$

To claim that A is the preferred option over B when F_A(h) FOSD F_B(h), I need to introduce the Pareto principle, which is required to make an inference about welfare from FOSD. The Pareto principle states that situation A is ranked better than situation B, if at least one individual is better off in A than B, while no one is worse off. In addition, the CDF should be increasing in all its arguments (Davidson, 2006). A Pareto optimal situation is where no one can be better off, without harming another. Furthermore, I assume that taller children are on average healthier, and healthier children are preferred. Thus, if F_A(h) FOSD F_B(h), then F_A(h) is preferred to F_B(h) by anyone who accepts the Pareto principle. Or, in other words, if the Pareto principle is accepted and F_A(h) FOSD F_B(h), then we prefer F_A(h) to F_B(h).

If F_A(h) is not always below F_B(h) – the distributions intersect or are equal at all heights – then F_A(h) does not FOSD F_B(h). This is graphically shown in figure 2.

Figure 2



Now SOSD can be used where the most equal distribution is preferred based on the level and inequality. It could be that the functions are close in terms of the mean nutritional status of children, but with big differences in variation of height.

Other than with FOSD where we compare the position of CDFs, with SOSD we compare the area under the CDFs, which can be computed by the integral of the function. F_A(h) stochastically dominates at second order F_B(h), if for every level of HAZ, the area under F_A(h) is smaller than or equal to the area under F_B(h), and there exists an area under F_A(h) that is smaller than the area under F_B(h) (Davidson, 2006). In other words, F_A(h) SOSD F_B(h) if there is at least one HAZ level where the integral of distribution A is smaller compared to B, and there is no HAZ level at which the area under distribution B is smaller compared to A. Mathematically this is defined as:

$$F_A(h) >_{SOSD} F_B(h) \; if \; \forall h_j = \{h_1, h_2, \dots, h_n\}, \int_{h_{min}}^{h_j} F_A(h)dh \le \int_{h_{min}}^{h_j} F_B(h)dh \; and \; \exists h_j, \int_{h_{min}}^{h_j} F_A(h)dh < \int_{h_{min}}^{h_j} F_B(h)dh$$

To claim that A is the preferred option over B, when F_A(h) SOSD F_B(h), I need to introduce the principle of health transfers (PHT) of Pigou-Dalton, which is (in combination with the Pareto principle) required to make an inference about welfare from SOSD. PHT states that a transfer of health from a healthier person to a less healthy person does not decrease social welfare if the ranking of individuals in terms of health does not change after the transfer (Bleichrodt & Van Doorslaer, 2006). Applied to HAZ distributions, this requires diminishing marginal health returns to height, which means that every additional unit of height, will result in a smaller increase in health (Wagstaff, 1986). If there are diminishing marginal health returns to height and mean height held constant, mean health will be higher in the more equal distribution of height. Thus, if $F_A(h)$ SOSD $F_B(h)$, then $F_A(h)$ is preferred to $F_B(h)$ by anyone who accepts the Pareto and PHT principles. Or, in other words, if the Pareto and PHT principles are accepted and $F_A(h)$ SOSD $F_B(h)$, then we prefer $F_A(h)$ to $F_B(h)$.

A generalised Lorenz curve (GLC) can be used to test for generalised Lorenz dominance (GLD), which is equivalent to SOSD (Shorrocks, 1983). If we find A GLD B, this means A SOSD B, thus A is preferred over B by Pareto and PHT principle. The GLC is used to capture both the level and absolute univariate inequality in the distribution of HAZ, and can be defined in the following way:

$$GLC_A(p) = \int_{-\infty}^{F_A^{-1}(p)} h dF_A(h)$$

The cumulative distribution function of HAZ in year A is given as $F_A(h)$, and the quantile function (the inverse of the distribution function) is denoted as $F_A^{-1}(p)$ with p between 0 and 1. A point on the generalised Lorenz curve specifies the proportion of mean height of the smallest p x 100 percent of the population. In addition, the ordinates of the GLC refer to cumulative average height proportion, thus $GLC_A(1)$ = mean μ (Jann, 2016).

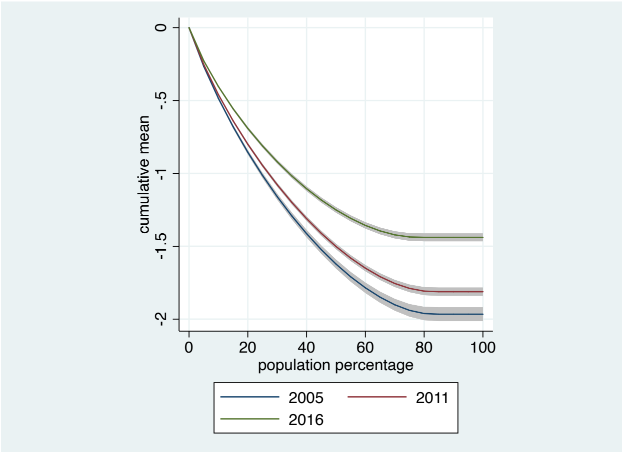
The GLD test assesses whether the difference between distributions is significant, by comparing generalised Lorenz curves. Mathematically GLD is defined as:

$$F_A(h) >_{GLD} F_B(h) \; if \; \forall p_j = \{p_1, p_2, \dots, p_o\}, GLC_A(p_j; h) \geq GLC_B(p_j; h) \; and \; \exists p_j, GLC_A(p_j; h) > GLC_B(p_j; h)$$

If for all percentiles (p_j), the generalised Lorenz curve in year A (GLC_A) is above or equal to the GLC in year B, and there exists a percentile where GLC_A is above GLC_B, then the distribution in year A ($F_A(h)$) generalised Lorenz dominates the distribution in year B ($F_B(h)$).

This is graphically shown in figure 3, with on the x-axis the cumulative proportion of the population from shortest to tallest and on the y-axis is the cumulative mean height deficit, i.e. min(HAZ, 0).

Figure 3: Comparison of generalised Lorenz curves



The GLC reaches the mean height deficit at its limit. Based on figure 3 it could be argued that 2016 GLD both 2011 and 2005, and 2011 GLD 2005.

Measurement of health inequality (Lorenz curves and indices)

To examine the relative and absolute univariate inequality in nutrition between 2005, 2011, and 2016 in Ethiopia, I compute relative and absolute inequality measures. These measures consist of (generalised) Gini indices and (generalised) Lorenz curves.

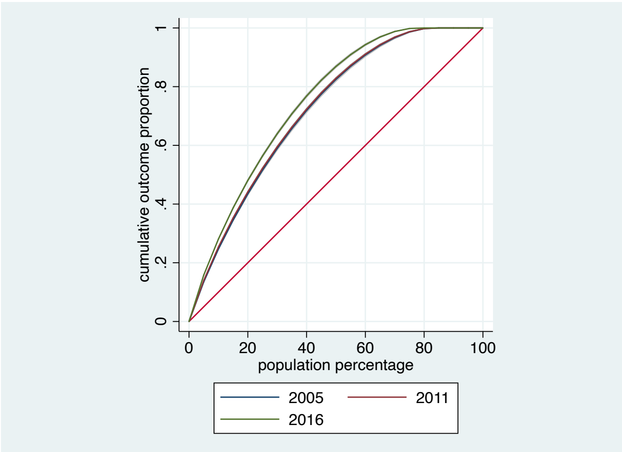
A generalised Gini index (GGI) is derived from the GLC and is calculated as twice the area between the GLC and the line of equality (Bleichrodt & Van Doorslaer, 2006). A GGI measures absolute inequality in the distribution of HAZ and does not change when a constant is added to the height of everyone in the population. The GGI takes values between 0 and the mean HAZ, where 0 is perfect equality and the mean is perfect inequality (Cowell, 2011).

A Lorenz curve is used to capture relative univariate inequality in the distribution of HAZ and can be defined as:

$$LC_A(p) = \frac{1}{\mu}\int_{-\infty}^{F_A^{-1}(p)} h dF_A(h)$$

Naturally, a point on the Lorenz curve specifies the proportion of total height of the smallest *p* x 100 percent of the population (Foster & Ok, 1999). In contrast to the GLC, the ordinates of the LC refer to cumulative outcome proportions; $LC_A(1) = 1$ (Jann, 2016). Thus, the LC is the GLC divided by the mean (Cowell, 2011). A comparison of Lorenz curves is graphically shown in figure 4.

Figure 4: Comparison of Lorenz curves



On the x-axis is the cumulative proportion of the population from shortest to tallest and on the y-axis is the cumulative proportion of height deficit. The red diagonal represents the line of perfect equality – the bottom X% of the population ranked by height has X% of the outcome proportion. The Lorenz dominance (LD) test assesses which Lorenz curve has the least inequality. Mathematically LD is defined as:

$$F_A(h) >_{LD} F_B(h) \; if \; \forall p_j = \{p_1, p_2, \dots, p_l\}, L_A(p_j; h) \leq L_B(p_j; h) \; and \; \exists p_j, L_A(p_j; h) < L_B(p_j; h)$$

If for all percentiles (p_j) the Lorenz curve in year A (L_A) is below or equal to the LC in year B (L_B), and there exists a percentile where L_A is below L_B, then the distribution in year A ($F_A(h)$) Lorenz dominates the distribution in year B ($F_B(h)$).

The Gini index (GI) is derived from the Lorenz curve and is calculated as twice the area between the Lorenz curve and the line of equality. The GI measures relative inequality in the distribution of HAZ. It changes when a constant is added to the height of everyone in the population. In the case in which the Lorenz curve lies above the diagonal (because the variable is non-positive), the GI lies between 0 and -1, where 0 is perfect equality and -1 is perfect inequality (Cowell, 2011).

Measurement of socioeconomic-related health inequality (concentration curves and indices)

Again, I use relative and absolute inequality measures, but here to measure the socioeconomic-related inequality of nutrition between 2005, 2011, and 2016 in Ethiopia. These measures consist of (generalised) concentration indices and (generalised) concentration curves.

The generalised concentration curve (GCC) is used to assess the level and absolute bivariate inequality in the distribution of HAZ. The GCC can be defined in the following way:

$$GCC_A(p) = \int_{-\infty}^{F_A^{-1}(p)} h dF_A(Y)$$

The cumulative distribution function of HAZ in year A is given as $F_A(Y)$, and the quantile function (the inverse of the distribution function) is denoted as $F_A^{-1}(p)$ with p between 0 and 1. A point on the generalised concentration curve specifies the proportion of mean height of the poorest p x 100 percent of the population. Thus, the independent variable is wealth (poorest to richest), and not height. A comparison of generalised concentration curves is graphically shown in figure 5.

Figure 5: Comparison of generalised concentration curves

It plots the cumulative mean of height deficit against the cumulative proportion of the population ranked according to a wealth indicator Y, from poorest to richest (Wagstaff, 2002; O'Donnell, O'Neill, Van Ourti & Walsh, 2016). The GCC reaches the mean height deficit at its limit. The generalised concentration dominance (GCD) test assesses whether differences in distributions are significantly different, by comparing generalised concentration curves. Mathematically GCD is defined as:

$$F_A(Y) >_{GCD} F_B(Y)\ if\ \forall p_j = \{p_1, p_2, \dots, p_o\}, GCC_A(p_j;Y) \geq GCC_B(p_j;Y)\ and\ \exists p_j, GCC_A(p_j;Y) > GCC_B(p_j;Y)$$

If for all percentiles (p_j), the generalised concentration curve in year A (GCC_A) is above or equal to the GCC in year B, and there exists a percentile where GCC_A is above GCC_B, then the distribution in year A ($F_A(Y)$) generalised Lorenz dominates the distribution in year B ($F_B(Y)$).

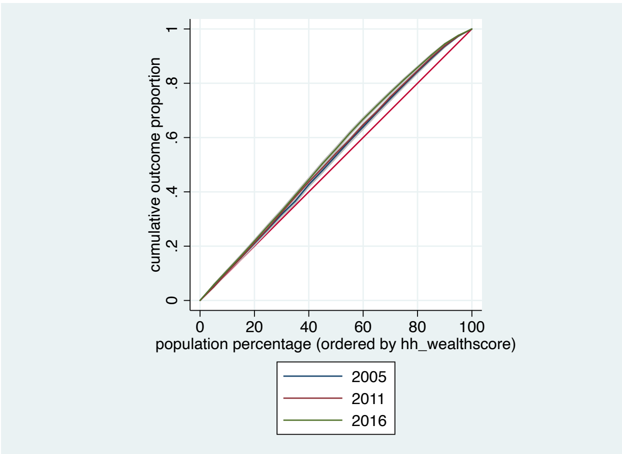
A generalised concentration index (GCI) is derived from the GCC and is calculated as twice the area between the GCC and the line of equality (Bleichrodt & Van Doorslaer, 2006). GCI measures absolute inequality in the distribution of HAZ in relation to a socioeconomic characteristic, such as wealth, and does not change when a constant is added to everyone in the population (O'Donnell et al., 2007). The GCI takes values between [-mean, mean] HAZ. 0 represents perfect equality and -mean/mean represents perfect inequality (Cowell, 2011).

The concentration curve (CC) is used to assess relative bivariate inequality in the distribution of HAZ and can be defined as:

$$CC_A(p) = \frac{1}{\mu}\int_{-\infty}^{F_A^{-1}(p)} hdF_A(Y)$$

Intuitively, a point on the concentration curve specifies the proportion of total height of the poorest p x 100 percent of the population. Thus, the CC is the GCC divided by the mean (Cowell, 2011). A comparison of concentration curves is graphically shown in figure 6.

Figure 6: Comparison of concentration curves



On the x-axis is the cumulative proportion of the population according to wealth Y, and on the y-axis is the cumulative proportion of height deficit. The red diagonal represents the line of perfect equality – the bottom X% of the population ranked by wealth has X% of the outcome proportion. The concentration dominance (CD) test assesses which concentration curve has the least inequality. Mathematically CD is defined for the case in which concentration curves lie above the diagonal as:

$$F_A(Y) >_{CD} F_B(Y) \; if \; \forall p_j = \{p_1, p_2, \ldots, p_l\}, C_A(p_j; Y) \leq C_B(p_j; Y) \; and \; \exists p_j, C_A(p_j; Y) < C_B(p_j; Y)$$

If for all percentiles (p_j) the concentration curve in year A (C_A), is below or equal to the CC in year B, and there exists a percentile where C_A is below C_B, then the distribution in year A ($F_A(Y)$) concentration curve dominates the distribution in year B ($F_B(Y)$).

A concentration index (CI) is derived from the CC and is calculated in the same way as the GCI. The CI measures relative inequality in the distribution of HAZ in relation to a socioeconomic characteristic, such as wealth, and changes when a constant is added to the height of everyone in the population (O'Donnell et al., 2007). The CI lies between -1 and 1, where 0 represents perfect equality and -1/1 represents perfect inequality (Cowell, 2011).

Methods

In this section, I introduce the data, which is extracted from the Demographic and Health Surveys. After this, I explain how I test for dominance and the inequality measures are implemented.

Data

The data for this thesis is extracted from the Demographic and Health Surveys (DHS). The DHS includes national household data that is collected with interviews and has a wide range of indicators for population, health, and nutrition, and provides a lot of information about topics such as wealth, education, and maternal/child health. The DHS started to collect data from 1984 onwards and evolves every year (DHS, "n.d.").

I use the Ethiopia Demographic and Health Survey (EDHS) for the years 2005, 2011, and 2016, which makes comparison across years possible. These datasets include important individual characteristics, such as weight, height, and age. Data are also available for the mother linked to the child. I only use data for children that are younger than 60 months (under 5 years). Variables that I need are HAZ and a wealth index. In Ethiopia, HAZ is available for each child under 5: 3,960 HAZ observations in 2005, 9,719 in 2011 and 8,771 in 2016. This gives reason to believe that the sample size is large enough. According to the DHS, the 2016 EDHS is representative for the whole of Ethiopia. Furthermore, the EDHS can be used by policymakers to evaluate and improve existing programs (Central Statistical Agency Ethiopia and ICF, 2017).

To measure the distribution of nutritional status across socio-economic groups in 2005, 2011, and 2016 in Ethiopia, I use a wealth indicator as a proxy for socio-economic status (SES). The index is obtained from a principal components analysis of assets, such as having a tv, bike, phone, land, and access to (drinking) water. The wealth index places each individual on a scale of relative wealth. This resulted in five wealth groups, with each individual in one quintile based on its relative wealth (Rutstein & Johnson, 2004; Filmer & Pritchett, 2001). Also, when drawing the CC and GCC, and computing the CI and GCI, I use ranks of the wealth index.

First- and second-order stochastic dominance

I test for first-order stochastic dominance using the Bennett (2013) bidirectional test. This test has four possible outcomes, i.e. (*a*) distributions are equal, (*b*) $F_A(h) >_{FOSD} F_B(h)$, (*c*) $F_B(h) >_{FOSD} F_A(h)$ or (*d*) distributions cross. The test consists of two stages, in the 1st stage the null hypothesis is *a* and, if rejected, in the 2nd stage *b and c* are tested. If *b* and *c* are also rejected, *d* is accepted. With this test, only two distributions can be compared, while I use three distributions. This means that I test each pairwise comparison: $F_A(h) >_{FOSD} F_B(h)$, $F_B(h) >_{FOSD} F_C(h)$, and $F_A(h) >_{FOSD} F_C(h)$.

Generalised Lorenz dominance holds when one GLC lies significantly above another GLC (Shorrocks, 1983). If the difference is significantly positive for every percentile *p* (ranked by censored HAZ), the contrasted GLC is dominated by the other GLC. In other words, if the difference $GLC_A(p)$ - $GLC_B(p)$ is significant for all *p*, this is when the lower bound of the 95% confidence interval is positive for all percentiles, then GLC_A dominates GLC_B.

Lorenz dominance and (generalised) concentration dominance

In the same way as for GLD, Lorenz dominance holds when the difference between two Lorenz curves is significantly positive for every percentile ranked by censored HAZ. Likewise, (generalised) concentration dominance holds when the difference between two (generalised) concentration curves is significantly positive for every percentile ranked by wealth score.

Results

In this section, I start by providing summary statistics, which involves the rate of child stunting and children's (censored) Height-for-Age z-scores in Ethiopia for 2005, 2011, and 2016. In addition, I include tests for equal rates of stunting and equal means of HAZ between two years. Next, I present the results of the first-order stochastic dominance tests of censored HAZ, generalised Lorenz curves that show second-order stochastic dominance and provide the respective generalised Gini indices. After this, I show results of inequality in child nutritional status, using Lorenz curves and dominance, and Gini indices. In the last part of this section, the results of socio-economic-related inequality in child nutritional status are given by the (generalised) concentration curves and dominance, and (generalised) concentration indices. All indices are tested for equality between years.

Summary statistics and stochastic dominance

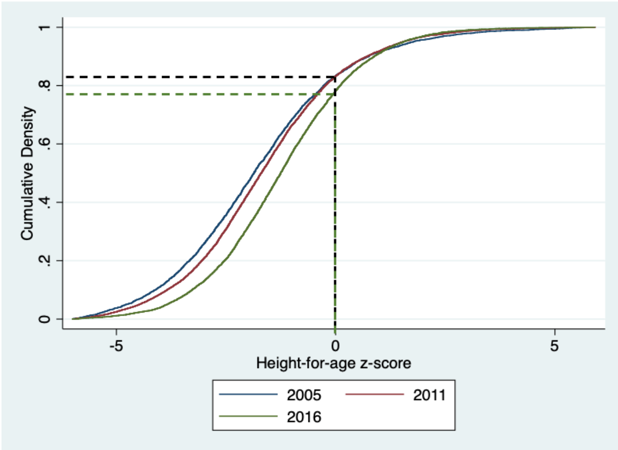
A summary measure of undernutrition is the average height deficit. In other words, what is the mean HAZ for children under 5 in Ethiopia in 2005, 2011 and 2016.

Table 1: Summary statistics of children's Height-for-Age z-scores (according to WHO) in Ethiopia for 2005, 2011 and 2016

Year	N	Mean	Min	Max	10%	25%	Median	75%	90%
2005	3960	-1.727	-6.000	5.880	-4.115	-3.050	-1.865	-0.620	0.750
2011	9719	-1.605	-6.000	5.920	-3.840	-2.770	-1.700	-0.520	0.720
2016	8771	-1.212	-6.000	5.910	-3.280	-2.280	-1.250	-0.170	0.880

In the DHS, all data points for HAZ that are outside of the interval [-6,6] are flagged as invalid and are left out. In table 1 is shown that the average height deficit for children under 5 in Ethiopia, compared to their reference group, is decreasing from 2005 to 2011 to 2016. The median height deficit is also decreasing from 2005 to 2011 to 2016. At every percentile, there is a smaller height deficit for the more recent year. In 2005, over 25% of the population is severely stunted and approximately over 45% is stunted. In 2011, roughly 20% is severely stunted and roughly 40% is stunted. In 2016, over 10% is severely stunted and around 25% is stunted. Based on these numbers, it seems that Ethiopia is improving its nutritional status. The distributions of the data that result in the numbers in table 2 are shown in figure 7.

Figure 7: Comparison of CDFs of HAZ



Most children under 5 in Ethiopia, compared to their reference group, have a height deficit. For 2005 and 2011, approximately 82% of the population is undernourished, while in 2016 roughly 78% is undernourished. Many are stunted or severely stunted in all years.

The full distribution of child nutritional status can be examined using dominance tests. FOSD involves comparing positions of CDFs. The results of the distributions in figure 7 are shown in table 2.

Table 2: Tests for first-order stochastic dominance of HAZ distributions in Ethiopia for 2005, 2011 and 2016

Variable	**Group variable**	**group 1**	**group 2**	**significance level**		**Outcome**
				1st stage	**2nd stage**	
HAZ	year	2005	2011	1%	10%	distributions cross
HAZ	year	2011	2016	1%	10%	distributions cross
HAZ	year	2005	2016	1%	10%	distributions cross

None of the distributions first-order stochastic dominates another distribution. This means that for all Bennett tests in the 1st stage, the null hypothesis that the distributions in both years are equal is rejected at the 1% level. Following that, for all Bennett tests in the 2nd stage, the null hypothesis that $F_A(h) >_{FOSD} F_B(h)$ or $F_B(h) >_{FOSD} F_A(h)$ is rejected at the 10% level, implying that the distributions cross.

Another summary statistic of malnutrition is the rate of stunting. In other words, what percentage of the population has a HAZ < -2.

Table 3: Estimates of prevalence and tests for equal rates of child stunting in Ethiopia for 2005, 2011 and 2016

Year	N	Mean	95% CI		Z-statistic of difference in Mean (row Mean - column Mean)		
					2005	2011	2016
2005	3960	0.466	0.451	0.482		4.231***	16.546***
2011	9719	0.427	0.417	0.436			15.808***
2016	8771	0.314	0.304	0.324			

****p < 0.001*

Looking at table 3 we see estimates of the proportion of children that were stunted every year and the z-statistic of the test for equal rates of stunting between the two years (using a two-sample test of proportions). In 2016 the average prevalence of child stunting is lower relative to 2011 and 2005, and the mean proportion of children that were stunted in 2011 is lower compared to 2005. Hence, the rate of stunting is decreasing over the measured years for children under 5 in Ethiopia, which could be an indication that Ethiopia is improving its nutritional status. All differences are significant at the 1% level.

From this point, I focus on height deficit = min(HAZ, 0) for two reasons. First, health risks arise from a height deficit, not a height surplus. So, policy interest is in the distribution of HAZ below 0. Second, some of the measures that are used in this thesis cannot handle both positive and negative values. Therefore, I censor the data by using HAZ = min(HAZ, 0). In table 4 the summary statistics of the censored data for Ethiopia in 2005, 2011 and 2016 are given.

Table 4: Summary statistics of children's censored Height-for-Age z-score (according to WHO) in Ethiopia for 2005, 2011 and 2016

Year	N	Mean	Min	Max	10%	25%	Median	75%	90%
2005	3960	-1.966	-6.000	0.000	-4.115	-3.050	-1.865	-0.620	0.000
2011	9719	-1.812	-6.000	0.000	-3.840	-2.770	-1.700	-0.520	0.000
2016	8771	-1.439	-6.000	0.000	-3.280	-2.280	-1.250	-0.170	0.000

Censoring the data has only changed the mean outcomes. The mean HAZ for children under 5 in Ethiopia, compared to their reference group, is increasing from 2005 to 2011 to 2016. Still, based on these censored results, it seems that Ethiopia is improving its nutritional status The distributions of the data that result in the numbers in table 4 are shown in figure 8.

Figure 8: Comparison of CDFs of censored HAZ

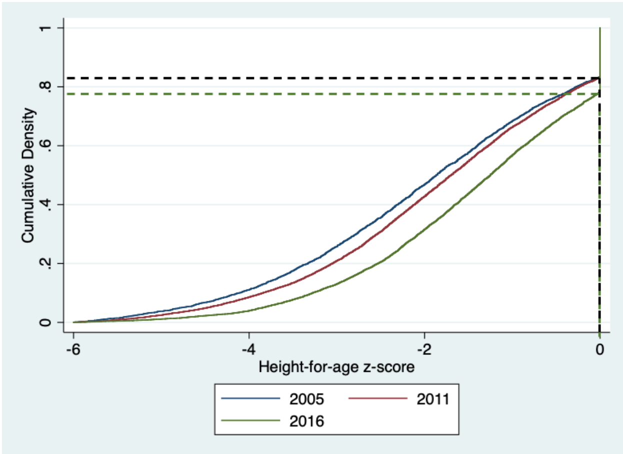


Figure 8 shows the distributions of the censored data. The 82% of the population that is undernourished in 2005 and 2011, and the 78% of the population that is undernourished in 2016, are now at the right limits of the graphs. Furthermore, I add tests for first-order stochastic dominance to examine if the distributions in figure 8 cross. The results are shown in table 5.

Table 5: Tests for first-order stochastic dominance of censored HAZ distributions in Ethiopia for 2005, 2011 and 2016

Variable	**Group variable**	**group 1**	**group 2**	**significance level**		**Outcome**
				1st stage	**2nd stage**	
HAZ	year	2005	2011	1%	10%	2011 dominates 2005
HAZ	year	2011	2016	1%	10%	2016 dominates 2011
HAZ	year	2005	2016	1%	10%	2016 dominates 2005

2011 first-order stochastic dominates 2005, and 2016 first-order stochastic dominates 2011 and 2005. This means that for all Bennett tests in the 1st stage, the null hypothesis that the distributions in both years are equal is rejected at the 1% level. Following that, for all Bennett tests in the 2nd stage, the null hypothesis that $F_A(h) >_{FOSD} F_B(h)$ or $F_B(h) >_{FOSD} F_A(h)$ cannot be rejected at the 10% level, implying that the distributions do not cross.

Finally, I tested the (censored) means for significant differences across years.

Table 6: Child's Height-for-Age Z-scores and tests for equal Means of HAZ in Ethiopia for 2005, 2011 and 2016

Year	N	Uncensored						Censored					
		Mean	95% CI		T-statistic of difference in Mean (row Mean - column Mean)			Mean	95% CI		T-statistic of difference in Mean (row Mean - column Mean)		
					2005	2011	2016				2005	2011	2016
2005	3960	-1.727	-1.788	-1.666		-3.371***	-14.348***	-1.966	-2.014	-1.919		-5.439***	-18.823***
2011	9719	-1.605	-1.641	-1.569			-15.484***	-1.812	-1.841	-1.783			-18.522***
2016	8771	-1.212	-1.246	-1.177				-1.439	-1.466	-1.412			

****p < 0.001*

Table 6 shows the (censored) means, 95% confidence intervals and t-statistics of difference in means between years. For example, subtracting the censored mean of 2011 (-1.812) from the censored mean of 2005 (-1.966) results in a difference between means of 0.154. The corresponding t-statistic of this difference is -5.439, which is significant at the 1% level ($p < 0.001$). All differences are significant at the 1% level.

First-order stochastic dominance can be inferred, meaning it is not necessary to further test for second-order stochastic dominance, which involves comparing both positions and shapes of CDFs. However, I still provide those results to give a complete picture.

Generalised Lorenz curves (equivalent to SOSD) are shown in figures 9 and 10.

Figure 9: Generalised Lorenz dominance test in contrast to 2005

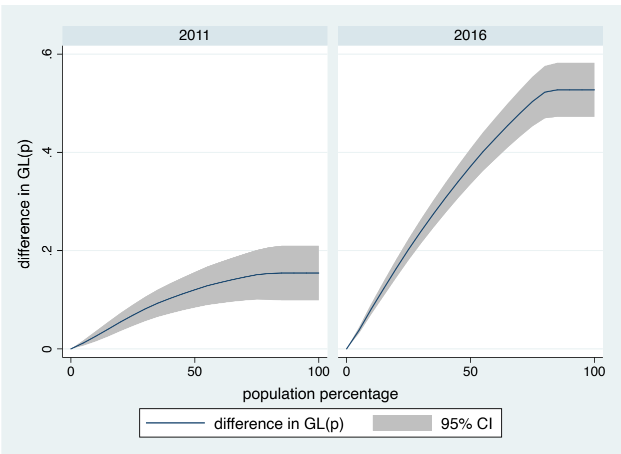


Figure 10: Generalised Lorenz dominance test in contrast to 2011

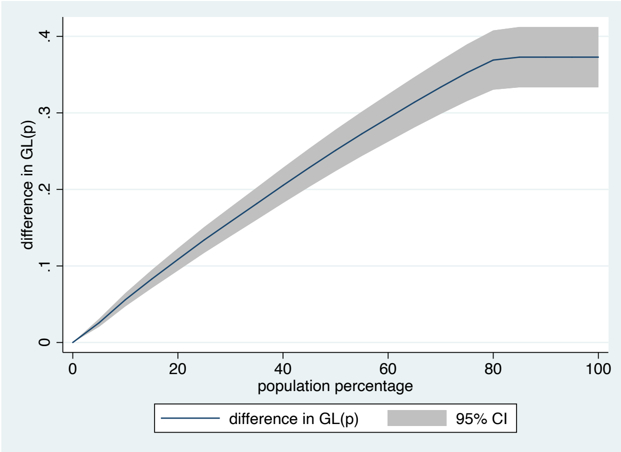


Figure 9 shows the difference between the 2011 GLC of censored HAZ and the respective 2005 GLC, as well as the respective difference between 2016 and 2005. Figure 10 shows the difference between the 2016 GLC of censored HAZ and the respective 2011 GLC. In both figures, the difference is significantly positive for every percentile ranked by censored HAZ, as the lower bound of the 95% confidence interval is always positive (Appendix 2.1 & 2.2). Thus, the contrasted GLCs are dominated by the other GLCs, meaning that at every percentile, the cumulative mean HAZ is higher in 2016 compared to 2011 and 2005, and in 2011 compared to 2005.

From the GLC, the GGI can be derived, which measures absolute inequality in the distribution of HAZ. The estimates (values between 0 and mean) and tests of equality of GGI are shown in table 7.

Table 7: Estimates and tests of equality of Generalised Gini Indices in Ethiopia for 2005, 2011 and 2016

Year	N	GGI	Robust std. error	Z-statistic of difference in GGI (row GGI - column GGI)		
				2005	2011	2016
2005	3960	0.870***	0.003			
2011	9719	0.814***	0.002	-13.280***		
2016	8771	0.720***	0.003	-32.730***	-24.330***	

****p < 0.001*

For all years, there is significant (p-value < 0.001) absolute inequality in child nutritional status as the index values are not equal to 0. The GGI is decreasing with every year that is measured, thus absolute inequality in the distribution of HAZ has improved in later years. This is in line with the generalised Lorenz dominance tests. In addition, the tests for statistically significant differences are also significant (p-value < 0.001, H0: diff=0 is rejected assuming a large sample).

Inequality in child nutritional status

To examine relative univariate inequality in the distribution of HAZ between 2005, 2011, and 2016 in Ethiopia, I use Gini indices and Lorenz curves. The Lorenz curves can be used for dominance tests and are shown in figures 11 and 12.

Figure 11: Lorenz dominance test in contrast to 2005

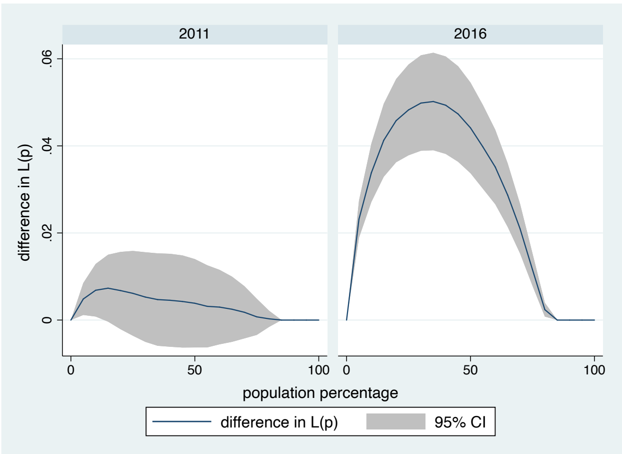


Figure 11 shows the difference between the 2011 LC of censored HAZ and the respective 2005 LC, as well as the respective difference between 2016 and 2005. Looking at 2011 in contrast to 2005, the curve is positive for the whole population ranked by censored HAZ, but not significant, as the lower bound of the 95% confidence interval is not positive for the 15th up to the 80th percentile of the population (Appendix 3.1). However, there are significant differences in one direction, and no significant differences in the other direction, implying dominance. Thus, the 2011 LC dominates the 2005 LC, implying relative inequality has increased in 2011 compared to 2005. For 2016 in contrast to 2005, the curve is positive for the whole population ranked by censored HAZ, and significant, as the lower bound of the 95% confidence interval is entirely positive (Appendix 3.1). Thus, we can infer that the 2016 LC dominates the 2005 LC, implying relative inequality has increased in 2016 compared to 2005.

Figure 12: Lorenz dominance test in contrast to 2011

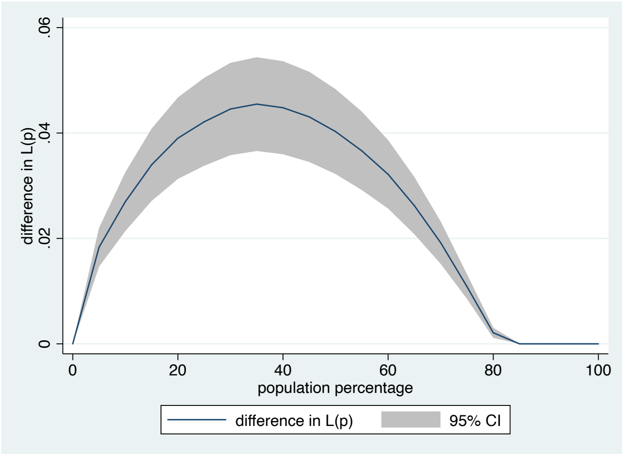


Figure 12 shows the difference between the 2016 LC of censored HAZ and the respective 2011 LC. The difference is significantly positive for every percentile ranked by censored HAZ, as the lower bound of the 95% confidence interval is always positive (Appendix 3.2). As a result, it can be inferred that the contrasted 2011 LC is dominated by the 2016 LC, implying relative inequality has increased in 2016, compared to 2011.

From the LC, the GI can be derived, and the estimates (values between 0 and -1) and tests of equality of GGI are shown in table 8.

Table 8: Estimates and tests of equality of Gini Indices in Ethiopia for 2005, 2011 and 2016

Year	**N**	**GI**	**Robust std. error**	**Z-statistic of difference in GI (row GI - column GI)**		
				2005	**2011**	**2016**
2005	3960	-0.443***	0.002			
2011	9719	-0.449***	0.001	-3.020**		
2016	8771	-0.500***	0.002	-21.020***	-20.460***	

***p < 0.005, ***p < 0.001*

For all years, there is significant (p-value < 0.001) relative inequality in child nutritional status as the index values are not equal to 0. The GI is decreasing with every year that is measured, which means its absolute value is increasing, implying greater relative inequality. This is in line with the Lorenz dominance tests. In contrary to absolute inequality, relative inequality in the distribution of HAZ has worsened in later years. The tests for statistically significant differences are also significant (p-value < 0.005, H0: diff=0 is rejected assuming a large sample).

To summarise, the 2016 GLC dominates the 2011 and 2005 GLC, and the 2011 GLC dominates the 2005 GLC, implying a decrease in absolute inequality. Moreover, the corresponding GGI suggest that there is significant absolute inequality in the distribution of HAZ and that this inequality is significantly decreasing in later years. In addition, the 2016 LC dominates the 2011 and 2005 LC, and the 2011 LC dominates the 2005 LC, implying an increase in relative inequality. Furthermore, the corresponding GI imply that there is significant relative inequality in the distribution of HAZ and that this inequality is significantly increasing in later years.

Socio-economic-related inequality in child nutritional status

To analyse absolute bivariate inequality in the distribution of HAZ between 2005, 2011, and 2016 in Ethiopia, I use generalised concentration indices and generalised concentration curves. These curves can be used for dominance tests and are shown in figures 13 and 14.

Figure 13: Generalised concentration dominance test in contrast to 2005

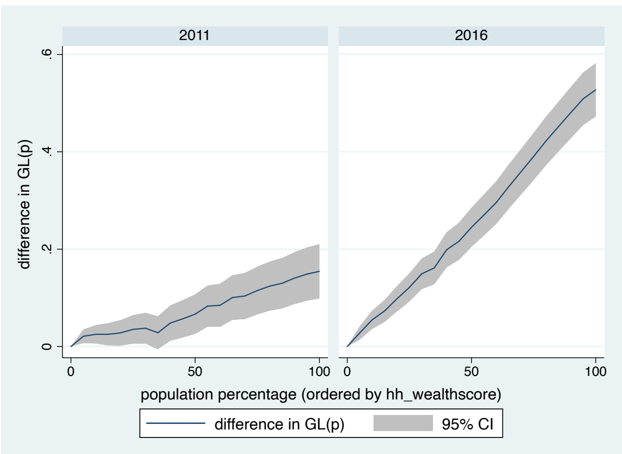


Figure 13 shows the difference between the 2011 GCC of censored HAZ and the respective 2005 GCC, as well as the respective difference between 2016 and 2005. Looking at 2011 in contrast to 2005, the curve is positive for the whole population ranked by wealth, but not significant, as the lower bound of the 95% confidence interval is not positive for the 35th percentile of the population (Appendix 4.1). However, there are significant differences in one direction, and no significant differences in the other direction, implying dominance. Thus, the 2011 GCC dominates the 2005 GCC, meaning that at every percentile, the cumulative mean HAZ is higher in 2011 compared to 2005. For 2016 in contrast to 2005, the curve is positive for the whole population ranked by wealth, and significant, as the 95% confidence interval is entirely positive (Appendix 4.1). As a result, we can infer that the 2016 GCC dominates the 2005 GCC, meaning that at every percentile, the cumulative mean HAZ is higher in 2016 compared to 2005.

Figure 14: Generalised concentration dominance test in contrast to 2011

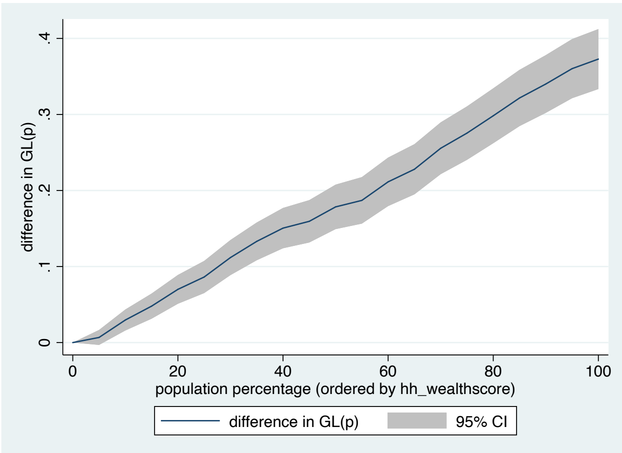


Figure 14 shows the difference between the 2016 GCC of censored HAZ and the respective 2011 GCC. The difference is positive for every percentile ranked by wealth, but not significant, as the lower bound of the 95% confidence interval is not positive for the 5th percentile of the population (Appendix 4.2). However, there are significant differences in one direction, and no significant differences in the other direction, implying dominance. As a result, it can be inferred that the contrasted 2011 GCC is dominated by the 2016 GCC, implying absolute inequality has decreased in 2016 compared to 2011.

From the GCC, the GCI can be derived, and the estimates (values between -mean and mean) and tests of equality of GCI are shown in table 9.

Table 9: Estimates and tests of equality of Generalised Concentration Indices in Ethiopia for 2005, 2011 and 2016

Year	N	GCI	Robust std. error	Z-statistic of difference in GCI (row GCI - column GCI)		
				2005	**2011**	**2016**
2005	3960	0.102***	0.014			
2011	9719	0.108***	0.008	0.370		
2016	8771	0.117***	0.008	0.920	0.760	

****p < 0.001*

For all years, there is significant (p-value < 0.001) absolute socio-economic-related inequality in child nutritional status as the index values are not equal to 0. The GCI is increasing with every year that is measured. Thus, absolute socio-economic-related inequality in the distribution of HAZ has worsened in later years. This is not in line with the generalised concentration dominance tests. However, the tests for statistically significant differences are not significant (p-value > 0.01, H0: diff=0 is not rejected).

To examine relative bivariate inequality in the distribution of HAZ between 2005, 2011, and 2016 in Ethiopia, I use concentration indices and concentration curves. These curves can be used for dominance tests and are shown in figures 15 and 16.

Figure 15: Concentration dominance test in contrast to 2005

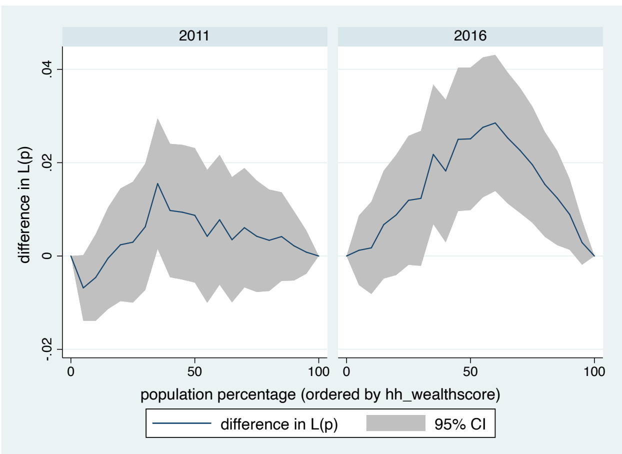


Figure 15 shows the difference between the 2011 CC of censored HAZ and the respective 2005 CC, as well as the respective difference between 2016 and 2005. Looking at 2011 in contrast to 2005, the curve is positive for the 15th and higher percentiles of the population ranked by wealth, but negative for the 5th and 10th percentiles. Moreover, the curve is not significant, as the lower bound of the 95% confidence interval is negative for all, but the 35th percentile of the population (Appendix 5.1). As there are almost no (apart from the 35th percentile) significant differences in one direction, it cannot be concluded that the 2011 CC dominates the 2005 CC. Further, considering 2016 in contrast to 2005, the curve is positive for the whole population ranked by wealth, but not significant, as the lower bound of the 95% confidence interval is not positive for the 5th up to the 30th percentile, as well as the 95th percentile of the population (Appendix 5.1). However, there are significant differences in one direction, and no significant differences in the other direction, implying dominance. As a result, we can infer that the 2016 CC dominates the 2005 CC, implying relative inequality has increased in 2016 compared to 2005.

Figure 16: Concentration dominance test in contrast to 2011

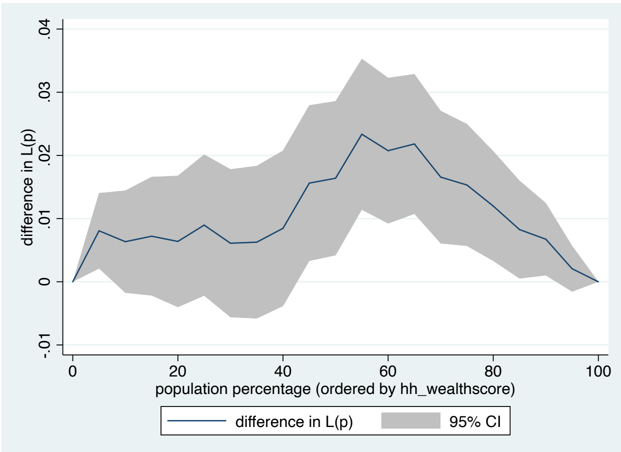


Figure 16 shows the difference between the 2016 CC of censored HAZ and the respective 2011 GCC. The difference is positive for every percentile ranked by wealth, but not significant, as the lower bound of the 95% confidence interval is not positive for the 10th up to the 40th percentile, as well as the 95th percentile of the population (Appendix 5.2). However, there are significant differences in one direction, and no significant differences in the other direction, implying dominance. Thus, it can be inferred that the contrasted 2011 CC is dominated by the 2016 CC, implying relative inequality has increased in 2016 compared to 2011.

From the CC, the CI can be derived, and the estimates (values between -1 and 1) and tests of equality of CI are shown in table 10.

Table 10: Estimates and tests of equality of Concentration Indices in Ethiopia for 2005, 2011 and 2016

Year	N	CI	Robust std. error	Z-statistic of difference in CI (row CI - column CI)		
				2005	**2011**	**2016**
2005	3960	-0.052***	0.007			
2011	9719	-0.060***	0.005	-0.920		
2016	8771	-0.081***	0.005	-3.290**	-3.040**	

***p < 0.005, ***p < 0.001*

For all years, there is significant (p-value < 0.001) relative socio-economic-related inequality in child nutritional status as the index values are not equal to 0. The CI is decreasing with every year that is measured, which means its absolute value is increasing, implying greater relative inequality. This is in line with the concentration dominance tests. Similarly, as with absolute socio-economic-related inequality, relative socio-economic-related inequality in the distribution of HAZ has worsened in later years. The tests for statistically significant differences are significant for 2016 in contrast to 2011 and 2005 (p-value < 0.005, H0: diff=0 is rejected assuming equal variances). However, this test is not significant for 2011 in contrast to 2005 (p-value > 0.01, H0: diff=0 is not rejected).

In sum, the 2011 GCC dominates the 2005 GCC, and the 2016 GCC dominates the 2005 and the 2011 GCC, implying a decrease in absolute inequality. Furthermore, the corresponding GCI suggest that there is significant absolute socio-economic-related inequality in the distribution of HAZ and that this inequality is (not significantly) increasing in later years. Additionally, the 2016 CC dominates the 2011 and 2005 CC, implying an increase in relative inequality, but the 2011 CC does not dominate the 2005 CC. Finally, the corresponding CI imply that there is significant relative socio-economic-related inequality in the distribution of HAZ and that this inequality is significantly increasing for 2016 compared to 2011 and 2005, and insignificantly increasing for 2011 in contrast to 2005.

Discussion

This research aims to make a robust comparison of child nutritional status in Ethiopia for 2005, 2011, and 2016. The rate of stunting among children under 5 is only one aspect of the distribution of nutritional status and gives an incomplete picture of a child's nutritional status (Perumal, Bassani & Roth, 2018). On the one hand, the proportion of stunted children could go down. On the other hand, the proportion of severely stunted children could go up. Moreover, mean height deficit (HAZ) relative to a well-nourished child of the same age and sex, and rathe te of stunted children do not say anything about inequality in nutritional status. A mean can arise from all children having the same height or from some being very tall and others being very short. In relation to this, we can be particularly concerned about inequality since, for a given mean, greater inequality implies more children with very poor nutrition that is associated with disease, poverty, and poor cognition. This thesis addresses not only changes over time in summary measures to understand whether the distribution of nutritional status in Ethiopia is improving but also changes in inequality. To be able to answer *if child nutritional status in Ethiopia has improved between 2005, 2011, and 2016*, I answer three sub-questions.

First, *has the mean HAZ improved, and the rate of stunting decreased between 2005, 2011, and 2016 in Ethiopia?*

The answer is yes. The rate of stunting decreased significantly from 47% in 2005 to 43% in 2011, to 31% in 2016. Mean (uncensored) HAZ increased significantly from -1.73 in 2005, to -1.61 in 2011, to -1.21 in 2016. Mean censored HAZ increased significantly from -1.97 in 2005 to -1.81 in 2011, to -1.44 in 2016.

Second, *has the full distribution of child nutritional status improved between 2005, 2011, and 2016 in Ethiopia?*

By accepting the Pareto principle, and since 2016 FOSD 2011 and 2005, and 2011 FOSD 2005, the full distribution of child nutritional status has improved. Dominance tests of HAZ show an increase in relative inequality in child nutritional status from 2005 to 2011 to 2016 in Ethiopia, but at every percentile, the cumulative mean HAZ is higher in 2016, compared to 2011 and

2005, and higher in 2011 compared to 2005. If A GLD B, and if the Pareto and PHT principles are accepted, then A is preferred to B, considering both the level of HAZ and the inequality in HAZ in the two distributions. In addition, the corresponding GGI imply that there is significant absolute inequality, which is significantly decreasing in later years. In contrast to the conclusion drawn from FOSD, the corresponding GI suggest that there is significant relative inequality, which is significantly increasing in later years.

Third, *has the full distribution of socio-economic-related child nutritional status improved between 2005, 2011, and 2016 in Ethiopia?*

By accepting the Pareto principle, and since there is generalised concentration dominance for 2016 in contrast to 2011 and 2005, and for 2011 in contrast to 2005, the full distribution of socio-economic-related child nutritional status has improved. Dominance tests of HAZ show an increase in relative in child nutritional status from 2011 to 2016 in Ethiopia, but not for 2011 compared to 2005. However, at every percentile, the cumulative mean HAZ is higher in 2016, compared to 2011 and 2005, and higher in 2011 compared to 2005. If A GLD B, and if the Pareto and PHT principles are accepted, then A is preferred to B, considering both the level of HAZ and the inequality in HAZ in the two distributions. In contradiction to the generalised concentration dominance tests, the corresponding GCI imply that there is significant absolute socio-economic-related inequality, which is (not significantly) increasing in later years. Additionally, the corresponding CI imply that there is significant relative socio-economic-related inequality, which is significantly increasing for 2016 compared to 2011 and 2005, and insignificantly increasing for 2011 in contrast to 2005.

Finally, *has child nutritional status in Ethiopia improved between 2005, 2011, and 2016?*

I find that the rate of stunting decreased significantly. Furthermore, there is FOSD of the censored distributions, which means that, if the Pareto principle is accepted, the full distribution of (socioeconomic-related) child nutritional status has improved. Based on this, I can conclude that Ethiopia is improving its child nutritional status between 2005, 2011, and 2016. Solely relying on the trend in the indicator used in SDG 2 – the rate of child stunting – is consistent with the conclusions about improved nutritional status among children in the more robust comparison I perform. However, the GI, GCI and CI are contradictory to the conclusions from the dominance tests, emphasising the importance of this thesis. Results that show improvements in nutrition between years are susceptible to the measures chosen.

Some limitations may limit the value of this thesis. First, even though stunting is prevalent among many African and Asian countries, big differences between and within countries are in place (WHO, 2020a). Therefore, findings for Ethiopia which lead to policy advice, pertain particularly to Ethiopia as a country, but might not be effective in certain sub-regions. A second limitation could be the wealth index, which is responsive to a particular set of owned assets. Other indicators of wealth, such as income, could lead to different outcomes. Another limitation could be that even though I estimate improvements in the mean level of HAZ or the rate of stunting of children between the years, there is no evidence to believe that this trend is still holding in the present. Due to the current COVID-19 pandemic, recent studies already examined back draws in terms of economic performance, which could also lead to worse (child or maternal) health (Geda, 2020 ; Roberton et al., 2020). On top of that, the current conflict in Ethiopia is putting over 4.5 million people in urgent need of assistance and causing thousands of deaths, which draws more attention to other indicators such as mortality rates (Dahir & Walsh, 2020).

For future research, I recommend promoting the uptake in the Demographic and Health Surveys. The DHS (Ethiopia Central Statistical Agency and ICF International, 2012 ; 2017) states that stunting is more common in Amhara (46%), compared to Addis Ababa (15%), and that children whose parents are poorer, and the mother has no education are also more likely to be stunted. Given that region and parental education and income play an important role, it could be interesting to adapt the survey to those factors primarily, to ease data collection. A higher number of observations would enable a more regional analysis, and more vulnerable populations could be better identified and targeted with policy interventions. Furthermore, it would be interesting to see if the COVID-19 pandemic has impacted the trend that I found over years in improvements in mean HAZ and reductions in the rate of stunting. Moreover, what does this mean for SDG 2? However, it would be difficult to make a causal inference, as the pandemic influences many indicators that also impact child nutritional status, which leads to bias.

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Appendix

1. Tests for first-order stochastic dominance of uncensored HAZ distributions in Ethiopia for 2005, 2011 and 2016

Variable	Group variable	group 1	group 2	significance level		Outcome
				1st stage	2nd stage	
HAZ	year	2005	2011	1%	10%	distributions cross
HAZ	year	2011	2016	1%	10%	distributions cross
HAZ	year	2005	2016	1%	10%	distributions cross

2016 does not first-order stochastic dominate 2011 and 2005, and 2011 does not first-order stochastic dominate 2005. In other words, for all Bennett tests in the 1st stage, the null hypothesis that the distributions in both years are equal is rejected at the 1% level. Following that, for all Bennett tests in the 2nd stage, the null hypothesis that $F_A(h) >_{FOSD} F_B(h)$ or $F_B(h) >_{FOSD} F_A(h)$ is rejected at the 10% level, which implies that the distributions cross. However, it could be that the distributions cross only for (very) well-nourished children (HAZ > 0 or HAZ > 2).

2.1. SOSD, equivalent to generalised Lorenz dominance – contrast 2005

```
. lorenz estimate hfa, generalized over(year) contrast(2005) graph

GL(p)                                        Number of obs     =     22,450

        2005: year = 2005
        2011: year = 2011
        2016: year = 2016

------------------------------------------------------------------------------
         hfa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
2011         |
           0 |          0  (omitted)
           5 |   .0120635   .0027213     4.43   0.000     .0067296    .0173974
          10 |   .0257513   .0052768     4.88   0.000     .0154083    .0360942
          15 |   .0401371   .0074902     5.36   0.000     .0254559    .0548184
          20 |   .0548855   .0093451     5.87   0.000     .0365685    .0732026
          25 |   .0685318   .0110086     6.23   0.000     .0469542    .0901093
          30 |   .0815159   .0126216     6.46   0.000     .0567767    .1062551
          35 |   .0930174   .0141141     6.59   0.000     .0653529     .120682
          40 |   .1028114   .0156068     6.59   0.000      .072221    .1334018
          45 |   .1119298   .0169765     6.59   0.000     .0786547    .1452048
          50 |   .1204136   .0184526     6.53   0.000     .0842452     .156582
          55 |    .128588   .0199494     6.45   0.000     .0894858    .1676903
          60 |    .134834   .0213822     6.31   0.000     .0929233    .1767446
          65 |   .1407786   .0227311     6.19   0.000      .096224    .1853331
          70 |   .1461342   .0242067     6.04   0.000     .0986873    .1935811
          75 |   .1510536   .0257132     5.87   0.000     .1006539    .2014533
          80 |   .1535886   .0273031     5.63   0.000     .1000727    .2071045
          85 |   .1544641   .0283986     5.44   0.000     .0988009    .2101273
          90 |   .1544641   .0283986     5.44   0.000     .0988009    .2101273
          95 |   .1544641   .0283986     5.44   0.000     .0988009    .2101273
         100 |   .1544641   .0283986     5.44   0.000     .0988009    .2101273
-------------+----------------------------------------------------------------
2016         |
           0 |          0  (omitted)
           5 |   .0377807   .0030882    12.23   0.000     .0317277    .0438338
          10 |   .0815787   .0055018    14.83   0.000     .0707948    .0923625
          15 |   .1228715   .0076451    16.07   0.000     .1078867    .1378564
          20 |   .1633696   .0095051    17.19   0.000      .144739    .1820002
          25 |   .2024621    .011125    18.20   0.000     .1806565    .2242678
          30 |   .2392445   .0127084    18.83   0.000     .2143352    .2641538
          35 |   .2744134   .0142311    19.28   0.000     .2465195    .3023073
          40 |   .3080647    .015701    19.62   0.000     .2772898    .3388397
          45 |   .3403933   .0170853    19.92   0.000     .3069049    .3738818
          50 |   .3714367   .0185572    20.02   0.000     .3350633    .4078101
          55 |   .4012384   .0200113    20.05   0.000     .3620148     .440462
          60 |   .4281366   .0214398    19.97   0.000     .3861131      .47016
          65 |   .4546802   .0228036    19.94   0.000     .4099836    .4993768
          70 |   .4797338   .0242307    19.80   0.000       .43224    .5272277
          75 |   .5035355    .025726    19.57   0.000     .4531108    .5539603
          80 |    .522628   .0271754    19.23   0.000     .4693623    .5758936
          85 |   .5273098   .0280113    18.82   0.000     .4724057    .5822139
          90 |   .5273098   .0280113    18.82   0.000     .4724057    .5822139
          95 |   .5273098   .0280113    18.82   0.000     .4724057    .5822139
         100 |   .5273098   .0280113    18.82   0.000     .4724057    .5822139
------------------------------------------------------------------------------
(difference to year = 2005)
```

2.2. SOSD, equivalent to generalised Lorenz dominance – contrast 2011

```
. lorenz estimate hfa if year!=2005, generalized over(year) contrast(2011) graph

GL(p)                                       Number of obs     =     18,490

        2011: year = 2011
        2016: year = 2016
```

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2016						
0	0	(omitted)				
5	.0257172	.0026689	9.64	0.000	.020486	.0309484
10	.0558274	.0044192	12.63	0.000	.0471654	.0644895
15	.0827344	.0060342	13.71	0.000	.0709068	.094562
20	.1084841	.0074158	14.63	0.000	.0939484	.1230198
25	.1339304	.0086148	15.55	0.000	.1170445	.1508162
30	.1577286	.0096583	16.33	0.000	.1387973	.1766599
35	.1813959	.0107137	16.93	0.000	.1603961	.2023958
40	.2052533	.0117635	17.45	0.000	.1821957	.2283109
45	.2284636	.0127735	17.89	0.000	.2034264	.2535007
50	.2510231	.013805	18.18	0.000	.223964	.2780822
55	.2726504	.0147707	18.46	0.000	.2436984	.3016024
60	.2933026	.0158036	18.56	0.000	.2623261	.3242791
65	.3139016	.0167736	18.71	0.000	.2810239	.3467794
70	.3335996	.0178203	18.72	0.000	.2986702	.368529
75	.3524819	.0189143	18.64	0.000	.3154081	.3895558
80	.3690393	.019756	18.68	0.000	.3303158	.4077629
85	.3728457	.0201293	18.52	0.000	.3333904	.412301
90	.3728457	.0201293	18.52	0.000	.3333904	.412301
95	.3728457	.0201293	18.52	0.000	.3333904	.412301
100	.3728457	.0201293	18.52	0.000	.3333904	.412301

(difference to year = 2011)

3.1. Lorenz dominance – contrast 2005

```
. lorenz estimate hfa, over(year) contrast(2005) graph

L(p)                                        Number of obs     =     22,450

        2005: year = 2005
        2011: year = 2011
        2016: year = 2016
```

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2011						
0	0	(omitted)				
5	.0048365	.0018756	2.58	0.010	.0011601	.0085128
10	.0068448	.0030846	2.22	0.026	.0007988	.0128908
15	.0073176	.0039225	1.87	0.062	-.0003708	.0150061
20	.006774	.0045266	1.50	0.135	-.0020984	.0156464
25	.0061371	.0049681	1.24	0.217	-.0036007	.015875
30	.0052841	.0052495	1.01	0.314	-.0050053	.0155735
35	.0047042	.0054168	0.87	0.385	-.0059131	.0153214
40	.0045422	.0054466	0.83	0.404	-.0061336	.015218
45	.0042665	.005399	0.79	0.429	-.0063159	.0148488
50	.0038599	.0051777	0.75	0.456	-.0062887	.0140085
55	.0031514	.0048145	0.65	0.513	-.0062853	.0125881
60	.0029757	.0043611	0.68	0.495	-.0055725	.0115238
65	.0024869	.0038235	0.65	0.515	-.0050074	.0099811
70	.0017848	.0030614	0.58	0.560	-.0042159	.0077854
75	.0007364	.0021188	0.35	0.728	-.0034166	.0048894
80	.0002802	.0009413	0.30	0.766	-.0015647	.0021251
85	0	(omitted)				
90	0	(omitted)				
95	0	(omitted)				
100	0	(omitted)				
2016						
0	0	(omitted)				
5	.0231524	.002176	10.64	0.000	.0188873	.0274175
10	.0338203	.0034197	9.89	0.000	.0271175	.0405231
15	.0412852	.0042758	9.66	0.000	.0329042	.0496661
20	.0457933	.0048765	9.39	0.000	.0362349	.0553516
25	.0482626	.0053196	9.07	0.000	.0378358	.0586894
30	.0498376	.0055936	8.91	0.000	.0388737	.0608015
35	.0501905	.0057132	8.79	0.000	.0389922	.0613887
40	.0493438	.0057108	8.64	0.000	.0381503	.0605373
45	.0473246	.0055992	8.45	0.000	.0363497	.0582994
50	.0441308	.0053126	8.31	0.000	.0337178	.0545438
55	.0397679	.0049067	8.10	0.000	.0301503	.0493854
60	.035138	.0043651	8.05	0.000	.0265821	.043694
65	.0286939	.0037253	7.70	0.000	.021392	.0359958
70	.0209714	.0029068	7.21	0.000	.0152739	.0266688
75	.0115956	.0019039	6.09	0.000	.0078639	.0153274
80	.0023809	.0008098	2.94	0.003	.0007937	.0039682
85	0	(omitted)				
90	0	(omitted)				
95	0	(omitted)				
100	0	(omitted)				

(difference to year = 2005)

3.2. Lorenz dominance – contrast 2011

```
. lorenz estimate hfa if year!=2005, over(year) contrast(2011) graph
```

L(p) Number of obs = **18,490**

2011: year = **2011**
2016: year = **2016**

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2016						
0	**0**	(omitted)				
5	.0183159	.0018647	9.82	0.000	.0146609	.021971
10	.0269755	.0028355	9.51	0.000	.0214176	.0325334
15	.0339675	.0034893	9.73	0.000	.0271283	.0408068
20	.0390192	.0039339	9.92	0.000	.0313084	.04673
25	.0421255	.0042474	9.92	0.000	.0338002	.0504508
30	.0445535	.0044598	9.99	0.000	.035812	.0532951
35	.0454863	.0045326	10.04	0.000	.036602	.0543706
40	.0448016	.0044952	9.97	0.000	.0359906	.0536125
45	.0430581	.0043589	9.88	0.000	.0345143	.0516019
50	.0402709	.0041025	9.82	0.000	.0322297	.0483121
55	.0366165	.0037881	9.67	0.000	.0291915	.0440415
60	.0321624	.0033046	9.73	0.000	.025685	.0386398
65	.0262071	.0027573	9.50	0.000	.0208025	.0316117
70	.0191866	.0020406	9.40	0.000	.0151869	.0231863
75	.0108592	.0011815	9.19	0.000	.0085434	.013175
80	.0021007	.0004798	4.38	0.000	.0011603	.0030412
85	**0**	(omitted)				
90	**0**	(omitted)				
95	**0**	(omitted)				
100	**0**	(omitted)				

(difference to year = 2011)

4.1. Generalised concentration dominance – contrast 2005

```
. lorenz estimate hfa, generalized pvar(hh_wealthscore) over(year) contrast(2005) graph
```

GL(p) Number of obs = **22,450**

2005: year = **2005**
2011: year = **2011**
2016: year = **2016**

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2011						
0	**0**	(omitted)				
5	.0210523	.0071176	2.96	0.003	.0071013	.0350032
10	.0251285	.009664	2.60	0.009	.0061863	.0440706
15	.0251109	.0116897	2.15	0.032	.0021983	.0480234
20	.028059	.0134176	2.09	0.037	.0017595	.0543585
25	.0352576	.0148906	2.37	0.018	.0060709	.0644442
30	.0376583	.0161478	2.33	0.020	.0060074	.0693091
35	.0283621	.0173071	1.64	0.101	-.0055609	.0622852
40	.0482272	.0185106	2.61	0.009	.0119451	.0845094
45	.0569274	.0195738	2.91	0.004	.0185614	.0952934
50	.0665456	.020619	3.23	0.001	.0261309	.1069604
55	.0831052	.0216031	3.85	0.000	.0407617	.1254487
60	.0846612	.0225123	3.76	0.000	.0405355	.1287869
65	.1005685	.0233819	4.30	0.000	.0547383	.1463986
70	.1038135	.0241803	4.29	0.000	.0564185	.1512085
75	.1149396	.0249768	4.60	0.000	.0659833	.1638958
80	.1240948	.0257255	4.82	0.000	.0736711	.1745186
85	.1299888	.0264219	4.92	0.000	.0782	.1817776
90	.1406072	.0271811	5.17	0.000	.0873303	.1938841
95	.1488516	.0279151	5.33	0.000	.0941362	.2035671
100	.1544641	.0283986	5.44	0.000	.0988009	.2101273
2016						
0	**0**	(omitted)				
5	.0277898	.0070284	3.95	0.000	.0140136	.041566
10	.0548031	.0095294	5.75	0.000	.0361248	.0734814
15	.0730559	.0115145	6.34	0.000	.0504866	.0956251
20	.098023	.0132835	7.38	0.000	.0719863	.1240596
25	.1214904	.0147606	8.23	0.000	.0925586	.1504222
30	.1494501	.016001	9.34	0.000	.1180869	.1808132
35	.161425	.0171733	9.40	0.000	.1277641	.1950859
40	.1987584	.0183965	10.80	0.000	.1626999	.2348168
45	.2163966	.0194639	11.12	0.000	.178246	.2545472
50	.2449857	.0204942	11.95	0.000	.2048158	.2851557
55	.2701024	.0214851	12.57	0.000	.22799	.3122147
60	.2960328	.022337	13.25	0.000	.2522508	.3398148
65	.3284901	.0231631	14.18	0.000	.2830888	.3738914
70	.3593623	.0238911	15.04	0.000	.3125341	.4061905
75	.3903889	.0246928	15.81	0.000	.3419892	.4387886
80	.4223532	.0254434	16.60	0.000	.3724824	.472224
85	.4516415	.0260715	17.32	0.000	.4005395	.5027435
90	.4806704	.026854	17.90	0.000	.4280346	.5333062
95	.5090898	.0275637	18.47	0.000	.455063	.5631165
100	.5273098	.0280113	18.82	0.000	.4724057	.5822139

(ordering with respect to **hh_wealthscore**)
(difference to year = 2005)

4.2. Generalised concentration dominance – contrast 2011

```
. lorenz estimate hfa if year!=2005, generalized pvar(hh_wealthscore) over(year) contrast(2011) graph

GL(p)                                         Number of obs     =     18,490

         2011: year = 2011
         2016: year = 2016
```

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2016						
0	0	(omitted)				
5	.0067375	.0050385	1.34	0.181	-.0031383	.0166134
10	.0296746	.0070557	4.21	0.000	.0158448	.0435045
15	.047945	.0084526	5.67	0.000	.0313771	.064513
20	.069964	.0096742	7.23	0.000	.0510016	.0889264
25	.0862329	.0108076	7.98	0.000	.0650489	.1074168
30	.1117918	.0117875	9.48	0.000	.0886873	.1348963
35	.1330628	.0126727	10.50	0.000	.1082232	.1579025
40	.1505311	.013528	11.13	0.000	.124015	.1770473
45	.1594692	.0142271	11.21	0.000	.1315828	.1873556
50	.1784401	.0149272	11.95	0.000	.1491815	.2076987
55	.1869972	.015612	11.98	0.000	.1563961	.2175982
60	.2113716	.0162852	12.98	0.000	.1794511	.2432921
65	.2279216	.0168494	13.53	0.000	.1948953	.2609479
70	.2555488	.0173835	14.70	0.000	.2214756	.289622
75	.2754493	.0179408	15.35	0.000	.2402837	.310615
80	.2982584	.0184329	16.18	0.000	.2621283	.3343885
85	.3216527	.0188912	17.03	0.000	.2846242	.3586812
90	.3400632	.0193818	17.55	0.000	.302073	.3780534
95	.3602381	.0198489	18.15	0.000	.3213325	.3991438
100	.3728457	.0201293	18.52	0.000	.3333904	.412301

```
(ordering with respect to hh_wealthscore)
(difference to year = 2011)
```

5.1. Concentration dominance – contrast 2005

```
. lorenz estimate hfa, pvar(hh_wealthscore) over(year) contrast(2005) graph

L(p)                                          Number of obs     =     22,450

         2005: year = 2005
         2011: year = 2011
         2016: year = 2016
```

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2011						
0	0	(omitted)				
5	-.0068409	.0035877	-1.91	0.057	-.0138731	.0001913
10	-.0046026	.004737	-0.97	0.331	-.0138875	.0046823
15	-.000482	.005555	-0.09	0.931	-.0113701	.0104061
20	.002407	.0061617	0.39	0.696	-.0096703	.0144843
25	.002958	.0066055	0.45	0.654	-.0099894	.0159053
30	.0062517	.0069153	0.90	0.366	-.0073028	.0198062
35	.0155104	.0071413	2.17	0.030	.001513	.0295079
40	.0097543	.0072954	1.34	0.181	-.0045452	.0240538
45	.0093828	.0073672	1.27	0.203	-.0050574	.0238231
50	.008722	.0073574	1.19	0.236	-.0056991	.023143
55	.004216	.0072689	0.58	0.562	-.0100316	.0184635
60	.0077696	.007101	1.09	0.274	-.0061488	.021688
65	.0034889	.0068537	0.51	0.611	-.0099449	.0169227
70	.0060687	.0065264	0.93	0.352	-.0067235	.0188609
75	.0042241	.0060922	0.69	0.488	-.0077171	.0161653
80	.0033639	.0055461	0.61	0.544	-.0075069	.0142347
85	.004166	.0048481	0.86	0.390	-.0053366	.0136686
90	.0021831	.0037939	0.58	0.565	-.0052531	.0096193
95	.0008251	.0023621	0.35	0.727	-.0038047	.0054549
100	0	(omitted)				
2016						
0	0	(omitted)				
5	.0012258	.003809	0.32	0.748	-.0062401	.0086918
10	.001745	.0050415	0.35	0.729	-.0081368	.0116267
15	.0067309	.0058979	1.14	0.254	-.0048295	.0182912
20	.0087928	.0065712	1.34	0.181	-.0040872	.0216728
25	.0119303	.0070498	1.69	0.091	-.0018879	.0257484
30	.0123536	.0073798	1.67	0.094	-.0021112	.0268185
35	.0217764	.0076288	2.85	0.004	.0068233	.0367294
40	.0182169	.0077965	2.34	0.019	.0029352	.0334986
45	.0250023	.0078391	3.19	0.001	.0096371	.0403674
50	.0251118	.0077925	3.22	0.001	.0098379	.0403857
55	.0275735	.0076538	3.60	0.000	.0125716	.0425754
60	.0285204	.0074433	3.83	0.000	.013931	.0431099
65	.0253022	.007165	3.53	0.000	.0112582	.0393461
70	.0226358	.0068451	3.31	0.001	.0092188	.0360527
75	.0195407	.0063442	3.08	0.002	.0071056	.0319757
80	.0153498	.0057377	2.68	0.007	.0041035	.026596
85	.0124269	.0051562	2.41	0.016	.0023204	.0225334
90	.0089215	.0038697	2.31	0.021	.0013366	.0165063
95	.0028934	.0024314	1.19	0.234	-.0018724	.0076592
100	0	(omitted)				

```
(ordering with respect to hh_wealthscore)
(difference to year = 2005)
```

5.2. Concentration dominance – contrast 2011

```
. lorenz estimate hfa if year!=2005, pvar(hh_wealthscore) over(year) contrast(2011) graph

L(p)                                          Number of obs     =     18,490

         2011: year = 2011
         2016: year = 2016
```

hfa	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2016						
0	0	(omitted)				
5	.0080667	.0030461	2.65	0.008	.0020962	.0140373
10	.0063476	.004127	1.54	0.124	-.0017418	.0144369
15	.0072129	.00479	1.51	0.132	-.002176	.0166018
20	.0063858	.0053038	1.20	0.229	-.0040101	.0167817
25	.0089723	.0057003	1.57	0.116	-.0022009	.0201455
30	.0061019	.0059734	1.02	0.307	-.0056064	.0178103
35	.0062659	.0061621	1.02	0.309	-.0058123	.0183441
40	.0084626	.0062802	1.35	0.178	-.0038472	.0207724
45	.0156194	.0062848	2.49	0.013	.0033007	.0279381
50	.0163898	.0062238	2.63	0.008	.0041905	.0285892
55	.0233576	.0060942	3.83	0.000	.0114123	.0353028
60	.0207508	.0058813	3.53	0.000	.009223	.0322786
65	.0218132	.005643	3.87	0.000	.0107525	.032874
70	.0165671	.0053533	3.09	0.002	.0060741	.0270601
75	.0153166	.0049207	3.11	0.002	.0056716	.0249615
80	.0119859	.0044316	2.70	0.007	.0032996	.0206721
85	.0082609	.0039518	2.09	0.037	.0005151	.0160067
90	.0067383	.0029216	2.31	0.021	.0010117	.012465
95	.0020683	.0018531	1.12	0.264	-.0015639	.0057005
100	0	(omitted)				

(ordering with respect to **hh_wealthscore**)
(difference to year = 2011)