Inequality of Opportunity in Child Health in Ethiopia

The Horn Economic and Social Policy Institute (HESPI)

Working Paper 05/16

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HESPI is a non-profit, non-political research institute that conducts economic, social and policy oriented research to promote high quality policy analysis and advisory service to assist African government, the private sector and other stakeholders with a special focus on the IGAD sub-region. HESPI conducts commissioned studies and interacts with principal institutions and entities to address the challenges the region faces. HESPI's focus also covers institutional capacity building and instilling values for better management of social and broad based sustainable economic growth aimed at prosperous future for the region.

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Abstract

Early childhood development such as child health and nutrition is shown to affect success and wellbeing later in adulthood. While child health and nutrition are influenced by among others, parental inputs and access to public services, the latter are not equitably distributed across children, leading to inequality of opportunity (IOp). Using standardized height-for-age and weight-for-height as health outcome measures, the study decomposes the total inequality in child health and nutrition in to a part attributable to child circumstances such as parental background, and access to public services—hence IOp in child health, and a part due to random variation in health. Using the young lives survey data in 2002 and 2006, the study then demonstrates that IOp in s and nutrition has increased over this period, regardless of the method of inequality decomposition used. Further scrutiny in to child circumstances driving IOp in height-for-age reveals that while access to infrastructure accounts for the highest share of IOp in 2002, mother's religion, household wealth, access to clean water and sanitation are more responsible for the increase in IOp in 2006. Likewise, IOp in weight-for-height is mainly driven by inequality in access to infrastructure, followed by disparities in geographic location and parental background.

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1. Introduction

Health and nutrition in the first few years of childhood are important determinants of health and wellbeing later in life. While good health and adequate nutrition earlier in childhood supports physical and cognitive development, lack thereof hampers these developments, leading to adverse productivity and wellbeing outcomes later in adulthood.

The physical and cognitive developments in childhood are determined by both genetics and child care, the latter being affected by parental inputs such as the quantity and quality of food; and public health services such as availability of clean water and sanitation. Nutrition and health services, however, are not equally distributed across children. The disparity in access to nutrition or health services due to circumstances in to which children are born (e.g. parental background, geographic location, etc) and thus children have no control over are known as Inequality of Opportunity (IOp). The IOp in nutrition or public health services across children can account for part of the observed total inequality in child health outcomes and thus is an important predictor of inequality in standards of living later in adulthood (UNESCO, 2006). Too low height of a child relative to his/her age (stunting) or too low weight of a child relative to her/his height (wasting) increases the risk of child mortality, child illness leading to poor adult health outcomes later in life (Black et al. 2008).

In this study, we try to estimate the IOp in child health in Ethiopia using data from the two rounds of young lives survey in the year 2002 and 2006. Because we have particular interest to associate part of the observed health inequality with IOp and the other part to random variation in health, we use decomposable General Entropy (GE) measures to determine health inequality. We do this using both parametric and non-parametric decomposition methods to determine part of the IOp in total health inequality. The parametric decomposition allows us to identify the individual contribution of circumstance variables such as household wealth, geographic location, and access to public service to the IOp in health outcomes.

We standardized our health outcome measure (height-for-age and weight-for-height) so they are comparable across age and sex of a child. This allows us comparing not only the change in total inequality and IOp in child health from year 2002 to 2006, but also identify which particular circumstance groups contributes most to IOp in over the two year periods.

As the literature in inequality of opportunity is relatively recent, only few studies have tried to estimate the inequality of opportunity in child health (see for example, Assad et al, 2012; Kraft & El-Kogali, 2013; Ersado & Aran, 2014; Kraft, 2015; and May & Timaeus, 2014). All have shown that significant IOp in child health and nutrition exist, though factors driving the existing IOp differ across studies. Assad et al (2012) have emphasized the role of geography and demographic characteristics in driving IOp in child health and nutrition, while Kraft (2015) have demonstrated the prominence in prenatal development and to some extent the role of clean water and sanitation in explaining disparities in child health and nutrition. May and Timaeus (2014) on the other hand attributed most of the existing inequality in child health to racial differences of children.

We are not aware of similar studies done previously for Ethiopia. This study helps policy makers in Ethiopia to be familiar with the existing level of IOp in child health and thereby design appropriate intervention to counter its subsequent adverse effects.

Our findings reveal that total inequality in child health in Ethiopia have declined in 2006 compared to 2002. On the contrary, however, IOp in child health have increased over the same period. Wealth index, access to public services (clean water and sanitation), as well as parental background were found to be important drivers of the increase in IOp in height in 2006. Likewise, infrastructure was found to explain the increase in weight-for-height in 2006.

The remaining section of the study proceeds as follows: Section 2 lays out the conceptual framework to understand inequality of opportunity in child health. Section 3 describes the data and data harmonization exercise made to make comparison in IOp across periods possible. Section 4 discusses methodology including standardizing health anthropometric measures and the parametric and non-parametric inequality decomposition techniques. Section 5 presents the findings and sections 6 concludes.

2. Inequality of Opportunity in child health: A Conceptual Framework

The study is inspired by and draws heavily on a growing literature following Roemer (1998) that emphasizes the difference between inequality of outcomes and inequality of opportunity. Roemer argues that inequality of outcomes that are due to differences in individuals' effort are morally acceptable, while the inequality due to circumstances of which the individual has no control over is morally unacceptable. In line with Roemer's argument, the latter represents inequality in outcome due to parental background, ethnicity, religion, etc. over which the individual has no control. It's this type of inequality that has been termed in the literature as the inequality of Opportunity.

Child health as measured by height-for-age and weight for height can be attributed to both nature and nurture. While the nature element comes from their genetic makeup inherited form their parents, the nurture factor constitutes nutrition and sanitation, among other things. While both nature and nurture affect child health, children have no control over these factors affecting their health. Hence, child health inequality due to differences in geographic location, parental background including ethnicity, religion, and education, access to public services such as clean water, sanitation and infrastructure are morally unacceptable. Thus, the study considers disparities in child health due to the above-mentioned factors as IOp in child health.

3. Data

Our data for the study comes from the young lives (YL) survey which was conducted in four rounds on children in Ethiopia in the years 2002, 2006, 2009 and 2013. Each round has a young and old cohort group to be tracked over time. The data has information on anthropometric measures i.e. child weight and child height measures, parental characteristics, economic wellbeing and community characteristics, among others. We used the young cohort data in the first two rounds, where children were on average one year olds in the first round and five year olds on the second round. As it's not theoretically sensible to use anthropometric measures as health outcome indicators for children whose ages are 8 or above, we chose not to use the third and fourth round data for children representing 8 year olds and 12 year olds respectively.

The young lives data was gathered using a purposive sampling method. First, four regions and one city administration that represent the diversity of Ethiopian children across the nine regions were selected. Second, 3-5 'woredas'[1] with a balanced proportion of rural-urban population were selected. Third, at least one 'kebele' from each 'woreda' was selected. Fourth, geographic clusters were selected in a semi-

[1] 'Woreda' and 'Kebele' are the 0the third largest and the smallest administrative units in Ethiopia

purposive approach within a 'kebele' (sentinel cite) and households were randomly selected from those clusters.

The study used data from two rounds i.e. in the year 2002 and 2006. Although most of the variables are measured and named consistently across rounds, we had to implement harmonization for some of the variables so they are comparable over the two year periods. For instance, we collapsed the mother's and father's education variable, measured in number of years completed, to a primary, secondary and post-secondary variable in order to allow comparison in parental education over the two rounds.

4. Methodology

We standardized our health outcome measures so they are comparable across age and sex. To disentangle part of the total inequality in health attributable to child circumstances, we adopt decomposable General Entropy measures that allow inequality decomposition in to within and group inequalities. Finally we employed both parametric and non-parametric methods to measure total inequality and IOp in child health.

4.1. Standardizing Anthropometric Measures

Height and weight are the two anthropometric measures used to construct the health outcome variables. As both height and weight variance naturally differ across age and sex, the z-score of a child's health and weight need to be computed from a distribution of similar age and weight. This will avoid the natural variation in height or weight due to age and gender difference of children (variation not due to inequality of opportunity). For this reason, we use the World Health Organization's (WHO) reference distribution for "healthy" children to compute the z-scores of the child's health and weight. Because the scales of measurement of the z-scores depend on the standard deviation of the reference distributions with specific age and sex groups, they are not readily comparable across age and sex groups. To be immune from arbitrary variation in inequality due to varying scale of measurement in z-scores, we standardize 'height' and 'weight' variables following a procedure by WHO (2006).

We transformed the height-for-age z-scores of every child to a standardized height of a 24 month old female with similar height-for-age z-scores. This procedure yields a standardized height for all children comparable across age and sex. Likewise, we transformed the weight-for-height z-scores of every child to a standardized weight–for-height of a 24 month old female with similar weight-for-height z-scores (see Tables 2 in the Appendix section for examples of height-for-age and weight-for-height transformations). Again, this procedure allows comparing weight-for-height across age and sex groups. Height-for-age and weight-for-height figures with z-scores less than -7 or greater than 7 are recoded as missing.

The formal procedures to transform height-for-age and weight-for-height are presented in equations 1 and 2 below:

Z-Score calculations for height-for-age and weight-for-height:

The method used to construct the standards based on weight, length/height and age, generally relied on GAMLSS with the Box-Cox power exponential distribution (Rigby and Stasinopoulos, 2004a).

However, the final selected models simplified to the LMS model (Cole and Green, 1992).

The z-score for a measurement *height-for-age and weight-for-height* was computed as:

$$Z_{ind} = \frac{\left({}^{Y}/_{M(t)}\right)^{L(t)} - 1}{S(t)L(t)} = \frac{Y - M(t)}{St.Dev\ (t)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

L(t), *M(t)* and *S(t)* respectively are the Box-Cox power, median and coefficient of variation corresponding to age (or height) . *StDev(t)* is the standard deviation at age *t* (derived from multiplying *S(t)* by *M(t)*).

Rearranging (1), yields an equation for standardized height or weight-for-height as follows:

$$Y = \left\{[Z * S(t) * L(t) + 1]M(t)^{L(t)}\right\}^{1/L(t)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

For height-for-age, *L(t)* is equal to 1, simplifying the Box-Cox normal distribution used in the LMS Method to the normal distribution , while for weight-for-height *L(t)= -0.3833.*

Using height-for-age z-scores of each child, S(t) and M(t) values for a 24 month old female, as well as assuming L(t) = 1 , we are able to compute a standardized height for each child comparable across different sex and age groups. Likewise, using weight-for-height z-score of each child, S(t) and M(t) values for a 24 month old female, as well as assuming L(t) = -0.3833 , we are able to compute a standardized weight-for-height for each child comparable across different sex and age groups.

4.2. Inequality Decomposition Methods

In order to compute the share of inequality of opportunity in total inequality and estimate the contribution of individual circumstances to IOp, we employ the well-known decomposable inequality measures—the General Entropy (GE) measures.

As in Duclos and Araar (2006), the general classes of GE indices for a distribution with a continuous outcome y are formally described as follows:

$$GE(\alpha) = \begin{cases} \int_0^1 ln\left(\frac{\mu}{V(p)}\right) dp & if\ \alpha = 0 \quad (3) \\ \int_0^1 \frac{V(p)}{\mu}\ ln\left(\frac{V(p)}{\mu}\right) dp & if\ \alpha = 1 \quad (4) \\ \frac{1}{\alpha(\alpha-1)}\left(\int_0^1 \left(\frac{V(p)}{\mu}\right)^{\theta} dp - 1\right) & if\ \alpha \neq 0{,}1 \quad (5) \end{cases}$$

μ is the mean of the distribution H; $y = V(p)$ is the quintile function and $H(V(p)) = p$. Also, $V(p)$ is the value of the outcome that marks the p proportion of the population. For instance, the 50th percentile (median) value of this distribution is $V(0.5)$.

$GE(0)$—also called Theil's L index—is the mean logarithmic deviation between $V(p)$ and μ and as such puts more weight for deviations of outcome values from the mean at the lower end of the distribution. $GE(1)$—also called Theil's T index—assigns more weight to deviations of outcome values from the mean at a higher level of the distribution. Finally $GE(2)$ puts more weight to deviations at the higher end of the outcome distribution. Accordingly, estimates of IOp vary depending on which of the above inequality indices used.

We chose general entropy indices because they are decomposable so we attribute part of the total inequality in to IOp and other factors. We set up groups constituting individuals with similar combination of circumstances and define within and between group inequalities. Within group inequality is due to factors other than differences in circumstances. On the other hand, between groups inequality occurs due to differences in circumstances characterizing each group, and hence is the inequality thereof is considered to be inequality of opportunity.

Given K different group types, each constituting individuals with a similar combination of circumstances, decomposition of inequality in to within and between groups can be shown by equation 6 below:

$$GE\ (\alpha)= \sum_{k=1}^{K} \rho(k) \left(\frac{\mu_k}{\mu}\right)^{\theta} GE(k;\alpha) + \overline{GE}(\alpha) \qquad (6)$$

Where $\rho(k)$ measures the proportion of the population in type k; μ_k is the mean outcome of type k; and $GE(k;\alpha)$ is the GE index of type k. On the other hand, $\overline{GE}(\alpha)$ measures outcome inequality if individuals in each group were given an outcome value equal to their group mean. Hence the first term measures the GE index of type k weighted by the product of the proportion of the population in type k and the ratio of mean outcome of type k to the total mean outcome—the within inequality. The second term, by eliminating differences in outcome within each group, measures between group inequalities.

We can measure IOp directly as a ratio of between group inequality to total inequality or indirectly as a residual by deducting the ratio of within group inequality to total inequality from unity (one). The former requires a smooth distribution of the outcome variable, thereby eliminating the within group inequality while the later requires a standardized distribution of the outcome variable, which eliminates the between group inequality.

A smooth distribution μ_k^i is constructed by replacing each y_k^i with the mean value of their type μ^k, thereby eliminating the within inequality. On the other hand, a standardized distribution is constructed by replacing each y_k^i with $v_k^i = \left(y_i^k \frac{\mu}{\mu^k}\right)$ where μ is the total mean and μ^k is the the mean of type k. by eliminating within group inequality, the smooth distribution gives a direct estimate of IOp.

$$\theta_d = \mathrm{I}\{\mu_k^i\} / \mathrm{I}\{y_k^i\} \qquad (7)$$

The standardized inequality, eliminating the between group inequality, allows indirect estimate of IOp as in equation (8) below:

$$\theta_r = 1 - \mathrm{I}\{v_k^i\} / \mathrm{I}\{y_k^i\} \qquad (8)$$

In practice, the number of groups created depend on the number of observed circumstances and whether each group has enough observation for statistical estimation. For this reason, the number of group types in practice are less than they actually are. As a result, the estimated IOp is interpreted as a lower bound.

We employed both parametric and non-parametric methods to estimate IOp. The two methods are discussed below.

4.2.1. Non-Parametric Method

In our non-parametric estimation of IOp, we employ the tranche method, following Checcii and Peragine (2010). This method divides individuals in each type in to deciles based on their place in the distribution of outcome within their type. Individuals in the same decile across types are members of the same "tranche". IOp in this case is inequality within tranches—inequality among individuals in the same position in the distribution of outcomes in each type.

The tranche approach allows measurement of IOp both directly and indirectly. We can measure IOp directly as inequality within tranche. To do this, we careate a standardized distribution $\{\lambda_i\}$ by replacing each y_i in the original distriubiton by $\lambda_i^e = y_i \left\{\frac{\mu}{\mu_e}\right\}$, where μ_e is the tranche mean and μ is the overall mean. The standardized distribution, λ_i^e, eliminates any between tranche inequality and retains within trance inequality. Hence, measureing IOp directly using the tranche approach can be done as in equation (9) below:

$$\theta_{tranche}^{d} = \mathrm{I}\{\lambda_i^e\} / \mathrm{I}\{y_i\} \tag{9}$$

The indirect (residual) method calculates IOp as between tranche inequality. To to this, we create a smooth distribution μ_e by substituting each y_i by the mean of each tranche, thereby eliminating the within tranche inequality. Thus, IOp can be computed as a residual as follows:

$$\theta_{tranche}^{r} = 1 - \mathrm{I}\{\mu_e\} / \mathrm{I}\{y_i\} \tag{10}$$

4.2.2. Parametric Method

The disadvantage in measuring IOp non-parametrically is that for a reasonable set of circumstances (C), the types will be too large to have enough observation in each type. In this case, we resort to estimating IOp parametrically, making parametric assumptions about how the outcome variable (Y) depends on C.

Assume Y depends on C as in equation (11) below:

$$y = C\varphi + \varepsilon \tag{11}$$

Where y is the outcome variable (e.g. height-for-age or weight-for-height); C is the circumstance vector ; φ is the coefficient vector that describes how each circumstance affects y; and ε is an error term representing the effect of luck or random variation on y.

As in the case of non-parametric estimation, IOp can be estimated directly/ indirectly by establishing a parametrically standardized/smoothed distribution of equation (11).

A standardized distribution can be formulated as in equation (12) below by simulating y when all circumstances are set at their mean and using $\hat{\varphi}$ and $\hat{\varepsilon}$ from the original regression in equation (11).

$$\tilde{\tilde{y}} = \bar{C}\hat{\varphi} + \hat{\varepsilon} \tag{12}$$

The standardized distribution in (12) neutralizes the variation that is due to circumstances and eliminates any "between" inequality. As such, IOp using the standardized distribution is measured indirectly as in equation (10) above, by substituting μ_e with $\tilde{\tilde{y}}$.

IOp can also be measured directly using a parametrically smoothed distribution as in equation (13) below, which can be obtained from the predicted value of y in the original regression equation (11):

$$\tilde{\tilde{z}}_i = C_i \hat{\varphi} \tag{13}$$

The smoothed distribution in equation (13) directly measures variation in the outcome variable due entirely to variation in circumstances. As such, IOp using this distribution can be measured directly as in equation (9) by substituting λ_i^e with $\tilde{\tilde{z}}_i$.

i. Partial effects in parametric estimation

One merit in estimating IOp parametrically is that it allows us to obtain the contribution of individual circumstances to total inequality. To obtain the contribution of circumstance J to total inequality, construct a counter factual standardized distribution as in equation (14) below:

$$\hat{\tilde{y}}_i^J = \bar{C}^J \hat{\varphi}^J + C^{j \neq J} \varphi^{j \neq J} \ \hat{\varepsilon} \tag{14}$$

Equation (14) is a variant of equation (12), where we neutralize the variation in y due to circumstance J, while maintaining variation due to other circumstances. $\hat{\varepsilon}$ is the estimated residual from equation (11). The share of inequality attributable to circumstance J is then given by:

$$\theta_r^J = 1 - \mathrm{I}\left\{\hat{\tilde{y}}_i^J\right\} / \mathrm{I}\left\{y_i\right\} \tag{15}$$

Bootstrapped Standard Errors

In practice, producing standard errors for the estimated inequality indices and decompositions is not automatic. For this reason, we produced bootstrapped standard errors following Ferreira and Gignoux (2008). This is done by estimating standard errors from the distribution of estimated inequality indices, which themselves are estimated from multiple sub-samples with a given number of replication.

5. Findings: Inequality Measurements and Decomposition

This section starts by discussing the evolution of inequity in child health from year 2002 to year 2006 using standardized weight-for-height and standardized height as measures of child health outcomes. It then proceeds to discuss contribution of IOp to total inequality during the two periods, using results from the parametric and non-parametric estimation of IOp. Finally, it discusses the partial effects of different circumstance groups to IOp using the findings from the parametric estimation.

5.1. Trend in Total Inequality and Inequality of Opportunity

Table 1 and Figure 1 below demonstrate how total inequality in child health evolves during 2002 to 2006 using standardized height-for-age and weight-for-height as health outcome measures. The GE (2) indices in Table 1 reveal that total inequality in height-for-age and weight-for-height have declined in 2006 compared to 2002. Total inequality in height-for-age declined from 0.003 in 2002 to 0.001 in 2006, while total inequality in weight-for-height declined from 0.009 in 2002 to 0.005 in 2006.

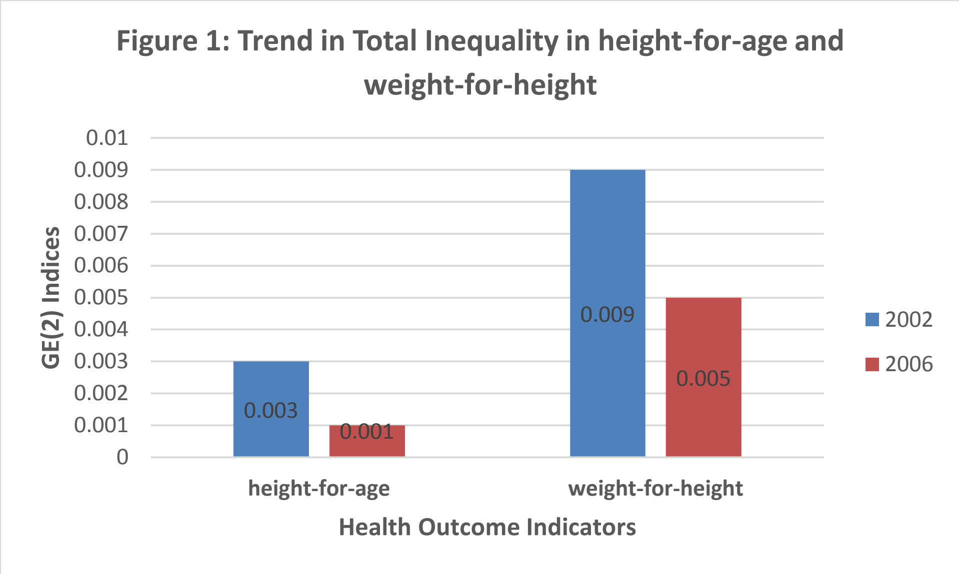
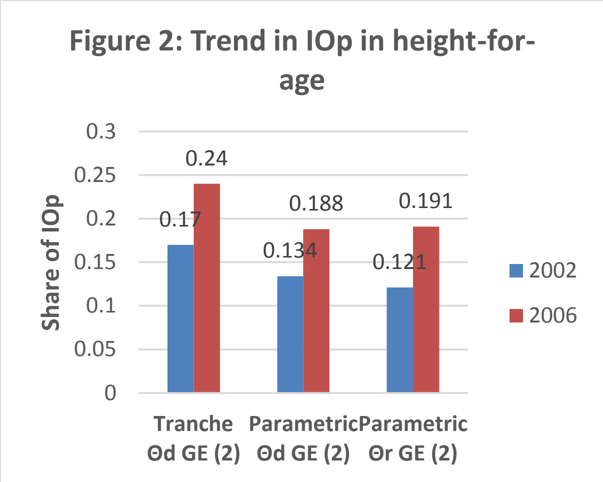
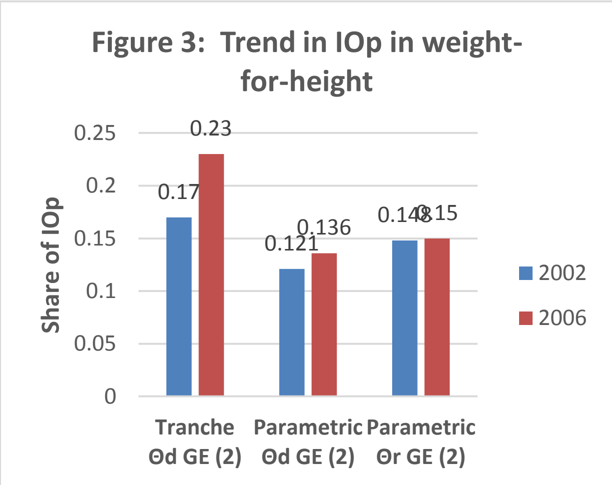


Table 1: Comparing Total Inequality indices for height-for-age and weight-for-height in 2002 and 2006

	Height-for-age		**Weight-for-height**	
	2002	**2006**	**2002**	**2006**
	GE (2)	**GE(2)**	**GE (2)**	**GE (2)**
Total Inequality	0.003*** (0.0001)	0.001*** (0.00006)	0.009*** (0.0003)	0.005*** (0.0005)

The change in total health inequality masks important changes in health inequality, particularly the changes in health inequality due to child circumstances over which they have no control—also considered to be IOp in child health. For this reason, we presented in Figures 2 & 3 below the changes in IOp in child health in Ethiopia, using parametric (direct and residual) and non-parametric/tranche (direct) decomposition, comparing the results in 2002 and 2006.





The IOp measures tell the proportion of total inequality attributed to circumstances. Contrary to the declining trend in total inequality, the IOp has increased from 2002 to 2006, both for height-for-age and weight-for-height outcomes. This is true both for the parametric and non-parametric (tranche) methods. The non-parametric estimates show that IOp has increased from 17% of total inequality in 2002 to 24% in 2006 for the height-for-age outcome measure. Likewise, IOp has increased from 17% in 2002 to 23% in 2006 for the weight-for-height outcome measure. The parametric estimates, both using the direct and residual methods, also show an increasing trend in IOp during 2002 to 2006 for both outcome measures (See also Table 3 in the Appendix section for IOp shares with estimated standard errors).

Most precise measure of IOp can be obtained by accounting for all the circumstances that affect child health and with most detailed and measure of the observable circumstances. In practice, however, one can control only some of the circumstances affecting IOp and measure circumstances with some level of aggregation due to data limitation. This means that our measure of IOp are by definition a lower bound estimates.

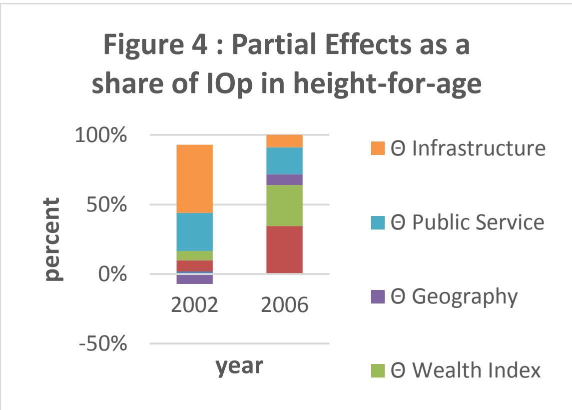
Moreover, the increasing IOp from 2002 to 2006 only tells us the trend due only to the controlled individual circumstance variables in the parametric estimation or due to the established set of circumstances in the tranche method. There is a portion of IOp we have not measured because we fail to account for all possible circumstance variable and we don’t measure the observable circumstance variables with the required detail and accuracy. There is also a portion of the total inequality due to random variation in the outcome variable, unrelated to circumstances. As such, the fact that the share of IOp is increasing for both height-for-age and weight-for-height while total inequality declines signify that the decline in either the share of circumstances we have not controlled or share of random variation in height-for-age and weight-for-height more than offset the increase in inequality of opportunity.

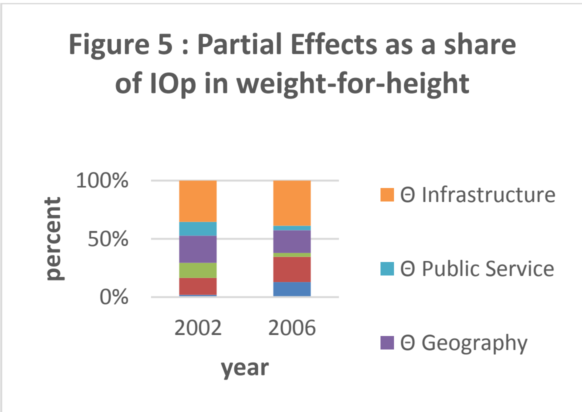
5.2. Partial Effects: Contribution of Circumstance Groups to Inequality of Opportunity

One advantage in estimating IOp parametrically is that it allows measuring the contribution of individual or group of circumstances to IOp. In order to identify the important circumstances contributing most to the IOp in height-for-age and weight-for-height, the study measures their partial effects. As we have a number of individual circumstances, we grouped those sharing common characteristics in to similar categories to avoid too extended discussion of individual partial contributions. As such we lumped together father's education, mother's education and mother's religion in to 'parent background'; toilet facility and drinking water quality in to 'public services', access to weekly market, access to health services in to 'infrastructure' ; rural/urban dummy, and regions dummies in to 'geography'; and wealth quintiles as 'wealth_index'.

The partial effects tell us the contribution of a given circumstance group to IOp, once the contribution of other circumstance groups is taken in to account. Figures 4 & 5 below demonstrate the relative importance of different circumstance groups in their contribution to IOp in height-for-age and weight-for-height for the years 2002 and 2006[2].

Access to infrastructure accounts for the largest share of IOp in height-for-age in 2002, although its role declined in 2006. Mother's religion is the second most important driver of IOp in height in 2002, with an even increasing role in 2006. Wealth index and public services (access to clean water and toilet facilities) in their order of importance are the two other most important drivers of IOp in height in 2006 in addition to mother's religion. Likewise, infrastructure accounts for the highest share of IOp in weight-for-height both in 2002 and 2006. Geographical location and parental background respectively are the second and third most important drivers of IOp in weight-for-height.





[2] See also table 3 in the appendix section for the estimated partial effects with their standard errors reported.

In principle the partial effects of all circumstances should all be positive as they measure proportion and are supposed to add up to 100%. However, in practice it's possible for some of the circumstance groups to have a negative partial effect given the way we measure partial effects (equation 14 and 15) and correlation structure between different circumstance groups. For this reason some of the partial effects reported in Table 5 are negative, albeit statistically insignificant.

Our findings are similar to Assad et al (2012) and Ersado & Aran (2014) that have shown the importance of geographic differences in driving IOp in child health and nutrition as well as Kraft (2015) that have shown the significance of clean water and sanitation in explaining IOp in child health and nutrition.

6. Conclusion

Health and nutrition in early years of childhood determining physical and cognitive development, affects significantly wellbeing and success later in adulthood. While these early child hood developments are influenced by parental inputs such as nutrition or access to public services such as clean water and sanitation, children have unequal access to these services.

Using standardized height-for-age as a long term health indicator and standardized weight-for-height as a short term nutrition indicator, this study shows the trend in total inequity in child health. Moreover, the study also shows the trend in the portion of total inequality in child health due to different child circumstances. Employing decomposable general entropy measures, the study has shown that total inequality in child height-for-age and weight-for-height has declined in 2006 compared to 2002. On the contrary, the portion of inequality in child health attributable to child circumstances—the IOp in child health—has increased over the same period. This is true for both health outcome measures and for both parametric and non-parametric measures of IOp.

Further scrutiny in to responsible factors influencing IOp in height-for-age reveals that while access to infrastructure explains most of the IOp in 2002, mother's religion, wealth of the household and access to clean water and toilet facilities are more responsible for the increase in IOp in height in 2006. This result makes sense, height being an indicator of long term health. Likewise, IOp in weight-for-height were mainly driven by inequality in access to infrastructure, followed by disparities in geographic location and parental background.

Children have no control over the circumstances causing inequality in their health. It's thus the responsibility of policy makers to narrow down the IOp in child health through different interventions and affirmative actions. The findings of the current study imply that expanding infrastructure, and public health services such as access to clean water and sanitation to rural areas would help to reduce the IOp in child health.

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8. Appendix

Table 2: Height-for-age and weight-for-height Transformation examples

Height for a male 57 months old	Zscore	Zscore	Standardized Height
=101 cm	-1.62	-1.62	==80.49 cm
Weight for a male with a height of 103 cm	Zscore	Zscore	Standardized Weight
= 14 kg	-1.81	-1.81	== 9.85 kg

Table 3: IOp in height and weight-for-height and partial effects as a share of IOp

Indices	**Height**		**Weight-for-Height**	
Non-Parametric Estimates (Tranche)				
	2002	**2006**	**2002**	**2006**
$\Theta_d\ GE(2)$	0.17*** (0.004)	0.24*** (0.014)	0.17*** (0.007)	0.23*** (0.044)
Parametric Estimates				
$\Theta_d\ GE(2)$	0.134*** (0.018)	0.188*** (0.028)	0.121*** (0.124)	0.136*** (0.0245)
$\Theta_r\ GE(2)$	0. 121*** (0.018)	0.191*** (0.028)	0.148*** (0.124)	0.150*** (0.0245)
Partial Effects				
Θ Gender	0.0177 (0.039)	0.0029 (0.007)	0.2376*** (0.0511)	0.1599* (0.0803)
Θ Mother's Education	-0.0161 (0.0438)	0.088 (0.066)	0.1418* (0.0606)	0.1118* (0.0482)
Θ Father's Education	-0.0408 (0.0444)	0.124 (0.085)	0.1634*** (0.0296)	0.1779* (0.0692)
Θ Mother's Religion	0.1008*** (0.0248)	0.218** (0.079)	0.0134 (0.0461)	0.1022* (0.0441)
Θ Parent Background	0.0814 (0.0692)	0.386* (0.152)	0.1262* (0.0534)	0.2693*** (0.0766)
Θ Wealth Index	0.0680 (0.1053)	0.330** (0.108)	0.1094* (0.0425)	0.0427 (0.0701)
Θ Geography	-0.0726 (0.1123)	0.090 (0.240)	0.2015*** (0.0625)	0.2409** (0.0862)
Θ Public Service	0.2756 (0.1496)	0.217* (0.108)	0.1023*** (0.0321)	0.0500 (0.0392)
Θ Infrastructure	0.4934** (0.1541)	0.100 (0.093)	0.3042*** (0.0523)	0.4825*** (0.1186)

Note: Standard errors in parentheses. * p<0.05, ** p<0.05, *** p<0.001

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