Child Undernutrition, Household Poverty and National Income in Developing Countries: Quantile Regression Results

Steven A. Block*, William A. Masters* and Priya Bhagowalia**

Affiliations and email addresses:
* Tufts University (steven.block@tufts.edu; william.masters@tufts.edu)
** TERI University (bhagowalia@alumni.purdue.edu)

Corresponding author:
W.A. Masters
Department of Food Policy and Applied Nutrition
Friedman School of Nutrition, Tufts University
150 Harrison Avenue, Boston, MA 02111
Phone 617.636.0424
www.nutrition.tufts.edu

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Summary
The eradication of child undernutrition and extreme poverty are important objectives for most societies. Countries with higher national incomes usually improve in both dimensions, but not always at the same rate. Using quantile regression, we show that poverty rates tend to decline with increased income at a roughly constant elasticity. In contrast, while the prevalence of child underweight declines at that same elasticity where it is most widespread, the elasticity becomes smaller as underweight becomes less prevalent. This finding suggests a need for increasingly targeted interventions to achieve a given reduction in undernutrition as its prevalence declines.

Keywords
Global poverty, millennium development goals, underweight, weight-for-height, income elasticity of bodyweight, income elasticity of poverty.

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I. Introduction

Countries with higher average national income tend to have fewer households in extreme poverty, and also have fewer undernourished children. This paper compares the degree to which these two distinct development goals have been tied to income growth, as opposed to other factors, in a sample of countries from Africa, Asia and Latin America over the past 25 years.

A large literature addresses the links between national income and poverty rates, and a separate literature focuses on undernutrition. For example, Besley and Burgess (2003) estimate the income elasticity for prevalence of extreme poverty across developing countries to have been -0.73, while Haddad et al. (2003) estimate income elasticities for the prevalence of extreme underweight that range from about -0.2 to -1.1. Our innovation is compare these two relationships across a wide range of developing countries from Africa, Asia and Latin America over the past 25 years, allowing for heterogeneity in these elasticities. The goal of these estimates is not to evaluate any particular program or policy, but to estimate income elasticities that, *mutatis mutandis*, capture all kinds of variance associated with differences in per-capita national income.

Reducing the prevalence of household poverty and of child undernutrition are both widely held objectives, listed together as the first of the United Nations' Millennium Development Goals (UN 2000). Poverty rates are typically measured as the fraction of households below some threshold of income per capita, while undernutrition is measured as the fraction of people below extreme thresholds of weight and height. In this paper, we focus on the weight-for-height ratios of children from 3 to 36 months of age, because that is the dimension and time period in which people are most vulnerable to shortfalls below their physical growth potential (Shrimpton et al. 2001). These shortfalls are clearly associated with greater levels of subsequent mortality (Pelletier 1994, Garenne et al. 2006) and a wide range of diseases later in life (Fishman et al. 2004).

We measure prevalence rates using conventional thresholds, classifying households as extremely poor when their income falls below $1.25 in purchasing-power parity income per capita (World Bank 2008), and classifying children as extremely underweight when their weight-for-height falls more than two standard deviations below the mean for healthy children at their age and sex (WHO 2006). These thresholds offer arbitrary but widely recognized definitions of extreme poverty and underweight. In both cases, we use Foster, Greer and Thorbecke (1984) measures to consider both the headcount prevalence and the depth of shortfalls below the extreme threshold.

Reductions in the prevalence and depth of both poverty and underweight could be associated with higher national income, but if that relationship breaks down then additional investment in more targeted interventions would be needed to achieve further reductions. Our income elasticities are estimated across dozens of countries, where higher incomes are associated with increased spending by households, governments and private organizations on a wide variety of actions to reduce both poverty and underweight. Our elasticity estimates ask how effective these responses have been, and where additional efforts might be most needed.

Our focus is on the simplest and perhaps most important dimension of heterogeneity across countries, namely the level of the problem itself. Where poverty and underweight are most widespread, have these problems persisted despite aggregate income growth? In that case, those high-prevalence countries would have low income elasticities, and the greatest need for more targeted programs aimed specifically at household poverty or child nutrition. It is equally possible, however, that these countries actually have high income elasticities of poverty reduction or nutrition improvement, and simply lack the national income needed to lift households out of poverty and improve child nutrition. At the opposite end of the spectrum, in countries with low prevalence rates, the remaining pockets of household poverty or child underweight could have weak links to aggregate income, thereby calling for more targeted efforts to achieve further improvement in those settings. Theory and previous empirical work provide little guidance, in part because there are many possible sources of nonlinearity in the relationship between per-capita income and the prevalence or depth of poverty and malnutrition.

One source of non-homotheticity in the link between per-capita income and child underweight is Engel's law, by which the fraction of income spent on food declines as income rises. Smith and Haddad (2002) test various pathways empirically, and find that higher per-capita income is linked to lower rates of child underweight not just through the quantity of food, but also through women's education, women's status, and public health. Each of these could vary non-homothetically, although in keeping with previous literature, Smith and Haddad assume that these relationships and the associated elasticities are constant across countries.

Household poverty rates could also respond non-homothetically to per-capita income, perhaps due to the Kuznets inverted-U or other relationships between the shape of the income distribution curve and average per-capita income. Bourguignon (2003) shows how poverty rates can respond nonlinearly to a change in average incomes for a wide variety of reasons, even if the shape of the income distribution curve remains constant. Similar possibilities apply to the distribution of nutritional status across children.

In our study, we address changes in both headcount prevalence and also the depth of shortfalls below targeted thresholds in household income and child underweight, using quantile regression to obtain comparable income elasticities of poverty and of underweight separately for each decile. The patterns of results that we find for household income and child underweight are strikingly different from one another, particularly for headcount indexes.

Our main result is that the income elasticity of poverty varies little across the distribution of poverty headcounts, and is consistent with the earlier estimates of Besley and Burgess (2003). The income elasticity of underweight, while consistent with the range of estimates from Haddad et al. (2003), declines with the prevalence of underweight. Specifically, we find that income elasticity of poverty is approximately -0.77 regardless of the prevalence of poverty in a given country, while the income elasticity of underweight shrinks monotonically from -0.81 in the decile with the most widespread underweight, to -0.13 in the decile with the least. This suggests that aggregate income growth has been associated with similar reductions in household poverty and child underweight where those problems are most severe – but in countries with less child underweight, further improvements in underweight have been harder to achieve through income growth alone. To continue reducing child underweight, more targeted interventions are needed than the changes that have been associated with income growth in our sample of countries.

II. The Data

Our dependent variables of interest are Foster-Greer-Thorbecke (FGT) indexes for headcount prevalence (FGT0) and cumulative gaps (FGT1) in household poverty and child underweight below reference thresholds, which we will then regress on per-capita national income. Dummy variables for year and region are used in the main specification to absorb secular trends and common shocks, and a variety of alternative specifications and robustness tests are applied. No other conditioning variables are introduced, however, so that our elasticities include all possible pathways by which higher per-capita income might be associated with reduced prevalence of household poverty and child underweight.

Table 1 provides summary statistics for all variables. The total sample for which relevant data are available consists of 129 country and year observations. National income is available for all of them from the Penn World Tables, as real GDP per capita in purchasing power parity (PPP) terms, measured in constant 2000 international dollars. To obtain internationally comparable measure household poverty we use PovcalNet[1] (World Bank, 2008), with extreme poverty defined as household income below $1.25 per capita, per day, at PPP prices. The result is a sample of 27 countries covering much of Asia, Africa and Latin America. The earliest observation is 1980 (from Madagascar) and the

[1] The World Bank's poverty data are available at http://go.worldbank.org/NT2A1XUWP0.

most recent are from 2005 (from Brazil, Dominican Republic, Egypt, Ethiopia, Senegal and Turkey). A full list of all observations is provided in Table A1.

For child underweight, we use data from the Demographic and Health Surveys (DHS) of Macro International (2008).[2] Our variable of interest is the weight-for-height ratio of children from three months to three years of age. At these ages, a child's weight-for-height fluctuates with recent calorie balances much like household income fluctuates with recent revenue and expenditure. The threshold we use to define extreme underweight is two standard deviations below the mean for well-nourished children of that age and sex (WHO 2006), which we compute in Stata using the *igrowup* command (WHO 2008). Standardized data are presented in the form of weight-for-height z scores (*whz*) for each child. We compute the resulting headcount prevalence and cumulative gaps for child underweight (*whz* < -2) in each country and year. This yields a total of 77 observations from 28 countries. The earliest surveys are from 1986 (Brazil, Dominican Republic, Colombia and Senegal) and the most recent are from 2005 (Egypt, India and Senegal). Countries and years are listed in Table A2.

Our dataset is designed to assure consistency in survey methods across countries and years. It would be possible to expand the number of surveys, for example by including the data on household poverty assembled by UNU WIDER (2008) and the data on child underweight in WHO (2010), but those compilations include various types of surveys from different agencies. Restricting ourselves to the more homogeneous set of data produced by PovcalNet and the DHS helps to rule out artifactual sources of heterogeneity, such as greater measurement error in lower-income countries.

[2] The DHS data are available at http://www.measuredhs.com.

Annex Tables A1 and A2 list the country and year coverage of the dataset, by region, and Tables A3 and A4 show the samples by decile. Tables A3 and A4 also provide mean income per capita (at PPP prices) and the mean headcount index by decile of the respective distributions for poverty and underweight. Comparing the decile-by-decile means for poverty and underweight with those countries' mean per-capita income reveals that poverty and underweight are imperfectly correlated with income, perhaps in ways that vary systematically across the deciles and are different for the two kinds of shortfall. Note that the data on household poverty and child underweight do not cover exactly the same sample of countries and years. The resulting sample-selection concerns are investigated at length in section V, below.

III. Estimation Strategy

Our basic model for estimating the income elasticities of poverty and underweight is a semi-log specification in which the dependent variable is either the headcount ratio (*FGT0*) or the cumulative gap (*FGT1*) for either household poverty (*pov)* or child underweight as measured by weight-for-height z scores (*whz)*, resulting in four different dependent variables (*FGT0_pov*, *FGT0_whz*, *FGT1_pov* or *FGT1_whz*). The independent variables include (log) per capita income at PPP prices, as well as a full set of year dummies and regional dummies for Africa, Europe and Central Asia, Latin America and the Caribbean, and Asia (excluding Japan)[3]:

(1)
$$y_{it} = \alpha + \beta_1 \log(gdppc_{it}) + \sum_{t=1981}^{2005} \gamma_t YrDum_t + \sum_{r=2}^{4} \varphi_r RgnDum_r + \varepsilon_{it}$$

[3] Our limited number of observations per country (2.8 on average) precludes estimation of a model with country fixed effects. Instead, we use year and region dummy variables to capture common trends and shocks associated with time and location.

In our main specification, *y* is the level of the FGT index, and we estimate the relevant income elasticities as $\hat{\beta}_1 / \bar{y}$, where $\bar{y}$ is the mean of the dependent variable. To test robustness, we also estimate the elasticity directly with *y* in log form.

Variations of this specification have been estimated numerous times, for instance by Besley and Burgess (2003) for the headcount index of poverty as the dependent variable and by Haddad et al. (2003) for the headcount index of underweight. Besley and Burgess estimate a log-log specification, while Haddad et al. estimate a semi-log regression from which the elasticity is computed as described above. Bourguignon (2003) and Kalwij and Verschoor (2007) derive the log-log form from a model in which the underlying inequality across households or individuals is captured by a log-normal distribution with fixed parameters. Actual distributions may vary, however, as shown for example by Battistin, Blundell and Lewbel (2009) for household income. Given that variation, for the specific purpose of comparing elasticities across countries with high and low prevalence rates, Klasen and Misselhorn (2008) offer a compelling argument in favor of the semi-log approach, to avoid the problem that each absolute change in prevalence looms larger in log terms among the observations with lower prevalence rates, and is relatively smaller among countries with high prevalence. Our primary results therefore use the semi-log approach for estimation and re-scale the resulting coefficients to compare across deciles, but we also present results using a log-log specification to test robustness.

By estimating equation (1) with quantile regressions rather than OLS, we are able to distinguish the effects of income on poverty and underweight at different points in the distributions of those dependent variables, thus relaxing previous studies' implicit assumption of uniform effects that are estimated only for the sample mean.[4] Using quantile regression allows us to consider heterogeneity in income elasticities, but requires that we estimate standard errors by bootstrapping. For each of the results reported below, we use bias-corrected bootstrapped confidence intervals. We further provide bootstrapped standard errors for tests of the differences between coefficient estimates across deciles (within each dependent variable).

IV. Results

Our quantile regressions reveal that while the effect of income in reducing poverty is similar across deciles of the poverty distribution, the effect of income in reducing underweight varies significantly and systematically across deciles of the underweight distribution. A given increase in income is associated with a much greater reduction in underweight in countries where it is widespread than in countries where the prevalence is already low.

We first illustrate these patterns graphically, by plotting the quantile regression estimates for $\hat{\beta}_1$ by decile. Figure 1 shows the relative uniformity of these coefficient estimates across deciles of the distribution for the headcount index of poverty. In strong contrast to this, the coefficient estimates for income's link to the headcount index of underweight, illustrated in Figure 2, are lowest at the first decile (q10) where underweight is already least widespread. The absolute values of these elasticities increase monotonically with the level of underweight, and differ statistically from the first decile

[4] Quantile regression has several other relevant features that make it a better choice than OLS for many applications, including its greater robustness to outliers and to non-normality in the error term (Buchinsky, 1998).

(q10) point estimate beginning with q60. The point estimate at q90 is over six times larger than the point estimate at q10.

We find a similar pattern when we redefine the poverty and underweight indices as gap indices (*FGT1*) rather than as headcounts (*FGT0*). Figure 3 presents estimates for $\hat{\beta}_1$ by decile when the dependent variable is the poverty gap index. As with the headcount index of poverty, the estimates vary neither widely nor systematically across deciles. The only statistically significant difference from the q10 point estimate occurs at q30, and this is a borderline case at the .10 level. Yet, as in the case of the headcount index of underweight, the gap index for underweight presented in Figure 4 also demonstrates a systematic and dramatic increase in the effect of income as the deciles of the distribution increase. Here, too, statistical differences from q10 begin with q60 and continue. Thus, we see that increased income is also substantially more effective in reducing the average shortfall in weight-for-height below the threshold for underweight in those settings where that gap is the greatest than it is in those settings where that gap is smallest.

Table 2 presents our estimated income elasticities of poverty and underweight for each decile of the dependent variables, as well as for the means (estimated by OLS), as computed from the coefficients presented in Figure 1-4. For each decile-specific elasticity, we also present t-statistics for tests of differences from zero, differences from the elasticity estimated at the mean of the dependent variable, and differences between the estimate for each decile and the first decile (q10). For the headcount index of poverty, the point estimate for the mean income elasticity is -0.77, as compared to -0.73 estimated by Besley and Burgess (2003) over a slightly different sample. While clearly different from zero, the elasticity estimated at the mean is never statistically different from any of the decile-specific point estimates (none of which themselves ever differ statistically from q10).

The second panel of Table 2 underscores the systematic pattern illustrated in Figure 3. At the mean of the distribution for the headcount of underweight, we estimate an income elasticity of -0.46, as compared with -0.51 estimated by Haddad et al. Yet, in contrast to the decile-by-decile uniformity of the point estimates for income elasticities of poverty, our point estimates for the income elasticity of underweight vary from -0.13 for the first decile up to -0.81 for the ninth decile. As with the underlying regression coefficients, these elasticities increase monotonically and dramatically with decile. The decile-specific point estimates all differ statistically from the estimate at q10. Indeed, with the exceptions of q50 and q60, they also differ statistically from the mean elasticity.

By comparison with the income elasticities of headcount poverty rates, the income elasticities of the poverty gap (in the third panel of Table 2) show somewhat greater variation across deciles, but they do not follow a systematic pattern. The elasticity estimates for the poverty gap index are also anomalous in that the point estimate for the mean elasticity lies outside the range for the decile-specific elasticities, reflecting the value of quantile regression in heterogeneous samples even for estimates intended to capture relationships at the sample mean.

The bottom panel of Table 2 presents our results for the “underweight gap” index. As with the income elasticities with respect to the headcount index of underweight, our estimates increase systematically and dramatically by decile, such that the elasticity at q90 is five times greater than the elasticity at q10. The pattern of t-statistics is also similar to that reported for the headcount index of underweight.

V. Robustness

We consider the robustness of these results to changes in the functional form and in the control variables. First, we compare our semi-log results with estimates obtained using log-log specifications. This produces the effect described by Klasen and Misselhorn (2008). A given absolute (percentage point) reduction in prevalence offers a larger proportional reduction where the initial rate is smaller, raising the estimated elasticity at lower deciles. This is illustrated for the prevalence of poverty in Figure A1 (as compared to our initial result in Figure 1), and for the prevalence of underweight in Figure A2 (as compared to Figure 2). Numerical results are presented in Table A5, for comparison with Table 2. With poverty rates, a log-log specification makes the estimated income elasticity among the lowest-prevalence countries about twice as large as it was with the semi-log specification (-1.42 as opposed to -0.71 at q10), whereas it remains similar to the semi-log result among the poorest, highest-prevalence countries (-0.77 in both specifications at q90).[5] With child underweight, the estimated income elasticity in the lowest-prevalence countries is about three times larger than it was with the semi-log specification (-0.42 as opposed to -0.13 at q10), and among the highest-prevalence countries it is slightly smaller (-0.74 as opposed to -0.81 at q90). This shift does not change our basic finding, in the sense that reductions in prevalence associated with higher national income are about the same for underweight and for poverty when their prevalence is high, but the elasticities for underweight are much smaller than those for poverty once their prevalence has been reduced.

[5] The point estimates in Figure A1 differ significantly from q10 beginning with q50.

We also test the robustness of our primary results to changes in the vector of control variables. For our base model, we use a full set of year and region dummies, to absorb any common shocks or trends. Following Bourguignon (2003) and Kalwij and Verschoor (2007), we may want to add a control for the Gini coefficient in our poverty regression, insofar as a country's level of inequality influences the fraction of people who are near the poverty line and might cross it when national income changes. In re-estimating our base model for the poverty headcount to include the Gini coefficient, our sample size falls from 129 to 92. Nonetheless, the coefficient pattern across deciles remains statistically flat, with implied elasticities ranging from -0.78 for q10 to -0.84 for q90 (see Table A5).

To complete the robustness tests vis-à-vis our control variables, we re-estimated the models for poverty and underweight headcounts excluding alternatively the year dummies, the region dummies, and both year and region dummies. These changes also leave our base results unchanged. Excluding from the poverty estimation either year or region dummies, we find no pattern and no statistical differences across deciles in the elasticity estimates; excluding both sets of dummies from the poverty estimation yields slightly greater elasticities at the high end of the poverty distribution, though the difference from q10 across deciles is significant only for q80 and q90 (where the point estimate for q90 is -0.81 as compared with -0.59 for q10). In contrast, similar re-estimations of our base model for the underweight headcount results in no meaningful changes from the primary results presented above. (Table A5 includes the point estimates for poverty and underweight excluding both region and year dummies.[6])

[6] Results excluding specifically the year or region dummies are available on request from the authors.

Our comparisons of the income elasticities of poverty and underweight require one caveat: the samples over which we estimate these elasticities of poverty and underweight overlap, but are not identical. In each case, we estimate the respective elasticities over the largest sample available (n=129 in poverty regressions and n=77 in the weight-for-height regressions). There were 17 observations in common across these two samples, raising a question of their direct comparability. Estimating these relationships over different samples creates the possibility that our finding of different patterns of elasticities by decile is driven by sample selection, rather than by differences in the same sample. Yet, to the extent that these 17 common observations are drawn from the same respective distributions as the remaining observations that are unique to either the poverty or the underweight samples, we can eliminate this concern.

The top panel of Figure A3 juxtaposes the kernel density functions for the poverty headcount distributions for the 17 observations in the common sample and the remaining 118 observations in our sample. The functions appear similar, and a t-test fails to reject the equality of the means of the two distributions (P = 0.92). Similarly, a Kolmogorov-Smirnov test fails to reject the null hypothesis of the equality of these two distributions (P = 0.94). The bottom panel of Figure A3 makes the same comparison for the kernel density functions of the underweight headcount distributions for the 17 observations in the common sample and the remaining 64 observations in our sample. In this case, as well, the distributions appear similar and a t-test fails to reject the equality of the means of the two distributions (P = 0.42), although a Kolmogorov-Smirnov test in this case does reject strict equality (P = 0.045).

Figure A4 presents similar comparisons for the distributions of the poverty gap and underweight gap indices, with similar results. In these cases, too, t-tests fail to reject equality of the means (in and out of the common sample) for both poverty and underweight. As with the headcount distributions, the Kolmogorov-Smirnov test gives mixed results, failing to reject equality for the poverty gap index while rejecting it for the underweight gap.

These comparisons and tests strongly suggest, though do not conclusively prove, that the differing patterns of income elasticities for poverty and underweight by decile presented above are not the result of sample selection.

VI. Conclusions

This paper provides comparable estimates of how the prevalence and depth of household poverty and child underweight vary with per-capita income, across a large sample of developing countries over the past 25 years. Poverty rates are measured using World Bank data on household income, capturing the headcount proportion of households (FGT0) and their cumulative poverty gap (FGT1) below the reference poverty line of US$1.25 per capita per day in PPP terms. Underweight is measured using Demographic and Health Survey data, as the headcount proportion and cumulative gap among children between 3 and 36 months whose weight for height ratio is less than two standard deviations below the mean of a reference population at each age and sex.

Eradicating both poverty and undernutrition are widely-held goals, appearing together at the top of the list of UN MDGs. Both are closely linked to aggregate national income, as richer countries have more of many things associated with lower rates of poverty and undernutrition. Their income elasticities may vary across countries, however, and where they are low, additional targeted interventions would be needed to achieve a given reduction beyond what is associated with the country's national income. Our contribution is to use quantile regression, asking whether and how elasticities might vary with the extent of the problem.

Our main result is that poverty and underweight rates both have similar income elasticities when their incidence is high, but when it is low the income elasticity of child underweight becomes much smaller than the income elasticity of household poverty. In the base specification, the income elasticity of poverty is similar across the sample, and is consistent with the earlier estimates of Besley and Burgess (2003): a ten percent increase in aggregate income is associated with a roughly eight percent decrease in both the poverty rate and the poverty gap. The income elasticity for underweight is about the same as the elasticity for poverty when the prevalence of underweight is high, but it becomes significantly smaller as the prevalence of underweight declines. In our base specification, in the decile with the least prevalence, ten percent higher income is associated with a further decline of only about one percent. These findings are robust to alternative functional forms and controls, and are unlikely to be due to sample selection bias.

The main policy implication of our results is that, to achieve a given percentage cut in household poverty and child undernutrition -- as specified for example in the first Millennium Development Goal – appropriate strategies vary with the extent of the problem. In countries where household poverty and child underweight are most widespread, aggregate income growth has been equally effective in alleviating both. Where these problems are less prevalent, achieving a given improvement would require relatively more investment in programs targeted specifically at child nutrition. Other dimensions of heterogeneity may also be very important, but applying quantile regression offers a relatively simple technique with which to identify differences and target interventions.

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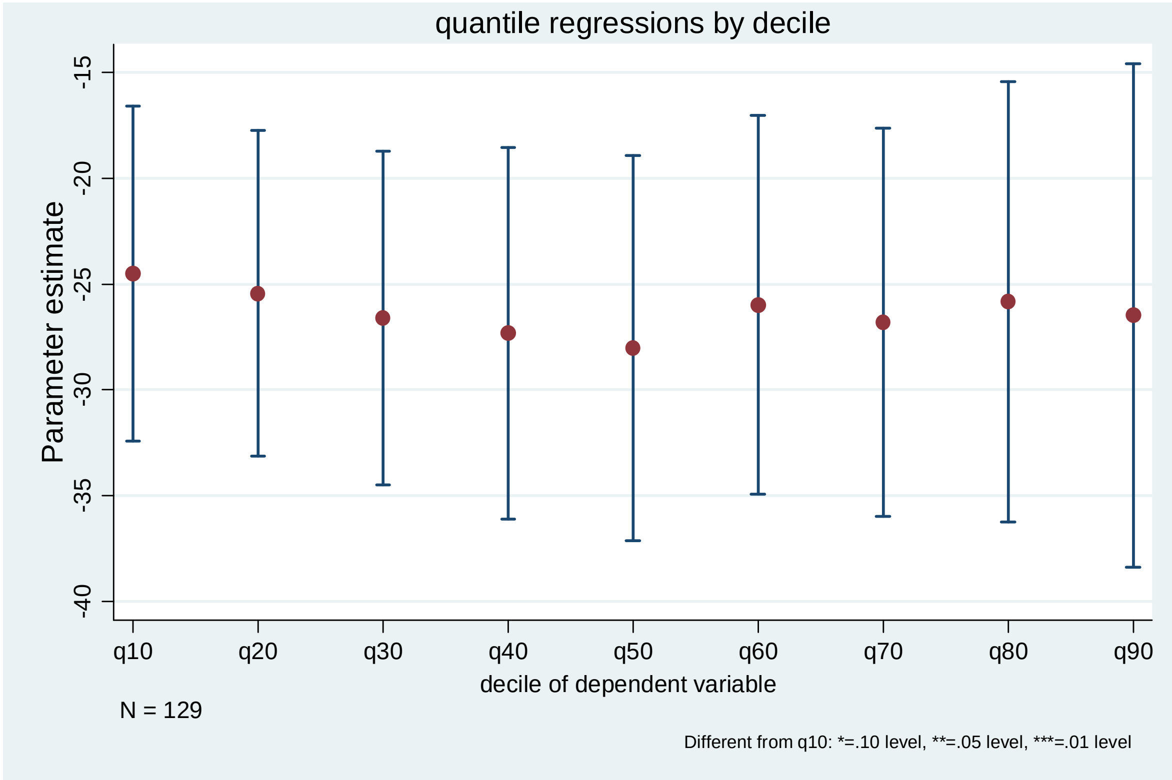

Figure 1. Coefficients on Income in Household Poverty Headcount (*FGT0_pov*)

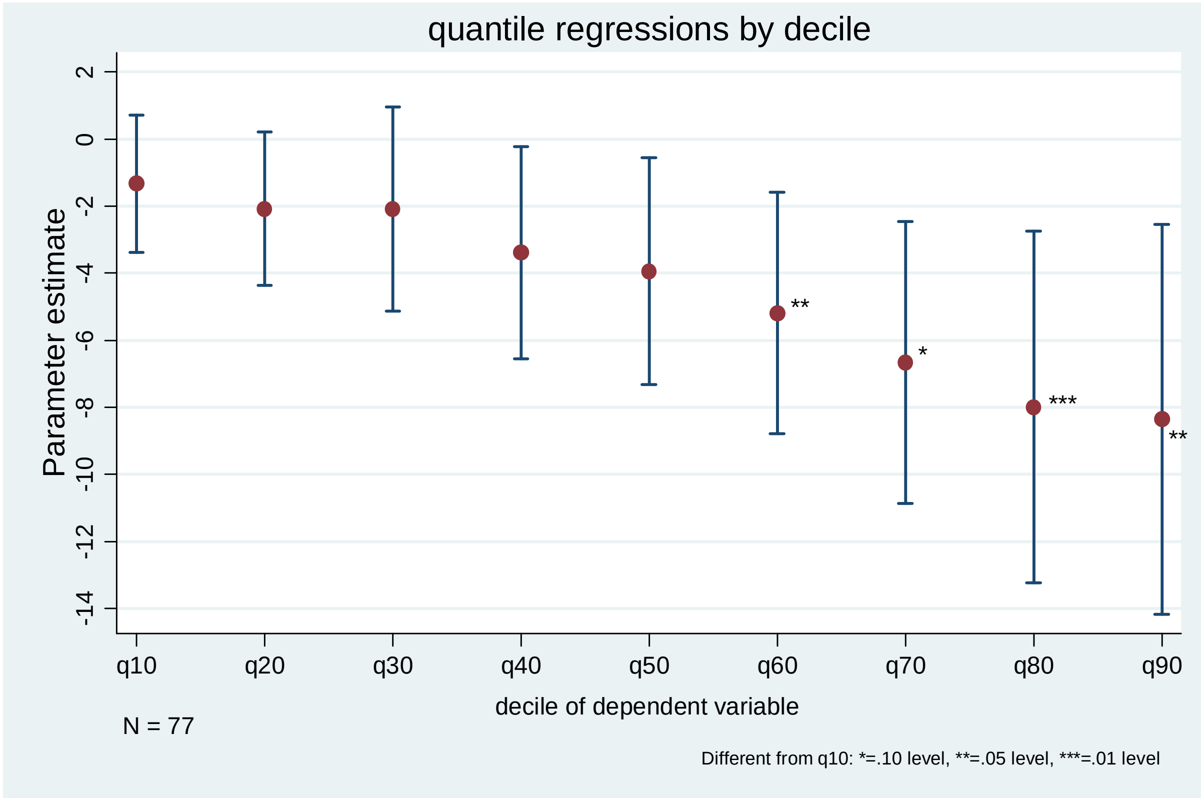

Figure 2. Coefficients on Income in Child Underweight Headcount (*FGT0_whz*)

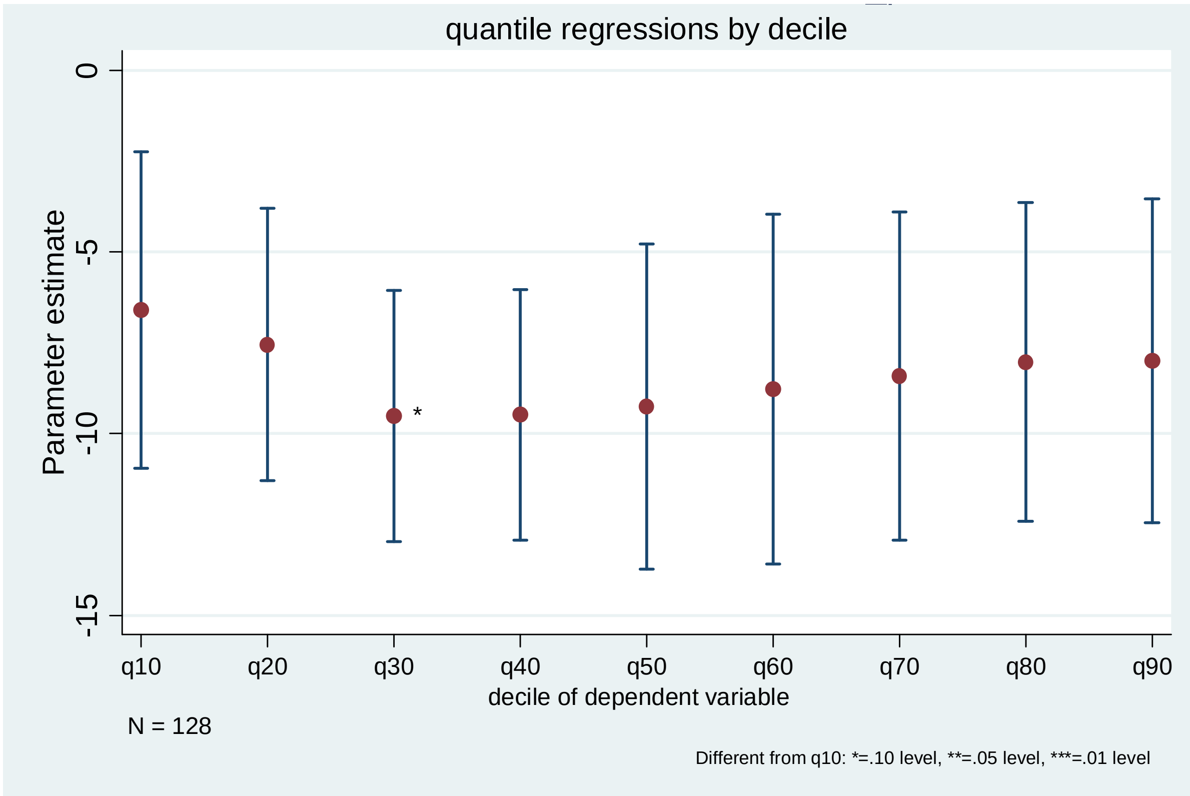

Figure 3. Coefficients on Income in Household Poverty Gap (*FGT1_pov*)

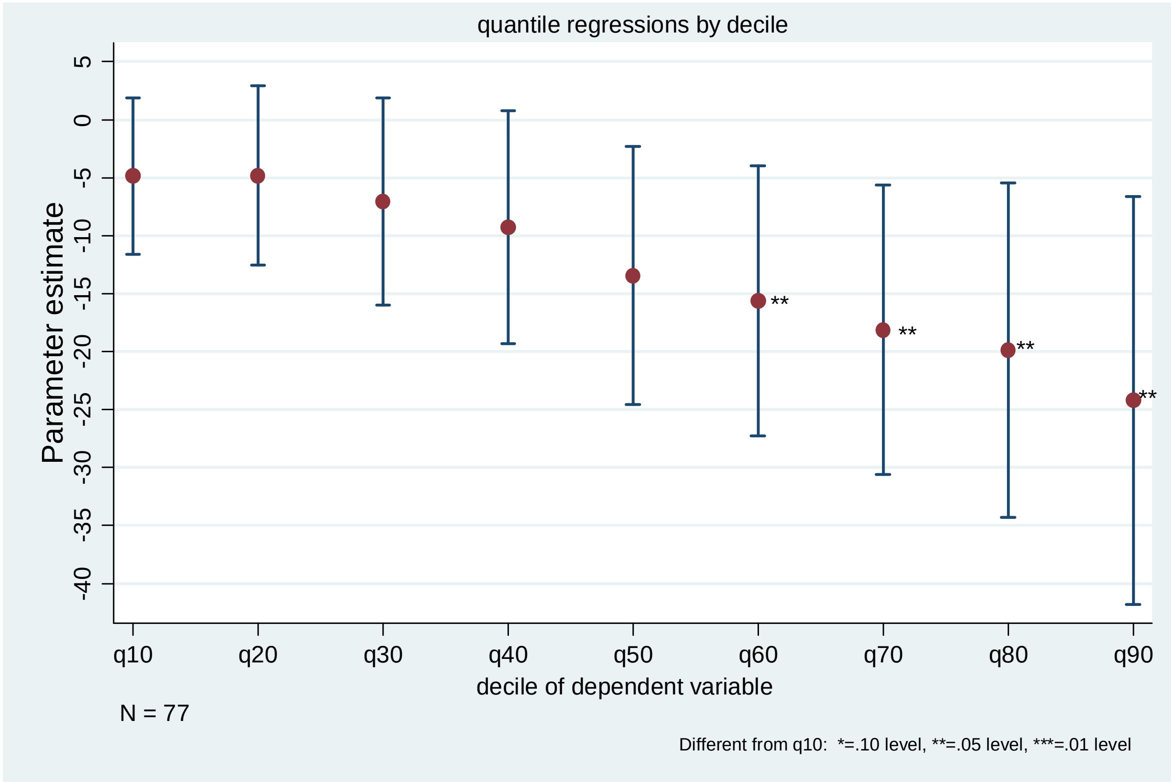

Figure 4. Coefficients on Income in Child Underweight Gap (*FGT1_whz*)

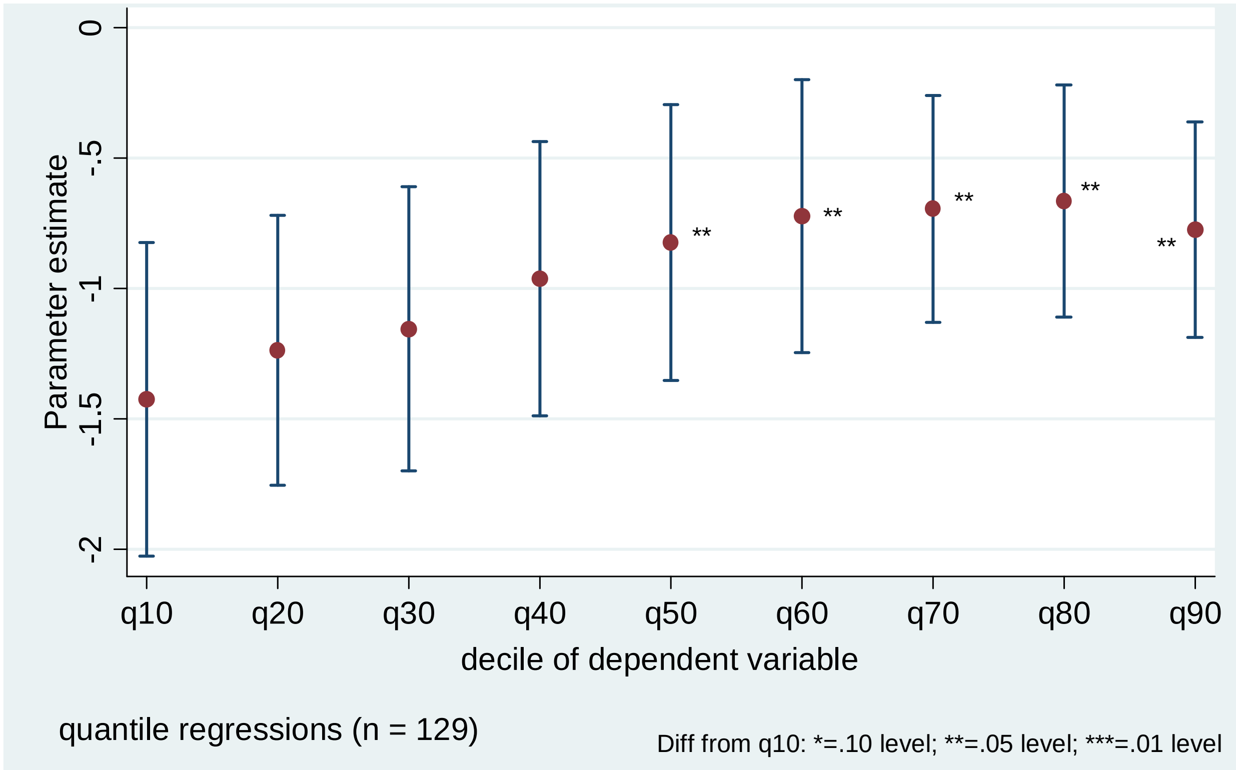

Figure A1. Coefficients on Income in Household Poverty Headcount, log-log specification

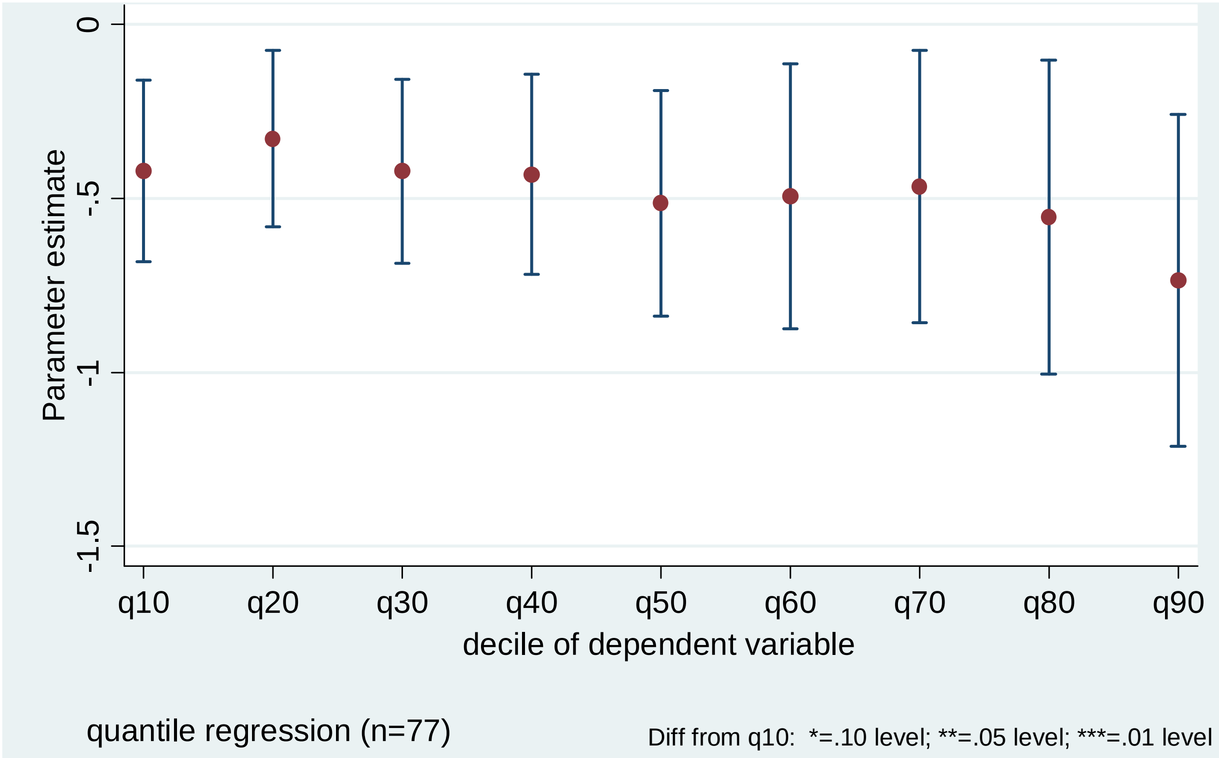

Figure A2. Coefficients on Income in Child Underweight Headcount, log-log specification

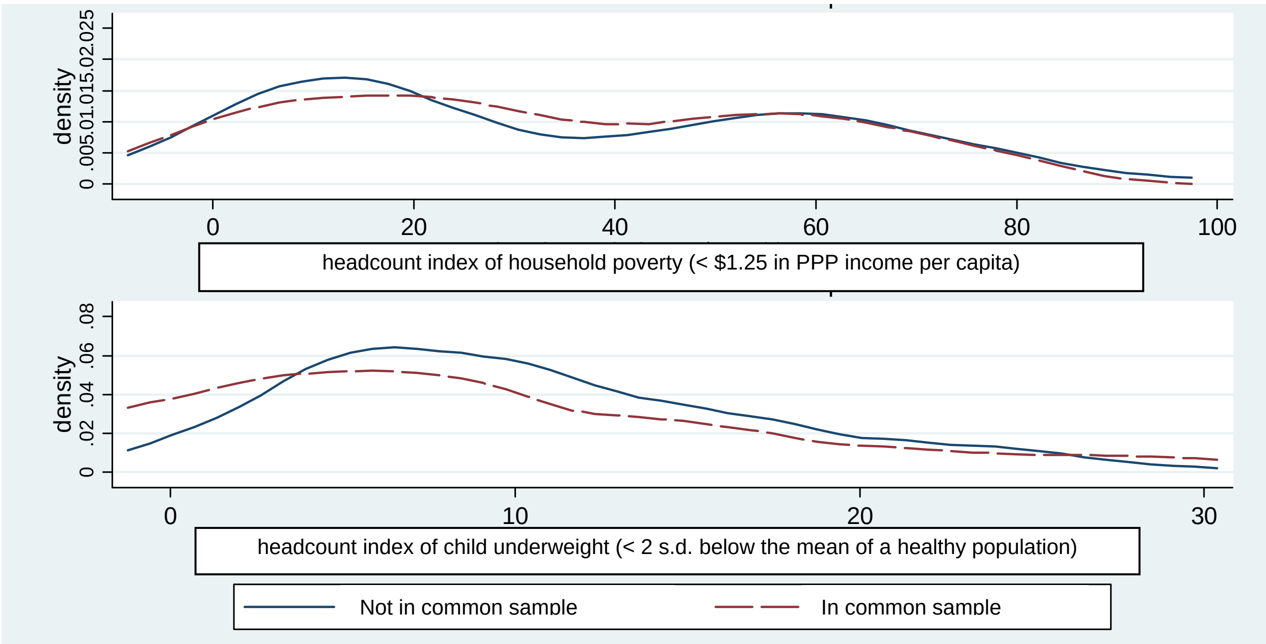

Figure A3. Kernel Density Functions for Poverty and Underweight Headcounts, by Sample

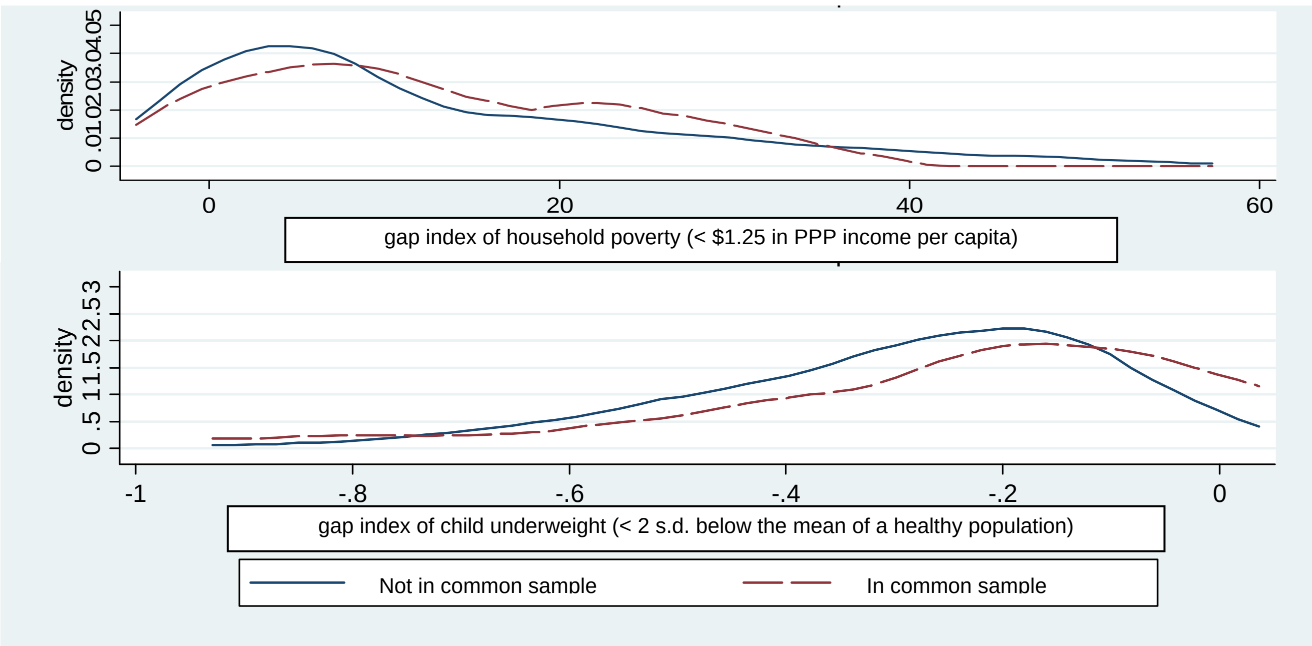

Figure A4. Kernel Density Functions for Poverty and Underweight Gaps, by Sample

Table 1. Descriptive Statistics

	obs	Mean	Std. Dev.	Min	Max
Poverty Headcount (*FGT_0_pov*)	129	34.51	25.52	0.4	88.52
Poverty Gap (*FGT1 _pov*)	129	12.91	12.71	0.03	53.09
Underweight Headcount (*FGT0 _whz*)	77	10.31	6.9	1.2	29.0
Underweight Gap (*FGT1 _whz*)	77	29.12	19.97	3.50	92.77
log GDP per capita at PPP prices	129	7.68	0.9	6.04	9.25

Note: See Tables A3 and A4 for decile-specific means.

Table 2. Quantile Regression Estimates of Income Elasticities of Poverty and Underweight, by Decile

	mean	q10	q20	q30	q40	q50	q60	q70	q80	q90
Poverty Headcount	-0.771	-0.710	-0.737	-0.771	-0.792	-0.812	-0.753	-0.777	-0.749	-0.767
(*FGT0_pov*)										
t-statistic: difference from zero	0.072***	0.109***	0.092***	0.111***	0.118***	0.103***	0.133***	0.143***	0.143***	0.161***
t-statistic: difference from mean		0.108	0.086	0.072	0.069	0.077	0.077	0.087	0.113	0.137
t-statistic: difference from q10			0.078	0.107	0.124	0.128	0.143	0.146	0.148	0.166
Underweight Headcount	-0.463	-0.129	-0.202	-0.202	-0.328	-0.382	-0.503	-0.646	-0.775	-0.810
(*FGT0_whz*)										
t-statistic: difference from zero	0.120***	0.094***	0.098***	0.134***	0.122***	0.120***	0.140***	0.149***	0.191***	0.242***
t-statistic: difference from mean		0.108***	0.107**	0.104***	0.101*	0.110	0.101	0.121*	0.175*	0.229
t-statistic: difference from q10			0.058***	0.094*	0.106**	0.126***	0.157***	0.160***	0.206***	0.261***
Poverty Gap	-0.831	-0.511	-0.585	-0.737	-0.734	-0.717	-0.680	-0.652	-0.622	-0.619
(*FGT1_pov*)										
t-statistic: difference from zero	0.109***	0.151***	0.143***	0.153***	0.172***	0.196***	0.195***	0.201***	0.224***	0.245***
t-statistic: difference from mean		0.152***	0.130*	0.107	0.097	0.103	0.108**	0.127**	0.138**	0.156**
t-statistic: difference from q10			0.103	0.130**	0.152*	0.169	0.213	0.229**	0.210**	0.230**
Underweight Gap	-0.452	-0.166	-0.166	-0.243	-0.318	-0.462	-0.536	-0.623	-0.683	-0.831
(*FGT1_whz*)										
t-statistic: difference from zero	0.128***	0.099**	0.129*	0.131***	0.156***	0.174***	0.161***	0.186***	0.193***	0.253***
t-statistic: difference from mean		0.128**	0.120**	0.120*	0.121	0.114	0.105	0.126*	0.181*	0.207**
t-statistic: difference from q10			0.076	0.121	0.140	0.166**	0.189***	0.211*	0.217***	0.260***

Note: All specifications control for year and region dummies. Mean elasticity estimated by OLS. All standard errors are bootstrapped,with bias-corrected confidence intervals. For underweight (*whz*) regressions, n = 77; for poverty (*pov*) regressions, n = 129 (see appendix tables for sample details).

Table A1. Country/Year Observations Included in Poverty Regressions (N = 129)

Africa		Asia		Latin America	
Country	Years	Country	Years	Country	Years
Burkina Faso	1994, 1998, 2003	Bangladesh	1983, 1985, 1988, 1991, 1995	Brazil	1981-1990, 1992-1993, 1995-1999, 2001-2003, 2005
Cameroon	1996, 2001	India	1983, 1987, 1993, 2004	Colombia	1995-96, 1999-2000, 2003
Chad	2002	Kazakhstan	2001, 2002	Dominican Republic	1986, 1989, 1992, 1996, 2000, 2003, 2005
Cote d'Ivoire	1985, 1987, 1988, 1993, 1995, 1998, 2002	Pakistan	1987, 1990, 1992, 1996, 1998, 2001, 2004	Nicaragua	1993, 1998, 2001
Egypt	1990, 1996, 2000, 2003, 2005	Sri Lanka	1985, 1990, 1995, 2002		
Ethiopia	1981, 1995, 1999, 2005	Thailand	1981, 1988, 1992, 1996 1999, 2002, 2004		
Ghana	1987, 1988, 1991, 1998	Turkey	1987, 1994, 2002, 2005		
Kenya	1992, 1994				
Madagascar	1980, 1993, 1999, 2001 2005				
Mali	1994, 2001				
Mozambique	1996, 2002				
Nigeria	1995, 1992, 1996, 2004				
Senegal	1991, 1994, 2001, 2005				
Tanzania	1992, 2000				
Uganda	1989, 1992, 1996 1999, 2002				
Zambia	1991, 1993, 1996, 1998, 2003, 2004				

Table A2. Country/Year Observations Included in Underweight Regressions (N = 77)

Africa		Asia		Latin America	
Country	Years	Country	Years	Country	Years
Benin	1996, 2001	Bangladesh	1996, 1999, 2004	Brazil	**1986, 1996**
Burkina Faso	1992, **1998, 2003**	Eqypt	1988, 1992, 1995, **2000**, 2003, 2005	Colombia	1986, **1995**, **2000**, 2004
Cameroon	1991, 1998, 2004	India	1992, 1998, 2005	Dominican Republic	**1986**, 1991, **1996**, 2002
Chad	1996, 2004	Pakistan	**1990**	Nicaragua	1997, **2001**
Cote d'Ivoire	1994, **1998**	Sri Lanka	1987		
Ethiopia	1992, 1997	Thailand	1987		
Ghana	**1988**, 1993, **1998**, 2003	Turkey	1993, 1998, 2003		
Kenya	1993, 1998, 2003				
Madagascar	1992, 1997, 2003				
Mali	1987, 1995, **2001**				
Mozambique	1997, 2003				
Nigeria	1990, 1999, 2003				
Senegal	1986, 1992, **2005**				
Tanzania	1991, 1996, 1999, 2004				
Togo	1988, 1998				
Uganda	1988, 1995, 2000				
Zambia	1992, **1996**, 2001				

Note: Boldface indicates membership in the common sample for both poverty and underweight.

Table A3. Country/Year Observations by Decile of Headcount Index of Poverty

Decile	Mean Poverty Headcount (*FGT0_pov*)	Mean GDPpc at PPP prices (US$)	Country/Year
1	1.83	6274.5	Dominican Rep. (2000); Egypt (1996, 2000, 2004); Kazakhstan (2001); Thailand (1996, 1999, 2002, 2004); Turkey (1987, 1994, 2002, 2005)
2	7.18	5312.4	Brazil (1995, 2002, 2003, 2005); Cote d'Ivoire (1985, 1987); Dominican Rep. (1992, 1996, 2003, 2005); Eqypt (1990); Kazakhstan (2002); Thailand (1992)
3	12.29	6226.7	Brazil (1986, 1992, 1993,1996, 1997, 1998, 1999, 2001); Colombia (1995, 1996); Cote d'Ivoire (1988); Dominican Rep. (1989); Sri Lanka (2002)
4	16.34	5484.2	Brazil (1981, 1982, 1985, 1987, 1989, 1990); Colombia (1999, 2000, 2003); Dominican Rep. (1986); Sri Lanka (1990, 1995); Thailand (1988)
5	21.14	3087.6	Brazil (1983, 1984, 1988); Cote d'Ivoire (1993, 1995, 1998, 2002); Nicaragua (1998, 2001); Pakistan (1992, 2004); Sri Lanka (1985); Thailand (1981)
6	38.13	1428.1	Bangladesh (1985); Benin (2003); Cameroon (2001); Ethiopia (2005); Ghana (1998); India (2004); Kenya (1992, 1994); Nicaragua (1993); Pakistan (1998, 2001); Senegal (2001, 2005)
7	50.42	1059.0	Bangladesh (1983, 1988, 1991, 1995, 2005); Cameroon (1996); Ghana (1987, 1988, 1991); India (1987, 1993); Nigeria (1992); Pakistan (1996)
8	57.75	918.7	Bangladesh (2000); Burkina Faso (2003); Chad (2002); Ethiopia (1995, 1999); India (1983); Mali (2001); Nigeria (1985); Senegal (1994); Uganda (1999, 2002); Zambia (1996, 1998)
9	65.69	1154.2	Ethiopia (1981); Madagascar (2005); Nigeria (1996, 2004); Pakistan (1987, 1990); Senegal (1991); Uganda (1989, 1996); Zambia (1991, 1993, 2003, 2004)
10	77.62	783.0	Burkina Faso (1994, 1998); Madagascar (1980, 1993, 1999, 2001); Mali (1994); Mozambique (1996, 2002); Tanzania (1992, 2000); Uganda (1992)

Table A4. Country/Year Observation by Decile of Headcount Index of Underweight

Decile	Mean Underweight Headcount (*FGT0_whz*)	Mean GDPpc at PPP prices (US$)	Country/Year
1	1.74	5206.4	Colombia (1986, 1995, 2000, 2004); Dominican Rep. (1991, 2002); Eqypt (1988); Turkey (2003)
2	2.96	4787.0	Brazil (1986, 1996); Dominican Rep. (1986, 1996); Egypt (2000); Nicaragua (2001); Turkey (1998); Uganda (1988)
3	5.09	3460.9	Egypt (1992, 2003, 2005); Nicaragua (1997); Senegal (1986); Tanzania (2004); Thailand (1987); Turkey (1993)
4	6.85	1376.6	Cameroon (1991); Egypt (1995); Mozambique (2003); Tanzania (1999); Togo (1988); Uganda (2000); Zambia (1996)
5	8.01	1252.7	Cameroon (1998, 2004); Kenya (1993, 2003); Madagascar (1992); Uganda (1995); Zambia (1992, 2001)
6	9.85	1143.9	Cote d'Ivoire (1998); Ghana (1988, 2003); Kenya (1998); Madagascar (1997); Senegal (2005); Tanzania (1991, 1996)
7	12.61	1294.3	Benin (2001); Cote d'Ivoire (1994); Ghana (1998); Mozambique (1997); Nigeria (2003); Senegal (1992); Sri Lanka (1987)
8	14.44	1053.2	Bangladesh (1999); Ethiopia (1997); Ghana (1993); Mali (1987); Nigeria (1990, 1999); Pakistan (1990); Togo (1998)
9	18.36	1001.2	Bangladesh (2004); Benin (1996); Burkina Faso (1992); Chad (2004); Ethiopia (1992); India (1998); Madagascar (2003); Mali (2001)
10	24.83	1111.1	Bangladesh (1996); Burkina Faso (1998, 2003); Chad (1996); India (1992, 2005); Mali (1995)

Table A5. Robustness Tests of Quantile Regression Estimates of Income Elasticities of Poverty and Underweight, by Decile

	mean	q10	q20	q30	q40	q50	q60	q70	q80	q90
Log-Log Spec. of *FGT0_pov*	-1.29	-1.42	-1.24	-1.15	-0.961	-0.822	-0.721	-0.693	-0.664	-0.774
t-statistic: difference from zero	0.164***	0.241***	0.234***	0.254***	0.289***	0.279***	0.260***	0.248***	0.228***	0.161***
t-statistic: difference from mean		0.206	0.172	0.156	0.177*	0.181***	0.169***	0.172***	0.169***	0.176***
t-statistic: difference from q10			0.182	0.239	0.279*	0.299**	0.300**	0.304**	0.298**	0.289**
Log-Log Spec. of *FGT0_whz*	-0.472	-0.421	-0.328	-0.421	-0.431	-0.513	-0.494	-0.466	-0.553	-0.736
t-statistic: difference from zero	0.100***	0.127***	0.130**	0.129***	0.131***	0.137***	0.150***	0.158***	0.199***	0.218***
t-statistic: difference from mean		0.110	0.105	0.095	0.084	0.085	0.100	0.114	0.161	0.181
t-statistic: difference from q10			0.072	0.100	0.125	0.143	0.165	0.176	0.207	0.227
Including Gini Coef in *FGT0_pov*[a]	-01.06	-0.775	-0.805	-0.842	-0.864	-0.886	-0.822	-0.848	-0.818	-0.838
t-statistic: difference from zero	0.085***	0.142***	0.143***	0.148***	0.149***	0.159***	0.156***	0.160***	0.183***	0.213***
t-statistic: difference from mean		0.113***	0.096	0.082	0.082	0.089	0.091	0.099	0.127	0.152
t-statistic: difference from q10			0.074	0.118	0.140	0.150	0.163	0.173	0.195	0.211
No control dummies in *FGT0_pov*	-0.699	-0.588	-0.592	-0.673	-0.660	-0.671	-0.634	-0.695	-0.737	-0.813
t-statistic: difference from zero	0.031***	0.068***	0.056***	0.050***	0.068***	0.065***	0.048***	0.046***	0.055***	0.072***
t-statistic: difference from mean		0.066*	0.054*	0.038	0.046	0.041	0.024***	0.028	0.033	0.055**
t-statistic: difference from q10			0.061	0.067	0.080	0.081	0.073	0.077	0.081*	0.095**
No control dummies in *FGT0_whz*	-0.503	-0.294	-0.308	-0.393	-0.407	-0.459	-0.515	-0.537	-0.670	-0.865
t-statistic: difference from zero	0.066***	0.058***	0.057***	0.058***	0.071***	0.080***	0.074***	0.085***	0.097***	0.135***
t-statistic: difference from mean		0.064***	0.057**	0.053**	0.057*	0.060	0.057	0.067	0.079**	0.121***
t-statistic: difference from q10			0.055	0.063	0.077	0.088*	0.087***	0.099**	0.111***	0.147***

Note: The first three specifications control for year and region dummies. Mean elasticity estimated by OLS. All standard errors are bootstrapped,with bias-corrected confidence intervals. For underweight (*whz*) regressions, n = 77; for poverty (*pov*) regressions, n = 129 (see Tables A1-A4 for sample details).
[a] n = 92