Explaining Urban Rural Malnutrition Inequality in Malawi

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Paper Prepared for the Special IARIW-SSA Conference on

Measuring National Income, Wealth, Poverty, and Inequality in African Countries

Cape Town, South Africa, September 28-October 1, 2011

Session 3: Multidimensional Inequality and its Persistence in South Africa

Time: Friday, September 30th, 8:30 AM-12:00PM

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Abstract

In this paper we look at asset-related inequality in child malnutrition between rural and urban areas in Malawi. We use data from the 2006 multiple indicator cluster survey (MICS). For each area, inequalities across the distribution of household assets in malnutrition as measured by a concentration index of the height-for-age z-scores (HAZ) are decomposed into their causes. We then decompose the rural-urban gap in inequality in malnutrition into the effects of changes in the means and inequalities in the determinants of malnutrition. Finally, the rural-urban difference in malnutrition inequality is decomposed into changes in the effects of the determinants of malnutrition. This allows us to dig deeper and pinpoint the changes within the changes in the elasticities. In each area, most of the asset-related inequality in malnutrition is explained by parental education and household economic status. The rural-urban difference in parental education and economic status is a major driver of the malnutrition inequality differential. Further to that, we find that it is the difference in the education elasticity rather than the difference in education inequality that accounts for the bulk of the gap associated with education.

Key words: Malnutrition; concentration index; Malawi.

1. Introduction

The reduction child malnutrition is a key developmental goal of most countries. To effectively fight child malnutrition with the right set of interventions, policymakers need to have a better understanding of its economic, social and policy determinants. Malnutrition during infancy may substantially increase vulnerability to infection and disease, and the risk of premature death. Malnutrition in children may also lead to permanent effects and to their having diminished health capital later in life as adults. For instance, Alderman et al. (2006) find that improvements in

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nutrition in pre-schoolers are associated with increased height as a young adult, and the number of grades of schooling completed.

Urban children generally have better nutritional status than rural children, and a number of studies have attempted to explain this difference in malnutrition between rural and urban children (e.g. Garret and Ruel, 1999; Smith et al., 2005). While there is a plethora of such studies, empirical work focusing on rural-urban differences in socioeconomic malnutrition inequalities is scanty. While focusing on Malawi, this paper adds to this scarce literature. To better understand what drives the rural-urban differences in socioeconomic malnutrition inequalities, we use tools from the programme evaluation literature to develop extensions of the inequality decomposition methods by Wagstaff et al. (2003). Specifically, the Wagstaff et al. (2003) decomposition does not address the common support problem. In our context, it basically assumes that all rural children are comparable to all urban children. The characteristics between the two areas may not overlap i.e. there may be a mismatch in characteristics. We propose using propensity score matching to resolve the common support problem. Equipped with this new framework, the paper seeks to do three things. First, for each area, inequalities across the distribution of household assets in malnutrition as measured by a concentration index of the height-for-age z-score are decomposed into their causes. Second, the rural-urban gap in inequality in malnutrition is decomposed into the effects of changes in the means and inequalities in the determinants of malnutrition. Finally, the rural-urban difference in malnutrition inequality is decomposed into changes in the effects of the determinants of malnutrition. This allows us to dig deeper and pinpoint the changes within the changes in the elasticities.

The remainder of the paper is organized as follows. Section 2 describes the data and the malnutrition situation in rural and urban Malawi. In Section 3 the methodology is presented and the variables used are discussed. This is followed by the empirical results in Section 4. Section 5 concludes.

2. Data and Malnutrition in Rural and Urban Malawi

2.1. Data

This paper uses data from the 2006 Multiple Indicator Cluster Survey (MICS) which was conducted by Malawi’s National Statistical Office. The main objective of the MICS was to obtain estimates at district level on the key indicators related to the well-being of children and women. The survey covers 26 districts with 2 districts, Likoma and Neno merged with other districts. From each district a total of 1200 households were sampled. Two-stage sampling was used to select the 1200 households. In the first stage in each district, 40 census enumeration areas (clusters) were selected. In the second stage a household listing was performed within the cluster and a systematic sample of 30 households was drawn to obtain 1,200 households per district. A total of 31200 households were selected in 1,040 clusters. This makes the MICS one of the largest nationally representative household surveys in Malawi. The survey collected information on; children under five, all women aged 15-49 years, and men aged 15-49 in every third household selected. Information on among other things child anthropometrics was collected, and this is of interest to this paper as it focuses on child malnutrition. We have a total of 53879 under five children in the sample. This total sample is subdivided into 48454 under five children from rural areas, representing 90 per cent of the sample, and 5425 from urban areas, constituting 10 per cent of the sample.

2.2. Malnutrition in Rural and Urban Malawi

In this paper, child nutritional status is measured using height-for-age z-scores. Height-for-age z-scores are expressed in standard deviations from the median of a reference population. Following a common empirical regularity, we use the U.S National Center for Health Statistics (NCHS) as recommended by the World Health Organization (WHO) as a reference population. We choose the height-for-age z-score over other anthropometric measures such as the weight-for-age z-score or weight-for-height z-score because it is a long-term indicator of child nutritional well-being or health. It is unaffected by acute episodes of stress occurring at or around the time of measurement (Sahn and Stifel, 2002). In this paper, we use the negative of the z-score to make the malnutrition variable easier to interpret-it is increasing in malnutrition. The most commonly used cut-off to define abnormal anthropometry is a value of 2 (it is -2 without the transformation), that is, two standard deviations above the reference median. Thus; a height-for-age z-score of greater than or equal to 2 indicates stunting. The WHO also has a more general malnutrition classification that distinguishes between mild (z-score $\geq$1), moderate (z-score $\geq$2), and severe malnutrition (z-score $\geq$3) (O'Donnell et al., 2008).

Table 1 reports the percentages of mildly, moderately, and severely stunted children in rural and urban Malawi. Means of the (negative of) height-for-age z-score are also displayed. The results show noticeable rural-urban differences in the proportion of children who are malnourished. About 66 per cent of urban children are mildly stunted compared to 74 per cent in rural areas. Severe stunting is higher in rural areas with about 19 per cent severely stunted, compared to 13 per cent in urban areas. The means of the indicators (last row in Table 1) tell a similar story to the malnutrition prevalence rates; which is that stunting is worse in rural areas than in urban areas. The results also indicate that the mean differences are statistically significant.

The above results show that the levels of malnutrition are higher in rural areas than in urban ones in Malawi, the reverse however holds for malnutrition inequalities. Table 2 reports Gini coefficients and concentration indices for rural and urban areas. The Gini coefficients measure univariate inequalities in malnutrition, while the concentration indices measure socioeconomic malnutrition inequalities. Univariate inequality focuses on the dispersion of the health outcome without regard to how they are correlated with socioeconomic characteristics (see for example Sahn and Stifel (2003) and Sahn and Younger (2006) for applications of this approach). In contrast, socioeconomic inequality makes comparisons in health outcomes across populations with different socioeconomic characteristics (see for example Lindelow (2006) and van Doorslaer et al. (2004) for applications of this approach). To compute the concentration indices, the transformed height-for-age z-scores are correlated with a wealth index (asset index) rank. The MICS data contains a wealth index constructed using principal components analysis. The index represents a composite measure of the cumulative living standard of a household by placing individual households on a continuous scale of relative wealth (see Filmer and Pritchett, 2001). The results show that both univariate and socioeconomic malnutrition inequalities are significantly worse in urban areas than in rural areas.

3. Econometric Analysis

In order to better understand what drives the rural-urban differences in socioeconomic malnutrition inequalities, we use tools from the programme evaluation literature to develop extensions of the inequality decomposition methods by Wagstaff et al. (2003). They proposed two methods for decomposing differences in socioeconomic inequalities. The first is a Blinder-Oaxaca-type decomposition (Blinder, 1973; Oaxaca, 1973). The second decomposes inequalities by using total differentials. A key limitation of the Wagstaff decompositions is that they ignore the common support problem since they require estimating malnutrition equations for all rural children and all urban children without restricting the comparison only to those children with comparable characteristics i.e. comparing like with like[1]. The decompositions are thus based on an out-of-support assumption. Individual child characteristics in rural and urban areas may not necessarily overlap. There may be a mismatch in child characteristics between rural and urban areas. For certain combinations of child characteristics it may be possible to find urban children, but not rural children (for example mothers with tertiary education in urban areas) while there are also combinations of characteristics for which it is possible to find rural children, but not urban children (for example drinking water from wells in rural areas). Ignoring the common support assumption may lead to biased results (Heckman, 1998).

3.1. Decomposing Malnutrition Inequalities Using Propensity Score Matching

Consider the following linear additive regression model of malnutrition, where malnutrition, y is measured by height-for-age z-scores:

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i \tag{1}$$

Where; x_k are determinants of malnutrition, β_k are coefficients and ε_i is an error term. Then, the concentration index for y, C, can be expressed as (Wagstaff et al., 2003):

$$C = \sum_k (\beta_k \bar{x}_k / \bar{y}) C_k + GC_\varepsilon / \bar{y} \tag{2}$$

Where; $\bar{y}$ is the mean of y, $\bar{x}_k$ is the mean of x_k, and C_k is the concentration index for x_k and takes a definition similar to C). GC_ε is a generalized concentration index for ε_i, defined as

$$GC_\varepsilon = \tfrac{2}{n} \sum_{i=1}^{n} \varepsilon_i R_{i,} \tag{3}$$

$R_{i,}$ is the fractional rank of the i[th] child in the asset distribution The concentration index C is composed of two parts. The first is the deterministic component, equal to a weighted sum of the concentration indices of the k covariates, where the weight or "share" for x_k, is simply the elasticity of y with respect to x_k (evaluated at the sample mean). The second is a residual component, and is given by the last term. It captures the inequality in malnutrition which is unexplained by x_k.

[1] Nopo (2008) and Frolich (2007) for example allow for the common support assumption in mean decompositions.

Let S^u be the support of characteristics for urban children, and S^r be the support of characteristics for rural children, then the common support (matched sample) of the two groups is given by $S^u \cap S^r$. Letting η_{kU} and η_{kR}, be the elasticities of y with respect to x_k for urban and rural children respectively, then the rural-urban inequality gap over the common support is decomposed as follows:

$$\Delta C\Big|_{S^u \cap S^r} = \left[\sum_k \eta_{kR} (C_{kU} - C_{kR}) + \sum_k C_k (\eta_{kU} - \eta_{kR}) + \Delta(GC_{\varepsilon U} / \bar{y}_U) \right]_{S^u \cap S^r} \qquad (4)$$

Instead of using rural elasticities, we can alternatively use urban elasticities as follows:

$$\Delta C\Big|_{S^u \cap S^r} = \left[\sum_k \eta_{kU} (C_{kU} - C_{kR}) + \sum_k C_{kR} (\eta_{kU} - \eta_{kR}) + \Delta(GC_{\varepsilon U} / \bar{y}_U) \right]_{S^u \cap S^r} \qquad (5)$$

Equations (4) and (5) decompose differences in asset-related inequality in malnutrition over the common support into changes in inequality in the determinants of malnutrition, on the one hand, and changes in the elasticities of malnutrition with respect to these determinants, on the other. But they do not permit one to disentangle changes going on within the elasticities. To address this problem, Wagstaff et al. (2003) propose a second decomposition method which is based on the total differential of equation (2), allowing for changes in turn in the regression parameters, the means, and the concentration indices of the covariates. To address the common support problem, the difference in concentration indices is then expressed as:

$$dC\Big|_{S^u \cap S^r} = \left[-\tfrac{C}{\bar{y}} d\alpha + \sum_k \tfrac{\bar{x}_k}{\bar{y}} (C_k - C) d\beta_k + \sum_k \tfrac{\beta_k}{\bar{y}} (C_k - C) d\bar{x}_k + \sum_k \tfrac{\beta_k \bar{x}_k}{\bar{y}} dC_k + d\, \tfrac{GC_\varepsilon}{\bar{y}} \right]_{S^u \cap S^r} \qquad (6)$$

The impact on C of a change in β_k, or in $\bar{x}_k$ on the common support depends on whether x_k is more unequally or less unequally distributed than y. This reflects two channels of influence-the direct effect of the change in β_k or $\bar{x}_k$ on C and the indirect effect working through $\bar{y}$. An increase in inequality in x_k will increase the degree of inequality in y. The impact is positively related to β_k and $\bar{x}_k$, and negatively related to $\bar{y}$.

The next issue is how to match the rural and urban children. Here we use propensity score matching (PSM). The PSM is the probability for an individual participating in a treatment given his/her observed covariates. In our case, the treatment variable is area of residence, rural vs. urban. Frolich (2007) shows that propensity score matching does not hinge on a selection on observables assumption. Rosenbaum and Rubin (1983) show that matching by propensity scores implies that the matched sample has the same distribution of covariates. The propensity scores are estimated by a probit model. We use caliper matching (also known as radius matching) as our matching algorithm. Under caliper matching, an individual from the comparison group is chosen as a matching partner for a treated individual that lies within the caliper (propensity range) and is closest in terms of propensity score. To deal with the presence of outliers in propensity scores, the trimming approach of Smith and Todd (2005) is used.

3.2. Variables Used

In terms of independent variables, In terms of independent variables, we have a child's age in months and its square to capture possible non linearities, sex of the child, and the status of being a twin, as twins frequently show lower birth weight (Hatkar and Bhide, 1999). We also control for the child's birth order by using the absolute birth order. Thus, higher values correspond to younger children. At the household level, we include the age difference between mother and father to capture the bargaining position of the mother. According to the bargaining literature on household decisions, bargaining status could influence those resources that the mother may receive for herself as well as for her child, possibly leading to adverse nutrition consequences (Smith et al., 2003; Linnemayr et al., 2008).

The economic status of a child's household is known to be a strong determinant of her or his nutritional status (see for example Dancer et al., 2008). Poor households and individuals often have low access to food, a necessary condition for food security. They also may have inadequate resources for care, and may not be able to utilize (or contribute to the creation of) resources for health on a sustainable basis (Smith et al., 2005). We measure household economic status by using a wealth index (asset index), and the households are categorized into five groups; poor, middle, richer, and richest. The poorest group is the base category. Parental education is included as a three class dummy variable indicating whether the mother/father has primary schooling, or has secondary or more education, no education for mothers and fathers represent the control group.

4. Results

PSM as expected reduces our sample significantly from 53879 under five children to 46664. The matched sample is distributed as follows; 90% rural and 10% urban. The rural-urban gap in the concentration index of 0.045 (see Table 2) is reduced to 0.027 after matching. The gap is still statistically significant. Descriptives statistics of the variables for common support sample are presented in Table 3. Briefly, the average ages for rural and urban children are 28 and 27 months respectively. About 60% of urban children belong to the richest families while only 11% belong to the richest households in rural areas. All the variables with the exception of gender are statistically significantly different between rural and urban areas.

4.1. Regression Results

Table 4 presents regression results of malnutrition models for rural and urban areas. The results are restricted to the common support sample. The hypothesis of joint significance is accepted in both models. Boys are significantly smaller than girls in both areas. For example, a male child in rural areas has on average a height-for-age z-score that is 0.08 standard deviations worse than that of a female child. We find that a child's age and malnutrition are nonlinearly related, and this relationship is statistically significant at 1% significance level. We find statistically significant negative birth-order effects in the rural model only, with later-borns having poorer height-for-age relative to earlier-borns.

Household wealth seems to matter more in improving height-for-age z-scores in rural areas than in urban areas. For example, a child born into the wealthiest quintile in rural areas has a height-for-age z-score that is 0.31 standard deviations better than that of a child from the poorest wealth quintile. Relative to a child whose mother has no education, a child who has a mother with primary education has on average a significantly better long term nutrition status in both rural and urban areas. Interestingly, in both rural and urban areas, only a father's secondary education or more negatively affects malnutrition. Primary education for fathers does not significantly influence malnutrition.

Table 5 reports the contributions of inequalities in the regressors to total malnutrition inequality in rural and urban areas. These are results for equation (2). The results show that explained inequalities dominate unexplained inequalities in both areas. The (negative) concentration indices in the last row show that malnutrition inequality is to the disadvantage of the poor in the two areas, but it is worse in urban areas. Most of the malnutrition inequality is explained by household economic status and parental education; both factors disfavor the poor (their concentration indices are mostly negative). Parental education and household economic status have larger concentration indices as well as elasticities, and this leads to a larger combined impact on malnutrition inequality. Here we have looked at the inequalities in the two areas separately, in the next subsection we explore the further the observed rural-urban gap in malnutrition inequality.

4.2. Decomposition Results[2]

In Table 5 we present Blinder-Oaxaca-type decomposition. These results address the common support problem by using PSM3. The results show that most of gap in malnutrition inequalities is driven by parental education and household economic status with household economic status being the biggest contributor. With respect to education, the results indicate that it is the education elasticity rather than the difference in education inequality that accounts for the bulk of the gap associated with education. A similar picture emerges for household economic status. In general taking the changes of all the determinants of malnutrition into account-the gap in inequality in malnutrition is roughly equally attributable to changing elasticities and changing inequalities in the determinants of malnutrition.

5. Concluding Comments

In this paper we look at asset-related inequality in child malnutrition between rural and urban areas in Malawi. We use data from the 2006 multiple indicator cluster survey (MICS). For each area, inequalities across the distribution of household assets in malnutrition as measured by a concentration index of the height-for-age z-scores (HAZ) are decomposed into their causes. We then decompose the rural-urban gap in inequality in malnutrition into the effects of changes in the means and inequalities in the determinants of malnutrition. Finally, the rural-urban difference in malnutrition inequality is decomposed into changes in the effects of the determinants of malnutrition. This allows us to dig deeper and pinpoint the changes within the changes in the elasticities. In each area, most of the asset-related inequality in malnutrition is explained by parental education and household economic status. The rural-urban difference in parental education and economic status is a major driver of the malnutrition inequality differential.

[2] Total differential results are yet to be computed.

[3] The final caliper parameter is set to 0.00002. In to check the quality of matches, we also tried different caliper parameters. The results are available on request

Further to that, we find that it is the difference in the education elasticity rather than the difference in education inequality that accounts for the bulk of the gap associated with education.

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Table1: Stunting prevalence rates

	Rural	Urban
Mild	74.0	65.7
Moderate	46.2	35.4
Severe	19.2	12.8
Mean	1.799	1.468***

Notes: own computations from MICS data. Malnutrition is classified as follows; mild (z-score ≥1), moderate (z-score ≥2), and severe malnutrition (z-score ≥3). We test the hypothesis that the mean of a malnutrition indicator in urban areas is greater than (that is less negative) that of rural areas.
The significance asterisks are defined as: * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Univariate and Asset-Related Malnutrition Inequalities

	Rural	**Urban**	**Difference**
Gini Coefficient	0.442	0.548	-0.106***
	(0.003)	(0.011)	(0.012)
Concentration Index	-0.038	-0.082	0.045***
	(0.002)	(0.008)	(0.008)

Notes: own computations from MICS data. In parenthesis are standard errors. We test the hypothesis of no difference in the inequality indices for urban and rural areas. The significance asterisks are defined as:
* p<0.10, ** p<0.05, *** p<0.01.

Table 3: Descriptive statistics of regressors

Variable	**Urban**		**Rural**			
	mean	SD	mean	SD	Difference	t-statistic
boy	0.518	0.500	0.496	0.500	-0.0142	(-1.84)
twins	0.026	0.159	0.029	0.169	0.00620*	(2.39)
child's age	28.052	18.930	27.019	19.210	-0.865**	(-2.91)
square of child's age	1145.205	1141.887	1099.083	1166.593	-44.87*	(-2.49)
birth order	3.755	2.305	4.531	2.518	0.785***	(20.52)
parental age difference	6.856	8.877	7.209	10.190	0.352*	(2.27)
mother primary education	0.684	0.465	0.685	0.465	0.00288	(0.40)
mother secondary education +	0.287	0.452	0.071	0.257	-0.206***	(-48.50)
father primary education	0.502	0.500	0.684	0.465	0.201***	(28.07)
father secondary education +	0.443	0.497	0.140	0.347	-0.314***	(-54.44)
poor	0.068	0.252	0.229	0.420	0.157***	(25.17)
middle	0.117	0.322	0.221	0.415	0.122***	(19.23)
richer	0.166	0.372	0.191	0.393	0.0272***	(4.50)
richest	0.599	0.490	0.111	0.314	-0.498***	(-95.31)
Observations	4673		41991			

Table 3: Regression results for malnutrition

Variable	Urban	SE	Rural	SE
Male	0.084**	(0.043)	0.024*	(0.014)
Twins	0.531***	(0.142)	0.344***	(0.041)
child's age	0.031***	(0.004)	0.025***	(0.001)
square of child's age	-0.000***	(0.000)	-0.000***	(0.000)
birth order	0.015	(0.011)	0.012***	(0.003)
Poor	0.080	(0.130)	-0.126***	(0.020)
Middle	-0.252**	(0.119)	-0.165***	(0.020)
Richer	0.110	(0.113)	-0.188***	(0.021)
Richest	-0.098	(0.105)	-0.307***	(0.026)
parental age difference	-0.005*	(0.002)	-0.000	(0.001)
mother primary education	-0.143**	(0.062)	-0.036**	(0.017)
mother secondary education +	-0.099	(0.073)	-0.169***	(0.032)
father primary education	-0.088	(0.072)	-0.024	(0.019)
father secondary education +	-0.421***	(0.077)	-0.238***	(0.026)
Constant	1.251***	(0.141)	1.659***	(0.031)
R^2	0.054		0.026	
F	17.666***		75.833***	
Observations	4673		41991	

Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Contributions of inequality in determinants to total malnutrition inequality

Variable	**Rural**			**Urban**		
	Elasticity	concentration	contribution	Elasticity	concentration	Contribution
Male	0.007	-0.005	-0.000034	0.0304	-0.014	-0.0004
Twins	0.006	0.0203	0.0001	0.009	0.049	0.0004
child's age	0.372	0.004	0.0015	0.609	0.001	0.00061
square of child's age	-0.2098	0.005	-0.0011	-0.382	0.004	-0.0015
birth order	0.030	-0.016	-0.0005	0.040	-0.053	0.0021
Poor	-0.016	-0.267	0.004	0.004	-0.7699	-0.0031
Middle	-0.021	0.171	-0.004	-0.019	-0.594	0.0113
Richer	-0.020	0.577	0.012	0.013	-0.369	0.005
richest	-0.019	0.876	-0.017	-0.042	0.379	-0.016
parental age difference	-0.0006	0.005	-0.000003	-0.022	-0.0301	0.0007
mother primary education	-0.014	0.021	-0.0003	0.068	-0.078	-0.005
mother secondary education +	-0.006	0.347	-0.002	-0.019	0.348	-0.007
father primary education	-0.009	-0.011	0.000099	-0.031	-0.1798	0.0056
father secondary education +	-0.0199	0.287	-0.006	-0.137	0.266	-0.036
Residual			-0.001			0.002
Total			-0.014			-0.040

Table 5: Blinder-Oaxaca -type decompositions of the malnutrition inequality gap

Variable	**Equation (6)**		**Equation (7)**		**Total**	
	ΔC*n*	Δ*n*C	ΔC*n*	Δ*n*C	Total	%
Male	-0.00006	0.0001	-0.00006	-0.0003	0.0004	-1.82
Twins	0.0002	0.00006	-.0002	0.0001	-0.0003	1.36
child's age	-0.001	0.0009	-0.001	0.0002	-0.0008	3.64
square of child's age	0.0002	-0.001	0.0002	-0.0007	-0.0005	2.27
birth order	-0.001	-0.0002	-0.001	-0.0005	-0.002	9.09
Poor	0.008	-0.005	0.008	-0.015	-0.007	31.82
Middle	0.002	0.0003	0.016	-0.0001	0.0159	-72.27
Richer	0.019	0.019	0.019	-0.012	0.007	-31.82
Richest	0.009	-0.02	0.009	-0.009	0.001	-12.67
parental age difference	0.00002	-0.0001	0.00002	0.0006	0.0006	-2.73
mother primary education	0.001	0.002	0.001	-0.006	-0.005	22.73
mother secondary education +	0.000006	-0.005	-0.000006	-0.005	-0.005	22.73
father primary education	0.002	0.0002	0.002	0.004	0.006	-27.73
father secondary education +	0.0004	-0.034	0.0004	-0.031	-0.003	13.64
Residual					-0.0004	1.82
Total	0.004	-0.007	0.053	-0.075	-0.022	