Measuring Children's Economic Well-Being in Four Developing Countries: Implications for inequality in health and education

PRELIMINARY; PLEASE DO NOT CITE

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Abstract

There are many ways to proxy for permanent income, or the perception of earnings capacity, to empirically characterize economic wellbeing in developing countries. Consumption expenditure and the wealth index are two of the most commonly used household-level economic indicators. This paper compares these two characterizations using the Young Lives survey of child poverty from Ethiopia, India, Peru, and Vietnam. I find that the correlation of household rankings produced by the two measures is moderate but highly stable over time, as are the weights assigned to consumer durables in two of the four countries using a principal components analysis. Regression models treating the panel data as multiple cross-sections suggest that the wealth index is more highly predictive of important health and education outcomes.

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However, regression models with child fixed effects - that control for time-invariant characteristics - suggest that the more limited variability of the wealth index may reduce its predictive capability in these specifications. Better understanding differences between these and other measures of socioeconomic status is important for appropriately characterizing economic inequalities in child wellbeing.

Introduction

The appropriate characterization of poverty and deprivation is important for a great many reasons including measuring inequality and progress towards the MDGs, and for establishing evidence-based public policy. These data are also essential in the grand majority of statistical analyses in the social sciences that control for socioeconomic status. But economic wellbeing - which can be thought of as individuals' perceptions of their credit capacity - is complex and not easily observable (Friedman, 1957). There are many measures available to proxy for perceptions of credit capacity, however, including income, wealth, and consumption, to name a few (Deaton, 2006).

Two measures of economic wellbeing in particular are used most widely in low-resource contexts: the wealth index and consumption expenditure (in demographic and health, and economic research, respectively). While both measures have strengths and weakness relating to ease of data collection, the possibility of measurement error, and their conceptual underpinnings, both are widely used in research and in policy-making. While consumption expenditure is generally preferred to income (which is usually unavailable in low-resource settings) because of its smoothness over time, the data necessary for its computation is onerous; researchers must collect area prices, for example, which can be very difficult to obtain and are generally fraught with measurement error (Case and Deaton, 2002). Additionally, consumption expenditure requires respondents to recall purchases and production undertaken over an extended period of time, sometimes up to a year; if this recall period is too long, responses to these questions will be unreliable (Sahn and Stifel, 2003).

Due in part to the challenges associated with collecting high quality consumption data from a sufficiently large sample, a wealth (also called "asset") index was developed in the early 2000s, which uses statistical methods to infer budget choices when prices are unavailable. This index most frequently distills household socioeconomic status into a list of consumer durables, housing quality, and access to services such as improved water and sanitation (Filmer and Pritchett, 2001; Sahn and Stifel, 2003), although each of these three sub-categories is not necessarily included. The most frequently used version of the wealth index is that of the Demographic and Health Surveys (DHS), in which it is described as "a survey-specific measure of the relative economic status of households based on analysis of household consumer durables and service amenities at a particular point in time" (Rutstein and Staveteig, 2014). The index is usually constructed using principal components analysis, a multivariate statistical technique that reduces the number of variables in a data set to a smaller number of "dimensions" that explain the variation in the original data (Vyas and Kumaranayake, 2006). The wealth index has been criticized extensively for leaving unclear why certain consumer durables are chosen for inclusion (Montgomery et al., 2000) and the fact that it "confuses genuine distal social determinants of health with more proximate ones such as quality of housing and environment" (Morris et al., 1999). The wealth index also does not do anything to correct for relative prices across regions or countries, although there have been some recent efforts to improve its international comparability (Rutstein and Staveteig, 2014).

Given that both economic measures - consumption expenditure and the wealth index - have benefits and drawbacks, and that there is no gold standard of poverty measurement with which they may be compared, investigating the ways in which these measures are different and what kind of information each may provide is an important area of inquiry. Wealth, for example, likely indicates something about a family's long-term planning and expectations for the future, while consumption, which is generally smoothed over time, provides a more detailed picture of the household's everyday lifestyle as well as access to information regarding large expenditures on medical care or a wedding/funeral; indeed, research on the latter finds that even in poor communities, outlays for this reason can be astoundingly high (Banerjee and Duflo, 2007).

The joint study of these measures has been undertaken previously (Canova, 2006; Lindelow, 2006; Montgomery et al., 2000). Most recently, Filmer and Scott (2012) compare a number of different versions of the wealth index with consumption expenditure using data from the Living Standards Measurement Study (LSMS) from 11 countries (4 in Sub-Saharan Africa, 3 in Latin America, 3 in Asia/Pacific, 1 in Europe). They comprehensively evaluate the differences between the measures by comparing their rankings of individuals as well as whether and how they are predictive of important outcomes such as education, health care use, fertility and child mortality. While they ask and answer a wide variety of important research questions, Filmer and Scott (2012) acknowledge that the major limitation to their study is their use of cross-sectional data; they are unable to evaluate changes in economic wellbeing over time or the implications of persistent disadvantage for important outcomes in health and education. This is the first gap in the literature that will be addressed in this paper.

Filmer and Scott (2012) have not produced the only research comparing economic measures of wellbeing in the LSMS data. Lindelow (2006) illustrates sensitivities to the way in which SES is measured, comparing consumption and assets (their version of the wealth index) in the LSMS with wealth in the Demographic and Health Surveys (DHS), finding that descriptive statistics differ greatly and that, for example, measured inequality in the utilization of health services is greater when individuals are ranked according to wealth index rather than consumption. Montgomery et al. (2000), also using the LSMS, find that while proxy variables like access to potable water, having electricity, and owning a motorcycle are very weak predictors of consumption, their use in the study of health and mortality is still relevant because: 1) consumption expenditures per adult vary considerably (so even weak proxies for/predictors of consumption are able to detect departures from the null) and 2) data sets are usually large in size, which further enhances the power of proxy-based tests. Finally, Canova (2006) evaluates different ways of putting the wealth index together using the Albania LSMS, finding the different measures to be only weakly correlated.

While this paper also compares the wealth index to consumption expenditure, it is the first to do so using panel data and therefore contributes both to literature on the measurement of wellbeing as well as that of persistent disadvantage. While some papers have used panel data to investigate chronic poverty, changes in economic indicators over time (Singh and Sarkar, 2014), and the intergenerational transmission of poverty and inequality (Behrman et al., 2013), no study to my knowledge has compared the wealth index to consumption expenditure using panel data, as recommended by Filmer and Scott (2012). Understanding the variation between - and the information contained within - various measures of socioeconomic status can contribute to a more nuanced analysis of economic gradients in important outcomes in child development such as children's educational attainment and health (Houweling et al., 2003).

I use the Young Lives study of international child poverty, which collected data on both consumption expenditure and the wealth index, to investigate the following research questions:

1. How similar are the two most commonly used measures of economic wellbeing across time and country?
2. Do the different measures produce consistent results when used to assess inequalities in health and school-going among children and adolescents?

The rest of the paper proceeds as follows: I compare the two economic measures (height for age and school-going) using a non-parametric approach, and then present bivariate and multivariate regression models to illustrate the role of model specification in highlighting the measures' differences. I first treat the data as multiple cross-sections and then as a panel in order to investigate - using multiple specifications - the association between the two health- and education-related outcomes and the economic indicators. Finally, I discuss the implications of the findings for both research and policy.

Data and Methods

Data

Young Lives is an international longitudinal study of child poverty run by the University of Oxford in the UK and jointly funded by the Department for International Development (DFID) and the Netherlands Ministry of Foreign Affairs. With their data and the resulting research, the investigators hope to "improve policies and programs for children" in developing countries (Young Lives, 2014). Data collection began in 2002 to follow 12,000 children from Ethiopia, the state of Andhra Pradesh in India, Peru and Vietnam for 15 years. Two age cohorts of children are followed in each country in order to collect information on each stage of childhood: 2,000 children born between 2001 and 2002 (the "younger" cohort) and 1,000 children born between 1994 and 1995 (the "older" cohort) (Young Lives, 2002). Both age cohorts were sampled at random from the same 20 sentinal sites in each of the four countries.

The Young Lives research team has produced reports on sampling and representativeness, which are slightly different in each country. In Ethiopia (Outes-Leon and Sanchez, 2008), Andhra Pradesh state in India (Kumra, 2008), and Vietnam (Nguyen, 2008), a multi-stage, purposive random sampling method was used to select the two age cohorts of children; 20 sentinel surveillance sites were chosen in each country to ensure a balanced representation of the country's "regional diversity as well as rural/urban differences" and children were randomly selected within these sites (Bourdillon, 2012). In Peru, researchers used a multi-stage, cluster-stratified random sampling method to select the two cohorts of children, which randomized households within a site as well as across 20 sentinel site locations. In all countries, only one child was selected per household.

While none of the samples is appropriate for monitoring national-level child indicators, they are all comprised of highly valuable data from which to analyze child health and wellbeing over time (Wilson and Huttly, 2004). In comparisons made between the Young Lives study sample and the nationally representative samples from the Demographic and Health Surveys temporally closest to Young Lives baseline data collection, Young Lives children are comparable on a number of living standards indicators like access to public services and caregiver's education in Peru, slightly poorer in Vietnam and slightly better off in Ethiopia and India (Barnett et al., 2012).

Finally, there is very limited loss to follow up in the Young Lives data (particularly as compared to other panel surveys undertaken in low resource contexts). As described by Barnett et al. (2012), attrition rates over the three rounds ranged from 2.2 percent in Vietnam to 5.7 percent in Ethiopia in the younger cohort, and from 2.4 percent in Vietnam to 5.0 percent in Peru for the older cohort; there is very little evidence of attrition bias. All analyses include only respondents sampled at both waves 2 and 3 (referred to hereafter as "Time 1" and "Time 2"); consumption expenditure was not evaluated at wave 1. The sample includes only respondents with non-missing data on all covariates of interest, a total 9,850 children and adolescents. The sample is comprised of 2,763 respondents in Ethiopia, 2,369 in India, 2,318 in Peru and 2,445 in Vietnam.

Variables

Economic wellbeing variables

The wealth index is computed as a composite (using principal components analysis) of information on consumer durables owned by the household, the quality of housing, and the surrounding services.[1] All variables that were asked in both waves 2 and 3 in all countries were included in the production of the wealth index. Principal components analysis (PCA) seeks a linear combination of variables such that the maximum variance is extracted, effectively reducing the complexity of the data (Revelle, 2015). This linear combination can be represented in the following way:

[1] Whether there were three or more people per room in the respondent's home; electricity; walls made of "improved" materials (brick or concrete); roof made of "improved" materials (brick or concrete); floor made of "improved" materials (anything but earth, wood, or "laminated material"); "improved" toilet (improved flush toilet/septic tank); "improved" cooking fuel (gas or electricity); and whether the household has a TV, radio, car, motor, bike, phone, mobile phone, fan

$$PC_m = a_{m1}X_1 + a_{m2}X_2 + ... + a_{mn}X_n \tag{1}$$

Where a_{mn} represents the weight for the m^{th} principal component and the n^{th} variable (Vyas and Kumaranayake, 2006). The m components are ordered such that the first explains the greatest variation in the data; the principal components are the eigenvectors, and the eigenvalues represent the amount of variation in the sample accounted for by each factor. A wealth index score for each respondent is computed by summing over the product of each variable response and that variable's factor loading from the first principal component (i.e. $m = 1$). This procedure is undertaken separately in all countries and waves. The first principal component explains such a large proportion of variation in the variables that it was not necessary to consider other principal components (see scree plots in the Appendix, Figures 1-4). Both the scores and the weights (i.e. factor loadings) from the first principal components procedure are included in the analyses presented in this paper. I use the covariance matrix in PCA implementation because all variables are dichotomous; it is also the R default (R Core Team, 2014). The distribution of scores in each of the four countries is depicted in Figure 1. Note that I do not use quintiles or other binning strategies to represent the wealth index scores, as is done in the Demographic and Health and other surveys. In the Young Lives data, quintiles do not distinguish well between very poor families in the poorer countries - Ethiopia in particular - where there is significant "heaping" in the bottom of the distribution.

Consumption (or total real consumption per capita) is more complex to compute than the wealth index because in addition to aggregating over food and non-food consumption and expenditure, this measure incorporates price information in order to account for regional and temporal differences (Deaton and Zaidi, 2002). There are many issues related to the computation of consumption expenditure, including whether to adjust for the different needs of adults and children (White and Masset, 2002), the evaluation of time and leisure, and how to deal with public goods and publicly supplied goods (see Deaton and Zaidi (2002) for a very thorough review). In the documentation that accompanies the data, the Young Lives survey administrators describe their well-defined methodology for the computation of these composite variables (Young Lives, a,b), which I outline below.

At times 1 and 2, respondents were asked a battery of questions regarding their purchase and production of food[2] and non-food[3] items. Prices to deflate nominal consumption aggregates were obtained from a community questionnaire in India (which is one of the better ways in which to assess the consumer environment facing the household, particularly when prices are ascertained more than once (Case and Deaton, 2002)), and external sources in the other countries: regional consumer price indices (CPI's) in Ethiopia, CPIs based on nationally representative household surveys in Peru, and survey data from Vietnam's statistical office (Young Lives, b). In India, prices of consumer durables were obtained twice from markets in or near the survey sentinel sites and averaged to ascertain respondents' economic environment as accurately as possible in order to adjust for the cost of living. In order to make temporal adjustments for time 2, the research team also used CPIs obtained from the Indian Labor Bureau for rural and urban areas in the interview months (Young Lives, n.d.).

For all countries, the computation of consumption expenditure per capita is undertaken by summing food and non-food items for each household and then dividing by the household size and the price deflator (except for Ethiopia, where the results are adjusted for adult equivalence (Dercon and Krishnan, 1995) and thus reported in 'per adult terms'):

$$\textit{per capita consumption expenditure} = \frac{\sum \textit{hh food expenditure} + \sum \textit{hh non-food expenditure}}{\textit{price deflator}_s * hhsize} \tag{2}$$

[2]Items consumed in the last 2 weeks from different sources: (1) food purchased; (2) food home-produced (from own harvest) or from stock; (3) food items received as gifts or transfers; (4) food received from employers as payment in-kind for services rendered. In the case of Peru, there is an additional question related to all food that was left over. Therefore, this amount is subtracted from the final aggregate. Each source is converted to monthly terms (by multiplying it by 2 because the recall period is 2 weeks) and finally aggregated (Young Lives, b) (see Young Lives questionnaire for full list at http://www.younglives.org.uk).

[3]Expenditure on (1) education; (2) health; (3) clothing and footwear; and (4) other non-food items (like rents, water supply, entertainment, etc.). The selection of the items was based on a comparability criteria (i.e. all those items that were included consistently in all rounds). Since this information was collected for different reference periods, answers were converted to months before aggregation (Young Lives, b).

In India, the price deflator is computed separately for each sentinal site:

$$\textit{price deflator}_s = \sum_{i=1}^{n} \frac{expenditure_{is}}{expenditure_{ts}} * \frac{price_{is}}{price_{im}} \tag{3}$$

Where price information was obtained for a total of n items in each sentinel site. Relative prices are determined by dividing the price of item i in each sentinel site ($price_{is}$) by the average price of that item ($price_{im}$). This is multiplied by the proportion of expenditure in each sentinal site devoted to item i ($\frac{expenditure_{is}}{expenditure_{ts}}$), the sum of which produces the price deflator in that sentinel site. The distribution of consumption expenditure in each of the four countries is depicted in Figure 2.

Outcome variables

In order to investigate the relationship between economic wellbeing - as measured by the wealth index or consumption expenditure - and important indicators of human development, I use two different dependent variables: height for age and school-going. Height for age z-score, or height for age relative to an international standard of healthy children, reflects past and present inputs into health and provides a cumulative picture of overall health status. The use of a reference population makes possible the comparison of children's height across different ages and contexts (Dibley et al., 1987). For the Young Lives data collection, supine length at age 1 and height thereafter was measured to the nearest 0.1 cm using a height board made for the purpose. Coupled with age of the child in days and the date of interview, these measurements form the inputs into the computation of height for age (Petrou and Kupek, 2010) which is transformed into a standardized z-score based on the 2006 World Health Organization standard (Organization, 2006) in the following way:

$$\textit{z-score}_i = \frac{x_i - x_{median}}{\sigma_x} \tag{4}$$

Where x_i is height for age for child i, x_{median} is the median height for age of the reference population of the same age and gender, and σ_x is the standard deviation of height in the reference population (Sahn and Stifel, 2003). The very few questionable z-scores in the Young Lives data above 6 and below -6 are recoded to missing. Table 1 contains means and standard deviations of height for age z-scores; at both time 1 and time 2, Young Lives children in all countries are significantly shorter on average than the international standard.

Whether the Young Lives child is going to school is evaluated only for the older cohort who are aged 12 on average at time 1 and aged 15 on average at time 2; the younger cohort is only 5 years old on average at time 2. Whether the Young Lives child is attending school is evaluated by the household head's answer to the following question from the household survey: "Is this person currently in full-time/regular education?" An answer for the Young Lives child of either "No" or "Yes, but attending irregularly" is coded as 0 and "Yes, attending regularly" is coded as 1. This question was unfortunately not available in both waves in Peru and analyses are thus undertaken for only the other three countries. Table 2 presents the proportion of Young Lives children attending school regularly at times 1 and 2, which decreases over time as expected but is in general surprisingly high overall, particularly at time 1.

Analyses

I begin by comparing the ways in which households are ranked over time by the same measure and how they are ranked by the two different measures. In terms of each measure's variation over time, I compute the Spearman rank correlation of households' wealth indices in time 1 and time 2 - and do the same with log of consumption expenditure. I then evaluate between-measure rank correlations of the wealth index and the log of consumption expenditure, first at time 1, and subsequently at time 2. While there certainly seems to be less variation in the wealth index over time as compared to the log of consumption expenditure, it is unclear whether the changes that do occur are due to changes in a) the weights attributed to each of the PCA components (i.e. the loadings) and/or b) the households' ownership of the relevant items. To address questions regarding the consistency of the weights associated with each item in the wealth index (and concerns regarding employing PCA-based scores in a longitudinal framework), I next investigate whether the item loadings produced by the PCA procedure are similar in the two different time periods in each country by presenting scatter plots of PCA loadings from time 1 on time 2. Given significant variability in Ethiopia and in particular in Vietnam, I evaluate the implications of not including the most egregious outliers (floor and cooking fuel) from the computation of the PCA in Vietnam.

Returning to comparisons between the wealth index and consumption expenditure, which are correlated and yet quite different from each other: while neither the wealth index nor consumption expenditure are necessarily the "correct" economic measure of welfare or wellbeing,[4] we can obtain a better sense of the information they may impart by evaluating their association with important health- and education-related outcomes. I therefore specify linear regression models of height for age and logistic regression models of school-going, regressing these outcomes on the wealth index and the log of consumption expenditure first separately and then together, by wave. These regression models are intended to illustrate the strength of the relationship between each economic indicator and the outcomes of interest, both separately and together.

I present partial correlations to illustrate which of the two measures contributes more - while controlling for the other - to explaining the variation in the two outcomes. The computation of a partial correlation for a linear model is shown in Equation 5 below; it is the complement of the ratio of residual sums of squares (RSS) from the "full" model (model 2) and the reduced model (model 1), and is interpreted as the proportion of additional variation explained by variable z, controlling for

[4]And we will never know which is better because 1) There is no gold standard with which to compare them, and 2) They may actually measure different aspects/components of welfare.

variable x.

$$\begin{aligned} \textit{partial correlation} &= 1 - \frac{RSS_2}{RSS_1} \\ &= 1 - \frac{\sum_{i=1}^{n}(y_i - (\alpha + \beta_1 x_i + \beta_2 z_i))^2}{\sum_{i=1}^{n}(y_i - (\alpha + \beta_1 x_i))^2} \end{aligned} \tag{5}$$

Where model 1 contains variable x_i predicting the outcome y_i, and model 2 contains variable x_i *and* variable z_i predicting the outcome y_i. The proportion of additional variation explained by the wealth index, controlling for the log of consumption expenditure, would be computed as follows:

$$\textit{partial correlation, lncons} = 1 - \frac{\sum_{i=1}^{n}(\textit{height for age}_i - (\alpha + \beta_1 wi_i + \beta_2 \textit{lncons}_i))^2}{\sum_{i=1}^{n}(\textit{height for age}_i - (\alpha + \beta_1 wi_i))^2} \tag{6}$$

Where $lncons$ is the log of consumption expenditure and wi is the wealth index. I compute a pseudo-partial correlation for logistic regression models using model deviance rather than the residual sum of squares.

Given that I find lower levels of variability in the wealth index as compared to consumption expenditure, but that the former exhibits a more robust and consistent association with the outcomes of interest when the data are treated as a cross-section, a natural next analytic step is to evaluate the behavior of these two indicators in models treating the data as what they are: a panel. I therefore specify regression models of height for age and school-going with a child fixed effect. These models hold all time-invariant characteristics of the Young Lives respondent constant and include the wealth index and the log of consumption expenditure as predictor variables.

Results

Table 3 presents the Spearman rank correlations for households over time separately by measure, with the first column presenting rank correlations between household wealth index in time 1 and household wealth index in time 2, and the second column presenting rank correlations between log of consumption expenditure in time 1 and time 2. Households' rankings by log of consumption expenditure are moderately correlated between times 1 and 2, but household's rankings by wealth index are highly stable over time. This suggests that the wealth index may be less variable over time as compared to the log of consumption expenditure. Table 4 contains direct comparisons between the economic measures regarding their ranking of households: rank correlations at time 1 (first column) and time 2 (second column). The rank correlation between the two measures is moderate but very stable over time, slightly higher in Vietnam and slightly lower in India. Overall, the rank correlation between differences in wealth index and consumption expenditure between time periods (i.e. do the two measures move together?) is a paltry 0.143.

A natural question that arises from analyses employing and comparing wealth index scores obtained from PCAs using data from more than one time point is whether the weights assigned to the items are consistent over time. If not, differences in the wealth index may be due to households gaining or losing consumer durables, but also possibly to different weights attributed to the items themselves. Figure 3 depicts PCA loadings from time 2 scattered on loadings from time 1; Figure 4 includes item labels to illustrate outliers. Weights in time 1 and time 2 are highly correlated in India and Peru and less so in Ethiopia and Vietnam, the latter having two highly significant outliers (floor and cooking fuel). Re-doing the analyses without the outliers does not substantively change the proportion of the variation explained by the first principal component, nor does taking each out separately reduce the outlying status of the other (results not shown). While taking out floor and cooking fuel from the Vietnam PCA would increase the average correlation between loadings at time 1 and time 2 for that country, in order to maintain cross-country comparability, I do not do so. In sum, while there is certainly variation over time in PCA loadings in Ethiopia and Vietnam, in India and Peru in particular we can be confident interpreting changes in the wealth index as being due to households obtaining or getting rid of consumer durables, rather than differences in weighting schemes. The consistency of loadings gives us moderate confidence in the reliability of the wealth index over time.

Is one or the other measure of economic wellbeing particularly associated with health and education? I first specify regression models with the economic measures included separately and then with them in the same model. Figures 5-8 depict the coefficients from regression models of height for age and school-going on wealth index and consumption expenditure, respectively (tables of coefficients from these models are available in the Appendix). All coefficients are statistically significant with the exception of the log of consumption expenditure in models of school-going. In models including both wealth index scores *and* the log of consumption expenditure, the wealth index appears to be more robustly associated with height for age in time 1 and school-going in both time periods.

Figure 9 displays the partial correlations between height for age and the wealth index (controlling for the log of consumption expenditure) and the log of consumption expenditure (controlling for the wealth index) from a linear regression model of height for age. In all countries except Vietnam, the wealth index explains much more of the variation in height for age when taking the log of consumption expenditure into account (as compared to vice versa). This would suggest that the wealth index may be more strongly associated with children's and adolescents' health than consumption expenditure. Figure 10 displays pseudo-partial correlations between school-going and the wealth index (controlling for the log of consumption expenditure) and the log of consumption expenditure (controlling for the wealth index) from a logistic regression model of school-going. Results are similar to those from models of height for age - the wealth index appears to explain more of the variation in the outcome (controlling for the log of consumption expenditure) than vice versa.

However, when treating the data as what they really are (a panel), results are quite different. Table 5 displays coefficients from child fixed effects regression models of height for age on the wealth index. While all coefficients are positive, none are statistically significant at the 5 percent level, suggesting that controlling for all things fixed over time (including the non-varying component of the wealth index), changes in household wealth measured in this way are not statistically significantly predictive of height for age. In contrast, Table 6 presents coefficients on the log of consumption expenditure from fixed effects regression models predicting height for age, three out of four of which are statistically significant. The pattern is similar for child fixed effects logistic regression models (Tables 7 and 8), where the wealth index is not associated with school-going in two of the three countries, but the log of consumption expenditure is highly statistically significantly associated with the outcome. In sum, it appears that in a cross-sectional empirical framework, the wealth index may be a particularly robust predictor of important health- and education-related outcomes, but that in a fixed effects framework, which controls for time-invariant characteristics, the limited variability of the wealth index over time restricts its predictive power.

Discussion

The motivation for this paper is the notion that there is something unobserved that researchers and policymakers call economic wellbeing, and that what underlies it - perceived credit capacity - is very difficult to measure, particularly in low-resource settings. The documentation of socioeconomic inequality in important indicators of human wellbeing such as health and education relies, however, on the empirical characterization of this perceived credit capacity. Since there is no gold standard with which to evaluate the different measures of economic wellbeing that are currently in use, we can simply compare and contrast them in different empirical scenarios. The findings presented here suggest that the two most commonly used measures, the wealth index and consumption expenditure, rank households moderately similarly, but that the wealth index is more stable over time. Regression models treating the data as repeated cross-sections suggest that the wealth index is a significantly more robust predictor of both health- and education-related outcomes for children and adolescents than consumption expenditure. However, when controlling for time-invariant characteristics of the children using fixed effects regression models, I find the opposite; the lesser variability of the wealth index over time may compromise the strength of its association with important outcomes in these types of regression specifications.

More generally, the differences between the two measures, both descriptively and in a variety of regression frameworks, highlights the importance of fully understanding the limitations and benefits of measures of economic wellbeing in low-resource settings - their characteristics may shape research results and thus policy recommendations. A better understanding of the way in which economic deprivation and its perpetuation is assessed is essential both empirically and conceptually as these measures form the basis of our understanding of the burden of poverty and inequality in low-resource settings and serve as control variables in almost every social science study. With more information about these measures, researchers, survey developers, and policy-makers can be more discerning users.

1 Tables and Figures

Figure 1: Violin plot of wealth index score densities in each country and time period

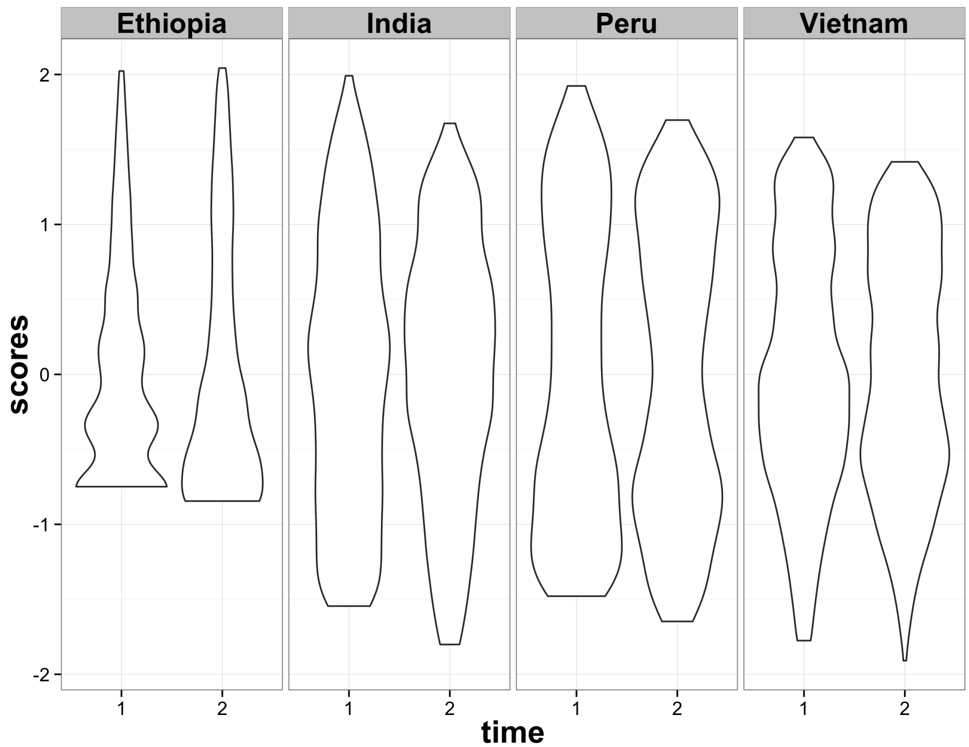

Figure 2: Violin plot of consumption expenditure densities in each country and time period

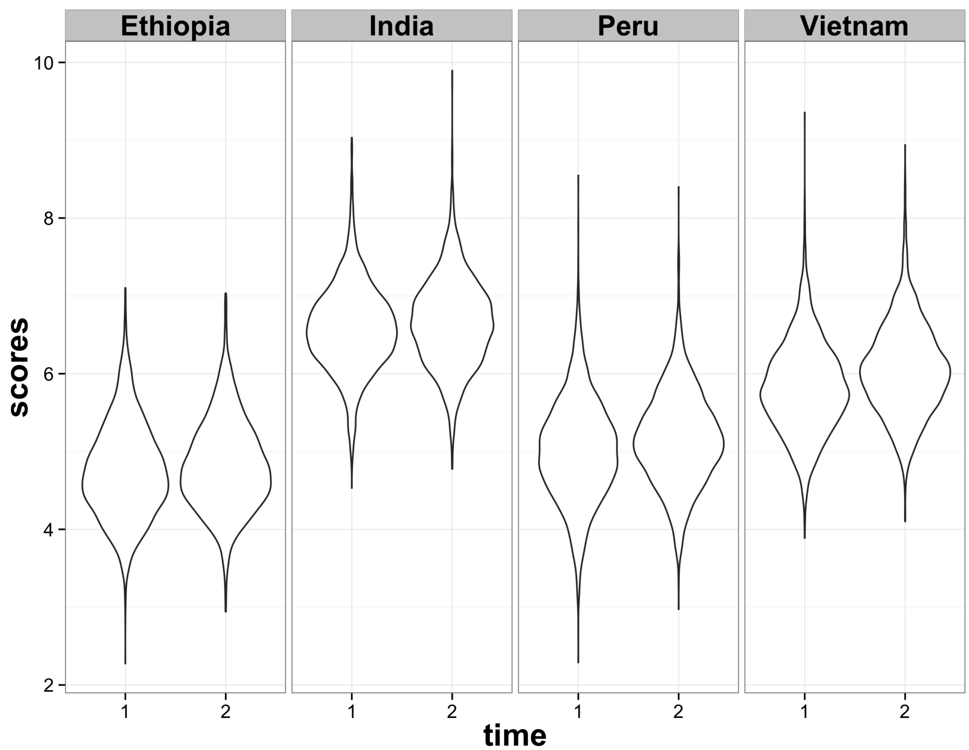

Table 1: Means and standard deviations of height for age by time

Country	Mean hfa, time 1	Sd hfa, time 1	Mean hfa, time 2	Sd hfa, time 2
Ethiopia	-1.430	1.143	-1.267	1.182
India	-1.591	1.014	-1.482	1.039
Peru	-1.544	1.100	-1.248	1.014
Vietnam	-1.326	1.034	-1.153	1.027

Table 2: Proportion of Young Lives children in the older cohort attending school regularly by time

Country	Proportion school-going, time 1	Proportion school-going, time 2
Ethiopia	0.945	0.900
India	0.882	0.797
Vietnam	0.972	0.793

Table 3: Spearman rank correlation over time of wealth index and consumption expenditure

Country	wealth index cor.	consumption cor.
Ethiopia	0.815	0.501
India	0.809	0.468
Peru	0.858	0.614
Vietnam	0.834	0.696

Table 4: Spearman rank correlation of pca scores and log of consumption expenditure

Country	Spearman rank correlation, time 1	Spearman rank correlation, time 2
Ethiopia	0.515	0.504
India	0.389	0.359
Peru	0.597	0.549
Vietnam	0.692	0.682

Figure 3: Scatter plot of loadings (time 2 on time 1) from the first principal component for each consumer durable

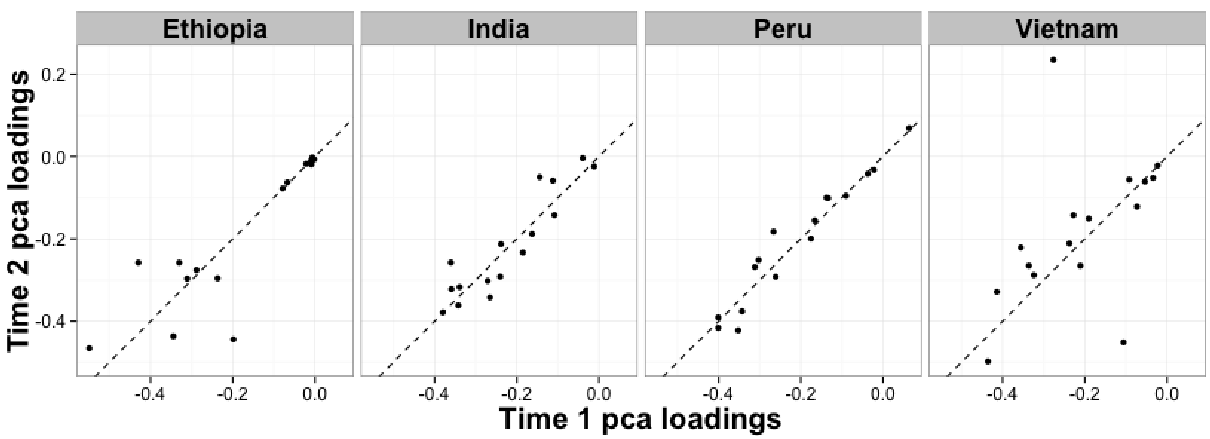

Figure 4: Scatter plot of loadings (time 2 on time 1) from the first principal component for each consumer durable - with names to illustrate outliers

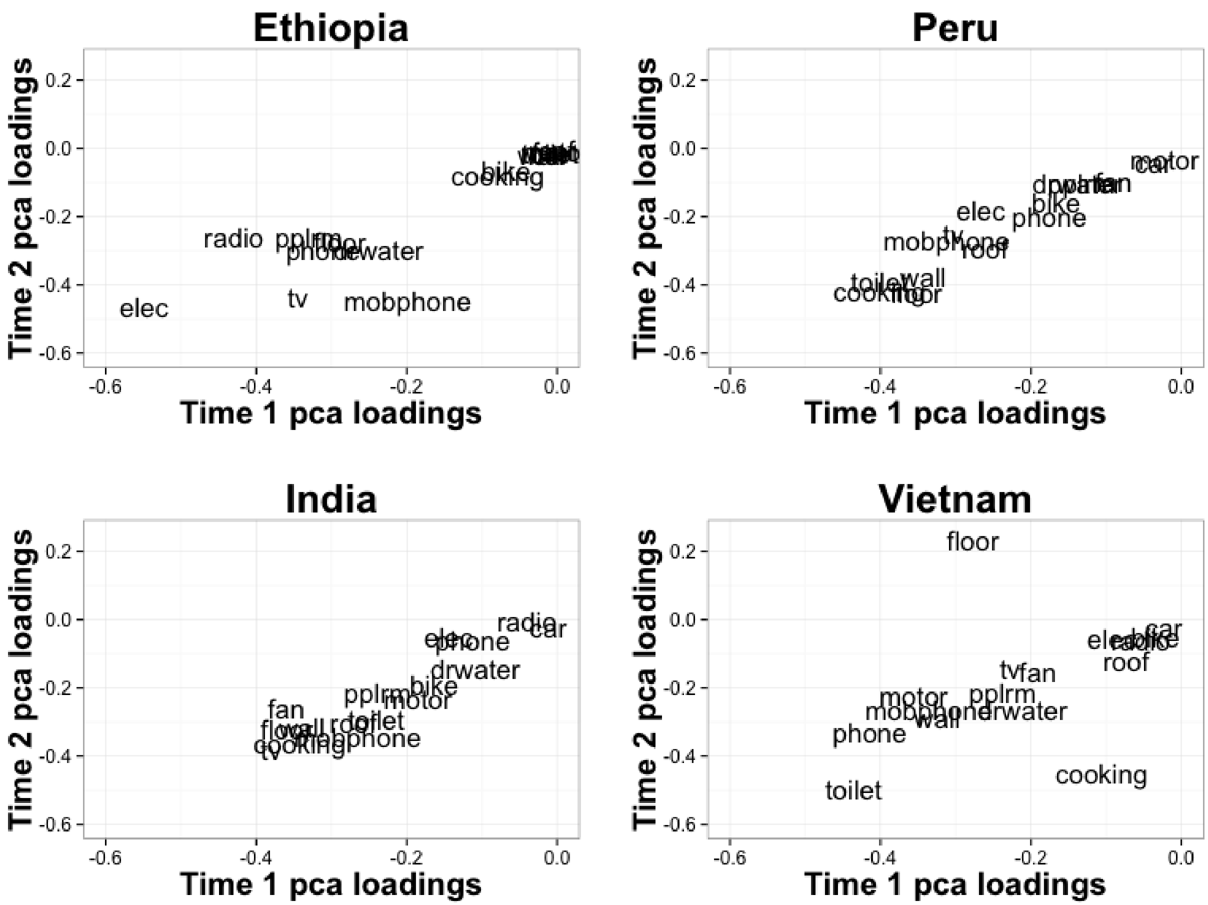

Figure 5: Linear regression of height for age on the wealth index score

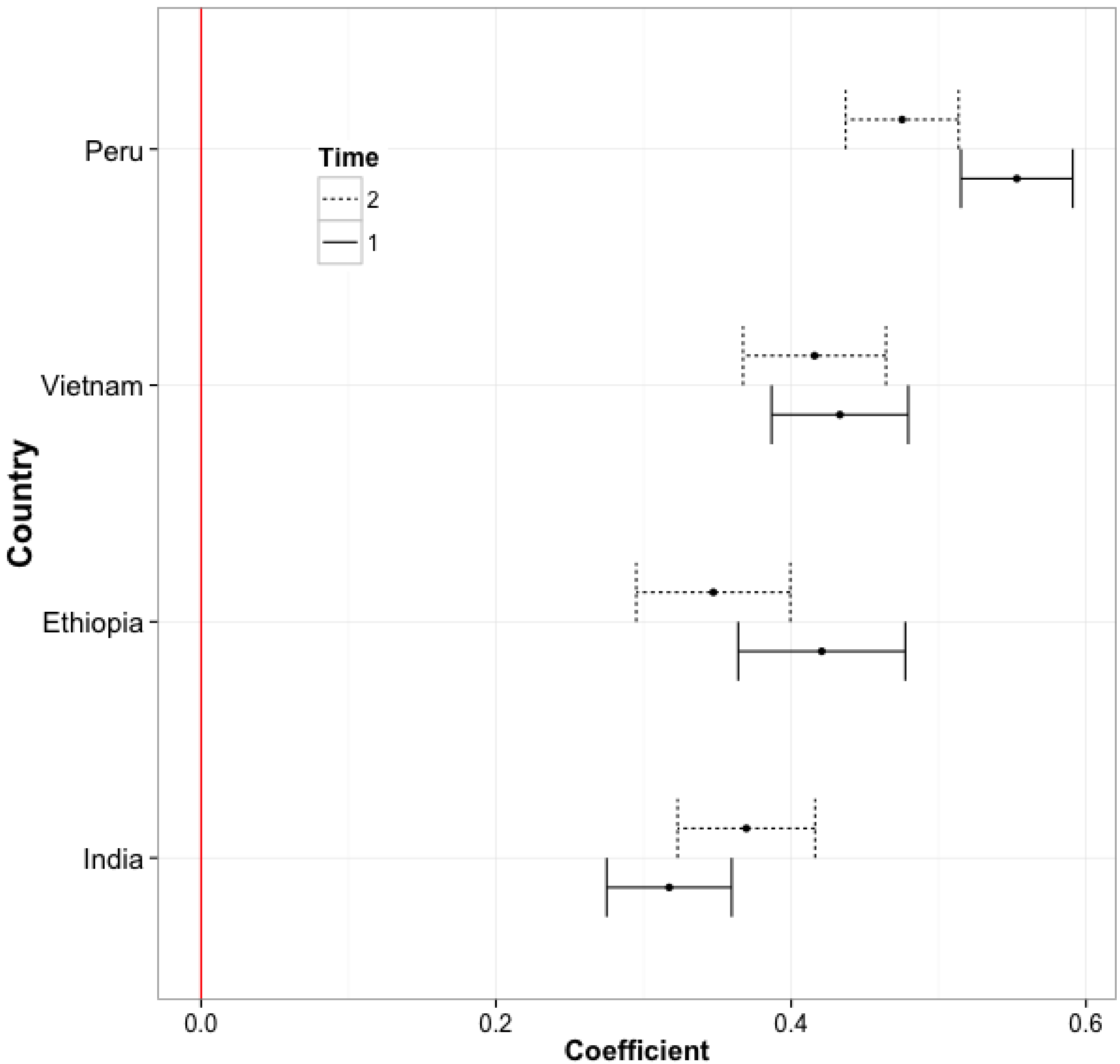

Figure 6: Linear regression of height for age on the log of consumption expenditure

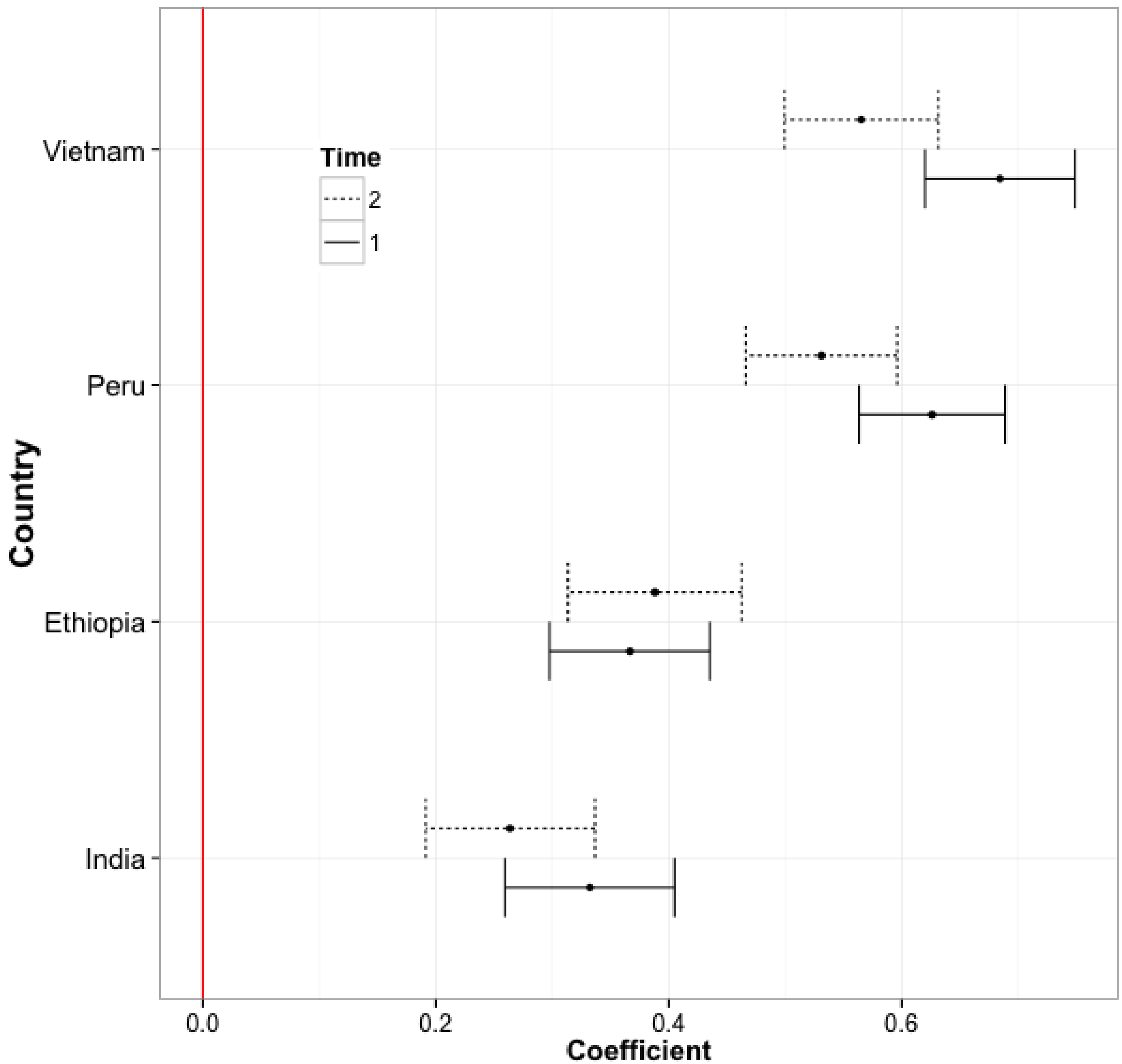

Figure 7: Logistic regression of school-going on the wealth index score

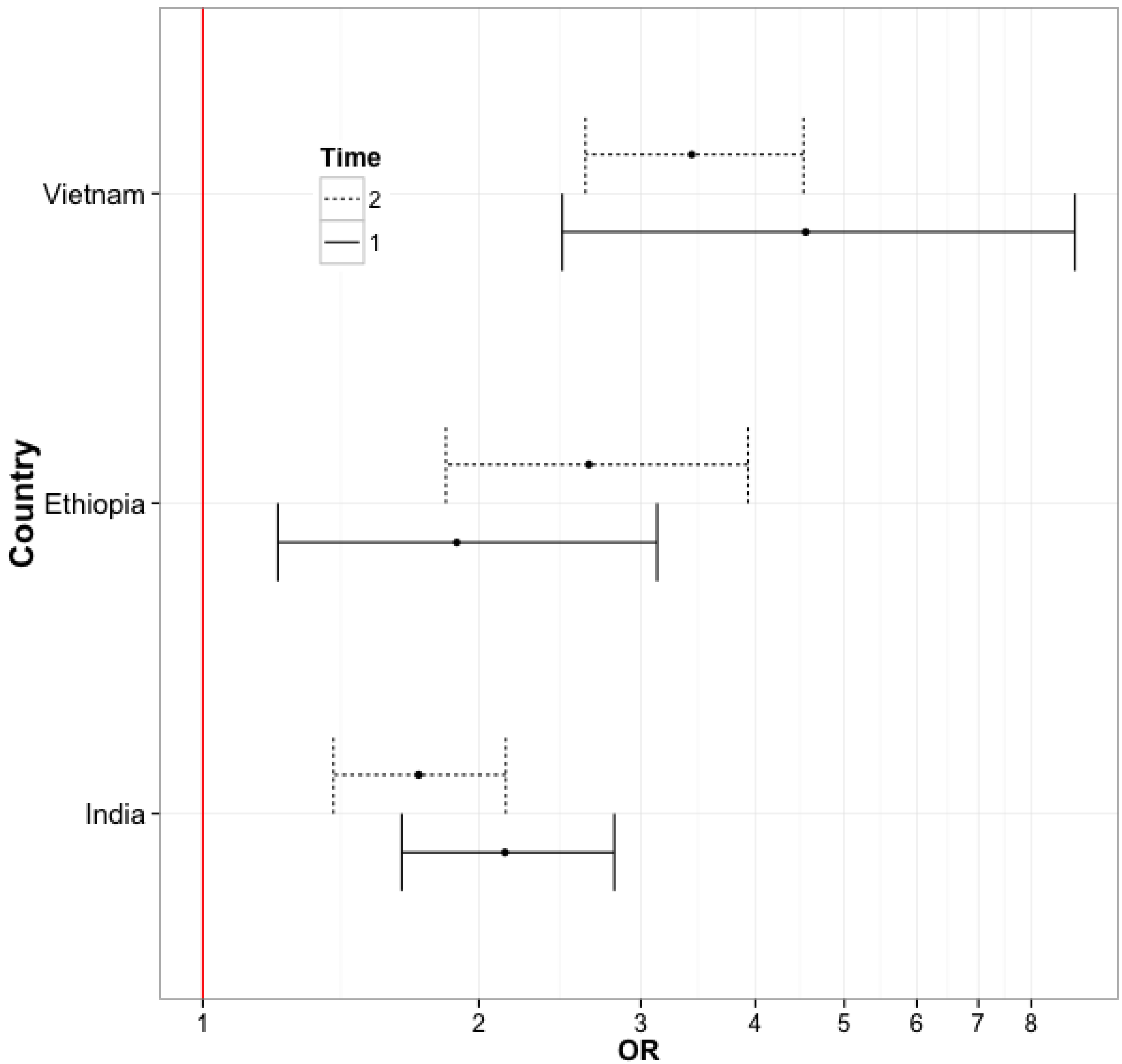

Figure 8: Logistic regression of school-going on the log of consumption expenditure

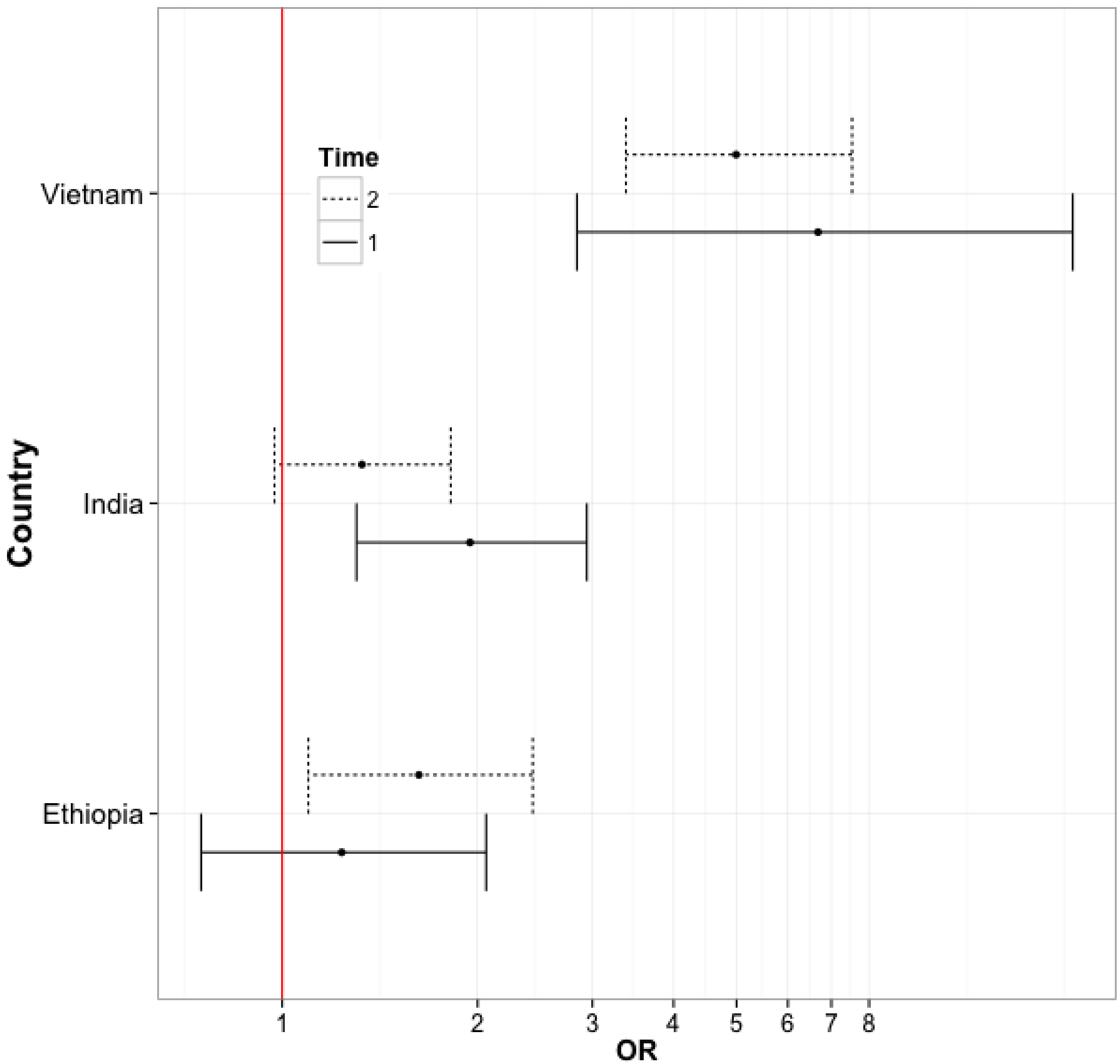

Figure 9: Partial correlation between regression outcome of height for age and the wealth index (controlling for the log of consumption expenditure), and the log of consumption expenditure (controlling for the wealth index)

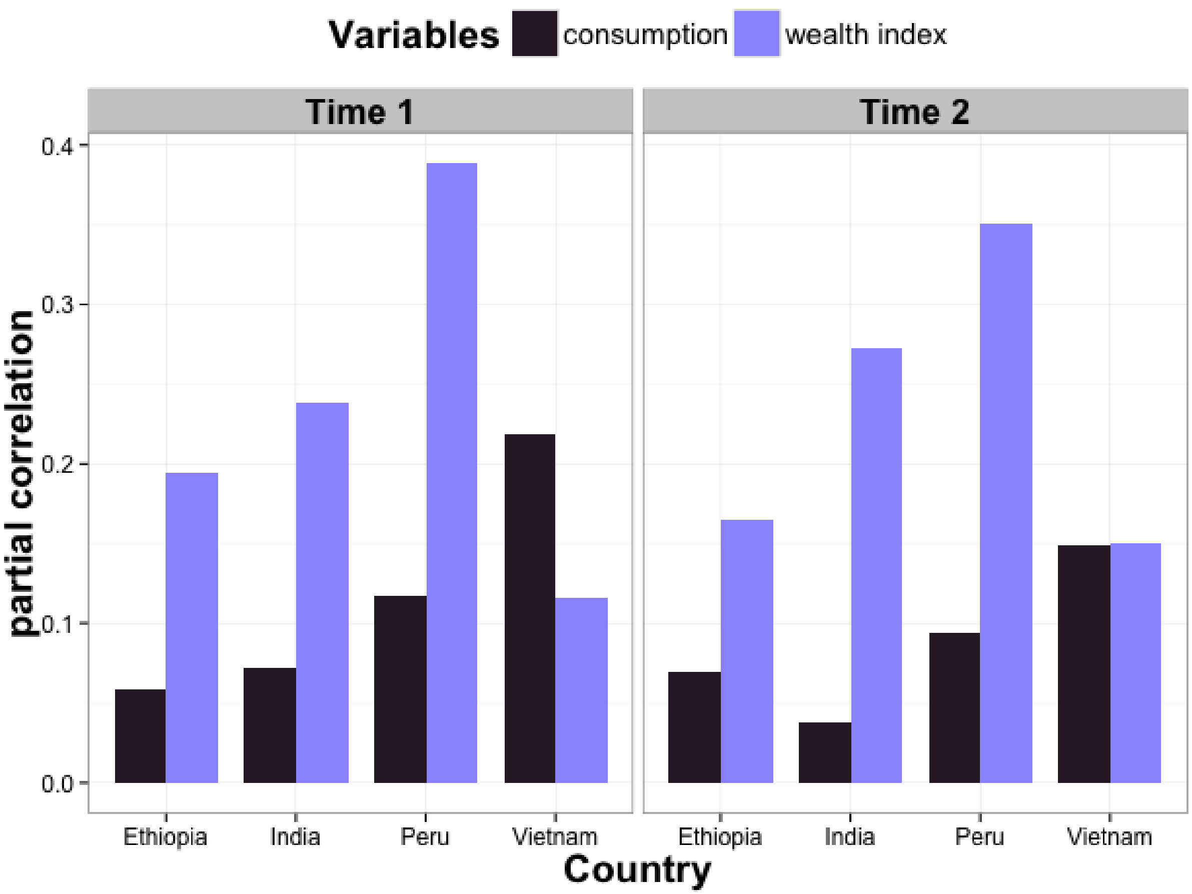

Figure 10: Partial correlation between logistic regression outcome of school-going and the wealth index (controlling for the log of consumption expenditure), and the log of consumption expenditure (controlling for the wealth index)

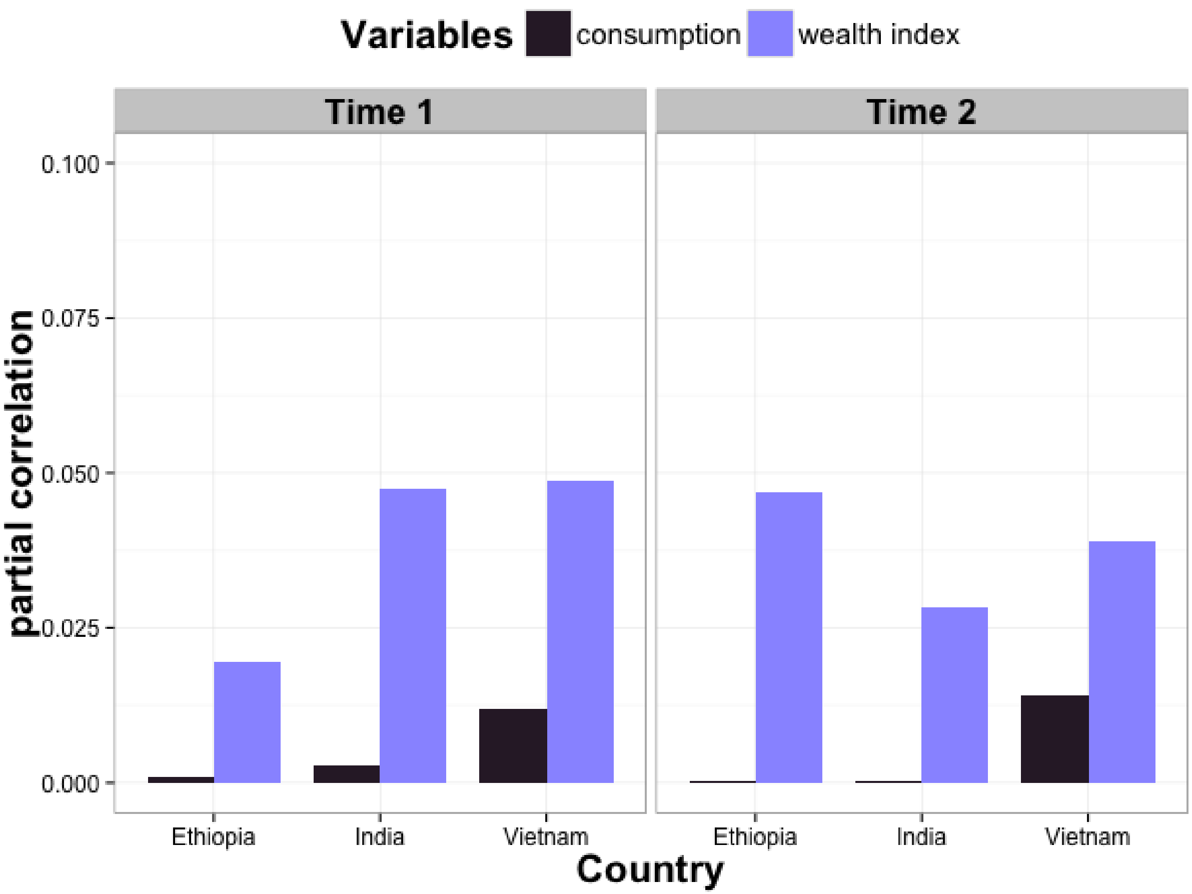

Table 5: Child fixed effects linear regression model of height for age on the wealth index

	Estimate	Std. Error	t value	Pr(>|t|)
Ethiopia	0.042	0.040	1.039	0.299
India	0.024	0.027	0.865	0.387
Peru	0.050	0.029	1.752	0.080
Vietnam	0.041	0.029	1.389	0.165

Table 6: Child fixed effects linear regression model of height for age on the log of consumption expenditure

	Estimate	Std. Error	t value	Pr(>|t|)
Ethiopia	-0.013	0.030	-0.425	0.671
India	0.092	0.026	3.517	< 0.001
Peru	0.194	0.025	7.637	< 0.001
Vietnam	0.169	0.026	6.382	< 0.001

Table 7: Child fixed effects logistic regression model of school-going on the wealth index

	OR	se	z-score	p-value
Ethiopia	0.590	0.709	-0.745	0.456
India	0.280	0.459	-2.772	0.006
Vietnam	0.647	0.438	-0.993	0.320

Table 8: Child fixed effects logistic regression model of school-going on the log of consumption expenditure

	OR	se	z-score	p-value
Ethiopia	0.417	0.437	-2.005	0.045
India	0.103	0.559	-4.065	< 0.001
Vietnam	0.007	0.672	-7.335	< 0.001

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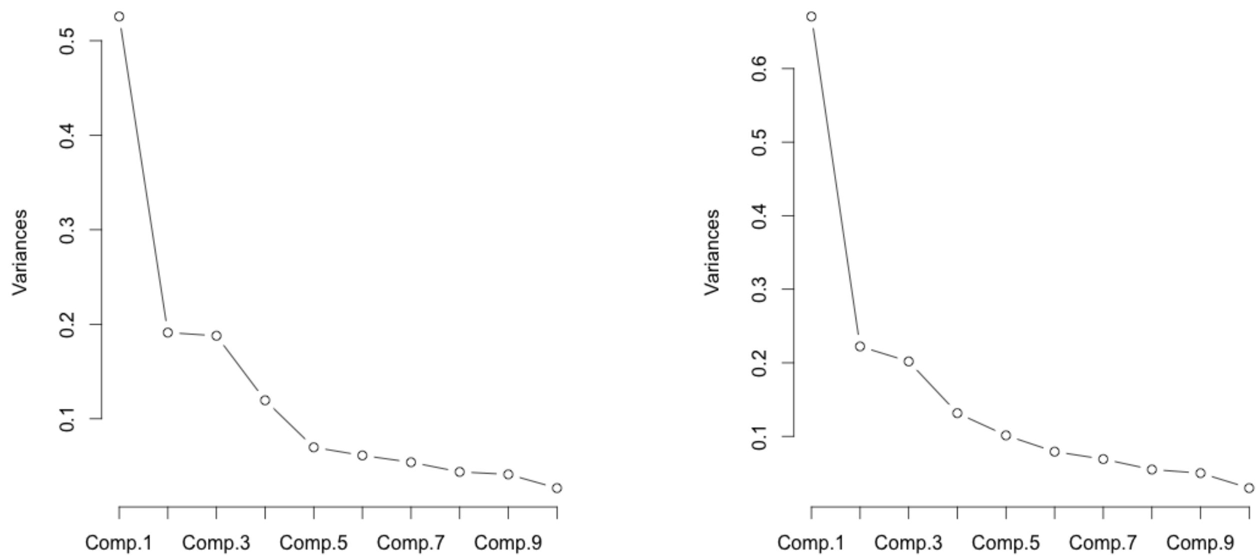
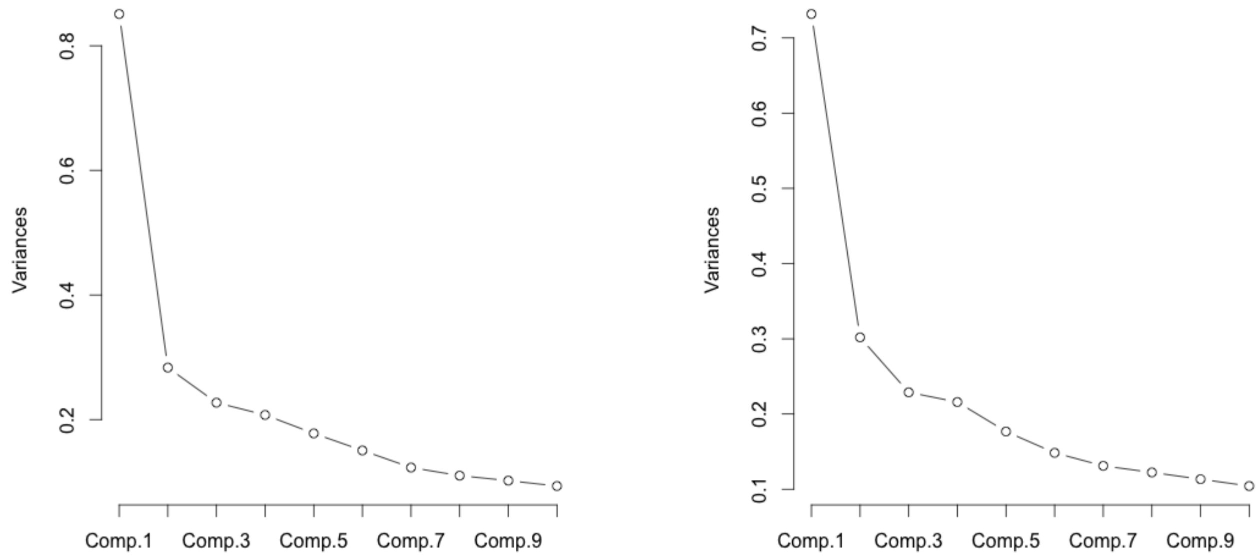
APPENDIX



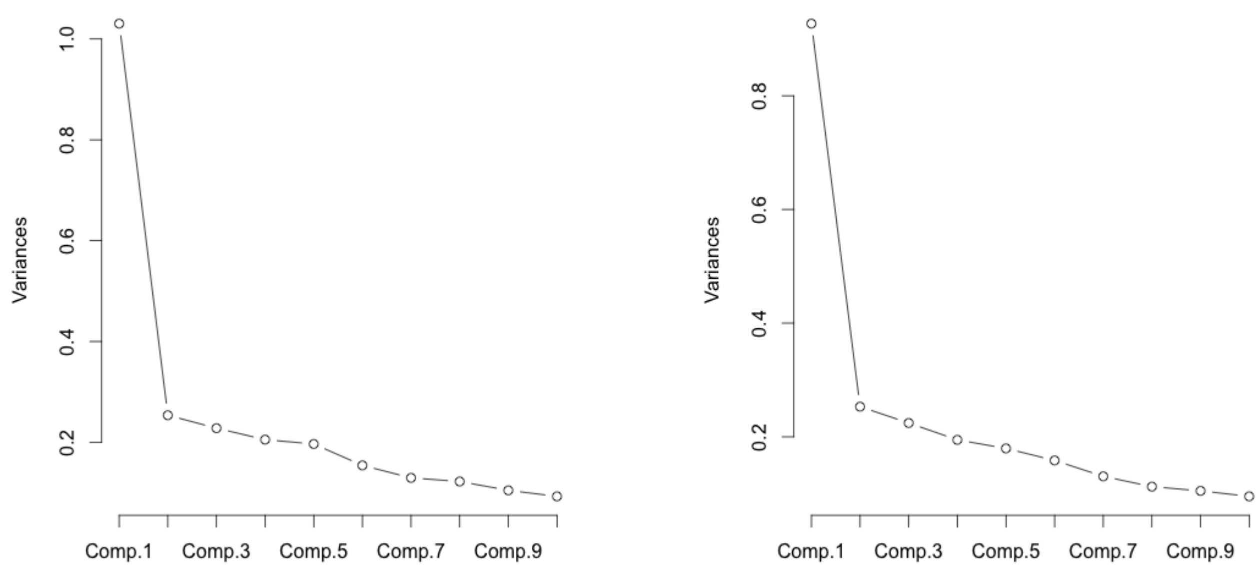
(a) Time 1 (b) Time 2

Figure 1: Scree plots from Ethiopia PCA



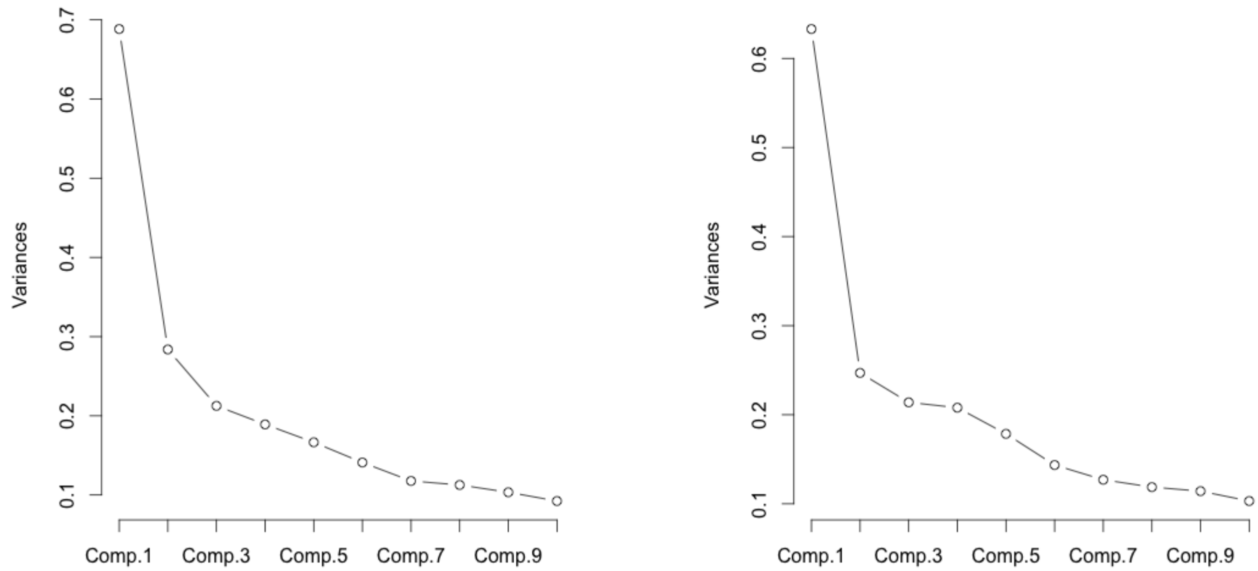
(a) Time 1 (b) Time 2

Figure 2: Scree plots from India PCA



(a) Time 1 (b) Time 2

Figure 3: Scree plots from Peru PCA



(a) Time 1

(b) Time 2

Figure 4: Scree plots from Vietnam PCA

Table 1: Height for age on wealth index (Time 1)

	Country			
	Ethiopia	India	Peru	Vietnam
	(1)	(2)	(3)	(4)
scores	0.421^{***}	0.317^{***}	0.553^{***}	0.433^{***}
	(0.029)	(0.022)	(0.019)	(0.024)
Constant	-1.430^{***}	-1.591^{***}	-1.544^{***}	-1.326^{***}
	(0.021)	(0.020)	(0.020)	(0.020)
Observations	2,763	2,369	2,318	2,445
Adjusted R^2	0.071	0.083	0.260	0.120

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 2: Height for age on wealth index (Time 2)

	Country			
	Ethiopia	India	Peru	Vietnam
	(1)	(2)	(3)	(4)
scores	0.347^{***}	0.370^{***}	0.475^{***}	0.416^{***}
	(0.027)	(0.024)	(0.020)	(0.025)
Constant	-1.267^{***}	-1.482^{***}	-1.248^{***}	-1.153^{***}
	(0.022)	(0.020)	(0.019)	(0.020)
Observations	2,763	2,369	2,318	2,445
Adjusted R^2	0.058	0.092	0.203	0.103

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 3: Height for age on consumption expenditure (Time 1)

	Country			
	Ethiopia	India	Peru	Vietnam
	(1)	(2)	(3)	(4)
ln_cons	0.366^{***}	0.332^{***}	0.626^{***}	0.685^{***}
	(0.035)	(0.037)	(0.032)	(0.033)
Constant	-3.171^{***}	-3.777^{***}	-4.678^{***}	-5.306^{***}
	(0.168)	(0.244)	(0.162)	(0.192)
Observations	2,763	2,369	2,318	2,445
Adjusted R^2	0.038	0.033	0.141	0.151

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 4: Regular regression of height on consumption exp (Time 2)

	Country			
	Ethiopia	India	Peru	Vietnam
	(1)	(2)	(3)	(4)
ln_cons	0.388^{***}	0.264^{***}	0.531^{***}	0.565^{***}
	(0.038)	(0.037)	(0.033)	(0.034)
Constant	-3.138^{***}	-3.239^{***}	-3.991^{***}	-4.576^{***}
	(0.185)	(0.248)	(0.173)	(0.205)
Observations	2,763	2,369	2,318	2,445
Adjusted R^2	0.036	0.021	0.099	0.103

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 5: School-going on wealth index (Time 1)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
scores	0.637^{**}	0.759^{***}	1.513^{***}
	(0.241)	(0.135)	(0.327)
Constant	2.913^{***}	2.176^{***}	4.122^{***}
	(0.154)	(0.128)	(0.329)
Observations	932	781	798

*p<0.05; **p<0.01; ***p<0.001

Table 6: School-going on wealth index (Time 2)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
scores	0.968^{***}	0.542^{***}	1.226^{***}
	(0.192)	(0.110)	(0.140)
Constant	2.348^{***}	1.403^{***}	1.521^{***}
	(0.129)	(0.093)	(0.103)
Observations	926	773	788

*p<0.05; **p<0.01; ***p<0.001

Table 7: School-going on consumption expenditure (Time 1)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
ln_cons	0.211	0.666^{**}	1.899^{***}
	(0.258)	(0.208)	(0.445)
Constant	1.859	-2.371	-7.031^{**}
	(1.211)	(1.357)	(2.401)
Observations	932	781	798

*p<0.05; **p<0.01; ***p<0.001

Table 8: School-going on consumption expenditure (Time 2)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
ln_cons	0.485*	0.283	1.608***
	(0.203)	(0.159)	(0.204)
Constant	−0.114	−0.535	−8.199***
	(0.960)	(1.071)	(1.196)
Observations	926	773	788

*p<0.05; **p<0.01; ***p<0.001

Table 9: Height for age on wealth index and consumption expenditure (Time 1)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
scores	0.362***	0.283***	0.185***
	(0.035)	(0.024)	(0.032)
ln_cons	0.126**	0.139***	0.503***
	(0.041)	(0.039)	(0.045)
Constant	−2.030***	−2.504***	−4.249***
	(0.198)	(0.260)	(0.264)
Observations	2,763	2,369	2,445
Adjusted R^2	0.074	0.087	0.162

*p<0.05; **p<0.01; ***p<0.001

Table 10: Height for age on wealth index and consumption expenditure (Time 2)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
scores	0.281^{***}	0.352^{***}	0.250^{***}
	(0.032)	(0.026)	(0.033)
ln_cons	0.166^{***}	0.070	0.336^{***}
	(0.045)	(0.038)	(0.045)
Constant	-2.069^{***}	-1.951^{***}	-3.186^{***}
	(0.219)	(0.256)	(0.274)
Observations	2,763	2,369	2,445
Adjusted R^2	0.062	0.093	0.123

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 11: School-going on wealth index and consumption expenditure (Time 1)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
scores	0.700^{**}	0.706^{***}	1.162^{**}
	(0.263)	(0.142)	(0.404)
ln_cons	-0.172	0.271	0.826
	(0.295)	(0.218)	(0.577)
Constant	3.727^{**}	0.380	-0.614
	(1.407)	(1.445)	(3.292)
Observations	932	781	798

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 12: School-going on wealth index and consumption expenditure (Time 2)

	Country		
	Ethiopia	India	Vietnam
	(1)	(2)	(3)
scores	1.000^{***}	0.529^{***}	0.895^{***}
	(0.210)	(0.115)	(0.173)
ln_cons	-0.092	0.065	0.785^{**}
	(0.245)	(0.163)	(0.252)
Constant	2.792^{*}	0.964	-3.186^{*}
	(1.184)	(1.100)	(1.505)
Observations	926	773	788

$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$