ESTIMATING HOUSEHOLD PERMANENT INCOME FROM OWNERSHIP OF PHYSICAL ASSETS

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1. INTRODUCTION

In theory, household income is an important determinant of many demographic process including fertility (Easterlin 1975), mortality (Kaplan 1996, Fiscella 1997), and migration (Massey 1990, Reardon 1997). However, many demographic surveys of households do not directly ask for information on household income, expenditure, or wealth. This includes the Demographic and Health Surveys. In the absence of direct measurement, researchers often use proxy indicators of income based on household ownership of physical assets, such as television, refrigerator, automobile, phone, watch.

One approach is to simply use an asset index based on the number of assets the household owns from a defined set (Howe, Hargreaves et al. 2008; Alkire and Santos 2010). Filmer and Pritchett, 2001, argue that the first principle component of the household's ownership of household physical assets is highly correlated with household expenditure and can be used as a reasonable proxy. Many studies have used this as their proxy of household income and the demographic and health surveys and Multiple Indicator Cluster Surveys now routinely include wealth quintiles based on the first principle component of household physical assets (Rutstein and Kiersten 2004). An alternative approach is to treat income as a latent variable and estimate this latent variable based on asset ownership (Ferguson et al 2003, Bollen, Glanville and Stecklov 2007) though in practice the results of the latent variable and principle component measures are very similar.

While these methods are reasonable and may be satisfactory in a single survey carried out in one country at a point in time there is a difficulty when we want to compare across surveys carried out in different countries or in one country in different years. In a single survey, in one country, in one year, it is reasonable to assume that all households face the same prices for assets. It is becoming increasing common however to merge survey data from several countries or to compare the evolution of outcomes in several surveys over time which raises the issue of comparability of the income proxy across surveys. Households in different countries they may face very different real prices of assets due to factors such as tariffs and national market imperfections. Where we compare households from different years, technological progress may change the price of some assets. For example, the ownership of mobile phones has expanded enormously in many developing countries, but this is due more to the falling prices of mobile phones than rising incomes. We therefore want to devise a method for estimating household income from ownership of assets that adjusts for the price of assets and allows comparison across countries and over time. Even within one survey we may want to adjust our income estimates for the fact that households in different regions, or urban and rural areas, may face different prices from each other (Deaton 2003).

We develop a theoretical approach to constructing a measure of household income using physical assets. The basis of our approach is that in theory the demand for goods depends on permanent income[1], prices, and preferences. We assume preferences, which are not observed, differ across households but are uncorrelated with permanent income. Then, given a household's ownership of physical assets, and the prices of those assets, we can in principle produce an estimate of the household's permanent income. In order to do this we use a first order approximation to a utility function. Our approach is conceptually similar to Young (2009) who

[1] Permanent income is equal to current income minus any temporary current shock; it is the level of income households expect in the future.

produces estimates of the growth rate of the standard of living in Sub-Saharan Africa that combine estimates of health, education, consumption, and time use, where the consumption component is proxied by asset ownership allowing for price changes over time. We show that in a single survey, in which prices faced by all households are the same, we can estimate a measure of household income as a common household random effect that affects the demand for each good. The latent variable, or common factor approach, produces estimates that are highly correlated with first principle component in practice. It follows that for a single survey in which households all face the same prices for assets our approach is very similar to existing methods.

The advantage of using our approach become evident when we consider comparisons across surveys that take place in different countries or in different years since we allow for differences in the price of assets faced by different households. A second advantage of our latent variable approach is that it allows for different surveys to have information on different sets of physical assets (so long as there is at least one asset in common). All asset information present in each survey can be used. In addition, if a household has missing data for an asset its income can still be estimated from the data on asset ownership that we do have. Having information on a restricted set of assets for some observations still allows us to estimate income for these households though the precision of the estimate will be reduced.

The estimates of household permanent income produced by our methods may be used in subsequent regression analysis by researchers who wish to allow for the effect of household income on other outcomes. Our estimates can be used to find the expected value of household permanent income given the observed prices and ownership of household physical assets. However our estimates contain parameter uncertainty, and noise, and therefore should not be used in the same way as direct observation. Using the permanent income index directly will tend to lead to underestimation of the effect of income. A simple parametric bootstrap can be used to generate a number of potential values of household income drawn from the underlying distribution of income conditional on prices and asset ownership. These multiple draws of potential values for household income can be used in subsequent regression analysis in the same way as data generated for missing observations through multiple imputation (Rubin 1987).

The paper is structured as follows. In section 2 we describe our theory-based estimation approach and show how our method can be used to construct estimates of income that are comparable over time and across countries. In section 3 we compare our permanent income index for a single survey with those from principle component analysis and with reported household income and expenditure using surveys that contain both ownership of physical assets and data on income and expenditure. In section 4 we estimate average national income for countries using survey data on ownership of physical assets adjusting for country specific asset prices and compare our estimates with the standard approach using national income accounts. We show how to generate multiple estimates of income using our method that can be used in subsequent regression analysis in section 5. In section 6, we discuss the limitations of our approach and possible future developments. Section 7 concludes.

2. THEORY

Consider household *i*, in a survey k that takes place in country in a particular year. There are n assets indexed by $j = 1,....,n$ whose ownership is determined by questions in at least one survey. In a parsimonious view of the world, we consider household utility as a function of asset ownership, A_{ij}, which takes the value either zero or one depending on whether household i owns asset j, and consumption of other goods by the household, M_i. We assume there is a common "basket" of goods that households can buy in addition to assets and M_i is the number of baskets the household purchases. "Other goods" represent all consumption except for the assets. We take this basket of goods to be the numéraire with a price normalized to one. Each asset costs a price, p_{jk}, which may vary between surveys and is measured in units of baskets of other consumption goods. Thus household utility can be expressed as a function of asset ownership and consumption of other goods. We can express the budget constraint for the household as

$$M_i + \sum_{j=1}^{h} p_j A_{ij} = Y_i$$

where Y_i is household income or total expenditure and the price of each asset is in terms of the number of baskets of consumption goods needed to buy it. We assume a one period model which income equals the total value of expenditure during the period. We can think of the budget constraint as holding within the period, not allowing saving. However it is possible to allow for saving and think of Y_i as total current expenditure or permanent income. With smoothing of consumption across time, the household adjusts current expenditure to the value of permanent income, which is income short of its short term fluctuations. Any transitory shocks to income, lead to adjustments to saving rather than expenditure. Our aim is to construct a robust method of transforming information on household asset ownership into a measure of income.

Household utility can be expressed as a function U_i of asset holding and consumption of other goods. As other goods represent all consumption except for the assets, we can express this consumption as income, *Y*, less the cost of all assets.

$$U_i(A_{i1}, A_{i2}, A_{i3}, ..., A_{ih}, M_i) = U_i(A_{i1}, A_{i2}, A_{i3}, ..., A_{ih}, Y_i - \sum_{j=1}^{n} p_{jk} A_{ij})$$

Taking a linear approximation around zero asset ownership we have

$$U_i(A_{i1}, A_{i2}, A_{i3}, ..., A_{ih}, M_i) \approx U_i(0,0,0,...,0,Y_i) + \sum_j \left(\frac{dU_i}{dA_{ij}} - \frac{dU_i}{dM_i} p_j \right) A_{ij}$$

where the derivatives are evaluated at $(0,0,0,...,0,Y_i)$. . .

Using this linear approximation a household *i* buys good *j* $(A_{ij} = 1)$ if it increases its utility which means that

$$\frac{dU_i}{dA_{ij}} \geq \frac{dU_i}{dM_i} p_{jk}$$

Taking the logs of both sides we get,

$$\log\frac{dU_i}{dA_{ij}} \geq \log\frac{dU_i}{dM_i} + \log p_{jk}$$

We assume utility takes the form

$$U_i(A_{i1}, A_{i2}, A_{i3}, ..., A_{in}, M_i) = \frac{M_i^{1-\phi}}{1-\phi} + \sum_j e^{\beta_j + \varepsilon_{ij}} A_{ij} + \sum_{j,j'} e^{\gamma_{jj'} + \varepsilon_{ijj'}} A_{ij} A_{ij'}$$

Hence the log of the derivatives evaluated at $(0,0,0,...,0,Y_i)$ can be written as

$$\log\frac{dU_i}{dA_{ij}} = \beta_j + \varepsilon_{ij}, \quad \log\frac{dU_i}{dM_i} = -\phi \log Y_i$$

This means our condition for buying the good can be written as,

$$\beta_j + \varepsilon_{ij} \geq -\phi \log Y_i + \log p_{jk}$$

$$\beta_j + \phi \log Y_i - \log p_{jk} \geq -\varepsilon_{ij}$$

Our separable utility function and linearization mean that the desire to buy any asset depends on income, price, and household preferences of the asset. The interactive effect from owning particular pairs of assets drops out with linearization. The linearization means we ignore any effect owning one asset has on the demand for other assets.

We now assume that $\log Y_i$ is distributed normally in each survey around a country survey specific mean. The assumption that income has a log normal distribution is a reasonable approximation to the distribution of income at a point in time in most countries since there are strong theoretical and empirical reasons why permanent income and expenditure should have a log normal distribution (Battistin, Blundell, and Lewbel, 2009).

This implies that we can write

$$\phi \log Y_i = \alpha_k + \mu_i$$

Where u_i is mean zero, independent, and normally distributed, and that α_k / ϕ is a survey fixed effect representing the mean level of log income. If we add the assumption that each ε_{ij} is independently distributed with a logistic distribution, we have a logit model for the consumption of each good with good specific fixed effects and a household random effect. Household i buys asset j if

$$\alpha_k + \beta_j - \log p_{jk} + \mu_i \geq \varepsilon_{ij}$$

Suppose we are dealing with only one survey, so we can drop in the index k. The condition for buying the asset reduces to

$$\alpha + f_j + \mu_i \geq \varepsilon_{ij}, \quad where\ f_j = \beta_j - \log p_j$$

We can estimate the ownership of household assets as depending on an asset fixed effects f_j and a household random effect μ_i. To do this we have to assume that the error terms ε_{ij} which represent household preferences for the assets are uncorrelated with the household random effect μ_i which depends on its income.

The advantage of our theory is that the asset fixed effect and household random effect have natural interpretations. The asset fixed effect is $f_j = \beta_j - \log p_j$. Households are more likely to buy the asset if the average marginal utility from the asset is high relative to the price. The household random effect comes from the fact that richer household are more likely to buy assets and the household random effect $\mu_i = \phi \log Y_i - \alpha$ is a linear transform log income.

It follows that we can estimate household permanent income from a data set of household asset ownership simply by running a regression explaining asset ownership as an asset fixed effect plus a household random effect. The household random effect can then be used for further research as a proxy for income on the understanding that it is a linear transform of log income. For many purposes this is all we need for further analysis. Adding our estimated household random effect will have the same effect as controlling for log household income.

If we want to have an estimate of actual household income we can estimate μ_i from a dataset that contains household asset ownership and use the equation

$$Y_i = e^{-(\alpha + u_i)/\phi}$$

to get an estimate of actual household income. To do this we need an estimate of ϕ, the coefficient of relative risk aversion and α the mean of log income. We can estimate α, ϕ from a dataset where we have data both on household income and household ownership of assets. We can use the resulting estimates of α, ϕ to calibrate our estimate of household permanent income given its ownership of assets.

The analysis above is based on all the data coming from one country and we used that fact that all households face the same price of the assets. This is not true when we look across countries or over time. Let p_{jk} be the price of asset *j* in survey *k* of particular country in particular year. These prices are measured in terms of a common basket of consumption goods that the household would buy if it did not buy the asset. We deal with the issue of measuring this in practice below. Given the country specific price of the asset, the household buys the asset if

$$\alpha_k + \beta_j - \log p_{jk} + \mu_i \geq \varepsilon_{ij}$$

Note that we keep β_j the same across countries and time. This means the asset is on average equally desirable in different countries and at different times. In one country we assumed that log income was normally distributed around a country mean. When we have several countries we assume that log income is normally distributed around a country mean in each country but the country means can vary across countries. We can estimate this equation by regressing asset ownership on a country fixed effect, an asset fixed effect, and a household random effect, and allowing for the effect of asset prices p_{jk} in each country, with a coefficient on the price effect that is constrained to be minus one. We can then use the estimated values $\alpha_k + \mu_i$ as a proxy for household income for household *i* in survey *k*. Note that in estimating this equation across surveys the fixed effects on survey and assets are collinear. We therefore drop one of the survey fixed effects, say α_0 on survey the baseline zero. This is not a problem if we wish only to have a proxy for income since again we have that $\alpha_k + \mu_i$ is a linear transformation of log household income. If we want to have an actual estimate for household income we need to calculate

$$Y_i = e^{-(\alpha_0 + \alpha_k + u_i)/\phi}$$

We can do this by calibrating the link between the latent household variable and income from the baseline survey to give estimates of α_0, ϕ and then use these estimates to give estimates of household income across all our surveys. This means that if we want actual estimates of household income we need to have a baseline survey in which we have both income and asset data. Using this to calibrate α_0, ϕ we can then generate estimates of income in all the other surveys using only their asset data.

Prices

To calculate the price of an asset in a survey we use data from the World Bank's International Comparison Program. This gives prices for categories of goods in local currency units. It also estimates the cost in local currency units of a common basket of goods based on the average consumption bundle bought worldwide. Let P_{jk} be the price of the asset j in the country at the time of the survey k measured local currency units. The International Comparison Program takes pains to try to measure prices of the same or comparable goods across countries to avoid quality differences. Let P_k be the price in local currency units of the common basket of goods as defined by the International Comparison Program in the same country at the same time. Then we have that the real price of asset j in survey k is

$$p_{jk} = P_{jk} / P_k$$

For example, comparing Egypt and Colombia using the p_{jk} for motorcycle and mobile phone: $p_{motorcycle,Egypt}$ = 4.52 is interpreted as 4.52 units of global basket of goods which can be purchased with an amount equivalent to 1 motorcycle in Egypt. Similarly, $p_{phone,Egypt}$ =2.51 indicates about 2.51 units of global basket of goods can be purchased with the same amount it takes to purchase a phone in Egypt. From this, we infer that a motorcycle in Egypt is more expensive than a phone. When we compare Egypt to Colombia, we calculated $p_{motorcycle,Egypt}$=4.52 and

$p_{motorcycle,Colombia}=3.72$. We infer that an individual in Egypt who purchases a motorcycle would forgo more units of global basket of goods compared to an individual in Colombia.

A common problem in this type of analysis is that the common basket of goods should be representative of what people in each setting actually buy. If the goods consumed in the two settings are very different the common basket may not be representative of either and resulting estimates of income based on common basket of goods may be misleading (Deaton 1975).

Statistical Analysis

To estimate permanent incomes, we employ a multilevel logit model of the following form:

$$\text{logit}(\Pr(A_{ijk}=1)) = \alpha_k + \beta_j - \log p_{jk} + \mu_i \quad (1)$$

where A_{ijk} is a binary indicator for holding an asset j in household *i* within survey *k*. Note that the number of observations in this regression is the number of surveys, times the numbers of households, times the number of assets. That is, we have a separate observation for each asset. If we are estimating with only one survey and can assume priced faced by each household are the same this reduces to

$$\text{logit}(\Pr(A_{ij}=1)) = \alpha + \beta_j + \mu_i$$

Where β_j is an asset fixed effect and μ_i is household income. We calibrate the model in four different economic contexts: Tanzania 2004, Peru 1994, South Africa 1994 and Egypt 1988, 2005 using data from Living Standard Measurement Study (LSMS) in each country that include information on household income and expenditure, and household assets. We treat each survey independently and compare our estimates of household income based on assets with the reported information on income and expenditure.

All available household assets except bicycle in the individual LSMS surveys were used in the generation of household permanent income estimate. Our model implies that ownership of each asset should increase on average with income. Preliminary studies showed that ownership of all other assets increased with income and expenditure. However, bicycle ownership first rises with income and then falls. It may be that car and bicycle ownership are strong substitutes. When households own a car the benefits of a bicycle become very small. This will appear in the interactive term between asset owned in our utility function but is ignored by our linearization. To properly model bicycle ownership we would require at least a second order approximation to the utility function that allowed for these interactive effects. We therefore propose that assets such as bicycles whose ownership does not increase with income be dropped from the analysis when our linear approximation to the utility function is used.

The permanent income estimates are compared with reported household income and expenditure. South Africa 1994 was further used in regressions between household expenditure and the estimated permanent income index, along with other socio-demographic covariates such as cluster-level electricity access, urban rural location, household highest education level, household size, percentage of children (<15 years old) and percentage of adult females. DHS Egypt survey 1988 and 2005 were used to demonstrate temporal comparison within a country. Seven asset types were used to generate the household permanent income estimates. Mean permanent income estimate percentiles were compared across the survey years to explore trends in household wealth. Cross-country comparison of absolute permanent income index uses households from 225 DHS and MICS surveys of 117 low- and middle-income countries completed as early as 1990 and as late as 2008.

Data Sources

Household level Data

The household level data sources for the empirical analysis are from the Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), and the Living Standards Measurement Study Surveys (LSMS). Each of these surveys contains data on fertility behavior and household health and socio-economic status. Table 1 shows the distribution of the surveys over time and across regions. Our sample consists of households from 225 surveys of 117 low- and middle-income countries completed as early as 1990 and as late as 2008.

The DHS is a nationally representative, cluster randomized household survey initiated in the late 1980s by the US Agency for International Development. The DHS contains household characteristics. And gives a particular focus on women aged 15-49 and children, but also information on men aged 15-54 or 59 in more recent surveys. The surveys have a common design, with some variation in specific questions across countries and a wider range of variables available in recent waves. The survey is an ongoing initiative, and has come to span 73 developing countries with up to five survey waves in each country. There are 181 standardized (recoded) and publicly available country surveys. We have merged these surveys into a single dataset for statistical analysis.

The Multiple Indicator Cluster Surveys (MICS), published by UNICEF, is a household survey carried out in a range of countries in 1998 designed to complement the DHS. The MICS focus on childhood health, and nutritional status, with additional data on standards of living based on household ownership of assets and housing construction. In our study, we used MICS Wave 3, which includes 44 surveys from 44 countries.

The Living Standards Measurement Study (LSMS) has the advantage of having detailed information on household income and expenditure, as well as individual earnings. It is used in our study to help elucidate the relationships between our permanent income estimate and self-reported, cross-sectional income and expenditure. From 1985 to present, there are 32 participating countries, with multiple survey waves in 17 countries and panel datasets for 9 countries. We will use data from three countries: South Africa, Peru, and Tanzania to validate and demonstrate application of our household permanent income index.

Country level Data

Country level data include country-specific prices of assets from the World Bank's International Comparison Program (ICP) and international indices from the Multi-Dimensional Poverty Index (MPI) and Human Development Indicator (HDI), as well as real GDP per capita estimates from the Penn World Tables (PWT).

The ICP provided country-specific, internationally comparable price levels and purchasing power parities (PPPs) from 2005. The PPPs are derived from global program of national surveys that priced nearly 1000 products and services from 146 economies. The country-specific PPPs and expenditures are further divided into 129 basic headings of similar goods or services such as "major household appliances", "small electric household appliances", "motor cars", "telephone and telefax equipment", "jewelry, clocks and watches". Prices at this level of basic headings are used as asset prices in our generation of permanent income estimates.

The Penn World Table (PWT) displays a set of national accounts economic time series covering many countries. Its expenditure entries are denominated in a common set of prices in a common currency so that *real* quantity comparisons can be made, both between countries and over time. It also provides information about relative prices within and between countries, as well as demographic data and capital stock estimates. PWT uses ICP benchmark comparisons as a basis for estimating PPPs for non-benchmark countries and extrapolates backward and forward in time. The PWT 6.3 covers 190 countries and territories, 1950-2009, with 2005 as reference year.

The Human Development Index (HDI), published by United Nations Development Programme (UNDP), provides a composite score based on three dimensions: 1. Life expectancy, 2. Education: mean years of schooling for adults and expected years of schooling of children 3. Living standards: gross national income per capita. The HDI uses the logarithm of income, to reflect the diminishing importance of income with increasing gross national income. The scores for the three HDI dimension indices are then aggregated into a composite index using geometric mean. The index covers 195 countries over 30 years. HDI uses life expectancy at birth provided by the UN Department of Economic and Social Affairs; mean years of schooling by Barro and Lee (2010); expected years of schooling by the UNESCO Institute for Statistics; and GNI per capita by the World Bank and the International Monetary Fund. For few countries, mean years of schooling are estimated from nationally representative household surveys such as the WFS and DHS.

The Multidimensional Poverty Index (MPI) is a new international measure of poverty developed by the Oxford Poverty and Human Development Initiative (OPHI) and the UNDP Human Development Report in 2010. It covers 104 developing countries. The MPI uses 10 dichotomized depravation indicators: nutrition, child mortality, year of schooling, school enrollment, and standard of living: cooking fuel, sanitation, drinking water, electricity, floor and asset ownership. The data is based on three sources: DHS, MICS and the World Health Survey. MPI is reported to be robust, where 95% of country comparisons do not change if the poverty cutoff ranges from 20% to 40% of the dimensions. MPI is also robust to weight variations. (MPI, 2010)

3. Household Income Within Country: Comparison with Principle Component Analysis

The approach used in this study offers an avenue to determine household level income from a list of asset holdings. The household level and the macro-cross country results allow us to discuss this methodological approach compared to existing methods and interpret the results with theoretical basis.

Household Level Validation of Permanent Income Index

While the aim is to estimate a measure of household permanent income that is comparable *across* countries, we will check our functional form for the utility of other goods and estimate correlation and the coefficient of relative risk aversion, ϕ , using data from surveys that contain both income and asset holdings. Examples of this are the LSMS data. We selected three countries for household level validation: Peru, Tanzania and South Africa.

Looking at the correlation between the generated permanent income index and self-reported household annual income and expenditure in the three surveys, we find that the correlation with income are consistently lower than with expenditure. Many households reported zero income in the past 12 months from the LSMS surveys. This dramatically reduce the sample size when we take the natural log of income in our model, i.e.in Tanzania LSMS 1994, sample size reduced by over 50% (Table 4).

Our correlation of permanent income estimates and household annual expenditure are 0.75, 0.70, 0.68, and with household annual income are 0.70, 0.40, 0.59 for South Africa, Tanzania and Peru, respectively. Compared to method of principal component analysis (PCA), the correlations with expenditure are similar in all three countries (Table 4). An important aspect of our income estimation model is the resulting constant coefficient of relative risk aversion. This coefficient enables extrapolation of household level income and expenditure from historical surveys that had data on asset holding but may not contain income or expenditure data. The coefficient, ρ, linearly transforms log of reported income or expenditure to permanent income estimate. The coefficient is based on the Arrow-Pratt measure of relative risk-aversion where the utility function changes from risk-averse to risk-loving as income changes. For income, the coefficient lies below 1.0; for expenditure, the coefficient lies close to 1.0 for all households (Table 5).

Figure 1 to 9 depict graphically the relationship between permanent income index and reported income, expenditure and asset index from PCA in three countries. Each household represent a data point in the graph. The lower the permanent income index, the poorer the households were according to the index generated by this approach. In South Africa, permanent income index is linearly associated with household reported income and expenditure. Each permanent income index value from the developed index corresponds to a range spanning approximately e^4 South African Rand (ZAR) of composite household income and household expenditure. The range begins to widen as households are positioned poorer on the estimation. This trend is more pronounced in Peru, where the range of household reported income and expenditure corresponding to permanent income index gradually increase toward the poorer end of the spectrum. In 1994 Peru LSMS, the maximum range in the lowest end of the permanent income index span e^4 Peruvian Nuevo Sol (PEN) in household reported income and expenditure. In Tanzania, the estimate exhibited a less defined linear association with household reported income and expenditure. The graphs exhibit bottom heavy association similar to South Africa and Peru. Furthermore, the permanent income index is discrete in the index due to finite combination of asset holdings in the households, whereas reported income and expenditure are continuous variables.

Permanent Income Index across Time: DHS Egypt 1988 and 2005

Egypt from DHS was selected as it satisfied the criteria of having multiple survey years in the standard DHS and survey years close to available benchmark price data from Penn World Table. Comparable benchmark data from 1985 and 2005 were used to adjust for asset-specific prices in generation of the permanent income index. There were 9,803 households surveyed in Egypt 1988 and 21,965 in 2005. The mean permanent income estimates for households surveyed in 1988 were similar to ones in 2005 in the richest and middle tertiles. In the poorest tertile, the mean permanent income estimate increased from -1.21 (SD 0.60) to -1.07 (SD 0.72) from 1988 to 2005. Figure 10 indicates a decrease in percent of households at -1 on the permanent income index and increase in percent of households with mid-range permanent income estimates. We note that the absolute minimum permanent income estimate for households is lower in 2005 than in 1988 even though more percentage of households scored below 0 on the permanent income estimate in 1988.

4. HOUSEHOLD INCOME ACROSS COUNTRIES: COMPARISONS WITH INTERNATIONAL INDICES

There were 2,291,362 total households across 117 countries from 1985 – 2008 included from 181 DHS and 44 MICS Wave 3. The seven assets holdings considered include television, refrigerator, motorcycle or scooter, car or truck, mobile phone, non-mobile phone, and watch. Table 7 shows the percentage of households reporting asset holdings averaged across countries by survey year. 47.0% of all households reported owning a TV, 34.1% owning a refrigerator, 8.9% own a motorcycle, 13.2% a car or truck, 22.5% a mobile phone, 19.3% a non-mobile phone and 10.7% a watch. There were considerable missing data from households for two assets: 57.8% of households had missing data on non-mobile phone and 83.9% on watch.

Stratified by survey year, we note that higher percent of households surveyed from 2001-2005 reported owning assets compared to households surveyed before 2001. We estimated the household permanent income index which has a distribution around the mean of 0.0243 with a standard deviation of 0.6313, a minimum of -1.9139 and maximum of 3.4954.

We selected the most recent surveys from 84 countries in the DHS and MICS3 and correlated their average household permanent income with Real Gross Domestic Income, the international dollar (I$) terms of trade adjusted GDP (Figure 11). The correlation is 0.64. We observe that countries with relatively higher GDP generally have a higher mean income measure and countries with relatively lower GDP have a lower mean income measure. The correlation is not high, that is, countries that reported similar GDP levels could have a mean income measure that differs by 2 to 3 units cross our permanent income estimate.

The independent variable is taken from the constant price Real Gross Domestic Income adjusted for Terms of trade changes in the Penn World Table 6.3

Table A1 displays the country rankings for permanent income estimate and four other indicators: the HDI, MPI, MPI Living Standard score (MPI-LS), and PWT. In the ranking a 1 indicates poorest by the particular measure, and higher numbers indicate higher degree of income by the measure. In our initial results, we find a high, though not perfect, degree of similarity between our global ranking and country ranks from other metrics. The correlations between the values of permanent income index and the values of GDP per household, HDI, MPI, MPI-LS, are 0.63, 0.65, 0.74, 0.83, 0.84 and 0.89, respectively. The lowest correlation is found with the measure of country GDP adjusted for household consumption, while the highest is found with the MPI-LS, which was derived from similar data.

5. Household Income used in Subsequent Regression Analyses

We performed sensitivity analysis by stratifying cluster-level electricity access in order to explore bias in using durable electrical goods as asset types. Clusters with high level of access to electricity are defined by more than 5% households reporting use of electricity for lighting. In correlating our permanent income estimate and self-reported income or expenditure, households that are in clusters with low level of access to electricity had much lower correlation with household income and expenditure than clusters with high level of electricity access.

Reported income and expenditure exhibit different correlation patterns with the permanent income estimate when stratified by electricity access. Compared with the correlation between permanent income estimate and reported income in all households, correlation based on households in clusters with high level of electricity access was slightly increased. The increased correlation is understandable since our permanent income estimate is generated by ownership of durable electrical goods such as TV and refrigerator. Conversely, households in clusters with low access to electricity have much lower correlation between reported income and permanent income estimate. This correlation pattern of permanent income estimate with reported income was found both in Tanzania and South Africa. All clusters in Peru had over 50% of households reporting access to electricity. Hence households in Peru were not stratified by cluster-level electricity access (Table 4).

The pattern was not apparent when correlating with expenditure. In Tanzania, all households and households in cluster with high electricity access and low electricity access had very similar level of correlation ($r = 0.69$). In South Africa, correlation in households in cluster with low electricity access have lower correlation ($r = 0.43$) than households in clusters with high electricity access ($r = 0.76$) and all households ($r = 0.78$).

Similar patterns from cluster-level electricity stratification were found in coefficient of relative risk aversion. The coefficients generated from households in clusters with high electricity access are greater than coefficient generated from households in clusters with low electricity access for household income and expenditure (Table 9)

Our permanent income estimate significantly associates with the log of household expenditure (p= < 0.001, $R^2 = 0.566$). When we incorporate additional socio-demographic variables such as electricity, education level and household composition, the association improved 11% ($R^2 = 0.631$). A joint F-test on all independent variables except permanent income estimate rejected the null hypothesis that none of the socio-demographic variables together have predictive power ($F = 199.07$, $p< 0.001$).

6. Discussion

There are five major findings from this study. First, the permanent income estimate generated from household asset holdings correlates closely with household expenditure within each country study and is comparable to the correlations between asset index generated from PCA and expenditure. Secondly, we generate from the permanent income estimate in LSMS the corresponding coefficient of relative risk aversion. From this coefficient, we are able to calculate household income and expenditure based on the generated permanent income estimate from a short list of asset holding data. The method allow for interpretation of the household random effect as the marginal utility of money. Thirdly, we used the index to demonstrated a shift in household income within a country through comparison across time. Moreover, cross-country comparison with established indices such as the trade and consumption adjusted GDP illustrated a high correlation at the country-aggregate level. We found that our index rank similarly with other indices such as the Multi-dimensional Poverty Index and the Human Development Index. Lastly, we incorporated socio-demographic factors along with our permanent income estimate to explore a more complex model associated with household income and expenditure. We found that the permanent income estimate accounts for over 57% of variance in household expenditure and the additional socio-demographic factors increase the association by approximately 11%. From our methods and results, we will discuss similarities and differences found across the country studies, corroboration and contradictions with other wealth indicators, the strengths and limitations of our approach and the usability and application for other researchers.

Permanent Income Index at the Household Level

Generating the Permanent Income Index in Peru, Tanzania and South Africa illustrated some overarching characteristics (Table 4). Overall, Peru and Tanzania had a lower correlation with household income than South Africa. Correlation with expenditure across the three countries are above 0.6, where South Africa has the highest correlation of the three. There is variation across countries in the performance of the permanent income estimate. Correlation with expenditure is consistently higher than with income in the three countries. The household annual income and expenditure from each country survey were constructed from various components of income and expenditure sources. There is evidence that income, expenditure measure constructed from component sources allow respondents to provide a more accurate amount earned and spent in the past 12 months including sources that may not be traditionally considered as income, such as remittance or crop sales and expenditure such as seasonal religious offerings. (Smeeding and Weinberg, 2001)

Stratification based on cluster access to electricity captures wealth gradient within the same neighborhood while adjusting for bias to ownership of electrical durable goods. The small percentage of households that reported having access to electricity may own a private generator. We stratified clusters into high and low access to electricity defined by at least 5% household reported using electricity as an energy source for lighting. We found that our index correlates with income much better in cluster with high electricity access than low electricity access (Table 8). In clusters with low electricity access, there is a 40 – 50% decrease in correlation, to 0.25 – 0.32. This pattern was also present in correlation with expenditure in South Africa. We wanted to test if the list of household durables would bias the income ranking of household with electricity access as a confounder. Since many of the asset types used in generating the permanent income index require electrical energy source (besides battery or gasoline powered items). This difference in correlation suggests that the permanent income index is a much stronger proxy for household wealth in areas where household access to electricity and is a weaker proxy in remote areas where access to electricity is very low. Although this difference exist, other commonly used methods in determining household wealth, such as the principal components analysis, is predominantly used regardless of electricity access. In our theoretical model, the control for electricity access would be one example of factors that shift preferences for certain types of assets. We will demonstrate later that our permanent income index remains robust proxy of household expenditure after adjusting for electricity access.

Comparison with Principal Components Analysis

Filmer and Pritchett (2001) incorporated asset ownership and household characteristics in creating an asset index as a proxy of long-term household welfare. They used statistical procedure of principal components to determine the weights for an index of the asset variables. They tested reliability of the PCA method in the context of India states. The results showed internal coherence, robustness in assets included and comparability to state-level poverty status. One of the drawbacks that they noted was also between urban and rural comparisons. When used only eight asset ownership variables, they had a 0.79 correlation coefficient in the classification of the poorest 40%, compared to when using their full model, where they included eight asset ownership, drinking water source, toilet type, housing characteristics and land acre ownership. Our permanent income estimates from LSMS South Africa, Peru and Tanzania correlate highly with the asset index using the PCA method (Table 4). Principal Components Analysis is predominately used when investigating questions within a region or a country, where all households face the same set of asset prices. When comparing across survey years and across multiple countries or regions, the proposed income estimation, adjusted for changing prices, provides an additional avenue to approach such research questions.

Permanent income estimate Across Survey Years

Increasing number of studies compare surveys of the same country or set of countries across years. To our knowledge, methods currently used to proxy income allow for a relative measure of household wealth within the pooled surveys or within each survey. For example, the top quintile of Egypt in the DHS 1988 survey and the top quintile of the 2005 survey would remain the top 20% of households in the country. Another issue is that since the wealth of household is proxied mainly by asset ownership, it is difficult to distinguish whether households acquired more durable goods as assets because they became wealthier or because the price of such goods became cheaper. One salient example is the growth of mobile phone technology, the drop of mobile phone prices and the subsequent increase in mobile phone ownership in developing countries in the early 2000s. Our approach allows for a price adjusted, absolute estimate of household permanent income across years. We used DHS Egypt survey year 1988 and 2005 because benchmark prices from Penn World Tables allowed us to use different set of asset prices in each year. According to the permanent income index, we found that the poorest tertile has an increase in household wealth from 1988 to 2005, whereas, no significant changes were found in the middle and rich tertile (Table 6). The asset prices used for each year are listed in Table 6b. Similar pattern across time was found when we did not control for prices of assets. When price data is unavailable, the results suggest that the proposed permanent income estimate maintains its robustness.

Permanent Income Index Across Countries

Results of permanent income index generated across countries using data from DHS and MICS were comparable to international indices such as the Penn World Table, Multidimensional Poverty Index and Human Development Index (Table A1). Since MPI uses WFS, DHS data sources similar to ones used in the current study, it is expected that the MPI Living Standard score correlates very closely with our index. The correlation with log of trade adjusted GDP suggests that in general, the mean permanent income estimate of each country is comparable with national GDP (Figure 11). At the same time, there are countries with similar ranking on the estimate but ranges by e2 in the real gross domestic income. Conversely, we see countries reported similar GDP levels would be ranked within a range across the estimate. This correlation pattern indicates that at the mean country level, the permanent income estimate should be interpreted descriptively with caution as a proxy for countries welfare or poverty level.

Incorporation of Socio-Demographic Factors

At the household level, our permanent income index performs well, accounting for 58% of the variance of the log of household expenditure demonstrated using LSMS South Africa 1994. Adding socio-demographic variables such as resident location, education, household size and composition, and electricity access at the cluster level improved the regression fit by 11% (Table 10). This suggests these additional factors have limited added value in predicting household expenditure, when our permanent income index is already present as a proxy. Returning to our theoretical model, by adjusting for additional socio-demographic factors, we can interpret the factors as preference shifters of the households. For example, if households reside in rural area, or have low electricity access, the household's preference for certain asset types might systematically differ, regardless of their household permanent income. This is a lead into further study on relaxing the assumption of random preferences in our theory. In general, adding additional socio-demographic factors does not improve our prediction of household expenditure drastically, supporting the use of the permanent income index as a reliable proxy for household expenditure and long-term welfare.

Strengths and Limitations

Our income estimation has a number of strengths as well as limitations. Firstly, the estimation is methodologically based on economic consumption theory. It uses a household utility function with a simple form of marginal utility for each person. The theoretical basis enables clear interpretation of the random effects as the marginal utility of money generated from our analysis. This allows researchers to probe deeper regarding wealth and wealth in relation to household consumption patterns. The theoretical framework also enables us to find the coefficient of relative risk aversion. This coefficient leads us to our second advantage of the income estimation. The coefficient developed from LSMS or other survey data which contains both asset holding and income or expenditure measures can be used in another comparable population to calculate income or expenditure values from household asset data given a constant coefficient of relative risk aversion, ρ. This provides a way to build reliable income measures from current data that lack detailed expenditure or income measures; to create panel or longitudinal datasets with historical data.

Across countries, we demonstrated using our permanent income index as an absolute wealth index by using a common set of household durable goods and adjusting price of assets across countries. The short list of asset types produced robust definition of wealth at the household level across countries. Having a price adjusted index to proxy permanent income across countries and years is the major added advantage in our approach over PCA. Furthermore, the method used in generating the household permanent income allows missing data of asset holdings to exist. Households with non-missing asset holdings data in at least one asset type would have a household random effect generated from it. These households are not excluded due to missing data unless all asset holding data are missing.

While applying this theoretically-based method, we are cognizant of its assumptions and limitations. We performed sensitivity analysis for two countries: Tanzania and South Africa. We used composite measure of income and expenditure to correlate with our permanent income index. Although composite measure of household income is a more reliable measure than a single self-reported amount of household income, many households reported zero income in the past 12 months in the LSMS surveys. This dramatically reduces the sample size when we take the natural log of income in our model. In Tanzania LSMS 1994, sample size reduced by over 50%. Other studies have noted that expenditure is a more reliable measure of standard of living and wealth across life span (Morris, Carletto et al, 2000). It also leads to questions concerning debt, or negative income, subsistence production of food and measurement error. This data limitation leads us to rely more on the expenditure measure provided.

Another limitation is that the permanent income index does not adequately capture income in areas with low electricity access. This low correlation with household income and expenditure in low electricity clusters are also observed using asset index generated by PCA. We attribute electricity access as a potential preference shifter in our theoretical model. This would require relaxing the assumption of household preference for certain asset types to be random and uncorrelated with the household income and asset price.

In our list of asset types, we considered land, livestock and non-electrical agricultural tools as potential asset types. These were not used because our theoretical framework applies to consumption items rather than production items typical of land, livestock and tools. Although we aim to select household consumer goods for consumption rather than production, there are items which are ambiguously categorized. Automobiles may be transportation mean to work place. Mobile phones have been shown as a crucial technological asset to allow farmers and producers of other goods to find a market that have better commodity offers and bids (Mukhebi, 2007) Moreover it is difficult to define goods such as bicycle as a normal good. Bicycle can be a mode of transportation when a household cannot afford motorcycle or cars, but can also be owned by wealthy households for leisure activities. The Indian Human Development Survey adopts a consumption per capita score where ownership of a typically more expensive good (e.g. motor cycle or car) would recode the household as owning a less expensive good (e.g. bicycle) as well. They found that without the modification, less expensive items did not scale well; a household might not own some items because they are too affluent or too poor. Our approach is not a summation scale of asset ownership, but the index is generated through price adjusted, constant preference utility function. One minor limitation would be these asset types must exist technologically before surveys can collect data on household ownership of these assets. One example in Peru 1994 LSMS used microwave as one of its household assets. When linking with historical data, common asset items should be used.

Across countries, we used a short list of seven asset types that are majority cultural invariant such as TV, refrigerator, motorcycle, mobile phones, etc. Considerable missing data from households for “non-mobile phone” and “watch” is a limitation. Earlier survey waves may have less comprehensive list of assets than later years and training of surveyors may have improved in subsequent waves of data collection. The prices for each asset are based on PPP from ICP report in 2005. Not all seven assets have its own distinct prices under ICP’s product categories, as we had access to only basic heading prices such as “major household appliances (electric or not)”, “telephone and telefax equipment” “audio-visual, photographic and information process equipment” and ‘jewelry, clocks and watches”, “motor cars”, “motor cycle”. Finer details in price data would improve income differentiation among households. Furthermore, as seen from the sensitivity analysis, the residual, ε, is not independent and identically distributed. Countries with large regional differences in culture and consumption patterns are also assumed to have similar preferences in asset ownership with α_k as a country-survey fixed effect. These assumptions are necessary to simplify household consumption behavior in our model, while capturing the diverse income and expenditure levels across countries and across time. Generating an absolute permanent income index from all households in all countries and survey waves within the DHS and MICS is computationally intensive. Moreover, each time a new country survey is added to the panel dataset, the corresponding permanent income index for the original set of households would change, incorporating the newly added data.

7. USABILITY AND FUTURE DIRECTIONS

We applied our theoretically-based approach in three different sources of micro-level data: DHS, MICS, LSMS. The model included price and country fixed effects when comparing across countries but excluded them when analyzing within country. We aim to bolster our understanding of this method by repeating the correlation analysis in other LSMS country surveys as well as datasets that contain detailed asset holding, composite income and expenditure data. Furthermore, correlation with household education attainment used similarly by Young (2005) as a proxy for income in DHS would test the robustness of this index as a standard of living measure.

A household permanent income index at the micro-level and comparable across countries will expand the type of international comparison studies which can be applied to poverty surveillance in a neighboring regions, comparing the link between economic wellbeing and healthy aging. Moreover, the permanent income index in relation to household expenditure improves rigorous studies on household consumption, for example, income shocks from retirement pension plans and consumption smoothing as aging adult transition out of the labor market.

Beyond validating this novel approach, we aim to device a new global poverty count used on the measure of wealth. We aim to compare this poverty count with other international indices such as the MPI which includes asset holdings, education, housing quality as well as other measures to denote deprecation in standard of living. Furthermore, the internationally comparable permanent income index can be used to measure inequality comparable to the Gini coefficient at the regional, national and global level. A reliable measure of income at the household level would be a useful tool to provide valuable information on distribution, divergence and trends on economic wellbeing.

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Table 1. Data Sources of Household Survey by Regions

	Demographic and Health Survey		Multiple Indicator Cluster Survey		Living Standard Measurement Survey	
Years	1990-2006		1998		1985-2004	
	Surveys	Countries	Surveys	Countries	Surveys	Countries
Sub-Saharan Africa	86	34	22	22	10	4
North Africa	14	5	2	2	1	1
Middle East	4	2	1	1	0	0
Asia	39	16	9	9	16	10
Other Regions	38	16	10	10	28	14
Total Surveys	**181**	**73**	**44**	**44**	**55**	**29**

Table 2. Price Data Example for Egypt and Colombia, 2005

	Egypt		Colombia	
	PPP_{jk}[1]	p_{jk}[2]	PPP_{jk}	p_{jk}
Television	4.67	2.88	1197.08	1.11
Refrigerator	4.47	2.76	1651.66	1.53
Motorcycle	7.32	4.52	4026.51	3.72
Car or truck	7.02	4.33	3863.49	3.57
Mobile phone	4.06	2.51	1599.01	1.48
Non-mobile phone	4.06	2.51	1599.01	1.48
Watch	3.08	1.83	1668.51	1.54

[1] PPP_{jk} where asset, j, and country, k, are based ICP PPP (US$=1) values in 2005 for basic headings of similar goods
[2] $p_{jk} = PPP_{jk} / PPP_k$ where PPP_{Egypt} = 1.62, $PPP_{Colombia}$ =1081.95 are based on ICP PPP values in 2005

Table 3. Descriptive Characteristics of Permanent Income Index and Self-reported Annual Household Income and Expenditure in Three LSMS Country Surveys

Country	Assets	Permanent Income Index			Reported Income			Reported Expenditure		
		N	Mean	SD	N	Mean	SD	N	Mean	SD
South Africa 1994 (ZAR)[1]	10	7869	-0.4032	1.1525	7530	20489.91	22338.53	7869	18614.95	16546.38
Tanzania 2004 (TZN)	13	2474	-0.2339	1.4302	942	501363.40	3115543.00	2474	240504.30	488874.10
Peru 1994 (PEN)	19	3532	0.00836	1.5620	3532	11216.26	12693.02	3532	9175.17	8852.12

[1] ZAR South African Rand, TZN Tanzanian Schillings, PEN Peruvian Nuevo Sol

Table 4. Correlation of Permanent Income Index with Reported Household Income and Expenditure in 3 LSMS Country Surveys

Table 4a. Correlations Matrix of Reported Expenditure, Permanent Income Index and PCA from Three LSMS Country Surveys

	South Africa 1994 N = 7869			Tanzania 2004 N = 2471			Peru 1994 N = 3532		
	Expend.[1]	PII[2]	PCA	Expend.	PII	PCA	Expend.	PII	PCA
Expenditure	1			1			1		
PII	0.752	1		0.697	1		0.677	1	
PCA	0.758	0.946	1	0.641	0.897	1	0.727	0.937	1

[1]Household Annual Expenditure
[2]Permanent Income Index

Table 4b. Correlations Matrix of Reported Income, Permanent Income Index and PCA from Three LSMS Country Surveys

	South Africa 1994 N = 7530			Tanzania 2004 N = 932			Peru 1994 N = 3532		
	Income[1]	PII	PCA	Income	PII	PCA	Income	PII	PCA
Income	1			1			1		
PII	0.702	1		0.400	1		0.586	1	
PCA	0.721	0.945	1	0.402	0.906	1	0.644	0.937	1

[1]Household Annual Income
Note: Household samples in Annual Household Income are smaller due to outliers and missing values

Table 5. Coefficients of Relative Risk Aversion (ρ) from Three LSMS Country Surveys

	Annual Household Income			Annual Household Expenditure		
Country	N	ρ	SE	N	ρ	SE
Peru 1994	3532	1.2252	0.0233	3532	1.5325	0.0226
Tanzania 2004	932	0.3097	0.0227	2474	1.0272	0.0216
South Africa 1994	7530	0.8006	0.0094	7869	1.0714	0.0106

Permanent Income Index = $\alpha + \rho*\log(\text{income}) + \epsilon$
Note: Household samples in Annual Household Income are smaller due to outliers and missing values

Table 6. Comparison of Household Permanent Income Index across Egypt DHS 1988 and 2005

			Richest Tertile		Middle Tertile		Poorest Tertile	
	Survey Year	N	Mean	SD	Mean	SD	Mean	SD
With prices	1988	9803	1.9506	0.4114	0.5638	0.0080	-1.1841	0.6134
	2005	21965	1.3801	0.5675	0.4669	0.1702	-1.0669	0.7105
Without prices	1988	9803	1.7760	0.6646	0.5025	0.2939	-1.2476	0.6212
	2005	21965	1.5656	0.4202	0.4433	0.2162	-1.0675	0.7120

Table 6b. Comparison of Asset Prices, p_{jk}[1], across Egypt ICP 1985 and 2005

Year	Television	Refrigerator	Motorcycle	Car or truck	Mobile phone	Non-mobile phone	Watch
1985	3.30	1.79	2.98	3.39	2.72	2.72	0.49
2005	2.88	2.76	4.52	4.33	2.51	2.51	1.90

[1] p_{jk} is the price for good *j* and country *k* calculated from 1985 and 2005 purchasing power parities provided by ICP and PWT 7.0

Table 7. Mean Percentage of Households Owned Assets in DHS and MICS3

	N	Television %	Refrigerator %	Motorcycle %	Car or truck %	Mobile phone %	Non-mobile phone %	Watch %
Total Average	2 291 362	46.95	34.05	8.87	13.19	22.53	19.32	10.66
Survey Year								
1990-1995	374,525	32.54	17.23	6.69	4.58	1.85	n/a	n/a
1996-2000	367,887	37.02	24.03	6.07	6.63	10.80	n/a	n/a
2001-2005	883,582	64.36	53.54	9.12	24.34	39.48	32.87	5.38
2006-2008	665,368	37.44	23.18	11.32	6.86	18.14	22.87	29.57

Table 8. Correlation of Estimate with Household Income and Expenditure in 2 LSMS Countries

Table 8a. Correlations Matrix with Expenditure Stratified by Electricity

	South Africa 1994 N = 7869				Tanzania 2004 N = 2471			
	High Electricity Access n = 5398				High Electricity Access n = 1891			
	Expend.[1]	PII[2]	High Electricity Access	PCA	Expend.	PII	High Electricity Access	PCA
Expenditure	1				1			
Permanent Income Index	0.764	1			0.6840	1		
High Electricity Access	0.766	0.997	1		0.6842	0.9994	1	
PCA	0.772	0.947	0.949	1	0.643	0.9032	0.9035	1
	Low Electricity Access n = 2471				Low Electricity Access n = 580			
	Expend.[1]	Permanent Income Index	Low Electricity Access	PCA	Expend.	Permanent Income Index	Low Electricity Access	PCA
Expenditure	1				1			
Permanent Income Index	0.406	1			0.6917	1		
Low Electricity Access	0.420	0.988	1		0.6928	0.9967	1	
PCA	0.403	0.755	0.796	1	0.6147	0.8704	0.8840	1

[1]Household Annual Expenditure
[2]Permanent Income Index

Table 8b. Correlations Matrix with Income Stratified by Electricity

	South Africa 1994 N = 7530				Tanzania 2004 N = 932			
	High Electricity Access n = 5213				High Electricity Access n = 736			
	Income.[1]	PII	High Electricity Access	PCA	Income.	PII	High Electricity Access	PCA
Income	1				1			
Permanent Income Index	0.711	1			0.4087	1		
High Electricity Access	0.713	0.997	1		0.4107	0.9993	1	
PCA	0.732	0.947	0.948	1	0.3984	0.9123	0.9127	1
	Low Electricity Access n = 2317				Low Electricity Access n = 196			
	Income.[1]	Permanent Income Index	Low Electricity Access	PCA	Income.	Permanent Income Index	Low Electricity Access	PCA
Income	1				1			
Permanent Income Index	0.323	1			0.2491	1		
Low Electricity Access	0.338	0.988	1		0.2530	0.9964	1	
PCA	0.335	0.753	0.793	1	0.2669	0.8937	0.9128	1

[1]Household Annual Income
[2]Permanent Income Index

Table 9. Estimates of the Coefficient of Relative Risk Aversion in 2 LSMS Countries Stratified by Electricity

Country	Income				Expenditure			
	N	ϕ	SE	Diff (%)	N	ϕ	SE	Diff (%)
Tanzania								
All households	961	0.3004	0.0219		2471	1.0402	0.0216	
With Electricity	760	0.3101	0.025	3.23%	1889	1.0454	0.0258	1.24%
Without electricity	201	0.1543	0.0452	-48.64%	578	0.8863	0.0399	-11.31%
South Africa								
All	7530	0.8006	0.0094		7869	1.0714	0.0106	
With Electricity	5213	0.8311	0.0113	3.81%	5398	1.1071	0.0127	3.33%
Without electricity	2317	0.2028	0.0117	-74.67%	2471	0.3244	0.0141	-69.72%

ρ = coefficient of relative risk aversion
Permanent Income Index = $\alpha + \rho$*log(income) + ϵ
Note: Household samples in Annual Household Income are smaller due to outliers and missing values

Table 10. Regression of Log of Household Expenditure to Permanent Income Index and Socio-Demographic Covariates in LSMS South Africa 1994

N =7869	(1)		(2)		(3)	
	Coefficient	(95% CI)	Coefficient	(95% CI)	Coefficient	(95% CI)
Permanent Income Index	0.528	(0.518, 0.538)	0.432	(0.420, 0.444)	0.410	(0.396, 0.424)
Resident location						
Metropolitan (ref)	-		-		-	
Urban	-		0.082	(0.052, 0.112)	0.072	(0.042, 0.102)
Rural	-		0.276	(0.245, 0.306)	0.255	(0.224, 0.286)
Education	-					
>10 years (ref)	-		-		-	
5-10 years	-		-0.315	(-0.347, -0.284)	-0.315	(-0.346, -0.283)
<5 years	-		-0.512	(-0.556, -0.469)	-0.513	(-0.557, -0.470)
Household composition	-					
Household size	-		0.035	(0.031, 0.039)	0.036	(0.032, 0.040)
% of children < 15	-		-0.130	(-0.188, -0.071)	-0.119	(-0.177, -0.060)
% of adult females	-		-0.263	(-0.306, -0.219)	-0.248	(-0.292, -0.205)
Cluster-level Electricity	-		-		0.095	(0.065, 0.125)
Constant	9.713	(9.701, 9.726)	9.860	(9.817, 9.902)	9.793	(9.745, 9.840)
N	7869		7869		7869	
R^2	0.566		0.629		0.631	
Joint F-test			190.19	p<0.0001	171.92	p<0.0001

Figure 1. Relationship between Permanent Income Index and Household Annual Income, 2004 Tanzania LSMS Survey

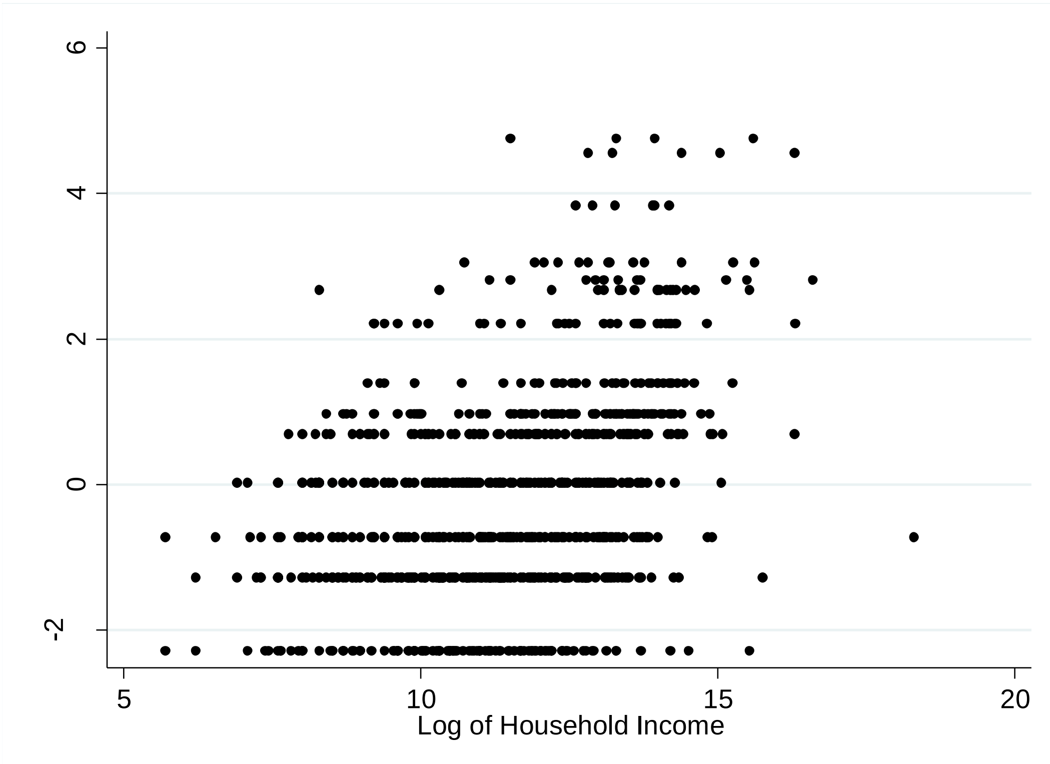


Figure 2. Relationship between Permanent Income Index and Household Annual Expenditure, 2004 Tanzania LSMS Survey

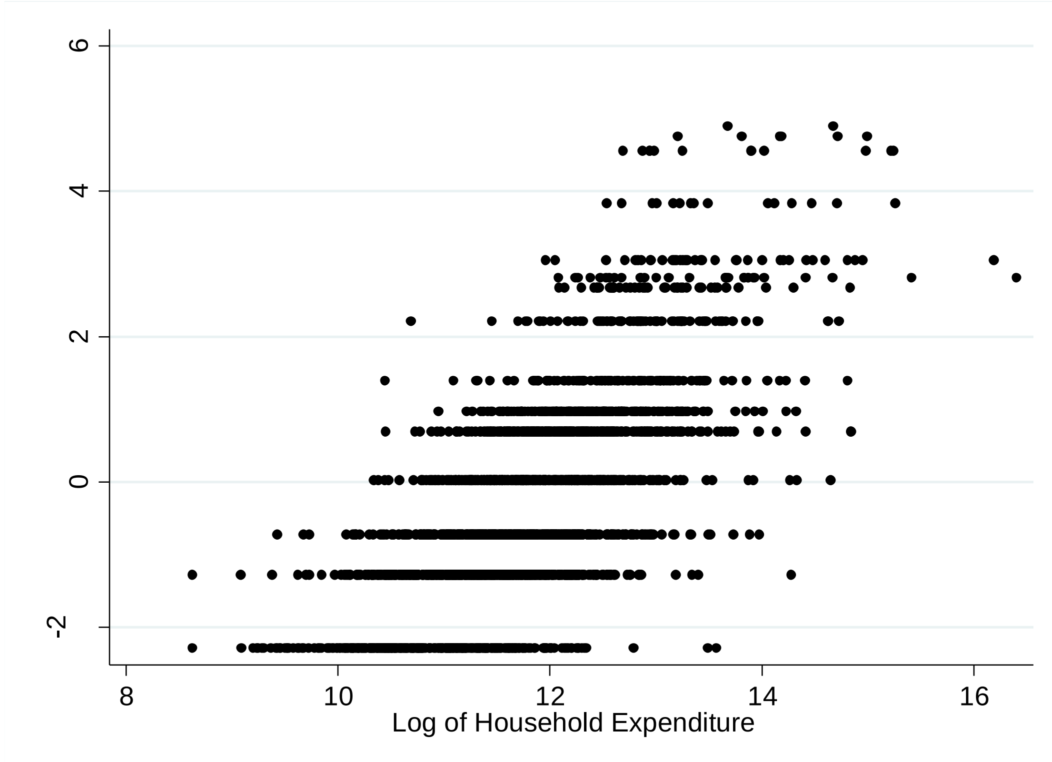


Figure 3. Relationship between Permanent Income Index and Asset Index by Principal Component Analysis, 2004 Tanzania LSMS

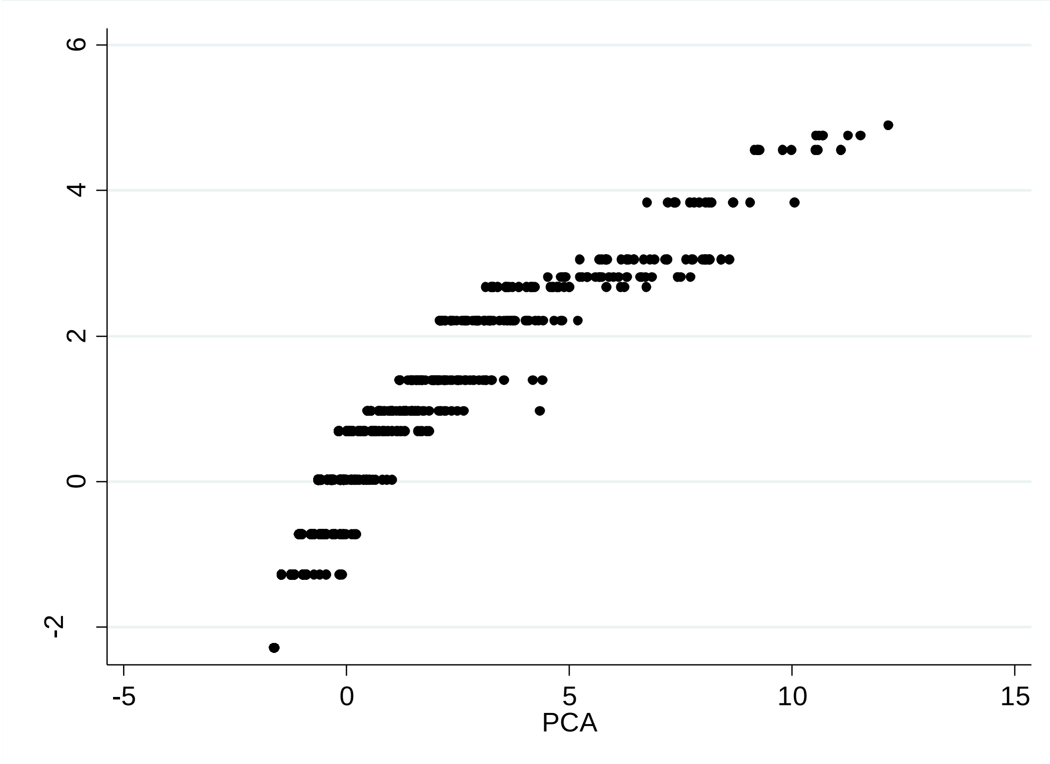


Figure 4. Relationship between Permanent Income Index and Household Annual Income from 1994 Peru LSMS Survey

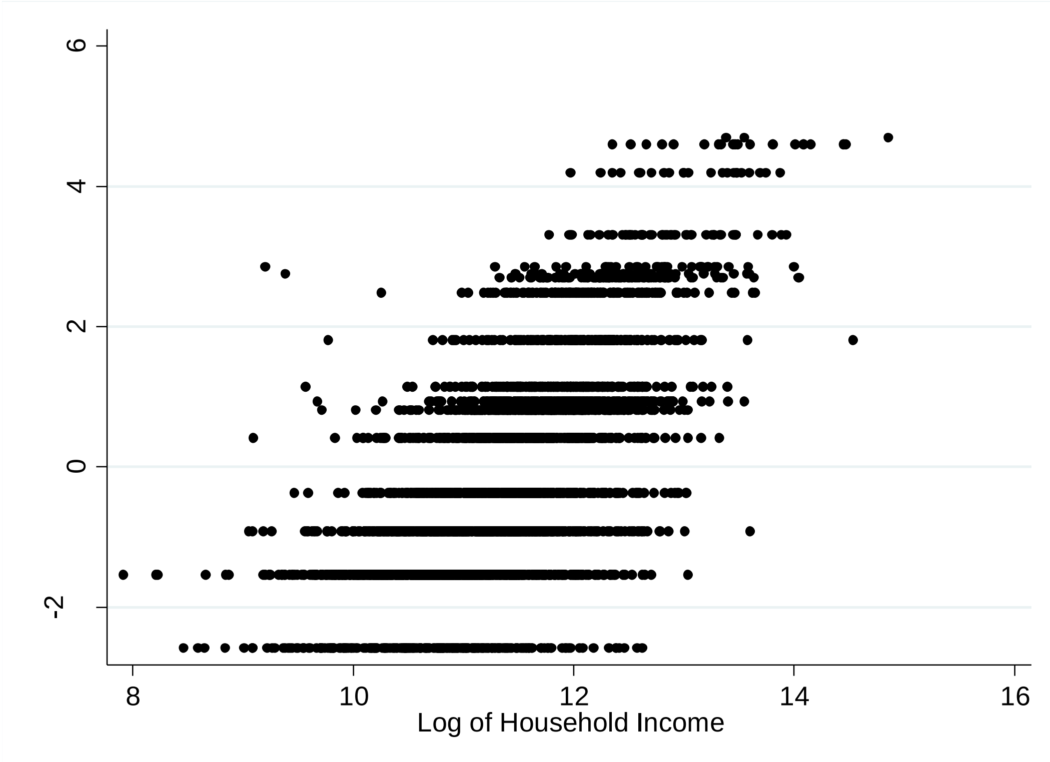


Figure 5. Relationship between Permanent Income Index and Household Annual Expenditure from 1994 Peru LSMS Survey

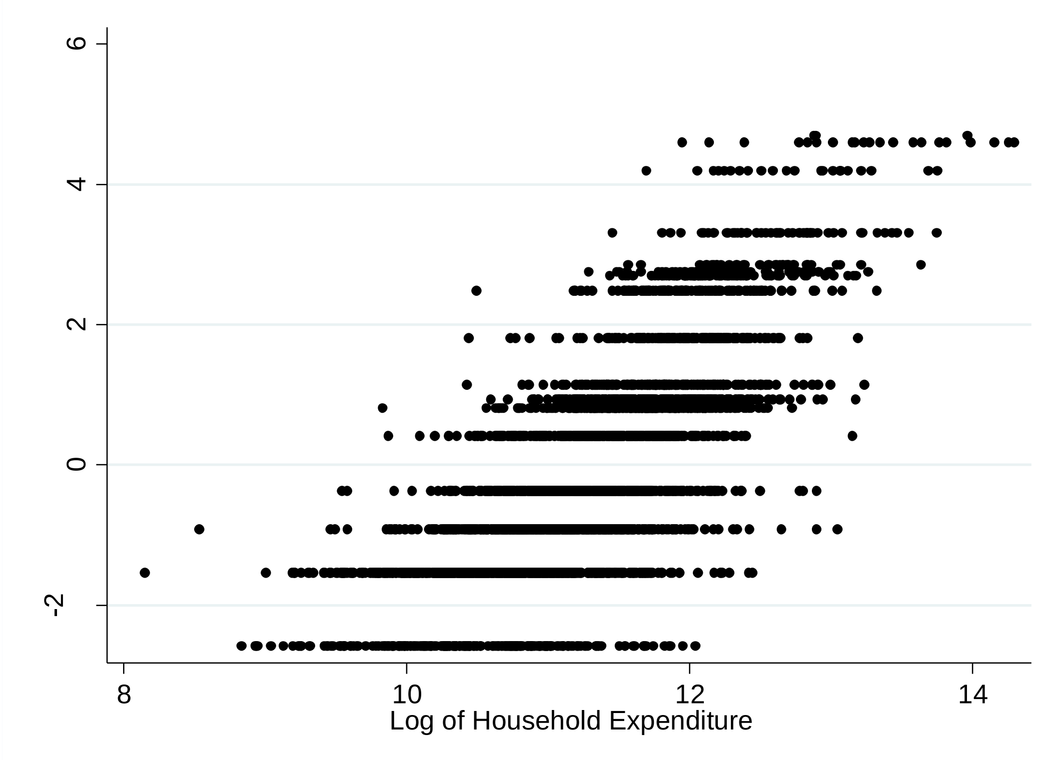


Figure 6. Relationship between Permanent Income Index and Asset Index by Principal Component Analysis from 1994 Peru LSMS

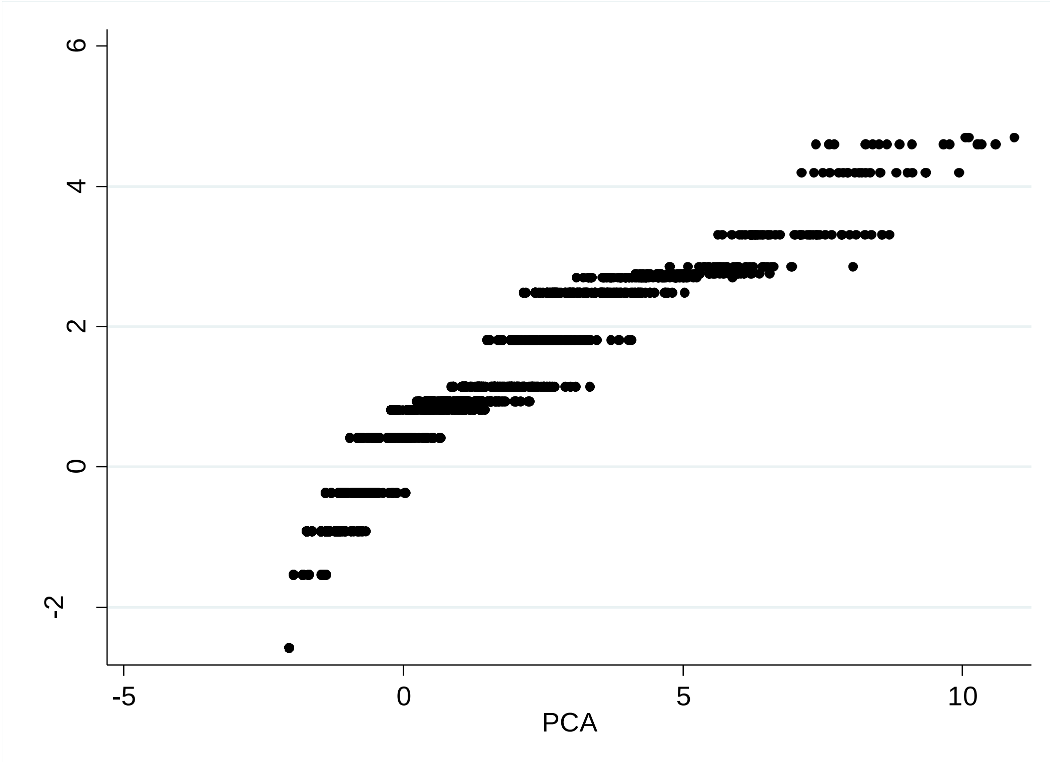


Figure 7. Relationship between Permanent Income Index and Household Annual Income from 1994 South Africa LSMS Survey

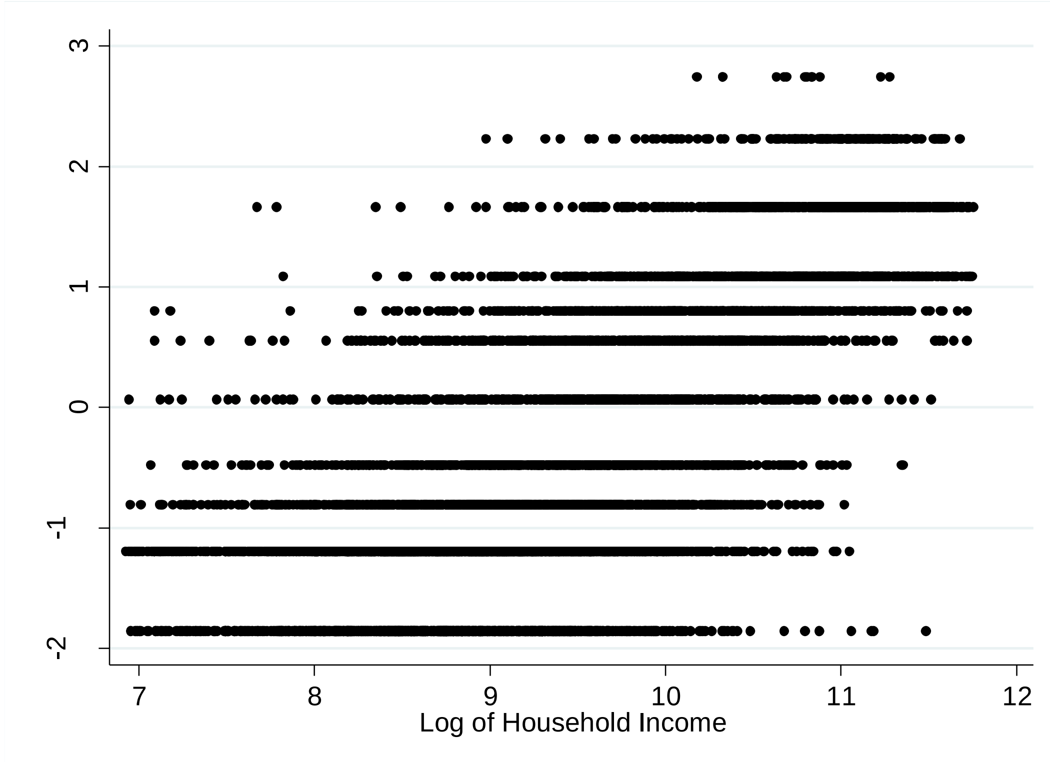


Figure 8. Relationship between Permanent Income Index and Household Annual Expenditure from 1994 South Africa LSMS Survey

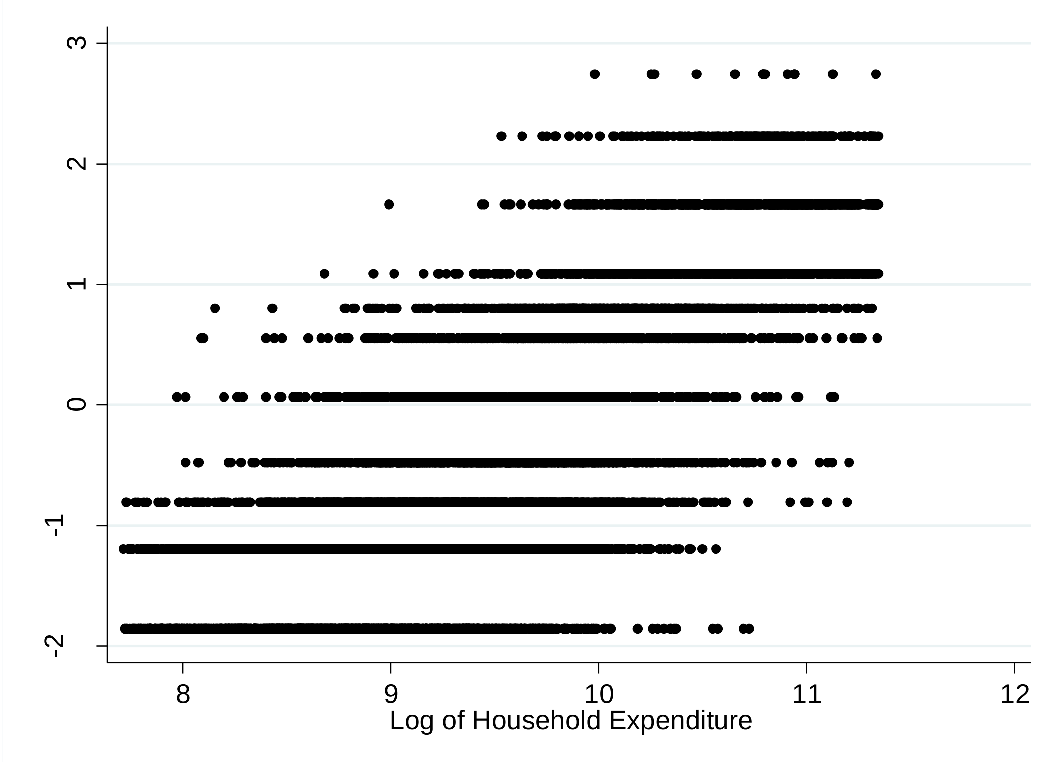


Figure 9. Relationship between Permanent Income Index and Asset Index by Principal Component Analysis from 1994 South Africa

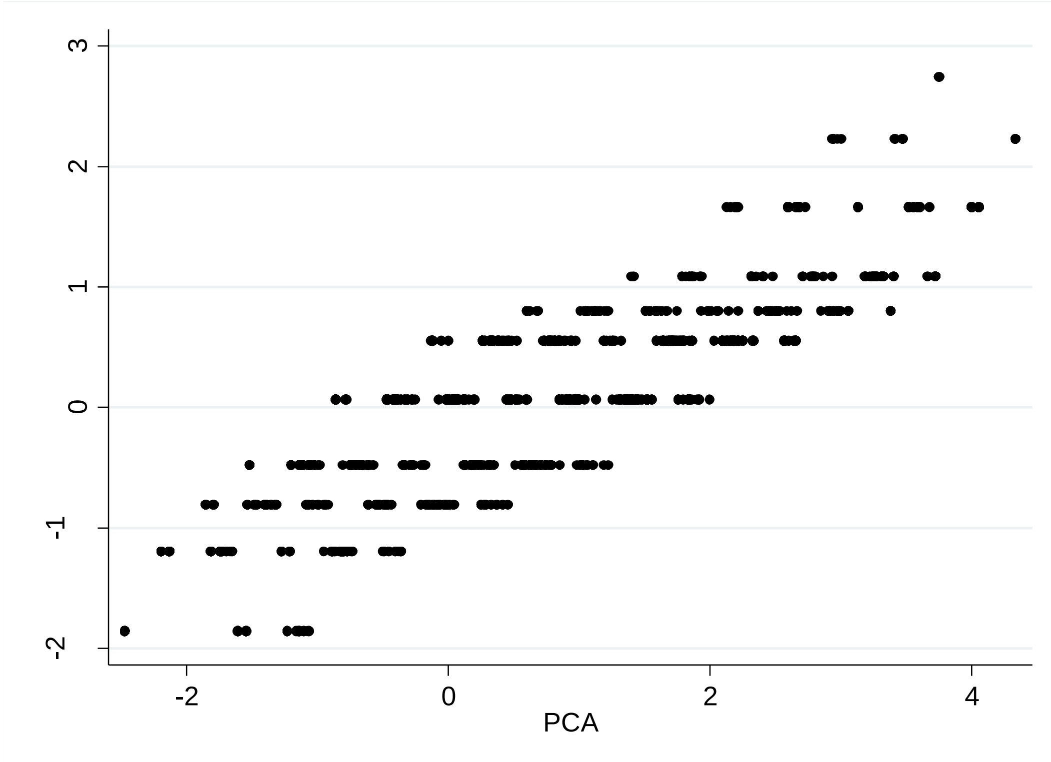


Figure 10. Permanent Income Index Distrbution in DHS Egypt 1988 and 2005

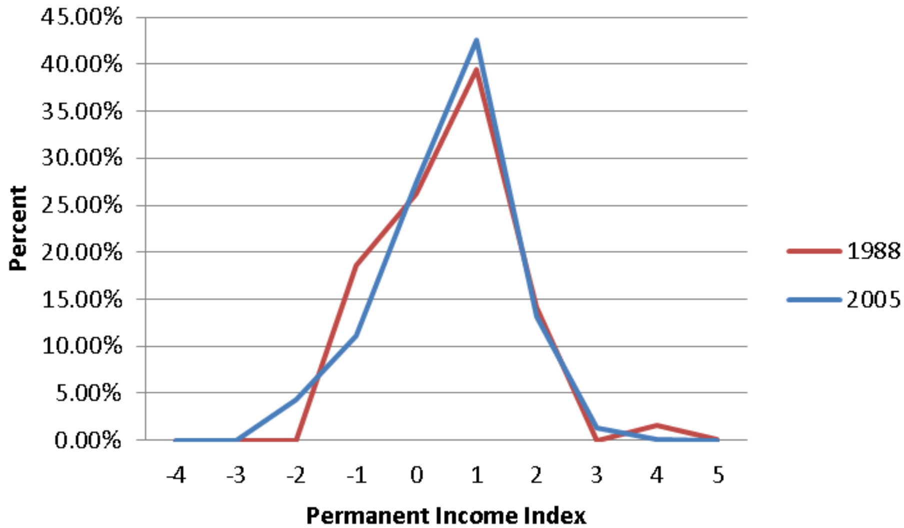
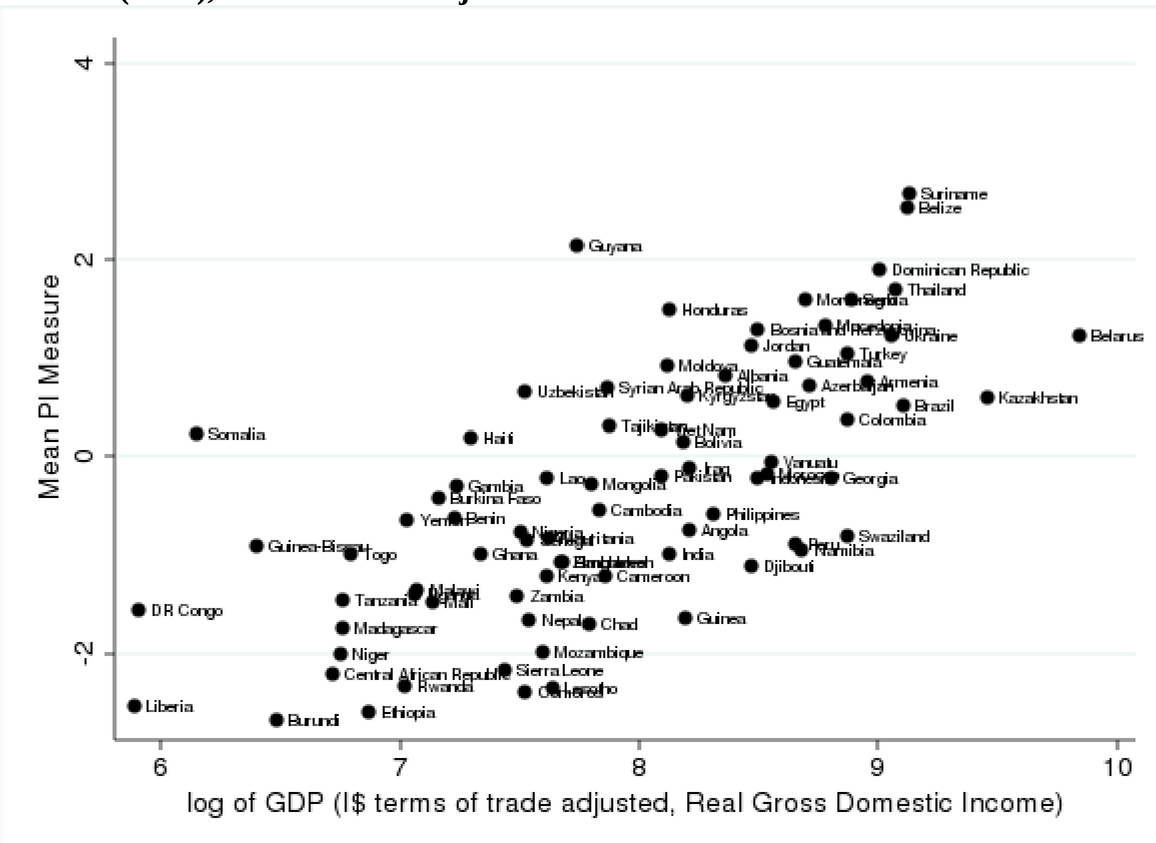


Figure 11. Country Mean Permanent Income Index (PI) and Log of Gross Domestic Product (GDP), terms of trade adjusted



H. Appendix

Table A1. Country Rankings by Indicators

Country	Survey Year	Permanent Income Index	GDP	HDI	MPI	MPI-LS
Burundi	2005	1	5	7	5	1
Ethiopia	2005	2	11	10	2	4
Liberia	2008	3	1	13	10	9
Comoros	1996	4	26	39	16	11
Lesotho	2004	5	33	24	39	19
Rwanda	2005	6	12	14	13	2
Central African Republic	2006	7	6	4	7	8
Sierra Leone	2005	8	22	2	9	7
Niger	2006	9	7	1	1	6
Mozambique	2003	10	29	9	11	14
Madagascar	2008	11	9	33	14	18
Chad	2004	12	37	11	24	3
Nepal	2006	13	28	34	23	25
Guinea	2005	14	49	12	8	17
DR Congo	2007	15	2	6	17	16
Mali	2006	16	16	3	3	12
Tanzania	2007	17	8	25	21	10
Zambia	2007	18	23	17	25	24
Uganda	2006	19	14	21	-	-
Malawi	2006	20	15	18	19	5
Republic of Congo	2005	21	-	42	36	29
Cameroon	2006	22	40	29	30	31
Kenya	2008	23	30	32	29	15
Djibouti	2005	24	56	28	47	52
Zimbabwe	2005	25	34		43	34
Bangladesh	2007	26	35	31	32	26
India	1992	27	46	41	31	38
Togo	2006	28	10	22	33	28
Ghana	2008	29	21	27	45	39
Namibia	2006	30	65	45	40	35
Guinea-Bissau	2006	31	4	8	-	-
Peru	2003	32	64	72	50	44
Senegal	2008	33	27	16	18	40
Mauritania	2007	34	32	26	22	32
Swaziland	2006	35	70	38	41	33

Nigeria	2008	36	24	23	20	30
Angola	2006	37	51	35	12	20
Yemen	2006	38	13	37	34	45
Benin	2006	39	18	20	15	22
Philippines	2008	40	53	60	53	55
Cambodia	2005	41	39	40	38	23
Cote d'Ivoire	2006	42	-	19	27	47
Burkina Faso	2006	43	17	5	4	21
Gambia	2005	44	19	15	26	36
Mongolia	2005	45	38	53	54	43
Indonesia	2007	46	58	56	49	49
Georgia	2005	47	69	65	80	64
Lao	2006	48	31	43	37	37
Pakistan	2006	49	44	36	35	41
Morocco	2003	50	60	44	46	54
Iraq	2006	51	52	-	56	63
Vanuatu	2007	52	61	47	-	-
Bolivia	2008	53	48	57	42	46
Haiti	2005	54	20	30	28	27
Somalia	2006	55	3	-	6	13
Viet Nam	2006	56	43	54	51	51
Tajikistan	2005	57	42	46	52	53
Colombia	2004	58	71	74	60	58
Brazil	1996	59	79	77	62	66
Egypt	2008	60	62	49	63	74
Kazakhstan	2006	61	83	73	81	71
Kyrgyzstan	2005	62	50	50	68	59
Uzbekistan	2006	63	25	51	71	67
Syrian Arab Republic	2006	64	41	59	66	70
Azerbaijan	2006	65	67	62	65	65
Armenia	2005	66	74	70	72	75
Albania	2005	67	54	79	77	73
Moldova	2005	68	45	52	70	62
Guatemala	1998	69	63	48	48	42
Turkey	2003	70	72	75	61	60
Jordan	2007	71	57	64	69	81
Belarus	2005	72	84	80	82	82
Ukraine	2005	73	77	71	74	80
Bosnia and Herzegovina	2006	74	59	76	79	78
Macedonia	2005	75	68	78	73	72
Honduras	2005	76	47	58	44	50
Montenegro	2005	77	66	81	75	79

Serbia	2005	78	73	82	78	77
Thailand	2005	79	78	69	76	69
Dominican Republic	2007	80	76	66	58	56
Guyana	2006	81	36	55	57	57
Belize	2006	82	81	68	64	61
Suriname	2006	83	82	63	59	68
Trinidad and Tobago	2006	84	-	83	67	76

HDI: Human Development Index 2003; *MPI*: Multi-dimensional Poverty Index, varying years; *MPI-LS*: MPI Living Standard score, same years as MPI; *PWT*: Penn World Tables estimates of real gross domestic income: GDP TT: GDP terms of trade adjusted, 2005; *Year*: Year of the survey from which data were used to compare with GDP.
*The HDI value for Haiti is from 2006, as opposed to 2005 for all other countries.

Table A2. List of Assets Used to Generate Permanent Income Index

Peru 1994	South Africa 1994	Tanzania 2004	Egypt, Columbia 2005	DHS, MICS3 1990 - 2006
Radio	Radio	Radio/cassette/record/ CD player	Television	Television
Refrigerator	Electric stove	Stove	Refrigerator	Refrigerator
Sewing machine	Gas stove	Sewing machine	Motorcycle	Motorcycle
Automobile	Primus cooker	Motor bike	Car or truck	Car or truck
Vacuum/buffer	Refrigerator	Refrigerator	Mobile phone	Mobile phone
Telephone	Television	Fan	Non-mobile phone	Non-mobile phone
Television (black/white)	Geyser	Camera	Watch	Watch
Television (color)	Electric kettle	Television/video equipment		
Washing machine	Telephone	Car		
Knitting machine	Motor vehicle	Watch/jewelry		
Motorcycle		Iron		
HiFi/turn tables		Telephone		
Blender/food processor/mixer		Carpet		
Electric fan				
Gas stove				
Videocassette player				
Personal computer				
Microwave				
Heater				