Vulnerability to asset-poverty in Sub-Saharan Africa

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Abstract

This paper presents a methodology to measure vulnerability to asset-poverty. Using repeated cross-section data, age-cohort decomposition techniques focusing on second-order moments can be used to identify and estimate the variance of shocks on assets and, therefore, the probability of being poor in the future. Estimates from the Ghana Living Standard Surveys show that expected asset-poverty is a reliable proxy for expected consumption-poverty. Applying the methodology to nine Demographic Health Surveys countries, urban areas are found to unambiguously dominate rural areas over the uni-dimensional distribution of expected future asset-wealth, as they also generally do over the bi-dimensional distribution of present asset-wealth and expected future asset-wealth.

Keywords: vulnerability; poverty; wealth; pseudo panel; stochastic dominance; Africa.

JEL Numbers: D12; D31; I32; O12; O15.

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1. INTRODUCTION

Over the past few years, the measurement of vulnerability has gained renewed interest. Since at least the publication of the World Development Report 2001—and the WDR 2010 more recently—development economists have been trying to figure out the consequences and policy implications of measuring vulnerability to risks and shocks (be they economic, climatic, etc.) in lieu of only considering more conventional poverty indices.[1] In particular, since both the poor and the non-poor can be vulnerable to shocks, social security or safety nets should benefit a larger population than the one currently targeted by poverty alleviation programs and assistance to the poor.

Various approaches to vulnerability measurement have been proposed in the literature as different definitions have emerged.[2] Vulnerability to poverty can first be defined as a probabilistic concept: it is the risk of falling into poverty when one's income or consumption falls below a predefined poverty line. This calls for a quantitative approach to vulnerability that implies estimating a probability as well as selecting a poverty line.[3] In order to estimate such a probability, Chaudhuri et al. (2002) proposed to estimate the expected mean and variance in consumption using cross-sectional data or short panel data.

As in Pritchett et al. (2000), Chaudhuri et al. (2002) consider the changes in consumption to be normally, independently and identically distributed. Following this assumption, it is easy to predict consumption expenditures through ordinary least-squares regression and directly obtain from those estimates the household probability to fall into poverty. One of the main strong points of this approach certainly resides in the fact that it is rather straightforward to implement on various types of datasets. Yet, one limitation of this approach when it is applied to a single cross-section is that it cannot take the temporal variability of parameters into account. What is more, the distributional assumptions are very strong since they allow for no unobservable heterogeneity and since consumption is supposed to follow a random walk, which is consistent with consumption-smoothing behaviour. Furthermore, the proposed framework appears to be inappropriate when it comes to accommodating measurement error.

An alternative approach is to use information on self-reported shocks in household surveys. For instance, Dercon and Krishnan (2000) provide evidence of the impact of various shocks on poverty using short panel data in Ethiopia (see also, among others, Glewwe and Hall, 1998, Datt and Hoogeveen, 2003). Christiaensen and Subbarao (2005) also use historical information on shocks in their econometric framework. First, pseudo panel data from Kenyan repeated cross-sections allow them to estimate the conditional effect of shocks on consumption. Second, knowing the variance of these shocks, the authors are able to provide vulnerability estimates as defined as expected poverty.

Pseudo panel data can be used as long as good quality panel data are seldom available in the developing countries where policies have to be implemented. As attrition and measurement error are often a problem with true panel data, repeated cross-sectional surveys can be used in order to track the birth cohorts of households through the data (Deaton, 1985). Indeed, attrition is much less a problem in pseudo panels, so that it is possible to consider dynamic behaviors such as consumption-smoothing and asset accumulation behaviors over longer periods of time than is usually possible with panel data (Antman and McKenzie, 2007). What is more, when it comes to taking into account unobservable heterogeneity and measurement errors, the pseudo panel approach appears to be reliable. This is due to the fact that grouped data can better accommodate measurement errors and also that correlated fixed effects can be ruled out using conventional estimators (Verbeek and Nijman, 1992, Verbeek, 2008).

This paper builds on previous approach and proposes to use pseudo panels in order to estimate the variance of shocks faced by households. As in Chaudhuri et al. (2002), we assume that the change in household welfare is normally, independently and identically distributed. However, contrary to previous approach, pseudo panel estimates will allow for the presence of unobservable heterogeneity in the form of individual specific effects. In order to estimate the variance of shocks, our proposed measurement approach relies on age-cohort decomposition techniques focusing on second-order moments, as pioneered by Deaton and Paxson (1994).

One important underlying assumption is that household welfare estimates from the repeated cross sections are comparable over time. This is not the case in the Christiaensen and Subbarao (2005)'s study, where the consumption estimates from the three repeated cross sections are not comparable. Hence, as the authors are not able to control for unobserved heterogeneity, this may lead to biased estimates of the mean equation coefficients if the unobserved characteristics are correlated with the observed ones. To overcome this problem, a second innovation in our approach consists in using an asset-based indicator in order to model household welfare dynamics, allow for unobserved heterogeneity and measure expected poverty. Various indicators of well-being are generally used to measure poverty such as per capita household expenditures or per capita household income. However, in developing countries, especially in Africa, good quality data on consumption or income prove to be hard to find in comparable surveys over time. Sahn and Stifel (2003) have listed several other problems in using household expenditures data such as measurement errors due to recall data or due to the lack of information concerning prices and deflators. Alternative measures of household's well-being such as the asset index should thus be considered.[4] Sahn and Stifel (2003) proposed to consider three categories of assets: household durables, housing quality and human capital.[5]

In this paper, we explore the dynamics of asset-poverty in sub-Saharan Africa. We first apply the methodology to three rounds of the Ghana Living Standard Survey (GLSS) and obtain comparable measures of vulnerability to asset-poverty, vulnerability to income-poverty and vulnerability to consumption-poverty. Then we turn to the Demographic Health Surveys (DHS) for several sub-Saharan African countries to analyze the vulnerability gap between urban and rural areas in these countries. We test for the robustness of this gap using stochastic tests of welfare dominance.

The rest of the paper is organized as follows. Section 2 presents a simple theoretical framework to motivate our approach as well as the empirical strategy for the original study. GLSS data and results are presented in section 3. Section 4 applies the methodology to the

DHS for several African countries and presents results on poverty and vulnerability. The last section concludes.

2. METHODOLOGY

2.1.Asset Based Approach

There are several arguments in favour of an asset-based approach to vulnerability. Firstly, since vulnerability is a dynamic concept, we can consider that consumption-poverty or income-poverty measurements, because they are static, are of limited use in capturing complex external factors affecting the poor as well as their response to economic difficulty (Moser, 1998). Secondly, owning assets reduces the risk for households to fall into poverty as a result of macroeconomic volatility (de Ferranti et al., 2000). Hence, accumulating assets—be they liquid or not (e.g., durable goods and housing), material or not (by fostering education, health, family and social networks)—helps people to insure themselves against falling into poverty and to cope with risks and shocks. Asset accumulation should thus be considered as a major factor in risk management.

Nevertheless, though an asset index can be a good proxy for living standards in order to measure poverty[6], two problems arise when using household wealth as an indicator of well-being in order to measure vulnerability to poverty.[7] On the one hand, if assets are used for consumption-smoothing, then an asset-based approach overestimates vulnerability since assets can fluctuate whereas consumption does not. On the other hand, if assets are not used to smooth consumption, the approach would underestimate vulnerability. So, knowing whether an asset-based approach deviates from a more standard consumption-based approach is mainly an empirical question.

Besides, we could ask whether, in some circumstances, an asset-based approach is not preferable when it comes to measuring vulnerability. Indeed, let us consider the most interesting and realistic case where productive assets contribute towards the income generation process and can also serve as buffer-stock in order to face a non-anticipated drop in income (Deaton, 1991, Carroll, 1992). Empirically though, many studies find little evidence supporting the buffer-stock hypothesis in developing countries.[8] For instance, Dercon (1998) shows that, given subsistence constraints and agent heterogeneity, rich households will accumulate assets more quickly than poor ones who will pursue low-risk, low-return activities. Interestingly enough, the evidence suggests that households with lower endowments are less likely to own cattle and returns to their endowments are lower. So, in presence of imperfect markets for credit and insurance, few households are able to smooth their consumption. What is more, when assets are mainly made up of productive assets, selling these assets would induce a permanent loss in income for the household who could then fall into a poverty trap.[9] For this reason, poor households will prefer to smooth their assets instead of smoothing their consumption.[10]

An asset-smoothing behaviour might be a desirable strategy for households to avoid falling into poverty traps. As pointed out by Zimmerman and Carter (2003) who build on Dercon (1998)'s approach by incorporating the role of endogenous asset price risks, portfolio strategies can bifurcate between rich and poor households. In this setting, poor agents respond to shocks by using consumption to buffer assets when they get close to a critical asset threshold.[11] So, this behaviour can have long-term consequences since food restrictions may induce, for instance, early childhood malnutrition, with permanent cognitive and psychomotor consequences. Hence, malnutrition may induce direct productivity loss due to bad physical conditions, indirect productivity loss due to cognitive and education deficits, as well as loss due to increasing health care costs. For this reason, malnutrition lowers economic growth and perpetuates poverty, from mother to child (Alderman et al., 2002, Behrman et al., 2004). Other cut in expenditure such as taking children out of school can also have long-term effects on living standards.

2.2.Theoretical Framework

To illustrate our asset-based approach and motivate our empirical analysis, this section provides a simple framework that allows for consumption and/or asset-smoothing behaviours. The optimization decision faced by the household *i* is

$$\max_{c_{i1},\ldots,c_{iT}} E_t\left[\sum_{t=1}^{T}\beta^{t-1}U(c_{it})\right],$$

subject to the constraint $a_{it+1} = (1-\delta_i(s_t))a_{it} - y_{it}$ for $t = 1,\ldots,T-1$, where β is the discount factor, a_{it} represents the household's assets, $\delta_i(s_t)$ is a depreciation rate which is supposed to be a negative function of the shock s_t that is $\partial\delta_i(s_t)/\partial s_t < 0$, and y_{it} is an offtake from the assets. As in McPeak (2005), we define the household's consumption, $c_{it} = f(a_{it}) + y_{it}$, assuming that for each period the household consumes the product from the assets $f(a_{it})$ and that part of the assets is sold for consumption or consumed directly by the household.

The Bellman's household equation for the maximization problem faced at time *t* is

$$V(a_{it}) = \max_{y_{it}} U(f(a_{it}) + y_{it}) + \beta E_t V((1-\delta_i(s_t))a_{it} - y_{it}).$$

The first order condition is $U'(c_{it}) = \beta E_t V'(a_{it+1})$. The envelope condition is $V'(a_{it}) = \beta(1-\delta_i(s_t))E_t V'(a_{it+1})$. So, putting these conditions together, we get the Euler equation $E_t\left[\frac{\beta(1-\delta_i(s_t))U'(c_{it+1})}{U'(c_{it})}\right] = 1$.

Assuming that the utility function is concave, a negative shock on assets that increases the rate of depreciation is going to decrease assets in *t+1*; thus both the product from the assets and household consumption will decrease in *t+1*. Furthermore, accordingly to the first order condition, a shock decreasing household assets in *t+1* will increase utility of income all else equal. So, since this shock has no impact on assets or on assets' product at time *t*, then y_{it} is going to decrease: we get $\partial y_{it}/\partial s_t > 0$. In this model, a negative shock on income will have the opposite effect: a drop in assets' product at time *t* will increase the marginal utility of income and, accordingly to the first order condition, y_{it} is going to increase. It will thus raise the amount of assets that the household is willing to sell or consume in order to smooth the household's consumption. In this case, assets are used as a "buffer" against shocks (Deaton, 1991, Carroll, 1992).

This simple framework illustrates the fact that an asset-based approach will formally consider that asset shocks are predominant in the economy or, at least, that income shocks and asset shocks are correlated. So, in presence of both asset shocks and income shocks, households may lower the offtake from their assets instead of smoothing consumption. This is because the liquidation of assets reduces expected future income and, thus, increases the probability to be poor in the future.

2.3.Econometrics

Let us now quantify vulnerability to poverty by considering the probability to be poor in the future that is having predicted future income or assets below a pre-defined threshold, conditional on household characteristics and exogenous shocks. This probability can be stated as follows:

$$\hat{v}_{it}^{c} = \Pr(a_{it+1}^{c} < z \mid x_{it}^{c}, x_{it+1}^{c}, a_{it+1}^{c}),$$

where a_{it+1} is household *i* welfare (using per capita asset index as a proxy) at time *t+1*, x_{it} and x_{it+1} are vectors of household characteristics at time *t* and *t+1* respectively that are not used in the definition of cohort *c*, and *z* is a given threshold. This probability is modelled using pseudo panel data. Indeed, in the absence of panel data, repeated cross-section data can be grouped together by age cohort, education, and geographic groups in order to implement the methodology. So, the welfare index can be modelled in logarithm as follows:[12]

$$\ln a_{it}^{c} = x_{it}^{c}\beta_{t}^{c} + \eta_{it}^{c},$$

where superscript c denotes cohort group. It is assumed that the residual term η_{it}^{c} can be decomposed into an individual specific effect α_{i}^{c} and an error term ξ_{it}^{c} as follows:

$$\eta_{it}^{c} = \alpha_{i}^{c} + \xi_{it}^{c},$$

where α_{i}^{c} can be modelled either as a fixed effect or as a random effect and ξ_{it}^{c} is supposed to follow a martingale that is

$$\xi_{it}^{c} = \xi_{it-1}^{c} + \varepsilon_{it}^{c},$$

with ε_{it}^{c} denoting an innovation term that is supposed to be normally, independently and identically distributed, with mean zero and variance $\sigma_{\varepsilon ct}^{2}$. Grouping households together by cohorts gives the possibility to estimate the model with repeated cross-section surveys. Estimating this model by focusing on second-order moments—as in Deaton and Paxson (1994)—yields estimates of $\sigma_{\varepsilon ct+1}^{2}$ that can directly be used to predict the degree of household vulnerability in cohort *c*. Indeed, by first drawing a value $\tilde{\varepsilon}_{it+1}^{c}$ in the normal distribution with mean zero and variance $\hat{\sigma}_{\varepsilon ct+1}^{2}$, we obtain the probability to become poor in *t+1* for household *i* in cohort *c*:

$$\hat{v}_{it}^{c} = \Pr(a_{it+1}^{c} < z \mid x_{it}^{c}, x_{it+1}^{c}, a_{it+1}^{c}) = \Phi\left(\frac{\ln z - x_{it+1}^{c}\hat{\beta}_{t+1}^{c} - \ln a_{it}^{c} + x_{it}^{c}\hat{\beta}_{t}^{c} - \tilde{\varepsilon}_{it+1}^{c}}{\hat{\sigma}_{\varepsilon ct+1}}\right),$$

where $\Phi(.)$ denotes the cumulative density of the standard normal distribution. Assuming, for simplicity sake, that $x_{it+1}^{c}\hat{\beta}_{t+1}^{c} = x_{it}^{c}\hat{\beta}_{t}^{c}$ gives $\hat{v}_{it}^{c} = \Pr(a_{it+1}^{c} < z \mid x_{it}^{c}, x_{it+1}^{c}, a_{it+1}^{c}) = \Phi\left(\frac{\ln z - \ln a_{it}^{c} - \tilde{\varepsilon}_{it+1}^{c}}{\hat{\sigma}_{\varepsilon ct+1}}\right)$, where $\hat{\sigma}_{\varepsilon ct+1}^{2}$ is the estimator of the slope of the age profile for the asset disturbance term variance $\sigma_{\eta ct}^{2}$. Indeed, we propose to decompose the residual variance into age and cohort effects as follows:

$$\sigma^2_{\eta ct} = \mu + \gamma_{ct} + \lambda_{at} + u_{ct} ,$$

where μ is a constant, γ_{ct} is a cohort effect, λ_{at} is an age effect, and u_{ct} is an error term which is supposed to be independent and identically distributed and of mean zero. Then, assuming that the cohort effect is time invariant as it should asymptotically be the case (Verbeek, 2008), we estimate the first difference (from *t* to *t+1*) of age effects—that is $\hat{\lambda}_{at+1} - \hat{\lambda}_{at}$ —for each cohort in order to get $\hat{\sigma}^2_{\varepsilon ct+1}$.

Following the previous methodology, the estimation steps to obtain the vulnerability index can be summarized as follows:

- *Step 1.* Create a pseudo panel from repeated cross-section surveys. The rationale for this is to choose time-invariant characteristics to group households in each survey into cohorts.[13] The number of cells constituted equals the number of cohorts multiplied by the number of periods/surveys available for the analysis. Cell size should be large enough in order to minimize the bias arising from using pseudo panel data and not genuine panel data.[14]

- *Step 2.* Estimate the residual variance of the logarithm of the asset index within each cell of the pseudo panel corresponding to cohort *c* at time *t*. Practically speaking, we regress for each cell at the household level the logarithm of the asset index on a set of variables (including gender dummy, age and age squared, education dummies, household size, number of children under 5 years old, urbanization dummy or localisation dummies) and estimate the residuals. The residual variance over cohorts corresponds to the variance of the residuals of the previous regression.

- *Step 3.* Regress the residual variance on cohort dummies and a polynomial function of age. Then, draw the estimated age effects on a graph to obtain the age-profile of the residual variance.[15] Estimate the slope of this age-profile for each cohort *c* which represents the estimated variance of the shocks faced by household, $\hat{\sigma}^2_{\varepsilon ct+1}$.

- *Step 4.* Draw a value $\tilde{\varepsilon}^c_{it+1}$ in the normal distribution with mean zero and variance $\hat{\sigma}^2_{\varepsilon ct+1}$ within each cohort *c* and combine it with the estimated coefficients of the observable characteristics to predict the vulnerability index $\hat{v}^c_{it}$ for each household *i* at time *t* belonging to cohort *c*. For that purpose, x^c_{it+1} can be predicted deterministically from x^c_{it} by incrementing age or assuming that characteristics are time invariant.

2.4.Stochastic Tests of Welfare Dominance

In this section, we present a methodology for temporal or spatial comparisons of joint distributions of present wealth and expected future wealth. As in Duclos *et al.* (2011), bi-dimensional orderings can first be defined using the following *bi-dimensional dominance surface*:

$$D^{\alpha_a,\alpha_{\tilde{a}}}\left(z_a, z_{\tilde{a}}\right) = \int_0^{z_a}\int_0^{z_{\tilde{a}}}\left(z_a - a\right)^{\alpha_a}\left(z_{\tilde{a}} - \tilde{a}\right)^{\alpha_{\tilde{a}}} dF(a,\tilde{a}),$$

where a denotes present wealth, $\tilde{a}$ denotes future wealth, $F(a,\tilde{a})$ is the bivariate distribution function of a and $\tilde{a}$, $\alpha_a \geq 0$ and $\alpha_{\tilde{a}} \geq 0$ are two integers, and z_a and $z_{\tilde{a}}$ are two poverty thresholds. This equation corresponds to a bi-dimensional generalization of the FGT index (Foster et al., 1984) when well-being is measured at two different periods of time. Using these notations, we can define a generalized index of vulnerability as the integral of the univariate dominance curve for $\tilde{a}$:

$$v(\alpha_{\tilde{a}}) = \int_0^{z_{\tilde{a}}}\left(z_{\tilde{a}} - \tilde{a}\right)^{\alpha_{\tilde{a}}} dF(\tilde{a}).$$

where $F(\tilde{a})$ is the univariate distribution function of $\tilde{a}$. A special case is $v(0)=F(z_{\tilde{a}})$ which is the expected poverty index considered previously. We can also rewrite previous equation as:

$$D^{\alpha_a,\alpha_{\tilde{a}}}\left(z_a,z_{\tilde{a}}\right)=\int_0^{z_a}\left(z_a-a\right)^{\alpha_a}\left[\int_0^{z_{\tilde{a}}}\left(z_{\tilde{a}}-\tilde{a}\right)^{\alpha_{\tilde{a}}}dF(\tilde{a}\mid a)\right]dF(a).$$

where $F(a)$ is the univariate distribution function of a and $F(\tilde{a}\mid a)$ is the distribution of $\tilde{a}$ conditional on a. According to this expression, the bi-dimensional dominance surface can be thought of as the integral of the *vulnerability curves*, conditional on a, weighted by the gaps in a to z_a.

Interestingly enough, the dominance surface is influenced by the covariance between a and $\tilde{a}$. Indeed, rewriting previous equation we get:

$$D^{\alpha_a,\alpha_{\tilde{a}}}\left(z_a,z_{\tilde{a}}\right)=\int_0^{z_a}\left(z_a-a\right)^{\alpha_a}dF(a)\int_0^{z_{\tilde{a}}}\left(z_{\tilde{a}}-\tilde{a}\right)^{\alpha_{\tilde{a}}}dF(\tilde{a})+\mathrm{cov}\left(\left(z_a-a\right)^{\alpha_a},\left(z_{\tilde{a}}-\tilde{a}\right)^{\alpha_{\tilde{a}}}\right).$$

Hence, comparing the correlation between present poverty and expected future poverty can indicate the order of dominance between joint distributions of present wealth and expected future wealth.

Finally, tests of welfare dominance can be stated as follows. Consider two joint distributions A and B of present wealth and expected future wealth and define $\Delta D^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)=D_A^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)-D_B^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)$ for any $s_a=s_{\tilde{a}}=1,2$. Distribution A is said to dominate distribution B at orders $\left(s_a,s_{\tilde{a}}\right)$ if $\Delta D^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)<0$, for all possible values of $\left(z_a,z_{\tilde{a}}\right)$. $\hat{D}^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)$ is estimated following Duclos *et al.* (2011)'s methodology and the variance of the difference, $\mathrm{var}\left(\Delta\hat{D}^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)\right)$, is estimated by bootstrapping. Statistical tests can thus be provided by using simple *t*-statistics for the null hypothesis of non-dominance that is $\Delta\hat{D}^{s_a-1,s_{\tilde{a}}-1}\left(z_a,z_{\tilde{a}}\right)=0$.

3. APPLICATION TO THE GHANA LIVING STANDARD SURVEYS

3.1. Data and Asset Index

We apply the previous methodology to the third (1991/92), fourth (1998/99) and fifth (2005/06) rounds of the Ghana Living Standard Survey (GLSS). These three nationally representative surveys are quite comparable and provide similar and good quality data on assets, income, consumption, education and other household demographic variables. On average, around 6,000 households are interviewed in each survey.[16]

In our attempt to measure vulnerability, we use an asset-based index. Among household assets, we first consider liquid assets since these assets can be sold to purchase basic commodities in the event of a drop in income. Second, we consider more durable assets such as housing and education, which can also be accumulated in order to protect households against poverty. Other intangible assets such as household relations and social capital may have been taken into account in the analysis, but they are not available in the data.[17]

The asset index is a composite indicator that is a linear combination of categorical variables obtained from a multiple correspondence analysis:[18]

$$a_i = \sum_{k=1}^{K} F_{1k} d_{ki} \ ,$$

where a_i is the value of the asset index for the ith observation, d_{ki} is the value of the kth dummy variable (with k=1,…,K) describing the asset variables considered in the analysis (liquid assets as well as housing variables and education of the head of the household), and F_{1k} is the value of the standardized factorial score coefficient (or asset index weights) of the first component of the analysis.[19] Built this way, the asset index can be described as the best regressed latent variable on the K asset primary indicators, since no other explained variable is more informative (Asselin, 2009).

Next, the methodology is developed in order to compare distributions of the asset index over time. The data sets for several years are then pooled and asset weights are estimated using factor analysis for the pooled sample. We obtain:

$$a_{i(t)} = \sum_{k=1}^{K} F_{1k} d_{ki(t)}$$

where the factorial score coefficients F_{1k} are supposed to be constant over time.

Results from multiple correspondence analysis for the pooled data set are presented in Table 1. Analysis considers liquid assets as well as housing and education variables. Weights have signs consistent with interpretation of the first component as an asset-poverty index. The first dimension of the multiple correspondence analysis explains 21.5% of total inertia. Variables such as having no toilet, having access to electricity or being not educated have the largest contribution to inertia (14.3%, 8.2% and 21.3% of partial inertia respectively). Table 1 also provides means and standard errors for the analysis, on the various variables used for the asset index as well as on household size, head of household's gender and age, and the number of children under five years old in the household. For instance, average household size is 3.9 in Ghana and 39.7% of household have access to electricity; 51.4% of head of households have no education.

Figure 1 presents the density function of household per capita asset index. This indicator is normalized to be bounded by 1 and 100. In comparison with the distribution of per capita household consumption expenditures, per capita household asset index appears to be more concentrated on the lower tail of the distribution, as it is also the case for per capita household income. Assets inequality and income inequality thus appear to be more pronounced than consumption inequality, with Gini coefficients being respectively 0.4811, 0.5790 and 0.4271.

Taking the analysis one step further, Table 2 presents the Spearman rank correlation between welfare indicators and shows that per capita household consumption is more correlated to per capita asset index than to per capita household income. These results are comparable to those obtained, for instance, by Sahn and Stifel (2003). Furthermore, the correlation between per capita asset index and other indicators appear to be higher in survey year 2005/06 than in 1991/92.

3.2.Estimates

Our estimates of the vulnerability index follow the different steps recalled in the methodology section. Table 3 presents the first-stage household-level regressions of the three welfare indicators (household per capita asset index, income and consumption) on various household's characteristics such as household size, household head age, gender and education, and household location. When comparing the different regressions, it appears that coefficient estimates have the same signs and are rather stable over the three survey years 1991/92, 1998/99 and 2005/06. While the R-squared is high for the per capita asset index (around 0.7-0.8), it is rather low for per capita income (around 0.1-0.2); it is intermediate at about 0.4 for per capita consumption expenditures. One explanation for such discrepancies is that large measurement errors generally occur when considering income data. It seems that this is particularly true of GLSS data.

One step further, we propose to measure vulnerability as expected poverty. So, in order to have a look at the dynamic of the welfare indicators, we regroup households from the GLSS into cells: households whose heads have the same date of birth (we define five-year cohorts), the same level of education (no education, primary and secondary and more) and live in the same region (greater Accra metropolitan area, other urban, rural coastal, rural forest and rural savannah) are regrouped into the same cells. After regrouping some low-sized cells,[20] 166 cells were constituted with the three GLSS surveys, with an average size of around 115.5 households in each cell.

As described earlier in the methodology section, we calculate for each cell the variance of the residuals of the first-stage household-level regression. We then regress the residual variance on cohort dummies (created by crossing household head date of birth, education and location dummies) and a polynomial function of age (generally of two degrees or more if statistically significant). From the age profile of the residual variance, we calculate the slope which is an estimate of the variance of asset, consumption or income. Note that this slope should necessary be positive (i.e. the amplitude of shocks grows with age) since the estimated variance should always be positive. This is generally the case. However, when it is not, contiguous cells have been regrouped for the estimates. Finally, once the variance of shocks is estimated for each cohort then the last estimation step consists in drawing values of shocks within the standard normal distribution and estimating the household vulnerability index using coefficient estimates.

Table 4 presents the percentage of vulnerable households estimated for four poverty thresholds corresponding to the 25th, 50th, 75th and 90th percentiles of the distribution in the last available survey and two vulnerability thresholds, 0.5 and 0.29. People are thus considered as vulnerable when they are more likely to fall into poverty in any period over two consecutive periods than to not be poor, that is $(1–P)^2 \leq 0.5$, where P is the probability to fall below the poverty line. So, previous condition can be rewritten as $P \geq 0.29$. Instead, a stricter condition is that people are considered as vulnerable when they are more likely to fall into poverty than to not be poor in the next period that is $P \geq 0.5$. Both vulnerability thresholds are used in our analysis.

Table 4 shows, for instance, that households in survey year 2005/06 with a poverty threshold corresponding to the 25th percentile and a vulnerability threshold of 0.5 are 26.9% to be vulnerable to asset-poverty, 29.7% are vulnerable to consumption-poverty and 32.6% are vulnerable to income-poverty. In general, we obtain from our estimates that the fraction of vulnerable households is higher than the poverty rate. However, in many cases this gap is larger for income-poverty than for both consumption-poverty and asset-poverty. It is also generally larger for consumption-poverty than it is for asset-poverty.

These results are consistent with our theoretical framework according to which households may rather smooth their assets over time instead of smoothing consumption or income. Consequently, expected asset-poverty underestimates expected consumption-poverty. The difference between both is however not very large. Table 5 shows that expected asset-poverty is a better proxy for expected consumption-poverty than is expected income-poverty. Indeed, Spearman rank correlation is higher between expected asset-poverty and expected consumption-poverty than it is between expected income-poverty and expected consumption-poverty, except for survey years 1998/99 and 2005/06 with poverty threshold of 90%. Furthermore, correlations are of the same order of magnitude as those in Table 2.

4. CROSS-COUNTRY ANALYSIS USING THE DEMOGRAPHIC HEALTH SURVEYS

4.1. Data

To implement the methodology, we have selected 9 sub-Saharan African countries with at least 3 standard Demographic Health Surveys (DHS) available (Burkina-Faso, Ghana, Kenya, Madagascar, Niger, Tanzania, Uganda and Zambia) plus Haiti, a little island in the Caribbean which is regularly hit by shocks. (See the list of countries in Table 6.) For our purposes, the DHS have two important characteristics. First, they are conducted in single rounds on nationally representative samples of around 10,000 households on average in each survey, with a minimum of about 8,000 households in Niger and a maximum of about 18,000 households in Madagascar. Large sample sizes is an important feature of the data since building cells over a large number of households reduces measurement error as well as bias in estimators based on pseudo-panel data. Second, although survey designs are not entirely uniform, they are reasonably comparable over time and across countries. This also proves to be an important feature for our estimates.

Table 7 presents asset index weights and contribution to inertia of the first component of the multiple component analysis. Several wealth items have been used: liquid assets (radio, television, refrigerator, bicycle, motorcycle, car), housing characteristics (tap water, surface water, flush toilet, no toilet, electricity, rudimentary floor, finished floor) and head of household's education (no education, primary education, secondary education and tertiary education). Several items are not available in some countries: motorcycle and car in Burkina-Faso and Kenya; motorcycle and rudimentary floor in Madagascar and rudimentary floor in Niger and Uganda. However, these items generally contribute to a relatively low percentage of inertia. We thus choose to keep them all when available for the analysis.

Results from multiple correspondence analysis are presented for each country separately after having pooled the data over the survey periods. Weights have signs consistent with interpretation of the first component as an asset-poverty index and weights are generally comparable between countries. However, variables contributions to inertia vary across countries. For instance, the contribution of having no education appears to be particularly high (26.1% in Ghana, 17.7% in Haiti, 38.2% in Kenya, 21.3% in Madagascar, 57.6% in Rwanda, 41.4% in Tanzania, 33.3% in Uganda, 22.2% in Zambia), except in Burkina-Faso (9.6%) and Niger (11.7%). Having no toilet also contributes in a large extent to inertia (except in Rwanda). Having access to surface water contributes to 21.5% of inertia in Haiti and 12.1% in Kenya. Owning a television and having access to electricity contribute to, respectively, 13.4% and 14.8% of inertia in Burkina-Faso. Other items contribute to less than 10% of inertia.

Table 8 provides descriptive statistics on the main variables for the analysis. Differences exist between countries. Having no toilets is more frequent in Niger (81.9%), Burkina-Faso (71.2%) and, to a lesser extent, Madagascar (49.3%) than in other countries. Countries also differ in terms of tap water access (low access rates, that is lower than 10%, in Burkina-Faso, Madagascar, Uganda), in terms of electricity access (low access rates in Burkina-Faso, Niger, Rwanda, Tanzania and Uganda) and in terms of head education (83.4% have no education in Burkina-Faso and 87.8% in Niger). Household size is higher in Burkina-Faso (6.7) and Niger (6.2) and lower in Ghana (3.8). More people live in urban areas in Ghana (42.6%), Haiti (38.6%) or Zambia (37.4%) than in Burkina-Faso (19.3%), Kenya (23.6%), Madagascar (18.7%), Niger (17.0%), Rwanda (12.3%), Tanzania (24.9%) and Uganda (14.7%).

4.2.Urban-Rural Comparisons

Several studies have outlined the differences between rural and urban areas in terms of living standards in Africa.[21] For instance, Sahn and Stifel (2003) provide evidence of large and persistent poverty gap between rural and urban areas using several African DHS. Yet, for years development economists and policy makers have advocated for the promotion of rural-focused and agricultural policies to support growth and reduce poverty and vulnerability. Furthermore, urbanisation trends should have increased inequalities in urban areas. Consequently, poverty and vulnerability gaps should have decreased over time. Furthermore, rural-urban differentials in terms of poverty and vulnerability should also vary across countries due to sectoral specifities or because economies have reached different stages of urbanisation.

In order to assess the poverty and vulnerability gaps between rural and urban areas in sub-Saharan African countries, we apply the different steps of our methodology to the DHS. First, pseudo-panels are built. Table 9 presents the number of cells and cells size constituted from the data. Mean average size ranges between 111.6 households in Zambia (with a minimum of 20 households and a maximum of 984 households) and 167.0 in Rwanda (with a minimum of 20 households and a maximum of 1584 households). The number of cells ranges from 133 in Burkina-Faso to 254 in Ghana.

Second, log per capita asset index has been regressed on variables presented in Table 8 (log of household size, age of the head and its square, education and gender of the head, location and the presence of children under 5 years old). Residuals are estimated from these regressions. As a result of step 3 and step 4 of the methodology, the percentage of vulnerable households is estimated and presented in Table 10. In all the countries, urban vulnerability appears to be higher than rural vulnerability. The gap is higher in Burkina-Faso, Niger and Madagascar than in other countries.

Finally, joint distributions of present wealth and expected future wealth can be compared using stochastic tests of welfare dominance as presented in the methodology section. To do so, we estimate bi-dimensional dominance surface for urban and rural areas using both the present asset index and the simulated (or future) asset index. Dominance surfaces are calculated for various thresholds corresponding to the deciles of both present and simulated future asset distributions. Then, t-statistics are computed for the difference between urban and rural areas. Differences are estimated at dominance orders (1,1) and (2,2). The results confirm that urban areas unambiguously dominate rural areas in terms of present wealth and expected future wealth in all the country considered. The results are statistically significant at less than 1 percent level for all thresholds and all countries. Results are presented for Madagascar in Table 11. Table 11 also reports differences in poverty incidence. All reported differences are statistically significant at less than 1 percent level.

5. CONCLUSION

In this paper, we present a simple and intuitively appealing framework to assess vulnerability to asset-poverty. The approach draws on a model of asset smoothing behaviour that is based on the idea that households will prefer to keep their assets unchanged when facing adverse shocks on them. We use age-cohort decomposition techniques focusing on second-order moments in order to identify and estimate the variance of shocks on assets. Estimates are used to simulate expected asset-poverty. This approach can be applied to repeated cross-section data that are available in many developing countries.

Applying this methodology to Ghana Living Standard Surveys, we find that expected asset-poverty slightly underestimates expected consumption-poverty. Furthermore, expected asset-poverty appears to be a better proxy for expected consumption-poverty than is expected income-poverty. In a second application, we use Demographic Health Surveys for several sub-Saharan African countries plus Haiti in order to assess vulnerability to asset-poverty. Cross-country comparisons show a clear vulnerability gap between urban and rural areas. What is more, joint distributions of present wealth and expected future wealth are compared using stochastic tests of welfare dominance. Welfare differences between urban and rural areas appear large, robust and statistically significant for all the country considered. Consequently, in these countries, policies and programs should aim at increasing or securing assets of the most vulnerable people in order to increase welfare in rural areas.

NOTES

[1] See, among others, Glewwe and Hall (1998), Pritchett et al. (2000), Chaudhuri et al. (2002), Chaudhuri (2003), Ligon and Schechter (2003), Christiaensen and Subbarao (2005), Calvo and Dercon (2005), Calvo (2008), Günther and Harttgen (2009).

[2] See, for instance, the literature review by Hoddinott and Quisumbing (2003).

[3] What is more, we have to choose a probability threshold under which people should be considered vulnerable. An intuitive threshold is when the probability of being poor in the future exceeds 50%: people should be considered vulnerable in this case since they are more likely to fall into poverty than to not be poor in the future (Pritchett et al., 2000).

[4] See, for instance, Sahn and Stifel (2000), Filmer and Pritchett (2001), Sahn and Stifel (2003), Booysen et al. (2008).

[5] This list of assets is not exhaustive and could be completed following Moser (1998)'s asset-based approach. In her asset vulnerability framework, Moser (1998) identifies several categories of assets and illustrates how portfolio management affects vulnerability. Asset management includes: labor (e.g., the number of earners in the family and their income level), human capital (education and health), productive assets (such as housing in urban areas or cattle in rural areas), household relations and social capital.

[6] Sahn and Stifel (2003) show that an asset index obtained from a factor analysis on household assets using multipurpose surveys from several developing countries is a valid predictor of child health and nutrition and, thus, long term poverty.

[7] I thank a referee for suggesting me this point.

[8] See, among others, Rosenzweig and Wolpin (1993), Morduch (1995), Fafchamps et al. (1998), Kazianga and Udry (2006), and Hoddinott (2006).

[9] Zimmerman and Carter (2003) and Carter and Barrett (2006), among others, have analyzed the existence of poverty traps when households are involved in various asset accumulation dynamics.

[10] Note that if households are able to diversify their portfolio of assets into risky and safe assets, then in presence of credit constraints they will choose to lower the proportion of risky assets held in order to smooth income over time (Morduch, 1994).

[11] The empirical evidence concerning the existence of such asset-poverty traps and thresholds are mixed with some authors finding evidence of its existence: see, for instance, Lybbert et al. (2004), Adato et al. (2006), Barret et al. (2006) or Carter et al. (2007). Carter and May (1999, 2001) also provide evidence of poverty traps although they are differently theoretically grounded.

[12] Bourguignon and Goh (2004) proposed a similar method for assessing vulnerability to poverty, although relying on earning dynamics.

[13] A cohort is typically defined by the year of birth, education level and location.

[14] As exposed by Verbeek and Nijman (1992), the bias in the standard within estimator based on pseudo panel data is decreasing with the number of individuals in each cell, more than with the number of cells. However, Verbeek (2008) notes that there is no general rule to judge whether cell size is large enough. Deaton (1985) also suggests that measurement error decreases as a function of the size of the cells.

[15] As in Deaton and Paxson (1994), we can normalize so that the fitted age effect at, for instance, age 35-40 equals the average residual variance of the logarithm of the asset index for 35-40 year-olds over all cohorts.

[16] See, e.g., Coulombe and Wodon (2007) for further description of the GLSS data.

[17] Note that estimates were replicated using a more restrictive definition of the asset index for which only liquid assets were included in the analysis; but no sizeable differences were obtained for the evaluation of vulnerability to poverty from these estimates.
[18] See Benzécri (1973) or, more recently, Asselin (2009).
[19] Alternatively, Sahn and Stifel (2000) used factor analysis, and Filmer and Pritchett (2001) used principal component analysis to measure their asset index. In reference to these methodologies, multiple correspondence analysis can be viewed as a principal component analysis applied to a contingency table with the chi2-metric being used on the row/column profiles, instead of the usual Euclidean metric. Multiple correspondence analysis provides information similar in nature to those produced by factor analysis and is less restrictive than principal component analysis.
[20] Note that cells with less than 20 households have been regrouped in order to minimize measurement error.
[21] See, e.g., Ravallion et al. (2007).

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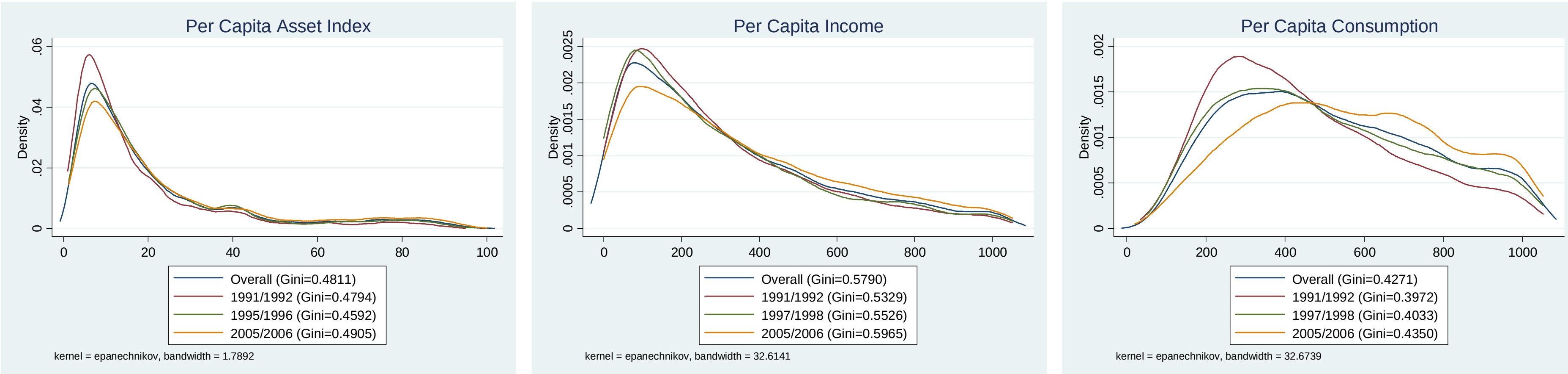
Table 1. Descriptive statistics and asset index weights for pooled data (GLSS)

Variables	Weights	% of partial inertia	Mean	Std
Liquid assets				
Radio	-0.222	0.7	0.297	0.457
Television	0.881	8.5	0.225	0.417
Refrigerator	1.046	8.3	0.156	0.363
Bicycle	-0.723	5.4	0.212	0.409
Car	1.080	1.4	0.025	0.155
Housing				
Tap water	1.073	8.0	0.143	0.350
Surface water	-0.924	9.6	0.230	0.421
Flush toilet	1.228	6.1	0.275	0.000
No toilet	-1.126	14.3	0.231	0.422
Electricity	0.652	8.2	0.397	0.489
Finished floor	-0.011	0.0	0.370	0.000
Head of household's education				
No education	-0.923	21.3	0.514	0.500
Primary	0.420	1.9	0.215	0.411
Secondary	0.659	5.5	0.258	0.438
Tertiary	1.178	0.9	0.013	0.114
Partial inertia (% of total inertia)		21.5		
Other household's characteristics				
Household size			3.9	2.6
Male head			0.691	0.462
Age of the head			44.8	15.4
Number of children under 5 years			0.7	0.9

Source: Author's computations using GLSS 1991/92, 1998/99 and 2005/06 (pooled survey data).

Figure 1. Kernel density estimates of welfare indicators (GLSS)



Source: Author's computations using GLSS 1991/92, 1998/99 and 2005/06. Note: Consumption and income are expressed in 2006 US$.

Table 2. Spearman rank correlations between consumption expenditures and alternative measures of welfare (GLSS)

Survey year	Asset index	Income
1991/92	0.62	0.53
1998/99	0.64	0.58
2005/06	0.68	0.58

Source: Author's computations using GLSS 1991/92, 1998/99 and 2005/06.
Note: Welfare indices are expressed *per capita*.

Table 3. First-stage household-level regressions (GLSS)

	Log per capita asset index						Log per capita income					
	1991/92		1998/99		2005/06		1991/92		1998/99		2005/06	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value	Coefficient	P-va
Constant	3.311	0.000	3.442	0.000	3.462	0.000	5.972	0.000	5.994	0.000	5.325	0.0
Log of household size	-0.692	0.000	-0.761	0.000	-0.801	0.000	-0.382	0.000	-0.353	0.000	-0.355	0.0
Age of the head	-0.004	0.304	-0.011	0.000	0.002	0.493	0.005	0.412	0.000	0.986	0.024	0.0
Age of the head squared / 100	0.006	0.104	0.014	0.000	0.000	0.977	-0.008	0.224	0.000	0.975	-0.022	0.0
Male head	-0.131	0.000	-0.200	0.000	-0.148	0.000	0.154	0.000	0.008	0.838	0.154	0.0
Primary education	0.862	0.000	0.819	0.000	0.640	0.000	0.233	0.000	0.223	0.010	0.236	0.0
Secondary education or more	0.895	0.000	0.930	0.000	0.730	0.000	0.634	0.000	0.431	0.000	0.739	0.0
Urban (outside GAMA)	-0.201	0.000	-0.119	0.000	-0.098	0.000	-0.220	0.000	-0.333	0.000	0.220	0.0
Rural coastal	-0.691	0.000	-0.344	0.000	-0.438	0.000	-0.574	0.000	-0.615	0.000	-0.057	0.3
Rural forest	-0.559	0.000	-0.377	0.000	-0.352	0.000	-0.303	0.000	-0.318	0.000	0.006	0.9
Rural savannah	-0.896	0.000	-0.759	0.000	-0.702	0.000	-0.661	0.000	-0.648	0.000	-0.262	0.0
Presence of children 5 years or lower	-0.071	0.000	-0.076	0.000	-0.009	0.153	-0.047	0.008	-0.084	0.000	-0.026	0.1
Number of observations	4493		5990		8682		4406		5786		8367	
R-square	0.7209		0.7833		0.7897		0.1782		0.137		0.1361	

	Log per capita consumption expenditures					
	1991/92		1998/99		2005/06	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Constant	6.911	0.000	7.289	0.000	6.886	0.000
Log of household size	-0.404	0.000	-0.413	0.000	-0.407	0.000
Age of the head	0.000	0.994	-0.004	0.284	0.012	0.000
Age of the head squared / 100	0.001	0.826	0.003	0.347	-0.013	0.000
Male head	-0.067	0.000	-0.072	0.000	-0.080	0.000
Primary education	0.210	0.000	0.153	0.000	0.205	0.000
Secondary education or more	0.395	0.000	0.312	0.000	0.534	0.000
Urban (outside GAMA)	-0.012	0.670	-0.273	0.000	0.100	0.000
Rural coastal	-0.339	0.000	-0.521	0.000	-0.188	0.000
Rural forest	-0.442	0.000	-0.475	0.000	-0.205	0.000
Rural savannah	-0.533	0.000	-0.823	0.000	-0.527	0.000
Presence of children 5 years or lower	-0.058	0.000	-0.083	0.000	-0.044	0.000

Number of observations	4493	5990	8682
R-square	0.4155	0.4243	0.4363

Source: Author's computations using GLSS 1991/92, 1998/99 and 2005/06.

Table 4. Percentage of vulnerable households (GLSS)

Vulnerability threshold	Poverty threshold	1991/92			1998/99			2005/2006		
		Asset index	Consumption	Income	Asset index	Consumption	Income	Asset index	Consumption	Income
29%	25%	25.6	27.2	28.9	36.0	35.6	37.9	26.9	29.7	32.6
	50%	50.5	51.8	54.2	56.8	57.9	59.8	51.8	54.0	56.5
	75%	75.9	76.1	78.7	78.8	79.9	80.7	76.0	77.1	79.0
	90%	90.2	90.6	91.1	91.6	92.2	92.6	90.9	91.0	91.6
50%	25%	25.2	25.6	26.9	35.7	34.2	36.4	26.6	28.4	30.9
	50%	50.1	50.0	51.5	56.4	56.5	57.8	51.4	52.8	54.2
	75%	75.5	75.0	75.7	78.5	79.0	78.6	75.6	76.4	77.1
	90%	89.7	90.2	90.1	91.4	91.8	91.5	90.6	90.5	90.6

Source: Author's computations using GLSS 1991/92, 1998/99 and 2005/06.
Note: Welfare indices are expressed *per capita*.

Table 5. Spearman rank correlations between expected consumption poverty and alternative expected poverty indices (GLSS)

Poverty threshold	1991/92		1998/99		2005/06	
	Asset index	Income	Asset index	Income	Asset index	Income
25%	0.46	0.42	0.55	0.46	0.59	0.51
50%	0.53	0.48	0.57	0.53	0.60	0.54
75%	0.52	0.46	0.49	0.48	0.53	0.49
90%	0.45	0.39	0.38	0.41	0.38	0.40

Source: Author's computations using GLSS 1991/92, 1998/99 and 2005/06.
Note: Welfare indices are expressed *per capita*.

Table 6. List of DHS countries

Country name	Survey years
Burkina-Faso	(1993, 1998-99, 2003)
Ghana	(1988, 1993, 1998, 2003, 2008)
Haiti	(1994-95, 2000, 2005-06)
Kenya	(1989, 1993, 1998, 2003)
Madagascar	(1992, 1997, 2003-04, 2008-09)
Niger	(1992, 1998, 2006)
Rwanda	(1992, 2000, 2005)
Tanzania	(1991-92, 1996, 1999, 2004-05)
Zambia	(1992, 1996, 2001-02, 2007)

Source: Demographic Health Surveys program (http://www.measuredhs.com/).

Table 7. Asset index weights (DHS)

Variables	Burkina-Faso		Ghana		Haiti		Kenya		Madagascar	
	Weights	% of partial inertia	Weights	% of partial inertia	Weights	% of partial inertia	Weights	% of partial inertia	Weights	% of partial inertia
Liquid assets										
Radio	0.123	0.4	0.111	0.4	0.310	2.1	0.098	0.3	-0.222	0.7
Television	1.576	13.4	0.769	7.7	0.976	7.4	0.746	4.7	0.881	8.5
Refrigerator	1.940	9.9	0.928	7.2	1.146	4.5	0.956	2.6	1.046	8.3
Bicycle	-0.313	3.2	-0.668	5.5	0.462	1.4	-0.034	0.0	-0.723	5.4
Motocycle	-	-	0.107	0.0	0.807	0.6	-	-	-	-
Car	-	-	0.898	2.0	1.216	2.2	-	-	1.080	1.4
Housing										
Tap water	1.306	10.1	0.642	4.4	0.392	2.0	0.445	3.0	1.073	8.0
Surface water	-0.636	3.7	-0.938	8.6	-1.145	21.5	-1.004	12.1	-0.924	9.6
Flush toilet	1.944	2.3	1.098	2.6	1.150	2.6	0.891	3.9	1.228	6.1
No toilet	-0.684	13.6	-1.319	20.9	-1.076	19.7	-1.889	19.0	-1.126	14.3
Electricity	1.615	14.8	0.558	6.6	0.805	8.0	0.806	5.3	0.652	8.2
Rudimentary floor	-0.981	0.0	0.587	0.0	-0.590	0.1	0.152	0.0	-	-
Finished floor	0.550	5.6	-0.013	0.0	0.351	2.9	0.496	4.3	-0.011	0.0
Head of household's education										
No education	-0.515	9.6	-1.235	26.1	-0.912	17.7	-1.793	38.2	-0.923	21.3
Primary education	0.500	1.2	-0.217	0.4	-0.005	0.0	-0.163	0.6	0.420	1.9
Secondary education	1.584	8.3	0.536	5.2	0.938	6.0	0.551	3.3	0.659	5.5
Tertiary education	2.110	4.1	0.904	2.4	1.309	1.5	0.917	2.6	1.178	0.9
Partial inertia (% of total inertia)		24.6		18.1		21.5		20.3		24.1

Variables	Niger		Rwanda		Tanzania		Zambia	
	Weights	% of partial inertia	Weights	% of partial inertia	Weights	% of partial inertia	Weights	% of partial inertia
Liquid assets								
Radio	0.150	0.5	0.236	1.5	0.150	0.7	0.221	0.9
Television	1.421	9.9	1.100	2.6	1.236	4.4	0.876	5.2
Refrigerator	1.594	6.8	1.103	1.9	1.317	3.9	1.053	4.2
Bicycle	0.505	1.1	0.441	1.2	-0.058	0.1	-0.220	0.6
Motocycle	1.058	3.4	1.200	1.7	1.240	2.3	1.044	0.6
Car	1.446	3.9	1.246	2.3	1.369	3.0	1.034	1.6
Housing								
Tap water	0.792	5.7	0.497	1.6	0.449	2.7	0.753	5.7
Surface water	-0.800	8.2	-0.669	6.0	-0.914	9.2	-0.862	9.1
Flush toilet	1.647	2.3	1.094	0.8	1.175	1.9	1.001	5.3
No toilet	-0.752	18.5	-0.994	3.1	-1.122	11.5	-1.221	19.2
Electricity	1.288	10.4	0.938	4.2	1.027	7.0	0.977	6.5
Rudimentary floor	-	-	-0.579	0.0	-0.998	0.0	0.739	0.0
Finished floor	0.977	9.8	0.661	4.5	0.637	6.1	0.624	5.9
Head of household's education								
No education	-0.552	11.7	-1.505	57.6	-1.512	41.4	-1.690	22.2
Primary education	0.458	0.8	0.403	5.1	0.144	0.7	-0.566	6.8
Secondary education	1.276	4.3	0.903	4.7	0.907	3.7	0.553	3.4
Tertiary education	1.720	2.9	1.108	1.1	1.239	1.5	1.017	2.8
Partial inertia (% of total inertia)		23.6		15.2		15.6		19.6

Source: Author's computations using Demographic Health Surveys (pooled survey data).

Table 8. Descriptive statistics (DHS)

Variables	Burkina-Faso		Ghana		Haiti		Kenya		Madagascar		Niger		Rwanda		Tanzania		Zambia	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Liquid assets																		
Radio	0.583	0.556	0.628	0.540	0.513	0.505	0.662	0.503	0.526	0.517	0.413	0.556	0.389	0.509	0.494	0.509	0.459	0.512
Television	0.097	0.420	0.297	0.511	0.226	0.422	0.181	0.484	0.128	0.351	0.061	0.373	0.025	0.290	0.042	0.263	0.180	0.416
Refrigerator	0.049	0.362	0.194	0.463	0.093	0.294	0.051	0.322	0.028	0.173	0.032	0.291	0.016	0.225	0.032	0.242	0.098	0.383
Bicycle	0.755	0.490	0.220	0.452	0.145	0.355	0.267	0.463	0.155	0.384	0.073	0.302	0.095	0.390	0.355	0.529	0.291	0.471
Motocycle	-	-	0.031	0.247	0.017	0.131	-	-	-	-	0.043	0.264	0.017	0.330	0.018	0.302	0.013	0.275
Car	-	-	0.055	0.304	0.040	0.198	-	-	0.022	0.205	0.026	0.293	0.019	0.339	0.024	0.321	0.039	0.327
Housing																		
Tap water	0.087	0.282	0.238	0.433	0.325	0.473	0.306	0.461	0.072	0.257	0.124	0.333	0.080	0.272	0.196	0.400	0.269	0.441
Surface water	0.215	0.410	0.201	0.407	0.342	0.479	0.269	0.443	0.343	0.473	0.325	0.473	0.224	0.418	0.223	0.419	0.276	0.444
Flush Toilet	0.013	0.114	0.048	0.217	0.054	0.228	0.097	0.296	0.011	0.106	0.008	0.090	0.008	0.090	0.020	0.139	0.150	0.355
No Toilet	0.712	0.453	0.198	0.405	0.378	0.490	0.117	0.321	0.493	0.498	0.819	0.389	0.051	0.220	0.130	0.338	0.287	0.450
Electricity	0.097	0.392	0.490	0.537	0.333	0.476	0.167	0.412	0.156	0.367	0.077	0.341	0.050	0.272	0.108	0.395	0.182	0.399
Rudimentary Floor	0.000	0.013	0.002	0.040	0.005	0.072	0.005	0.073	-	-	-	-	0.000	0.015	0.001	0.026	0.002	0.041
Finished Floor	0.341	0.474	0.861	0.352	0.560	0.501	0.371	0.483	0.234	0.422	0.130	0.340	0.125	0.332	0.237	0.428	0.391	0.485
Head of household's education																		
No education	0.834	0.372	0.326	0.477	0.476	0.504	0.236	0.424	0.268	0.441	0.878	0.331	0.418	0.494	0.311	0.466	0.168	0.372
Primary Education	0.091	0.288	0.191	0.400	0.333	0.476	0.466	0.499	0.483	0.498	0.071	0.259	0.497	0.501	0.613	0.490	0.488	0.497
Secondary Education	0.058	0.233	0.417	0.501	0.167	0.377	0.237	0.425	0.218	0.412	0.037	0.192	0.075	0.264	0.055	0.229	0.273	0.443
Tertiary Education	0.017	0.128	0.064	0.249	0.024	0.154	0.060	0.238	0.029	0.168	0.011	0.107	0.009	0.092	0.018	0.133	0.068	0.251
Other household's characteristics																		
Household size	6.7	4.4	3.8	2.6	4.8	2.6	4.5	2.7	4.9	2.6	6.2	3.9	4.7	2.3	5.1	3.1	5.4	3.0
Urban	0.193	0.394	0.426	0.503	0.386	0.492	0.236	0.425	0.187	0.388	0.170	0.380	0.123	0.329	0.249	0.435	0.374	0.481
Male head	0.920	0.271	0.650	0.485	0.577	0.499	0.674	0.469	0.781	0.412	0.857	0.354	0.684	0.466	0.768	0.425	0.782	0.410
Age of the head	45.9	16.2	43.9	16.5	46.9	16.1	44.1	15.9	43.0	15.4	45.1	15.8	43.8	16.0	44.6	15.9	42.9	15.1
Number of children under 5 years	1.3	1.4	0.6	0.9	0.8	1.0	0.8	1.0	0.9	1.0	1.4	1.3	0.9	1.0	1.0	1.1	1.1	1.1

Source: Author's computations using Demographic Health Surveys.

Table 9. Cell sizes (DHS)

	Mean	Minimum	Maximum	Number of cells
Burkina-Faso	143.2	20	819	133
Ghana	117.5	20	1226	254
Haiti	146.2	20	1039	167
Kenya	134.7	20	1172	252
Madagascar	157.6	20	2879	250
Niger	153.1	20	1117	123
Rwanda	167.0	20	1584	157
Tanzania	134.1	20	1058	159
Zambia	111.6	20	984	249

Source: Author’s computations using Demographic Health Surveys.

Table 10. Percentage of vulnerable households (DHS)

Vulnerability threshold	Poverty threshold	Burkina-Faso	Ghana	Haiti	Kenya	Madagascar	Niger	Rwanda	Tanzania	Zambia
					Rural					
29%	25%	37.0	39.2	39.7	39.6	34.3	44.6	36.4	34.3	36.6
	50%	66.8	62.5	71.9	67.5	64.2	77.6	58.2	58.5	63.7
	75%	91.2	83.2	89.5	86.2	87.6	96.1	80.6	81.9	84.5
	90%	98.6	96.1	95.9	97.0	95.7	99.1	92.3	94.7	94.0
50%	25%	35.3	37.6	39.5	36.4	32.2	43.7	34.4	30.9	35.3
	50%	65.4	61.7	71.9	64.9	62.3	76.7	55.8	55.0	63.1
	75%	90.8	82.3	89.5	85.4	86.7	95.7	78.4	80.0	84.3
	90%	98.5	95.1	95.9	96.3	95.3	99.0	92.1	93.6	93.8
					Urban					
29%	25%	6.8	18.6	8.4	6.3	4.8	9.6	18.9	18.4	9.9
	50%	13.2	41.9	24.6	23.1	13.8	19.5	44.8	36.5	32.5
	75%	36.8	68.5	59.5	56.6	44.3	47.2	70.9	61.8	62.3
	90%	70.1	84.8	83.4	79.0	75.9	76.9	86.9	83.0	84.5
50%	25%	6.6	18.1	8.1	5.7	4.5	8.8	17.5	17.6	9.3
	50%	12.6	41.2	22.9	21.4	13.0	18.3	41.8	34.8	31.0
	75%	35.7	68.1	57.6	54.4	42.1	45.6	68.9	60.6	61.0
	90%	69.0	84.4	82.3	78.7	74.3	76.1	86.4	82.4	83.6
					All					
29%	25%	29.7	30.2	26.8	28.9	26.9	33.8	32.8	30.8	26.5
	50%	53.9	53.4	52.4	53.2	51.5	59.7	55.4	53.6	52.0
	75%	78.1	76.8	77.1	76.7	76.7	81.0	78.6	77.5	76.1
	90%	91.7	91.1	90.8	91.2	90.7	92.2	91.2	92.1	90.4
50%	25%	28.4	29.0	26.5	26.6	25.2	33.0	30.9	28.0	25.6
	50%	52.7	52.7	51.7	51.0	49.9	58.7	52.9	50.5	51.0
	75%	77.5	76.1	76.3	75.4	75.5	80.2	76.5	75.7	75.5
	90%	91.4	90.4	90.3	90.6	90.0	91.9	90.9	91.1	90.0

Source: Author's computations using DHS. Note: These indicators are calculated using the last available round of the Demographic Health Surveys. Poverty thresholds are calculated for the whole population.

Table 11. Stochastic tests of welfare dominance; rural-urban difference in dominance surfaces (DHS for Madagascar)

	Present wealth (decile)									
	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
	0.046	0.164	0.279	0.378	0.453	0.513	0.516	0.445	0.302	0.096
										Uni-dimensional dominance order 1
D1	0.038	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
D2	0.046	0.155	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167
D3	0.046	0.166	0.255	0.273	0.273	0.273	0.273	0.273	0.273	0.273
D4	0.046	0.166	0.265	0.366	0.375	0.375	0.375	0.375	0.375	0.375
D5	0.046	0.166	0.265	0.382	0.446	0.457	0.457	0.457	0.457	0.457
D6	0.046	0.166	0.265	0.382	0.458	0.515	0.523	0.523	0.523	0.523
D7	0.046	0.166	0.265	0.382	0.458	0.520	0.520	0.517	0.516	0.516
D8	0.046	0.166	0.265	0.382	0.458	0.520	0.521	0.461	0.448	0.448
D9	0.046	0.166	0.265	0.382	0.458	0.520	0.521	0.453	0.312	0.302
D10	0.046	0.166	0.265	0.382	0.458	0.520	0.521	0.453	0.306	0.099
Simulated (future) wealth (decile)										Bi-dimensional dominance orders (1,1)
D1	0.002	0.005	0.008	0.010	0.011	0.013	0.015	0.017	0.019	0.024
D2	0.005	0.027	0.044	0.059	0.073	0.085	0.100	0.116	0.133	0.168
D3	0.008	0.044	0.079	0.112	0.142	0.169	0.202	0.235	0.273	0.350
D4	0.009	0.059	0.111	0.164	0.214	0.261	0.315	0.371	0.435	0.564
D5	0.011	0.073	0.140	0.214	0.287	0.356	0.437	0.520	0.615	0.806
D6	0.013	0.085	0.167	0.260	0.356	0.449	0.560	0.672	0.802	1.062
D7	0.015	0.100	0.199	0.315	0.437	0.559	0.706	0.856	1.028	1.375
D8	0.017	0.115	0.232	0.371	0.520	0.672	0.857	1.043	1.256	1.685
D9	0.019	0.133	0.270	0.436	0.616	0.803	1.031	1.259	1.511	2.014
D10	0.024	0.168	0.345	0.564	0.807	1.062	1.377	1.688	2.013	2.598
Simulated (future) wealth (decile)										Bi-dimensional dominance orders (2,2)

Source: Author's computations using DHS for Madagascar. Note: Thresholds are computed as mean asset-wealth of each decile. All reported differences are statistically significant at less than 1 percent level.