World Development Vol. 36, No. 6, pp. 1113–1130, 2008

0305-750X/$ - see front matter

www.elsevier.com/locate/worlddev

doi:10.1016/j.worlddev.2007.10.008

Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries

FRIKKIE BOOYSEN
University of the Free State, Bloemfontein, South Africa

SERVAAS VAN DER BERG, RONELLE BURGER
University of Stellenbosch, South Africa

MICHAEL VON MALTITZ
University of the Free State, Bloemfontein, South Africa

and

GIDEON DU RAND *
University of Stellenbosch, South Africa

Summary. — Using comparable, nationally representative surveys and extending the work of [Sahn, D. E., & Stifel, D. C. (2000). Poverty comparisons over time and across countries in Africa. *World Development, 28*(12), 2123–2155], an asset index is used to investigate changes in poverty in seven African countries. Poverty declined in five of the seven countries. Improvements in the asset index are driven by progress in the accumulation of private assets, while access to public services has deteriorated. However, the method has some shortcomings. Assets are slow-changing and discrete. The index therefore may not capture changes in well-being accurately. The poor discrimination ability of the index at the lower end of the scale also makes it an inappropriate tool for studying ultra-poverty.

Key words — poverty, asset index, multiple correspondence analysis, Africa

1. INTRODUCTION

While the conventional approach to the measurement of poverty is money-metric and uses income and/or expenditure data, multidimensional approaches employ several socio-economic indicators to compile these indices. This is done either to simulate income or expenditure poverty measures in the absence of more accurate money-metric information, or alternatively as an attempt to compile a superior measure of deprivation by focusing on additional dimensions of poverty—such as access to public services—that are not captured by money-metric measures. This paper attempts to navigate a third way by incorporating both private assets that approximate money-metric

* This work was carried out with financial and scientific support from the Poverty and Economic Policy (PEP) Research Network, which is financed by the Australian Agency for International Development (AusAID) and the Government of Canada through the International Development Research Centre (IDRC) and the Canadian International Development Agency (CIDA). This paper is based on the corresponding working paper emanating from the project (Booysen, Van der Berg, Burger, Von Maltitz, & Du Rand, 2007). We wish to thank Jean-Yves Duclos and Louis-Marie Asselin for their advice, Cobus Burger and Derek Yu for technical assistance, and two anonymous reviewers for comments on an earlier version of this paper. Final revision accepted: October 5, 2007.

measures of poverty and also public assets to supplement the money-metric indicators.

The asset index method is one of the most popular applications of the multidimensional approach. Due to the widespread availability of the demographic and health surveys (DHS) for many of the poorest countries, the absence of money-metric data in these surveys and few alternative surveys containing money-metric data, the asset index method is often applied to this series of data sets (Filmer & Pritchett, 2001; Sahn & Stifel, 2000, 2003; World Bank, 2000a). Sahn and Stifel (2000) employed DHS data in an analysis of poverty in nine African countries using an asset index, while Filmer and Pritchett (2001) analyzed poverty in Indian states. Like Sahn and Stifel (2000), we also apply the asset index to African countries using a collection of DHS.

Our analysis, however, differs from previous studies in important respects. *Firstly*, we employ multiple correspondence analysis (MCA) rather than factor analysis (FA) (used by Sahn & Stifel, 2000) or principal components analysis (PCA) (as in Filmer & Pritchett, 2001; Sahn & Stifel, 2003) to construct the asset index. MCA and FA are more appropriate methodologies for the analysis of categorical rather than continuous variables (all variables in our asset index are categorical). *Secondly*, we investigate the robustness of our conclusions on poverty trends by reporting results using both an asset index based on pooling across countries and indices constructed for each country separately. We test the robustness of our results to sampling and measurement errors and to the choice of poverty lines. *Thirdly*, using some more recent surveys than those used by Sahn and Stifel (2000), allows us to compare poverty over three rather than two periods. Thus, our conclusions regarding trends in poverty in African countries apply to more recent experience and are more stable because they cover a longer time span.

In these three ways, the paper aims to make a contribution to a vital, emergent literature that attempts to use the standardized DHS series to learn more about recent changes in poverty and inequality in African countries. These surveys are an important data source because little is known about changes in poverty over time or differences in poverty between African countries. Although the increased availability of income or expenditure surveys in many African countries over the past two decades has considerably expanded our knowledge of poverty on the continent, Sahn and Stifel (2000, p. 2123) maintain that, "in the vast majority of African countries, we remain unable to make inter-temporal comparisons of poverty," due to problems with the comparability of survey designs and the quality of price deflators. Studies such as these are thus not necessarily intended as a rival to conventional methods of poverty measurement, but rather as a supplement: they can provide estimates to interrogate and triangulate more conventional poverty estimates.

This paper is structured as follows. Section 1 describes the data, while Section 2 elaborates on the method employed in the construction of the asset index and in the poverty analysis. Section 2 also describes aspects of the asset index in more detail, in particular its ability to discriminate adequately between households enjoying different levels of welfare. Section 3 uses the asset index to assess poverty over time and location (urban–rural) in these seven African countries. Section 4 concludes.

2. DATA

More than 70 nationally representative demographic and health surveys (DHS) were conducted in more than fifty countries between 1984 and the late 1990s (Sahn & Stifel, 2000, p. 2127), a number that has increased since (UNFPA, 2002). The standardisation of certain sections and the resulting comparability across specific questions counts as a major strength of these surveys.

The aim is to track changes in poverty over a period of 10–15 years. Consequently, the sample was limited to those Sub-Saharan African countries with at least three demographic and health surveys between the late 1980s and early 2000s: Ghana, Kenya, Mali, Senegal, Tanzania, Zambia, and Zimbabwe. Appendix A lists the sample sizes for each of the surveys and outlines the general characteristics of these DHS surveys, for example, the year, sample size and breakdown by gender and location.

For the purposes of cross-country comparison, surveys are numbered in the order in which they were completed (e.g., Ghana Periods 1, 2, and 3), rather than indicating the survey year. The first period surveys date from the period 1986 to 1992, the second from 1992 to 1996, and the third from 1997 to 2001. Tanzania and Zambia's first period surveys were completed by March 1992, while Senegal's second period survey commenced in November 1992.

For DHS prior to 1990 (Ghana 1988, Kenya 1989, Mali 1987, Senegal 1986, and Zimbabwe, 1988), questions on asset ownership, access to public services, and housing characteristics formed part of the individual-level questionnaire and not of the household-level questionnaire. However, as only certain individuals were included in the individual questionnaires (e.g., selection by age and gender), some household-level questionnaires cannot be matched to any individual-level questionnaires. Households for which data were available represented 73% (Ghana), 66% (Kenya), 78% (Mali), 40% (Senegal), and 71% (Zimbabwe) of households sampled in these surveys. This should be borne in mind when comparing poverty reported for these surveys to that of successive periods.

The countries in our sample range from relatively small in terms of population size (Senegal 9.8 million) to relative large (Tanzania 33.4 million). All countries are relatively poor, with gross national income *per capita* below US$ 500 *per capita*—and thus ranked 159th or lower out of 208 countries in gross national income *per capita* in the UNDP's Human Development Report (UNDP, 2003).

3. METHOD

(a) *Selecting an appropriate method for compiling the asset index*

In the current literature, principal components analysis (PCA) and factor analysis (FA) are most widely used for the construction of asset indices. However, PCA was essentially designed for continuous variables. In contrast, multiple correspondence analysis (MCA) makes fewer assumptions about the underlying distributions of indicator variables and is more suited to discrete or categorical variables. According to Blasius and Greenacre (2006), the most important difference between these two methods is that MCA imposes fewer constraints on the data. Principal component analysis (PCA) requires linear constraints: It assumes that the distances between the categories are the same and that the categories are ordered. [1] For these reasons, we opt for MCA rather than PCA in constructing the asset index.

Asselin (2002, p. 14) describes the calculation of a composite poverty indicator using MCA as a four-stage process. *Firstly*, one constructs an indicator matrix (of ones and zeros) that shows the asset ownership of each household. If the households are displayed as rows, each asset is represented by the inclusion of a column for each possible (mutually exclusive and exhaustive) ownership category of that asset. In other words, each categorical asset ownership variable is reduced to a set of binary indicators. In this way, every household will indicate a "1" in exactly one of each asset's set of columns or categories, and a "0" in all other columns. *Secondly*, the profiles of the households relative to the categories of asset ownership are calculated. The row profiles of a matrix are the rows of that matrix, each divided by its row sum. *Thirdly*, MCA is applied to the original indicator matrix, and provides a set of category-weights from the first dimension or factorial axis of the analysis results. Fourthly, these MCA category-weights are applied to the profile matrix. A household's MCA composite indicator score is calculated by adding up all of that unit's weighted responses. The calculation of the household's asset index score can be represented as follows:

$$\mathrm{MCA}_i = R_{i1}W_1 + R_{i2}W_2 + \cdots + R_{ij}W_j + \cdots + R_{ij}W_j, \qquad (1)$$

where MCA_i is the ith household's composite wealth indicator score, R_{ij} is the response of household i to category j, and W_j is the MCA weight for the first dimension applied to category j.

The PCA process is similar, except that the PCA weights are the category loadings in the first principal component arising from PCA (unrotated principal component analysis), and these category-weights are then applied to the normalized responses of the household. A household's score is the sum of its weighted normalized responses. This score serves as a relative measure of poverty for that household, relative to all the households used in the calculation of the weights.

It is interesting to note that the two methods arrived at similar weighting of index components, although we found some discrepancies. In the MCA analysis, for example, "smart floor" as expected ranks higher than "cement floor," whereas the relationship between the weights for these two variable categories is reversed in the case of PCA analysis. [2] This anomaly may be the result of PCA having less discriminatory power than MCA, given the exclusion from the analysis of "other" types of floor material. The MCA asset index was highly and statistically significantly correlated with the index based on PCA ($r = 0.957$, $p < 0.01$), and somewhat less with the index based on FA ($r = 0.902$, $p < 0.01$). PCA and MCA do not necessarily place households in the same welfare quintile, although deviations for the most part are restricted to one quintile up or down.

To make our asset indices comparable over time, they can be constructed using either "pooled" weights, estimated across all three periods and seven countries, or "baseline" weights obtained from the first period for all countries. On practical grounds, we opted for "baseline" weights that can be applied to subsequent surveys without recalculating weights. Moreover, the asset index calculated based on "pooled" rather than "baseline" weights was extremely highly correlated with the index based on "baseline" weights ($r = 0.996$, $p < 0.01$). Moreover, each country carries the same weight, irrespective of country size. Thus, the pooled data from all seven countries cannot be interpreted meaningfully and we cannot say anything about trends in poverty in sub-Saharan Africa in general. Consequently, the emphasis here is on an inter-temporal and urban–rural comparison of poverty in each of the seven individual countries.

(b) *Construction of the asset index*

The DHS rarely includes questions on income and expenditure, and it can therefore not be used to derive conventional money-metric poverty measures. Following Filmer and Pritchett (2001), Sahn and Stifel (2000), and Asselin (2002), we created a composite poverty indicator or asset index from a selection of variables from the DHS surveys. To ensure comparability, only variables that appear in all 21 questionnaires and were phrased similarly are included. Table 1 lists these variables, with the categories for each variable outlined in the second column. The construction of the asset index was based on binary indicators on four private household assets, namely the presence or absence of a radio, TV, fridge, and bicycle, and categorical indicators on three variables, namely the type of sanitation, the type of flooring (both with four categories each), and the main water source (five categories). The set of seven variables available for this analysis is limited due to the inclusion of fewer questions and few options per question in the first rounds of these surveys. [3]

Table 1. *Variables included in and weights obtained from MCA*

Variable	Categories	Weights
Radio	Owns a radio	0.282
	Does not own a radio	−0.225
TV	Owns a TV	1.608
	Does not own a TV	−0.100
Fridge	Owns a fridge	1.682
	Does not own a fridge	−0.096
Bicycle	Owns a bicycle	0.004
	Does not own a bicycle	−0.001
Toilet	No toilet	−0.300
	Flush toilet	1.164
	Pit latrine	−0.088
	Other toilet facility	−0.160
Floor material	Earth floor	−0.266
	Cement floor	0.354
	Smart floor	1.832
	Other floor material	0.395
Water source	Piped water	0.885
	Public water	−0.026
	Well water	−0.225
	Surface water	−0.222
	Other source of water	−0.197

Although the limited set of variables included constrains the poverty analysis—as discussed in more detail in the next section—a fair proportion of the variables measures private assets, which tend to be closely associated with money-metric poverty. Thus, even though the index measures more than only money-metric poverty, it can be expected to respond strongly to improvements in money-metric well-being.

Table 1, which also reports the weights for each index component, shows that those components that reflect higher standards of living contribute positively to the asset index, while components that reflect lower standards of living contribute negatively to the asset index. For example, owning an asset, having access to a flush toilet or piped water, or having a smart floor, increases a household's asset index score; while not owning an asset, having no access to or lower quality sanitation and water supply, or living in a dwelling with lower quality floor material, decreases a household's asset index score, that is, measured level of welfare. The first dimension explained 93.9% of inertia. [4]

Following the construction of the asset index, we employed this index to estimate poverty measures for each country using the appropriate household survey weights. As negative index values complicate poverty analysis (e.g., FGT measures for P_1 or P_2), a value equal to the greatest negative value is added to each asset index value, so that the lowest observed values become zero. [5] A small further magnitude is also added to make the lowest value non-zero, as some poverty decomposition programs in Stata ignore zero values. Here, the transformation entailed adding just more than the minimum value of −1.213 to the index.

The transformation of these values to positive numbers affects the resulting poverty measures (see e.g., Sahn & Stifel, 2003), as it does not preserve the mean (but leaves the variance unchanged). This transformation consequently implies that FGT measures other than the headcount ratio only have meaning in the context of the research. As the distribution is the same as before the translation, poverty measures still have meaning in a relative sense, enabling comparisons of the resulting estimates of the asset index across time, countries, or location.

Due to the discrete nature of the underlying assets, asset indices are imperfect approximations of income and expenditure poverty. Asset indices are generally slow-moving compared to income and expenditure (public assets are more so than private assets). Due to their durability, assets are expected to be asymmetric in their ability to reflect changes in income: they are more likely to portray increases in income than to capture decreases in income.

Given the slow-moving nature of assets, there are a few surprising discontinuities in the asset index: in Tanzania the proportion of the population with bicycles jumped from 21.5% to 31.9% from Period 1 to Period 2, while the proportion with piped water declined from 8.6% to 3.1% between Periods 2 and 3. It is likely that these large shifts are at least partly attributable to sampling design errors or other problems complicating comparability between surveys.

(c) *Descriptive analysis of the asset index*

Different combinations of the household characteristics described in Table 1 give different levels that the asset index can assume. Table 2 reports the main descriptive statistics for the asset index, before adjustments to the index values. In this case, there are only 657 unique values. Given sample sizes ranging from 1,493 to 12,331, many households will therefore have the same asset index score. The discrimination ability of the index is lowest at the bottom end of the scale.

Considering this problem of discriminating between households, particularly at the lower end of the distribution, it is necessary to determine how these unique values are composed. As shown in Table 3, access to public services is more important at the lower end of the asset index, while private asset ownership matters

Table 2. *Descriptive statistics for asset index*

Statistic	Value
Mean	−1.215
Standard deviation	1.856
Mode	−1.001
Minimum	−1.213
Maximum	7.457
Unique values: Total	674
Unique values: Quintile 1	15
Unique values: Quintile 2	16
Unique values: Quintile 3	44
Unique values: Quintile 4	149
Unique values: Quintile 5	450

Table 3. *Composition of some unique asset index values*

Closest to	Index value	Freq.	Presence of				Types of		
			Radio	TV	Fridge	Bicycle	Toilet	Flooring	Water
Lowest value	−1.213	0.0658	No	No	No	No	None	Earth	Well
Mode	−1.001	0.0710	No	No	No	No	Pit latrine	Earth	Well
25th percentile	−0.998	0.0599	No	No	No	No	Pit latrine	Earth	Surface
Median	−0.489	0.0458	Yes	No	No	Yes	Pit latrine	Earth	Well
75th percentile	0.325	0.0233	Yes	No	No	No	Pit latrine	Cement	Public tap
Highest value	7.457	0.028	Yes	Yes	Yes	Yes	Flush	Smart	Piped

Notes: The unique values of the asset index shown are those where the frequency of the index value was greater than 500 closest to the value of the descriptive statistic in the left most column. This was to avoid reporting anomalous index values (corresponding to only a few households).

more at the upper end of the distribution. Access to water or sanitation to a large degree is a reflection of geography. The limited discrimination ability at the lower end of the scale makes the asset index a poor tool for distinguishing between segments of the population who may be almost equally poorly served by public services. [6] This problem may be reduced by the addition of variables that reflect other correlates of household income or expenditure, such as employment, where these are available. [7]

Using the Ghanaian Living Standards Survey of 1998/1999, we assessed the robustness of an asset index—constructed in the same way as for the DHS surveys in this paper—as a poverty measure by comparing it to household *per capita* expenditure. The analysis shows that the index fares reasonably well: it has a significant and positive correlation coefficient and Spearman rank correlation with household *per capita* expenditure (0.421 and 0.493, respectively). The World Bank (2003) has documented that the correlation coefficients between such indices and expenditure usually range between 0.20 and 0.40. Our findings here are thus in line with previous work, but appear to sit at the upper end of the scale.

(d) *Measuring poverty*

The choice of poverty line is crucial for poverty analysis using FGT measures. [8] There is no apparent non-arbitrary level at which to set it. [9] The poverty lines set by Sahn and Stifel (2003) were, compared to their earlier study (Sahn & Stifel, 2000), set at relatively high levels, where the discrimination ability of asset indices was somewhat better. We chose two relative poverty lines close to the conventional lines used in the poverty literature. Using the 40th percentile as a poverty line accords with what is often suggested by the World Bank for poverty analysis. A second and higher poverty line set at the 60th percentile is also included because Africa has substantially more poverty than other world regions and the asset index does not discriminate well at very low levels. Moreover, to the clustering of index values and rounding by program commands, the actual weighted population in poverty in Period 1 pooled across countries is lower than 40% and 60% respectively. An additional poverty line is estimated using the weighted sum of categories deemed to represent an adequate standard of living in a poor country: radio, bicycle, no refrigerator, no TV, cement floor, public water, and a pit latrine. Whereas the former two poverty lines represent relative poverty lines, this represents an absolute poverty line. This line is higher than the other two lines, as almost 80% of the weighted population falls below this line in Period 1. These three poverty lines are subsequently employed to illustrate how the choice of poverty line affects the analysis.

It is important to note that all the three poverty lines employed here are derived from the aggregate data, given the need for inter-temporal and inter-country comparability. Due to this approach, there may be concerns about the comparability of rural and urban poverty. It may be argued that the assets included in the asset index are by their nature urban rather than rural and therefore are conceptually biased against rural areas. Indeed, most African governments consider the provision of formal housing, water, and sanitation as naturally urban services. There are, however, also reasons to think that the variables here may capture the aspects of rural deprivation. As countries develop, it would not be amiss for the rural population to strive toward having piped water, flush toilets, and "smart" floors. Additionally, private assets such as radios, TVs, and fridges play an important role in moving people out of asset poverty, particularly at the higher poverty line. Access to these assets may be a better reflection of people's performance in the market and thus also their ability to maintain a higher standard of living.

Due to concerns regarding the omission of rural income correlates such as livestock and land, [10] we investigated whether the correlation with expenditure and income is systematically lower in rural areas than in urban areas. Using the Ghanaian Living Standards Survey of 1998/1999, we did find some evidence of such a gap. Although the correlation between our index applied to that dataset and household expenditure *per capita* was virtually indistinguishable for rural and urban areas (*cf.* 0.303 and 0.302, respectively), there was a greater concentration of rural households in the bottom quintiles of the asset index than for the bottom quintiles by household expenditure *per capita*; although these differences are not very large: According to the asset index, approximately 93% of those below the 40th percentile was rural, while it was only 81% when the classification was by household expenditure *per capita*. None of the traditionally rural income correlates such as livestock and land were available for every period and every country of our sample. Thus, some bias may remain and these results should be interpreted with due care.

We confine our poverty analysis to the poverty headcount ratio (P_0) [11] and the investigation of stochastic poverty dominance, which is based on a comparison of the cumulative density curves (also called poverty incidence curves). Such an analysis is particularly important because of the difficulty of making fine distinctions at the bottom end of the distribution, where asset values are bunched more closely and where there are fewer unique index values. As the cumulative density curves show no first order stochastic poverty dominance in a number of cases, one would expect little consistency in poverty rankings across P_0, P_1, and P_2 for these countries over time.

4. ANALYSIS OF POVERTY USING THE ASSET INDICES

(a) *Inter-temporal and inter-country differences in the incidence of poverty*

Table 4 reports poverty headcount ratios for the seven countries in each of the three periods as well as on average, based on the pooled data for each country. Results are reported separately for each of the three poverty lines: the

Table 4. *Poverty headcount ratios (%)*

Country	Period	40th Percentile poverty line		60th Percentile poverty line		Absolute poverty line	
		Headcount ratio (%)	Std. error	Headcount ratio (%)	Std. error	Headcount ratio (%)	Std. error
Ghana	1	21.6	*0.00723*	37.5	*0.00851*	83.2	*0.00658*
	2	10.6	*0.00403*	26.6	*0.00579*	72.6	*0.00585*
	3	8.8	*0.00357*	21.5	*0.00527*	64.7	*0.00646*
	All periods	12.2	*0.00266*	26.9	*0.00362*	71.7	*0.00376*
Kenya	1	29.5	*0.00811*	59.6	*0.00834*	79.9	*0.00616*
	2	34.0	*0.00600*	60.1	*0.00616*	78.8	*0.00514*
	3	26.3	*0.00537*	55.0	*0.00615*	71.4	*0.00568*
	All periods	29.9	*0.00364*	58.0	*0.00388*	76.2	*0.00330*
Mali	1	47.0	*0.01127*	80.5	*0.00736*	95.6	*0.00333*
	2	38.0	*0.00548*	75.3	*0.00485*	88.8	*0.00354*
	3	24.7	*0.00472*	66.8	*0.00536*	80.9	*0.00441*
	All periods	31.9	*0.00350*	71.4	*0.00347*	85.3	*0.00272*
Senegal	1	16.3	*0.00955*	47.1	*0.01292*	75.8	*0.01109*
	2	17.2	*0.00635*	41.7	*0.00830*	59.5	*0.00826*
	3	18.2	*0.00582*	40.4	*0.00791*	57.3	*0.00862*
	All periods	17.6	*0.00392*	41.9	*0.00529*	60.9	*0.00551*
Tanzania	1	49.1	*0.00685*	73.0	*0.00657*	88.4	*0.00461*
	2	41.3	*0.00599*	70.4	*0.00536*	88.9	*0.00364*
	3	41.0	*0.01122*	68.6	*0.01106*	92.1	*0.00573*
	All periods	44.5	*0.00424*	71.2	*0.00402*	89.3	*0.00264*
Zambia	1	39.4	*0.00630*	52.7	*0.00653*	69.6	*0.00610*
	2	41.8	*0.00593*	60.3	*0.00614*	74.3	*0.00570*
	3	43.4	*0.00613*	60.8	*0.00626*	75.2	*0.00578*
	All periods	41.6	*0.00353*	58.2	*0.00364*	73.2	*0.00338*
Zimbabwe	1	27.7	*0.00824*	41.9	*0.00909*	63.5	*0.00887*
	2	28.8	*0.00608*	43.8	*0.00678*	63.7	*0.00684*
	3	18.7	*0.00493*	31.7	*0.00605*	57.0	*0.00692*
	All periods	24.4	*0.00355*	38.4	*0.00410*	60.8	*0.00431*

40th and 60th percentiles of the asset index (the two relative poverty lines) and the absolute poverty line.

The analysis shows that poverty in Zambia has increased between Periods 1 and 3, regardless of the choice of poverty line employed. In contrast, poverty declined over this period in five of the seven countries: Ghana, Kenya, Mali, Senegal, and Zimbabwe. For Tanzania, there was a decline in the poverty headcount in Tanzania when using a 40th or 60th percentile poverty line, but at the absolute poverty line, poverty increased. This illustrates how the choice of a different poverty line may translate into different conclusions on poverty trends.

To assess the robustness of the poverty analysis to the choice of poverty line we investigate poverty comparisons between seven countries for each of the three time periods. In all the cases, a change in the poverty line affects the poverty rankings of countries. However, a number of consistencies do emerge from these relative rankings. Tanzania in each period ranked among the bottom two countries, whereas Senegal and Zimbabwe ranked among the top three countries in each period. Kenya in turn consistently ranked in the middle (3rd or 4th) in each period.

A comparison of the general trends in poverty observed here and trends reported in money-metric poverty for roughly equivalent periods reveals that most trends observed here are consistent with money-metric poverty trends. It is, however, important to note that there are differences in the time periods covered and the poverty line set and that this complicates such comparisons.

Chen and Ravallion (2004) reportes that poverty in Sub-Saharan Africa has declined during 1987–99, even if only slightly, from 46.8% to 45.7%. [12] This is consistent with the positive trend in five of the seven countries in our analysis. Poverty in Ghana is reported to have declined from 50% to 39.5% during 1992–98 (World Bank, 2005), or from 53% to 45% during 1988–98 (Teal, 2001). This is consistent with the decline shown in our data between Period 1 and Period 3. Likewise, poverty in Tanzania declined from 38.6% to 35.7% during 1991–2000 (World Bank, 2005), consistent with our results for the relative (high) poverty line, but not for the others. In Zambia, poverty increased from 69.2% to 72.9% during 1996–98 (World Bank, 2005), which is again in agreement with our results from Period 2 to Period 3 for all the poverty lines. The World Bank (2005) shows an increase in Zimbabwe's poverty (rising from 25.8% to 34.9% during 1990–95) found by the World Bank (2005), which is in line with our results for all the poverty lines for Period 1 to Period 2.

However, there are also exceptions. Our index shows a decline in asset poverty in Kenya between Periods 2 and 3, poverty estimates derived from other data sources suggest that poverty has been on the rise in the 1990s (Republic of Kenya, 2004; World Bank, 2005).

(b) *Cumulative density curves*

Most cumulative density curves based on these asset data have a strong slope at the lower end of the distribution, reflecting the small number of unique values, clustering of observations at some of these values (giving rise to some vertical segments of the curves), and the consequent difficulty of fine discrimination at lower asset value levels. In most cases it is not possible to reach strong conclusions on poverty trends in each of these seven countries based on the cumulative density curves in Figures 1a, 1b–1g. Tanzania is perhaps the clearest case in point. The cumulative density curve for Period 3 does not always lie below that for Period 1 (Figure 1e), giving rise to uncertainty as to whether there has been progress in terms of poverty incidence. In places the three curves are almost indistinguishable, thus visual inspection of the cumulative density curve does not provide clear answers. However, in the main poverty relevant range, say where the poverty headcount ranges between 20% and 60%, stochastic dominance is more common in the seven countries. In other words, at these welfare levels the incidence of headcount poverty did decline (or increase) across the distribution. However, where curves cross at lower levels of the asset index, no unequivocal conclusion is possible on poverty dominance for P_1 and P_2 even if there is first order dominance in the poverty relevant range. In Ghana and Mali, the curves for later periods meet but do not cross the curve for Period 1, thus poverty has clearly not become worse, irrespective of the poverty line used, and for all FGT poverty measures.

Cumulative density curves for all the seven countries in each of the periods (not depicted here) show that poverty is most prevalent in Tanzania, Mali, and Zambia. Ghana, Zimbabwe, and Senegal have least poverty. Yet, first order stochastic poverty dominance is relatively

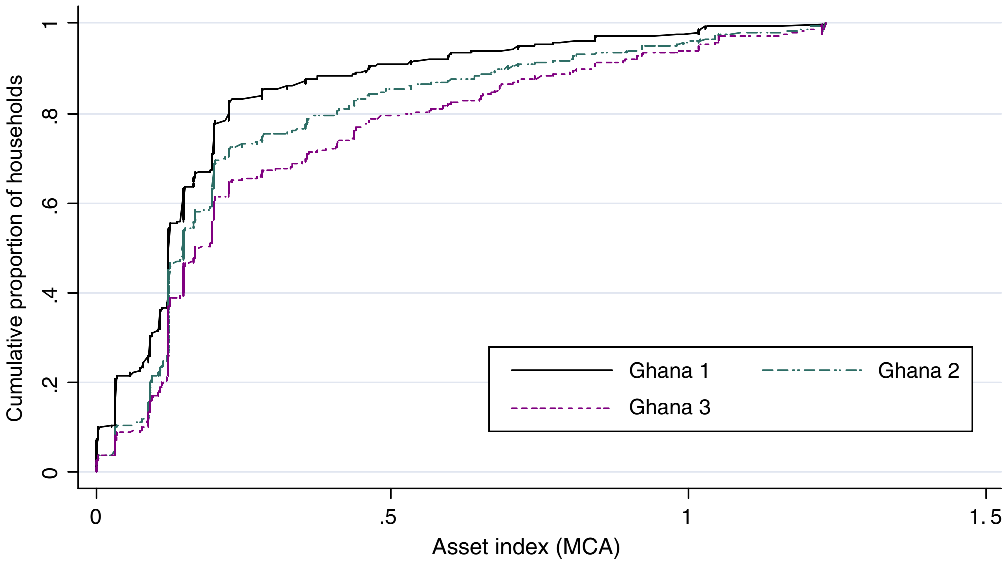

Figure 1a. *Cumulative density curves for Ghana by period.*

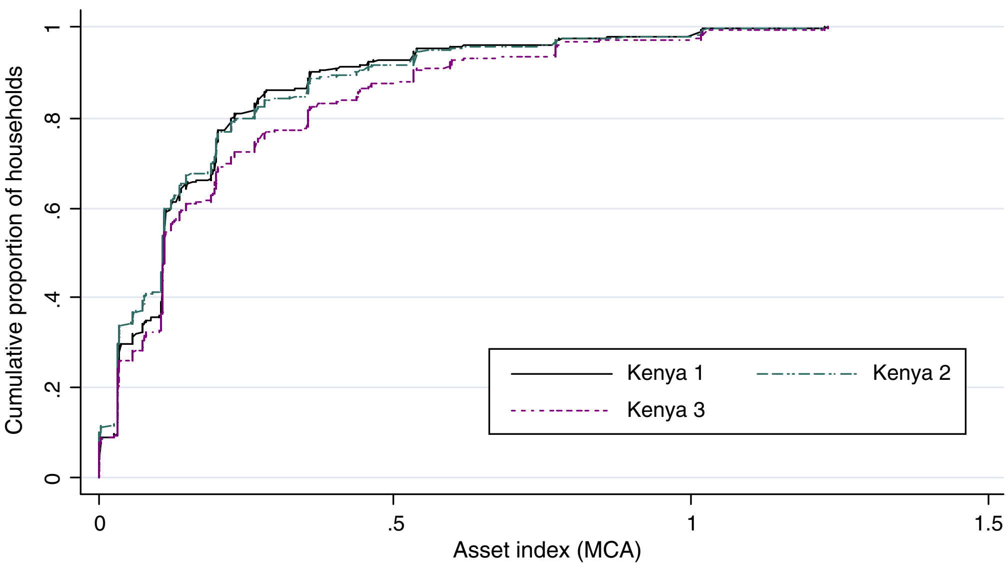

Figure 1b. *Cumulative density curves for Kenya by period.*

uncommon, that is, many of the lines cross in places. Ghana, for instance, has least poverty at low levels of the index, but has more than Senegal and Zimbabwe at higher poverty lines. Thus, as Table 4 illustrates, poverty rankings are relatively sensitive to the choice of poverty line.

(c) *Do country-specific weights and poverty lines change the conclusions?*

Sahn and Stifel (2000) also used pooled weights to make inter-country comparisons, but they used country-specific weights for inter-temporal comparisons. Are our results

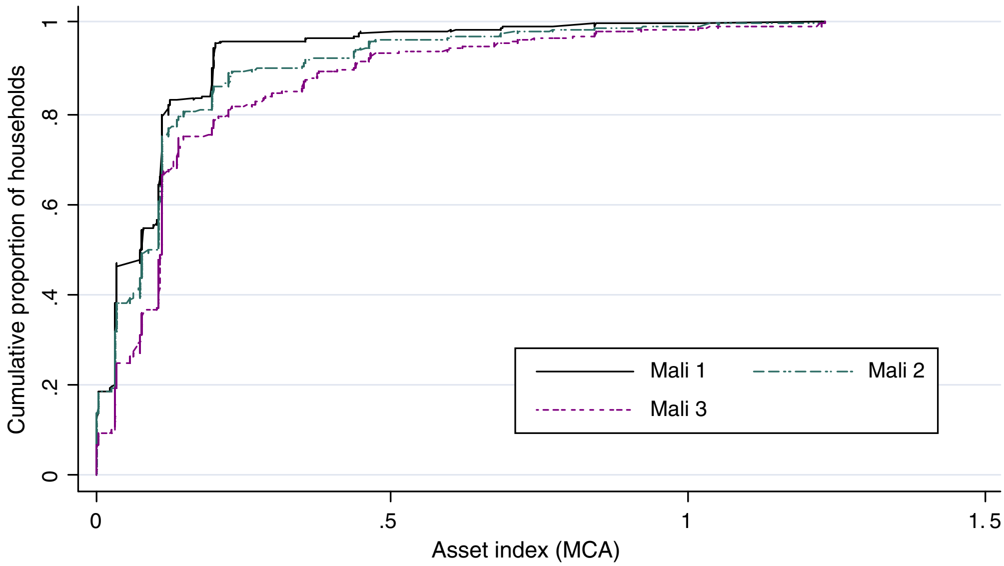

Figure 1c. *Cumulative density curves for Mali by period.*

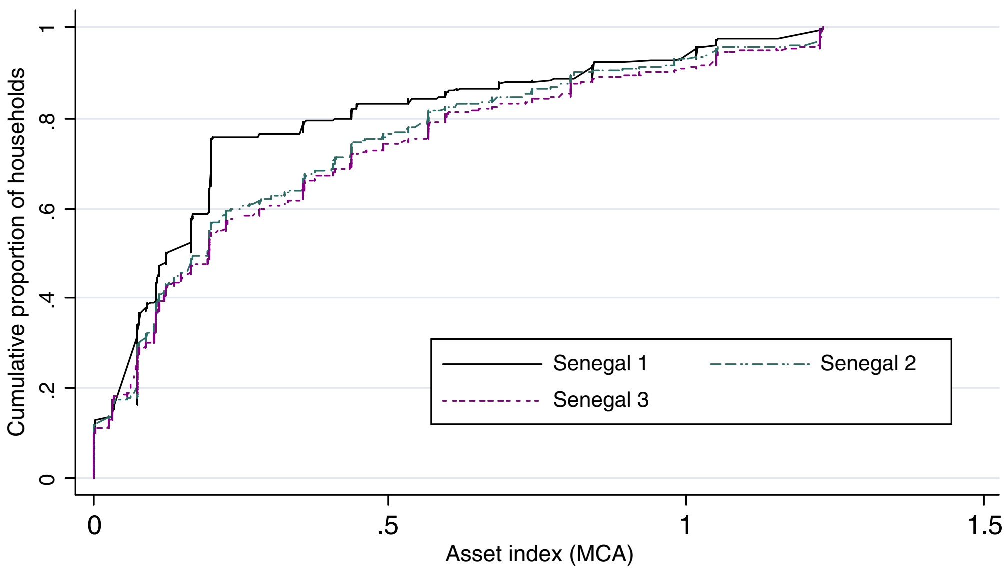

Figure 1d. *Cumulative density curves for Senegal by period.*

regarding trends in poverty robust to using country-specific weights (and by implication, also country-specific poverty lines) rather than pooled weights and common poverty lines?

To answer this question and test for the robustness of our results, country-specific weights were also applied to Period 1 data and poverty lines assigned for each country at the unique value of the asset index closest to, but below, the two relative poverty lines. The results are presented in Table 5; inter-country comparisons are not possible based on these poverty lines. Note that poverty levels and consequently the poverty lines used often lie some

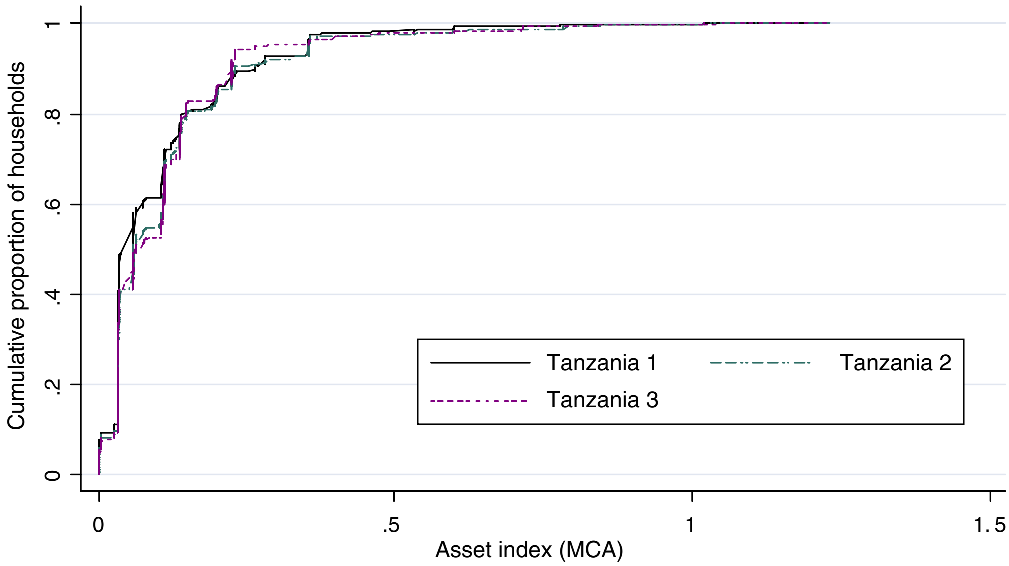

Figure 1e. *Cumulative density curves for Tanzania by period.*

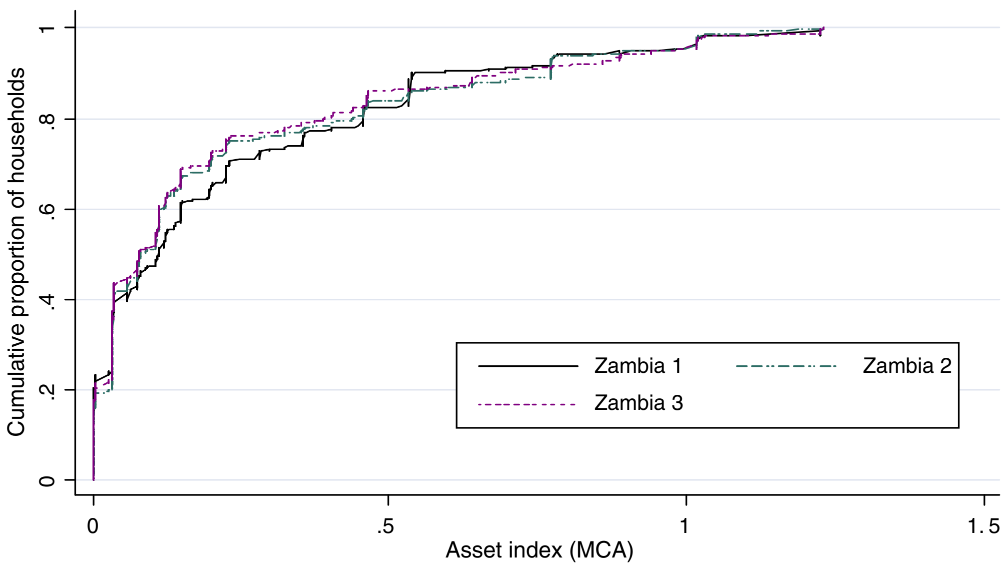

Figure 1f. *Cumulative density curves for Zambia by period.*

way below the 40th and 60th percentiles in Period 1, due to the clustering (few unique asset values) at the lower end of the distribution, a problem exacerbated when using country-specific rather than pooled weights. In three out of 14 cases for the 40th percentile poverty line, the direction of the poverty trend between any two consecutive periods differed between the pooled weights (shown in Table 4) and the country-specific weights used in Table 5. In all the three cases (Tanzania between Period 2 and Period 3, and Senegal in both periods), the pooled weight data showed only a very small movement in poverty. For the 60th percentile poverty line, there was not a single case where the direction of poverty movement

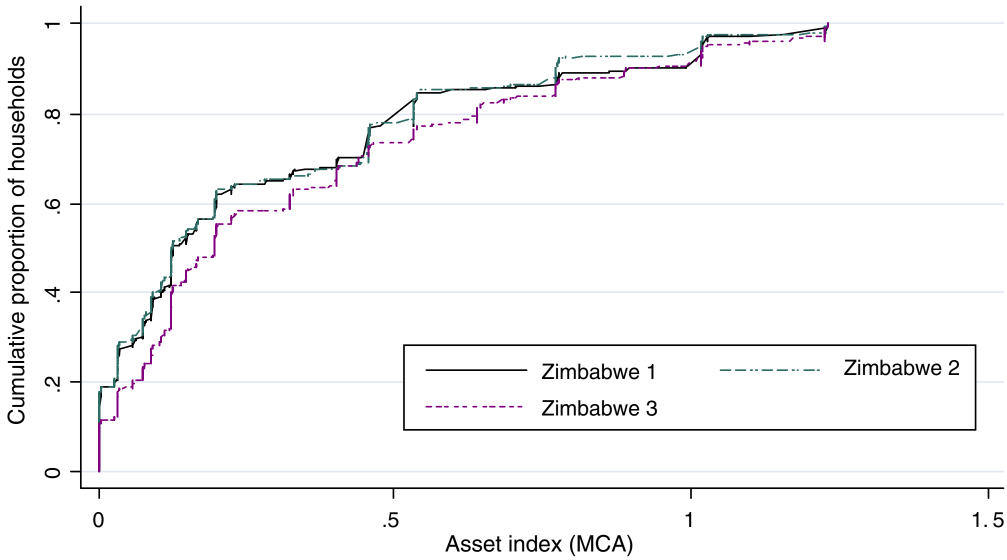

Figure 1g. *Cumulative density curves for Zimbabwe by period.*

Table 5. *Poverty headcount ratios (%) using country-specific asset weights and poverty lines*

Country	Period	40th Percentile poverty line	60th Percentile poverty line
Ghana	Period 1	32.6	58.6
	Period 2	23.2	50.9
	Period 3	19.2	42.8
Kenya	Period 1	35.5	59.7
	Period 2	41.3	59.9
	Period 3	32.6	54.9
Mali	Period 1	33.3	57.3
	Period 2	30.9	49.7
	Period 3	21.4	37.9
Senegal	Period 1	38.2	58.3
	Period 2	34.7	51.5
	Period 3	33.8	49.7
Tanzania	Period 1	27.4	59.7
	Period 2	20.4	52.1
	Period 3	23.8	49.7
Zambia	Period 1	39.4	56.8
	Period 2	41.8	64.1
	Period 3	43.4	65.0
Zimbabwe	Period 1	38.5	59.7
	Period 2	39.2	61.0
	Period 3	28.1	53.1

differed, that is, the results between the weights pooled across countries and country-specific weights were completely consistent in terms of the direction of poverty movement between periods. It is understandable that the results may be a little less robust at the lower poverty line, where there are fewer unique values.

To test whether PCA gave similar results as MCA based on the pooled weights, the same exercise was undertaken to compare the direction of recorded movements in poverty between the indices based on pooled MCA weights *versus* those derived from pooled PCA weights. In this case, the two weighting systems gave different results in eight out of the possible 28 cases (seven countries × two movements between periods × two poverty lines), four for each of the two relative poverty lines employed. Thus, despite the relatively good correlation between MCA and PCA values, the conclusions they come to on poverty trends in this dataset are quite different. PCA does not achieve similar results as the more appropriate MCA approach.

(d) *Urban–rural decomposition of poverty estimates*

The data sets at our disposal do not allow us to identify what *explains* differences in the incidence of poverty. However, the location is one dimension of intra-country differences in welfare that can be analyzed further. Table 6 shows that urban poverty measured by these assets is low, whereas rural poverty is very com-

Table 6. *Incidence of poverty in urban and areas (%), all periods pooled*

	40th Percentile poverty line		60th Percentile poverty line		Absolute poverty line	
	All periods	Std. error	All periods	Std. error	All periods	Std. error
A. Incidence of poverty in urban areas (%)						
Ghana	1.0	*0.00138*	6.1	*0.00334*	39.5	*0.00688*
Kenya	3.4	*0.00277*	11.1	*0.00498*	33.9	*0.00762*
Mali	9.2	*0.00434*	26.0	*0.00661*	56.9	*0.00741*
Senegal	2.4	*0.00230*	6.9	*0.00399*	24.4	*0.00729*
Tanzania	10.4	*0.00633*	26.6	*0.00953*	63.8	*0.00929*
Zambia	5.8	*0.00280*	13.1	*0.00405*	37.4	*0.00598*
Zimbabwe	0.4	*0.00097*	0.7	*0.00139*	3.9	*0.00319*
B. Incidence of poverty in rural areas (%)						
Ghana	18.2	*0.00388*	38.1	*0.00492*	89.0	*0.00328*
Kenya	36.8	*0.00433*	70.3	*0.00410*	87.3	*0.00291*
Mali	39.8	*0.00427*	87.1	*0.00313*	95.2	*0.00198*
Senegal	28.3	*0.00600*	66.6	*0.00641*	86.7	*0.00471*
Tanzania	55.2	*0.00461*	85.1	*0.00331*	97.3	*0.00145*
Zambia	63.9	*0.00428*	86.3	*0.00314*	95.5	*0.00198*
Zimbabwe	37.1	*0.00487*	58.4	*0.00500*	91.1	*0.00289*

mon. Estimates of urban and rural poverty for these countries reported in the *World Development Indicators* likewise in all the cases show rural poverty to exceed urban poverty (World Bank, 2005).

Detailed results for each period similar to those in Table 6 (not shown here) indicate that poverty has declined from Period 1 to Period 3 in both urban *and* rural areas in five of the seven countries: Ghana, Kenya, Mali, Tanzania, and Zimbabwe. [13] In Zambia, however, urban poverty has increased, while poverty in rural areas has declined. For Senegal, the very low levels of urban poverty increased, but trends for rural poverty differed, depending on the poverty line chosen. The World Bank (2005) confirms that rural poverty has declined in Tanzania (from 40.8% to 38.7% during 1991–2000) and increased in Zimbabwe (from 35.8% to 48% during 1990–95, i.e., Period 1 to Period 2). In Kenya's case, however, we find that poverty declined between Periods 2 and 3 in urban and rural areas, whereas poverty estimates derived from money-metric data sources suggest that poverty has been on the rise in the 1990s, in particular in urban but also in rural areas (Republic of Kenya, 2003; World Bank, 2005).

To determine what drives the differences between urban and rural welfare as measured by the asset index, Table 7 shows mean asset ownership and access broken down by urban *versus* rural location based on the pooled dataset. The main differences in water provision lie in urban areas having more access to piped water in the home or public water (standpipes). In sanitation, the most evident difference is in the greater prominence of flush toilets in urban areas. Rural dwellers more commonly have earth floors *versus* the very prevalent cement floors in urban homes; and in private asset ownership, urban areas have an advantage in most assets, apart from bicycles, which are more common in rural areas.

OLS regressions of the asset index, regressed on location, country, period, and interactions between country dummies and the urban dummy highlight patterns in the asset index. *Firstly*, it is clear that urban location is important for asset wealth. A full 36% of the variation in asset wealth can be explained by the locational factor alone (of the 40% that all the variables combined explain). Variation between countries is a much smaller factor than variation between urban and rural areas. *Secondly*, there is evidence of country-specific effects. Tanzania often ranks at the bottom, while Zimbabwe and Senegal frequently rank high. *Lastly*, there is a clear improvement in the asset index over time.

(e) *Poverty of what?*

This section considers the driving forces behind observed shifts in the asset index. This presents an avenue for tying changes in welfare to specific policies, particularly the provision of public services. Figure 2 shows much improvement in access to private assets of households in

Table 7. *Mean access to assets by location, all countries and periods pooled*

Indicator		Urban	Rural	Total
Average household size		5.29	5.63	5.52
Private assets	Radio	68.4%	43.2%	50.8%
	TV	31.4%	3.2%	11.7%
	Fridge	19.4%	1.0%	6.6%
	Bicycle	17.6%	29.1%	25.6%
Sanitation	Flush toilet	34.9%	1.5%	11.5%
	Pit latrine	58.1%	65.7%	63.4%
	Other toilet	2.4%	0.7%	1.2%
	No toilet	4.6%	32.1%	23.8%
Floor of dwelling	Smart floor	13.8%	1.4%	5.1%
	Cement floor	66.5%	22.7%	35.9%
	Earth floor	18.6%	75.3%	58.3%
	Other floor	1.2%	0.6%	0.8%
Water	Piped water	43.4%	4.0%	15.9%
	Public water	35.3%	11.4%	18.6%
	Water from well	15.8%	52.4%	41.4%
	Surface water	3.9%	30.7%	22.7%
	Other water	1.6%	1.4%	1.5%

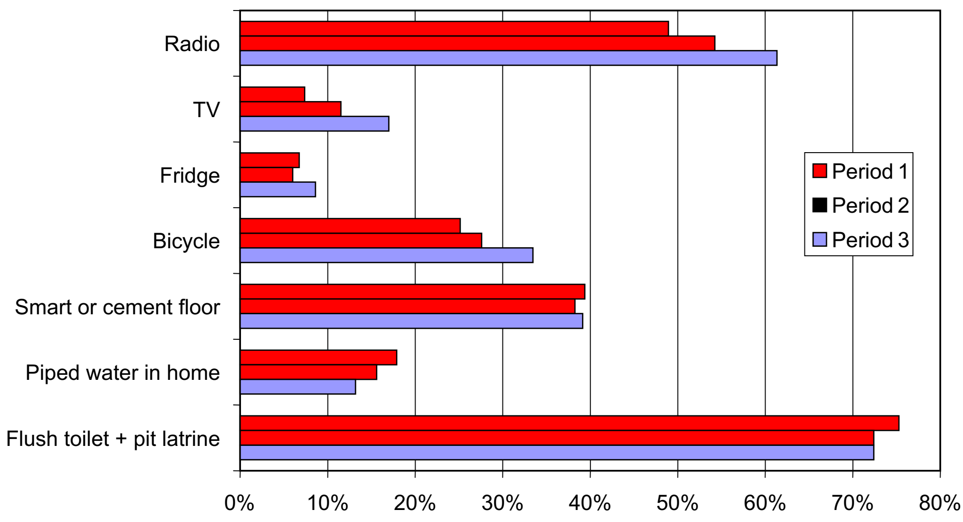

Figure 2. *Asset access by period and type of asset for all countries pooled.*

the pooled sample. In the approximate decade between Period 1 and Period 3, radio ownership expanded by 12.4% points, TV ownership by 9.6% points, fridge ownership by 1.9% points, and bicycle ownership by 8.3% points. Although this does not reflect particularly rapid economic progress, it shows a broadening of ownership that links to money-metric welfare. The proportion of dwellings with cement or "smart" (carpeted, tiled, and wooden) floors—the outcome of a mixture of public and private provision—shows a marginal decline of 0.2% points. In contrast, government-provided assets all exhibit a relative decline. Access to piped water and flush toilets declined: piped water in the home fell by 4.7% points and access to flush toilets or pit latrines was 2.9% points lower.

As the mean asset index reflects the net effect of *weighted* changes in each indicator variable, it may increase despite deteriorations in relative access to certain assets, or vice versa. Figure 2, however, shows the changes over time in mean access to *individual* assets in the pooled dataset. We also decomposed the change in the mean asset index between consecutive periods for each country into its various positive and negative indicator components. In cases where the mean asset index increased between consecutive periods, access to private assets (in particular televisions and fridges) most often featured among the top three items explaining improvements in access to assets. However, a decline in access to public assets, especially water and sanitation, often reduced such recorded gains. In Mali and Tanzania, declining access to good water sources is particularly problematic, while in Zimbabwe access to both water and sanitation deteriorated in the 1990s. In cases where the mean asset index deteriorated, declines in access to water and sanitation were most often responsible, particularly in Kenya and Zambia. The deterioration in household asset welfare would often have been even worse had access to private assets not improved, particularly ownership of a television set. This applied particularly to Zambia.

When we consider this decomposition of assets, we can be far less sanguine about the progress made, for the public services that have been shown to be a vital component of human development. These results, therefore, hint at a very important role for continued efforts at improved service delivery, particularly regarding the expansion of access to water and sanitation.

5. CONCLUSION

Our analysis of trends in poverty in seven African countries toward the end of the 20th century, using an asset index constructed by multiple correspondence analysis from internationally standardized, comparable and nationally representative surveys, shows that poverty declined over this period in five of the seven countries: Ghana, Kenya, Mali, Senegal, and Zimbabwe. In the case of Zambia, poverty increased, while for Tanzania the conclusion depends on the poverty line chosen. Poverty has declined for lower poverty lines, but not when the poverty line is set higher. Poverty is most prevalent in Tanzania, Mali, and Zambia, while Ghana has least poverty, followed by Kenya and Zimbabwe. Rural poverty everywhere exceeds urban poverty, as is expected. Trends in urban and rural poverty for the most part mirror these in overall poverty. Poverty has declined in urban and rural areas in five of the seven countries.

Even though multiple correspondence analysis is the appropriate approach when all the variables are categorical, as in this study, indices based on MCA are highly correlated with those based on PCA. However, poverty trends based on MCA differ in a number of cases from those based on principal component analysis applied to the same pooled data, the method thus far dominating published analysis in this field. Specifically, in a substantial number of instances the direction of poverty trends is reversed when applying PCA rather than the more appropriate MCA.

A further useful result in our finding is that using a single pooled weighting system across all the seven countries in our sample (similar to the approach in Sahn & Stifel, 2000) does not greatly affect conclusions on the evolution of poverty over time compared to country-specific weights (as used by Sahn & Stifel, 2003). When the focus is on tracking trends in poverty in a single country, country-specific weights may be more appropriate.

These results, however, should be interpreted with caution. *Firstly*, the asset index is compiled using a relatively small number of variables and limited number of variable categories. This problem is exemplified by the relative lack of overlap between the welfare rankings of Ghanaian households based on the asset index as opposed to other poverty measures. In the *second* instance, the analysis illuminates one of the major deficiencies of asset indices. Unlike income or expenditure, which can be relatively volatile or where mobility can be relatively rapid, asset indices are relatively slow-moving, because of the slow rate of change in the underlying asset variables. Thus, it is possible that they may not adequately and rapidly reflect important changes in the economic situation of many households. That being the case, our analysis cautions against using asset indices to assess short or medium term economic change. Moreover, the limited discrimination ability at the lower end of the scale makes the asset index a poor tool for analyzing ultra-poverty.

NOTES

1. A distinction that has to be made when applying MCA and PCA to the same data relates to the structure of the survey data matrix underlying the multivariate analysis. In a matrix where there are Q questions, J_q categories for question q, and J categories in total, the important difference between MCA and PCA is that in MCA each household (or row) has to answer "yes" or "1" to one category in every question, that is, the categories represent all possible answers for question q. This forces every row in the matrix to have a total of Q. In the matrix used in PCA, the redundant category for each question is left out of the analysis.

2. We applied PCA to the variables employed in our MCA analysis to construct an asset index similar to that of Filmer and Pritchett (2001), using the *factor* command in Stata8 (Statacorp, 2003). The index was calculated as follows: ${}^{\mathrm{PCA}}P_i = \{(R_{i1} - A_1)/S_1\}W_1 + \{(R_{i2} - A_2)/S_2\}W_2 + \cdots + \{(R_{ij} - A_j)/S_j\}W_j$, where ${}^{\mathrm{PCA}}P_i$ represents the ith household's composite poverty indicator score arising from PCA, R_{ij} is the response of household i to category j, W_j is the PCA weight applied to category j, and A_j and S_j are the mean and standard deviation of the responses to category j. The first factor explained 23.5% of variance in the underlying construct "household welfare." For more information on PCA, consult Green (1978)

3. Booysen (2002) employed data from 19 variables in using the asset index approach for the South African DHS, and the Health, Nutrition and Population (HNP) country reports used 15 variables (World Bank, 2000), but Sahn and Stifel (2000) employed only eight variables in their analysis of poverty in nine African countries. The first two of these studies used principal component analysis, the last factor analysis.

4. The MCA command in Stata8 (Statacorp, 2003; Van Kerm, 1998) estimates "an adjusted simple correspondence analysis on the Burt matrix" that is constructed with the selected variables. (MCA applied on the Burt matrix is equivalent to MCA applied to the indicator matrix.) Given that "a simple correspondence analysis applied to this matrix usually results in maps of apparently poor quality… *MCA* adjusts the obtained principal inertias (eigenvalues) following a method suggested by Benzecri and presented in Greenacre (1984)" (Van Kerm, 1998, p. 214). According to Van Kerm (1998, p. 214), the reported inertia explained by the first dimension is relatively high "due to the fitting of [these] diagonal sub-matrices." Greenacre (2006, p. 68) describes the nature of this transformation and proposes that it should be routinely reported. Despite the huge difference in the reported proportion of inertia or variance explained by the first principal component (PCA: 23.5%) and the first dimension (MCA: 93.9% adjusted and 48.1% unadjusted) respectively, it should be remembered that these statistics are not directly comparable, given that MCA employs the $\chi 2$-distance and not the Euclidian distance in its calculation. In addition, there is less latitude on the weights from PCA, given the exclusion of the "other" category in the three non-binary categorical variables included in the analysis. The choice, therefore, of an index being based on MCA or PCA cannot be informed by this statistic. Thus the preference for MCA over PCA, as explained elsewhere, is based rather on the nature of the raw data and the statistical characteristics of the MCA method than on any supposed superiority of MCA in explaining a greater proportion of variance in the underlying "poverty" construct than PCA.

5. Asselin (2002) and Sahn and Stifel (2003) motivated similar transformations.

6. Interestingly, the addition of more variables to the asset index does not always enhance its discriminating ability. This is evident from a comparison of this paper's results with those from descriptive analysis of a similar asset index constructed for Uganda based on a set of 15 variables (compared to the seven in our asset index) from the 1995 DHS survey. In the Uganda case, the asset index included even fewer unique values (437). The 2nd (1), 3rd (1), and 4th quintiles (12) of the asset index also included very few unique values, despite the fact that the index incorporated twice as many variables as the one employed here. As in this study, access to public services was more important at the lower end of the distribution for Uganda, while private asset ownership mattered more at the upper end. Thus, merely adding more variables—and particularly variables that are similar—need not improve the discriminating ability of the composite index.

7. MCA is inappropriate to use with continuous variables. If one or more continuous variables were available to be added to improve discriminating ability, a more appropriate approach would be to convert the continuous variable to a categorical one, e.g., by using cluster analysis. MCA can be used if the continuous variables are transformed to discrete variables. Alternatively, categorical PCA may be considered. The MCA routine in SPSS (called "Homogeneity Analysis") offers an option for converting continuous variables into discrete ones. (We wish to thank Louis-Marie Asselin for pointing this out to us.) However, if there are a large number of continuous variables available, the appropriateness of such a route may have to be reconsidered.

8. The Foster–Greer–Thorbecke (FGT) class of poverty measures is often employed to analyse poverty. The basic formula of the poverty measure in its non-continuous form is $P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^\alpha$, where P_α is the poverty measure and α can take on any non-negative value, although it is conventionally only analyzed for $\alpha = 0$, 1, and 2; n is the number of households in the sample; q is the number in poverty; z is the poverty line; and y_i is the welfare indicator (in money-metric poverty measurement, usually income or expenditure) of the ith household. An important benefit of the FGT class of poverty measures, apart from their more general form and their conformity with the most important welfare axioms, is that they are additively decomposable, that is, the weighted values of subgroups add up to the aggregate.

9. Money-metric poverty lines are often derived from the food consumption required to meet caloric needs, based on prevailing consumption patterns (the food poverty line method) or the costs of a basket of basic goods. Alternatively, international poverty lines are used, such as the $1 a day *per capita* level often used by the World Bank (2000b). For asset indices, however, there is no comparable indication of what would be an appropriate poverty line. In their more recent paper that focuses on comparing urban and rural poverty within countries, Sahn and Stifel (2003) derived the asset index value that corresponded to World Bank estimates of money-metric poverty at the $1 per person per day level in each country, and then used these country-specific poverty lines for their further intra-country analysis. Their asset indices also used unique weights for each country (pooled across samples for the same country). In our case—as in part of the earlier study by Sahn and Stifel (2000)—we require a shared poverty line to enable comparisons across countries.

10. Given the largely urban nature of these assets, results are biased against rural areas, resulting in under-representation of expenditure in rural areas. Normally, employing poverty lines specific to different geographical areas in money-metric poverty analysis tends to shrink disparities between rural and urban areas and may even reverse rankings (Duclos & Araar, 2004). However, our variables should capture the most important dimensions of poverty in rural areas and are furthermore not subject to price effects, which often encumber urban–rural comparisons in money-metric studies of poverty.

11. Given the transformation to make all index values non-negative and the rather arbitrary poverty lines, it was not deemed appropriate to also calculate P_1 and P_2 (though these would still have meaning in a comparative sense). This choice is strengthened if one considers that the discriminatory ability of the asset index is weak at the lower end of the distribution, precisely those observations that are heavily weighted by P_1 and P_2.

12. For a more recent period, Chen and Ravallion (2004) conclude that these gains have been reversed.

13. Note that population shifts (migration) mean that it is in principle possible that both urban and rural poverty could have worsened, while overall poverty improved.

REFERENCES

Asselin, L-M. (2002). *Multidimensional poverty: Composite indicator of multidimensional poverty*. Lévis, Québec: Institut de Mathématique Gauss.

Blasius, J., & Greenacre, M. (2006). Correspondence analysis and related methods in practice. In M. Greenacre, & J. Blasius (Eds.), *Multiple correspondence analysis and related methods* (pp. 3–40). London: Chapman & Hall.

Booysen, F. le R. (2002). Using demographic and health surveys to measure poverty: An application to South Africa. *Journal for Studies in Economics and Econometrics, 26*(3), 53–70.

Booysen, F. le R.,Van der Berg, S., Burger, R., Von Maltitz, M., & Du Rand, G. (2007). Trends in poverty and inequality in seven African Countries. Poverty monitoring, measurement and analysis (PMMA) Working Paper 2007-06. Québec, Canada: Poverty and Economic Policy Network.

Chen, S., & Ravallion, M. (2004). How have the World's poorest fared since the early 1980s? World Bank Policy Research Working Paper Series No. 3341. Washington: World Bank.

Duclos, J-Y., & Araar, A. (2004). *Poverty and equity measurement policy and estimation*. Québec, Canada: Department of Economics and CIRPEE, Laval University.

Filmer, D., & Pritchett, L. (2001). Estimating wealth effects without expenditure data—or tears: An application of educational enrollment in states of India. *Demography, 38*(1), 115–132.

Green, P. E. (1978). *Analyzing multivariate data*. Hinsdale, IL: Dryden Press.

Greenacre, M. J. (1984). *Theory and applications of correspondence analysis*. London: Academic Press.

Greenacre, M. (2006). From simple to multiple correspondence analysis. In M. Greenacre, & J. Blasius (Eds.), *Multiple correspondence analysis and related methods* (pp. 41–76). London: Chapman & Hall.

Republic of Kenya (2003). Millennium development goals progress report for Kenya. Government of Kenya: Ministry of Planning and National Development.

Sahn, D. E., & Stifel, D. C. (2000). Poverty comparisons over time and across countries in Africa. *World Development, 28*(12), 2123–2155.

Sahn, D. E., & Stifel, D. C. (2003). Urban–rural inequality in living standards in Africa. *Journal of African Economies, 12*, 564–597.

Statacorp (2003). Stata Statistical Software: Release 8.0. College Station, TX: Stata Corporation.

Teal, F. (2001). Education, incomes, poverty and inequality in Ghana in the 1990s. CSAE Working Paper Series No. 2001-21. Oxford: Centre for the Study of African Economies.

UNDP (2003). Human development report. Washington: UNDP.

UNFPA (2002). State of the world population: People, poverty and possibilities. New York: UNFPA.

UN Population Division (2002). World population prospects: The 2002 revision. Population database. <http://esa.un.org/unpp/p2k0data.asp> Retrieved from 18.5.2004.

Van Kerm, P. (1998). Simple and multiple correspondence analysis in Stata. *Stata Technical Bulletin, 42*, 210–217.

World Bank (2000a). Country reports on health, nutrition, population and poverty. <http://www.worldbank.org/poverty/health/data/intro.html> Retrieved from 13.2.2001.

World Bank (2000b). World development report 2000/2001. Washington, DC: World Bank.

World Bank (2003). Measuring living standards: Household consumption and wealth indices. Quantitative techniques for health equity analysis—Technical Note 4. Washington DC: World Bank.

World Bank (2005). World development indicators. Washington, DC: World Bank.

APPENDIX A. CHARACTERISTICS OF DEMOGRAPHIC AND HEALTH SURVEYS CONDUCTED IN SELECTED COUNTRIES, AND CORRESPONDING POPULATION ESTIMATES

Country	Year	Sample (*n*)			Population (2000) (thousand)	Urban population (2000) (thousand) (urban share)
		Households	Females	Males		
Ghana	1988	4,406	4,488	943 (*h*)	14,417	5,045 (35.0%)
	1993	5,822	4,562	1,302	16,580	6,407 (38.6%)
	1998	6,003	4,843	1,546	18,732	7,939 (42.4%)
Kenya	1989	8,173	7,150	1,130 (*h*)	22,765	5,392 (23.7%)
	1993	7,950	7,540	2,336	25,799	7,159 (27.7%)
	1998	8,380	7,881	3,407	29,244	9,769 (33.4%)
Mali	1987	3,048	3,200	970	8,377	1,850 (22.1%)
	1996	8,716	9,704	2,474	10,649	2,930 (27.5%)
	2001	12,285	12,817	3,390	12,266	3,785 (30.9%)
Senegal	1986	3,736	4,415	–	6,558	2,490 (38.0%)
	1992	3,528	6,310	1,436	7,727	3,205 (41.5%)
	1997	4,772	8,593	4,306	8,745	3,952 (45.2%)
Tanzania	1992	8,327	9,238	2,114	27,884	6,594 (23.6%)
	1996	7,969	8,120	2,256	31,608	8,817 (27.9%)
	1999	3,615	4,029	3,542	34,000	10,575 (31.1%)
Zambia	1992	6,209	7,060	–	8,650	3,333 (38.5%)
	1996	7,286	8,021	1,849	9,572	3,525 (36.8%)
	2001	7,126	7,658	2,145	10,541	3,731 (35.4%)
Zimbabwe	1988	4,107	4,201	–	9,753	2,682 (27.5%)
	1994	5,984	6,128	2,141	11,467	3,569 (31.1%)
	1999	6,369	5,907	2,609	12,461	4,140 (33.2%)

Notes: The "h" in italics with the male sample size refers to those surveys that interviewed the husbands or partners of female respondents and did not draw a random sample of male respondents from the sampled households.

Source: www.measuredhs.com; Population data obtained by interpolation based on data from UN Population Division (2002). *World Population Prospects: The 2002 Revision*. Population Database. Online: http://esa.un.org/unpp/p2k0data.asp.