Tracking Poverty Over Time in the Absence of Comparable Consumption Data

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Following the endorsement by the international community of the Millennium Development Goals, there has been an increasing demand for practical methods for steadily tracking poverty. An economically intuitive and inexpensive methodology is explored for doing so in the absence of regular, comparable data on household consumption. The minimum data requirements for this methodology are the availability of a household budget survey and a series of surveys with a comparable set of asset data also contained in the budget survey. This method is illustrated using a series of Demographic and Health Surveys for Kenya. JEL codes: C81, I32

The worldwide endorsement of the Millennium Development Goals and the shift to results-based lending in supporting developing countries have intensified the importance of being able to reliably gauge the evolution of poverty. The common approach to measuring poverty is anchored in utility theory and is empirically based on household consumption or income measures, which are usually derived from nationally representative household budget surveys (Ravallion 1996a; Deaton 2003). Obtaining reliable measures of household consumption presents a series of challenges in practice.[1] These challenges increase when comparing poverty over time.

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1. Among the challenges are determining the optimal recall period, valuing home consumption, and deciding how to treat consumption of housing, education, and health services, as well as appropriately accounting for the consumption of public goods. Deaton and Zaidi (2002) provide excellent guidelines on how to meet such challenges.

THE WORLD BANK ECONOMIC REVIEW, VOL. 21, NO. 2, pp. 317–341 doi:10.1093/wber/lhm010
Advance Access Publication 19 June 2007

First, nationally representative household budget surveys are often unavailable at regular intervals. Second, when available, they are frequently not comparable in design, and appropriate price deflators are usually difficult to come by. That changes in questionnaire design may systematically affect the resulting household consumption and welfare measures has been well documented (Scott and Amenuvegbe 1990; Appleton 1996; Pradhan 2001) and is most vividly illustrated by the "great Indian poverty debate".[2]

One way to circumvent the absence of regular household budget surveys is to link the annual series of national accounts to existing consumption surveys (Hoogeveen and Demombynes 2004). While the method is straightforward, the predicted evolution of poverty holds only under a series of stringent assumptions such as distribution-neutral growth, a correct attribution of sectoral GDP growth to households (World Bank 2005), and a close correspondence between growth observed in the national accounts and income or consumption growth measured in household surveys (Ravallion 2003; Deaton and Kozel 2005). Using household data instead, Ravallion (1996b) explores the use of subjective indicators of poverty and Sahn and Stifel (2000) propose tracking poverty by tracking household assets, which they combine into a single index based on statistical association.

Building on insights from the Indian poverty debate (Deaton and Drèze 2002; Kijima and Lanjouw 2003; Sen and Himanshu 2004) and developments in the literature on the dynamics of poverty (Simler, Harrower, and Massingarela 2004; Azzarri and others 2006), this article explores an "economic" asset index approach that is anchored in consumption and uses advanced prediction techniques akin to those applied in the poverty mapping literature (Elbers, Lanjouw, and Lanjouw 2003). By linking the different assets directly to consumption, the article provides a theoretical welfarist foundation for aggregating assets, an important enrichment over the "statistical" asset index approach of Sahn and Stifel (2000). Doing so also facilitates estimation of different poverty and inequality measures.

Further, in contrast to Kijima and Lanjouw (2003), Simler, Harrower, and Massingarela (2004), and Azzarri and others (2006), this analysis excludes assets with returns that are more prone to change over time (education, labor, and land) and includes location-specific factors (such as rainfall, prices, and malaria incidence) that vary annually and are likely to affect returns to assets. The inclusion of more time-variant variables is an important innovation—it mitigates changes in returns to other assets and improves the capture of (transitory) changes in welfare and poverty. Subjective indicators of welfare could also be included, though they have been found to add little to

2. For a review of efforts to correct poverty estimates for India following a change in the recall periods for expenditure items in the 55th round of the National Sample Survey, see Deaton and Kozel (2005).

the method's performance and have displayed limited correspondence with changes in poverty based on consumption measures in other settings (Ravallion 1996b; Azzarri and others 2006). They were also not available in the surveys used here.

The economic asset index approach is applied to a series of standardized Demographic and Health Surveys for Kenya. The high degree of standardization in survey and questionnaire design across rounds means that comparability issues are minor. These surveys are also freely available for many sub-Saharan African countries. Yet the proposed approach can be applied to any carefully selected set of assets or poverty predictors that are regularly collected, including those under the Core Welfare Indicator Questionnaire surveys developed by the World Bank.

The empirical application uses the asset information from the 1993, 1998, and 2003 Kenyan Demographic and Health Surveys and the consumption measure from the 1997 Welfare Monitoring Survey (WMS). Estimates derived from these indicate a continuous decline in poverty between 1993 and 2003 in rural Kenya and stagnation in poverty in urban Kenya. Trends were diverging in Nairobi (poverty declining) and other urban areas (poverty increasing), though these trends were not individually statistically significant. The direction of these findings is broadly consistent with those from the statistical asset index, the national accounts, other rural surveys as well as the initial poverty estimates from the national 2005/06 Kenya Integrated Household Budget Survey that became available as this article was going to press. They are also in line with the observed evolution of key nonmonetary indicators such as school enrollment and child malnutrition during this period.

I. Methodological and Empirical Considerations

Let $W(c_t)$ denote the value at time t of a population welfare measure (for example, poverty or inequality) that depends on individual consumption levels c at time t. Given comparable observations on c_t at different time intervals, the evolution of W can be tracked. Without such observations, but with comparable observations for the individual, household, and location assets x_t that underpin $c_t = c_t(x_t)$, the evolution of c_t (and thus W_t) can be tracked, provided that one has an empirical understanding of the mapping of x_t into c_t.[3] Tracking W_t by tracking x_t requires essentially three steps: developing an accurate empirical model of c_t as a function of x_t; estimating c_{t+k} as a function of x_{t+k}, where k is a positive or negative integer; and generating an estimate of expected W_{t+k} from the estimated c_{t+k}.

3. The components of x_t are not restricted to contemporaneous assets. For example, current consumption is likely to depend on lagged rainfall given the lag in agricultural production.

The basic features of the empirical methodology are as follows.[4] It starts with a log linear approximation to individual consumption c_t:

$$\ln c_t = x_t'\beta_t + u_t \tag{1}$$

Next, estimates of $\ln c_{t+k} = x_{t+k}'\ \beta_{t+k} + u_{t+k}$ are calculated using estimates of u_{t+k} and β_{t+k} drawn from the estimated distributions of u_t and β_t obtained in estimating equation (1). In doing so, the methodology imposes the assumption that the distributions of β_t remain constant over time—that is, the distributions of β_{t+k} and β_t are the same. Further, although the distribution of u_t is updated with x_{t+k} to estimate u_{t+k}, the relationship determining the heteroskedastic nature of the data-generating process is also assumed to be constant. The combination of $\hat{u}_{t+k}$ and $\hat{\beta}_{t+k}$, along with the updated asset data x_{t+k}, yields:

$$\ln \hat{c}_{t+k} = x_{t+k}'\hat{\beta}_{t+k} + \hat{u}_{t+k} = x_{t+k}'\hat{\beta}_{rt} + \hat{u}_{rt+k} \tag{2}$$

where r denotes one draw from the estimated distributions of u_{t+k} and β_t.[5] Since the value of $\hat{c}_{t+k}$ depends heavily on the values of x_{t+k} and their anchoring in consumption through $\hat{\beta}_t$ and $\hat{u}_{t+k}$, estimates of c_{t+k} can also be seen as estimates of an economic asset index. Finally, an estimate of W_{t+k} is calculated using $\hat{c}_{t+k}$. An estimate of the expected value of W_{t+k} is obtained by simulating the process described above for different draws r. The procedure is outlined in detail in the appendix.

In pursuing precise and consistent estimates of W_{t+k} in the absence of observations on the true c_{t+k}, it is important to minimize the errors involved in estimating W_{t+k}. Four sources of error are distinguished. In addition to the idiosyncratic, model, and computational errors discussed in Elbers, Lanjouw, and Lanjouw (2003), estimates of W_{t+k} are also subject to sampling error.

The *idiosyncratic error* component follows from the fact that only the stochastic c_{t+k} is known, not the actual c_{t+k}. The stochastic nature of c_{t+k} is assumed through the distributional features of u_{t+k}; that is, $E[W(x_{t+k}, \beta_{t+k},$

4. The approach largely follows Elbers, Lanjouw, and Lanjouw (2003), who developed econometric techniques for small-area predictions of poverty and inequality. Poverty mapping differs from the economic asset index approach in that poverty mapping predicts a geographically disaggregated distribution of poverty by mapping from a household budget survey to a same-year (or close) census. An economic asset index approach predicts poverty (at an aggregate level) over time from a household budget survey to another national survey in another year that collected information on the same assets in a comparable manner.

5. In contrast, Azzarri and others (2006) use only $x_{t+k}'\hat{\beta}_t$ to predict $\ln \hat{c}_{t+k}$ resulting in an underestimate of the variance of the distribution of $\ln c_{t+k}$, and a bias in both the estimated level and change in poverty. The direction and extent of bias of the estimated change in poverty is not clear a priori. The approach proposed here obtains consistent estimates of both the mean and the variance of poverty. This yields a consistent estimate of the change in poverty, the statistical significance of which can further be tested.

$u_{t+k})]$ is calculated rather than $W(c_{t+k})$. The *model error* component arises from the fact that the parameters β_{t+k} are estimated as well as those describing the distribution of u_{t+k}; that is, $E[W(x_{t+k}, \hat{\beta}_t, \hat{u}_{t+k})]$ is calculated rather than $E[W(x_{t+k}, \beta_{t+k}, u_{t+k})]$. As the expectation is often analytically intractable, it is approximated through simulation, thereby generating a *computational error*. Finally, the *sampling error* follows from imputing from a survey and not a census; that is, the x_{t+k} terms are obtained from a survey.

The size of the idiosyncratic error component depends critically on the size of the target population, with the size of the error declining the larger the target population to which the welfare measure is imputed and increasing the smaller the population. This feature is critical in constructing small-area welfare estimates as it determines "how low one can go" (Alderman and others 2002). The interest in this article is in tracking welfare and poverty measures over time for major groups or areas for which representative data have been collected. Since these populations (rural, urban, province) are usually large, the idiosyncratic error component tends to be small.

This idiosyncratic error component further depends on the explanatory power of the x variables in the model.[6] Careful selection of the different subgroups for which the consumption model (equation 1) is estimated and inclusion of key deterministic and stochastic location-specific variables (for example, rainfall variability and rainfall levels) are important to reduce idiosyncratic error in the welfare estimate.

The magnitude of the model error component is in general determined by the precision of the coefficient estimates, the sensitivity of the welfare indicator to errors in the estimated consumption measures, and the extent to which the levels of the x variables in the target population deviate from the population of origin (Elbers, Lanjouw, and Lanjouw 2002).

A second general source of model error derives from the assumption that the estimated distributions of $\hat{\beta}_t$ and the parameters used to estimate $\hat{u}_{t+k}$ are stationary.[7] While it is difficult to theoretically examine the magnitude of the error introduced this way, theory and past empirical research can provide guidance to mitigate errors due to nonstationarity in specifying the consumption model.

First, not all parameters are equally prone to change over time. For instance, while returns to labor and especially to education may change with changes in market conditions (Juhn, Murphy, and Pierce 1993; Ferreira and Paes de Barros 1999; Alwang, Mills, and Taruvinga 2002), estimated associations between consumer durables and other less frequently purchased

6. While consumption is clearly measured with error in practice, error-free consumption measures are assumed. See Chesher and Schluter (2002) for rules to approximate the effect of measurement error in estimating welfare measures.

7. The assumption of stationary empirical distributions is implicit in practice in many poverty-mapping exercises as household budget survey data and census data are typically collected in adjacent years rather than the same year.

items are arguably more stable. The Engel relationship between these items and full consumption is likely to hold (Deaton and Kozel 2005), especially when consumption is predicted only for limited periods into in the future or the past.

Second, risks of nonstationarity can be mitigated through the explicit inclusion of the sources of nonstationarity, such as prices and rainfall. Controlling for rainfall patterns is especially important in agriculture-based economies. Further partial corrections can be introduced by updating the x_t variables with x_{t+k} in the estimated means and variance–covariance matrices for $\hat{u}_{t+k}$. In sum, while potential model error from nonstationarity cannot theoretically be eliminated, careful selection of assets can go a long way in substantially mitigating the risks of such errors. An empirical range of their magnitude could be established if there were a series of consumption surveys with comparable consumption and asset data.[8]

A third source of model error arises from differences in the asset variables across the surveys arising from (small) differences in definition or ranking of questions in the questionnaire. To mitigate this potential, selection of the common asset variables is based on careful empirical comparison of the distributional characteristics of the x variables.

Elbers, Lanjouw, and Lanjouw (2003) find that the computational error depends on the computational method. It is small when a sufficient number of simulations are used. The sampling error depends on the sampling design, the sample size, and the population variance of the consumption measure.

II. Welfare, Assets, and Rainfall in Kenya

The application of this methodology to Kenya focuses on tracking poverty between 1993 and 2003. Three major sources of data are used: the 1997 Welfare Monitoring Survey and district-level malaria data constructed from the 1992–97 WMS;[9] the 1993, 1998, and 2003 Demographic and Health Surveys; and district-level data on infrastructure from the 1999 census, and district-level rainfall data obtained from the Famine Early Warning System.[10]

8. Sen and Himanshu (2004) show that it is sometimes possible to test the stability of the coefficients even in the absence of additional consumption data, though their test was not applicable here.

9. Only the third of a series of WMS surveys between 1992 and 1997 is used for the poverty analysis because differences in the timing of the survey and the questionnaire design rendered the reported poverty numbers noncomparable (World Bank 2003). A new national expenditure survey was fielded in 2005, but the data were unavailable at the completion of this study.

10. Rainfall data were available for 21 of the 36 districts in the analysis. These data were further used to impute rainfall patterns to the remaining 15 districts based on their geographic proximity.

The 1997 WMS is a national survey containing information on household consumption; household demographics; and individual, household, and community assets. The survey was conducted between February and May 1997 and covered 10,874 households.[11] The consumption measure derived from the data is a geographically deflated measure of aggregated household expenditures including consumption of own production, as revised by the World Bank (2003). The World Bank (2003) estimated the rural poverty headcount at 52.8 percent and urban poverty at 43.1 percent. The 1997 WMS together with the secondary data from the census, the malaria data from 1992–97 WMS, and the Famine Early Warning System are used to estimate the distributional parameters in equation (1).

Three Demographic and Health Surveys of about 8,000 households each were carried out in Kenya at five-year intervals between 1993 and 2003.[12] As these surveys are not designed for economic analysis, there are generally no data on income or expenditures. However, several of the asset variables collected under the 1997 WMS are also tracked in the Demographic and Health Surveys. Furthermore, Demographic and Health Surveys are known for their comparability over time (and across countries). Survey instruments remain largely unchanged, and consistent sampling designs are maintained. Although the samples were intended to be nationally representative, the seven districts not covered in the 1993 and 1998 samples are excluded from the analysis.[13]

To construct the economic asset index, a subset of assets (x_{t+k}) is selected from the larger set of assets that are commonly available in the two surveys. This is the "zero stage" in the poverty mapping literature. Three criteria are used to select this subset, all motivated by an effort to optimize the trade-off between maximizing explanatory power (minimizing idiosyncratic error) and minimizing model error.

First, to reduce potential error due to parameter instability, the set of assets is restricted to those for which parameters are likely to remain stable over time. Assets such as labor and education, which are more prone to parameter instability following economic or polity change, are therefore excluded.[14] Only consumer durables and housing characteristics as well as more time-variant rainfall and individual health variables are included. The first two sets of

11. For reasons of logistics, insecurity, and inaccessibility, Isiolo, Mandera, Samburu, and Turkana districts were not covered. As such, the sample is not entirely representative at the national level, though consistency is maintained in the comparisons over time and across data sets by excluding these districts from all of the data and analysis.

12. The 1989 survey contained very limited household information.

13. These are Garissa, Mandera, and Wajir in North Eastern Province; Samburu and Turkana in Rift Valley Province; and Isiolo and Marsabit in Eastern Province.

14. Deaton and Kozel (2005) consider the inclusion of household size, education of household members, and household land holdings to be the main weakness of Kijima and Lanjouw's (2003) poverty predictions for India, which use a similar technique.

variables capture the more nearly permanent part of household consumption, while the second two capture transitory aspects.[15]

Second, to ensure that the structure of the model estimated in the WMS data is appropriate for the Demographic and Health Survey data, only assets that are similar in the WMS and the adjacent Demographic and Health Surveys are retained. In particular, only variables for which there is 95 percent confidence that their means in the 1997 WMS and the 1998 Demographic and Health Survey do not differ are kept. Assets such as televisions and bicycles, for which one-year changes are possible, are kept if the difference in the means from 1997 to 1998 is no greater than the difference in the means from 1993 to 1998.

Third, step-wise regression models using the resulting common subpool of assets are applied to identify the set of variables that are statistically significant (at the 5 percent level) while maximizing the explanatory power (as captured by the R-squared statistic).[16] Balancing the trade-off between maximizing explanatory power and minimizing model error also motivated the choice of different regression specifications for rural, other urban, and Nairobi households because the differences in their livelihood systems suggest a different relationship between a household's consumption and its asset base. The assets that are retained based on these three criteria include housing quality and sanitation variables, consumer durables, child nutritional status, cluster and district averages of the household-level variables, district measures of malaria incidence averaged across the 1992, 1994, and 1997 WMSs, and district rainfall measures (table 1). The table also presents selected household demographic and education variables, which are used for sensitivity analysis in section IV.

Since the food expenditure share is on average above 60 percent (1997 WMS), children's nutritional status is likely associated with household consumption and is a good proxy for transitory changes in household consumption.[17] The average height-for-age z-score for children under five in the household is used instead of weight for age, because height is a longer term measure of nutrition that corresponds more closely to the dependent variable,

15. Consumer durables and housing characteristics may display downward rigidity and as a result may not appropriately capture potential declines in welfare resulting from moderate declines in household incomes. Yet households with durables and better housing conditions usually also have better access to credit, enabling them to better smooth their consumption levels in the face of such income shocks. Moreover, the flow of services derived from these goods persists, even when incomes temporarily decline, and should be reflected in the consumption predictions. Nonetheless, it is important to build sufficient flexibility into the model to help capture both the more permanent and the more transitory parts of household consumption. This is achieved through the addition of more time-variant explanatory variables in the model, such as rainfall shocks and health and nutrition variables, that genuinely fluctuate from year to year and likely affect income and welfare.

16. For all variables that were retained after applying the first two criteria, cluster and district averages were also computed and included in the stepwise regression models to better capture location characteristics. The cluster averages are estimated from the survey data, while the district averages are calculated from the 1999 household census.

17. The authors thank an anonymous referee for suggesting the inclusion of nutritional status as an asset.

TABLE 1. Levels (proportions) and Changes in Individual, Household, and Location Assets Held by Rural, Other Urban, and Nairobi Households in Kenya During 1993–2003

	Rural				Other urban				Nairobi			
	WMS	Changes			WMS	Changes			WMS	Changes		
	1997	1993–1997	1998–2003	1993–2003	1997	1993–1997	1998–2003	1993–2003	1997	1993–1997	1998–2003	1993–2003
Variable												
Housing Characteristics												
Dummy Variable: House Floor of Low Quality (Mud, Dung, Sand) (1 = yes)	**0.79**	−0.02***	−0.02**	−0.05***								
Dummy Variable: House Roof of Low Quality (Thatch) (1 = yes)	**0.36**	−0.06***	−0.08***	−0.15***					**0.02**	0.01	0.00	−0.00
Dummy Variable: Drinking Water, Piped or Public Tap (1 = yes)									**0.90**	−0.02	−0.12***	−0.10***
Dummy Variable: Flush Toilet (1 = yes)	**0.01**	−0.004**	0.001	0.003								
Household Durables												
Dummy Variable: Owns a Radio (1 = yes)	**0.59**	0.07***	0.14***	0.24***	**0.77**	0.04**	0.02	0.10***				
Dummy Variable: Owns a Television (1 = yes)	**0.04**	0.02***	0.07***	0.11***	**0.31**	0.00	0.02	0.09***				
Dummy Variable: Owns a Refrigerator (1 = yes)	**0.01**	0.00	0.01***	0.01***	**0.13**	−0.03*	−0.04**	−0.06***	**0.18**	0.00	0.07***	0.11***
Dummy Variable: Owns a Bike (1 = yes)	**0.29**	0.02**	0.08***	0.11***								

(Continued)

Table 1. Continued

	Rural				Other urban				Nairobi			
	WMS	Changes			WMS	Changes			WMS	Changes		
	1997	1993–1997	1998–2003	1993–2003	1997	1993–1997	1998–2003	1993–2003	1997	1993–1997	1998–2003	1993–2003
Cluster and District Characteristics												
Cluster Average Household with Low Quality Floors					***0.19***	*0.03****	*0.01*	*0.08****				
Cluster Average Household with Access to Piped Water					**0.79**	−0.04***		−0.46***	−0.53***			
Cluster Average Household Owns Refrigerator	**0.01**	0.001*	0.005***	0.005***	**0.11**	−0.02**	−0.04***	−0.05***				
District Average Household with Access to Electricity	**0.06**	0.002***	0.001	−0.001								
Rainfall and Health												
Rain, Early Rainy Season Deviation from Long-run Average	**− 0.21**	0.22***	0.02**	0.45***	**− 0.12**	0.39***	−0.07***	0.49***				
Malaria Prevalence in District (Average in 1990s)	***0.109***	*−0.001*	*−0.003****	*−0.002****	***0.147***	*0.003*	*−0.001*	*0.003*				
Average Household Height-for-Age z-score	**− 1.28**	0.14***	0.07***	0.16***								
Household Demographics												
Dependency Ratio	***0.52***	*−0.04****	*−0.02****	*−0.04****	***0.41***	*−0.01*	*0.00*	*0.00*	***0.34***	*0.01*	*−0.02*	*−0.03***
Household Size	***6.42***	*−0.36****	*−0.06*	*−0.76****								
Education												
Share of Household Members with Secondary Education	**0.11**	0.03***	0.00	0.02***								
Share of Household Members with Post-secondary Education	**0.02**	0.02***	0.01***	0.02***								

(Continued)

Table 1. Continued

	Rural				Other urban				Nairobi			
	WMS	Changes			WMS	Changes			WMS	Changes		
	1997	1993–1997	1998–2003	1993–2003	1997	1993–1997	1998–2003	1993–2003	1997	1993–1997	1998–2003	1993–2003
Dummy Variable: Household Head with Primary Education					**0.33**	0.01	0.09***	0.10***				
Dummy Variable: Household Head with Secondary Education	**0.20**	0.05***	−0.03***	0.03***								
Dummy Variable: Household Head with Post-secondary Education					**0.09**	0.04***	0.07***	0.11***				
Cluster Average Share with Post-secondary Education	**0.02**	0.02***	0.01***	0.02***	**0.05**	0.03***	0.05***	0.07***				
Cluster Average Head with Primary Education					**0.33**	−0.01	0.08***	0.08***				
Cluster Average Head with Secondary Education												
Cluster Average Head with Post-Secondary Education					**0.09**	0.04***	0.07***	0.10***	**0.14**	0.10***	0.09***	0.19***

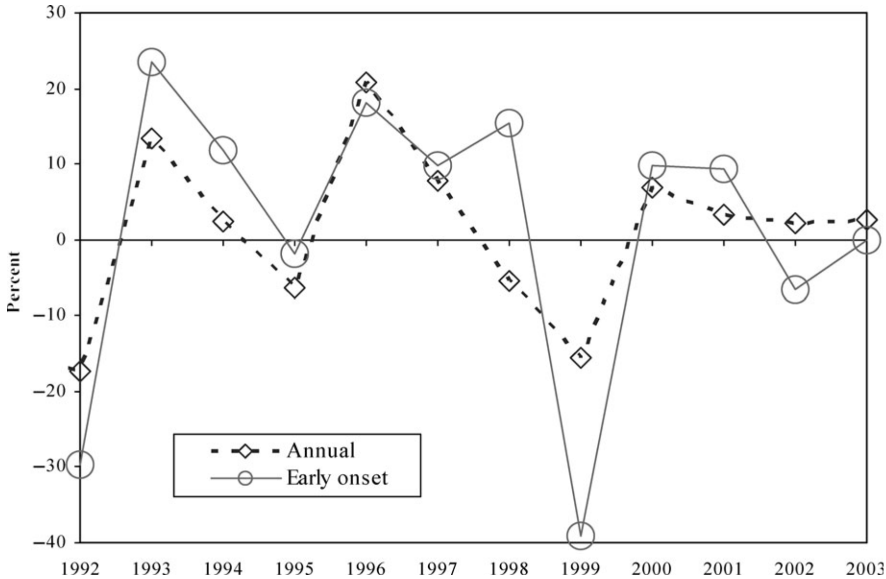
*Significant at the 10 percent level; **Significant at the 5 percent level; ***Significant at the 1 percent level.

WMS is Welfare Monitoring Survey.

Note: Italicized variables are those to which negative weights are assigned. A decrease in the means of these assets is associated with a predicted increase in mean household expenditure. For variables that are not italicized, an increase in the mean is associated with a predicted increase in mean household expenditure.

Source: Authors' analysis based on data described in the text.

FIGURE 1. Deviation of Annual Rainfall and Early Onset of Rainfall from Long-Run Average in Kenya, 1992–2003



Note: Early onset of rain is defined as the percentage deviation in the amount of rainfall during the first month of the long rains from the long-run average (1992–2003) amount for that month. Selection of the first month differs by district and is based on the district-specific rainfall patterns in the Famine Early Warning System data.

Source: Authors' analysis based on Famine Early Warning System data.

annual consumption per adult equivalent, whereas weight can vary seasonally within a given year. After the stepwise regression is applied, the anthropometric variable was only retained in the rural model.

From (figure 1), 1992 emerges as a very dry year with rainfall starting late and the overall amount well below the long-run average; 1996 and 1997 were above average both in timing (early or on time) and overall level. Similarly, rainfall in 2002 was slightly above normal, though it was slightly later in coming.[18] Given the large fluctuations in both level and timing of rainfall and their independent importance for welfare—rural households in Kenya are often unable to protect consumption from drought shocks (Christiaensen and Subbarao 2005)—it is important to account for actual rainfall patterns in tracking poverty over time. The timing of the onset of the long rains rather than the level of rainfall in that year is included as an asset in the predicting models. While they are correlated,[19] timing yielded a better fit.

18. Given the lag in agricultural production, the relevant rainfall patterns are mostly those in the year preceding the survey year.

19. The correlation coefficient for these two measures of rainfall is 0.53.

The coefficients (which can be viewed as asset weights) from the three different first-stage models (rural, other urban, Nairobi) are presented in table 2.[20] Since these are the results of stepwise regressions, each parameter estimate is significant at the 95 percent confidence level or higher. Although the signs are generally as expected, plausibility of the parameter estimates is not critical since consistency of the predicted dependent variable does not rely on consistent estimation of the parameters.

For the rural sample of 8,807 households in the WMS, 13 variables are kept in the model. Twenty-one percent of the variation in log per adult equivalent expenditure is explained by the model. The stepwise regressions led to the retention of eight variables resulting in an *R*-squared of 0.25 for the other urban models and to three variables and an *R*-squared of 0.35 for the Nairobi models. In the Nairobi models only six explanatory variables passed the comparability test between the WMS 1997 and the Demographic and Health Survey 1998, from which only three were kept in the stepwise regression.

III. The Evolution of Poverty in Kenya

The simulated poverty rates for all four data sets/years are shown in table 3. The 1997 poverty rates constitute the baseline as these were estimated using the sole household budget survey (WMS). Due to a persistent 1–2 percentage point underestimation of the simulated poverty prevalence in the baseline data compared with the actual poverty prevalence directly observed in the baseline data using the official poverty line, the poverty line is allowed to be determined endogenously to replicate these 1997 poverty levels. This adjusted poverty line is then applied to all four data sets to maintain comparability. Adjustments were minor and did not affect the magnitudes of the predicted changes in poverty; only the levels were affected. As such, the simulated poverty headcount ratios in 1997, the base year, are consistent with those reported in World Bank (2003).[21] They are 52.8 for rural areas, 43.2 for other urban areas, and 40.0 for Nairobi. Taken together, about half of the Kenyan population was estimated to be poor in 1997.

The economic asset index suggests that poverty prevalence in Kenya fell from 55.8 percent in 1993 to 50.8 percent in 1997, and continued to fall to 45.0 percent in 2003. Although the fall is not statistically significant after 1997, it is for 1993–1997 and for 1993–2003. With most poor people residing in rural

20. Hausman tests, described in Deaton (1997), were used to determine whether sampling weights should be used in the final regression models. For all three models the weighted versions of the explanatory variables added to equation (1), were jointly significant at the 99 percent level of confidence. Consequently, sampling weights were used in all of the prediction models.

21. The urban and rural poverty lines constructed by the World Bank (2003) were based on a nonparametric approach to adding basic nonfood requirements to the food poverty lines. The food poverty lines were themselves based on the monetary value of a food basket that allowed minimum nutrient requirements (2,250 calories) to be met. Finally, they were adjusted for regional price differences.

TABLE 2. Estimated Coefficients or Asset Weights from First-Stage Regressions (Dependent Variable = Log Consumption Per Adult Equivalent, 1997)

	Rural	Other Urban	Nairobi
Housing Characteristics			
Dummy Variable: House Floor of Low Quality (Mud, Dung, Sand) (1 = yes)	−0.26		
Dummy Variable: House Roof of Low Quality (Thatch) (1 = yes)	−0.11		1.73
Dummy Variable: Drinking Water, Piped or Public Tap (1 = yes)			0.25
Dummy Variable: Flush Toilet (1 = yes)	0.24		
Household Durables			
Dummy Variable: Owns a Radio (1 = yes)	0.12	0.09	
Dummy Variable: Owns a Television (1 = yes)	0.32	0.36	
Dummy Variable: Owns a Refrigerator (1 = yes)	0.32	0.19	1.20
Dummy Variable: Owns a Bike (1 = yes)	0.07		
Cluster and District Characteristics			
Cluster Average of Households with Low Quality Floors		−0.48	
Cluster Average of Households With Access to Piped Water		0.10	
Cluster Average of Households Owning a Refrigerator	0.60	0.24	
District Average of Households With Access to Electricity	0.76		
Rainfall and Health			
Rain, Early Onset (Deviation From Long-Run Mean), District Level	0.09		
Rain, Early Onset, Squared	0.13	0.22	
Malaria Prevalence in District (Average in 1990s), District Level	−0.03	−0.01	
Average Household Height-for-Age z-Score Among Under Five Year Olds	0.02		
Constant	10.14	10.23	10.04
Adjusted R^2	0.21	0.25	0.35
Number of Clusters	888	168	30
Number of Variables	13	8	3
Number of Observations	8,807	1,552	280

Source: Authors' analysis based on data described in the text.

areas (80 percent in 2003), the evolution of rural poverty between 1993 and 2003 is very similar to that observed at the national level. Nairobi also experienced a decline in poverty as the prevalence dropped from 40.7 percent in 1993 to 35.1 percent in 2003. In contrast, poverty prevalence in other urban areas rose from 39.0 percent to 46.0. Yet, the simulated poverty changes in both Nairobi and other urban areas were not statistically significant. The (simulated) evolution of the more distribution-sensitive poverty measures (the poverty gap and poverty severity indices) across the rural, other urban, and Nairobi populations are broadly consistent with the picture emerging from the headcount figures.

To provide insights into the factors behind the emerging pattern of the evolution of poverty, the average evolution of assets across the different survey years is presented in table 1. The evolution in the asset base is broadly consistent with the observed evolution of poverty across the different groups. Caution should be

TABLE 3. Asset Poverty in Kenya, 1993–2003

	Levels				Test Statistics for Changes			
	1993 (DHS)	1997 (WMS, base)	1998 (DHS)	2003 (DHS)	1993–1997	1997–1998	1998–2003	1993–2003
Economic Asset Index								
Headcount Ratio (P_0)								
National	55.8	50.8	48.1	45.0	−1.99**	−1.09	−0.90	−3.17***
	(1.9)	(1.7)	(1.8)	(2.8)				
Rural	57.2	52.8	50.6	48.0	−1.54	−0.81	−0.87	−2.87***
	(2.2)	(1.9)	(1.9)	(2.4)				
Other Urban	39.0	43.2	41.3	46.0	0.70	−0.34	0.73	1.03
	(4.5)	(4.0)	(4.0)	(5.0)				
Nairobi	40.7	40.0	38.5	35.1	−0.05	−0.11	−0.28	−0.44
	(9.5)	(10.0)	(8.8)	(8.7)				
Poverty Gap (P_1)								
National	19.9	17.4	16.4	15.2	−1.45	−0.67	−0.61	−2.26**
	(1.3)	(1.1)	(1.2)	(1.6)				
Rural	21.0	18.4	17.2	15.5	−2.23**	−1.11	−1.29	−4.04***
	(1.0)	(0.7)	(0.8)	(1.0)				
Other Urban	12.8	14.4	13.8	15.9	0.58	−0.21	0.65	0.96
	(2.0)	(1.9)	(1.9)	(2.6)				
Nairobi	12.3	11.9	11.6	10.3	−0.07	−0.05	−0.25	−0.36
	(4.2)	(4.3)	(3.7)	(3.6)				
Poverty Severity (P_2)								
National	9.7	8.3	7.7	7.1	−0.99	−0.41	−0.40	−1.61
	(1.1)	(0.9)	(1.0)	(1.2)				
Rural	10.3	8.8	8.2	7.3	−2.06**	−1.00	−1.17	−3.73***
	(0.6)	(0.4)	(0.5)	(0.5)				
Other Urban	5.8	6.5	6.3	7.4	0.51	−0.15	0.60	0.91
	(1.1)	(1.1)	(1.1)	(1.5)				
Nairobi	5.1	4.9	4.8	4.2	−0.08	−0.03	−0.23	−0.33
	(2.2)	(2.1)	(1.9)	(1.9)				
Statistical Asset Index								
Headcount Ratio (P_0)								
National	57.9		50.8	45.1				
Rural	60.0		53.0	46.5				
Other Urban	42.2		42.4	47.3				
Nairobi	49.8		39.7	28.2				

*Significant at the 10 percent level; **Significant at the 5 percent level; ***the Significant at the 1 percent level.

WMS is Welfare Monitoring Survey and DHS is Demographic and Health Survey.

Note: Numbers in parentheses are standard errors.

Source: Authors' analysis based on data described in the text.

taken in interpreting the results for Nairobi, however, as household ownership of refrigerators appears to be driving the poverty predictions. This highlights the need to ensure comparability in designing base and target data sets.

The substantial reduction in rural poverty between 1993 and 1997 compared with the reduction between 1997/1998 and 2003 is partly related to the underlying rainfall pattern (very bad in 1992, exceptionally good in 1997, and modest in 2002; see figure 1). Nonetheless, the improvements in rural welfare between 1993 and 2003 appear genuine and shared by the poorer segments of the population. To test this notion, poverty was predicted for 2003 using the 2003 Demographic and Health Survey data and the 1992/93 Famine Early Warning System rainfall data. The resulting 50.1 percent headcount ratio suggests that the better rainfall accounted for only 22.8 (2.1/9.2) percent of the overall fall in rural poverty between 1993 and 2003.

IV. Are the Results Empirically Robust?

To gauge the reliability of the poverty trends emerging from the economic asset index, these trends are briefly compared with those based on other indicators, and the plausibility of the assumptions underpinning the economic asset-based poverty numbers in the Kenyan context is examined. First, the trends are compared with the picture emerging from the trends in the statistical asset index developed by Sahn and Stifel (2000), who apply factor analysis to a set of assets common to the three Demographic Health Surveys.[22] Since the weights applied to these assets are derived in a purely statistical manner, this index is considered a statistical asset index. The results of this sensitivity analysis appear at the bottom of table 3.[23] The trends are similar to those derived from the economic asset index for rural and other urban areas despite different weighting schemes and a different asset bundle. While the direction of change for Nairobi is the same, the declines in poverty are markedly larger with the statistical asset index.

The findings here are also broadly consistent with the evolution of per capita consumption observed in the national accounts. Per capita private consumption observed in the national accounts grew 2.8 percent a year between 1993 and 1998, consistent with the simulated reduction in national poverty incidence from 55.8 percent to 48.1 percent. While growth in per capita private consumption essentially stagnated thereafter,[24] poverty continued to decline according to the simulations in this study, though the change was less

22. These assets include household characteristics (source of drinking water, toilet facilities, and house construction material) and household durables (ownership of radio, television, refrigerator, and bicycle). The 1997 WMS is excluded to avoid dropping assets for lack of commonality, as was necessary for the economic asset index.

23. The poverty lines are defined in order to replicate the 1997 poverty rates in the 1998 Demographic and Health Survey.

24. Average annual growth in per capita private consumption between 1998 and 2003 was estimated at -0.1 percent in the national accounts.

pronounced and no longer statistically significant. However, further decomposition of the national accounts between 1998 and 2003 shows that the stagnation in overall per capita GDP growth was driven by contraction of the industrial sector and stagnation of the services sector, while per capita agricultural GDP continued to grow, albeit at a slightly slower pace.[25] This is consistent with the simulated decline in rural poverty and the increase in poverty in other urban areas (though not with the decline in poverty in Nairobi).

Other surveys also suggest a continuing decline in rural poverty between 1998 and 2003. Nyoro, Muyanga, and Komo (2005) find, for example, that \$1 a day poverty dropped between 1997 and 2004 among a panel of 1,500 predominantly maize-growing smallholders. Preliminary estimates from the national 2005 Kenya Integrated Household Budget Survey also suggest a decline in rural poverty, with the decline similar in magnitude to that predicted in the approach followed here. The new poverty estimates also point to an increase in poverty in other urban areas and a decrease in Nairobi in 2005.[26]

Finally, the poverty trends reflected by the economic asset-based poverty indices are broadly similar to the evolution of key nonmonetary indicators of well-being in Kenya, such as primary and secondary enrollment rates and stunting prevalence. Comparison of these indicators across the population in rural areas, other urban localities, and Nairobi between 1993 and 2003 based on the Demographic and Health Surveys (table 4) shows substantial improvements in primary and secondary enrollment rates and stunting prevalence in rural areas, even stronger improvements in these indicators in Nairobi, and a mixed picture in other urban areas, with primary enrollment rates increasing, secondary enrollment rates falling marginally, and stunting prevalence increasing by 6 percentage points.[27]

The plausibility of the assumptions underlying the economic asset index may also affect the empirical performance. To reduce the likelihood of model error following from nonstationarity of the estimated parameters, the prediction model included rainfall and nutritional status. Further, although there were no dramatic shifts in the economic and political regime during the periods considered here, such assets as household labor supply and educational attainment were excluded as a precaution.[28]

25. During 1993–98 per capita agricultural GDP grew at 0.9 percent, industrial GDP at −0.56 percent, and service GDP at 0.96 percent and during 1998–2003 they grew at 0.75 percent, −0.99 percent, and 0.14 percent, respectively.

26. These poverty estimates became available as this article was going to press.

27. The evolution of infant mortality, which increased by 9.4 children per 1,000 born in rural areas between 1993 and 2003, appears at odds with the estimated evolution in household welfare. However, in-depth multivariate analysis of the determinants of enrollment rates and health outcomes in Kenya using the 1993, 1998, and 2003 Demographic and Health Survey data (Stifel and Christiaensen 2006) shows that while household consumption is positively associated with (primary) enrollment rates and nutritional status, there is no correlation between consumption and infant mortality.

28. Land and livestock, which are absent from the Demographic and Health Surveys, also fall in this category.

TABLE 4. Nonmonetary Indicators of Well-Being in Kenya, 1993–2003

	Level			Changes			Deterioration (−) or Improvement (+)		
	1993	1998	2003	1993–1998	1998–2003	1993–2003	1993–1998	1998–2003	1993–2003
National Enrollment Rates									
Primary (Ages 6–13)	75.6	85.5	90.1	9.8	4.6	14.5	+	+	+
Secondary (Ages 14–17)	76.8	75.1	77.4	−1.7	2.3	0.6	−	+	+
Stunting Prevalence	33.3	33.0	30.9	−0.2	−2.1	−2.4	+	+	+
Infant Mortality	73.8	78.6	82.4	4.8	3.8	8.6	−	−	−
Rural Enrollment Rates									
Primary (Ages 6–13)	75.3	85.4	89.8	10.0	4.5	14.5	+	+	+
Secondary (Ages 14–17)	78.4	77.6	79.8	−0.7	2.1	1.4	−	+	+
Stunting Prevalence	34.8	34.7	32.5	−0.1	−2.3	−2.3	+	+	+
Infant Mortality	75.8	81.1	85.2	5.2	4.2	9.4	−	−	−
Other Urban Enrollment Rates									
Primary (Ages 6–13)	80.8	85.6	91.3	4.9	5.7	10.6	+	+	+
Secondary (Ages 14–17)	65.8	61.9	65.6	−3.9	3.7	−0.2	−	+	−
Stunting Prevalence	20.7	24.1	26.7	3.4	2.6	6.0	−	−	−
Infant Mortality	62.0	62.0	62.0	0.0	0.0	0.0	Ns	Ns	Ns
Nairobi Enrollment Rates									
Primary (Ages 6–13)	74.1	87.3	92.9	13.2	5.7	18.9	+	+	+
Secondary (Ages 14–17)	54.8	56.1	62.9	1.3	6.7	8.1	+	+	+
Stunting Prevalence	22.5	25.7	18.5	3.2	−7.2	−4.0	−	+	+
Infant Mortality	55.0	55.0	55.0	0.0	0.0	0.0	Ns	Ns	Ns

Ns = Changes are not statistically significant.

Source: Authors' analysis based on data described in the text.

Table 5 presents economic asset index-based poverty estimates when these assets are included and compares them with the original predictions. The labor supply variables include household size and the dependency ratio, while the education variables include information about educational attainments at the household and cluster levels as well as for the household head (see table 1).[29] While the precision of the estimates (as reflected in the lower standard errors) improved slightly (except for the Nairobi poverty estimates), general trends remained unchanged.

The larger simulated decline in poverty for Nairobi counsels caution in the use of education variables to track changes in poverty, especially in more sophisticated urbanized settings. Not only is the wage gradient usually much steeper in such settings, it is also likely to be more sensitive to the performance

29. The first-stage parameter estimates are available on request from the authors.

of the (formal) economy. It is likely that the returns to higher education declined in Nairobi in the face of the rapid expansion of the supply of highly educated professionals[30] and the stagnation and contraction of the urban economy.[31] That said, the massive investment by households in their education may well have enabled some to escape poverty in Nairobi, despite a decline in the rate of return.

Finally, part of the simulated poverty reduction results from the substantial increase in ownership of durables (radios, televisions, and refrigerators). Further inspection indicates that their relative prices (in terms of the overall consumer price index) declined substantially, possibly because of technological innovation, trade liberalization, or exchange rate misalignment (in particular, real exchange rate overvaluation). If these durables were perfect substitutes for other goods in the consumption basket of the poor, the economic asset index would substantially overestimate poverty reduction since the increase in demand for these durables would have been offset by a decrease in demand for other goods. It is unlikely, however, that the poor substitute electronics and household appliances for food at substantial rates. Consequently, the observed increase in the demand for these goods must result largely from an increase in people's incomes. Moreover, the estimated association between some consumer durables (for example, radios and televisions) and consumption reflects not only wealth levels, but also the flow of services derived from the possession of these goods (such as improved access to information, which may in turn improve the returns to other assets). There is no reason to believe that the utility derived from these goods would change drastically over time. Thus, any downward shift in the distribution of the estimated coefficients on durables between 1997 and 2003 is probably very small, and the simulated poverty reduction is likely only slightly overestimated, if at all.

In light of these findings and in the absence of further empirical evidence by way of an empirical counterfactual, a strategy of limiting, on theoretical and empirical grounds, the choice of assets to those whose returns are unlikely to change over time (consumer durables, housing characteristics, rainfall, and health) and of excluding those whose returns are more prone to variation over time (land, labor, education) is appropriate. Although there are no a priori reasons to suspect that the stationarity assumption is substantially violated, the extent to which stationarity holds for each asset and the way violation of stationarity might affect predictions of welfare ultimately remain an empirical matter that can be tested only through another consumption survey.

30. The proportion of households whose head has some post-secondary education increased by 19 percentage points in Nairobi between 1993 and 2003.

31. Average annual per capita growth in the services sector, which accounts for about 55 percent of the Kenyan economy, stagnated at about 0.14 percent during 1998-2003, while average annual per capita GDP growth in the industrial sector, which accounts for about 20 percent of the Kenyan economy, was estimated at -0.99 percent.

TABLE 5. Economic Asset Index Poverty for Different Models

	Headcount Ratio (P_0)				Test Statistics for Changes				Change in P_0
	1993 (DHS)	1997 (WMS, base)	1998 (DHS)	2003 (DHS)	1993–1997	1997–1998	1998–2003	1993–2003	1993–2003
Rural									
Base	57.2	52.8	50.6	48.0	−1.54	−0.81	−0.87	−2.87***	**−9.2**
	(2.2)	(1.9)	(1.9)	(2.4)					
Base + Demographics	58.4	52.8	49.9	45.9	−2.47**	−1.32	−1.44	−4.46***	**−12.5**
	(1.8)	(1.4)	(1.7)	(2.1)					
Base + Demographics + Education	58.7	52.8	50.2	47.9	−2.63***	−1.25	−0.86	−3.95***	**−10.8**
	(1.8)	(1.4)	(1.6)	(2.1)					
Other urban									
Base	39.0	43.2	41.3	46.0	0.70	−0.34	0.73	1.03	**+7**
	(4.5)	(4.0)	(4.0)	(5.0)					
Base + Demographics	37.5	43.2	41.0	46.6	1.06	−0.41	0.95	1.53	**+9.1**
	(4.0)	(3.5)	(4.0)	(4.3)					
Base + Demographics + Education	39.5	43.2	41.8	47.2	0.70	−0.31	1.05	1.33	**+7.7**
	(4.1)	(3.3)	(3.1)	(4.0)					
Nairobi									
Base	40.7	40.0	38.5	35.1	−0.05	−0.11	−0.28	−0.44	**−5.6**
	(9.5)	(10.0)	(8.8)	(8.7)					
Base + Demographics	39.7	40.0	38.4	36.2	0.02	−0.11	−0.18	−0.26	**−3.5**
	(10.0)	(10.9)	(8.9)	(9.0)					
Base + Demographics + Education	44.4	40.0	38.1	30.1	−0.28	−0.13	−0.62	−0.96	**−13.3**
	(11.9)	(10.6)	(9.0)	(9.1)					

*Significant at the 10 percent level; **Significant at the 5 percent level, and ***Significant at the 1 percent level.

Note: Numbers in parentheses are standard errors.

Source: Authors' analysis based on data described in the text.

V. Concluding Remarks

This article contributes to the growing literature on inexpensive and economically intuitive methods for tracking poverty in the absence of comparable consumption data. The minimum data requirements are a household budget survey and a series of other surveys with a set of comparable data on assets. An application to Kenya using a series of Demographic and Health Surveys and secondary data provides poverty predictions that are broadly consistent with other indicators for Kenya during the period 1993–2003. Rural poverty declined, while urban poverty stagnated, with diverging trends in other urban areas (an increase) and Nairobi (a decrease), though the urban trends were not statistically significant.

The economic asset index approach for tracking poverty proves promising, especially given the high costs involved in collecting comprehensive consumption data and the readily available PovMap software to conduct the predictions.[32] It can be easily extended to track mean consumption levels and inequality, an important additional advantage over the statistical asset index method. Furthermore, its empirical precision can be strengthened substantially through careful preselection of the tracked assets based on the theoretical and empirical plausibility of their "returns" being constant over time and on their predictive power using econometric analysis of existing household budget surveys. Inclusion of key time-variant variables such as rainfall, health status, and prices is critical both to control for shocks that may affect these returns and to better capture transitory changes in welfare and poverty since consumer durables and housing characteristics may display some downward rigidity.

Nonetheless, despite the great care taken in asset selection to avoid violating the stationarity assumption, regular recalibration of the model is advisable, and predicting too far into the future or the past should be avoided. Going forward, comparing economic asset-based poverty measures with those derived from household budget surveys using actual consumption data emerges as an important research agenda for applied economists to shed further light on the empirical validity of the stationarity assumption.

Appendix. Empirical Strategy

Individual consumption is approximated by household log per adult equivalent expenditures and estimated at the geographic levels for which the data are representative and for which comparisons over time are meaningful. Equation (1) is estimated for each region with the vector of disturbances u_t distributed $F(0,\Sigma)$. To minimize model error in the predictions, efficient estimates of the β_t parameters are sought by exploring a heteroskedastic specification of the individual

32. The software can be found at http://iresearch.worldbank.org/PovMap/index.htm.

disturbance terms and estimating equation (1) using generalized least squares (GLS) and an estimate of Σ.

In doing so it is assumed that u_t ($u_{cht} = \eta_{ct} + \epsilon_{cht}$) is made up of a cluster- or location-specific term (η_{ct}) and a household-specific term (ϵ_{cht}), which are independent and uncorrelated with any of the observable characteristics, x_t. This structure allows for both spatial autocorrelation (a "location effect" for households in the same cluster) and heteroskedasticity at the household level.[33] As such Σ is an $N \times N$ block-diagonal matrix.

To estimate Σ, equation (1) is initially estimated by ordinary least square yielding $\hat{u}_{cht}$ in the form of the residuals from this regression. The location component is then estimated as the within-cluster mean of the overall residuals,

$$\hat{\eta}_{ct} = \frac{1}{N_c} \sum_{h=1}^{N_c} \hat{u}_{cht} \tag{A.1}$$

where N_c is the number of households in cluster c. The idiosyncratic household component estimate ($\hat{\varepsilon}_{cht}$) is the overall residual less the location component,

$$\hat{\varepsilon}_{cht} = \hat{u}_{cht} - \hat{\eta}_{ct}. \tag{A.2}$$

To allow for household-specific heteroskedasticity and to estimate $\sigma^2_{\varepsilon,cht}$, $\hat{\varepsilon}^2_{cht}$ is modeled using the z_{cht} variables derived from x_{cht}, their squares, and interactions that best explain its variation. The conditional variance is estimated using a logistic function, as outlined in Mistiaen and others (2002). The estimated variance of $\hat{\varepsilon}_{cht}$ ($\hat{\sigma}^2_{\varepsilon,cht}$) can then be obtained in a straightforward manner. $\hat{\sigma}^2_{\eta t}$, the estimated variance of η_{ct}, and its sample variance $\hat{V}(\hat{\sigma}^2_{\eta t})$ are estimated following Elbers, Lanjouw, and Lanjouw (2002).

Armed with $\hat{\sigma}^2_{\eta t}$ and $\hat{\sigma}^2_{\varepsilon cht}$, and thus an estimator for Σ ($\hat{\Sigma}$), final efficient estimates of the betas in the original first-stage model (equation 1) can be obtained using GLS and the household budget survey data. This GLS estimation produces $\hat{\beta}_{tGLS}$ and the variance–covariance matrix of this estimator, var($\hat{\beta}_{tGLS}$), which concludes stage 1.

To obtain estimates of the expected welfare indicator in stage 2, a vector of beta coefficients ($\tilde{\beta}^s_t$) is first drawn from a multivariate normal distribution with a mean $\hat{\beta}_{tGLS}$ and variance–covariance $\hat{V}(\hat{\beta}_{tGLS})$ and applied to the target data x_{t+k} to predict household log expenditures ($x'_{cht+k}\tilde{\beta}^s_t$). This highlights the importance of acquiring efficient estimates of the beta coefficients.

Second, for each simulation the distribution of the location disturbance is allowed to vary. As such, the simulated location disturbance ($\tilde{\eta}^s_{ct}$) is drawn from a distribution with zero mean and simulation-specific variance

33. Following Elbers, Lanjouw, and Lanjouw (2003), heteroskedasticity is limited to the household-specific term since the number of clusters in the consumption survey is usually too small to allow for heteroskedasticity in the cluster component.

$(\tilde{\sigma}^2_{\eta t})^s$, itself drawn from a gamma distribution defined so as to have a mean of $\hat{\sigma}^2_{\eta\ t}$ and a variance $\hat{V}\hat{\sigma}^2_{\eta\ t}$.

Third, the simulated idiosyncratic component ($\tilde{\varepsilon}_{cht+k}$) is determined by first drawing an alpha coefficient ($\tilde{\alpha}^s_t$) from a normal distribution with mean $\hat{\alpha}_t$ and variance $\hat{V}\ (\hat{\alpha}_t)$. This is then applied to the data to determine the household variance, $\hat{\sigma}^2_{\varepsilon,cht+k}$.[34] Finally, $\tilde{\varepsilon}^s_{cht+k}$ is drawn from a distribution with mean zero and variance, $\hat{\sigma}^2_{\varepsilon,cht+k}$.

Fourth, these three components are combined to simulate the value of household per adult equivalent expenditures, $\hat{c}^s_{cht+k} = \exp(x'_{cht+k}\tilde{\beta}^s_t + \tilde{\eta}^s_{ct} + \tilde{\varepsilon}^s_{cht+k})$. Using the full distribution of simulated household expenditures ($\hat{c}^s_{cht+k}$) in the target data, welfare measures (in this case the Pα poverty measures) are calculated for each simulation.

This procedure is carried out for 100 simulations and yields a distribution of welfare measures. The means of the poverty measures are reported as the point estimates, and the standard deviations as the standard errors of these measures (see table 3). Various distributional forms for the location (η_c) and idiosyncratic (ϵ_{ch}) components of the disturbance term were used. These include normal, t (with varying degrees of freedom), and nonparametric distributions. As the results were robust to these different distributions, only the poverty estimates from simulations with normal distributions are reported.

34. Note that this variance is a function of the target data.

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