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Tracking Poverty over Time in the Absence of Comparable Consumption Data

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Abstract:

Following the endorsement of the Millennium Development Goals, there is an increasing demand for methods to track poverty regularly. This paper develops an economically intuitive and inexpensive methodology to do so in the absence of regular, comparable data on household consumption. The minimum data requirements for the 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. The methodology is illustrated using a series of Demographic Health Surveys from Kenya.

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1 Introduction

Given the worldwide endorsement of the Millennium Development Goals and the shift to results-based lending in supporting developing countries, the ability to reliably gauge the evolution of poverty is becoming increasingly important. Yet, tracking national poverty trends in developing countries is typically fraught with methodological and data problems. This is especially the case in Sub-Saharan Africa (SSA).

The common approach to measuring poverty is anchored in utility theory and empirically based on household consumption or income measures. These are usually derived from nationally representative household budget surveys (Ravallion, 1996; Deaton, 2003).[2] Obtaining reliable measures of household (and individual) consumption however presents a series of challenges in practice.[3] These challenges are usually further exacerbated when comparing poverty over time.

First, nationally representative household budget surveys are often not available at regular time intervals. Second, even when available, they are often not comparable in design and appropriate price deflators are often difficult to come by, rendering it difficult to construct comparable poverty measures. 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; Demery and Mehra, 1996; and Pradhan, 2001) and is most vividly illustrated by the recent experience in India (Deaton, 2001a, 2001b; Datt and Ravallion, 2002).

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[2] While predominant, this "money metric utility" approach to poverty measurement has also been criticized for being reductionist as it is unable to fully capture the multiple dimensions of welfare and poverty (Sen, 1985).

[3] Challenges include the determination of the optimal recall period, the valuation of home consumption, the treatment of consumption of housing, education and health services as well as appropriate accounting for the consumption of public goods. Deaton and Zaidi (2002) provide an excellent review of the issues involved in measuring consumption as well as guidelines on how to go about it in practice.

One attempt 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 straightforward, the resulting predicted evolution of the income distribution and poverty rates only holds under a series of stringent assumptions such as distribution neutral growth and close correspondence between GDP or private consumption growth reflected in the national accounts, and household expenditure measures obtained from the survey (Ravallion, 2003). It also relies on a correct attribution of sectoral GDP growth to households (World Bank, 2005). Furthermore, national accounts data are often not without measurement problems themselves.

This paper develops a more theoretically grounded and empirically robust methodology to track poverty trends in the absence of regular, comprehensive and comparable measures of consumption. In particular, it explores the potential of an "economic" asset index anchored in consumption using advanced prediction techniques akin to those applied in the poverty mapping literature (Elbers, Lanjouw, and Lanjouw, 2003). In doing so, the paper extends the "statistical" asset index approach to track poverty developed by Sahn and Stifel (2000). In particular, in contrast to Sahn and Stifel, who combine household assets into one index based on statistical association, the approach followed here provides a theoretical/welfarist foundation for aggregating the different assets. By linking the different assets directly to consumption, the common welfare indicator for poverty calculus, it also becomes straightforward to estimate the different poverty measures. Reliable and comparable estimates of household assets are relatively inexpensive to collect, which increases the practical applicability of the economic asset index to track poverty.

We illustrate our approach using the series of standardized Demographic and Health Surveys (DHS). Given the high degree of standardization in survey and questionnaire designs across the different rounds of the DHS, comparability issues are minor. The DHS are also freely available for many Sub-Saharan African countries. Nonetheless, the proposed approach can be applied to any regularly collected set of assets or poverty predictors such as those collected in the Core Welfare Indicator Questionnaire surveys developed by the World Bank in the mid-to-late 1990s.

In particular our empirical application uses the asset information from the 1993, 1998 and 2003 Kenyan DHS and the consumption measure from the 1997 Welfare Monitoring Survey. Our estimates suggest a continuous decline in poverty between 1993 and 2003 especially in rural areas and Nairobi, though the latter are less precisely estimated, and a stagnation of poverty incidence in the other urban areas. These findings are consistent with the evolution of the national accounts between 1993 and 1998, though we did not find an increase in poverty thereafter despite a limited decline in per capita GDP between 1998 and 2003. Yet, our estimates are in line with the observed decline in poverty among a panel of 1500 maize growing smallholders purposively sampled in 22 districts and surveyed between 1997 and 2004. The results are also supported by the statistical asset index estimates of poverty and broadly correspond to the evolution of key non-monetary welfare measures such as enrollment rates and child malnutrition observed in the same DHS.

The paper proceeds by discussing the methodology (Section 2) and reviewing the data (Section 3). The empirical results are presented in Section 4 and their robustness is discussed in Section 5. Section 6 concludes.

2 Methodological and empirical considerations

Let $W(c_t)$ denote the value at time t of a population welfare measure (e.g. poverty or inequality) that depends on individual consumption levels c at t. Given comparable observations on c_t at different time intervals, the evolution of W can be tracked. In the absence of such observations, but in the presence of comparable observations on 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 also be tracked, provided that we have an empirical understanding of the mapping of x_t into c_t.[4]

Tracking W_t by tracking x_t requires essentially three steps:

1) developing an accurate empirical model of c_t as a function of x_t;

2) estimating c_{t+k} as a function of x_{t+k} where k is a positive/negative integer; and

3) generating an estimate of expected W_{t+k} from the estimated c_{t+k}.

The basic features of the empirical methodological approach are as follows.[5] First, we consider a log linear approximation to individual consumption c_t:

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

Second, 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 respectively obtained in

[4] The components of x_t are not restricted to contemporaneous assets. Lagged variables can also be included if they affect current consumption. For example, current consumption is affected by lagged rainfall as the lag in agricultural production means that current rainfall patterns are not the relevant ones to consider.

[5] The approach followed here draws heavily on the prediction techniques developed by Elbers, Lanjouw and Lanjouw (2003) for small area predictions of welfare used in poverty and inequality mapping. Poverty mapping differs from the economic asset index proposed here in that the former predicts a geographically disaggregated distribution of poverty by mapping from a household budget survey to a same-year (or close) census. In the latter, we do not estimate disaggregated levels of poverty, rather poverty is predicted over time from a household budget survey to another national survey in another year which collected information on the same assets in a comparable manner.

estimating equation (1). The combination of $\hat{u}_{t+k}$ and $\hat{\beta}_{t+k}$ along with the updated asset data (x_{t+k}) yields

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

where r denotes one draw from the estimated distributions of u_t and β_t.[6] 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 through simulating the process described above for different draws r. The procedure is outlined in detail in Appendix A.1.

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

The *idiosyncratic* error component follows from the fact that we don't know/use actual c_{t+k}, but rather stochastic c_{t+k} whereby the stochastic nature of c_{t+k} is known/assumed through the distributional features of u_{t+k}, i.e. we calculate $E[W(x_{t+k}, \beta_{t+k}, u_{t+k})]$ as opposed to $W(c_{t+k})$. The *model* error component arises from the fact that we estimate the parameters β_{t+k} as well as those describing the distribution of the u_{t+k}, i.e. we calculate $E[W(x_{t+k}, \hat{\beta}_{t+k}, \hat{u}_{t+k})]$ as opposed to $E[W(x_{t+k}, \beta_{t+k}, u_{t+k})]$. As the expectation is often analytically intractable, we approximate it through simulation, thereby generating a *computational* error. Finally, the *sampling* error follows from

[6] Given that 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 $\hat{u}_t$, estimates of c_{t+k} can also be seen as estimates of an "economic asset index".

imputing from a survey and not a census, i.e. x_{t+k} are obtained from a survey (not a census).

The size of the idiosyncratic error component depends critically on the size of the target population with error declining (increasing) the larger (smaller) the target population to which the welfare measure is imputed. This feature is critical in constructing small area welfare estimates as it determines "how low one can go" (Alderman, et al., 2002) In this paper, we are mainly interested in tracking welfare/poverty measures over time for major groups or areas for which representative data have been collected. Given that these populations (e.g. rural/urban, province) are usually rather 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.[7] Careful selection of the different subgroups for which the consumption model (1) is estimated and inclusion of key deterministic and stochastic location specific variables (e.g. rainfall variability and rainfall levels) is 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 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). To increase efficiency of the coefficient estimates, the heteroskedastic nature of the consumption model is carefully examined and modeled in the empirical

[7] While consumption is clearly measured with error in practice, we will assume error free consumption measures in our application. We refer to Chesher and Schluter (2002) for rules to approximate the effect of measurement error in estimating welfare measures.

application (see Appendix A.1). In particular, we allow for both a location effect and individual specificity in the error component in (1).

A second source of model error may derive from the assumption that the estimated distributions of $\hat{\beta}_t$ and $\hat{u}_t$ are stationary.[8] While it is difficult to theoretically examine the magnitude of the error introduced this way, it is possible to establish an empirical range on the magnitude of the model error caused this way given a series of consumption surveys with comparable consumption and asset data. In the absence of such an empirical range, careful specification of the consumption model through inclusion of key time varying assets such as rainfall and prices – critical sources of non-stationarity in addition to important changes in the economy and polity – can go a long way in mitigating these errors, especially when consumption is only predicted for limited distances in the future or the past. Further partial corrections can be introduced through updating the x_t variables in the estimated means and variance-covariance matrices for $\hat{\beta}_t$ and $\hat{u}_t$ with x_{t+k}.

A third source of model error arises from differences in the asset variables across the surveys which may arise due to (small) differences in definition or ranking of the concerned questions in the questionnaire. To mitigate this potential source of model error selection of the common asset variables are based on careful empirical comparison of the distributional characteristics of the x variables.

Elbers, Lanjouw and Lanjouw (2003) found the computational error to be dependent on the computational method and small when sufficient simulations are used.

[8] Note that the assumption of stationary empirical distributions is implicit in many poverty mapping exercises as the household budget survey and the census data are in practice most often collected in adjacent and not the same years.

The sampling error depends on the sampling size and the population variance of the consumption measure.

3 Welfare, Assets and Rainfall in Kenya

The application of this methodology to Kenya focuses on tracking poverty between 1993 and 2003 and uses three major sources of data: 1) the 1997 Welfare Monitoring Survey (WMS), 2) the 1993, 1998 and 2003 Demographic and Health Surveys (DHS) and 3) district level data on malaria incidence, infrastructure from the 1999 census, and district level rainfall data obtained from the Famine Early Warning System (FEWS).[9] This analysis only uses the third of a series of WMS surveys between 1992 and 1997, because differences in the timing of the survey and the questionnaire design rendered the reported poverty numbers incomparable (World Bank, 2003). No national expenditure surveys have been fielded since 1997. As a result, there is currently a lack of clear understanding of the evolution of poverty in Kenya over the past 15 years.

The 1997 Welfare Monitoring Survey (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.[10] The primary monetary 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

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

[10] Due to logistical reasons, insecurity and inaccessibility, Mandera, Samburu, Turkana and Isiolo 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 datasets by excluding these districts from all of the data and analysis.

(2003) estimated the rural and urban poverty headcount at 52.8 and 43.1 percent respectively. The 1997 WMS together with the secondary data from the census and FEWS are used to estimate the respective distributional parameters in equation (1).

Three DHS surveys of about 8,000 households each were carried out in Kenya at 5 year intervals between 1993 and 2003.[11] As the DHS surveys are not designed for economic analysis, there is generally no data on income or expenditures. However, several of the asset variables collected under the 1997 WMS are also tracked in the DHS surveys. Furthermore, DHS surveys are known for their comparability over time (and across countries) – survey instruments remain largely unchanged across surveys and consistent sampling designs are maintained. Household sampling weights are used to generate representative statistics at national, rural and urban levels. Although the samples were intended to be nationally representative, we exclude the seven districts not covered in the 1993 and 1998 samples from our analysis.[12] We also redefined some of the districts in the 2003 DHS to be consistent with those that appear in the 1993 and 1998 datasets. Due to re-districting, there were more districts in 2003 than in 1993. These districts were also mapped to be consistent with those that appear in the 1997 WMS data.

The set of assets (x_{t+k}) chosen to construct our economic asset index is taken from the larger set of assets that are commonly available to the WMS and DHS. The first criterion for selection into the common variable set is 95 percent confidence that the means of the variables for which we would not expect a one-year change in the 1997 WMS and the 1998 DHS are not different. Step-wise regression models using the

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[11] Because of the limited household information collected in the 1989 survey, the analysis here is limited to the three latter surveys.

[12] The excluded districts include three districts in North Eastern Province (Garissa, Mandera and Wajir), two districts in Rift Valley Province (Samburu and Turkana), and two districts in Eastern Province (Isiolo and Marsabit).

resulting common pool of assets are subsequently applied to identify this set of variables which are statistically significant (at the 5 percent level) while maximizing the explanatory power (as captured by the r-squared statistic). This procedure is followed in an effort to balance the trade-off between maximizing explanatory power (r-squared) and minimizing model error. This balance also motivates the choice of different regression specifications for rural, other urban and Nairobi households as the differences in their livelihood systems suggest a different relationship between household consumption and its asset base. Table 1 provides an overview of the different assets used in the regressions and their evolution over time.

The variables that are chosen include household demographics, household education, housing quality, durables, and cluster/district averages of the household level variables[13] and district measures of malaria incidence averaged across the 1992, 1994 and 1997 WMS. Rainfall plays an important role in Kenyan livelihoods, especially in rural areas where most households continue to earn their living in agriculture or agriculture related activities. Moreover, households are often unable to protect their consumption from rainfall shocks (Christiaensen and Subbarao, 2005). From Figures 1 and 2, 1992 emerges as a very dry year with rainfalls starting late and overall rainfall well below the long-run average; 1996 and 1997 were above average both in terms of rainfall coming early (or on time) and the overall level. Similarly, rainfall in 2002 was slightly above normal, though it was late in coming.[14] Given the large fluctuations in both the level and timing of rainfall, it is thus important to account for the actual rainfall patterns in tracking

[13] The cluster averages are estimated from the survey data, while the district averages are calculated from the 1999 household census.

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

poverty over time. Specifically, we included the timing of the onset of the rainfall of the long rains as opposed to the level of rainfall in that year as an asset in our predicting models. While they are correlated,[15] the former yielded a better fit.

The coefficients (which can be viewed as asset weights) from the three different models (rural, other urban, Nairobi) are presented in Table 2. Since the threshold for inclusion in the step-wise regressions was 5 percent, each of these parameter estimates is significant at the 95 percent level of confidence or higher. The signs for the 25 variables of the rural model are in keeping with our priors based on economic theory and similar empirical analyses of expenditure models reported in the literature. Negative weights are placed on household size and the dependency ratio capturing competition for resources and the number of income earners. Given that one already controls for many assets which distinguish female headed from male headed households, it is a priori not clear how the gender of the headship affects household welfare.[16] While larger shares of household members with primary education appear associated with lower household welfare, taken together with the effect of primary education of the household head, primary education is strongly associated with higher levels of welfare. Positive weights are also associated with the other education indicators.

Low quality housing measures receive negative weights, while the possession of durables at the household and community level, and access to sanitation and electricity positively affect consumption. For this sample of 8,807 households, the share of the variation in log per adult equivalent that is explained by the model is a respectable 32 percent.

[15] The correlation coefficient for these two measures of rainfall is 0.53.
[16] Lack of significance of the gender of headship (or even a negative sign) has been observed in other studies as well (see Quisumbing, Haddad and Pena, 2001 for a review).

Stepwise regression led us to retain nine and eight variables resulting in r-squares of 0.29 and 0.49 for the other urban and Nairobi models, respectively. The signs on the coefficients are in line with expectations except for primary education which appears negatively associated with welfare in the other urban model (and is not retained in the Nairobi model), possibly suggesting that higher than primary levels of education are necessary in urban settings in Kenya to make a positive difference. Female headed households appear at a particular disadvantage in Nairobi.

4 The Evolution of Poverty in Kenya

The simulated poverty rates for all four datasets/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 one-to-two percentage point underestimation of the simulated poverty incidence compared to the actual poverty incidence directly observed in the baseline data using the official poverty line, we allow the poverty line to be determined endogenously to replicate these 1997 poverty levels. Adjustments were minor and did not affect the magnitudes of the predicted changes in poverty, only the levels were affected.[17] As such, the simulated poverty headcount ratios in 1997, the base year, are consistent with those reported in World Bank (2003). They are 52.8, 43.2 and 40.0 percent respectively for rural areas, other urban areas and Nairobi. Taken together, about half of the Kenyan population was estimated to be poor in 1997.

The economic asset index suggests that poverty incidence in Kenya fell from 54.8 percent in 1993 to 50.8 percent in 1997, after which point it continued to fall, to 47.6

[17] Simler et al. (2004) experienced a similar phenomenon when gauging the evolution of poverty using Living Standard Measurement Surveys and Core Welfare Indicator Questionnaire surveys from Mozambique.

percent in 2003. Although the fall in poverty is not statistically significant for the latter half of the decade, it is for the first and for the decade as a whole. Given that the majority of the poor people resides in rural areas (80 percent in 2003), the evolution of rural poverty between 1993 and 2003 is very similar to the evolution observed at the national level. In contrast to the decline observed in rural areas, poverty incidence in other urban areas hovered around 43 percent throughout the entire 1993-2003 period. Nairobi on the other hand, witnessed the largest decline in poverty incidence from 51 percent in 1993 to 27 percent in 2003. Yet, the latter decline has been imprecisely estimated and is only statistically significant at the 10 percent confidence level. The (simulated) evolution of the more distribution sensitive poverty measures (the poverty gap and poverty severity indices) are broadly consistent with the picture emerging from inspecting the headcount figures, though the estimated change in poverty in Nairobi is actually no longer statistically significant. Overall, national poverty incidence is estimated to decline by about 13 percent while, poverty severity declined by about 20 percent between 1993 and 2003.

To better understand the driving factors behind this emerging pattern Tables 4-6 present the average evolution of assets across the different survey years.[18] Asset holdings and housing quality among households in rural areas and Nairobi systematically increased over the 1993-2003 period with the improvements even more pronounced in Nairobi. Similarly, overall educational attainments improved both among rural households and households in Nairobi. In contrast, changes in asset holdings, sanitation

[18] The variables that are shaded are those to which negative weights are assigned. Consequently, a decrease in the means of these assets is associated with a predicted increase in mean household expenditure. Conversely, for those variables that are not shaded, an increase in the mean is associated with a predicted increase in mean household expenditure.

facilities and educational attainment were mixed among households in other urban areas with improvements in radio and TV ownership and educational attainments offset by deteriorating sanitary conditions. This is consistent with the stagnation in people's welfare reflected in the simulations. Broadly speaking the evolutions in the broad asset base across the different periods appear consistent with the observed evolution of poverty across the different groups.

The substantial reduction in rural poverty between 1993 and 1997 compared with the poverty 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 Figures 1 and 2). Nonetheless, overall, the improvements in rural welfare between 1993 and 2003 appear genuine and shared by the poorer segments among the population. To test this notion, we predicted poverty in 2003 using the 2003 DHS data and the 1992/3 FEWS rainfall data. The resulting 52 percent headcount ratio suggests that the better rainfall accounted for only one third of the overall fall in rural poverty between 1993 and 2003.

5 Are our results empirically robust?

To further gauge the reliability of the poverty trends emerging from the economic asset index, we briefly review the secondary evidence from other indicators and data sources and discuss the plausibility of the assumptions underpinning the economic asset based poverty numbers in the Kenyan context. We begin by comparing our findings with the picture emerging from the trends in the statistical asset index developed by Sahn and

Stifel (2000). In this approach, factor analysis is applied to a set of assets common to the three Demographic Health Surveys.

In particular, household characteristics (water source, toilet facilities, and construction material), household durables (ownership of radio, television, refrigerator, and bicycle) as well as education of the household head as a way of capturing human capital were selected as common variables. We assume that there is a common factor, "wealth," that explains the variance in the ownership of these assets, and allow the factor analysis to define that factor as a weighted sum of the individual assets. The weights derived from factor analyses are consistent with our expectations (Appendix A.2). As these index weights are derived in a purely statistical manner, we refer to this index as a "statistical asset index".

Applying these weights to the household assets in the DHS data and defining poverty lines to replicate in 1998 the poverty rates estimated using the 1997 WMS, results in the estimated levels and changes in poverty incidence reported in Table 7. The trends (and observed levels) across the different groups are similar to those derived from the economic asset index, despite different weighting schemes and a different asset bundle.

Though not statistically significant, poverty incidence among rural households appears lower in 2003 than in 1998 according to our estimates, despite an overall decline in GDP per capita during that period. Our results are nonetheless consistent with those reported by Nyoro, Muyanga, and Komo (2005) who find that US$1/day poverty dropped between 1997 and 2004 among a panel of 1500 predominantly maize growing smallholders which were purposively sampled from 24 districts and surveyed

successively in 1997, 1998, 2000, 2002, and 2004 by the Tegemeo Institute and Michigan State University.[19]

The poverty trends reflected by the economic asset based poverty indices are also broadly consistent with the evolution of key non monetary indicators of well-being in Kenya such as primary and secondary enrollment rates, infant mortality and stunting prevalence. In particular, comparison of these indicators across the population in rural areas, other urban localities and Nairobi between 1993 and 2003 based on the different DHS (Table 9) shows that there have been substantial improvements in both 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 while secondary enrollment rates marginally declined and stunting prevalence increased by six percentage points. While it is a priori possible that trends in household income and indicators of educational attainment and health diverge[20] – indeed infant mortality increased by 9.4 children per 1000 born between 1993 and 2003 – the broad correspondence between the emerging picture of the evolution of the human development indicators and the economic asset based poverty indices provides additional confidence that people's welfare is improving as suggested by the economic based poverty indices.

The empirical performance of the economic asset index based approach to track poverty also depends on the plausibility of its (implicit) assumptions. As discussed in section two, the performance of the approach is partly determined by the explanatory power of the model and thus the choice/availability of the assets/explanatory variables

[19] The income module is only comparable for the 1997, 2000 and 2004 surveys.
[20] For example, Sahn and Stifel (2003) found a divergence between changes in infant mortality and changes in poverty in Burkina Faso, urban Madagascar, rural Senegal, and rural Zambia.

(x_t). In particular, it could be argued that two important assets are missing from our list of assets in an agriculturalist/pastoralist society, i.e. land and livestock holdings. These were not included because they were absent from the DHS data. To empirically assess the impact of these omissions, we used the 1997 WMS data, which contains information on livestock and land holdings, to construct an economic asset based poverty measure based on a model with and a model without land and livestock holdings. Inclusion of livestock and landholdings did not change our results.[21] This suggests that the effect of land and livestock holdings is in effect mostly captured by the coefficient on the remaining assets in the rural model.

Imprecision in the estimated asset based poverty measures might also arise from non-stationarity in the coefficients. To be precise, note that the economic asset based approach does not assume that the actual coefficients are constant over time, but only that their distribution remains constant. Non-stationarity may arise from substantial climatic, economic or political change. We reduced the likelihood of such changes by controlling explicitly for rainfall in the prediction model. There were also no dramatic shifts in the economic/political regime during the 1993-1997 and the 1997-2003 periods considered in the study.

Part of the simulated poverty reduction results from the substantial increase in the ownership of durables (radio, TV, and refrigerator). Yet further inspection indicates that their relative price (in terms of the overall CPI) declined substantially (see Figure 3). If these durables and the other goods in the consumption basket of the poor were perfect

[21] The sensitivity was tested two ways. First, the Spearman rank correlation between the restricted economic asset index and the economic asset index including these two assets is 0.98 for rural areas. This suggests that re-ranking is very marginal. Second, the poverty results obtained by predicting poverty with the economic asset index including these two assets is very similar to the estimated poverty numbers reported in Table 3 (which do not include livestock and land holdings).

substitutes, the economic asset based welfare index would substantially overestimate poverty reduction as the increase in the demand for these durables would have been offset by a decrease in the demand for other goods. It is unlikely that the poorer segments of the population will substitute food for electronics at a substantial rate. Consequently, the cross-price elasticity of the demand for radios, TVs and refrigerators is likely very small and the observed increase in the demand of these goods must largely result from an increase in people's income/consumption. Thus, if there were any downward shift in the distribution of our estimated coefficients on the durables between 1997 and 2003, it is probably very small, and the simulated poverty reduction is likely only slightly overestimated, if at all.

In sum, while there are no a priori reasons to suspect that the stationarity assumption is substantially violated, the extent to which non-stationarity holds for each of the different assets and how it affects predictions of welfare remains ultimately an empirical matter, which can only be tested given another consumption survey. We therefore rather prefer to interpret our results in terms of broad directions in poverty change among different groups rather than be focused on the exact numerical changes. Similarly, we refrain from predictions too far in the future or the past. The secondary evidence at hand and a review of the implicit assumptions supports the emerging picture of the evolution of poverty in Kenya over the past 15 years of one of improvement in living standards in rural areas and a stagnation in other urban areas. While the results indicate a significant reduction in poverty in Nairobi, this estimated change was not statistically significant and the difficulties involved in properly capturing the evolution of welfare in the expanding slum areas in Nairobi through surveys whose sampling frames

are based on dwelling structures, counsel caution in the interpretation of these results. While the Central Bureau of Statistics (CBS) has made explicit efforts to capture beggars and street children by including slum areas in their sampling frames, those who are the most destitute and the evolution of their livelihoods may still not have been properly accounted for.

6 Concluding remarks

The paper develops and illustrates an economically intuitive methodology to track poverty over time in the absence of comparable consumption data using innovative econometric techniques. The minimum data requirements are a household budget survey and a series of other surveys with a set of comparable asset data also contained in the budget survey. An application to Kenya using a series of Demographic Health Surveys and secondary rainfall data suggests that rural poverty in Kenya declined while poverty in urban areas (exclusive Nairobi) likely stagnated between 1993 and 2003. While the estimates also indicate a substantial decline in poverty in Nairobi, this change was not statistically significant.

While the economic asset index approach to track poverty proves promising, especially given the costs involved in collecting comprehensive consumption data, it should be emphasized that its empirical precision can in practice be strengthened substantially through careful pre-selection of the assets to be tracked based on their predictive power using econometric analysis of existing household budget surveys. This would substantially reduce the model error in predicting poverty. Inclusion of key time varying variables such as rainfall and prices is also important. Nonetheless, given the

implicit stationarity assumption, regular recalibration of the model is advisable and one should refrain from predicting too far in the future or the past. Comparison of economic asset-based poverty measures with those derived from household budget surveys using actual consumption data can shed further light on the empirical validity of the stationarity assumption, an important research agenda for applied economists.

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Appendix A.1: Empirical strategy

We begin by selecting the set of x variables that are common to both the household budget survey and the surveys used for the asset data. These variables are chosen based on the similarity of their summary statistics across surveys. In particular, we use a threshold of 95 percent confidence that the sample means for those variables for which we would not expect a one-year change are the same in the budget survey and the nearest asset-data survey as the criterion for selection.

Individual consumption is approximated by household log per adult equivalent expenditures and estimated at the geographic/group level j for which the data are representative and for which comparisons over time are meaningful. We estimate equation (1) for each region/group j (subscript j dropped) with the vector of disturbances u_t, distributed $F(0,\Sigma)$. In order to minimize the model error in our predictions, we strive to obtain efficient estimates of the β_t parameters by exploring a heteroskedastic specification of the individual disturbance terms and estimating equation (1) using Generalized Least Squares (GLS).

In particular, we assume u_t to be made up of a cluster or location specific (η_{ct}) and a household-specific (ε_{cht}) term, which are independent and uncorrelated with any of the observable characteristics x_t (i.e. $u_t = \eta_{ct} + \varepsilon_{cht}$). This structure allows for both spatial autocorrelation (a "location effect" for households in the same cluster) and heteroskedasticity at the household level. 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.[22]

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

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

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,

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

To allow for households specific heteroskedasticity, $\hat{\varepsilon}^2_{cht}$ is modeled using variables z_{cht} derived from x_{cht}, their squares and interactions that best explain its

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[22] As such, Σ is an N x N block-diagonal matrix of the following form,

$$\Sigma = \begin{bmatrix} \sigma^2_\eta + \sigma^2_{\varepsilon,1,1} & . & . & \sigma^2_\eta & & & & & \\ . & . & & & & & & & \\ . & & . & & & & & & \\ \sigma^2_\eta & . & . & \sigma^2_\eta + \sigma^2_{\varepsilon,1,N_1} & & & & & \\ & & & & . & & & & \\ & & & & & . & & & \\ & & & & & & \sigma^2_\eta + \sigma^2_{\varepsilon,C,1} & . & . & \sigma^2_\eta \\ & & & & & & . & . & & . \\ & & & & & & . & & . & . \\ & & & & & & \sigma^2_\eta & & & \sigma^2_\eta + \sigma^2_{\varepsilon,C,N_C} \end{bmatrix},$$

where σ^2_η is the variance of the cluster component (η_c), $\sigma^2_{\varepsilon,cht}$ is the *household-specific* variance of the idiosyncratic component (ε_{cht}), and C is the number of clusters.

variation.[23] We estimate the conditional variance using the estimation procedure outlined in Mistiaen et al. (2002). In short, we estimate this using a logistic function, where the prediction is bounded below by zero and above by five percent above the maximum observed value. If we define the upper bound as A,

$$A = (1.05) * \max[\hat{\varepsilon}^2_{cht}],$$

then the model estimated is

$$\ln\left[\frac{\hat{\varepsilon}^2_{cht}}{A - \hat{\varepsilon}^2_{cht}}\right] = z'_{cht}\alpha + r_{cht}.$$

By obtaining estimates of the vector of parameters α, we can then obtain the household-specific estimator for the variance of the idiosyncratic error component $\hat{\sigma}^2_{\varepsilon,cht}$. The sampling variance of this variance $(\hat{V}(\hat{\sigma}^2_{\varepsilon,cht}))$ can then be estimated in a straightforward manner. We estimate $\hat{\sigma}^2_{\eta}$, the variance of η_{ct}, and its sample variance $\hat{V}(\hat{\sigma}^2_{\eta t}))$ following Elbers, Lanjouw and Lanjouw (2002).

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

To obtain estimates of the expected welfare indicator we begin by drawing a vector of beta coefficients ($\tilde{\beta}^s_t$) from a multivariate normal distribution with a mean

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[23] Since the expected value of $\hat{\varepsilon}_{cht}$ is zero, modeling its square is the same as modeling its variance. Again, z_{cht} is not restricted to contemporaneous variables.

$\hat{\beta}_{tGLS}$ and variance-covariance $\hat{V}(\hat{\beta}_{tGLS})$) and apply them to target the data x_{t+k} to predict household log expenditures ($x'_{cht+k}\tilde{\beta}_t^{\,s}$). 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 ($\tilde{\eta}_{ct}^{s}$) is drawn from a distribution with zero mean, and simulation-specific variance $\left(\tilde{\sigma}_{\eta t}^{2}\right)^{s}$, itself drawn from a gamma distribution defined so as to have a mean of $\hat{\sigma}_{\eta t}^{2}$ and a variance $\hat{V}(\hat{\sigma}_{\eta t}^{2})$.

Third, the simulated idiosyncratic component ($\tilde{\varepsilon}_{ch_t}^{s}$)is determined by first drawing an alpha coefficient ($\tilde{\alpha}_t^{\,s}$) 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 $\hat{V}(\hat{\sigma}_{\varepsilon,cht+k}^{2})$. Finally, $\tilde{\varepsilon}_{ch}^{s}$ is drawn from a distribution with mean zero and variance $\hat{\sigma}_{\varepsilon,ch}^{2}$.

Fourth, these three components are combined to simulate the value of household per adult equivalent expenditures, $\hat{c}_{cht+k}^{s} = \exp\left(x'_{cht+k}\tilde{\beta}_t^{\,s} + \tilde{\eta}_{ct}^{s} + \tilde{\varepsilon}_{cht}^{s}\right)$. Using the full distribution of simulated household expenditures ($\hat{c}_{cht+k}^{s}$) in the target data, welfare measures are calculated for each simulation. Specifically, we use the class of P_α-poverty measures as our welfare measures.

This procedure is carried out for 100 simulations and provides as output a distribution of welfare measures. The means of the poverty measures are reported as the point estimates, while the standard deviations are the reported standard errors of these measures (Table 3). The latter arise from the idiosyncratic, model, errors mentioned

above. We experimented with various distributional forms for the location (η_c) and idiosyncratic (ε_{ch}) components of the disturbance term. These included normal, t (with varying degrees of freedom) and nonparametric distributions. As the results were robust to these different distributions, we report only those poverty estimates from the simulations in which normal distributions were assumed.

Appendix A.2: Statistical Asset Index

Factor analysis was applied to the rural, other urban and Nairobi population separately pooled over the three DHS surveys. Table A.1 presents the weights which are consistent with expectations. Positive weights are placed on all of the assets except those considered to be negative (i.e. low quality floors and roofs, and no toilet).[24] In addition, they differ for the groups. For instance, the weights for housing are much larger for rural households than for urban households. Similarly, no toilets (relative to a pit latrine) have a larger weight in rural areas, whereas flush toilets have larger weights in urban areas. An electricity connection also more decisively differentiates households in urban areas than in rural areas.

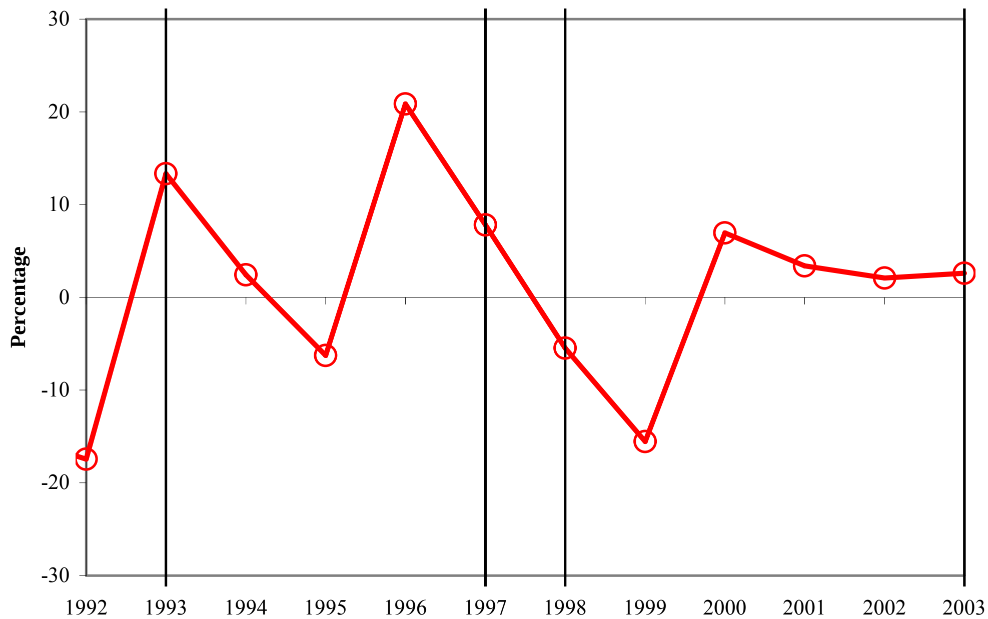
Table A.2.1: Weights for Statistical Asset Index

	Rural	Other Urban	Nairobi
House floor of low quality (mud, dung, sand)	**-0.25**	**-0.16**	**-0.14**
House roof of low quality (thatch)	**-0.15**	**-0.08**	**-0.01**
Drinking water - piped or public tap	**0.10**	**0.07**	**0.05**
Flush toilet	**0.13**	**0.18**	**0.23**
No toilet	**-0.11**	**-0.06**	**-0.04**
Electricity connection	**0.20**	**0.30**	**0.37**
Owns a radio	**0.13**	**0.10**	**0.09**
Owns a TV	**0.20**	**0.25**	**0.22**
Owns a refrigerator	**0.11**	**0.14**	**0.12**
Owns a bike	**0.05**	**0.02**	**0.02**
Years of head's educational attainment	**0.14**	**0.11**	**0.07**

Shaded area indicates a “negative” asset.

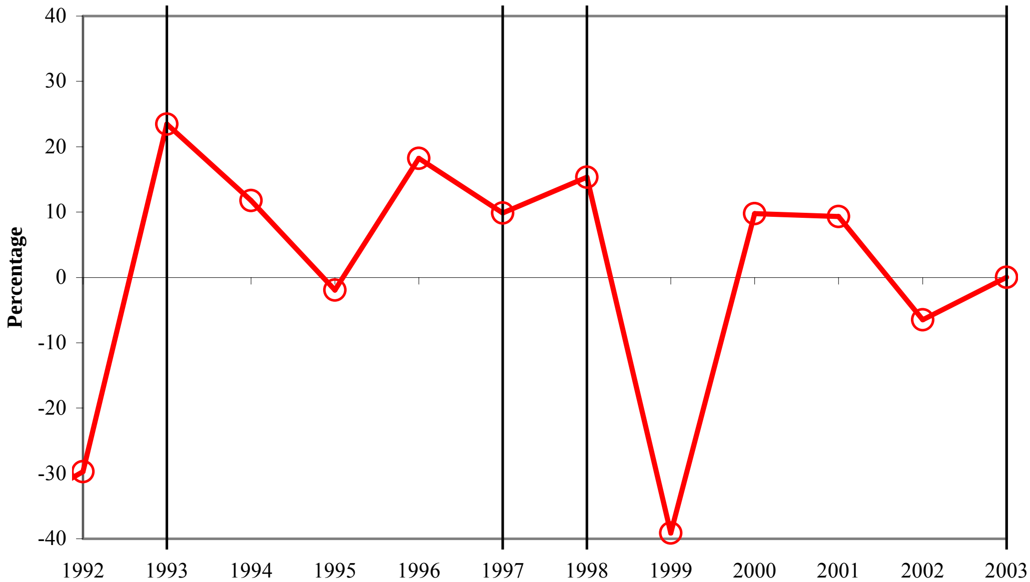
[24] “Negative” assets are included because the factor analysis procedure creates a distribution of asset indexes that has a mean of zero and a variance of one.

Figure 1: Annual Deviation (%) of Rainfall from Long Run Average in Kenya, 1992-2004



Source: Own calculations from Famine Early Warning System.

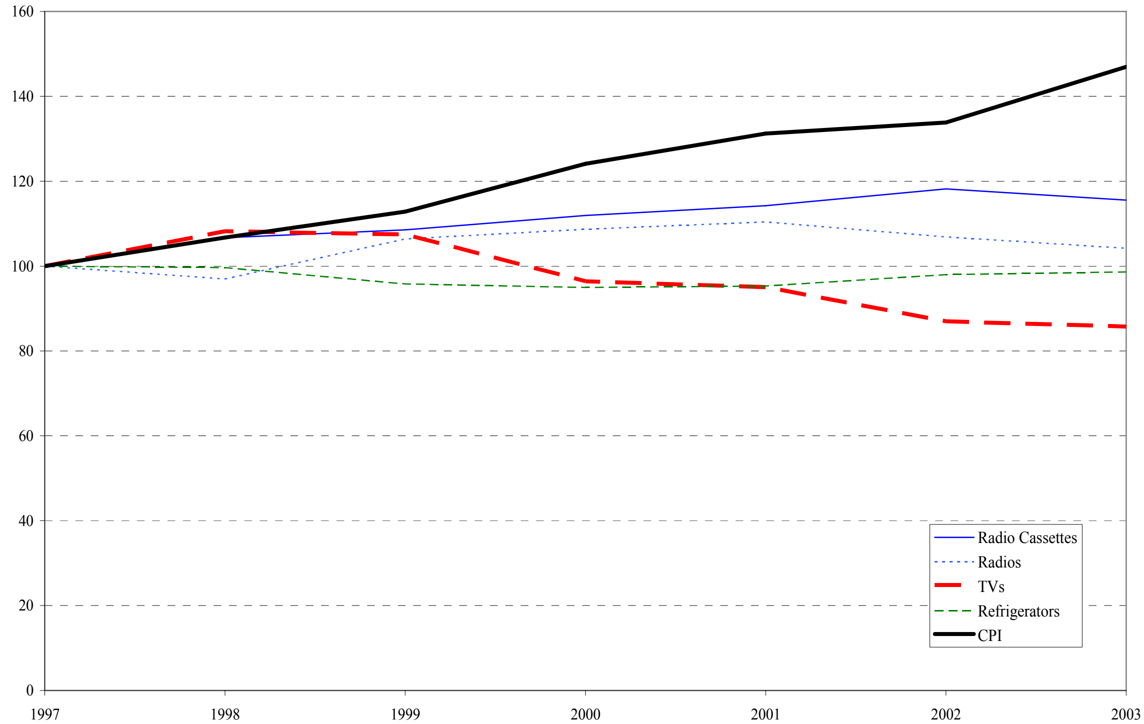
Figure 2: Annual Deviation (%) of Onset of Rainfall from Long Run Average in Kenya[1)], 1992-2004.



[1)] Early onset of rain is defined as the percent that the amount of rainfall during the first month of long run rains deviates from the long-run average amount for that month. Selection of first month differs by district and is based on the district-specific rainfall patterns in the FEWS data. The long run average has been taken over 1992-2004.

Source: Own calculations from Famine Early Warning System.

Figure 3: Evolution of the CPI and prices of key durables in Kenya, 1997-2003.



Source: Own calculations based on CPI data base from Central Bureau of Statistics Kenya.

Table 1: Individual, household and location assets held by rural, other urban and Nairobi households in Kenya during the period 1993-2003.

	Rural				**Other Urban**				**Nairobi**			
	DHS 1993	WMS 1997	DHS 1998	DHS 2003	DHS 1993	WMS 1997	DHS 1998	DHS 2003	DHS 1993	WMS 1997	DHS 1998	DHS 2003
Household Demographics												
Share of HH members age 0-5	-		-	-	-	-	-	-	0.16	0.14	0.14	0.14
Share of HH members girls age 6-15	-	-	-	-	-	-	-	-	0.08	0.10	0.09	0.08
Share of HH members women age 16-25	-	-	-	-	-	-	-	-	0.14	0.15	0.14	0.15
Dependency Ratio	0.57	0.52	0.54	0.52	0.41	0.41	0.41	0.41		-	-	-
Household size	6.78	6.42	6.08	6.02	-	-	-	-		-	-	-
Dummy: HH head is male	0.69	0.75	0.70	0.70	-	-	-	-	0.81	0.82	0.81	0.82
Household Education												
Share of HH members with primary education	0.52	0.53	0.56	0.53	-	-	-	-	-	-	-	-
Share of HH members with secondary education	0.09	0.11	0.11	0.10	0.28	0.29	0.27	0.20	0.03	0.09	0.09	0.14
Share of HH members with post secondary education	0.00	0.02	0.01	0.02	0.02	0.04	0.03	0.08	-	-	-	-
Dummy: HH head with primary education	0.51	0.47	0.51	0.55	0.32	0.33	0.33	0.41	-	-	-	-
Dummy: HH head with secondary education	0.15	0.20	0.20	0.18	-	-	-	-	-	-	-	-
Dummy: HH head with post secondary education	0.00	0.04	0.02	0.06	0.05	0.09	0.09	0.16	-	-	-	-
Housing & Assets												
Dummy: House floor of low quality (mud, dung, sand)	0.81	0.79	0.78	0.76	-	-	-	-	-	-	-	-
Dummy: House roof of low quality (thatch)	0.42	0.36	0.35	0.28	-	-	-	-	-	-	-	-
Dummy: Drinking water - piped (public or private)	-	-	-	-	-	-	-	-	0.91	0.90	0.93	0.81
Dummy: Flush toilet	0.01	0.01	0.02	0.02	0.49	0.36	0.37	0.21	-	-	-	-
Dummy: Owns a radio	0.53	0.59	0.63	0.77	0.73	0.77	0.81	0.83	-	-	-	-
Dummy: Owns a TV	0.03	0.04	0.07	0.14	0.30	0.31	0.37	0.39	-	-	-	-
Dummy: Owns a refrigerator	0.01	0.01	0.01	0.01	0.16	0.14	0.14	0.10	-	-	-	-
Dummy: Owns a bike	0.27	0.29	0.30	0.38	-	-	-	-	-	-	-	-

	Rural				Other Urban				Nairobi			
	DHS 1993	WMS 1997	DHS 1998	DHS 2003	DHS 1993	WMS 1997	DHS 1998	DHS 2003	DHS 1993	WMS 1997	DHS 1998	DHS 2003
Cluster & District Characteristics												
Cluster average head with primary education	0.00	0.02	0.01	0.02	0.43	0.39	0.43	0.45	-	-	-	-
Cluster average head with secondary education	-	-	-	-	-	-	-	-	0.04	0.14	0.15	0.24
Cluster average share with post secondary education	-	-	-	-	-	-	-	-	0.03	0.09	0.09	0.16
Cluster average HH with access to piped water	0.18	0.22	0.17	0.11	-	-	-	-	-	-	-	-
Cluster average HH owns TV	0.02	0.04	0.06	0.12	-	-	-	-	-	-	-	-
Cluster average HH owns refrigerator	0.01	0.01	0.01	0.01	-	-	-	-	-	-	-	-
Cluster average HH owns bike	0.24	0.25	0.27	0.35	-	-	-	-	-	-	-	-
District average HH with access to piped water	-	-	-	-	0.38	0.35	0.34	0.36	-	-	-	-
District average HH with access to electricity	0.06	0.06	0.06	0.06	-	-	-	-	-	-	-	-
Rain - early onset (deviation from long run mean)	-0.43	0.21	-0.42	-0.41	-	-	-	-	-	-	-	-
Rain - early onset – squared	0.27	0.28	0.26	0.25	-	-	-	-	-	-	-	-
Malaria prevalence in district (average in 1990s)	11.01	10.92	11.15	10.82	-	-	-	-	-	-	-	-
Number of observations	6,546	8,807	6,725	5,176	886	1,552	1,155	1,540	488	280	1,155	1,201

Source: Own calculations from 1997 Welfare Monitoring Survey and 1993, 1998, 2003 Demographic and Health Surveys.

Table 2: Estimated Coefficients or Asset Weights First Stage Regression

Log consumption per adult equivalent 1997	Rural	Other Urban	Nairobi
Household Demographics			
Share of HH members age 0-5	-	-	-1.09
Share of HH members girls age 6-15	-	-	-1.32
Share of HH members women age 16-25	-	-	-0.36
Dependency Ratio	-0.06	-0.58	-
Household size	-0.06	-	-
Dummy: HH head is male	-0.05	-	0.18
Household Education			
Share of HH members with primary education	-0.11	-	-
Share of HH members with secondary education	0.25	-	-
Share of HH members with post secondary education	0.28	-	0.44
Dummy: HH head with primary education	0.13	-0.12	-
Dummy: HH head with secondary education	0.17	-	-
Dummy: HH head with post secondary education	0.12	0.17	-
Housing & Assets			
Dummy: House floor of low quality (mud, dung, sand)	-0.22	-	-
Dummy: House roof of low quality (thatch)	-0.09	-	-
Dummy: Drinking water - piped (public or private)	-	-	0.45
Dummy: Flush toilet	0.15	0.06	-
Dummy: Owns a radio	0.14	0.10	-
Dummy: Owns a TV	0.27	0.35	-
Dummy: Owns a refrigerator	0.24	0.25	-
Dummy: Owns a bike	0.11	-	-
Cluster & District Characteristics			
Cluster average head with primary education	-	-0.34	-
Cluster average head with secondary education	-	-	1.06
Cluster average share with post secondary education	0.30	-	1.53
Cluster average HH with access to piped water	0.03	-	-
Cluster average HH owns TV	0.14	-	-
Cluster average HH owns refrigerator	0.35	-	-
Cluster average HH owns bike	0.06	-	-
District average HH with access to piped water	-	0.34	-
District average HH with access to electricity	0.45	-	-
Rain - early onset (deviation from long run mean)	0.08	-	-
Rain - early onset – squared	0.11	-	-
Malaria prevalence in district (average in 1990s)	-0.03	-	-
Constant	10.4	10.3	9.8
Adjusted R^2	0.32	0.29	0.49
Number of observations	8,807	1,552	280

Table 3: Economic Asset Index Poverty in Kenya 1993-2003
Standard Errors in Italics

	Levels				**Test Statistics for Changes**			
	1993 (DHS)	**1997** (WMS, base)	**1998** (DHS)	**2003** (DHS)	1993 to 1997	1997 to 1998	1998 to 2003	1993 to 2003
Headcount Ratio (P_0)								
National	**54.8**	**50.8**	**50.7**	**47.6**	-1.82 +	-0.05	-1.08	-2.44 *
	1.9	*1.1*	*1.8*	*2.3*				
Rural	**56.2**	**52.8**	**52.9**	**50.2**	-1.56	0.04	-0.90	-1.97 *
	1.8	*1.2*	*1.7*	*2.5*				
Other Urban	**43.6**	**43.2**	**42.4**	**43.9**	-0.06	-0.13	0.26	0.06
	4.3	*3.8*	*4.1*	*3.9*				
Nairobi	**50.6**	**40.0**	**38.9**	**26.6**	-0.72	-0.08	-1.19	-1.92 +
	11.1	*9.6*	*8.7*	*5.7*				
Poverty Gap (P_1)								
National	**20.4**	**17.6**	**18.0**	**16.4**	-1.69 +	0.30	-0.79	-1.82 +
	1.5	*0.8*	*1.3*	*1.6*				
Rural	**21.1**	**18.4**	**19.1**	**17.5**	-2.43 *	0.68	-1.19	-2.50 *
	0.9	*0.6*	*0.8*	*1.1*				
Other Urban	**13.7**	**13.7**	**13.1**	**14.2**	0.01	-0.21	0.42	0.21
	2.0	*1.8*	*1.9*	*1.8*				
Nairobi	**18.7**	**14.2**	**13.6**	**9.4**	-0.62	-0.10	-0.89	-1.49
	5.6	*4.6*	*3.8*	*2.7*				
Poverty Severity (P_2)								
National	**10.0**	**8.5**	**8.7**	**7.9**	-1.11	0.17	-0.50	-1.22
	1.2	*0.6*	*1.0*	*1.2*				
Rural	**10.4**	**8.9**	**9.3**	**8.4**	-2.22 *	0.63	-1.13	-2.37 *
	0.6	*0.4*	*0.5*	*0.6*				
Other Urban	**5.9**	**6.0**	**5.6**	**6.3**	0.04	-0.24	0.47	0.26
	1.2	*1.0*	*1.1*	*1.1*				
Nairobi	**9.3**	**6.9**	**6.1**	**4.6**	-0.56	-0.23	-0.56	-1.30
	3.2	*2.8*	*2.1*	*1.6*				

Note: '+' indicates 90% confidence level, '*' indicates 95% confidence level, and '**" indicates 99% confidence level.

Table 4: Changes in Assets for Households in Rural Kenya, 1993-2003.[1)]

	WMS 1997		1993 to 1997	1998 to 2003	1993 to 2003
Household Demographics	Mean	Std. Dev.			
Dependency Ratio	0.522	0.21	-0.04 **	-0.02 **	-0.04 **
Household size	6.419	2.80	-0.36 **	-0.06	-0.76 **
Dummy: HH head is male	0.749	0.43	0.055 **	-0.003	0.005
Household Education					
Share of HH members with primary educ	0.527	0.26	0.01	-0.03 **	0.01 **
Share of HH members with secondary educ	0.114	0.18	0.03 **	-0.004	0.018 **
Share of HH members with post secondary educ	0.019	0.08	0.02 **	0.01 **	0.02 **
Dummy: HH head with primary education	0.469	0.50	-0.04 **	0.03 **	0.03 **
Dummy: HH head with secondary education	0.199	0.40	0.05 **	-0.03 **	0.03 **
Dummy: HH head with post secondary education	0.038	0.19	0.04 **	0.04 **	0.06 **
Housing & Assets					
Dummy: House floor of low quality (mud, dung, sand)	0.790	0.41	-0.02 **	-0.02 *	-0.05 **
Dummy: House roof of low quality (thatch)	0.360	0.48	-0.06 **	-0.08 **	-0.15 **
Dummy: Flush toilet	0.009	0.10	0.00 *	0.001	0.003
Dummy: Owns a radio	0.593	0.49	0.07 **	0.14 **	0.24 **
Dummy: Owns a TV	0.044	0.21	0.02 **	0.07 **	0.11 **
Dummy: Owns a refrigerator	0.007	0.08	0.0004	0.01 **	0.01 **
Dummy: Owns a bike	0.285	0.45	0.02 *	0.08 **	0.11 **
Cluster & District Characteristics					
Cluster average share with post secondary education	0.021	0.04	0.02 **	0.01 **	0.02 **
Cluster average HH with access to piped water	0.221	0.33	0.04 **	-0.06 **	-0.07 **
Cluster average HH owns TV	0.039	0.08	0.02 **	0.06 **	0.10 **
Cluster average HH owns refrigerator	0.006	0.03	0.001 +	0.005 **	0.005 **
Cluster average HH owns bike	0.248	0.22	0.01 **	0.08 **	0.11 **
District avarage HH with access to electricity	0.064	0.06	0.002 **	0.001	-0.001
Time Varying					
Rain - early onset (deviation from LT mean)	0.205	0.48	0.63 **	0.01 *	0.02 **
Malaria prevalence in district (average in 1990s)	10.917	3.74	-0.09	-0.34 **	-0.19 **

The variables that are shaded are those to which negative weights are assigned. Consequently, a ecrease in the means of these assets is associated with a predicted increase in mean household expenditure. Conversely, for those variables that are not shaded, an increase in the mean is associated with a predicted increase in mean household expenditure.

Source: Own calculations from 1997 Welfare Monitoring Survey and 1993, 1998, 2003 Demographic and Health Surveys.

Table 5: Changes in Assets for households in other urban areas in Kenya, 1993-2003.

	WMS 1997		1993 to 1997	1998 to 2003	1993 to 2003
Household Demographics					
Dependency Ratio	0.410	0.24	-0.005	0.000	-0.003
Household Education					
Dummy: HH head with primary education	0.330	0.47	0.01	0.09 **	0.10 **
Dummy: HH head with post secondary education	0.085	0.28	0.04 **	0.07 **	0.11 **
Housing & Assets					
Dummy: Flush toilet	0.357	0.48	-0.14 **	-0.15 **	-0.28 **
Dummy: Owns a radio	0.775	0.42	0.04 *	0.02	0.10 **
Dummy: Owns a TV	0.308	0.46	0.00	0.02	0.09 **
Dummy: Owns a refrigerator	0.136	0.34	-0.03 +	-0.04 **	-0.06 **
Cluster & District Characteristics					
Cluster average head with primary education	0.333	0.21	-0.01	0.08 **	0.02 **
District avarage HH with access to piped water	0.346	0.26	-0.04 **	0.02 +	-0.02 *

The variables that are shaded are those to which negative weights are assigned. Consequently, a decrease in the means of these assets is associated with a predicted increase in mean household expenditure. Conversely, for those variables that are not shaded, an increase in the mean is associated with a predicted increase in mean household expenditure.

Source: Own calculations from 1997 Welfare Monitoring Survey and 1993, 1998, 2003 Demographic and Health Surveys.

Table 6: Changes in Assets for households in Nairobi, Kenya, 1993-2003.

	WMS 1997		1993 to 1997	1998 to 2003	1993 to 2003
Household Demographics					
Share of HH members age 0-5	0.156	0.17	-0.014	0.002	-0.018 *
Share of HH members girls age 6-15	0.075	0.13	0.02 *	-0.01 +	0.01
Share of HH members women age 16-25	0.141	0.18	0.01	0.01	0.01
Dummy: HH head is male	0.808	0.39	0.01	0.01	0.01
Household Education					
Share of HH members with post secondary educ	0.026	0.12	0.06 **	0.05 **	0.11 **
Housing & Assets					
Dummy: Drinking water - piped (public or private)	0.915	0.28	-0.02	-0.12 **	-0.10 **
Cluster & District Characteristics					
Cluster average share with post secondary education	0.031	0.08	0.06 **	0.07 **	0.19 **
Cluster average head with post secondary education	0.043	0.11	0.10 **	0.09 **	0.13 **

The variables that are shaded are those to which negative weights are assigned. Consequently, a decrease in the means of these assets is associated with a predicted increase in mean household expenditure. Conversely, for those variables that are not shaded, an increase in the mean is associated with a predicted increase in mean household expenditure.

Source: Own calculations from 1997 Welfare Monitoring Survey and 1993, 1998, 2003 Demographic and Health Surveys.

Table 7: Statistical Asset Index of Poverty Incidence (%) in Kenya

	1993	1998	2003
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

Source: Own calculations from 1993, 1998, 2003 Demographic and Health Surveys.

Table 8: Poverty incidence among rural maize growing smallholders

Zone	Percentage Earning Less than A Dollar per Day		
	1997	2000	2004
Coastal Lowlands	67.5	83.1	83.7
Eastern Lowlands	70.1	73.9	64.3
Western Lowlands	89.2	93.2	81.9
Western Transitional	85.5	68.7	76.2
High Potential Maize Zone	63.6	66.2	56.4
Western Highlands	91.7	84.1	81
Central Highlands	44.8	41.7	47.3
Marginal Rain Shadow	75.5	69.4	50
Total	**70.3**	**69.4**	**62.1**

Source: Nyoro, Muyanga and Komo, 2005.

Table 9: Non-Monetary Indicators of Wellbeing in Kenya, 1993-2003

	Levels			Changes			Deterioration (-) or Improvement (+)		
	1993	1998	2003	1993 to 1998	1998 to 2003	1993 to 2003	1993 to 1998	1998 to 2003	1993 to 2003
National									
Enrollment Rates									
Primary (6-13 years)	75.6	85.5	90.1	9.8	4.6	14.5	+	+	+
Secondary (14-17 years)	76.8	75.1	77.4	-1.7	2.3	0.6	-	+	+
Infant Mortality	73.8	78.6	82.4	4.8	3.8	8.6	-	-	-
Stunting Prevalence	33.3	33.0	30.9	-0.2	-2.1	-2.4	+	+	+
Rural									
Enrollment Rates									
Primary (6-13 years)	75.3	85.4	89.8	10.0	4.5	14.5	+	+	+
Secondary (14-17 years)	78.4	77.6	79.8	-0.7	2.1	1.4	-	+	+
Infant Mortality	75.8	81.1	85.2	5.2	4.2	9.4	-	-	-
Stunting Prevalence	34.8	34.7	32.5	-0.05	-2.3	-2.3	+	+	+
Other Urban									
Enrollment Rates									
Primary (6-13 years)	80.8	85.6	91.3	4.9	5.7	10.6	+	+	+
Secondary (14-17 years)	65.8	61.9	65.6	-3.9	3.7	-0.2	-	+	-
Infant Mortality	62.0	62.0	62.0	0.0	0.0	0.0	NS	NS	NS
Stunting Prevalence	20.7	24.1	26.7	3.4	2.6	6.0	-	-	-
Nairobi									
Enrollment Rates									
Primary (6-13 years)	74.1	87.3	92.9	13.2	5.7	18.9	+	+	+
Secondary (14-17 years)	54.8	56.1	62.9	1.3	6.7	8.1	+	+	+
Infant Mortality	55.0	55.0	55.0	0.0	0.0	0.0	NS	NS	NS
Stunting Prevalence	22.5	25.7	18.5	3.2	-7.2	-4.0	-	+	+

NS = Changes are not statistically significant.