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Publication date:
2008

Document version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Arndt, C., Nhate, V., & Silva, P. C. D. (2008). *On the Robustness of Poverty Predictors*. Paper presented at Nordic Conference on Development Economics, Stockholm, Sweden.

On the Robustness of Poverty Predictors

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DRAFT: April 2008

Abstract: Monitoring of poverty requires timely household budget data. However, such data are not available as frequently as needed for policy purposes. Recently, statistical methods have emerged to predict poverty overtime by combining detailed household consumption and expenditure data with more frequent data collected from other surveys. In this paper we compare poverty predictions for Mozambique using different source data to test the robustness of the predicted poverty statistics. A critical element in this exercise of predicting poverty overtime is the stability of the parameters that determine household consumption. We find that the assumption of stable consumption determinants does not hold for Mozambique during the time period examined. We also examine what drives the resulting predicted poverty statistics. The paper then considers the policy implications of these findings for Mozambique and other developing countries.

Key words: Poverty prediction, household survey, Mozambique

We would like to thank Ken Simler and Astrid Mathiassen for their careful comments and suggestions, and participants at the Inaugural Conference of the Institute for Social and Economic Studies on the “Challenges of Social and Economic Research in Today’s Mozambique, held in Maputo on 19 of September, 2007, for additional comments and suggestions.

1. Introduction

The demand for data to inform policy and monitor poverty is increasing in developing countries. Goal one of the Millennium Development Goals (MDGs)—to halve the number of people in extreme poverty—can only be measured and monitored using household budget survey data. These surveys contain detailed consumption and expenditure information, from which income poverty statistics can be obtained. Income poverty indicators are also frequently embedded in Poverty Reduction Strategy Papers (PRSPs) and timely household budget data are thus important for the evaluation of the success of poverty reduction policies.

The interval between household budget surveys is long, frequently five or more years. This makes monitoring the impact of public policy on poverty more difficult. To overcome this problem, less extensive household surveys, without consumption and expenditure information, have been developed to monitor other poverty indicators. The Core Welfare Indicator Questionnaire (CWIQ), developed by the World Bank in the mid 1990's, is one example of a non-monetary poverty monitoring survey. These "light" monitoring surveys focus on non-monetary poverty indicators, such as school attendance and literacy rates, access to health and other services, employment, household ownership of assets, etc, and are thus quicker and relatively less expensive to implement than household budget surveys. Obtaining a precise measurement of how many households fall below the poverty line, however, is not directly possible from such surveys.

Some of the household information obtained in these light surveys, however, overlaps with information available from household budget surveys. Recently, statistical techniques have been developed to combine these different datasets to estimate household consumption and poverty status for the population in non expenditure surveys. Elbers, Lanjouw, and Lanjouw (2003) use small area estimation techniques to generate poverty predictions for census datasets. The method applied, which is now commonly referred to as the poverty mapping method, combines detailed data from household budget surveys with larger population census surveys. The population census surveys provide limited information about households, but generally cover a much larger number of households than budget surveys, and are thus representative at smaller geographical units. The poverty mapping literature combines these different data sources to obtain poverty estimates at a lower level of spatial aggregation than household surveys are designed to be representative.

The poverty mapping methodology has also been recently applied to derive poverty estimates overtime (Stifel and Christiaensen, 2007; Mathiassen, 2007, Simler et al, 2003). In other words, by combining different household surveys in different years, one can use the determinants of household consumption estimated from the available expenditure survey in one year to predict consumption levels for households at an earlier or later time period when consumption and expenditure data are not available. A critical element in this exercise of predicting poverty overtime is the stability of the parameters that determine household consumption. In order to predict poverty in future years, one must assume that the determinants of consumption are stable overtime. This becomes a strenuous assumption the more dynamic the economy is and the longer the time span between surveys.

In this paper, we apply the poverty mapping method developed by Elbers, Lanjow, and Lanjow (2003) and compare poverty estimates for Mozambique using two different household budget surveys. Because we use data from two household budget surveys, this allows us to evaluate the poverty predictions against actual poverty figures for another time period. It also allows us to test whether the determinants of household consumption are stable between the two household budget surveys, as normally assumed with prediction of poverty overtime.

We find that the assumption of stable consumption determinants does not hold for Mozambique during the time period examined. The paper then considers the policy implications of these findings for Mozambique and other developing countries.

The paper is structured as follows. Section 2 provides a brief review of poverty trends in Mozambique. Section 3 reviews the literature on poverty prediction methods and describes the empirical approach employed in the analysis. Section 4 describes the data used for the analysis. Section 5 discusses the results of the analysis and Section 6 concludes.

2. Poverty Trends in Mozambique

Mozambique emerged from a prolonged civil war which ended in 1992, and was unarguably one of the poorest countries in the world—with an estimated GDP per capita of US\$80 in 1995. In 1996, the first nationally representative household budget survey—the *Inquerito Nacional aos Agregados Familiares* (IAF)—was carried out and analysis of the survey data indicated a poverty headcount of 69 percent. As Table 1 shows, poverty was higher in rural areas (71 percent) compared to urban areas (62 percent), and in some provinces the poverty headcount exceeded 80 percent. A second nationally representative household budget survey was carried out in 2002 to measure the progress in poverty reduction efforts. The second IAF survey showed that poverty declined considerably in the intervening years, with 54 percent of the population falling below the poverty line. Although the gap between rural and urban communities narrowed, poverty remained higher in rural areas, at 55 percent of the population. The estimated decline in poverty rates was consistent with overall economic growth development in the post war period (Ministry of Planning and Finance, 2004).

Table 1. Poverty Headcount in Mozambique 1996 and 2002

| | 1996-97 | | 2002-03 | |
|-----------------|-------------------|----------------|-------------------|----------------|
| | Poverty Headcount | Standard Error | Poverty Headcount | Standard Error |
| National | 69.4 | 1.14 | 54.1 | 1.36 |
| Urban | 62.0 | 2.67 | 51.5 | 2.25 |
| Rural | 71.3 | 1.25 | 55.3 | 1.68 |
| North | 66.3 | 2.28 | 55.3 | 2.57 |
| Center | 73.8 | 1.60 | 45.5 | 2.40 |
| South | 65.8 | 1.96 | 66.5 | 1.35 |
| Niassa | 70.6 | 3.78 | 52.1 | 5.44 |
| Cabo Delgado | 57.4 | 4.19 | 63.2 | 3.41 |
| Nampula | 68.9 | 3.29 | 52.6 | 3.82 |
| Zambesia | 68.1 | 2.60 | 44.6 | 4.60 |
| Tete | 82.3 | 3.22 | 59.8 | 4.22 |
| Manica | 62.6 | 5.95 | 43.6 | 4.11 |
| Sofala | 87.9 | 1.46 | 36.1 | 2.76 |
| Inhambane | 82.6 | 2.45 | 80.7 | 2.16 |
| Gaza | 64.6 | 3.26 | 60.1 | 2.60 |
| Maputo Province | 65.6 | 5.41 | 69.3 | 2.83 |
| Maputo City | 47.8 | 4.06 | 53.6 | 3.09 |

Note: Standard error of poverty headcount estimates corrected for sample design effects

A detailed analysis of the determinants of household welfare and poverty status followed the first IAF survey (Datt et al, 2000). The analysis found that some of the important determinants of household consumption in 1996 were: education (particularly completion of primary education), sector of employment (with high levels of poverty in agriculture sector suggesting low levels of productivity in the sector), lack of economic infrastructure in rural areas (such as roads, markets, banks, extension and communications services), and high dependency burdens. These results are in line with a similar analysis of poverty carried out by the World Bank (Fox, et al, 2005), which looked at the determinants of household consumption in both 1996 and 2002. Like Datt et al (2000), they find that household demographic characteristics, education, and sector of employment matter for household welfare and poverty status. They also find significant differences between the impact of these variables in rural and urban areas. The analysis for 2002, however, shows that some of the determinants of consumption have changed—particularly for households in the urban areas. Fewer household demographic characteristics are significant in 2002 and the impact of employment in some sectors has changed, suggesting possible structural changes in the economy. Education continued to be an important determinant of household welfare and poverty status; however, the lower coefficients in the later survey period suggest a lower return to primary education completion, particularly in urban areas. The returns to post secondary education, on the other hand, increased in urban areas.

In order to analyze the developing poverty trends in Mozambique, several researchers have combined household budget data from the IAF surveys with a core welfare indicator questionnaire data, which was carried out in 2000, to predict poverty rates in years between the two IAF surveys. Simler et al (2003) use data from the 1996 IAF as the basis for their prediction of poverty rates in 2000. Mathiassen and Hansen (2005), on the other hand, use data from the 2002 IAF for their prediction of poverty in both 2000 and 2004. The forward poverty predictions based on the 1996 IAF data seem to suggest faster poverty reduction rates than the backward poverty prediction based on the 2002 IAF data.

A significant difference between these two studies which could explain their divergent poverty predictions for Mozambique in 2000 is the consumption model estimated which is used for the poverty predictions. Simler et al (2003) analysis is based on a consumption model estimated separately for each of the ten provinces in Mozambique. Mathiassen and Hansen (2005), on the

other hand, estimate a consumption model that distinguishes between rural and urban areas in each of the three regions of Mozambique. Maputo city is treated separately in both estimations. The literature on poverty determinants suggests that there are significant differences in poverty determinants between rural and urban areas and that it is generally harder to obtain good predictors of consumption and poverty for rural models.

The different poverty estimates for 2000 reported by these two studies could thus be attributed to either differences in the consumption model used as a basis for poverty predictions or the use of a different time period used to estimate the consumption model. In this paper, we assess the robustness of poverty estimates for Mozambique by examining the cause of these different poverty estimates. If the difference in predictions is driven primarily by the use of different base year for the consumption model estimated, this would suggest that the determinants of consumption in Mozambique were not stable during the time period in question. We thus formally test for the stability of consumption determinants, using the two household budget surveys. If the consumption determinants are not stable overtime and the use of different data sets generate different predictions, then the usefulness of the application of poverty prediction techniques overtime must be carefully considered..

3. Model Specification

The basic idea behind poverty prediction methods is to first estimate household consumption per capita, the indicator of household welfare and poverty status, based on a set of explanatory variables common to both the household budget survey and the non-budget survey. By restricting the set of explanatory variables in this way, the estimated regression coefficients from the consumption model can then be used generate estimates of consumption levels for the population represented in the non-budget survey.

We begin with a general consumption model specified as follows:

$$\ln(y_{hc}) = \beta' X_{hc} + \sigma \varepsilon_{hc} \quad (1)$$

where y_{hc} is per capita consumption of household h in the sample cluster c at time t , X_{hc} is a set of household and community characteristics that are found in both surveys, and ε_{hc} is the error term. Following Simler et al (2003), the consumption model is estimated separately for each of the ten provinces in Mozambique and for Maputo city, using a stepwise procedure to select the relevant explanatory variable for each provincial equation. The estimated parameters $\hat{\beta}$ and $\hat{\sigma}$ are then used to predict per capita household consumption for the later survey at time $t+k$, conditional on the values of X_{t+k} observed in the later survey:

$$\ln(\hat{y}_{t+k}) = X'_{t+k} \hat{\beta} + \hat{\sigma} \varepsilon_{t+k} \quad (7)$$

The Foster-Greer-Thorbecke (FGT) poverty measures are then calculated based on the predicted consumption levels for the later Mozambican household survey.

The probability that household h 's consumption falls below the poverty line Z is given by:

$$\hat{p}_{hc} = \text{prob}(\ln y_{hc} < \ln z) = \text{prob}(\beta' X_{hc} + \sigma \varepsilon_{hc} < \ln z) = \Phi((\ln z - \beta' X_{hc}) / \sigma)$$

As Mathiassen (2007) shows, the estimator for the probability of being poor will be biased because it depends on the parameters β and σ in a nonlinear way. This is the case even if the estimated

parameters $\hat{\beta}$ and $\hat{\sigma}$ are unbiased estimates of β and σ . In our estimation of the poverty headcount ratio, we employ the bias correction suggested by Mathiassen (2007).

[[[Channing to add something on standard error of predictions]]]

A critical assumption in the prediction of poverty overtime is that the estimated parameters $\hat{\beta}$ and $\hat{\sigma}$ of the consumption model are stable overtime—in other words, the relationship between consumption and the explanatory variables used to estimate it does not change in the span of time between the two surveys. This is the assumption adopted in previous studies that make poverty predictions overtime. In some of the poverty prediction studies, the poverty predictions are only a few years away from the original household expenditure survey (Simler et al, 2003, Mathiassen and Hansen 2005), whereas in at least one study, the time span covered is much longer (Stifel and Christiaensen, 2007). However, the more dynamic the economy and the more time that passes between the surveys, the more likely it is that the estimated model parameters are unstable—in other words, the estimated parameters change overtime (Mathiassen and Hansen, 2005). We thus compare how poverty predictions vary overtime, by basing our predictions for several time periods on both the 1996 and 2002 IAF surveys. We also formally test whether the assumption of stable consumption determinants holds for Mozambique using the two household budget surveys from 1996 and 2002.

4. Data

The analysis in this paper is based on several household survey data from Mozambique. In particular, we use household expenditure survey data from 1996-97 and 2002-03 to test the stability of the estimated consumption coefficients used for predicting poverty. We also use data from the 2000 Questionario de Indicadores Basicos de Bem-Estar (QUIBB) survey and the 2004 Inquerito Integrado da Force de Trabalho (IFTRAB). The QUIBB 200 and IFTRAB 2004, however, are not expenditure surveys, so it is not possible to evaluate how good the predictions for 2000 and 2004 are against the actual poverty levels. We use these dataset set to establish a time profile of poverty evolution in Mozambique.

The 1996 IAF household expenditure survey was the first nationally representative survey to measure poverty since the end of the civil war which followed its independence. The survey was conducted from February 1996 through April 1997, with 8,274 household interviewed. The survey covered all 10 provinces in Mozambique and covered Maputo city as a separate stratum. The survey is representative at the national, rural, urban and provincial level. The 1996 IAF is a detailed survey, in which households were visited three times during a seven day period. Three instruments were used to collect information at the individual and household level: a principal questionnaire, a daily household expenditure questionnaire, and a daily personal expenditure questionnaire administered to all income earning individuals in the household. In addition to these, there were two survey instruments used to collect information at the community level—one collecting information on available infrastructure, access to services, and community characteristics, and the other collecting market price information for different goods traded in major markets in the area. Poverty statistics are based on measures of comprehensive consumption, which includes expenditures for food and all non food items, the value of food and other household own produced goods, and the imputed value of owner occupied housing and household durable goods. The poverty line is based on the cost of basic needs approach. Further details of how consumption and poverty is measured can be found Datt, et al (2000) and National Directorate of Planning and Budget, et al. (2004).

The subsequent household expenditure survey, the 2002 IAF, took place between July 2002 and June 2003 and covered 8,700 households. To ensure the data is also temporally representative, the survey interviewed one quarter of households in each stratum in each time period. This was

designed to take into account the significant fluctuations in the price of agricultural products due to season effects observed in the previous survey. Significant efforts also went into constructing regional poverty lines that reflect the same standards of living throughout the country.

The other two surveys used in this analysis are the QUIBB 2000 and the IFTRAB 2004. These are larger surveys, covering about 13,770 and 17,500 household respectively, but which do not contain consumption or expenditure information. However, each survey contains many questions that overlap with the household expenditure surveys. The QUIBB 2000 was the first formal core welfare indicator survey carried out in Mozambique. The key welfare indicators collected by the QUIBB cover ownership of assets and quality of housing. Information is also collected on the education attainment and a set of poverty indicators. These include whether questions on household seasonal employment, receipt of remittances, and expenditures on specific items such as soap, different types of food, clothing, etc. These indicators are chosen because of their high correlation with household poverty status. The IFTRAB 2004 is similar to the QUIBB, but contains an extended section on employment activities of household members. The IFTRAB, however, does not contain the section on poverty indicators found in the QUIBB 2000.

For our analysis, we focus on the information that overlaps between the IAF, the QUIBB and the IFTRAB surveys. In this context, it is particularly important to ensure that the questions regarding variables of interest for the analysis are consistent in each of the surveys. Definitional changes that may occur between surveys would cause problems for implementation of the type of analysis pursued here. In Table 2, we present an overview of the variables used in the analysis and examined the trends in these variables overtime. In cases where changes in variables' definition are suspected, we drop the variables from the analysis.

[INSERT Table 2 HERE]

(add comments on variation of key variables overtime)

5. Results

In this section we present the results of our analysis—poverty predictions overtime based on two sources of data: the 1996 IAF and the 2002 IAF. We begin our discussion of the results by first examining the poverty predictions based on the 1996 IAF. Table 3 suggests that nationally poverty has declined considerably overtime Mozambique—by nearly 20 percentage points in a little less than a decade. Both rural and urban areas experienced considerable poverty reduction, although poverty remains higher in rural areas. The South region has experience the most poverty reduction—nearly halving poverty over the relevant time period. A look at the provincial poverty predictions shows varying performance in poverty reduction results. The predictions suggest that some provinces, such as Manica, Sofala, and Gaza, experienced significant poverty reduction. However, in two provinces, Cabo Delgado and Tete, the predictions suggest poverty has actually increased over time.

In order to evaluate the fit of these predictions, we first compare how our model predicts poverty in sample. In other words, we estimate the consumption model based on the determinants of consumption in 1996 and predict poverty using the estimated model in the 1996 sample data itself. This allows us to compare the prediction results against the actual poverty rates, without introducing any disturbances due to the instability of consumption determinants. Our results show that the predicted poverty rates all fall within the 95 percent confidence interval of real poverty rates. Next we evaluate how well the model predicts poverty in 2002, since the IAF 2002 is a consumption survey and we know what the actual poverty rates are for that year. We find that most (13 out 17) of our predictions for 2002 fall outside of the 95 percent confidence interval of the actual poverty rates for 2002. These results are rather disappointing. We find that in most cases (9 out 14), the model tends to under predict the actual poverty rate.

Table 3. Poverty predictions based on 1996 data

| | <i>1996*</i> | <i>2000</i> | <i>2002</i> | <i>2004</i> |
|-----------------|--------------|-------------|-------------|-------------|
| National | 66.1 | 54.3 | 52.2 | 45.5 |
| Urban | 59.9 | 45.6 | 43.7 | 39.3 |
| Rural | 67.7 | 58.3 | 56.1 | 48.4 |
| North | 63.5 | 49.7 | 50.5 | 47.8 |
| Center | 70.5 | 61.0 | 59.5 | 50.1 |
| South | 62.0 | 51.1 | 43.0 | 34.1 |
| Niassa | 68.5 | 57.1 | 52.6 | 58.3 |
| Cabo Delgado | 53.9 | 45.3 | 68.4 | 74.2 |
| Nampula | 66.3 | 49.8 | 42.7 | 31.5 |
| Zambezia | 64.4 | 56.4 | 78.7 | 58.0 |
| Tete | 79.5 | 69.2 | 98.5 | 87.2 |
| Manica | 58.6 | 28.2 | 17.5 | 11.9 |
| Sofala | 85.6 | 77.6 | 17.4 | 28.2 |
| Inhambane | 78.0 | 68.1 | 65.8 | 42.4 |
| Gaza | 58.7 | 52.0 | 10.5 | 8.4 |
| Maputo Province | 63.9 | 47.6 | 56.1 | 57.2 |
| Maputo city | 45.6 | 31.2 | 41.1 | 18.4 |

Notes: *1996 are the in sample predictions.

In order to examine the robustness of our results, we estimate the re-estimate the consumption model using the 2002 IAF data and compare the predicted poverty rates between 1996 and 2004 with our previous results. As Table 4 shows, the results based on the 2002 suggest a different time path for the evolution of poverty in Mozambique. These results suggest that although poverty decreased overall between 1996 and 2004, the evolution of poverty did not follow the same linear decline as in Table 3. Rather, poverty declined at first, between 1996 and 2000, then increased somewhat by 2002, falling again in 2004. While the rural urban poverty gaps are similar in both predictions, the regional ranking differs, with the South region experiencing the least poverty reduction over the time period. At the provincial level, we find most follow the national trend described above—with poverty declining at first, then increasing in 2002 and falling again in 2004. In two of the provinces, Cabo Delgado and Gaza, poverty increased relative to predicted levels from 1996. Manica, which based on the 1996 results had the second lowest predicted poverty rate, has the highest predicted poverty rate based on the 2002 results. In Gaza, where poverty increased between 1996 and 2002, the lowest poverty rate is predicted.

When we compare the 2002 predictions for 1996 poverty rates against the actual poverty rates, we find that again, most of the predictions (12 out of 17) fall outside of the 95 confidence interval of the actual 1996 poverty rates. The widely different results based on the two IAF surveys suggests that the source of the problem may not be the poverty prediction methodology per say, but rather the underlying assumption of stability of consumption determinants. During the 6 years between the two household budget surveys, Mozambique experience significant economic changes. We thus test whether the determinants of consumption changed between the two survey years. No previous studies have actually compared their predict poverty results against actual poverty estimates, as we do here. We find that in all but two provinces, we must reject the hypothesis that the coefficients of the consumption model are equal in the two time periods. This could very well explain why so many of the predict poverty rates are outside the confidence interval of the actual poverty rates.

Table 4. Poverty predictions based on 2002 data

| | <i>1996</i> | <i>2000</i> | <i>2002*</i> | <i>2004</i> |
|--------------|-------------|-------------|--------------|-------------|
| National | 60.1 | 46.6 | 53.7 | 45.5 |
| Urban | 53.3 | 43.2 | 49.2 | 40.6 |
| Rural | 62.1 | 48.2 | 55.9 | 47.6 |
| North | 65.4 | 49.1 | 54.1 | 49.9 |
| Center | 56.2 | 40.0 | 47.1 | 40.1 |
| South | 60.2 | 51.9 | 63.3 | 48.5 |
| Niassa | 46.2 | 39.3 | 48.4 | 47.3 |
| Cabo Delgado | 53.3 | 48.7 | 57.3 | 55.1 |
| Nampula | 75.1 | 51.5 | 54.2 | 48.0 |
| Zambezia | 44.0 | 20.2 | 45.9 | 29.5 |
| Tete | 74.8 | 55.3 | 63.9 | 58.3 |
| Manica | 95.6 | 96.6 | 46.7 | 82.8 |
| Sofala | 43.1 | 32.1 | 34.7 | 15.5 |
| Inhambane | 76.5 | 68.5 | 80.7 | 63.7 |
| Gaza | 36.5 | 32.3 | 54.6 | 40.6 |
| Maputo P | 76.2 | 65.4 | 65.9 | 56.6 |
| Maputo city | 55.6 | 38.5 | 49.5 | 26.8 |

Notes: *2002 are the in sample predictions.

In order to better understand the variation in results for the predictions based on different data sources, we examine the differences between the poverty predictions for two provinces: Manica and Gaza. Looking at the regression coefficients for Manica, we find that most of them changed considerably between 1996 and 2002. In other words, the determinants of poverty for the later period were substantially different—on average differing by more than 3 standard deviations. In particular, changes to some of the coefficients of variables associated with household infrastructure appear to be driving the differing results from the 1996 and 2002 predictions. We find a significant increase in households with permanent walls and latrines in their homes at the later time period. In the case of permanent walls, in 1996 fewer households had them and their impact on determining household welfare was quite large. In 2002, however, saw a tremendous increase in households reporting permanent walls in their homes in Manica and at the same time, the impact of permanent walls diminished substantially. Thus when one combines the large importance of permanent walls to household welfare suggested by the 1996 regression coefficients with large levels of households having permanent walls in 2002, this will lead to a prediction of large poverty reduction. A similar pattern appears to hold for household access to latrines.

In Gaza, the difference in the predictions based on 1996 and 2002 data appear driven by changes in education. Whereas most variables' regression coefficients for Gaza are not substantially changed, we do find some significant changes for some education related variables. In particular, we find that the impact of the percentage of children in school, the percentage of household members literate, and the maximum level of education in the household changed substantially. The levels of all education related variables increased between the two surveys. However, the impact of these variables on household welfare changed during this time as well. The positive impact of higher levels of education within the household and the percentage of children in school diminished, whereas the beneficial impact of higher literacy rates increased. Thus it appears that very different changes in each particular province are driving the difference in the predicted poverty rates based on the 1996 and 2002 data sources. This insight confirms the finding of the instability of the determinants of consumption in Mozambique in the time period examined.

6. Conclusions

Recently, analytical techniques have been developed to predict poverty using “light” monitoring surveys. These light monitoring surveys are generally less expensive to implement than household budget surveys and thus can be carried out more frequently. In this paper, we assess the robustness of poverty prediction methods which combine household budget survey data with other survey data to predict poverty developments overtime in Mozambique. We do this using household budget survey data from 1996 and 2002, and data from other surveys which took place in 2000 and 2004.

Prediction of poverty overtime relies on the assumption that the determinants of consumption be stable overtime. We find that this assumption does not hold for Mozambique for the time period between 1996 and 2002. Consequently, poverty prediction using different data sources can produce a wide range of poverty estimates. We find these differences are more pronounced at the provincial level, whereas aggregated poverty predictions at the national, urban and rural, or regional level, appear less volatile. This suggests that great care must be employed in interpreting the results from poverty prediction methods to fill in information gap between household budget surveys. A continuing assessment of poverty through the collection of household budget surveys remains important. Our results suggest that periodic household budget surveys are thus important not just to measure poverty, but also to understand how the determinants of poverty are changing overtime.

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