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Mozambique's poverty reduction from a dynamic perspective – an application of synthetic panels

Vincenzo Salvucci [a] and Finn Tarp [a]

[a] University of Copenhagen.

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Abstract

Mozambique has achieved rapid poverty reduction over the past two decades with poverty rates falling from about 70% to 46% in the latest available national poverty assessment. However, given the lack of longitudinal data, little is known about poverty dynamics and trajectories. In this paper we attempt to shed some light on the poverty dynamics in Mozambique using the synthetic panels approach introduced by Dang, Lanjouw, Luoto and McKenzie (2014) and Dang and Lanjouw (2013; 2014). We apply the synthetic panels methodology to the 1996/97, 2002/03, 2008/09 and 2014/15 cross-sectional household budget surveys. Our results suggest that in most year-to-year comparisons there is a greater proportion of people getting out of poverty than falling into poverty, consistent with the poverty reduction process observed, but the percentage of people staying in poverty over time appears to be substantially higher, involving about a third of the population in most years. Further analyses on the 2008/09 and 2014/15 surveys permit to obtain point estimates of poverty transitions and confirm the high degree of poverty immobility in Mozambique, but they also show that the movements between the poverty and non-poverty states occur in both directions and in comparable magnitudes. We also obtain a vulnerability line based on the synthetic panels approach and estimate that for an individual who was in the vulnerable group in 2008/09, there is a 60 percent probability of remaining in the same group, whereas the probability of becoming non-vulnerable is lower than the probability of entering poverty. This constitutes the first attempt to provide an insight into poverty dynamics in Mozambique using all the available survey data.

Long Abstract

Mozambique has achieved rapid poverty reduction over the past two decades with poverty rates falling from about 70% to 46% in the latest available national poverty assessment. However, given the lack of longitudinal data, little is known about poverty dynamics and trajectories. In this paper we attempt to shed some light on

the poverty dynamics in Mozambique using the synthetic panels approach introduced by Dang, Lanjouw, Luoto and McKenzie (2014) and Dang and Lanjouw (2013; 2014). We apply the synthetic panels methodology to the 1996/97, 2002/03, 2008/09 and 2014/15 cross-sectional household budget surveys.

Our results suggest that in most year-to-year comparisons there is a greater proportion of people getting out of poverty than falling into poverty, consistent with the poverty reduction process observed, but the percentage of people staying in poverty over time appears to be substantially higher, involving about a third of the population in most years. This is also reinforced by the estimate that the probability of remaining poor given that the individual was also poor in a previous year is on average much larger than the probability estimated for the transition from poor to non-poor (about twice as much).

Further analyses on the 2008/09 and 2014/15 surveys permit to obtain point estimates of poverty transitions and confirm the high degree of poverty immobility in Mozambique. We estimate that there is a sizeable percentage of the population that is poor in both years (37 per cent), or that is non-poor in both years (39 per cent), but also that the movements between the poverty and non-poverty states occur in both directions and in comparable magnitudes. We also obtain a vulnerability line based on the synthetic panels approach and estimate that for an individual who was in the vulnerable group in 2008/09, there is a 60 percent probability of remaining in the same group, whereas the probability of becoming non-vulnerable is lower than the probability of entering poverty.

This constitutes the first attempt to provide an insight into poverty dynamics in Mozambique using nationally representative, information-rich survey data. The study aims to contribute to the policy discussion in that it provides important insights into the dynamics of poverty, adding a tool to the fight against transitory and chronic poverty. Covering two decades of the post-conflict development of Mozambique, this study aims to contribute to finding viable solutions to reach the Sustainable Development Goal 1.

Introduction

Mozambique has achieved rapid poverty reduction over the past two decades with poverty rates falling from about 70% to 46% in the latest available national poverty assessment (DEEF, 2016). While this presents a great achievement in the development of this low-income country, Mozambique remains one of the poorest countries in the world. Recent economic and environmental shocks seem to have slowed down this race. For Mozambican households, what matters most to escape poverty requires still more research. Development economists have investigated movements out of and into poverty in several poor countries, relying on the availability of longitudinal data, that is household survey data following the same households over many years and collecting data at different points in time (e.g. Dercon and Krishnan, 2000 and 2003; Kumar and Quisumbing, 2013). With such data one can ask the question which local, household or individual characteristics are associated with positive or negative trajectories respectively. Further, researchers can estimate the impact of specific policies or shocks, such as the recent cyclones hitting the central and northern regions of Mozambique. Another important question to ask is whether some households are trapped in poverty while others pursue a sustainable pathway towards higher levels of welfare and if so, which factors determine these different trajectories? This question can only be analyzed with data that allows to compare households among each other but also to follow them over time.

However, such household panel data spanning over a period of a few years are generally not available for Mozambique. Nationally representative cross-sectional household budget survey data exist, but they are only collected every five or six years (*Inquérito aos Agregados Familiares Sobre Orçamento Familiar*, abbreviated as IAF or IOF). Therefore, most existing studies focusing on poverty and other welfare indicators and aggregates lack the dynamic dimension in their analyses. In their 2017 paper, Dang and Dabalen (2017) included Mozambique among the countries used to evaluate the chronic or transitioning poverty situation of African countries, but they limited their analysis to the household budget surveys 2002/03 and 2008/09.

With the household budget survey 2014/15 already available and the 2019/20 in the field, in this paper we try to gather all the cross-sectional information available for the country and analyse poverty dynamics using the synthetic panels approach introduced by Dang et al. (2011, 2014) and by Dang and Lanjouw (2013). This methodology permits to construct synthetic panel data from repeated cross sections. It is based on an imputation procedure through which the values of the relevant welfare aggregate, income or consumption, for households observed at time one, are estimated using households and community characteristics and welfare aggregates measured at time zero (Dang et al., 2011 and 2014; Dang and Lanjouw, 2013). This approach relies on imputation models and on the presence of time-invariant correlates of consumption in the survey. An extensive validation work based on actual panel data has been carried out by various researchers over recent years for different sets of countries. This work seems to suggest that the methodology is sufficiently reliable as an alternative to actual panels when it comes to estimating income/consumption dynamics (Dang and Lanjouw, 2015; Dang, Lanjouw and Swinkels, 2014; Bierbaum and Gassmann, 2012; Bourguignon and Moreno, 2015; Cruces et al., 2015; Dang and Lanjouw, 2018). Actually, the methodology described presents even some advantages in terms of sample numerosity compared to standard existing panels (Dang et al., 2011 and 2014; Dang and Lanjouw, 2013). We apply the synthetic panels methodology to the last four available cross-sectional household budget surveys for Mozambique: the 1996/97 (IAF96), 2002/03 (IAF02), 2008/09 (IOF08) and 2014/15 (IOF14) household budget surveys.

This constitutes the first attempt to provide an insight into poverty dynamics in Mozambique using all the available nationally representative survey data. The study aims to contribute to the policy discussion in that it provides important insights into the dynamics of poverty, adding a tool to the fight against transitory and chronic poverty. For policy makers, this is relevant as more transitory poverty can be addressed for example with safety net programmes that can be adjusted to the local or sectoral context, whereas households trapped in poverty will require different interventions that address the structural factors constraining these households from moving out of poverty. The paper develops as follows: Section 2 presents the context; Section 3 describes the data and Section 4 presents the methodology. The results are discussed in Section 5, while Section 6 concludes.

2. Context

After emerging from a devastating and prolonged conflict during the 1980s and the early 1990s, Mozambique experienced sustained economic growth. This led the country to having one of the best economic performances in the region. The most recent 2014/15 poverty assessment available for Mozambique (DEEF, 2016) presented positive results in terms of poverty reduction and welfare improvements over a period of about 20 years (1996/97-2014/15). In international comparative perspective, the gains registered by

Mozambique over the 18-year span covered by the surveys in reference are notable. The consumption poverty headcount fell by about 25 points. International comparisons for the multidimensional measures are also very favorable. Consumption poverty estimates from 2014/15 suggest that 46.1 per cent of the Mozambican population were poor from a consumption point of view, with huge differences depending on the province and urban/rural location. This represents a reduction compared to 2008/09, when 51.7 per cent of the Mozambican population were poor (DEEF, 2016). Regarding the poverty reduction process over time, the four available National Poverty Assessments state that: (i) at the national level, a substantial fall in poverty occurred between 1996/97 and 2002/03; (ii) between 2002/03 and 2008/09 the poverty rate stabilized and there was essentially a stagnation in poverty rates at the national level; (iii) poverty decreased between 2008/09 and 2014/15 (DNPO, 1998; DNPO, 2004; DNEAP, 2010; DEEF, 2016). In Table 1 the consumption poverty results are presented for all years at national level and at different levels of disaggregation (rural/urban, north, center and south, and provinces). However, as discussed in the introduction, no information is provided with respect to poverty dynamics and transitions, given that only cross-sectional data exist for Mozambique.[1] As mentioned, Dang and Dabalen (2017) included Mozambique among the countries used to evaluate the chronic or transitioning poverty situation of African countries, but they limited their analysis to the household budget surveys 2002/03 and 2008/09, which is the only period in which a stagnation in poverty rates at the national level was observed.[2] Extending the analysis backward, with the use of the IAF96, and forward, including the household budget survey IOF14 in the analysis, in this paper we try to gather all the cross-sectional information available for the country in order to analyse poverty dynamics in more detail.

Table 1. Consumption poverty rates, 1996/97-2014/15 (%)

Area	1996/97	2002/03	2008/09	2014/15
National	69,7	52,8	51,7	46,1
Urban	61,8	48,2	46,8	37,4
Rural	71,8	55,0	53,8	50,1
North	67,3	51,9	45,1	55,1
Centre	74,1	49,2	57,0	46,2
South	65,5	59,9	51,2	32,8
Niassa	71,9	48,3	33,0	60,6
Cabo Delgado	59,1	60,3	39,0	44,8
Nampula	69,4	49,1	51,4	57,1
Zambézia	67,6	49,7	67,2	56,5
Tete	81,9	60,5	41,0	31,8
Manica	62,4	44,7	52,8	41,0
Sofala	87,8	41,3	54,4	44,2
Inhambane	83,0	78,1	54,6	48,6
Gaza	64,8	55,4	61,0	51,2
Maputo Province	65,6	59,0	55,9	18,9
Maputo City	47,1	42,9	29,9	11,6

Note: Percentage of poor people over the total population for different areas and for all IAF / IOF.
Source: DEEF (2016).

[1] The IOF14 is a mini-panel: households were interviewed three times during the 12-month survey period, but there is not a longitudinal dimension that links this survey to previous ones, so here we consider it as a cross-section.

[2] Dang and Dabalen (2017) analyse poverty in many African countries and hence prefer to use the international poverty line equivalent to $1.9/day in 2011 PPP dollars. In this study, we prefer to use the national poverty lines for Mozambique. This makes our results not immediately comparable to those found in Dang and Dabalen (2017).

3. Data

In this study we use data from all the Household Budget Surveys that are available for Mozambique and that are nationally representative. They are the Household Budget Surveys 1996/97 (IAF96), 2002/03 (IAF02), 2008/09 (IOF08) and 2014/15 (IOF14). All of them were implemented by the National Institute of Statistics of Mozambique (INE), whereas the consumption and poverty analysis has always been performed by the Ministry of Economics and Finance (DNPO, 1998; DNPO, 2004; DNEAP, 2010; DEEF, 2016; INE, 2004; 2010; 2015). In several respects, the various IAF/IOFs are very similar. Despite the existence of some differences in the structure of the questionnaires, the four surveys are comparable with regard to their main objective: measuring consumption poverty and other dimensions of well-being at a given point in time. They contain data on households' food consumption expenditure and are representative of Mozambique as a whole, rural and urban areas and each of the eleven provinces, including Maputo City. Each family was interviewed at different times of the year, with questions about general characteristics, employment, education, access to basic services such as health units or primary schools, daily expenses and household consumption from own production, possession of durable goods, housing conditions, receipts and transfers received and paid, income from various sources, as well as less frequent expenses. In all surveys, data collection took place over the period of one year.[3] Additional information is found in a series of documents produced by both the National Institute of Statistics of Mozambique (INE) and the Ministry of Economics and Finance (DNPO, 1998; DNPO, 2004; DNEAP, 2010; DEEF, 2016; INE, 2004; 2010; 2015).

4. Methodology

The methodology implemented in this article is based on the synthetic panels approach introduced by Dang et al. (2011, 2014) and Dang and Lanjouw (2013). As introduced, this methodology permits to construct synthetic panel data from repeated cross sections. It is based on an imputation procedure through which the values of the relevant welfare aggregate, income or consumption, for households observed at time one, are estimated using households and community characteristics and welfare aggregates measured at time zero (Dang et al., 2011 and 2014; Dang and Lanjouw, 2013).

In summary, cross sectional survey data do not provide information on household consumption for the same households over time, but under a series of assumptions it is possible to estimate the consumption that round 2 households would have had in round 1 specifying a consumption model for round 1 that is only based on time-invariant household characteristics (Dang et al., 2011).[4] Hence, round 1 consumption is first projected on

[3] Contrary to previous surveys where each household was surveyed only once a year, in the IOF14 each household was supposed to be surveyed in each of the four quarters during data collection. However, the household survey was only conducted in the first, second and fourth quarters.

[4] The first assumption is that the underlying population must be the same in all rounds of the survey, which makes it possible to use time-invariant household characteristics to predict household consumption. This implies for example that the sampling methodology is not modified over time. Based on the technical household budget survey documents issued by the National Statistics Institute (INE), it seems that the sampling methodology was not changed across different survey rounds (INE, 2004; 2010; 2015). However, the underlying population might also change due to changes in the household composition (births, deaths , migration, etc.), but this difficulty can be overcome by restricting the sample, as explained in what follows. The second assumption is that the correlation between the error terms of the consumption model in the two survey rounds should be non-negative. Dang et al. (2011) outline the reasons why this assumption is expected to be satisfied in most applications, and state that the two abovementioned assumptions are generally satisfied if the sample is restricted to households whose household head is between 25 and 55 years old, as derived from the pseudo-panel

time-invariant characteristics; subsequently, the OLS parameters that are estimated in this consumption model are applied to the same time-invariant household characteristics, but using the information collected in round 2. In this way, we can obtain an estimate of household consumption in round 1 for households interviewed in round 2.

More formally, for the population as a whole, the linear projection of round 1 consumption or income, y_{i1}, onto x_{i1} is given by:

$$y_{i1} = \beta_1' x_{i1} + \varepsilon_{i1} \quad (1)$$

Where x_{i1} is a vector of characteristics of household *i* in survey round 1 which are observed in both round 1 and round 2 surveys. This could include language, religion, and ethnicity, but also time-invariant characteristics of the household head such as sex, education, place of birth, parental education and age.[5] Similarly, the linear projection of round 2 consumption or income, y_{i2} onto x_{i2} is given by:

$$y_{i2} = \beta_2' x_{i2} + \varepsilon_{i2} \quad (2)$$

Where x_{i2} is the set of household characteristics in round 2 that are observed in both the round 1 and round 2 surveys. The poverty line in period 1 and period 2 are indicated as z_1 and z_2, respectively. Now, in order to estimate the degree of mobility in and out of poverty we want to estimate, for example, what fraction of households in the population is poor in round 1 and non-poor in round 2,[6] or:

$$P(y_{i1} < z_1 \; and \; y_{i2} > z_2) \quad (3)$$

However, we do not know y_{i1} and y_{i2} for the same households. Dang et al. (2011) provide and discuss the assumptions that need to be made in order to be able to estimate bounds for such quantities (Dang et al., 2011, pp. 4-10). Moreover, they consider two approaches to estimate the bounds on mobility: a non-parametric approach, where no assumptions are made about the joint error distribution and a parametric approach where it is assumed that the joint error distribution is bivariate normal. In what follows, we apply the non-parametric approach to the analysis of mobility using all the available survey data – IAF96, IAF02, IOF08 and IOF14 –, and the parametric approach to the analysis of poverty transitions using only the two most recent survey data, the IOF08 and IOF14.

Estimating the upper and lower bounds in the non-parametric approach requires a number of steps, which are explained in detail in Dang et al. (2011, pp. 10-12). In general, depending on the assumptions that are made regarding the joint distribution of the error terms in round 1 and round 2, estimated mobility will be greater the less correlated are the error terms, as this implies that round 1 consumption is less correlated with consumption in round 2. When no correlation is assumed, the upper bounds for poverty mobility are obtained; when perfect correlation is assumed, we obtain the lower bounds for poverty mobility. If we indicate with ρ the correlation coefficient between the error terms in round 1 and round 2, then the non-parametric estimates

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literature (Dang et al., 2011). Therefore, we restrict the sample to households whose household heads is aged 25 to 55 in the first survey round, and the age range is restricted accordingly in subsequent survey rounds.

[5] x_{i1} could also include time-varying characteristics of the household that can be recalled for round 1 in round 2 (Dang et al., 2011). For example, whether or not the household head is employed in round 1, and his or her occupation, their place of residence in round 1, etc.

[6] In Dang et al. (2011) poverty mobility indicates that households have a different poverty status in the two survey rounds, whereas poverty immobility indicates that households have the same poverty status in the two survey rounds.

for the lower and upper bound of poverty mobility correspond to assuming ρ being equal to either 1 or 0, respectively (Dang et al., 2011).

The estimated bounds for poverty mobility, as will be observed, can be relatively wide. However, when they are too wide, they can provide little information on the underlying poverty transitions and be of little practical use. The width can be greatly reduced by improving the quality of the underlying consumption model. In particular, our model sensibly improved when regional characteristics were included in the analysis.

As introduced, an extensive validation work based on actual panel data has been carried out by various researchers over recent years for different sets of countries. This work seems to suggest that the methodology is sufficiently reliable as an alternative to actual panels when it comes to estimating income/consumption dynamics (Dang and Lanjouw, 2015; Dang et al., 2014; Bierbaum and Gassmann, 2012; Bourguignon and Moreno, 2015; Cruces et al., 2015; Dang and Lanjouw, 2018). Actually, Dang and Lanjouw (2013) and Dang et al. (2014) suggest that the methodology described could present some advantages in terms of sample numerosity compared to standard existing panels.

The non-parametric method discussed until now only requires a few assumptions to estimate bounds for poverty mobility. However, if only a limited number of time-invariant characteristics can be used in the consumption model, the bounds obtained can be rather wide. If additional assumptions on the joint distribution of the error terms are introduced, then bounds can be sharpened and it is even possible to obtain point estimates for poverty mobility. Dang et al. (2011) present this parametric approach as a variant of their basic approach. This latter approach has the advantage of being applicable even in those cases in which the available number of time-invariant variables is very limited, which seems to be the case in most cross-sectional household surveys. In the parametric approach, the joint distribution of the error terms in round 1 and round 2 is assumed to be bivariate normal.[7] Dang et al. (2011) show that when the joint error distribution is assumed to be bivariate normal, then quantities of interest such as the fraction of the population that is poor in round 1 and non-poor in round 2 can be derived as follows:

$$P^E(y_{i1} < z_1 \; and \; y_{i2} > z_2) = P(\beta_1' x_{i1} + \varepsilon_{i1} < z_1 \; and \; \beta_2' x_{i2} + \varepsilon_{i2} > z_2) = \Phi_2\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon 1}}, \frac{z_2 - \beta_2' x_{i2}}{\sigma_{\varepsilon 2}}, -\rho\right) \quad (4)$$

Where Φ_2 indicates the bivariate normal cumulative distribution function and σ_ε represents the standard deviation of the error term, ε, in round 1 or 2. Expressions to derive the other quantities of interest are also provided in Dang et al. (2011). As previously discussed, it is clear from this equation that a lower value of ρ implies a higher probability of mobility between round 1 and round 2. Hence, obtaining a better estimate for ρ rather than just using the boundaries ρ=0 and ρ=1 may greatly help in obtaining more precise estimates of poverty mobility. In this respect, Dang and Lanjouw (2013) propose a way to obtain actual point estimates of poverty mobility by computing reasonable values for the correlation coefficient, ρ. They show that, under a number of assumptions, ρ should be bounded from above by the simple correlation coefficient between household consumption in round 1 and round 2, which can be approximated by the synthetic panel cohort-level simple correlation coefficient, ρ_{yi1yi2}, and from below by the expression $\frac{\beta_1' var(x_i)\beta_2}{\sqrt{var(y_{i1})var(y_{i2})}}$, where β_1 and β_2 are the vectors of estimated coefficients from the consumption model and x_i represents the vector of

[7] This assumption may hold in a number of cases; indeed, the distribution of income or consumption is often approximated using a log-normal distribution (Dang et al., 2011).

household time-invariant characteristics. The partial correlation coefficient, ρ, can then be estimated using the following equation (Dang and Lanjouw, 2013, pp. 9-15):[8]

$$\rho = \frac{\rho_{y_{i1}y_{i2}}\sqrt{var(y_{i1})var(y_{i2})} - \beta_1' var(x_i)\beta_2}{\sigma_{\varepsilon 1}\sigma_{\varepsilon 2}} \tag{5}$$

Once ρ is estimated, the procedures to compute the point estimates for poverty mobility are also provided in Dang and Lanjouw (2013, pp. 15-25) and Dang and Lanjouw (2014).

Moreover, following Dang and Lanjouw (2014), we also implement an analysis of vulnerability by identifying a group of vulnerable individuals within the non-poor group. The analysis of vulnerability permits to define a vulnerability line and in turn create three groups: i) the poor, defined as those individuals whose daily real consumption per capita lies below the poverty line; ii) the vulnerable, those individuals whose daily real consumption per capita lies between the poverty line and the vulnerability line; and iii) the non-vulnerable (alternatively defined in Dang and Lanjouw (2014) as "middle-class", "secure" or "prosperous"), those individuals whose daily real consumption per capita lies above the vulnerability line. Dang and Lanjouw (2014) propose not to set the vulnerability line at a value that is an arbitrary scaling up of the poverty line, but deriving the vulnerability line from a specified index of vulnerability, which is defined either as the probability of becoming poor at time 2 conditional on being in the middle-class at time 1 or as the probability of becoming poor at time 2 conditional on being vulnerable at time 1. The former is indicated as P^1, and is then defined as "insecurity index". Given two survey rounds, 1 and 2, and a specified insecurity index, P^1, the vulnerability line in round 1, v_1, should satisfy the equality: $P^1(y_2 \leq z_2 \mid y_1 > v_1)$. Conversely, when the index of vulnerability is defined as the probability of becoming poor at time 2 conditional on being vulnerable at time 1, then it is indicated as P^2 and is defined "vulnerability index". In this case, given two survey rounds, 1 and 2, and a specified vulnerability index, P^2, the vulnerability line in round 1, v_1, should satisfy the equality: $P^2(y_2 \leq z2 \mid z1<y1<v1$. For the properties of these indexes, see Dang and Lanjouw (2014).

Thus, the procedure outlined in Dang and Lanjouw (2014) permits to estimate a vulnerability line and to link it directly with a vulnerability index, derived for example from budgetary planning, social welfare objectives or relative concepts of well-being. Once the value of the insecurity index, P^1, or the value of the vulnerability index, P^2, are selected, it is possible to derive the value for the vulnerability line.

If we assume, as described earlier in this section, that the error terms in survey round 1 and 2 have a bivariate normal distribution with correlation coefficient ρ, then quantities of interest such as the fraction of the population that is poor in round 1 and vulnerable in round 2 can be derived as follows:

$$P^E(y_{i1} < z_1 \; and \; z_2 < y_{i2} < v_2) = \Phi_2\left(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon 1}}, \frac{v_2-\beta_2' x_{i2}}{\sigma_{\varepsilon 2}}, \rho\right) - \Phi_2\left(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon 1}}, \frac{z_2-\beta_2' x_{i2}}{\sigma_{\varepsilon 2}}, \rho\right) \tag{6}$$

Expressions to derive the other quantities of interest are also provided in Dang and Lanjouw (2014). We use the same procedures described earlier in the section to obtain estimates for the correlation coefficient of the error terms in survey round 1 and 2, ρ.

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[8] Dang and Lanjouw (2013) also propose an alternative approximation for ρ: $\rho = \frac{\rho_{y_{i1}y_{i2}} - \sqrt{R_1^2 R_2^2}}{\sqrt{1-R_1^2}\sqrt{1-R_2^2}}$, with the simple correlation coefficient as upper bound and the expression $\sqrt{R_1^2 R_2^2}$ as lower bound, where R_1^2 and R_2^2 represent the coefficients of determination obtained from estimating the consumption model in round 1 and round 2.

5. Results

In this section, we present the main results with respect to poverty dynamics. In subsection 5.1 we make use of all the available surveys, from 1996/97 to 2014/15, presenting the consumption model and the upper and lower bounds estimated for poverty mobility and immobility. In subsection 5.2, a more detailed analysis of poverty dynamics is presented for the period 2008/09–2014/15, corresponding to the last two available surveys in Mozambique. The upper and lower bounds estimated for poverty mobility and immobility are presented, but the poverty dynamics results obtained using a parametric estimation approach are also described. Moreover, in subsection 5.4 an analysis of vulnerability is provided, following Dang and Lanjouw (2014) and Dang and Dabalen (2017).

5.1 Poverty dynamics, 1996/97-2002/03-2008/09-2014/15

In order to analyze poverty dynamics in the period 1996/97 to 2014/15, we implemented a rather parsimonious consumption model regression, only including those covariates that were considered more likely to be time-invariant: gender and age of the household head, education level of the household head, provincial and rural dummies.[9] As discussed in footnote 4, the sample is restricted to households whose household head is between 25 and 55 years old in the first survey round under analysis, and the age range is restricted accordingly in subsequent survey rounds (see Dang et al. (2011) for details).

Summary statistics for the variables included and for all survey rounds, obtained without the restrictions imposed on the age of the household head, are found in Table A1 in the Appendix. Results concerning the consumption model implemented for all available surveys are presented in Table 2. Based on the coefficients obtained from the consumption model, we computed the conditional and unconditional probabilities presented in Tables 3 and 4. It can be immediately noticed that the boundaries of the estimated poverty dynamics are rather wide. As discussed in the methodology section, the width of the estimated boundaries depends on the quality of the underlying consumption model, namely, the overall explanatory power and the statistical significance of the individual regressors. Since we only had relatively few time-invariant characteristics that could be reasonably included in the consumption model presented, we decided to use the urban/rural and the province dummies as well. Including these regional characteristics greatly increased the quality of the overall model and helped taking into account shocks occurred at the urban-rural/provincial level (Dang et al., 2011). All the models are estimated at the household level and make use of population weights and cluster settings; the dependent variable is the log of real household consumption per capita, which is obtained as described in DNPO (1998), DNPO (2004), DNEAP (2010) and DEEF (2016).

In Table 3 unconditional probabilities are presented. They give the fraction of population in the selected age range that is in each of the four categories displayed – ‘Poor, poor’, ‘Poor, non-poor’, ‘Non-poor, poor’ and ‘Non-poor, non-poor’ –. For example, 'Poor, poor' indicates the fraction of population that was poor in year 1 and poor in year 2. This information is important to study poverty mobility and poverty immobility. Notwithstanding the relatively wide bounds, in the Mozambican case we can notice that a big fraction of the population falls in the category ‘Poor, poor’ in all years. This percentage is lowest when the years 2002/03 and 2014/15 are considered (22.5-35.6 per cent), but in general it appears that about a third of the population is consistently in this category. Looking at the categories ‘Poor, non-poor’ and ‘Non-poor, poor’, we estimate much lower fractions of the population in these categories, whereas nonnegligible fractions of the population

[9] The coefficients for provincial and rural dummies are omitted in Table 2, but are displayed in Table A2 in the Appendix.

are estimated in all years for the category ‘Non-poor, non-poor’. These results may point to a situation in which mobility between the different poverty states is not very likely, which is confirmed when analyzing conditional probabilities. Conditional probabilities represent the probability of each of the four states displayed in Table 3: ‘Poor to poor’, ‘Poor to non-poor’, ‘Non-poor to poor’ and ‘Non-poor to non-poor’. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1. In this case, the estimated bounds are even wider than in the unconditional probability case, but the estimated conditional probabilities with respect to the two states ‘Poor to poor’ and ‘Non-poor to non-poor’ are on average much larger than those estimated for the two states ‘Poor to non-poor’ and ‘Non-poor to poor’.

Table 2. Consumption model synthetic panel Mozambique, 1996/97-2002/03-2008/09-2014/15.

Dependent variable: log of household consumption per capita	1996/97	2002/03	2008/09	2014/15
Household head gender	-0.034	0.007	-0.013	-0.010
	(0.029)	(0.040)	(0.030)	(0.020)
Household head age	0.000	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Primary school (1st cycle, 5 years)	0.177	0.114	0.025	0.132
	(0.028)***	(0.033)***	(0.031)	(0.019)***
Primary school (2nd cycle, 7 years)	0.329	0.417	0.195	0.224
	(0.046)***	(0.055)***	(0.050)***	(0.024)***
Secondary school (1st cycle, 10 years)	0.522	0.725	0.387	0.496
	(0.087)***	(0.064)***	(0.050)***	(0.030)***
Secondary school (2nd cycle, 12 years)	1.021	1.105	0.799	0.856
	(0.100)***	(0.079)***	(0.069)***	(0.044)***
Tertiary or higher (13+ years)	1.775	2.339	0.993	1.564
	(0.261)***	(0.296)***	(0.113)***	(0.053)***
Constant	3.256	3.242	3.599	3.769
	(0.074)***	(0.088)***	(0.084)***	(0.062)***
Adjusted R2	0.163	0.191	0.126	0.251
N	5,757	6,130	7,765	22,578

Notes: For education level dummies, the years in parentheses represent the corresponding education years. Provincial and rural dummies omitted (shown in Table A2 in the Appendix). * p<0.1; ** p<0.05; *** p<0.01
Source: Authors’ calculations.

Table 3. Poverty dynamics. Non-parametric estimates of unconditional probabilities of poverty mobility and poverty immobility, 1996/97-2002/03-2008/09-2014/15.

Years	Category	Bounds		Years	Category	Bounds	
1996/97–	Poor, poor	0.529	0.337	2002/03–	Poor, poor	0.409	0.230
2002/03	Poor, non-poor	0.168	0.271	2008/09	Poor, non-poor	0.036	0.183
	Non-poor, poor	0.003	0.195		Non-poor, poor	0.121	0.300
N=5,969	Non-poor, non-poor	0.300	0.197	N=6,716	Non-poor, non-poor	0.435	0.288
1996/97–	Poor, poor	0.498	0.303	2002/03–	Poor, poor	0.366	0.205
2008/09	Poor, non-poor	0.115	0.243	2014/15	Poor, non-poor	0.083	0.206
	Non-poor, poor	0.035	0.230		Non-poor, poor	0.102	0.263
N=6,263	Non-poor, non-poor	0.352	0.224	N=18,047	Non-poor, non-poor	0.449	0.326
1996/97–	Poor, poor	0.461	0.273	2008/09–	Poor, poor	0.438	0.231
2014/15	Poor, non-poor	0.160	0.275	2014/15	Poor, non-poor	0.091	0.224
	Non-poor, poor	0.003	0.191		Non-poor, poor	0.034	0.241
N=16,889	Non-poor, non-poor	0.376	0.261	N=20,781	Non-poor, non-poor	0.437	0.304

Notes: The probabilities presented are estimated using the national poverty lines provided in the household surveys. The table provides the fraction of population in the selected age range that is in each of the four categories. For example, 'Poor, poor' indicates the fraction of population that was poor in year 1 and poor in year 2. The upper-bound estimates for poverty mobility (and lower-bound estimates for poverty immobility) are obtained by taking their average values over 50 repetitions (see Dang et al., 2011).
Source: Authors' calculations.

Table 4. Poverty dynamics. Non-parametric estimates of conditional probabilities of poverty mobility and poverty immobility, 1996/97-2002/03-2008/09-2014/15

Years	Category	Bounds		Years	Category	Bounds	
1996/97-	Poor to poor	0.760	0.555	2002/03-	Poor to poor	0.920	0.557
2002/03	Poor to non-poor	0.240	0.445	2008/09	Poor to non-poor	0.080	0.443
	Non-poor to poor	0.009	0.497		Non-poor to poor	0.217	0.510
	Non-poor to non-poor	0.991	0.503		Non-poor to non-poor	0.783	0.490
1996/97-	Poor to poor	0.813	0.555	2002/03-	Poor to poor	0.815	0.499
2008/09	Poor to non-poor	0.187	0.445	2014/15	Poor to non-poor	0.185	0.501
	Non-poor to poor	0.090	0.506		Non-poor to poor	0.186	0.447
	Non-poor to non-poor	0.910	0.494		Non-poor to non-poor	0.814	0.553
1996/97-	Poor to poor	0.742	0.498	2008/09-	Poor to poor	0.828	0.508
2014/15	Poor to non-poor	0.258	0.502	2014/15	Poor to non-poor	0.172	0.492
	Non-poor to poor	0.009	0.423		Non-poor to poor	0.072	0.442
	Non-poor to non-poor	0.991	0.577		Non-poor to non-poor	0.928	0.558

Notes: The probabilities presented are estimated using the national poverty lines provided in the household surveys. The table provides the probability of each of the four states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1. The upper-bound estimates for poverty mobility (and lower-bound estimates for poverty immobility) are obtained by taking their average values over 50 repetitions (see Dang et al., 2011).
Source: Authors' calculations.

5.2 An analysis of poverty dynamics in most recent surveys, 2008/09-2014/15

In this section a more detailed analysis of poverty dynamics is presented for the period 2008/09-2014/15. The household budget surveys IOF 2008/09 and IOF 2014/15 are the last two available surveys in Mozambique and are also the richest in terms of available information and sample numerosity. Consequently, the analysis of poverty mobility using these two survey rounds is probably the one that deserves more attention and that is more useful for policy making purposes.

We report here as well, for comparison, the upper and lower bound probabilities estimated for poverty mobility and immobility as presented in Tables 3 and 4; however, in this case we also present the poverty dynamics results obtained using the parametric estimation approach briefly described in the methodology section and presented in detail in Dang et al. (2011; 2014) and Dang and Lanjouw (2013), and applied for example in Dang and Dabalen (2017). In order to get the point estimates for poverty mobility, we need an estimate for the correlation coefficient between household consumption in the two survey rounds, ρ. Following Dang and Lanjouw (2013), we first approximate the simple correlation coefficient with the synthetic panel cohort-level simple correlation coefficient, and then compute the partial correlation coefficient, ρ, using the equations provided in the methodology section. With an estimate for ρ in hand, we may then turn to obtaining the point estimates for poverty mobility.

In our case, using Equation 5 we estimate a value of ρ equal to 0.736. This is in line with theory that expects a value of ρ to be bounded in the interval [0, 1]. Plus, validation analyses of the synthetic panel approach implemented using surveys from other countries have found that ρ is generally found within the interval [0.2, 0.8] (Dang and Lanjouw, 2013).[10] The point estimates for the unconditional and conditional poverty transition probabilities obtained using this estimate of ρ, together with the lower and upper bounds already shown in Tables 3 and 4, are presented in Table 5 and Figure 1. This analysis confirms that there is a high percentage of the population that is poor in both the first and the second period (37 per cent), or that is non-poor in both the first and the second period (39 per cent). The percentage of the population that is estimated to be poor in 2008/09 and non-poor in 2014/15 is about 15 percent, only 5 percentage points bigger than the proportion of the population that is non-poor in 2008/09 and poor in 2014/15 (about 10 percent), meaning that overall poverty mobility is not very likely, but also that the movements between the poverty and non-poverty states occur in both directions and in comparable magnitudes.

With respect to conditional probabilities, we estimate that the probability of a person being poor in 2014/15 given that he/she was poor in 2008/09 is substantially higher than the probability of becoming non-poor (69 versus 31 per cent). The high degree of poverty immobility is also reinforced by the high probability of remaining non-poor given that the person was non-poor in the previous period (79 percent), as opposed to a probability of 21 percent of becoming poor given that the individual was non-poor in 2008/09. Thus, conditional probabilities show that upward mobility is still more likely than downward mobility (31 versus 21 percent), but still less likely than remaining in the initial poverty or non-poverty state.

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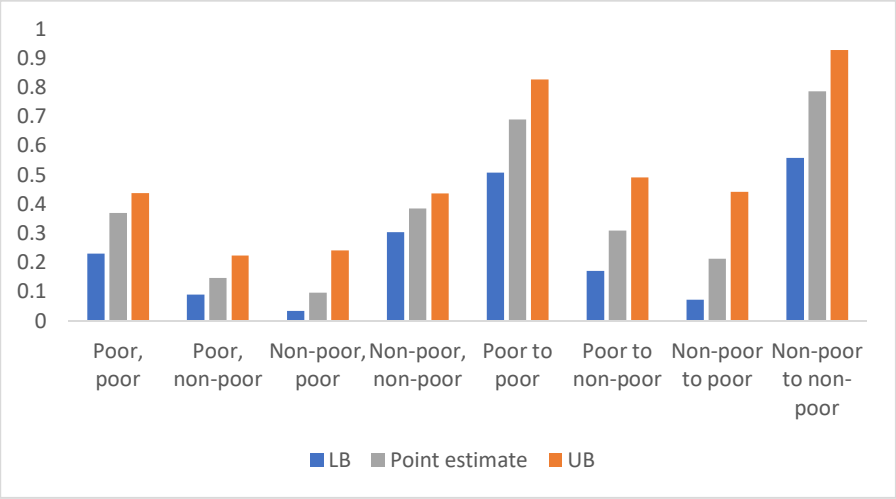
[10] As mentioned in footnote 8, Dang and Lanjouw (2013) propose an alternative approximation for ρ: $\rho = \frac{\rho_{y_{i1}y_{i2}} - \sqrt{R_1^2 R_2^2}}{\sqrt{1-R_1^2}\sqrt{1-R_2^2}}$, where ρ_{yi1yi2} is the simple correlation coefficient, and R_1^2 and R_2^2 represent the coefficients of determination obtained from estimating the consumption model in round 1 and round 2. Using this alternative approximation, we obtain a value for ρ equal to 0.655.

Table 5. Unconditional and conditional probabilities for poverty mobility, point estimates and bounds, 2008/09 and 2014/15.

	State	Bounds		Point estimate
Unconditional probabilities	Poor, poor	0.438	0.231	0.371
	Poor, non-poor	0.091	0.224	0.147
	Non-poor, poor	0.034	0.241	0.097
	Non-poor, non-poor	0.437	0.304	0.385
Conditional probabilities	Poor to poor	0.828	0.508	0.690
	Poor to non-poor	0.172	0.492	0.310
	Non-poor to poor	0.072	0.442	0.213
	Non-poor to non-poor	0.928	0.558	0.787

Notes: The probabilities presented are estimated using the national poverty lines provided in the household surveys. The "unconditional probabilities" panel provides the fraction of population in the selected age range that is in each of the four categories. For example, 'Poor, poor' indicates the fraction of population that was poor in year 1 and poor in year 2. The "conditional probabilities" panel provides the probability of each of the four states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1. The upper-bound estimates for poverty mobility (and lower-bound estimates for poverty immobility) are obtained by taking their average values over 50 repetitions (see Dang et al., 2011).
Source: Authors' calculations.

Figure 1. Unconditional and conditional probabilities for poverty mobility, point estimates and bounds, 2008/09 and 2014/15.



Notes: LB and UB stand for lower bound and upper bound, respectively. The probabilities presented are estimated using the national poverty lines provided in the household surveys. The "unconditional probabilities", presented first, provide the fraction of population in the selected age range that is in each of the four categories. For example, 'Poor, poor' indicates the fraction of population that was poor in year 1 and poor in year 2. The "conditional probabilities" provide the probability of each of the four states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1. The upper-bound estimates for poverty mobility (and lower-bound estimates for poverty immobility) are obtained by taking their average values over 50 repetitions (see Dang et al., 2011).
Source: Authors' calculations.

5.3 An analysis of poverty and vulnerability dynamics in most recent surveys, 2008/09-2014/15

In what follows, an analysis of vulnerability is provided, following the approach outlined in Dang and Lanjouw (2014). We already discussed in the methodology that this is based on the identification of a group of

vulnerable individuals out of the group of the non-poor. In particular, the vulnerable are those individuals whose daily real consumption per capita lies between the poverty line and the vulnerability line. Consequently, the non-vulnerable (also defined as "middle-class", "secure" or "prosperous") are the individuals whose daily real consumption per capita lies above the vulnerability line. In this analysis, following Dang and Lanjouw (2014), we do not set the vulnerability line at a value that is an arbitrary scaling up of the poverty line, but we derive the vulnerability line from a specified vulnerability index,[11] which is defined either as the probability of becoming poor at time 2 conditional on being in the middle-class at time 1 or as the probability of becoming poor at time 2 conditional on being vulnerable at time 1. The former is indicated as P^1, and is then defined as "insecurity index". Conversely, when the index of vulnerability is defined as the probability of becoming poor at time 2 conditional on being vulnerable at time 1, then it is indicated as P^2 and is defined "vulnerability index". Once the value of the insecurity index, P^1, or the value of the vulnerability index, P^2, are selected – derived for example from budgetary planning, social welfare objectives or relative concepts of well-being (Dang and Lanjouw, 2014) –, it is possible to compute the value for the vulnerability line and derive the transition probabilities for the three groups: poor, vulnerable and middle-class. In the Mozambican case, we do not have a clear guidance from economic and policy reports on these vulnerability-related targets, so in what follows we present a general analysis that can be subsequently tailored to the objectives of national policy makers once they become available and/or official.

Computing the vulnerability line for different values of the insecurity and of the vulnerability index, it appears that the probability of falling in poverty in 2014/15 given that the individual was vulnerable or even middle-class in 2008/09 is higher than in other contexts (see Dang and Lanjouw, 2014; Dang and Dabalen, 2017).[12] Hence, in the present analysis we start with a vulnerability index, P^2, of 25 percent. This means fixing the probability of becoming poor in 2014/15 conditional on being vulnerable in 2008/09 at 25 per cent. This entails setting the vulnerability line at a value of 75.3 Meticais, which in turn corresponds to scaling up the original poverty line by about 158 per cent and considering about 40 percent of the population as "vulnerable".[13]

The proportion of the population in each group is shown in Table 6.[14] Poverty reduced in the 2008/09–2014/15 period by about 5.5 percentage points, whereas the vulnerable group increased only slightly in percentage terms, and the middle-class expanded.[15]

The unconditional and conditional probabilities of mobility among the three groups identified by the poverty line and the newly computed vulnerability line are presented in Table 7.[16] With respect to unconditional probabilities, we have already noted that a big proportion of the population is estimated to be poor in both periods (37 percent); nonetheless, a substantial proportion of the entire population, about 14 percent, is found

[11] Dang and Dabalen (2017) and Dang and Lanjouw (2016) present the advantages of their approach with respect to choosing the cutoff points identifying the different income groups using for example a range of fixed percentiles of the income distribution (as in Alesina and Perotti, 1996) or some absolute cutoff thresholds (as in Banerjee and Duflo, 2008).

[12] As an example, Dang and Dabalen (2017) in their study use a vulnerability index of 15 percent, but in the present case if we implemented the same vulnerability index, we would get a very high vulnerability line that would leave in the middle-class group only a tiny percentage of the population.

[13] With this vulnerability line, the insecurity index, P^1, corresponds to 3.4 percent.

[14] These numbers differ, even if not very substantially, from the official poverty estimates for Mozambique because of the restrictions in the age range adopted in the synthetic panel analysis.

[15] This scenario, in which the first group reduces, and the second and third group expand, is defined in Dang and Dabalen (2017) as a scenario of "more positive pro-poor growth", which is the second possible best scenario in their classification.

[16] In what follows, only the point estimates for poverty transitions obtained using the parametric approach are presented.

in the state “poor, vulnerable”, reflecting the reduction in poverty observed between the two surveys. At the same time, about 23 percent of the population is found to be vulnerable in both periods, highlighting that even for households that are not in poverty, there is a relatively high chance to remain in the vulnerable group for relatively long periods. With respect to the middle-class, only a small proportion of the population is in this category, and the proportion of the population that is middle-class in both periods is even smaller (about 6 percent). Overall, there seems to exist a greater mobility between the poor and the vulnerable group, whereas a much more limited mobility towards the middle-class is observed.

Concerning conditional probabilities, and given the selected vulnerability index and vulnerability line, it appears that there is a nonnegligible probability for the poor in 2008/09 to become vulnerable in 2014/15, about 28 percent, but it seems extremely unlikely for the poor to become middle-class (about 2 percent). Conversely, for an individual who was in the vulnerable group in 2008/09, there is a high probability of remaining in the same group (59 percent), whereas the probability of becoming middle-class is lower than the probability of entering poverty (16 versus 25 percent). At the same time, for individuals who were middle-class in 2008/09 it is only slightly more likely to remain in the same group than becoming vulnerable, which seems surprising and it highlights the relatively high risk of a downward transition faced by even relatively well-off households.

Table 6. Proportion of the population in the poor, vulnerable and middle-class group with an insecurity index, P^2, set at 25%, 2008/09–2014/15

Year	Poor	Vulnerable	Middle-class
2008/09	0.527	0.397	0.076
2014/15	0.472	0.415	0.113

Notes: The proportions presented are estimated using the national poverty lines provided in the household surveys and the newly computed vulnerability line.
Source: Authors’ calculations.

Table 7. Point estimates for poverty-vulnerability transitions with an insecurity index, P^2, set at 25%, 2008/09–2014/15

Unconditional probabilities		Conditional probabilities	
Poor, poor	0.370	Poor to poor	0.692
Poor, vulnerable	0.137	Poor to vulnerable	0.284
Poor, middle-class	0.008	Poor to middle-class	0.024
Vulnerable, poor	0.096	Vulnerable to poor	0.250
Vulnerable, vulnerable	0.227	Vulnerable to vulnerable	0.592
Vulnerable, middle-class	0.063	Vulnerable to middle-class	0.158
Middle-class, poor	0.003	Middle-class to poor	0.034
Middle-class, vulnerable	0.037	Middle-class to vulnerable	0.446
Middle-class, middle-class	0.060	Middle-class to middle-class	0.520

Notes: The probabilities presented are estimated using the national poverty lines provided in the household surveys and the newly computed vulnerability line. Only the point estimates for poverty transitions obtained using the parametric approach are presented. The “unconditional probabilities” panel provides the fraction of population in the selected age range that is in each of the nine categories. For example, 'Poor, poor' indicates the fraction of population that was poor in year 1 and poor in year 2. The “conditional probabilities” panel provides the probability of each of the four states. For example, 'Poor to poor' indicates the probability of being poor in year 2, given that the individual was also poor in year 1.
Source: Authors’ calculations.

Conclusions

From the lack of longitudinal data in many developing countries it derives that not much is known about poverty dynamics and trajectories. Distinguishing between the chronic poor and those that only happen to be in poverty for a limited period of time is key to address the different facets of poverty and to design effective policies. Indeed, policy makers could consider addressing more transitory poverty for example with safety net programmes that can be adjusted to the local or sectoral context, such as sustainable insurance schemes for farmers exposed to weather shocks, well-designed social protection systems, employment insurance, among others. Conversely, households trapped in poverty will require different interventions that address the structural factors constraining these households from moving out of poverty, such as smallholder agriculture reduced productivity, gender discrimination, restricted access to land, poor infrastructure and others. It is a consolidated result in the literature that the longer people stay in poverty, the lesser seems to be their chance of getting out of it.

In this paper, we attempted to shed some light on the poverty dynamics in Mozambique, one of the poorest countries in Africa and in the world. However, there are no available household panel data spanning over a period of a few years for Mozambique. Hence, we gathered all the cross-sectional information available for the country and analyzed poverty dynamics using the synthetic panels approach introduced by Dang et al. (2011 and 2014) and by Dang and Lanjouw (2013; 2014), which permits to construct synthetic panel data from repeated cross sections. We found that an increasing proportion of people gets out of poverty over time, which is consistent with the poverty reduction process observed, but both the percentage of people staying in poverty and the percentage of people remaining out of poverty over time appear to be far higher, showing a sizeable degree of immobility with respect to the initial poverty status. The probability of being poor given that the individual was also poor in a previous survey round is on average much larger than the one estimated for the transition from poor to non-poor. Looking more thoroughly at the most recent household surveys, we also find that about a third of the population that was poor in 2008/09 is also poor in 2014/15, with a probability of a person being poor in 2014/15 given that he/she was poor in 2008/09 of about 70 per cent. Our estimates of conditional probabilities also show that upward mobility is still more likely than downward mobility (31 versus 21 percent), but it is still less likely than remaining in the initial poverty or non-poverty state. When the non-poor are further divided into vulnerable and middle-class, we get a richer analysis with respect to poverty dynamics and trajectories: i) we find that there seems to exist a greater mobility between the poor and the vulnerable group, whereas a much more limited mobility towards the middle-class is observed; also ii) it emerges that in the Mozambican case about 23 percent of the population is estimated to be vulnerable in both periods, highlighting that even for households that are not in poverty, there is a relatively high chance to remain in the vulnerable group for relatively long periods; iii) for an individual who was in the vulnerable group in 2008/09, there is a 60 percent probability of remaining in the same group, whereas the probability of becoming middle-class is lower than the probability of entering poverty (16 versus 25 percent); iv) at the same time, for individuals who were middle-class in 2008/09 it is only slightly more likely to remain in the same group than becoming vulnerable, which highlights the relatively high risk of a downward transition faced by even relatively well-off households.

This constitutes the first attempt to provide an insight into poverty dynamics in Mozambique using nationally representative survey data. For policy makers, this analysis provides important insights: given the high degree of poverty immobility and the high probability of remaining in the vulnerable group even if one manages to

escape poverty it seems reasonable to adopt a mix of temporary and chronic poverty approaches to tackle the poverty-vulnerability phenomenon in Mozambique. However, the value added of this analysis lies exactly in this attempt to quantify the proportion of people transitioning from one state to the other across different rounds and provide an estimation of the probabilities of escaping poverty and/or vulnerability over time. Covering two decades of the post-conflict development, this study contributes to finding viable solutions to reach the Sustainable Development Goal 1 for Mozambique.

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Appendix

Table A1. Summary statistics for the variables used in the analysis, 1996/97-2002/03-2008/09-2014/15

Variable	1996/97					2002/03				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Household real consumption pc	8,250	5.350	5.864	0.3	335.6	8,700	10.924	16.439	0.4	1574.9
Household head gender	8,273	0.825	0.380	0	1	8,700	0.795	0.404	0	1
Household head age	8,261	43.152	13.544	14	95	8,659	43.160	14.087	15	95
No education	8,273	0.690	0.462	0	1	8,700	0.697	0.460	0	1
Primary school (1st cycle, 5y)	8,273	0.203	0.402	0	1	8,700	0.177	0.382	0	1
Primary school (2nd cycle, 7y)	8,273	0.078	0.267	0	1	8,700	0.070	0.255	0	1
Secondary school (1st cycle, 10y)	8,273	0.019	0.137	0	1	8,700	0.034	0.182	0	1
Secondary school (2nd cycle, 12y)	8,273	0.009	0.096	0	1	8,700	0.020	0.140	0	1
Tertiary or higher (13+ y)	8,273	0.001	0.025	0	1	8,700	0.002	0.039	0	1
Niassa	8,273	0.050	0.218	0	1	8,700	0.051	0.220	0	1
Cabo Delgado	8,273	0.077	0.267	0	1	8,700	0.084	0.278	0	1
Nampula	8,273	0.188	0.390	0	1	8,700	0.188	0.391	0	1
Zambézia	8,273	0.193	0.395	0	1	8,700	0.192	0.394	0	1
Tete	8,273	0.068	0.251	0	1	8,700	0.077	0.266	0	1
Manica	8,273	0.057	0.232	0	1	8,700	0.067	0.250	0	1
Sofala	8,273	0.101	0.302	0	1	8,700	0.084	0.277	0	1
Inhambane	8,273	0.072	0.259	0	1	8,700	0.074	0.261	0	1
Gaza	8,273	0.070	0.255	0	1	8,700	0.070	0.255	0	1
Maputo Province	8,273	0.057	0.231	0	1	8,700	0.056	0.230	0	1
Maputo City	8,273	0.067	0.250	0	1	8,700	0.057	0.233	0	1
Rural	8,273	0.789	0.408	0	1	8,700	0.679	0.467	0	1

Variable	2008/09					2014/15				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Household real consumption pc	10,832	23.829	31.742	0.596	2844.9	33,185	47.092	99.732	0.049	12012
Household head gender	10,832	0.758	0.428	0	1	32,293	0.762	0.426	0	1
Household head age	10,813	42.592	13.973	13	105	32,293	43.854	14.107	14	99
No education	10,832	0.265	0.441	0	1	32,293	0.307	0.461	0	1
Primary school (1st cycle, 5y)	10,832	0.470	0.499	0	1	32,293	0.383	0.486	0	1
Primary school (2nd cycle, 7y)	10,832	0.143	0.351	0	1	32,293	0.151	0.358	0	1
Secondary school (1st cycle, 10y)	10,832	0.080	0.271	0	1	32,293	0.092	0.289	0	1
Secondary school (2nd cycle, 12y)	10,832	0.022	0.148	0	1	32,293	0.045	0.207	0	1
Tertiary or higher (13+ y)	10,832	0.020	0.139	0	1	32,293	0.022	0.147	0	1
Niassa	10,832	0.059	0.236	0	1	33,185	0.064	0.245	0	1
Cabo Delgado	10,832	0.078	0.269	0	1	33,185	0.074	0.261	0	1
Nampula	10,832	0.192	0.394	0	1	33,185	0.195	0.396	0	1
Zambézia	10,832	0.190	0.393	0	1	33,185	0.188	0.391	0	1
Tete	10,832	0.090	0.286	0	1	33,185	0.098	0.297	0	1
Manica	10,832	0.070	0.255	0	1	33,185	0.075	0.263	0	1
Sofala	10,832	0.081	0.273	0	1	33,185	0.079	0.270	0	1
Inhambane	10,832	0.061	0.240	0	1	33,185	0.058	0.234	0	1
Gaza	10,832	0.063	0.243	0	1	33,185	0.055	0.228	0	1
Maputo Province	10,832	0.063	0.243	0	1	33,185	0.066	0.248	0	1
Maputo City	10,832	0.052	0.222	0	1	33,185	0.049	0.215	0	1
Rural	10,832	0.696	0.460	0	1	33,185	0.683	0.465	0	1

Notes: All estimates are weighted with population weights.

Source: Authors' calculations.

Table A2. Consumption model synthetic panel Mozambique, 1996/97-2002/03-2008/09-2014/15

Dependent variable: log of household consumption per capita	1996/97	2002/03	2008/09	2014/15
Household head gender	-0.034	0.007	-0.013	-0.010
	(0.029)	(0.040)	(0.030)	(0.020)
Household head age	0.000	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Primary school (1st cycle, 5 years)	0.177	0.114	0.025	0.132
	(0.028)***	(0.033)***	(0.031)	(0.019)***
Primary school (2nd cycle, 7 years)	0.329	0.417	0.195	0.224
	(0.046)***	(0.055)***	(0.050)***	(0.024)***
Secondary school (1st cycle, 10 years)	0.522	0.725	0.387	0.496
	(0.087)***	(0.064)***	(0.050)***	(0.030)***
Secondary school (2nd cycle, 12 years)	1.021	1.105	0.799	0.856
	(0.100)***	(0.079)***	(0.069)***	(0.044)***
Tertiary or higher (13+ years)	1.775	2.339	0.993	1.564
	(0.261)***	(0.296)***	(0.113)***	(0.053)***
Niassa	-0.328	0.015	-0.059	-0.885
	(0.085)***	(0.079)	(0.086)	(0.060)***
Cabo Delgado	-0.046	-0.102	-0.127	-0.584
	(0.086)	(0.100)	(0.079)	(0.059)***
Nampula	-0.273	-0.014	-0.306	-0.748
	(0.082)***	(0.084)	(0.082)***	(0.053)***
Zambezia	-0.215	-0.002	-0.460	-0.772
	(0.073)***	(0.084)	(0.077)***	(0.055)***
Tete	-0.519	-0.316	-0.270	-0.488
	(0.080)***	(0.087)***	(0.094)***	(0.059)***
Manica	-0.099	-0.032	-0.405	-0.591
	(0.103)	(0.095)	(0.082)***	(0.057)***
Sofala	-0.723	0.204	-0.450	-0.595
	(0.078)***	(0.077)***	(0.141)***	(0.067)***
Inhambane	-0.481	-0.541	-0.248	-0.594
	(0.077)***	(0.084)***	(0.083)***	(0.061)***
Gaza	-0.096	0.004	-0.435	-0.655
	(0.089)	(0.077)	(0.094)***	(0.066)***
Maputo Province	-0.197	-0.224	-0.405	-0.121
	(0.080)**	(0.071)***	(0.060)***	(0.056)**
Rural	0.024	0.011	-0.015	0.075
	(0.053)	(0.044)	(0.049)	(0.028)***
Constant	3.256	3.242	3.599	3.769
	(0.074)***	(0.088)***	(0.084)***	(0.062)***
Adjusted R2	0.163	0.191	0.126	0.251
N	5,757	6,130	7,765	22,578

Notes: For education level dummies, the years in parentheses represent the corresponding education years. * p<0.1; ** p<0.05; *** p<0.01

Source: Authors' calculations.