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Analysis of poverty dynamics in Mozambique by Markov chains and pseudo panels

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Résumé In this paper, we explore household poverty dynamics in Mozambique. We construct a pseudo-panel from recurrent cross-section surveys based on a matching procedure with respect to time invariant characteristics. To describe the poverty dynamics in the pseudo-panel we use continuous time Markov-chain theory. It appears a powerful tool to estimate poverty measures beyond the commonly reported transition probabilities. The added measures include the stationary situation, the sojourn time in a certain poverty state and an index of mobility. We also provide probit regression results identifying the factors that influence the movements between poverty states.
Keywords : Poverty dynamics ; pseudo panel data, continuous time Markov chain ; stationary measures, Mozambique

6.1 Introduction

Several studies have observed that certain populations are characterized by considerable rates of transitions between poverty states over time (see, e.g. [13, 7]). Therefore poverty must be regarded as a dynamic phenomenon and one needs to complement the static perspective with a dynamic perspective that distinguishes between chronic and transitory poverty [9, 16] since chronic poverty can be expected to have a much larger affect on wellbeing (e.g., [5]). Accordingly, studies of poverty nowadays focus on the improvement of the well-being of the households who are currently poor but also on preventing others from falling into poverty [3].

Poverty dynamics are commonly analyzed in the framework of transition tables between subsequent poverty states [15, 6]. Those transition probabilities are best estimated from household panel data where poverty indicators are measured at multiple points in time. Unfortunately, true panel data are rare and, when available, they only represent part of the population. Furthermore, potential concerns with panel data include the attrition of the movers and the over-representation of those with rather stable conditions.

Several studies propose the use of repeated cross sectional (RCS) data to construct pseudo panels as an alternative to true panel data (e.g. [15, 6]). For instance, Dang et al. [6] used repeated cross sectional data to study poverty mobility and showed based on comparison with true panel estimates that the procedure performs well and provides reliable results. For many countries, a series of representative cross sections is available and contain a wealth of information on the evolution of poverty.

In this paper, we construct a pseudo-panel from two survey rounds in Mozambique. We analyze the transitions between poverty classes based on a continuous-time Markov chain approach. By applying the results of the theory of Markov chains (see, e.g. [8]) one can expand the common analysis beyond the description of the transitions between poverty states and derive a set of additional measures of interest. In a second step, we attempt to understand the determinants of poverty dynamics via probit regression and conditional analysis.

6.2 The Markov chain approach to poverty dynamics

Our model of the poverty dynamics of the households is a continuous time homogenous Markov chain X_t with infinitesimal generator Q on a set of poverty classes $S = \{\ s_0 = poor;\ s_1 = non\ poor\}$. Assumptions of the model imply that the transition probabilities are independent from the history of the household given its present state and that they remain constant over time.

When the chain is observed at regular time intervals of length δ, the obtained transition matrix equals $P(\delta) = e^{\delta Q}$ corresponding to the discrete-time embedded Markov chain (δ-skeleton) X_n, where X_n is the household poverty status at observation date t_n with $t_n - t_{n-1} = \delta,\ \forall n > 1$. Given two survey rounds, the transition matrix $P = P(\delta)$ is estimated using maximum likelihood method (e.g., [2]). The infinitesimal generator Q is obtained from P under the conditions that ensure the embedability of the discrete chain in the continuous-time process. A stochastic 2 by 2 matrix P is embeddable if and only if $det(P) > 0$ or equivalently $trace(P) > 1$ [12].

If the Markov chain is irreducible then it admits a unique stationary vector $v = (v_i)_{i \in S}$ where v_i represents the probability of a household to be in state i after a sufficiently long time irrespective of its initial state (also the stationary proportion of households in state i). Other measures that can be derived include the mean sojourn time in each poverty state.

A mobility measure that is commonly reported is the Shorrocks mobility index [17]. In its normalized form it writes for a given observation period

$$SMI\,(P) = 1 - Trace\,(P)\,/N, \text{ where } N = card(S).$$

6.3 Empirical results and discussion

We use two frames of a recurring household survey in Mozambique covering the years 2003 and 2009 [10, 11]. The data are used to construct a pseudo panel by means of a matching procedure based on time-invariant characteristics such as language, religion, and ethnicity and also sex, education, year of birth, place of birth, area of residence and education of the household head.

6.3.1 Results

The total number of households in the 2003 survey is 8678 of which 8560 have been matched. The poverty status of households in both surveys is calculated based on a national poverty line methodology [4, 1, 14].

The estimated transition matrix P of the observed discrete chain between two survey frames is $P = \begin{pmatrix} 0.5651 & 0.4349 \\ 0.3591 & 0.6409 \end{pmatrix}$ from which we also calculate Q. Their common stationary vector is given by $v = (0.4522, 0.5478)'$.

The off-diagonal elements of P as well as the Shorrocks mobility index (0.3970) show that the proportion of movers is considerable. The poverty prevalence will be around 45% in the long run. On average, a poor household stays 6.9 years in this status before moving, while the non-poor households stay a bit longer in their class (8.4 years).

Probit regression for factors influencing the transitions :

Probit regression results show some of the factors that have significant influence on the transition probabilities. For the poor class, these factors include household head literacy status, the presence of elderly, residence area (urban/rural) and household size. At the same time, the contribution of the age of the head of the household is small.

For the non-poor, the sex and the literacy status of the household head, the presence of elderly, residence area and the number of children are the most influential factors.

Conditional transition probabilities

Having identified some of the factors influencing the transition probabilities, we draw special attention to the duration of poverty and non-poverty spells in sub-groups of the population. Particular conditions are examined in the following :

1. Residence area (urban/rural) : Rural households have a high probability to stay in poverty if they are poor (0.63) or to slip into poverty if they are not (0.50). They spend in average 7 years in poverty state but less (5.1 years) in non-poverty state. At the opposite, poor urban households have higher probability to get out of poverty (0.6) and they stay shorter in poverty state (4.3 years). The non-poor urban households have probability 0.74 to remain and they stay 9.9 years in non-poverty state on average. In the long run, only 30% of the households in the urban area will be poor as opposed to 58% of the households in the rural area.

2. Literacy status of the household head : Households with a literate head have higher probability to move out of poverty and lower probability to slip into it as compared to households with an illiterate head. They also spend in average less time in poverty state and more time in non poverty state. In the long run, 38% of households with literate head will be in poverty state as compared to 55% in the opposite group.

3. Sex of the household head : The results don't show much influence of the sex of the household head on the poverty dynamics measures, though male headed households seem at a slight disadvantage.

4. Residence is rural area and illiteracy of the household head : Under these conditions the probability to be poor in the long run is 0.59 and the main sojourn time is 7.5 years in poverty state and 5.2 years in non-poverty state.

6.4 Conclusion

This paper tries to contribute to the debate on poverty dynamics in Mozambique between 2003 and 2009. To achieve this aim, we construct a pseudo panel using a matching technique then we construct a continuous Markov chain model. This approach expands the analysis beyond the estimation of transition probabilities and provides a set of useful measures such as the long run poverty prevalence and the mean time spent in each poverty state.

Empirically, the results show that poverty in Mozambique is high and persistent. Mobility in and out of poverty is considerable. Rural households are more severely hit by poverty while education is consistently among the factors that can reduce poverty in Mozambique.

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