POVERTY DYNAMICS IN NAIROBI'S SLUMS, TESTING FOR STATE DEPENDENCE AND HETEROGENEITY

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Abstract: In this paper, we have been able to offer some insights in the dynamics of poverty in Nairobi's slums. A very interesting result of this paper is that there is substantial state of dependence in poverty after controlling for initial poverty status and for panel retention.

Keywords: Poverty dynamics, state dependence, unobserved heterogeneity, attrition, simulated maximum likelihood, urban poverty.

JEL Classification: C15, C35, I32, O18, R23

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1. Introduction

What are the factors associated with becoming or remaining poor? Who are the individuals at risk of entering or exiting poverty? Is it the same individuals who are stuck in poverty? In other words, does poverty experienced in one period has a causal effect on future poverty? Do individuals who are poor have particular characteristics making them prone to poverty? Answers to these questions are central to understand poverty and then inform public policies aimed at fixing it.

Furthermore, when poverty persists over time, policy makers have good reasons for concern over the impact of such long lasting deprivation. Also, since public resources are limited, it is important to understand the dynamic of poverty for a better targeting of the poverty alleviation policies. This paper explores poverty persistence and the determinants of transition into and out of poverty using panel data collected in two Nairobi's demographic surveillance sites.

There are two main processes that may generate poverty persistence. First, the fact of experiencing poverty in a specific time period, might in itself increase the probability of being poor in subsequent periods (through human capital deterioration, decreasing self-esteem, *etc*.). Such a process is said to exhibit *state dependence* (Heckman, 1978). Second, differences in characteristics that make individuals prone to poverty might increase the chance of falling into poverty and persistent over time. In that case, individuals who experience poverty at time t because of these (possibly unobserved) characteristics will also be likely to be poor in any other period because of the very same characteristics. This process is referred as *unobserved heterogeneity* effects.

Distinguishing between the two processes is important, since the policy implications are very different. If poverty persistence is due to state dependence effects, then a policy aimed at fighting poverty *via* monetary transfers makes sense. Such a policy will help not only wiping out current poverty but also preventing future poverty. In contrast, if poverty persistence is due to unobserved heterogeneity effects, a policy of monetary transfers will not be the most effective option.

However, if understanding these two sources of poverty persistence is crucial for designing effective and successful poverty alleviation policies, it is worth noting that few studies in Africa have investigated these issues, despite the priority given to fighting poverty in most the African countries. The reason is that tackling these issues requires accurate and comprehensive socio-economic data collected regularly on the same individuals or households over time. Alas, such data are not oftenly collected in the region.

This paper takes advantage of the uniquely rich dataset from the Nairobi Urban Health and Demographic Surveillance System (NUHDSS). The NUHDSS is run by the African Population and Health Research Center (APHRC). It was set up in 2000 to provide a platform for investigating changing linkages between urbanization, poverty and health and to evaluate the impact of interventions aimed at improving the wellbeing of slum residents. It covers about 60,000 people living in 15,000 households in two slum settlements in Nairobi City, Korogocho and Viwandani. The surveillance involves visits to all the households once every four months to update information on pregnancies and pregnancy outcomes, migration, episodes of morbidity, health seeking behavior, mortality and causes of death, vaccination coverage, marital status, school attendance, livelihood sources, possessions, shocks, and vulnerabilities, including coping strategies of households and individuals.

The paper is structured as follows. Section 2 reviews the related literature. The estimation strategy is outlined in the section 3. Section 4 describes the data and discusses the explanatory variables. Discussion of the results follows in section 5, while section 6 concludes.

2. Related literature

Since Heckman's works (1978, 1981), the question arises whether persistence in economic phenomena is due to differences in individual characteristics or due to causal effects of past on future outcomes. Examples range from unemployment issues (Heckman, 1978, 1981; Arulampalan *et al.*, 2000), persistence in low pay (Stewart and Swaffield, 1999; Cappellari and Jenkins, 2004) and analysis of poverty persistence (Biewen, 2004; Cappellari and Jenkins, 2002).

Different approaches have been used to study the dynamics and persistence of these economic phenomena. A seminal work by Lillard and Willis (1978) uses the estimation of components-of-variance models to study poverty in relation to the evolution of earnings or income over time in a sample of male household heads. Using their estimates of the permanent and transitory variance components of male earnings, Lillard and Willis derived probabilities of various time sequences of poverty or low-earnings status.

Bane and Ellwood (1986) use a hazard rate approach to measure poverty persistence. They study individual spells of poverty and estimate the probability of ending these poverty spells, allowing for duration dependence in the hazard rate. But a major drawback of Bane and Ellwood is that it focuses on single spells while many individuals in their sample experience more than one poverty spell in the observed time frame. Using the hazard rate approach to study individual poverty persistence over life time, Stevens (1999) addresses this issue. She accounts for multiple spells of poverty and incorporates spell duration, individual and household characteristics, and unobserved heterogeneity. Her findings highlight the importance of considering multiple spells in an analysis of poverty persistence, with half of those who end poverty spells returning to poverty within four years.

What is common in these previous studies is the effort to capture the effects of current on future poverty. However, except Stevens (1999), they do not clearly distinguish between the potential sources of poverty persistence. Recent studies explore the causes of poverty persistence using dynamic discrete choice models which control for state dependence and unobserved heterogeneity. Noticeable studies include Stewart and Swaffield (1999), Cappellari and Jenkins (2002, 2004), Devicienti (2002), Poggi (2003). Most of these studies, assume a first-order stationary Markov chain for state dependence, and combine it with individual fixed-effect or random-effects models to fix the unobserved heterogeneity issue. But it is worth noting that the model proposed by Cappellari and Jenkins (2004) goes further, allowing accounting for multiple endogenous selection mechanisms with panel data such as attrition, initial conditions, etc.

3. Estimation strategy

State dependence effects are usually analyzed using dynamic discrete models with unobserved heterogeneity. If I_{it} denotes poverty status of individual $i = 1,\ldots,N$ at time $t = 1,\ldots,T$,

$$I_{it} = \mathbf{1}\{\alpha\, I_{it-1} + \varphi\, z_{it} + \delta_i + \varepsilon_{it} < c\} \tag{1}$$

$\mathbf{1}\{\cdots\}$is an indicator function describing the evolution of poverty conditional on *i*'s poverty status at the previous period, a vector of exogenous variable z_{it}, and two unobserved characteristics δ_i and ε_{it}. The individual-specific term δ_i stands for all unobserved determinants of poverty that are time-invariant for a given individual. The residual term ε_{it} is idiosyncratic and is assumed to follow a normal distribution with zero mean, unit variance: $\varepsilon_{it} \rightarrow \aleph(0,1)$. The binary variable I_{it} is equal to 1 if the disposable income[1] is below the threshold *c* referred as the poverty line, and 0 otherwise.

The value of α determines how I_{it} takes in state dependence. If $\alpha > 0$, experiencing poverty at time *t-1*($I_{it-1} = 1$) increases the chance of being poor at time *t* ($I_{it} = 1$):

$$\Pr(I_{it} \mid I_{it-1} = 1, \delta_i) > \Pr(I_{it} \mid I_{it-1} = 0, \delta_i)$$

[1] The disposable income is specified here as a linear function of individual poverty status at time t-1, personal characteristics and a normally distributed error term.

$$\approx$$

$$\Pr(\varepsilon_{it} < -\delta_i - \alpha) > \Pr(\varepsilon_{it} < -\delta_i)$$

However, it is noteworthy that the specification above does not properly control for individual observed or unobserved heterogeneity. In the presence of individuals' characteristics, such as ability, motivation, or intelligence, that make them prone to poverty, we will also observe $\Pr(I_{it} \mid I_{it-1} = 1, \delta_i) > \Pr(I_{it} \mid I_{it-1} = 0, \delta_i)$ given that these characteristics persist over time and even though $\alpha = 0$. Therefore, for testing of genuine state dependence, it is crucial to correctly control for individual heterogeneity.

A strategy to address this issue consists of imposing a distribution structure to δ_i and interpreting equation (1) as a random-effect model. Then one can obtain a likelihood function for α by integrating out the unobserved term δ_i (Arellano and Honoré, 2001; Cappellari and Jenkins, 2002, 2004; Biewen, 2007). But the question arises whether results depend on the imposed function forms and distribution assumptions.

Another issue is that poverty status in the initial period may also be correlated with the factors captured by δ_i. This issue is usually referred as the initial condition problem. Ignoring it can lead to distorted estimates, particularly in short panels (Arulampalan *et al.*, 2000; Heckman, 1981). The initial conditions problem can be solved in different ways. One way to deal with it, suggested by Wooldridge (2005/2002), is to let the initial conditions be random by using the joint distribution of all outcomes of the endogenous variables conditional on observed and unobserved heterogeneity.

In this paper, we investigate the state dependence effects while accounting for these heterogeneity issues using Cappellari and Jenkins' model (2002, 2004). Cappellari and Jenkins build on Stewart and Swaffield (1999) and develop a model of transition probabilities that accounts for initial conditions problem but also for panel attrition between times *t-1* and *t*. The interest in Cappellari and Jenkins' model is that it allows accounting simultaneously for multiple endogenous selection issues (e.g. initial conditions, attrition, etc.) and testing for ignorability of one or more of these selection mechanisms. Moreover, the setting proposed by Cappellari and Jenkins circumvents the assumption of no feedback effect from the dependent variable on future value of the explanatory variables, unlike most of the models investigating poverty persistence (see Biewen, 2004, 2007; Aassve *et al.*, 2004).

In Cappellari and Jenkins model, equation (1) is re-specified as a dynamic probit model as follows:

$$\Pr\left(I_{it}=1 \mid I_{it-1}, R_{it}=1\right)=\Phi\left(\alpha\, I_{it-1}+\varphi\, z_{it-1}+\delta_i+\varepsilon_{it}\right),\;\; \left(\upsilon_{it}=\delta_i+\varepsilon_{it}\right) \rightarrow \aleph(0,1) \quad (2)$$

Where I_{it-1} and R_{it} represent initial poverty status and attrition status respectively. The model allows a simple test for state dependence based on whether $\alpha > 0$; if true, poverty state at time *t* depends on being poor at time t-1.

The initial condition for poverty status is implemented by a probit model as follows:

$$\Pr\left(I_{it-1}=1\right)=\Phi\left(\beta\, x_{it-1}+\lambda_i+\mu_{it-1}\right),\quad \left(\theta_{it-1}=\lambda_i+\mu_{it-1}\right) \rightarrow \aleph(0,1) \quad (3)$$

The retention status (i.e. the probability of not suffering from attrition between *t-1* and *t*) is also given as a probit model:

$$\Pr\left(R_{it}=1\right)=\Phi\left(\chi\, w_{it-1}+\eta_i+\xi_{it}\right),\quad \left(\psi_{\mathrm{it}}=\eta_i+\xi_{it}\right) \rightarrow \aleph(0,1) \quad (4)$$

Where: x_{it-1} and w_{it-1} are vectors of explanatory variables of initial poverty status and retention status equations.

The joint estimation of the three equations involves the evaluation of the log-likelihood over *i = 1,…,N* based on a joint trivariate probability. The contribution if each individual to the log-likelihood is as follows:

$$\begin{aligned} LogL = R_{it}\, Log\left[\Phi_3\left(\kappa_T\left(\alpha' I_{it-1}+\varphi' z_{it-1}\right), \kappa_R \chi' w_{it-1}, \kappa_I \beta' x_{it-1}; \kappa_T \kappa_R \rho_3, \kappa_T \kappa_I \rho_2, \kappa_R \kappa_I \rho_1\right)\right] \\ + \left(1\text{-}R_{it}\right) Log\left[\Phi_2\left(\kappa_R \chi' w_{it-1}, \kappa_I \beta' x_{it-1}; \kappa_R \kappa_I \rho_1\right)\right] \end{aligned} \quad (5)$$

Where:

$$\kappa_T = 2I_{it}-1;\quad \kappa_R = 2R_{it}-1;\quad \kappa_I = 2I_{it-1}-1$$

$\kappa_{T,R,I}$ are the corresponding sign variables that to 1 or -1 depending on whether the observed binary outcome equals 1 or 0.

The estimation assumes that the error terms of the three equations (2), (3), and (4) are multivariate normal distributed with zero mean, unit variances, and a covariance matrix Σ. We allow, however, for correlated disturbances:

$$\begin{aligned} \rho_1 &= corr\left(\theta_{it-1}, \psi_{it}\right)=\operatorname{cov}\left(\lambda_i, \eta_i\right) \\ \rho_2 &= corr\left(\theta_{it-1}, \upsilon_{it}\right)=\operatorname{cov}\left(\lambda_i, \delta_i\right) \\ \rho_3 &= corr\left(\psi_{it}, \upsilon_{it}\right)=\operatorname{cov}\left(\eta_i, \delta_i\right) \end{aligned} \quad (6)$$

These three correlation coefficients ($\rho 1$, $\rho 2$, $\rho 3$) will be estimated and will represent the extent to which unobserved covariates jointly determine the outcomes of interest. It is worth mentioning that proceeding this way, the coefficient estimates from the trivariate probit model will account for unobserved correlation among the outcomes and will be therefore less biased and more efficient than those produced by three independent models.

The estimation of (5) requires the computation of derivatives of third order integrals for which no general solutions exist. However, the problem can be addressed by recently developed simulation techniques. The method of simulated maximum likelihood allows the estimation of a trivariate probit model by using the GHK (Geweke-Hajivassiliou-Keane) smooth recursive estimator (see Greene, 2003). The GHK smooth recursive estimator decomposes the original three-dimensionally correlated error terms into a linear combination of uncorrelated one–dimensional standard normal variables. The trivariate distribution is thus transformed into three sequentially conditioned univariate distributions. In order to evaluate the resulting integral, D Halton draws of these standard normal variables are taken from truncated normal distributions, and a sample average of the simulated likelihoods is used to estimate the probability that enters the likelihood function.

4. Data and descriptive statistics

The analysis is based on data from the Nairobi Urban Health and Demographic Surveillance System (NUHDSS) run by APHRC since 2002. The dataset contains information on the well-being of the approximately 13,000-15,000 households (60,000 individuals) that live at any one point in time in two of Nairobi's main informal settlements Viwandani and Korogocho; in particular the 3rd and 13th round of the DSS undertaken in 2003 and 2006. Data on livelihood, possessions, shocks, and vulnerabilities, including coping strategies of households and individuals have been collected during these two rounds.

The focus of this paper is on household expenditure as a measure of welfare. An individual is defined as poor if her household equivalent expenditure is less than a given poverty line. The latter corresponds to Nairobi official poverty line from Kenya National Bureau of Statistics (KNBS). The Nairobi poverty lines are 2640 and 2913 Kenya Shillings per month per person (in adult equivalent terms) in 2003 and 2006 respectively. The expenditure variable considered is the "equivalent household expenditure, obtained after adding up all expenses of the household comprising food, non-food and durable items, and then dividing the total by the number of equivalent adults (considering a child as half of an adult). Our unit of analysis is the individual. We assume an equal sharing of resources within the household; each member receives the same value of the equivalent household expenditure.

Table 1 shows the raw poverty transition matrix constructed from the dataset. The first part of the table indicates poverty transition for all individuals present in the two rounds.

Table No 1: Poverty inflow and outflow between rounds 3 and 13 (row %)
with and without missing

Poverty status round 3	Poverty status round 13		
	Non poor	Poor	Missing
1. Sample (missing at round 3 excluded)			
Not Poor	75.30	24.70	
Poor	14.58	85.42	
Total	33.55	66.45	
2. All individuals			
Not Poor	35.30	11.58	53.12
Poor	8.83	51.74	39.43
Total	18.62	36.89	44.49

Results indicate that one quarter of those who were not poor in round 3 have become poor in round 13 while only 15 % of those who were poor in 2003 were no longer poor in 2006. In round 13, the poverty rate among those previously poor is 60 percentage points higher than the poverty rate among those non-poor in round 2. Yet, this clearly indicate that the poverty status in a given period depend substantially on past poverty status. There is inertia in the dynamic of the poverty status that suggests a state dependence effect.

The second section of table shows of the poverty transition matrix taking into account the high mobility observed in the slums. Results in this section confirm what have been already in the first part of the table. But what is worth highlighting is the difference in the retention status regarding the previous poverty status. The proportion of those who have left the slums is higher among those not poor in round 3. This suggests that the slums just constitute a transit platform for the non-poor. Then, if this is case, the retention in the panel is non-random. To get consistent estimates, we should therefore specify an equation characterizing the retention mechanism and jointly estimate it with the poverty transition equation.

The variables we use in our estimations are: household characteristic (household size, household composition, gender of the head of household, age of the head of household, occupational status of the head of household, number of workers within the household), individuals' characteristic (gender, age and age square, occupational status, occupational sector using 4 categories) and dummy variables for housing tenure, living areas, and ethnic groups. All these variables are measured using their value in round 3, and assumed exogenous. These variables are included in each of the vectors x_{it-1}, w_{it-1} and z_{it-1}. The retention and initial poverty equations include a number of additional variables excluded from the poverty transition equation for model identification. For the retention equation, we consider two excluded variables. The first is a dummy variable indicating whether the household or one of its members have experienced a shock such theft, rape, fire, mugging or demolition in the year preceding the survey. The second excluded variable corresponds to a binary variable which indicates whether the individual was enumerated when the DSS started in 2002 or whether she has joined it latter. For the initial poverty equation the excluded variables correspond to the shock dummy mentioned above and a binary variable indicating if one household member has experienced severe illness during the year preceding the survey.

Table A1 provides descriptive statistics of selected variables.

5. Estimation results

Table 2, 3 and 4 present the results from the trivariate probit regression. Estimates of the cross-equations correlations between the unobserved characteristics provide insights about the endogenous selection processes. Results in table 3 indicate that the correlations associated with the sample retention are not significant. This suggests that the sample retention mechanism could be ignored. In contrast the correlation associating initial condition and poverty transition equations cannot be firmly rejected event the correlation is not strongly significant. The test of ignorability confirms the rejection of the endogeneity of panel retention. The test also rejects the null hypothesis that initial poverty status is exogenous for poverty transition. Further, the test for the joint significance of the three correlation coefficients suggests that they are jointly significant at 5 percent.

Table No 2: Estimated correlation coefficients of unobservable and tests of ignorability

Correlations of unobservable	Coefficients	Std. Errors
$\rho_1 = \text{cov}(\lambda_i, \eta_i)$: Initial poverty status, retention	-0.005	(0.008)
$\rho_2 = \text{cov}(\lambda_i, \delta_i)$: Initial poverty status, poverty transition	-0.178	(0.061)*
$\rho_3 = \text{cov}(\eta_i, \delta_i)$: retention, poverty transition	0.040	(0.068)
Wald tests of ignorability	**Chi-2**	**P-Value**
Exogeneity of panel retention : $\rho_1 = \rho_3$	0.84	0.6573
Exogeneity of Initial condition : $\rho_1 = \rho_2$	0.657	0.0136
Joint exogeneity : $\rho_1 = \rho_2 = \rho_3$	8.98	0.0296

Table 3 shows the impacts explanatory variables on poverty transition. Evidence clearly indicates a significant and sizeable state dependence effect. Being poor in the past increases the chance of experiencing future poverty once the heterogeneity is controlled for. This confirms our descriptive findings in table 1. Further, there are few explanatory variables with significant effect. Individuals living in households with many members or households with high proportion of children are associated with a high probability of being poor. It also appears that individuals living in their house within the slums are very prone to poverty. In contrast, having a male as a head of household is associated with a lower probability of becoming or remaining poor. It is worth highlighting that the covariates related to employment have no significant effects.

Table No 3: Poverty transition

Explanatory variables	Coefficients	Std. Error
Initial poverty	1.859	(0.097)***
Household Characteristics		
Housing tenure	0.083	(0.026) ***
Household size	0.037	(0.008) ***
Number of workers	-0.001	(0.009)
Household composition (reference: adults [35-49])		
children [0-5}	0.564	(0.085) ***
Children [6-12]	0.295	(0.084) ***
Children [13-17]	0.550	(0.089) ***
Adults [18-34]	0.101	(0.054) *
Old [50-59]	-0.006	(0.079)
Old [60 +[	-0.005	(0.118)
Individual's characteristics		
Sex (Male)	-0.047	(0.018) ***
Age	-0.003	(0.002) *
Age square	0.000	(0.000)
Employee informal sector	0.049	(0.031)
Self-employee informal sector	0.039	(0.029)
Other sector	-0.068	(0.087)
Kikuyu	-0.072	(0.032) **
Kamba	-0.117	(0.038) ***
Luo	-0.207	(0.035) ***
Luhya	-0.112	(0.039) ***
Kisii	-0.036	(0.059)
Somali	0.093	(0.055) *
Head of household Characteristics		
Age	0.003	(0.005)
Age square	0.000	(0.000)
Sex (Male)	0.007	(0.022)
Occupational status	-0.066	(0.093)
Korogocho	0.048	(0.041)
Constant	-1.238	0.180***
Log-likelihood	-78602.154	
Model chi-square (d. f. = 28)	9202.40 (p < 0.000)	
Number of observations	57627	

Table No 4: Initial poverty and retention estimates

	Initial poverty		Retention	
	Coeff.	St. Error	Coeff.	St. Error
Household Characteristics				
Housing tenure	-0.191	(0.018) ***	0.370	(0.017) ***
Household size	0.175	(0.005) ***	0.028	(0.004) ***
Number of workers	0.150	(0.006) ***	-0.003	(0.005)
Household composition (reference: adults [35-49])				
children [0-5}	0.797	(0.052) ***	0.520	(0.059) ***
Children [6-12]	0.402	(0.056) ***	0.776	(0.051) ***
Children [13-17]	-0.538	(0.063) ***	0.368	(0.059) ***
Adults [18-34]	0.223	(0.036) ***	-0.138	(0.033) ***
Old [50-59]	0.084	(0.059)	-0.045	(0.055)
Old [60 +[	0.377	(0.089) ***	-0.156	(0.087) *
Individual's characteristics				
Sex (Male)	-0.001	(0.012)	0.065	(0.011) ***
Age	-0.002	(0.001)	0.002	(0.001) **
Age square	0.000	(0.000)	0.000	(0.000) ***
Employee informal sector	0.360	(0.019) ***	-0.053	(0.018) ***
Self-employee informal sector	0.216	(0.020) ***	0.032	(0.019) *
Other sector	0.065	(0.068) ***	0.112	(0.062) *
Kikuyu	0.252	(0.023) ***	-0.042	(0.002) *
Kamba	0.333	(0.025) ***	-0.120	(0.024) ***
Luo	0.322	(0.025) ***	-0.215	(0.023) ***
Luhya	0.382	(0.026) ***	-0.162	(0.024) ***
Kisii	0.451	(0.037) ***	0.152	(0.036) ***
Somali	-0.383	(0.041) ***	-0.048	(0.039)
Head of household Characteristics				
Age	-0.017	(0.003) ***	0.016	(0.003) ***
Age square	0.000	(0.000) ***	-0.000	(0.000) ***
Sex (Male)	-0.046	(0.016) ***	0.048	(0.015) ***
Occupational status	-0403	(0.071) ***	0.161	(0.066) **
Korogocho	0.654	(0.014) ***	0.782	(0.013) ***
Shock	-0141	(0.016) ***	-0.187	(0.015) ***
Severe illness	-0230	(0.022) ***		
Migrant			0.372	(0.012) ***
Constant	-1.216	(0.115) ***	-1.406	(0.107) ***
Log-likelihood	-78602.154			
Model chi-square (d. f. = 28)	9202.40 (p < 0.000)			
Number of observations	57627			

6. Conclusion

In this paper, we have been able to offer some insights in the dynamics of poverty in Nairobi's slums. A very interesting result of this paper is that there is substantial state of dependence in poverty after controlling for initial poverty status and for panel retention. Indeed, our results show some heterogeneity effects but few covariates in the poverty transition equation are statistically significant.

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