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Poverty Dynamics in Nairobi's Slums: Testing for State Dependence and Heterogeneity Effects

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Abstract

We investigate the factors underlying poverty transitions in Nairobi's slums focusing on whether differences in characteristics make people more prone to enter poverty and persist in, or whether past experience of poverty matters on future states. Understanding these issues is essential for the design of effective policy programs aimed at enhancing the lives of the poor. The paper uses an endogenous switching model, which accounts for initial conditions, non-random attrition, and unobserved heterogeneity. Estimations are based on a panel dataset from the Nairobi Demographic Surveillance System. Results indicate that true state dependence (TSD) constitutes the major factor driving poverty persistence. There are little heterogeneity effects. Even when household and individual observed characteristics differ notably, the TSD size remains very large. Active anti-poverty programs aimed at breaking the cycle of poverty constitute then the most appropriate policies for taking people out of poverty and preventing them to fall back in.

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1. Introduction

What are the factors that make people entering poverty or remaining in? Who are the individuals at risk of entering or exiting poverty? Is it the same individuals who are stuck in poverty over time? In other words, does poverty experienced in one period impact upon the risk of experiencing poverty at another? Do individuals who are poor have particular characteristics making them prone to persistent or "chronic" poverty? Addressing these questions is crucial for understanding poverty and for informing public policies aimed at tackling it.

When poverty persists over time, policy makers have good reasons to be concerned over the impact of such long lasting deprivation. In addition, since public resources are limited, it is important to understand the dynamics of poverty for better targeting of the poverty alleviation policies. This paper explores poverty persistence and the determinants of transition into poverty, using panel data collected in two slum settlements in Nairobi city during the early 2000s.

The persistence into poverty is comparable to many other economic situations (unemployment, low-pay, health or nutritional status, etc.) where those who have experienced an event in the past have higher probability of experiencing that event in the future, as compared to those who have not experienced it previously. Two possible sources of this persistence are unobservable heterogeneity and true state dependence (Heckman, 1981). Heterogeneity arises because of differences in characteristics that make an individual prone to experience the same events repeatedly. Some of those characteristics will be observables (for instance human capital endowments) and controllable for in empirical analysis. The difficulty arises with unobservable characteristics that affect the probability of being poor. Examples that could reflect unobserved heterogeneity are ability, risk attitude, laziness, culture of dependency, or individual-specific genetic, biological or health traits that are unknown by researchers. These characteristics make those concerned individuals susceptible to some conditions that increase their chance of falling into poverty. If these traits persist over time, they will induce persistence into poverty. Then, failure to account for them could lead to serious bias. That is, one might falsely attribute persistence to causal effects of past to future poverty (spurious state dependence effect). On the contrary, true state dependence (TSD) emerges when the fact of experiencing an event in one period might per se increase the chance of living the same event repeatedly in the subsequent periods. That is, past events cause future events.

Distinguishing a true state dependency from a spurious one due to unobserved heterogeneity has substantial policy implication. If the persistence in poverty is mainly driven by unobserved heterogeneity, short-run policies such as cash transfers will not be justified since they will have little impacts on factors driving individual's long-term deprivation status. Then the most appropriate policy response would be policies aimed at addressing those characteristics so as to prevent people falling in poverty. In contrast, in the presence of true state dependency, policies addressing current poverty situations will have much more impacts, as they not only fix current poverty situation but also will allow preventing future ones. When true state dependency prevails, short-run actions yield long-lasting effects.

However, given the crucial importance of distinguishing between state dependence and individual heterogeneity, it is surprising that few studies in Africa have investigated these issues, despite the priority given to fighting poverty in the continent. One explanation for such a situation might be data related. In order to study these issues, it is necessary to have accurate and comprehensive socio-economic data collected regularly on the same individuals or households over time. Unfortunately, such data are not often readily available in the region. This paper takes advantage of the uniquely rich dataset from the Nairobi Urban Health and Demographic Surveillance System (NUHDSS), which was set up by the African Population and Health Research Center (APHRC) in 2002 to provide longitudinal data for investigating issues related to urbanization, poverty, and health outcomes, and to evaluate the impact of interventions aimed at improving the wellbeing of slum residents.

Given the projections (UN-Habitat, 2007) that more than half of Africans will live in urban areas by 2035, and that the majority of urban dwellers are living in conditions of abject poverty in slum settlements, urban poverty will increasingly shape national and regional poverty levels and dynamics in Africa. Nonetheless, there is a huge dearth of empirical evidence to show not only the levels, but also the dynamics in poverty among the rapidly expanding poor urban population in Africa. Until recently, poor urban settlements were neglected by both researchers and development programs because of the understanding that poverty is mostly concentrated in rural areas. Additionally, collecting research data or carrying out development programs in slum settlements is a challenge due to the high population mobility, social fragmentation, and insecurity. Most data that are used by policy makers and planners to assess and monitor poverty do not disaggregate slum and non-slum locations in urban areas, and are cross-sectional in nature. Therefore, it is not possible to use them for detailed analyses of poverty dynamics and factors driving those dynamics among the urban poor, let alone the broader urban or rural areas. This paper makes a substantive contribution to the knowledge base on understanding poverty transitions and the main factors underlying the transitions over a four year period by analyzing unique longitudinal data collected among Nairobi city's poorest residential settlements.

Indeed, there has already been some research done on poverty transition and persistence in Africa, namely Bigsten and Shimeles (2008, 2011), Islam and Shimeles (2007). However, our approach is methodologically different. We study at the poverty dynamics in a systematic way controlling for endogenous selection mechanisms (panel attrition, initial condition) and using a very short panel dataset. Bigsten and Shimeles use two modeling approaches (spells approach and lagged dependent variable model) to study poverty dynamics in Ethiopia using a panel dataset that covers 10 years (1994–2004) in five waves. They work with a balanced panel; which may reduce the precision of their estimates. The problem is that a balanced sample may be a nonrandom sub-sample of all respondents. Unobserved characteristics associated with panel retention may be associated with the unobserved characteristics that affect the probability of being poor. Our analysis shows that it is essential to account for panel attrition for modeling poverty dynamics in urban areas in Africa.

Overall, our estimation approach to poverty transition provides some useful insights into the factors underlying poverty persistence and entry in Nairobi's informal settlements. Our results indicate that TSD constitutes the major factor driving persistence into poverty. There is little heterogeneity effects; only 10 percent of poverty persistence is likely due to heterogeneity. Moreover, even when household and individual observed characteristics differ notably, the TSD size remains very large. Conversely, the estimation results show that only a limited number of covariates are significantly different from zero with respect to the poverty persistence and poverty entry equations. This implies that active anti-poverty programs aimed at breaking the cycle of poverty constitute the most appropriate policies for taking people out of poverty and preventing them to fall back in. However, one caveat should be mentioned. Our estimation sample is limited to only two waves of the corresponding panel dataset; then the poverty dynamics analysis is restricted to a period of just four years. Consequently, our results are more related to poverty experience over a limited period (four years), rather than the experience of poverty over a longer period. An analysis over more waves would provide richer insights into the determinants of poverty dynamics in Nairobi's slums.

The paper is structured as follows. Section 2 reviews the related literature and Section 3 provides background information on the context. The estimation strategy is outlined in the Section 4. Section 5 describes the data and discusses the explanatory variables. Discussion of the results follows in Section 6, while Section 7 concludes.

2. Related Literature

Since Heckman's groundbreaking work (1981), the question arises whether persistence in economic phenomena is due to individual heterogeneities or due to past experiences of the phenomenon. Examples include issues related to unemployment issues (Heckman, 1981; Arulampalam et al., 2000), persistence in low pay (Stewart and Swaffield, 1999; Cappellari and Jenkins, 2004), and of poverty persistence (Cappellari and Jenkins, 2002; Biewen, 2009).

Various approaches to study the dynamics and persistence of these economic phenomena exist. Seminal work by Lillard and Willis (1978) uses the estimation of components-of-variance models to study poverty over time relating it with changes in earnings or income of a sample of male household heads. Lillard and Willis use the estimates of the permanent and transitory variance components of these male earnings and derive the likelihood of a series of 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. However, a shortcoming of Bane and Ellwood approach is that they consider only the first spell of poverty for each individual. Thus, they ignore the fact that, within the period considered, many individuals experience more than one spell of poverty. Using the hazard rate approach to study individual poverty persistence over lifetime in the USA, Stevens (1999) addresses this issue. She investigates the case with multiple spells of poverty, accounting for spell duration, individual, and household characteristics, and unobserved heterogeneity. She demonstrates the importance of considering multiple spells in poverty persistence analysis showing that most of those who already ended poverty spells fell back in within a timeframe of four years.

What is common in the aforementioned studies is the effort to capture the effects of current on future poverty. However, with the exception of Stevens (1999), these studies do not clearly distinguish between the potential sources of poverty persistence. Recent studies explore the causes of poverty persistence using dynamic discrete choice models that control for state dependence and unobserved heterogeneity. Noticeable studies include Stewart and Swaffield (1999), Cappellari and Jenkins (2002, 2004), Devicienti (2002), Poggi (2007). Most of these studies consider a first-order stationary Markov chain for state dependence, combining it with individual fixed-effect or random-effects models to fix the unobserved heterogeneity issue. In contrast, Cappellari and Jenkins (2002, 2004) propose a transition model, which allows accounting for multiple endogenous selection mechanisms related to panel data including attrition and initial conditions.

Overall the above studies mainly underline the importance of true state dependence (TSD) in poverty persistence even after controlling for unobserved heterogeneity. For instance, Biewen (2009) found that TSD has a sizeable and statistically significant effect on poverty persistence in Germany. This suggests that past poverty status contributes to the probability of experiencing poverty in the future. Cappellari and Jenkins (2004), using the British Household Panel (BHPS) for the 1990s, concluded that heterogeneity explains only 41 percent of poverty persistence in Britain. Also, looking at social exclusion dynamics in Spain from 1994 to 1999, Poggi (2007) found evidence of individual heterogeneity and true state dependence, even after controlling for observed individual differences. The exception comes from Giraldo et al. (2002) who found that poverty persistence in Italy over the period 1995–2004 is driven only by two household unobserved heterogeneities, which consist of the household permanent income at initial time and the variation of this income over time in relation with permanent shocks. They concluded that, the dynamics of poverty in Italy does not feature any TSD after controlling for these two unobserved heterogeneities. In contrast, using the Italian sample of the ECHP, waves 1 to 8, Devicienti and Poggi (2011) found a sizable presence of state dependence in both poverty and social exclusion.

In sub-Saharan Africa, empirical works on factors driving poverty persistence are not numerous. Few studies have been developed using mainly Ethiopian data. For instance, Aassve et al. (2006) found that TSD is particularly strong in urban Ethiopia. In addition, they found evidence of TSD in rural Ethiopia, although estimates are sensitive to poverty measurement (equivalence scale). As well, using longitudinal data from rural and urban Ethiopia, Islam and Shimeles (2007), and Bigsten and Shimeles (2008), in addition to unobserved heterogeneity and TSD effects, consider a third possible source of poverty persistence, which is the effect of time-varying shock not specific to individuals, such as price fluctuations, natural calamities, general economic stagnation or slow-down. They concluded that TSD—as well as unobserved heterogeneity and serially correlated error components—has a significant impact in poverty dynamics in Ethiopia. Moreover, they discovered that the TSD effect is greater (almost twice) in urban areas than in the rural ones. As well, Bigsten and Shimeles (2011) explain TSD as an important factor of poverty persistence in urban Ethiopia regardless of the measure of poverty used, and after controlling for unobserved heterogeneity. Also, it is worth mentioning Bokosi (2007) who studied household poverty dynamics in Malawi using bivariate probit model, which accounts for initial conditions' endogeneity. He concluded that the exogenous selection into initial poverty conditions is strongly rejected and ignoring this distorts the estimated coefficients of the explanatory factors. He also found evidence of true state of dependence.

3. Context and Preliminary Evidence

In Kenya, the two nationally representation datasets that can be used to assess poverty are the 1997 Welfare Monitoring Survey (WMS) and the 2005/6 Kenya Integrated Household Budget Survey (KIBHS). First examination of these data suggest that there is no need to worry too much about urban poverty since urban areas in Kenya experienced a consumption gain of 23.8% compared to 1.5% in rural areas between 1997 and 2005/6 (World Bank, 2008). However it is not possible from these headline data to tell whether these gains affected all sections of the urban population equally, including the urban poor, who mostly live in slum settlements. A different picture emerges if one examines alternative indicators of socioeconomic wellbeing. For example, data for the same period shows that while the unemployment rate fell nationally from 15% to 12.5%, the urban rate rose from 18.5% to 20.6%. Additionally, comparative studies on health outcomes show that slum dwellers have poorer health outcomes than rural population (APHRC, 2002).

In Nairobi specifically, the population annual growth rate is about seven percent, which makes it one of the fastest growing cities in Africa. This growth results mainly from massive rural-urban migration rather than from international immigration or natural increase (APHRC, 2002). Migrants are attracted by the opportunities offered by the city in which around one fifth of the population lives on European-like standards. However, most migrants to Nairobi settle in slum areas. Thus, 60 percent of Nairobi population subsists in slums and squatter settlements. Moreover, that 60 percent is crowded onto only five percent the Nairobi's land—without adequate water, decent sanitation, sufficient living area (no overcrowding), security of tenure, and durability of housing (UN-Habitat, 2003, 2007). This creates a dramatic demographic pressure in a limited space.

Faye et al. (2011) document that hunger and food insecurity are widespread in these slums. Only one household in five is food secure, and nearly half of all households are "food insecure with both adult and child hunger". Besides, most of residents in these slums earn their living through low paying unstable jobs in the formal and informal sector, petty trade, and small businesses. Few are in stable and salaried employment. The World Bank survey (2006) shows that only 49% of adult slum dwellers have regular or casual employment, 19% of households engage in micro enterprise, and 26% are unemployed. The World Bank survey also estimates that between 70 and 75% of Nairobi's slum dwellers are poor. Yet, data from KIBHS and WMS indicate that poverty in Kenya has declined over time, from an estimated 51 percent in 1997 to 47 percent in 2005/6 (World Bank, 2008). Reported to the previous finding, this suggests then that Kenya's recent overall poverty reduction did not likely bear much fruit for slum populations in Nairobi. Why that is so? This analysis attempts shedding lights on this question looking at what drives poverty dynamics in Nairobi slums using data from Korogocho and Viwandani located about 5-10 km from the city center and 3 km from each other.

The two slums are medium sized (in terms of population) among the numerous slum settlements in Nairobi and they represent some of the key distinguishing characteristics of slum communities in the city in terms of community and population stability. Korogocho represents a stable poor urban community with a more settled population since many of the residents have resided there for many years and about a quarter of its residents aged 12 and above was born in the community. In contrast, Viwandani (situated in the proximity of the industrial area) represents a more transient community which attracts a youthful and highly mobile population seeking job opportunities in the nearby industries. Only 5 percent of Viwandani residents aged 12 and above reported having been born in the community. In addition, studies showed marked differences between the two areas in terms of economic and health outcomes (Emina et al., 2011; Beguy et al., 2010; Muindi et al., 2009; Zulu et al., 2006).

Table 1 gives a synopsis of the different aggregate poverty transition probabilities for individuals in the above mentioned two slums over the period 2003–2006. The poverty transition probability (between times $t-1$ and t) gives the propensity of being poor or non-poor in 2006, conditional on the poverty status in 2003. Poverty is measured here following the Kenya National Bureau of Statistics (KNBS) approach, comparing adult equivalent household expenditure against the Nairobi official poverty line. In 2003 and 2006 the Nairobi poverty line corresponded to 2,640 and 2,913 Kenya Shillings per month per adult equivalent, respectively (Section 5 provides further details on the poverty measurement method).

The first part of the table focuses on the sub-sample comprising only individuals present in both of the two rounds, while the second part includes all those who were present in 2003. Overall, figures reported in this table clearly confirm that slum dwellers in Nairobi did not much benefit from the overall urban poverty alleviation reported recently (World Bank, 2008). In fact, many more people fell into poverty than transitioned from it between 2003 and 2006.

The first section of the table shows very low transition probabilities from poverty to non-poverty and vice versa. The chance of getting out poverty in 2006 for those who were poor in 2003 is only 13 percent. Meanwhile the probability of becoming poor for those non-poor in 2003 amounts to 24 percent. In contrast, the probability of being poor is much higher for those who have been poor in 2003. Those who were poor in 2003 have 87 percent of chance of being in the same plight. Likewise, the change of being non-poor in 2006 is much more elevated for those were previously non-poor. Their probability to remain out of poverty is 76 percent. In fact, the probability of being poor (non poor) in 2006 is 63 percentage points higher for those who were poor (non poor) in 2003 than for those non-poor (poor). This is indicating that the poverty status in a given period is likely dependent on past poverty status. This inertia in the dynamic of the poverty status is therefore suggestive of a substantial state dependence effect. It is worth noting, however, that these aggregate transition probabilities could as well derive from observed or unobserved heterogeneity. In what follows, we use an econometric model to distinguish between the various sources of these observed transition probabilities and estimate how much each component contribute to individual's transitions in and out of poverty.

Table 1
Transition probabilities with and without missing, 2003–2006 (row %).

Poverty status in 2003	Poverty status in 2006		
	Not poor	Poor	Missing
1. Non-attriting subsample			
Not Poor	76	24	
Poor	13	87	
Total	33	67	
2. Sample (All individuals)			
Not Poor	35	11	54
Poor	8	52	40
Total	18	36	46

The second section of Table 1, taking into account the high population mobility observed in the slums, confirms the likely presence of a state dependence effect. However it is worth noting that almost half of individuals in the sample (about 46 percent) could not be traced in 2006, as they had moved out of the DSS area. The prospect of leaving the sample in 2006 is very important regardless the poverty status in 2003. Indeed, the probability of attriting is higher among those were not poor, but almost one-half of those poor in 2003 also quitted the sample. The attrition propensity is about 54 percent for those non-poor in 2003 while it is 40 percent for the poor. This suggests that the slums are likely a transit platform for urban migrants who may move out to more decent settings once they are better off or may move back upcountry or elsewhere when their conditions do not improve. Thus, if this is case, the retention in the panel is non-random. Therefore to get consistent estimates, we need to specify an equation characterizing the retention mechanism and jointly estimate it with the poverty transition equation.

On the other hand, an interesting question is: Are the same individuals that are continuously poor or is there a steady entry or exit from poverty, with the aggregate level remaining more or less the same over time? Table 2 provides information on the poverty dynamics of each individual. It depicts remarkable high persistence of individual in both states (never or always poor). Looking at the sub-sample without missing, we note that about 83 percent of the individuals do not change status between 2003 and 2006. Almost 24 percent of the individuals have never been poor, while 59 percent have always been poor. We also note substantial dynamics in individuals' poverty statuses. The second part of the table shows that about one-fifth of non-attriting individuals did experience transitions into or out of poverty between 2003 and 2006. About seven percent of the individuals fell into poverty during the period while nine percent became non-poor.

Also, it is important to mention that a significant proportion of individuals (46 percent) left the sample during the period 2003–2006. One-quarter (one-fifth) of those who were poor (non-poor) in 2003 left the sample in 2006. However, despite that, the persistence rates are still quite important even if these are much lower as compared to the non-attriting subsample. We note that 13 percent of individuals in the sample were never been poor and 32 percent were always poor. Meanwhile, only five percent escaped poverty while four percent fell in.

Table 2
Persistent and non-persistent states with and without missing, 2003–2006 (column %).

	Non-attriting subsample	Sample (All individuals)
Persistent		
Never	24	13
Always	59	32
No persistent		
Poverty Entry	7	4
Poverty Exit	9	5
Poor who exited the sample		25
Non poor who exited the sample		21
Total	100	100

4. Data

This study uses data from the Nairobi Urban Health and Demographic Surveillance System (NUHDSS), the first urban-based Health and Demographic Surveillance Systems (HDSS) in Africa. The HDSS is a methodological approach to monitoring demographic and health outcomes in a registered and defined population living in a circumscribed geographic area. The data collected comprise at least information on vital events (births and deaths) and in- and out-migration. These basic demographic indicators constitute the key tools for tracking the population in the covered HDSS site at any time during the follow-up. Thus, unlike pure cohort studies, HDSS sites adopt the concept of an open cohort that allows new members to join and existing members to leave and return to the system, as long as they are regular residents in the clearly defined geographic area under surveillance, often referred to as the Demographic Surveillance Area (DSA). A HDSS starts with an initial census of the population living in the defined geographical areas, followed by regular visits to update information on births, deaths, migration, and other demographic and health facts. After the initial census, one can become an HDSS member only through birth or in-migration into the DSA. Conversely, someone ceases being a HDSS member either through death or through out-migration.

The NUHDSS was set up by the African Population and Health Research Center in two of the numerous informal settlements in Nairobi city—Korogocho and Viwandani—in 2002. It was piloted in four slum settlements in Nairobi city between 2000 and 2002. The baseline census that defined the initial population was carried out in July–August 2002. Thereafter, subsequent visits are made every 4 months by fieldworkers to all residential housing units and households in the DSA, which are tagged using unique identification numbers. Thus, once every quarter, information are collected from households on key demographic and health events, including births, migrations, deaths, and causes of death (through verbal autopsies). Other events being monitored (though not necessarily in every visitation round) include immunization coverage, morbidity, health-seeking behavior, school attendance, marital status, household possessions and amenities, and livelihood sources. Between 2003 and 2009, the NUHDSS followed an average of about 71,000 individuals living in about 28,500 households in the two settlements (Emina et al., 2011).

The sample used for the empirical analysis is restricted to data from the 3rd and 13th rounds of the NUHDSS, which were collected in 2003 and 2006, respectively. We focus on these two rounds as in 2004, 2005, and 2007 the module "household amenities and livelihoods" of the NUHDSS survey instrument concerned only a small subsample of the population. Moreover, after 2007, the questions in this module changed a bit, and this does not allow too much comparison with the previous years. Thus, our analysis is based on a two-wave panel covering the period 2003 and 2006. Indeed, we acknowledge that the time dimension of our panel is not long enough to allow estimating the duration of poverty spells as done by Bane and Ellwood (1986), Cappellari and Jenkins (2004), or Andriopoulou and Tsakloglou (2011). However, this time dimension is largely sufficient to allow for meaningful empirical estimations to identify the determinants of poverty transitions, accounting for unobserved heterogeneity across individuals and for potential non-random attrition (see Bokosi, 2007). In our analysis, we tracked all individuals (adults and children) over time, unlike most commonly-used practice (see instance Cappellari and Jenkins, 2004; Biewen, 2009). Hence, our estimation sample is an unbalanced panel of 52,005 person-round observations living in 13,494 households. It is important to mention that the population in our sample is highly mobile. About 46 percent of the people who were residents of the DSA in 2003 exited the sample in 2006. This echoes previous finding that the majority of Nairobi's slums residents spend less than three years on average in the area and that a quarter of them stay for less than one year (Beguy et al., 2010). We account for this high mobility looking at what constitute the determinants and how it links with individual's poverty status.

One problem with empirical investigations of poverty is to find an indicator that allows identifying poor people. This problem can become rather complex. In fact, here exist several approaches that may however sometimes bear different policy implications in terms of fighting poverty. As well, a common concern is data quality problems and associated measurement errors, which may lead to biased poverty orderings. There is a substantial literature with deeper discussion on these issues.

The analysis in this paper uses monthly household consumption expenditure as the main measure of welfare in successive periods. The consumption variable considered is the "monthly adult equivalent household consumption expenditure, obtained after dividing total household consumption by the number of equivalent adults (considering a child as half of an adult). Total household consumption is obtained after adding up all household expenses in food and non-food items, excluding spending in durables and their use values. Durable goods are distinguished by their ability to provide services through repeated use over time. Therefore, it would be inappropriate to consider the total purchase cost at the time the good is bought. Deaton and Zaidi (2002) recommend using the value of the service that the household receive from the durable goods in its possession over the relevant time period. However, in our dataset there lacks information on the age and replacement value of these durables. Hence, we do not account for the durable goods in the consumption aggregate. In contrast, following Deaton and Zaidi (2002), all education-related expenses are included in the consumption aggregate.

Once a year, the NUHDSS collects household expenses data in the module "household amenities and livelihoods" using the same questions. The information is gathered using an interview.

Respondent are asked to report both large and small amounts of household expenses on the different items. The survey uses a twelve-month recall period for durable items, and a one-month recall period for expenditures on electricity, rent, healthcare and medication, religious obligations, and school related expenses. In contrast, a shorter recall period (seven days) is used to capture expenses related to food items, energy (paraffin, charcoal, etc), water, financial gift, and transport. We restrict our analysis to items purchased within the 7-day and one-month recall periods. However, a major problem in this exercise concerns the accuracy of the respondents' reporting. So, the question is whether our welfare indicator is not biased due to potential measurement errors. In fact, measurement error in household expenditure surveys is a well-known problem. It may occur at any stage through the data-collection process. Four primary sources are identified in that process: the questionnaire (topics, length, wording/phrasing of questions), the method or mode of data collection (mail, diary, face-to-face interview), the interviewer (incorrect reading or interpretation of answers), and the respondent (interpretation of questions, memory loss, socially desirable answering).

However, based on Faye et al. (2011) validity analysis, it is worth noting that measurement errors in the data do not distort our indicator. Using the same dataset, Faye et al. generate a food insecurity scale and test how it correlates with household income ranking based on the monthly household adult equivalent expenditure. They found that food deprivation has significant and negative association with household income level. Household food status scale worsens significantly as its income is low. Food deprivation is higher for households at the bottom of the income distribution. Thus, food deprivation scale is perfectly consistent as expected with household income status. This provides evidence of the validity our poverty measure.

In what follows, although we are considering a variable related to the household as poverty indicator, our unit of analysis is the individual. This is necessary to allow for individuals to move from one household to another over time (Stevens, 1999). It is worth noting, however, that in poverty dynamic analysis there no unanimity in the choice of the unit of analysis. The controversy is about choosing individuals or households. Various studies, which include Lillard and Willis (1978), Bane and Ellwood (1986), Stevens (1999), Cappellari and Jenkins (2002), Betti et al. (2002), Devicienti (2002), Biewen (2009), have discussed this issue. Most of these studies identify as a unit of analysis the individual, when analyzing of poverty dynamics. In such a context, it would be difficult to consider the household as a unit of analysis in any rigorous ways (Betti et al., 2002). It is easier to follow an individual over time than a household. Changes in household demographic structure due to events such as marriage, divorce, migration, death and the birth of children make it not homogeneous over time. Nevertheless, it would be interesting to check how changes in household demographic structure interact with poverty dynamics. However, this is out of the scope of the paper. We leave it to further research.

We assume an equal sharing of resources within the household, accounting for each member's adult equivalent value. An individual is defined as poor if his/her adult equivalent expenditure is lower than the Nairobi official poverty line, which is defined by the Kenya National Bureau of Statistics (KNBS). In 2003 and 2006 the Nairobi poverty line was set at 2,640 and 2,913 Kenya Shillings per month per person (in adult equivalent terms) respectively. We use the Nairobi poverty threshold since—according to the Kenya Food Security Steering Group – Short Rain Assessment (KFSSG, 2009)—Nairobi slum residents procure almost all their household food (90 percent) and non-food items from the market. KFSSG (2009) also indicates that there is not much opportunity for food production in Nairobi, which means that food access in Nairobi is mainly dependent on cash exchange. As a consequence, ability to access food in Nairobi can be perceived in terms of household income relatively to prices of food and non-food items.

5. Estimation Strategy

In order to look at the dynamics of an individual i's poverty status, consider the following dynamic reduced form model:

$$I_{it} = \mathbf{1}\{y_{it} = \alpha I_{it-1} + \varphi z_i t + \mu_{it} < \tau_t\} \tag{1}$$

Where: I_{it} is a binary response denoting the poverty status of individual $i(=1,\ldots,N)$ at time $t(=1,\ldots,T)$; $\mathbf{1}\{\ldots\}$ is an indicator function describing the evolution of poverty conditional on i's poverty status at the previous period; y_{it} is assumed representing individual i's disposable income;[1] z_{it} is a vector of exogenous variables; μ_{it} captures the effects of unobserved factors; and τ_t corresponds to an income threshold referred as the poverty line. The binary variable I_{it} is equal to 1 if $y_{it} < \tau$, and 0 otherwise.

The unobserved term μ_{it} is assumed to have the following structure:

$$\mu_{it} = \delta_i + \varepsilon_{it}; \mu_{it} \rightarrow N(0,1)$$

Where: δ_i is an individual-specific term that stands for all unobserved determinants of poverty that are time-invariant for a given individual; and ε_{it} is a residual term, which assumed to be idiosyncratic and follow a normal distribution with zero mean and unit variance: $\varepsilon_{it} \rightarrow N(0,1)$.

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 ($I_{it} = 1$):

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

It is worth emphasizing however that the specification above does not properly control for individual unobserved heterogeneity. Even if $\alpha = 0$, $Pr(I_{it}|I_{it-1} = 1) > Pr(I_{it}|I_{it-1} = 0)$, owing to the presence of δ_i. Then, for testing of true state dependence, it is crucial to correctly control for individual heterogeneity.

Cappellari and Jenkins (2002, 2004) propose an approach to deal with the question of unobserved heterogeneity and true state of dependence in poverty dynamics.

Building on Stewart and Swaffield (1999), Cappellari and Jenkins develop an endogenous switching model of poverty dynamic that allows estimating that jointly poverty transition and

[1] The disposable income is specified as a linear function of individual poverty status at time $t-1$, a set of explanatory variables, and a normally distributed error term (Stewart and Swaffield, 1999; Cappellari and Jenkins, 2004).

poverty persistence. The interesting feature in the model is that it allows accounting simultaneously for multiple endogenous selection issues (e.g., initial conditions, panel attrition, etc.) and testing for ignorability of these selection mechanisms. We adopt this model to investigate the state dependence effects while accounting for both initial condition problem and panel attrition process in the presence of unobserved heterogeneity.

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

$$(I_{it}|I_{it-1}, R_{it} = 1) = \mathbf{1}\{[(I_{it-1})\gamma_1' + (1 - I_{it-1})\gamma_2']z_{it-1} + \delta_i + \varepsilon_{it} < \tau_t\} \tag{2}$$

Where: I_{it-1} is a binary indicator representing the poverty status in the base year: it stands for the initial condition; R_{it} is a binary indicator that captures panel retention whether an individual i has been observed consecutively in times $t-1$ and t; and γ_1 and γ_2 are vectors of parameters to be estimated. This specification indicates that I_{it} is conditional on $R_{it} = 1$. Moreover, the impact of explanatory variables[2] on current poverty status may differ ('switch') according to whether the individual was poor at $t-1$ ($I_{it-1} = 1$) or not ($I_{it-1} = 0$). Thus the Cappellari and Jenkins' specification provides estimates of the determinants of both poverty persistence and poverty entry. Following Arulampalam et al. (2000), it is possible to identify a true state dependence (TSD) effect if there is significant difference between the coefficients γ_1 and γ_2 in equation (2). Then we test for the absence of true state dependence using the null hypothesis $H_0 : \gamma_1 = \gamma_2$. A rejection of H_0 indicates that I_{it} depends on I_{it-1}.

A probit model implements the initial condition for poverty status as follows:

$$I_{it-1} = \mathbf{1}\{\beta' x_{it-1} + \theta_{it-1} < \tau_{t-1}\}; \;\; (\theta_{it-1} = \delta_i + \xi_{it-1}) \to N(0,1) \tag{3}$$

Where: x_{it-1} is a vector of explanatory variables; β is a vector of parameters; and the composite error term θ_{it-1} is the sum of an individual-specific effect λ_i plus a residual term ξ_{it-1}, which is assumed to be idiosyncratic and follow a standard normal distribution. I_{it-1} equal one if the disposable income is below the threshold τ_{t-1}, and zero otherwise.

The retention status R_{it} describes a selection mechanism indicating whether an individual i remain in the sample between $t-1$ and t. R_{it} equal to one if the individual i is observed at both $t-1$ and t, and zero if she has been observed only at $t-1$ (attrition). R_{it} is also given as a probit model:

$$R_{it} = \mathbf{1}\{\chi' w_{it-1} + \psi_{it} = 0\}; \;\; (\psi_{it} = \eta_i + \theta_{it}) \to N(0,1) \tag{4}$$

Where: w_{it-1} is a vector of explanatory variables; χ is a vector of parameters; and the composite error term ψ_{it} is the sum of an individual-specific effect η_i plus a residual term θ_{it}, which is assumed to be idiosyncratic and follow a standard normal distribution.

The model is completed assuming that the composite error terms μ_{it}, θ_{it-1},and ψ_{it} are multivariate normally distributed with zero mean, unit variances, and a covariance matrix Σ, so that the distributions the of unobserved heterogeneity are parameterized by the cross-equation correlations (given the necessary normalizations of the variances of the composite error to equal one).

[2] Cappellari and Jenkins (2004) used lagged values as explanatory variables, but this is not essential. One could also use contemporaneous values, i.e., z_it rather than z_{it-1}.

There are three correlations corresponding to the covariance between the individual-specific error components:

$$\begin{cases} \rho_1 = corr(\theta_{it-1}, \psi_{it}) = cov(\lambda_i, \eta_i) \\ \rho_2 = corr(\theta_{it-1}, \mu_{it}) = cov(\lambda_i, \delta_i) \\ \rho_3 = corr(\psi_{it}, \mu_{it}) = cov(\eta_i, \delta_i) \end{cases} \tag{5}$$

The estimate of ρ_1 provides a test of the association between unobservable individual-specific traits determining base year poverty status and panel retention. The estimate of ρ_2 summarizes the correlation between unobservable individual-specific characteristics determining initial poverty status and current poverty. The estimate of ρ_3 summarizes the association between unobservable individual-specific traits determining panel retention and those determining current poverty status. If $\rho_1 = \rho_3 = 0$, the attrition issue can be ignored; the model reduces to a bivariate model. If $\rho_1 = \rho_2 = 0$, the initial condition does not hold; then poverty status at $t-1$ may treated as exogenous. Finally, if $\rho_1 = \rho_2 = \rho_3 = 0$, the system reduces to a univariate probit model; both processes of poverty entry and exit are exogenous (Cappellari and Jenkins, 2002, 2004).

The joint estimation of the three equations (2), (3), (4) involves the evaluation of the log-likelihood of the sample using on a joint trivariate probability. The sample log-likelihood corresponds to the sum of the individual log-likelihood function; it is defined as follows:

$$\ln \mathcal{L} = \sum_{i=1}^{N} L_i \tag{6}$$

Where L_i corresponds to individual i log-likelihood function, which depends on both the individual retention status (R_{it}) and his/her poverty status at $t-1$ (Cappellari and Jenkins, 2004).

The estimation of (6) requires the computation of derivatives of third order integrals for which no general solutions exist. Then, we address the problem using the simulated maximum likelihood method. More precisely, we use the GHK (Geweke-Hajivassiliou-Keane) smooth recursive estimator method. The GHK smooth recursive estimator decomposes the original three-dimensionally correlated error terms into a linear combination of uncorrelated one-dimensional standard normal variables. Our trivariate distribution is thus transformed into three sequentially conditioned univariate distributions (Train, 2003). We evaluate the resulting integral with 100 Halton draws using a multivariate density function proposed by Cappellari and Jenkins (2006), which is based on the GHK smooth recursive conditioning simulator.

Furthermore, the model allows predicting poverty persistence and poverty entry rates using all individuals including those who exited the sample. Then, using these predicted transitions rates; one can compute the aggregate state dependence (ASD) which is the difference between the average probability of being poor at time t for those poor in $t-1$ and the probability of being poor at t for those non poor in $t-1$. As well, the model allows both testing for the presence of true state dependence (TSD) and then quantifying its magnitude. TSD magnitude is evaluated estimating the average across all individuals of the difference between predicted probabilities of being poor at time t conditional on the two states in time $t-1$, as follows:

$$\text{TSD} = \frac{1}{N}\sum_{i=1}^{N}[Prob(I_{it}=1|I_{it-1}=1) - Prob(I_{it}=1|I_{it-1}=0)].$$

TSD measure is based on individual-specific probabilities; therefore, it controls for individuals' heterogeneities in contrast to ASD, which encompasses both processes. As a consequence, we can assess the heterogeneity effect using the difference between ASD and TSD.

The covariates used for estimations comprise household and individual characteristics, and labor market attachment of individuals living in the household. Household characteristics include household living arrangements, number of workers within the household, housing tenure, and the characteristics of the head of household. Household living arrangements information is captured using a series binary variables indicating the presence of children (less than 5, 6-11, and/or 12-17 years-old) and older persons (55-59 years old and/or 60 and more). The head of household characteristics include gender, age, marital status, and his occupation. Individual characteristics consist of their gender, age, and age square, ethnic group, and occupational status. We also include individuals' occupational profiles using 7 categories. These are: formal own business, informal own business, formal casual worker, formal salaried, informal casual worker, informal salaried, and other. All covariates 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}.

We estimate the model assuming free correlation coefficients. Thus, for model identification, we include in retention and initial conditions equations a series of additional variables that are excluded from the poverty transition equation. For the retention equation, we consider a binary variable that indicates whether the individual was enumerated when the NUHDSS started in 2002 or whether he/she joined the DSA latter. Our choice builds on previous finding, which indicates that a sizable proportion of residents have been living in the slums for long periods of time (over ten years). Also, it is documented that these residents have weaker ties with their place of origin; therefore, they are less likely to engage into circular migration (Beguy et al., 2010). As instruments for the retention equation, we also include indicators of shocks that a may experience such as theft or mugging. For the initial condition equation we use as instrument a variable that reveals whether individuals in the households are recent migrants or not. Analysis has shown that recent migrants are most vulnerable as they have not yet an established network and they are more subject to shocks. We capture this instrument using an indicator on the duration of stay in the DSA.

6. Estimation Results

The presentation of the results is organized as follows. First, we discuss briefly the validity of our estimation strategy looking at the validity of our identification approach, the correlations between the unobserved factors, and the endogeneity of the selection processes. Then, we discuss the impact of the explanatory variables. Thereafter, we discuss the extent of the true state dependence and heterogeneity effects. Note that, in our estimations, the standard errors are defined robust to heterogeneity and clustered at household level. Moreover, a household is defined in the period when it is first observed (in 2003) and it remains identical over the subsequent periods.

6.1 Testing the Proposed Estimation Approach

Table 3 reports the tests of validity of our instruments (excluded variables), the estimates of the cross-equation correlations between the unobserved characteristics, and the tests of exogeneity of the selection equations. Table 3 gives the results of the validity test of our identification strategy. Following Cappellari and Jenkins (2004), we test for the instruments relevance looking at whether the instruments are statistically significant in the selection equations (initial conditions and retention), and not significant in the transition equation (from which the instruments are excluded). The test results indicate that the instruments we used are generally significant (separately and jointly) in the relevant selection equations. The tests also show that these instruments can be excluded from the transition equation as they are not statistically significant, both separately and simultaneously. It means thus that the validity of our instruments is supported by the data.

Moreover, in order to check robustness of our results we calculate several statistics. We check the Wald statistic (Wald = 2740.38) and the Likelihood ratio statistic (LR = 2(82262.86-73904.26) = 16717.20), and both tests are in favor of the model. In addition, we calculate the predicted probability of poverty entry and exit rate, and thereafter we compare the results with the observed rates. We observe that the model predicts that 20.57% of those who were non-poor in the previous period enter into poverty in the current year while the observed entry rate is 23.63%. Also, the model predicts that 15.88% of those who were poor previously have exited poverty in the current period; the observed poverty exit rate is 13.14%.

To test for the endogeneity of the initial conditions and the panel retention, we look at both separate and joint significance of the correlation coefficients associated with each selection equation. Results from Table 3 also indicate that the correlation associating unobserved factors affecting both initial poverty and sample retention (ρ_1) is positive and significant, suggesting a higher retention propensity among those initially poor compared to those non-poor in 2003 (see Table 1). This selective attrition of the non-poor might potentially lead to an under-representation of those non poor in the non-attriting subsample, as compared to the sample. The implication is that an estimation ignoring the sample retention mechanism would likely yield biased results. Also, the correlation between initial condition and poverty transition equations (ρ_2) is positive, meaning that those initially poor have a higher propensity to become or remain poor. However, ρ_2 is not statistically significant. Finally, the correlation associating retention and poverty transition (ρ_3) is instead negative, but non-significant.

Conversely, the joint tests of significance on the correlation coefficients suggest that the two selection processes should not be ignored when estimating poverty transitions. Initial conditions and panel retention are both endogenous processes for poverty transitions. Results from Table 3 show that all tests of joint significance on the correlations are significantly different from zero (the P-value of the tests: $\rho_1 = \rho_2 = 0$; $\rho_1 = \rho_3 = 0$; and $\rho_1 = \rho_2 = \rho_3 = 0$ is always zero). This means that estimating the poverty transitions model without simultaneous estimation of the

Table 3
Estimated correlation coefficients of unobservable and tests of exogeneity.

a. Correlation coefficients of unobservable	Coefficients	Std. Errors
$\rho_1 = cov(\lambda_i, \eta_i)$: Initial poverty status, retention	0.080***	(0.017)
$\rho_2 = cov(\lambda_i, \delta_i)$: Initial poverty status, poverty transition	-0.115	(0.216)
$\rho_3 = cov(\eta_i, \delta_i)$: retention, poverty transition	0.062	(0.190)
b. Wald tests of exogeneity	Chi-2	P-Value
Exogeneity of panel retention: $\rho_1 = \rho_3$	22.10	0.000
Exogeneity of Initial condition: $\rho_1 = \rho_2$	22.10	0.000
Joint exogeneity: $\rho_1 = \rho_2 = \rho_3$	22.34	0.000
c. Instruments validity		
Inclusion of 'Duration of stay' in Initial Conditions equation ($d.f. = 1$)	18.06	0.000
Inclusion of 'Enumeration status' in Retention equation ($d.f. = 1$)	78.82	0.000
Inclusion of 'Mugging experience' in Retention equation ($d.f. = 1$)	16.12	0.000
Inclusion of 'Theft experience' in Retention equation ($d.f. = 1$)	02.01	0.1565
Join inclusion of 'Enumeration status', 'Mugging experience', and 'Theft experience' in Retention equation ($d.f. = 3$)	100.22	0.000
Exclusion of 'Duration of stay' from transition equation ($d.f. = 1$)	0.20	0.6527
Join exclusion of 'Enumeration status', 'Mugging experience', and 'Theft experience' from transition equation ($d.f. = 3$)	05.23	0.1559
Join exclusion of all excluded variables from transition equation ($d.f. = 4$)	05.58	0.2331
d. Test of state dependence		
No state dependence, $H_0 : \gamma_1 = \gamma_2$ ($d.f. = 32$)	69.81	0.000

Note: *p<0.05, **p<0.01, ***p<0.001.

initial conditions and the panel retention leads to biased results. The three equations should not be estimated separately.

Overall, the series of tests from Table 3 clearly indicate that the data support our estimation strategy.

6.2 The Extent of True State Dependence and Heterogeneity

As mentioned above, the presence of TSD is investigated based on the null hypothesis that there is no difference in poverty transitions parameters that can be attributed to the different poverty states in the previous period after controlling for observed and unobserved heterogeneities (recall H_0: $\gamma_1 = \gamma_2$). A sufficient condition for the presence of TSD is the rejection of the null hypothesis. Panel (d) of Table 3 gives the χ^2 statistic derived from this test. The value of the statistic corresponds to 69.81 ($d.f. = 32$) with a p-value = 0.000, suggesting a strong rejection of the null hypothesis of no difference in poverty parameters associated with the different past poverty states. This means that the variations in the parameters associated with differences in previous poverty states reflect the presence of TSD effects.

Table 4 shows the predicted transition rates and state dependence measures computed from the model estimates. Remarkably, the predicted transition probabilities are quite similar to the raw transitions probabilities reported in Table 1. For those non-attriting individuals, predicted poverty persistence and entry rates are 85.93 and 22.14 percent, respectively. These figures are very close to the raw transitions rates displayed in Table 1 with the observed poverty persistence and entry rates corresponding to 87 and 24 percent, respectively. This suggests that the model fits perfectly the data.

We assess the robustness of our results by re-estimating the model without the retention equation. The objective was to see whether or not accounting for the retention mechanism improves the model under such a huge attrition rate. When we exclude the retention equation, we obtain an estimated poverty persistency rate of 92.17% and an estimated poverty entry rate of 14.07%. In the model including the retention equation, the estimated poverty persistence rate and poverty entry rate correspond to 85.93% and 22.14%, respectively. These are closer to the observed rates, which are 87% and 24% for the poverty persistence rate and the poverty entry rate, respectively. Thus, it is obvious that the introduction of retention equation in improve clearly the fitness of the model.

Table 4 also reports both ASD and TSD estimates. The ASD estimates correspond to differences in the predicted transitions rates (persistence and entry). It is estimated to 64 percent; meaning that those who have been observed poor in 2003 have 64 percent of chance of being poor in 2006, as compared to those non-poor in 2003. This excess exposure to poverty is likely due to both heterogeneity and TSD effects. Moreover, the results indicate that the ASD value is almost the same for both the non-attriting subsample and the overall sample (the latter comprises all individuals present in 2003). Likewise, the TSD estimate is also quite identical for the two groups. The estimated value of the TSD corresponds to about 58 percent. These similarities suggest that the propensity to persist into poverty is quite alike for both individuals who left the sample and or stayed in. Moreover, since poverty transition rates may differ with respect to household and individual observed heterogeneity, we calculated the predicted transition rates and state dependence for a series of groups of individuals separately. The results, presented in the second panel of Table 4, reveal that both ASD and TSD are relatively homogenous across the different groups and compared to the whole sample. This means that individuals in our sample, regardless their observed profiles, have almost the same propensity to remain poor in 2006 once they have been in poverty in the previous period.

Furthermore, the results indicate that TSD constitutes an outsized proportion of ASD: about nine-tenth. Thus, there appears to be little heterogeneity effects. Only 10 percent of poverty persistence is likely due to heterogeneity. Moreover, even when household and individual observed characteristics differ notably, the TSD size remains very large. This means that the probability of remaining poor is quite exclusively influenced by the TSD effects. Indeed, this result is consistent with findings evoked in the previous section, as few covariates were found statistically significant with respect to the poverty transition equation. This suggests that diversity among people (heterogeneity) makes little differences against poverty persistence, which contrasts with general expectations. In fact, it is logical to expect that diversity induces notable differences in the probabilities of transition into and out of poverty. For instance, 'more educated' or 'more able' people are supposed to be able to exit poverty more easily and less likely to get in.

Conversely, we check the sensitivity of our results looking at whether our model is flexible enough to capture the distributional effect of unobserved heterogeneity. We also check whether

Table 4
Predicted transition rates and state dependence (%).

Characteristics	Predicted transition rates Persistence	Entry	State dependence Aggregate	True
Sample average	84.91	20.57	64.34	58.20
Non-attriting sub-sample	85.93	22.14	63.79	58.30
Basic case #1: Head of household is male, married, not educated, working, living in a rented house, without dependent (i.e. no child, no older person)	78.81	17.16	61.65	58.58
Case #2: As basic case, except head of household educational level is primary	75.75	15.30	60.45	57.72
Case #3: As basic case, except head of household educational level is at least primary	73.54	14.11	59.43	57.08
Case #4: As case #2 , except there is at least one child aged 5 or less	82.83	24.44	58.39	58.34
Case #5: As case #4 , plus at least one child aged 6-11	86.86	30.68	56.18	56.54
Case #6: As case #5 , plus at least one older person	90.61	34.78	55.83	56.08
Case #7: As case #2 , except there is at least one dependent (i.e. one child or one older person)	86.46	25.74	60.72	58.14
Case #8: As case #2 , except house is not rented	79.13	17.05	62.08	59.00

or not the estimated share of the true-state-dependence is over estimated. Thus, we re-estimate the model by dropping individual characteristics. We observe that some variables became non-significant with the new specification. For instance, the estimated coefficient of the marital status of head of household is 0.0621 with a standard error corresponding to 0.058 while in the previous estimation (full specification) this coefficient was 0.120 with a standard error of 0.67. We also notice that the estimated share of the TSD (91.8%) with new specification is almost similar to the estimated value that we obtained from the full specification (91.39%). In addition, the log-likelihood statistic (-73904.26) of the full specification appears much better than the one obtained with the parsimonious specification (-75331.53). These results suggest then that our model is flexible enough to capture the distribution of unobserved heterogeneity.

The aforementioned preeminence of TSD among factors driving poverty persistence for all individuals in the sample suggests that they almost face the same economic constraints that may maintain them into poverty. Thus, there are mainly two mechanisms that make poverty persisting: labor market constraints and financial market failure. In urban areas workers face shortages of opportunities in the labor market. Only skilled and some lucky individuals may get employed and enjoy a non-poor living standard. In contrast, the majority is rationed out of the labor market and gets stuck at low level of living. Meanwhile, individuals may face two types of financial market failures. First, they cannot borrow against future income earnings in order to either accumulate assets more rapidly, or to protect their current consumption against the effects of shocks. As well, they do not access to insurance (contingent claims) market to prevent asset losses or to allow them engaging in risky but profitable activities. Addressing these labor and financial market failures may then be an appropriate option for breaking the cycle of poverty.

6.3 Parameter Estimates

Table 5 reports different estimates of the explanatory variables with respect to the poverty transition equation. Like in Stewart and Swaffield (1999) and Cappellari and Jenkins (2004), we note that only a limited number of covariates are with statistically significant effects on poverty persistence and poverty entry.

None of the household characteristics appears having impact on poverty transition, except two covariates indicating the presence of a least a child aged 12-17 years old or a child who is 5 or less. However, the latter only affect poverty persistence and not entry. Thus, individuals living in households with a child in either of these age categories are likely associated with higher probability of persisting into poverty. In addition, the characteristics of the head of household do not significantly affect the probability of entering or staying into poverty but the age. The older is the head of household, higher is the probability of remaining poor for those living in the household.

In terms of individuals' characteristics, being married likely reduces the propensity to remain poor, while this does not significantly affect the probability of entering poverty. As well, the age has inverted U-shape effect on the probability of remaining poor; younger and older people have lower probability to stay poor from one period to the next. In contrast, with respect to the probability of entering poverty, the age coefficients are not significantly different from zero. Being educated makes individuals less likely to enter poverty: there are significant differences between those educated (primary or secondary) and those who have never attended school. Conversely, with respect to the probability of persisting into poverty, the effect of education is not uniform. Having only primary educational level does not significantly makes a different, as compared to not being educated. In contrast, higher education generates statistically significant effect on the probability of remaining poor. Thus, those having at least secondary educational level are more likely to remain poor from one period to the next even if the impact is not very strong. This result seems a bit counter-intuitive. However, it suggest that the higher educated likely have lower opportunities to find employment matching their human capital profiles, and in case of a shock, they likely leave the labor force rather than take a job below their profile. Thus, they appear to be more susceptible to cycling in poverty.

Moreover, individuals who are working have lower probability of entering poverty, but this does not significantly affect their chance of persisting in poverty. Also, the working sector does not make difference in terms of poverty persistence. There is no significant difference between sectors, as compared to being salaried in the formal sector. However, with respect to the probability of entering poverty, a significant difference appears when comparing casual informal workers to those who are salaried in the formal sector. The former have higher probability of entering poverty.

Table 6 gives the parameter estimates of poverty status in initial period and the retention equation. The overview of the results indicates that many covariates are significantly different from zero in both equations, in contrast to the transition equation. Looking at the initial

Table 5

Poverty transitions: Poverty status in 2006, conditional on poverty status in 2003.

	Poverty Persistence		Poverty Entry	
Explanatory variables	Coefficients	(St. Err.)	Coefficients	(St. Err.)
1. Household Characteristics				
Housing tenure: Own	0.097	(0.073)	0.056	(0.069)
Housing tenure: Free of charge	-0.064	(0.137)	0.080	(0.117)
Number of workers in the household	0.030	(0.039)	0.048	(0.038)
Presence of a child aged 5 or less in the household	0.225*	(0.094)	0.213	(0.111)
Presence of a child 6-11 in the household	0.059	(0.072)	0.121	(0.090)
Presence of a child 12-17 in the household	0.177**	(0.059)	0.074	(0.067)
Presence of an older person aged 55-59 in the household	0.050	(0.085)	0.053	(0.079)
Presence of an older person aged 60+ in the household	0.043	(0.140)	0.181	(0.125)
2. Head of household characteristics				
Age	0.007*	(0.003)	0.001	(0.003)
Gender: Female	0.037	(0.070)	0.051	(0.058)
Marital status: Married	0.115	(0.067)	0.090	(0.061)
Education level: Primary	-0.002	(0.084)	0.044	(0.090)
Education level: Secondary	-0.159	(0.097)	-0.056	(0.105)
Working	-0.015	(0.092)	-0.177	(0.098)
3. Individual's characteristics				
Gender: Female	0.013	(0.031)	0.006	(0.035)
Age	0.014**	(0.004)	0.009	(0.006)
Age square	-0.000**	(0.000)	-0.000	(0.000)
Marital status: Married	-0.189***	(0.037)	0.001	(0.042)
Education level: Primary	0.025	(0.029)	-0.119**	(0.039)
Education level: Secondary	0.096*	(0.041)	-0.131*	(0.052)
Working	-0.076	(0.246)	-0.608*	(0.283)
Ethnic group (ref. Other ethnic groups)				
Kikuyu	-0.151	(0.098)	-0.080	(0.077)
Kamba	-0.229*	(0.112)	-0.088	(0.093)
Luo	-0.207	(0.111)	-0.172	(0.112)
Luhya	-0.153	(0.111)	-0.096	(0.101)
Kisii	-0.126	(0.144)	0.029	(0.122)
Somali	0.188	(0.188)	-0.027	(0.139)
4. Individual's type of activity (ref. Formal salaried)				
Self formal business	0.101	(0.284)	0.475	(0.293)
Self informal business	0.073	(0.248)	0.505	(0.280)
Formal casual worker	0.074	(0.278)	0.352	(0.301)
Informal casual worker	0.224	(0.271)	0.606*	(0.299)
Informal salaried	0.016	(0.340)	0.240	(0.413)
Constant	0.627*	(0.311)	-0.953**	(0.307)
Log-likelihood	-7.39e+04			
chi2 (*d.f.*)	2744.023 (112)			
P-Value	0.000			
Number of observations (persons-rounds)	52,005			

Note: *p<0.05, **p<0.01, ***p<0.001.

condition equation, we note the presence of dependent (either a child of any age or an older person) in the household increases the probability of being poor in the initial period. Conversely, having a working or educated head of household reduces the propensity to be poor. As well,

Table 6

Selection mechanisms: Initial Condition and Retention estimates.

	Initial condition		Retention	
Explanatory variables	Coefficients	(St. Error)	Coefficients	(St. Error)
1. Household Characteristics				
Housing tenure: Own	-0.036	(0.053)	0.355***	(0.040)
Housing tenure: Free of charge	-0.043	(0.092)	0.420***	(0.075)
Number of workers in the household	0.039	(0.029)	-0.005	(0.022)
Presence of a child aged 5 or less in the household	0.678***	(0.033)	0.184***	(0.027)
Presence of a child 6-11 in the household	0.439***	(0.035)	0.283***	(0.029)
Presence of a child 12-17 in the household	0.193***	(0.042)	0.186***	(0.032)
Presence of an older person aged 55-59 in the household	0.104	(0.072)	0.016	(0.051)
Presence of an older person aged 60+ in the household	0.313**	(0.109)	-0.126	(0.076)
2. Head of household characteristics				
Age	-0.003	(0.002)	0.014***	(0.002)
Gender: Female	-0.044	(0.045)	0.010	(0.037)
Marital status: Married	0.024	(0.043)	-0.064	(0.035)
Education level: Primary	-0.199**	(0.067)	-0.106*	(0.050)
Education level: Secondary	-0.318***	(0.071)	-0.179***	(0.054)
Working	-0.315***	(0.063)	-0.001	(0.053)
3. Individual's characteristics				
Gender: Female	-0.075***	(0.020)	0.065***	(0.019)
Age	0.026***	(0.001)	-0.022***	(0.002)
Age square	-0.000***	(0.000)	0.000***	(0.000)
Marital status: Married	-0.060**	(0.019)	0.219***	(0.018)
Education level: Primary	-0.135***	(0.021)	-0.029	(0.019)
Education level: Secondary	-0.189***	(0.028)	-0.090***	(0.025)
Working	-0.470***	(0.096)	-0.288**	(0.105)
Ethnic group (ref. Other ethnic groups)				
Kikuyu	0.180**	(0.065)	-0.102*	(0.049)
Kamba	0.097	(0.065)	-0.410***	(0.051)
Luo	0.524***	(0.071)	-0.042	(0.053)
Luhya	0.395***	(0.070)	-0.142**	(0.054)
Kisii	0.178	(0.094)	-0.174*	(0.078)
Somali	-0.026	(0.135)	0.166	(0.096)
4. Individual's type of activity (ref. Formal salaried)				
Self formal business	-0.226	(0.121)	0.405**	(0.126)
Self informal business	0.117	(0.103)	0.422***	(0.110)
Formal casual worker	0.140	(0.112)	0.104	(0.122)
Informal casual worker	0.415***	(0.110)	0.309**	(0.117)
Informal salaried	0.127	(0.161)	0.164	(0.172)
5. Exclusion restrictions				
Duration of stay in the setting	0.025***	(0.006)		
Enumerated in 2002			0.207***	(0.023)
Household experienced mugging			-0.162***	(0.040)
Household experienced theft			-0.060	(0.043)
Constant	-0.041	(0.118)	-0.078	(0.139)
ρ_1: Initial Condition - Retention		0.080 (0.017)***		

Note: *p<0.05, **p<0.01, ***p<0.001.

individuals who are educated, working, female, and married are less likely to be initially poor. Besides, the covariates age and age-square suggest that younger and older people have lower probability to be poor at the beginning. Moreover, the probability of being initially poor is statistically different from zero for some ethnic groups. Thus, Kikuyu, Luo, and Luhya people are more likely to be poor at the initial period. This result may appear counter-intuitive as these are the major ethnic groups in the country, and likely they control most economic sectors. One explanation could be an over-representation of these ethnic groups among the poor living in the slums. Kikuyu, Luo, and Luhya being the better-off of the country, then those who are poor among them may be more tempted to migrate to Nairobi and settle the slums in search of better livelihood opportunities. We note also that individuals working as informal casual workers have higher probability to be poor, as compared to salaried in the formal sector.

Turning to the retention equation, the results show home tenure is a significant determinant of mobility. Individuals living in household which is not paying rent are less likely to move out. As well, the presence of children (of all age) in the household induces higher probability of staying in the DSA. Similarly, having a head of household who is female or not educated likely reduces chances to move out. The age has U-shape influence on the probability of exiting the DSA. Younger and older people likely have lower probability to quit. On the contrary, higher educated are significantly more prone to leave out the DSA. Likewise, those were found working in 2003 display a lower propensity to stay in DSA. This echoes a previous result from Table 1, which suggests that those better off are more likely to move out. It is important to mention however that the working sector influences the probability of leaving or not. Thus, we note a higher probability to stay for those running their own business (formal or informal) or working casually in the informal sector.

Overall, our estimation approach to poverty transition provides some useful insights into the factors underlying poverty persistence in Nairobi's informal settlements. However, one caveat should be mentioned. Our estimation sample is limited to only two waves of the corresponding panel dataset; then the poverty dynamics analysis is restricted to a period of just four years. Consequently, our results are more related to poverty experience over a limited period (four years), rather than the experience of poverty over multiple spells. An analysis over more waves would provide richer insights into the determinants of poverty dynamics in Nairobi DSA. Moreover, more waves would also allow accounting for the effect of time-varying shock not specific to individuals, such as price fluctuations, natural calamities, general economic stagnation or slow-down, etc.

7. Conclusion

The paper uses an endogenous switching model, which accounts for initial conditions, non-random attrition, and unobserved heterogeneity. The estimations are based on a two-wave sample of a panel dataset from the Nairobi Urban Health and Demographic Surveillance System (NUHDSS), the first urban-based Health and Demographic Surveillance Systems (HDSS) in Africa. Estimation results indicate a positive and significant link between unobserved factors affecting both the initial condition and the attrition equations, which suggest that those initially poor have a lower attrition propensity. Then an estimation ignoring the sample retention mechanism would likely yield biased results. As well, results show that the initial conditions and the panel retention are both endogenous processes for poverty transitions; should not be ignored when estimating poverty dynamics. Conversely, with respect to the poverty transitions, the estimation results show that only a limited number of covariates significantly different from zero. In contrast, many parameter estimates are statistically significant in both initial conditions and panel retention equations.

Overall, the paper provides evidence on the factors that drive poverty persistence in Nairobi's informal settlements. Results indicate that TSD constitutes the major factor underlying poverty transitions in the DSA. There is little heterogeneity effects; only 10 percent of poverty persistence is likely due to heterogeneity. Moreover, even when household and individual observed characteristics differ notably, the TSD size remains very large. This implies that active anti-poverty programs aimed at breaking the cycle of poverty constitute the most appropriate policies for taking people out of poverty and preventing them to fall back in. Indeed, this does not exclude policies focusing on individual heterogeneities. Active policies for improving individual's education, personal skills and capacities, or living environment would also allow preventing people entering poverty or persisting in.

However, one caveat should be mentioned. The estimation sample used in this paper is restricted to only two waves of the corresponding panel dataset. The poverty dynamics analysis concerns then a limited period of just four years. Consequently, our results are more related to poverty experience over a limited period (four years), rather than the experience of poverty over a longer period. An analysis over more waves would provide richer insights into the determinants of poverty dynamics in Nairobi's slums.

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