Journal of Econometrics and Statistics
Vol. 4, Issue 1, 2024, pp. 105-140
https://doi.org/10.47509/JES.2024.v04i01.06

Poverty Persistence and True State Dependence in Uganda

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ABSTRACT

This paper estimates the dynamic random effect probit models and endogeneous switching regression using the Ugandan household panel survey. After controlling for observed and unobserved differences in individual characteristics, the paper still finds strong evidence of state dependence, which is that past poverty increases the risk of future poverty. In the presence of genuine state dependence, short run polices are more effective. It is of important to keep households not to fall into poverty in the first place. Otherwise, they are more likely to develop unfavorable (poverty induced behaviors) attitudes that precipitate the chance being in an extended poverty. Hence, targeting households whose consumption is slightly above the poverty line using short term financial instruments (credit and insurance service) can be a viable option. In the transition probability model, the impact of an explanatory variable switches depending on whether an individual is poor or not in the previous round. Education, large proportion of adult household members and having electronic device such as TV-radio always reduce the incidence of poverty. They keep individuals from falling into poverty in the first place and/or assists them to escape poverty. On the other hand, being married, drought and the incidence of civil strife increase both the poverty persistence as well as poverty entry probabilities.

KEYWORDS

Poverty, state-dependence, dynamic models, attrition, Uganda.

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Article History

Received : 02 March 2024; Revised : 28 March 2024; Accepted : 03 April 2024; Published : 15 April 2024

To cite this paper

Seid Mohammed Yimer (2023). Poverty Persistence and True State Dependence in Uganda. *Journal of Econometrics and Statistics*. 4(1), 105-140.

1. Introduction

An individual is said to be in a state of poverty if he/she fails to meet a certain level of consumption needed to stay healthy and productive. It is of important to ask why some people escape poverty while others remain in it for un-interrupted periods. An individual with low standard of living today is more likely to stay in that state in the future. After controlling for individual heterogeneity, genuine state dependence arises if those who were poor in the past are more likely to be poor today than those who were not. It reflects the situation that two individuals having identical attributes behave differently in the future because one of them is poor today. Thus, past poverty experience may lead to a higher risk of future poverty. It is also of important to identify who is at a risk of poverty and the characteristics that make individuals to persist or entering into poverty.

Poverty persistence has been studied since Heckman's ground break work in 1981 (Cappellari and Jenkins,2004,2002; Poggi,2007; Biewen,2009) and recently, recognized as a main social indicator in public and academic discussion. True state dependence, unobserved and observed heterogeneity are the most important sources of persistent poverty (Heckman,1981). Thus, efficient policy design against poverty depends on availability of information on the extent of true state dependence and heterogeneity in the aggregate poverty persistence. Households are heterogeneous in terms of their observable productive characteristics or individual specific unobserved attributes. The empirical challenge is to disentangle the impact of poverty induced attributes from determinants of initial poverty and time constant individual characteristics.

If heterogeneity is the main source poverty persistence, long term policies that address those characteristics will lead to better outcome. If persistent poverty is explained by the true state dependent (poverty induced effect), short run policy would be the most effective and it includes cash transfer program such as safety nets, and aid in the form of consumption goods such as wheat (Faye et al,2011). Other things remain constant, if current poverty is mainly affected by the poverty in the previous year, then we call it state dependent poverty and thus, policies that aim to reduce just current poverty are more likely to reduce future poverty, leading to lower poverty in the steady state. On the contrary, if there are idiosyncratic shocks, they can cause people to fall into poverty today and people are less likely to move out of their poverty tomorrow. But it is an empirical issue whether lagged poverty is statistically significant or not. We find that it is significant in our studies, and it implies that short term negative or positive shocks determines poverty. Thus, if true state dependent is more important than heterogeneity, then the relevant policy would be to prevent individuals from falling into poverty in the first place. Once they are in poverty, it is of difficult for them to leave that state irregardless of what their initial characteristics would be (Nilsson,2012). The objective of the paper is therefore to determine the amount of true state dependence in the overall poverty persistence.

Deininger and Okidi (2003) examine the link between growth and poverty reduction in Uganda and yet, they do not study the poverty transition dynamics. Bigsten and Shimeles (2008) examine poverty transition and persistence in Ethiopia based on Heckman (1981) and Wooldrige's (2005) approaches for initial condition problem in dynamic non-linear panel data. These standard approaches, however, require a balanced panel data and observations that do not appear in all rounds are omitted. Sample selection is ignorable though this assumption is ubiquitous. In addition, it discards useful information, leading to efficiency loss. Instead, this paper estimates the Wooldridge and the Heckman versions for unbalanced panel.

The main contribution of the paper is that it examines the impact of past poverty on current poverty after controlling for differences in observed and unobserved individuals characteristics. To extent of my knowledge, this is the first study in Uganda. The paper applies the endogenous switching regression model to analyze the poverty Dynamics in Uganda. It is a transition probability model where the impact of an explanatory variable switches depending on the previous period poverty status of individuals (Cappellari and Jenkins, 2004). In addition, the paper improves the original Wooldridge (2005) conditional maximum likelihood estimator and the Heckman's (1981a) for dynamic non-linear panel data in a way to be estimated using unbalanced panel data. The paper applies the same Geweke Hajivassilliou Kean (GHK) integral evaluator technique for all models so that differences from approximation methods of multivariate integrals have been virtually removed. The efficiency gain in the model convergence and parameter stability is substantial even at a low halton draws. The paper estimates these alternative models to obtain comprehensive evidence on whether there exists genuine state dependence or not in Uganda. Both the dynamic random effect probit models and endogenous switching regression consider the problem of initial condition and endogenous sample attrition. Initial poverty can be correlated with unobserved heterogeneity because the start of stochastic process does not coincide with initial period for which data is collected.

To maintain the representatives of the sample overtime, the Uganda household panel was designed such that about 20 percent of the 2005/06 households are randomly chosen for further tracking of all their members (all individuals members who leave their parent household and join another household) in subsequent waves. The newcomer (the split of individual) and another household members to which the split joins are interviewed in their new location (see the data section for detail). This paper uses individuals as a unit of analysis so that the split of individuals and the characteristics of the new household to which they belong are included in the econometric specification and estimation. This is also an added value as none of the previous studies in Uganda consider this issue in empirical estimation. In addition, the paper estimates spatial and inter-temporal utility consistent poverty lines using the panel data, which are used as inputs in this study.

The observed poverty persistence is found to be 26%, suggesting that those who were poor in the past have 26% higher probability to remain as poor than those who were not poor. After controlling for individual heterogeneity, the impact of past poverty(genuine state dependent) is 18.7%. Depending on the samples being considered, between 61%-72% of the poverty persistence is attributable to the effect of true state dependence. It finds that incidence of civil strife is an important variable that increases both poverty persistence and entry probabilities. Similarly, drought risk also increases the poverty persistence and entry rates. Education and ownership of TV-radio are found to reduce the likelihood of being in a persistence poverty. They also keep individuals from falling into poverty in the first place.

The paper is structured as follow. Section 2 offers the data. The methodology is portrayed in section 3. section 4 offers the discussion and interpretations of the estimated parameters based on the different methodological approaches. Section 5 concludes.

2. Data

Uganda Bureau of Statistics(UBOS) has conducted a large scale national household survey in 2005/06 (May 2005 til 2006) with the core objective of updating poverty estimates. As part of the living Standard Measurement Study- Integrated Survey on Agriculture(LSMS-ISA), both UBOS and the World Bank group were participating in the collection of the panel data. The initial 2005/06 household survey involves two stages stratified random sampling. In the first stage, census enumeration areas (EA) were selected from four geographical regions (west ,north ,south and east) with probability proportional to size, indicating that a region with higher population has higher EA. As a result, the survey is virtually representative of the target population . Then a household listing activity was held from which households were drawn in the second stage. 10 households were randomly selected from each enumeration areas. The structure and the core content of the questionnaire in consumption and household modules are consistent across all survey periods. The list of food and non-food consumption items,the unit of measurement and recall period, which are of relevant to compute total consumption per household, are consistent and comparable overtime. The Uganda panel data consists of four waves: 2005/06, 2009/10,2010/11 and 2011/2012. In all waves, food expenditure comprises consumption from own production, purchases and free gifts. Consumption out of home production , which was valued at farm gate price, is revalued now with current market prices. Imputed value of rent was constructed for owner occupied houses.

The consumption expenditure comprises food and non-food components. For semi-durable and durable consumption items, the flow of services is estimated and part of the total consumption. It is not the purchase price of the house included in housing consumption but the imputed value of the rent in a month: Housing rent is the most important non-food consumption expenditure for urban household in African countries. Imputed service is a flow which is taken as part of non-food consumption. It is an income, not a stock or asset used to analyze poverty. The services obtained out of an asset are relevant to the consumption well-being of an individual. Standard of living is assessed with time and imputed services are computed accordingly. If total consumption expenditure is below a certain level in a year (consumption poverty line), then an individual is poor. Poverty is a flow concept, not static .

Concerning food consumption, information on quantity purchased or quantity consumed out of own production is available in the survey. Each household offers the price paid for the quantity purchased or estimates the price if they would decide to sell. The median unit price for a given food item is obtained from households purchasing it and this price is used to revalue non-purchased home consumption because some households are both produce and consumer. They produce and consume part of it and that quantity consumed must be converted to monetary values using median price of the same item but purchased by another consumer. Gifts, in kind receipts and quantity consumed from own production are re-valued with the market price. Real consumption expenditure per adult has been constructed. Unlike the extant research in Uganda (Duponchel et al.2014; Lawson et al.2006; Mckay and Lawson,2003) who use an outdated poverty line constructed by Appleton (1999), I construct utility consistent poverty lines using the four waves panel following Arndt and

Simler (2007,2010). The weighted national poverty line is 34618 Ugandan shillings. I can offer the do file upon on request..

To minimize the possible attrition rates, the Living Standard Measurement Study (here after denoted by LSMS) tracked households who shifted into new location or individuals who left the household and joined a new household. 20 percent of the 2005/06 households, randomly chosen, were eligible for split off tracking of all their members in the next round. In other word, the rule of tracking was to choose two households randomly from each enumeration area in 2005/06. Only about 624 (20% *3123) households were selected for split off tracking for the following rounds and they are called eligible original households (parent households). The original households consist of eligible(parent) and non-eligible households. Since this is done ex ante by statistical agency(UBOS), the identification particulars of all household members selected for split off tracking were known. When the household members of the eligible household leave the original household or when the household itself shifts into a new location, all split offs will be tracked in their new location.

The split off households are the newly formed households who are entering into the survey through an individual/individuals leaving the eligible original households. By adding new households into the sample, this method maintains the representativeness of the sample.

When the household is the unit of analysis, there exists three distinct groups of households. The first group is the panel households: those households whose identification particulars is observed in all four waves. The second group consists of attriting households: households observed in 2005/06 but not observed in all other three waves. The third group is the split off households: new households are entering into the sample from members of a household selected for split off tracking in 2005/06. The first group has been used in most empirical analysis in the existing literature. The balanced sample, however, may discard significant amount of information. Instead, this paper fills this lacuna using individuals as a unit of analysis. This allows to include split off individuals and the characteristics of their household in the regression. Incorporating the household members heterogeneity (individual and household level characteristics) as determinants of poverty is of an innovative research exercise (Cappellari and Jenkins,2004; Faye et al.,2011) It is of important to scrutinize whether there exists systematic difference between the split off households, and original households in Uganda. Table 1 presents their average and the median real consumption per adult across years for the sub-sample of households (national, urban and rural).

It is of important to scrutinize whether there exists systematic difference between the split off households, and original households in Uganda. Table 1 presents their average and the median real consumption per adult across years for the sub-sample of households (national,urban and rural).

In the third panel survey (2010/11) which is denoted by 2009 /10 to 2010/11 in table 1, there is no difference between the split off and the original households based on the national and urban sub samples. In the fourth round (2011/12), the number of split of households is four times higher compared to the number in the third round. Both test-statistics suggest that not only the mean but also the median consumption is higher for split off households than for the original households. This suggests that splits are not completely random. Rural splits are better off compared to rural original households.

The sample size for 2005/06 is 3120 households. Since the data is panel, the total sample sized pooled over four rounds is 10222(see table 3). As we move from 2005/06 to 2009/10, only 2564 households remain in the sample out of 3120 households in 2005/06. Similarly, as we move from 2009/10 to 2010/11, only 2326 households are interviewed out of 2564. Non -attrited households in each survey round are presented in table 2. The total number of non-attrited households is 10195(3120+2564+2326+2185). However, there are 27 new households (also head of the household) entering the survey due tracking splits household members. Thus, the total pooled sample size is 10222.

Finally, table 2 portrays the characteristics of attrited and non-attrited households across the four waves of the panel survey. It is of interest to investigate the attrition of the original households since the year 2005/06.[1]. As revealed in table 2, there is high attrition rate between the first and second rounds , which may be due to the longer gap between the two rounds. Out of 3120 households in the base year (2005/06), 556 households are not tracked and interviewed in 2009/10, suggesting an attrition rate of 17.8%. The number of households who are tracked and interviewed in all three waves (2005/06 , 2009/10 and 2010/11) was 2326, indicating a 9.3% (238/2564) attrition rate in 2010/11. Similarly, the attrition rate in 2011/12 was 6.8% (149/2326). Attrition rate continuously declines as we move from 2005/06 to 2011/12.

One can can test whether consumption differs between attrited and non-attrited households. In the first round, attrited households were wealthier to start with. In all other waves, at-

[1] the attrition rate of split off households after they appear in 2009/10 is not calculated

trited households were generally better off. Consumption patterns are systematic and thus, attrition is not random. Those who leave the sample may have different productive characteristics than the average population. With respect to attrition, urban households have higher attrition than rural households. In addition, attrited urban households have always higher average and median consumption than non-attrited urban households.

Household level attrition is often different from individual level attrition. The control variables are organized into 2 groups: individual and household level characteristics. The outcome variable is the poverty status of an individual. Table 3 presents the characteristics of both the household and the head of the household.

The rural sample is chosen than the urban sample because of its large sample size and land holding as a determinant of poverty is not available for most urban households. The poverty transition rates and individual attrition rates are offered in table 4 for national and rural subsamples. The poverty transition matrix shows the overall transition probabilities between t-1 and t over the period 2005/06 and 2011/2012. The transition matrix is obtained without controlling for observed and unobserved heterogeneity.

The first panel consists of the transition probabilities of all individuals observed at t-1 (i.e includes attritors). The second panel comprises the conditional transition propensity of individuals who are observed in both t-1 and t. The propensity of being poor at t is affected by whether an individual was poor or not at t-1. Based on the balanced sub-sample, individuals who were poor at t-1 have 58.7% probability to remain poor at t while those who were non-poor at t-1 have low probability(27.9%) of entering into poverty. This implies that those who were poor in the previous period,on average, have 30.8% higher probability than those who were not. This is suggestive of high true state dependency effect of past poverty on current poverty. The 30.8% poverty persistence, which is a measure of aggregate state dependence in poverty, is the combined effects of heterogeneity and true state dependence (effect of past poverty). The econometric method allows us to distinguish the contribution of heterogeneity and poverty dynamics (true state dependence) in the poverty persistence.

The poverty transition matrix using all individuals(age above 14) at t-1 is presented in table 4. An individual observed at t-1 can be poor or non-poor or exit the sample at t and table 4 presents the probability of occurrence of these events. The missing in the table offers the percentage of attrited individuals according to their past poverty status. Individuals who were poor in the past have 25.8% chance to leave the sample while it is 29% for initially non-poor. Initially richer individuals are more likely to leave the sample than initially poor though the difference in attrition is small(3%). Just focusing only on the balanced part of the sample offers too pessimistic a view on poverty alleviation over the sample period.

3. Methodology

There is no single and universally accepted methodology useful to analyze economic event. Impact analysis always faces identification problem and as a result, different methods require different assumptions depending on the nature of the data and state-of-the-art. This paper applies the random effect dynamic models and endogenous switching regression to determine the true impact of past poverty onto current as well as identify the determinants of poverty persistence.

3.1. Endogeneous switching regression(ESR)

This model is used to determine the level of poverty persistence and distinguish the heterogeneity effect from true state dependence effect of poverty persistence(Cappellari and Jenkin's (2002,2004). Based on a binary poverty variable(P_{it}), an individual can be classified as either poor ($P_{it} = 1$) or non-poor ($P_{it} = 0$) depending on whether the real consumption per capita at time t falls below the poverty line or not (34618 Ugandan shilling a month). ESR is a transition probability model that takes into account multiple endogenous selection issues such as initial condition and panel attrition in the presence of unobserved heterogeneity. Based on trivariate probit model, the poverty transition between two consecutive years, $(t-1)$ and (t) consists of 4 parts. First, the determination of current poverty status at t conditional on the poverty status at $(t-1)$. Second, the determination of poverty status at the base year $(t-1)$ so as to capture the initial condition problem. Third, the determination of individuals' attrition between (t) and $(t-1)$. Fourth, the correlation of the unobservables affecting all the three process. When the initial distribution of poverty is not a random sample of the population, the base year poverty status would be an endogenous process. Thus, the latent poverty propensity at $(t-1)$ for an individual i takes the following form.

$$P^*_{it-1} = \beta' x_{it-1} + \mu_i + \delta_{it-1} \tag{1}$$

where $P_{it-1} = I(P^*_{it-1} > 0)$. x_{it-1} includes individual and household level characteristics. These control variables are listed in table 3 in the descriptive section. β is a vector of parameters to be estimated. μ_i and δ_{it-1} are individual specific time invariant and orthogonal white noise errors respectively. The composite error term ($u_{it-1} = \mu_i + \delta_{it-1}$) is assumed to follow the standard normal distribution: $u_{it-1} \sim N(0,1)$

Let r_{it} denotes the observed retention status of an individual. The corresponding latent propensity of retention for individual i between t and $t-1$ is given by:

$$r_{it}^{*} = \phi^{'} w_{it-1} + \eta_i + \epsilon_{it} \tag{2}$$

w_{it-1} is a vector of covariates describing individual and household characteristics. ϕ is the parameters to be estimated. The composite error term (ω_{it}) is the sum of unobserved individual specific effect, η_i and the idiosyncratic orthogonal white noise error, ϵ_{it}. ω_{it} follows a standard normal distribution: $\omega_{it} \sim N(0,1)$. equation(1) and equation(2) are called initial and retention equations respectively. In the poverty transition probability model,the impact of an explanatory variable switches depending on whether an individual is poor or not in the past. The latent propensity of poverty will be given by:

$$p_{it}^{*} = [p_{it-1}\gamma_1^{'} + (1-p_{it-1})\gamma_2^{'}]z_{it-1} + \tau_i + \zeta_{it} \tag{3}$$

The first term in square bracket indicates the poverty persistence while the second term denotes the poverty entry rate. $\gamma_2^{'}$ are parameters associated to factors that affect poverty entry rate while $\gamma_1^{'}$ are estimated coefficients obtained from poverty persistence determinants. If $\gamma_1^{'}$ and $\gamma_2^{'}$ are equal, current poverty is not affected by the base year poverty status and this implies absence of true state dependence. z_{it-1} represents a vector of explanatory variables. Most of the variables that are in x_{it-1} are also included in z_{it-1}. Variables that are only in $x_(it-1)$ but not in z$_(it-1)$ are whether father deceased, mother deceased and mobility experience of the head. All other variables in the regression (see table 3 and 5) appear in both $x_(it-1)$ and $z_(it-1)$. We prepare exclusion restriction(variables in x_{it-1} but not in z_{it-1}) by looking for variables that affect the initial poverty but not the transition probabilities. Since the model is non-linear, of course, identification can be achieved without looking for exclusion restriction variables (Cappellari and Jenkin, 2004). The composite error term $\vartheta_{it} = \tau_i + \zeta_{it}$ is assumed to take a standard normal distribution. The three equations are estimated jointly using a multivariate probit. u_{it-1} ,ω_{it} and ϑ_{it} are multivariate normally distributed with mean zero and covariance matrix Ω.

The correlations of unobservables from the three equations(initial ,retention,transition) which are freely estimated would be written as:

$$\rho_1 = corr(u_{it-1}, \omega_{it}) = cov(\mu_i, \eta_i)$$
$$\rho_2 = corr(\vartheta_{it}, \omega_{it}) = cov(\tau_i, \eta_i)$$
$$\rho_3 = corr(\vartheta_{it}, u_{it-1}) = cov(\tau_i, \mu_i) \tag{4}$$

When ρ_1 is positive,those who are initially poor are more likely to retain in the sample and the opposite holds when it is negative. A positive sign for ρ_2 suggests that non-attriting individuals are more likely to remain poor or fall into poverty. A positive ρ_3 indicates that initially poor are more likely at the risk of higher future poverty than initially non-poor. If ρ_1=ρ_2, attrition is ignorable. If ρ_1=ρ_3, then initial condition is exogeneous. If ρ_1=ρ_2=ρ_3, then it implies that both attrition and initial poverty are not endogeneous and the system is reduced to a univariate probit model (Cappellari and Jenkins,2002,2004). The three equations(eq(1),eq(2)and eq(3))are estimated simultaneously with free correlation of unobservables to test the null hypothesis of exogenous initial poverty and sample attrition.

Using the Geweke Hajivassiliou Kean (here after denoted by GHK) (Kean,1994) multi-dimensional integral evaluator, both trivariate and bivariate cumulative distribution function (cdf) are computed for each individual. t-1 and t+1 are the base years for transitions into t and t+2. This approach is adapted following Nilsson (2012. Since we have many individuals on the same household at given time and also repeated observations for the same individual, I use the Pseudo Simulated Maximum Likelihood method(SML) for clustering the standard error (Cappellari and Jenkins,2004; Nilsson,2012).

Train(2003) provides the details on how to approximate the multivariate normal cdf based on GHK approach. The GHK estimator recursively decomposes the three dimensional correlated error terms into a uni-variate standard normal variable (see,Train,2003). Up on using GHK simulator, 100 halton draws are used. Finally, the model helps to predict poverty persistence and entry rates which are of crucial to determine the size of true state dependence(Arulampalam et al.2000, Cappeillari and Jenkins(2002,2004),Nilsson,2012). Poverty persistence($Persist_{it}$) and poverty entry rates($Entry_{it}$) are defined as transition probabilities conditional on the base period poverty status as follow:

$$Persist_{it} = prob(p_{it}|p_{it-1} = 1) = \frac{\Phi_2(\gamma_1' z_{it-1}, \beta' x_{it-1}; \rho_3)}{\Phi(\beta' x_{it-1})} \tag{5}$$

$$Entry_{it} = prob(p_{it}|p_{it-1} = 0) = \frac{\Phi_2(\gamma_2' z_{it-1}, -\beta' x_{it-1}; -\rho_3)}{\Phi(-\beta' x_{it-1})} \tag{6}$$

Poverty persistence indicates the probability of being poor at t, conditional on being poor at t-1 while poverty entry rate is the propensity of slipping into poverty at t conditional on being non-poor at t-1. The difference between the poverty persistence and poverty entry probabilities for each individual and then averaging it overall individuals gives rise to the size of true state dependence(TSD). Poverty persistence and entry probabilities can be predicted for individuals leaving the sample. Since explanatory variables are measured at t-1 and forecasts out of the sample can be applied for the attritors. TSD is computed after controlling for the two endogenous selection process in panel data. It quantifies the pure effect of past poverty :

$$TSD = \frac{1}{N}\sum_{i=1}^{N}(prob(p_{it} = 1|p_{it-1} = 1) - prob(p_{it} = 1|p_{it-1} = 0)) \tag{7}$$

On the other hand, aggregate state dependence(ASD) without controlling for heterogeneity is computed as the difference between the average probability of being poor for those who were poor in t-1 and the average probability of being poor for those who were not poor in t-1. ASD is given by:

$$ASD = \frac{\sum_{i\in(p_{it-1}=1)} prob(p_{it} = 1|p_{it-1} = 1)}{\sum_{i=1}^{N} p_{it-1}} - \frac{\sum_{i\in(p_{it-1}=0)} prob(p_{it} = 1|p_{it-1} = 0)}{\sum_{i=1}^{N}(1 - p_{it-1})} \tag{8}$$

Heterogeneity effect on poverty persistence is the difference between ASD and TSD (Cappellari and Jenkins,2002,2004). Alternatively, ASD can be obtained as the difference between average predicted poverty persistence and average predicted poverty entry rates.

3.2. Random effect dynamic probit model(RE)

Random effect dynamic probit is estimated to complement the results of the switching regression model. Wooldridge (2005) and Heckman (1981a,1981b) propose methods for solving the initial condition problem in random effect dynamic probit model (RE). To examine the impact of past poverty on current poverty, lagged poverty has often been included as explanatory variable in a random effect probit model. This variable, however, is endogenous unless the entire stochastic process for poverty coincides with start of the sample for which data is obtained. However, these households already exist before we get the first wave of the panel and they were already at the risk of poverty. The observed poverty status of an individual at the first wave may be the effect of the past poverty history, which triggers to develop unfavorable characteristics such as lack of motivation (which is not observed to researcher). Thus, initial poverty can be correlated with unobserved heterogeneity and it is no longer exogenous. Cappeillari and Jenkins (2002,2004) use endogenous switching while Wooldridge (2005) and Heckman (1981) propose correlated random effect model to the initial condition.

The conditional random effect dynamic probit model is denoted by RE while endogenous switching regression is by ESR. Both ESR and CRE approaches distinguish the impact of past poverty on poverty persistence from the impact of unobserved heterogeneity. The difference is that the standard CRE considers non-response or attrition as random and exogenous where as it is endogenous in ESR. After controlling for both observed and unobserved heterogeneity, the coefficient associated to the lagged poverty is taken to be the true measure of state dependence in CRE. After controlling for household heterogeneity, TSD is calculated if the returns to individual characteristics differ between initially poor and non-poor households. Instead of ignoring attrition as in the standard CRE, this paper estimates unbalanced data where unbalancedness is correlated with unobserved individual effects. Individuals who leave the sample may have peculiar unobserved characteristics than those available in all waves. In this case, the estimated coefficients may be biased and inconsistent

Plum (2014) illustrates the application of simulated maximum likelihood for unbalanced data. However, unbalancedness is independent of individual effect. This paper follows Albarran et al. (2015) and yet, the difference is that I use the GHK simulator based on simulated maximum likelihood (SML) method[2]. The SML method is computationally less intensive

[2] I have developed a user defined stata program to implement this

and model convergence is achieved with low halton draws (Plum,2014; Cappellari and Jenkins,2004). So that all models used in this paper including endogenous switching model are estimated using simulated maximum likelihood. I briefly present on how to include unbalancedness in the Wooldridge and Heckman models.

It is noted that γ is a measure of true state dependence. To determine the magnitude of true state dependence (TSD), its average partial effect (APE) has to be derived from the random effect models. For instance, the latent dynamic probability p_{it}^{*} equation based on the Wooldrige version, for $t \geq 2$, can be written as: $p_{it}^{*} = b_0 + bp_{i1} + \gamma_{p_{it-1}} + \alpha\overline{x_i} + \beta x_{it}^{'} + v_{it}$, where v_{it} is the composite error ($v_{it} = u_{it} + \eta_i$). The assumption of equi-correlation of the composite error is often asserted in the standard models. That is, $corr(v_{it},v_{is}) = \lambda = \sigma_{\eta}^2/(\sigma_u^2 + \sigma_{\eta}^2)$,for $t \geq 2$ and $t \neq s$. σ_u^2 is normalized to be 1. Let $x_{it}^{'}$ denotes all explanatory variables except the lagged poverty. From this transition probability model, we can predict the poverty persistence (s_{it}) and poverty entry rates(e_{it}):

$$\begin{aligned} s_{it} = pr(p_{it} = 1|p_{it-1} = 1, \beta x_{it}^{'}) = \Phi[(\beta x_{it}^{'} + \gamma) * (1-\lambda)^{0.5}] \\ e_{it} = pr(p_{it} = 1|p_{it-1} = 0, \beta x_{it}^{'}) = \Phi[(\beta x_{it}^{'}) * (1-\lambda)^{0.5}] \end{aligned} \tag{9}$$

$\frac{1}{(1-\lambda)^{0.5}}$ is the standard error of v_{it}. Arulampalam et al. (2000), Cappellari and Jenkins (2008) and Stewart (2007) calculate the average of s_{it} and e_{it} separately and the difference between the two means constitutes the average partial effect(APE). If we assume that unbalancedness is not independent of unobserved heterogeneity, we have different λ coefficients associated to each unbalanced sub-samples.

4. Estimation results and discussion

4.1. Testing the validity of joint estimation

This paper estimates the random effect dynamic model and endogenous switching regression and the results of the latter model is reported first. If all unobservable individual effects are uncorrelated, then one can estimate the probit model for initial, transition and retention equations independently. To start with, the validity of exclusion restriction has been tested and reported in table 5. Instruments should be jointly and separately insignificant in the poverty transition but significant in either initial or retention equation. Parental background information and pre-labour market entry have been used as instruments for initial condition (Heckman 1981b, Cappellari and Jenkins,2004). For retention equation , this paper uses the binary variable that indicates whether the head of the household has lived in another location for more than 6 months at a time from 2001 to the first survey in 2005.

The impact of previous migration experience may not be apriori determined. However, those who experience circular migration are less likely to retain in the sample. Rural-urban migration by way of changing the original place of residence for unintended period is basically driven by economic and non-economic reasons. Individuals who have strong cultural ties with their place of origin may not engage in an extended migration for more than 6 months. If this is the case, individual's mobility cexperince in the past an be taken as a good indicator of sample retention without directly affecting poverty transition. The variable partially captures some of the reasons for individual attrition.

The parental background of the head such as whether the head was orphan or not can affect the initial poverty status of the head. These individuals may be more vulnerable or face social exclusion. In addition, the socio -economic conditions of parents while the child grow up are crucial determinants of the child's long term accumulation of human capital (health and education). Occupational difference among parents when respondents were at the age of 14 can be a good instrument (Cappellari and Jenkins,2004,2002). This is, however, less important for rural households because they mainly rely on a single economic activity (i.e farming). Instead, I use whether the head had lost his parents (mother or father) or not as a predictor of initial poverty status.

Table 5 reports that mother's death has been significantly correlated with initial poverty. Both the death of the father and mother are separately and jointly excluded from the transition equation. Moreover, past mobility experience of the head is significant in the endogenous sample retention equation. These variables are good instruments and their validity is confirmed by the data.

To investigate whether the two selection mechanisms are exogenous, it is of important to look at the statistical significance of the correlation coefficients in the relevant selection equations. ρ_1 indicates the correlation between unobservable individual effects affecting initial poverty and sample retention. ρ_1 is positive and statistically significant suggesting that those who were poor at t-1 are more likely to retain in the sample (i.e both at t-1 and t) compared to the non-poor individuals. Thus, poor households leave the sample compared to non-poor, a finding like Faye et al.(2011) for Kenya.

The correlation between unobservables affecting poverty transition and uonbservables affecting retention is given by ρ_2 and it is positive and statistically different from zero. This implies that non-attriting individuals are more likely to fall into poverty or remain persistently poor compared to the dropouts. Since ρ_1 and ρ_2 are separately and jointly significant, sample attrition is not random because it affects both initial poverty and conditional current poverty. The null hypothesis of exogenous attrition, ρ_2 =ρ_1=0, has been rejected at 1 percent significance level. ρ_3), which is negative and statistically significant, captures the correlation between unobserved individual effects determining initial poverty and poverty transition. This negative coefficient implies that initially poor are more likely to escape poverty. It means that the initial difference in the consumption expenditure between poor and non-poor tends evaporate in the course of time. The high propensity of consumption convergence towards the mean is known as Galatonian regression (Stewart and Swaffield,1999).

Exogeneity of panel retention would imply that ρ_2 and ρ_1 can be jointly zero but this assertion has been rejected. Similarly, the null hypothesis of exogenous initial condition is rejected because ρ_1 and ρ_3 are jointly different from zero. The null hypothesis that all correlation coefficients are jointly zero($\rho_1 = \rho_2 = \rho_3 = 0$) has also been rejected. Thus, both initial condition and panel retention are endogenous for poverty transition, implying that selection is non-ignorable. The two sources of sample selection should be considered in the poverty dynamics model. Hence, initial,retention and poverty transition equations should be estimated simultaneously.

4.2. Estimated parameters from endogenous switching regression

Table 6 presents the estimates for poverty transition, initial poverty and panel retention using rural households sub-sample. The estimates associated to poverty persistence(γ_1) show the impacts of explanatory variables on current poverty conditional on being poor at t-1. On the other hand, the parameters associated to the poverty entry rates (γ_2) describes the effects of covariates on the risk of being poor for those who were non-poor initially. The parameter estimates of these two components of the poverty transition model are respectively offered in columns 3 and 4 in table 6. The estimates for retention and initial condition are presented in columns 1 and 2 respectively. [3]

[3] significance level: * 10(%, ** 5(% ,*** 1(% is presented in the footnote of the table. If an explanatory variable has an impact on retention or on initial poverty or on poverty transition, it must have a significance level of 5 percent or 1 percent.

Concerning the impacts of explanatory variables on poverty transition, several variables affect both poverty persistence and entry probabilities. Since poverty persistence is defined as the probability of being poor every year, the negative sign shows the importance of a given variable in reducing the chance of being persistently poor. The negative sign of an explanatory variable in the poverty entry transition probability, on the other hand, suggests that the variable keeps individuals from slipping into poverty. The most important covariates that significantly affect poverty persistence and entry rates are education, whether the household owns TV and radio or not, whether the household has experienced civil strife in 2001 or not, marital status of an individual, the proportion of adult members in the household and whether the household is affected by drought in 2001 or not. The explanatory variables are measured at t-1 and somehow they are exogenous to predict conditional current poverty. Those who have education are less likely to remain in poverty or fall into poverty compared to those individuals without education. Secondary and primary education offer individuals an opportunity to exit poverty and/or reduces the propensity of falling into poverty. Education is seen to be vital in the aim to fight against poverty.

Ownership of radio and TV is found to be key determinant of poverty alleviation. Those who own TV and radio have higher propensity to slipping out of poverty. They are also less likely to slipping into poverty from their favorable non-poor state and thus, the variable helps not to be poor in the first place as shown in table 6.

For a sustained economic growth, first and foremost, political stability must be a prerequisite for any economic, social and political reforms. Though people realize the importance of democratization and stability, unfortunately, civil unrest has been repeatedly observed in many African countries. The civil conflicts in the northern part of Uganda since 1990's displaced thousands from their home. To capture the impact of civil disorder on poverty, households are asked whether their economic activities have been affected by civil strife in year 2001 and 2005. Civil strife can arise because of lack of education, wealth expropriation in the presence of cash crop, lack of adequate infrastructure, unequal distribution of public investment across districts and corruption by the government officials. Due to these reasons, civil strife can be an outcome variable. To circumvent this problem, the civil strife information from 2001 has been taken as a predetermined variable to the current poverty. Of course, the variable is less affected by the problem of endogeneity because the incidence of civil strife at the district level is not a choice variable (Deininger,2003) and migration as a response to this incidence is not available to all individuals or is associated with a very high cost when it happens. The estimated parameter is positive and statistically significant in poverty transition and initial poverty suggesting that civil strife is a serious handicap that keeps households in poverty or causes them to fall into poverty. It tends to increase the risk of being poor. As indicated in the table, drought also increases the risk of being poor.

As to the marital status of an individual, being married significantly increases both the propensity to remain poor and the propensity of entering into poverty. It is of important to study the impacts of age composition of intra-household members and their heterogeneous labor market status on household's poverty transition. A high proportion of adult members (15-64) tends to decrease poverty persistence and entry probabilities significantly. These household members are less dependent and economically more productive. Intuitively, rural activities are labor demanding that requires physical strength of individual members .

To conclude, education, ownership of TV-radio,civil strife ,being married and composition of working household members are crucial determinants of poverty transition in Uganda. The paper does not study the mechanism how these variables affect productivity of rural households. For instance,ownership of TV-radio may have different channels through which productivity is affected. One can argue that TV-radio can boost agricultural productivity by offering farmers relevant and timely information on the use of technology and agricultural extension services, crop harvesting and planting. The news propagated through public media is deemed to be an important input for agricultural production. TV-radio and mobile can serve as consumption and production goods. As production input, they can substitute labor. With the already existing equipment and labor input, a better land improvement system can be available to the farmer. News about pre-prevention of adverse shocks can also be transmitted through public and non-public channels to create awareness for the society at large. Through radio-TV, and mobile electronic devices, the daily prices of agricultural products at different towns are disseminated and help farmers to take advantage of lower marketing margin or reduce transaction costs. The empirical result suggests that those who have TV-radio are less likely to entering poverty as well as persist in poverty compared to those without. From policy perspective, investment on information technology (by public and private sectors) is crucial. The fact that the consumption flow from TV and radio is included in the total consumption expenditure does not affect the statistical and economic importance of the variable on household poverty. The model is re-estimated after removing the consumption flow of TV and Radio and the result is still robust. To start with, the share of expenditure ascribes to TV-radio is meager in the data.

The impact of covariates on initial poverty and retention are offered in table 6. In contrast to poverty transitions, many of the explanatory variables are now statistically significant. Cappellari and Jenkins(2004); Nilsson (2012) and Faye et al.(2011) find many insignificant parameters, which are quite high compared to ours, in the transition probability model.. Accounting for sample selection problems and using small sub-samples for conditional poverty are the possible explanations for weak effects of coefficients. Education, TV-radio and civil strife affect both poverty persistence and entry rates. Government can break the cycle of poverty by using these variables as policy instruments. For instance, family planning policy can be in place to cut down the dependency ratio. Public and private investment in off-farm activity can also be a viable policy option to decrease underemployment. A possible policy instrument to reduce the adverse impact of drought is to induce risk mitigating and management strategies such as crop insurance and access to credit.

As reported in table 6, all variables maintain the expected sign in initial poverty specification. Being educated, having large fraction of adult members in the household(15-64),owning productive assets like tv-radio and mobile phone are crucial variables that decrease the propensity of being poor in the initial period. Civil strife, drought,and unemployed variable(include children below 14, pensioners,and other dependents who are not participating in any paid and unpaid economic activities) increase initial poverty.

Concerning the determinants of panel retention, it finds that married individuals, those with access to all weather road, and mobile device are more likely to remain in the sample. The better the road infrastructure, the more likely the household can be reached and be part of the panel sample. Possibly, mobile phone may help enumerators to contact the respondents even if they shift to another districts or towns in the country. Educated individuals are less likely to stay in the sample. The higher proportion of male and female adult members in the household increases the chance to leave the panel sample. An individual living in a household with large number of dependent and unemployed members is more likely to quit the sample. They may not have sedentary type of life , possibly due to disintegration or job search.

Does attrition overestimate the average poverty persistence? Does it under-estimate average poverty entry rates? First, the probability of being poor at t conditional on being poor at t-1 has been predicted for each individual observed at t-1 and these probabilities are averaged over the whole observations to get the average poverty persistence and it is found to be

0.38. This includes attritors because their probabilities are predicted based on their initial characteristics, that is what would be their probabilities had they been observed at t. Second, the average poverty persistence is calculated only for observations appearing both at t and t-1. Using this balanced sub-sample, the average poverty persistence stands to be 0.4. This calculation excludes sample dropouts. Thus, attrition overestimates the poverty persistence by about 2 percent. In other word, the poverty persistence for those leaving the sample is less than the population average poverty persistence. Similarly, attrition overstates the poverty entry rates. The predicted poverty entry probabilities are averaged separately over the balanced sub-sample or over the whole observations observed at t-1. The average poverty entry rates are 0.205 and 0.16 for the balanced sub-sample and entire observations (including attritors) respectively. Attritors have low poverty entry rates than the population average entry rates.

4.3. The size of genuine state dependence and heterogeneity

After controlling for household heterogeneity in observed and unobserved characteristics, the presence of genuine state dependence (GSD) has been tested. When $\gamma_1 = \gamma_2$, there is no genuine state dependence. In this case, the difference between the poor and non-poor is just encapsulated partly by their observed productive characteristics and partly by their unobserved attributes. This is known as heterogeneity effect. However, the hypothesis that $\gamma_1 = \gamma_2$ is rejected at any reasonable significance level(H_0: $\gamma_1 = \gamma_2$, chi-square(df=15)=55.96 and p-value=0.000) and this confirms the presence of genuine state dependence(see table 5 in panel D). Table 7 presents the size of aggregate state dependence (ASD) ,true state dependence and heterogeneity effect. Note that ASD is computed based on eq(8) using raw poverty transition rates while the true state dependence (TSD) is derived from eq(7). Heterogeneity effect of persistence poverty is obtained as the difference between ASD and TSD. Alternatively, ASD can be computed based on the predicted probabilities of poverty entry and persistence. The ASD obtained from the raw transition probabilities is comparable with the ASD obtained from predicted conditional probabilities, suggesting that our data better fit the multivariate normality assumption of unobserved heterogeneity. ASD is estimated to be 26.1% based on the whole observations at t-1(unbalanced data).[4]. This implies that those who were poor at t-1 have 26.1% more chances to be poor at t compared to those non-poor

[4]the missing transitions are replaced by their predicted probabilities from the model using the formula as $entry_{it}/(entry_{it} + 1 - Persist_{it})$

at t-1. After controlling for heterogeneity effect(0.074), the true state dependence is 18.7%. Other things being equal, being poor in the past increases the likelihood of future poverty by 18.7%.

true state dependence explains 71.8%(0.187/0.26) of the observed poverty persistence. The remaining 27.2 percent is attributable to heterogeneity effect. TSD accounts for a substantial part of ASD. Hence, past poverty experience explains a non-trivial portion of poverty persistence, a finding consistent with Cappellari and Jenkins (2004). The findings from this paper can be compared with the findings from other related empirical studies. TSD explains 50% of the aggregate state dependence in Biewen (2009) ; 60% in Cappellari and Jenkins (2004) and $78\% - 76\%$ in Nilsson (2012). These studies use urban households from advanced countries. Evidences from urban African countries are mixed. Faye et.al (2011) for Kenya show that TSD explains 90% of the poverty persistence.

Why those who were poor at t-1 are more likely to remain as poor at t? The first reason for poverty persistence is that some individuals may have characteristics that are hardly to change and hence they are more likely poor every time. For instance ,low level of education may increase the risk of poverty. Poverty will persist as long as the characteristics that are causing them persist. In other word, poverty persistence may arise because individuals likely to remain poor were over-represented among those who were poor in the first period. This selection mechanism is called the problem of initial condition (Heckman,1981). The second reason is that poverty persistence may arise even after controlling for the observed and unobserved heterogeneity. Past poverty may be a genuine cause for future poverty. Two identical persons in observed and unobserved heterogeneity except that one of them is poor in the first period may have different future poverty outcome as the person who experiences poverty may develop unfavorable attitudes that lead to persistent poverty.

4.4. Parameter estimates from random effect dynamic probit model

While the true state dependence effect based on the first order Markov model (switching regression) has been discussed so far, the Wooldridge (2005) version has been estimated to determine the level of TSD. Estimating different models under different assumptions helps understand the robustness of the TSD effect. Using simulated maximum likelihood method, the Heckman and the Wooldidge models for unbalanced data are estimated. The results are reported in table 8

I start with estimating the random effect probit(RE) model that assumes exogenous initial condition. The second column reports with exogenous initial condition and equicorrelation of error terms for different periods. The third column reports with exogenous initial poverty and it also dispenses the equi correlation assumption by allowing for the covariance structure to be unconstrained except that the variance at first period is normalized to be unity for identification. The second column is a RE model under restricted covariance structure while the third column removes the equi-correlation structure. The effect of lagged poverty on current poverty is found to be higher under unconstrained covariance structure (0.578) than under constrained covariance structure(0.464) in the second column. Thus, high poverty persistence is found under free correlation structure.

Columns 2 and 3 present the standard random effect dynamic probit model which assumes exogenous initial conditions. Whereas the other columns rather consider endogenous initial condition. Column 2 assumes that there are no correlations of composite errors across periods (constant lamda). Under this assumption, one can see which independent variables are significant or which are not(example see the effect of lagged poverty). In column 3, we allow correlation between composite errors. The joint correlation coefficient (Lamda) is presented in the table. Random effect model however assumes exogenous initial condition. We dispense this assumption by using the Wooldridge conditional maximum likelihood (with endogenous initial condition) and the results are presented in column 4. Finally, in which this paper relies on for interpretation of results, we use the unbalanced panel data in the regression and column 5 offers the results. Though estimation requires intensive software implementation, the model considers all information available in the data.

Assumption about exogenous initial condition in random effect probit model is, however, a stringent assumption. Initial poverty may be endogenous unless the stochastic poverty process coincides with the year in which the first survey is conducted. In the fourth column, initial poverty is endogenous while sample retention is exogenous. The coefficient associated to the lagged dependent variable is a measure of TSD in Heckman and Wooldrige models.

As we move from random effect probit model with exogenous initial condition (second and third columns) into the Wooldridge models with endogenous initial condition (in the fourth and fifth columns of table 8), the impact of lagged poverty has declined by almost half. Assuming exogenous initial condition substantially overstates the impact of true state dependence. Nevertheless, the lagged coefficients are still statistically significant even after controlling for observed and unobserved individual specific heterogeneity. The unobserved heterogeneity is modeled as a function of initial poverty, time invariant observed characteristics, initial characteristics of time varying variables, and within-mean time varying covariates (cf,Rabe-Hesketh and Skrondal,2013). Time varying variables averaged overtime (except the first period) have been included as additional covariates just to allow for correlation between explanatory variables and unobserved heterogeneity (Chamberlain,1984;Rabe-Hesketh and Skrondal,2013). For brevity,we do not report the parameters associated to initial period characteristics and time averaged characteristics. As shown in table 8, initial poverty is found to be positive and statistically significant suggesting that unobserved heterogeneity is indeed correlated with initial poverty. Being poor in the first year leads to a higher risk of future poverty and that impact is permanent.

The parameter θ in the Heckman model (see the last two columns) is significant, suggesting that initial poverty is endogenous. As one moves from an estimator that uses the balanced sample to an estimator that uses the whole observations (attritors and non-attritors), the coefficient associated to past poverty declines, suggesting that those who quit the sample have a lower poverty persistence. For each sub-sample , the variance of unobserved heterogeneity (σ_η^2) has been estimated and these variances are significant suggesting that unbalancedness is correlated with unobserved heterogeneity and hence panel retention is an endogenous process. The two sources of selections are also confirmed in the endogenous switching regression model.

Both the Wooldridge and Heckman estimators share many significant variables. Variables that reduce the risk of poverty include ownership of radio and TV, ownership of mobile phone, secondary and higher education, high proportion of male and female adult members (age 15-65) in the household and access to all weather road. On the other hand, the dependent ratio, as captured by the unemployed variable, and the proportion of disabled household members increase the risk of being poor.

The average partial effect for the lagged coefficient, which is the natural measure of the size of genuine state dependence, is calculated based on equation(9) in section 4.2. For the random effect models with exogenous initial condition (in the second column), the average partial effect is about 14.6%. For random effect models with endogenous initial condition, the Woodlrige model offers a low APE (0.07) compared to the APE (0.134) in Heckman model. Re-estimating these models with unbalanced data (as shown in the fifth column) does not significantly change the estimated APE(0.061). In the Heckman version, the estimate stands to be 0.125. Even after controlling for the observed and unobserved individual differences in characteristics, past poverty raises current poverty by 6 and 12.5 percentage points respectively using the Wooldrige's and Heckman's models respectively. To conclude, the risk of being poor is noticeable if poverty has been experienced in the previous year. Given the aggregate state dependence effect of 26 percent, the APE accounts for 23% (0.61/0.26) and 43%(0.125/0.26) of the poverty persistence respectively for the Wooldrige's and Heckman's models.

This paper provides evidence of true state dependent and concludes that 63.5%-72% of the poverty persistence is accounted for by the true state dependence using the first order Markov models (switching regression) while it accounts for 23%-43.5% using random effect models that controls for initial condition. Giardo et al (2006) find that all poverty persistence in Italy during the period 1995-2004 was only driven by unobserved heterogeneity.

In particular, Biewen (2009) uses the Wooldrige random effect model with feedback effect from past poverty onto employment and fertility to determine the APE effect (0.22) of the lagged poverty. Biewen (2009) concludes that about half of the poverty persistence in Germany is attributable to TSD. Biewen (2009) interprets the APE as the causal impact of past poverty on current poverty because the possible feedback effect from past poverty onto future employment and household composition were controlled for in a simultaneous random effect model. The argument that past poverty can affect the risk of future employment has little relevance in my study of rural poverty as households are employed in a single farming activity. The current fertility decision is also more of exogenous in rural areas and is less likely to be affected by the past poverty status of an individual.

Kedir et al.(2005) for Ethiopia find that lagged poverty has no significant effect on childbearing event in the rural sub-sample, suggesting no causal feedback effect from poverty to childbearing. In my study, endogeneous attrition has been considered but not by Biewen (2009) and Kedir et al. (2005). Finally, it must be noted that there is no problem of endogeneity from lagged poverty for endogenous switching regression.

4.5. Sensitivity analysis

This section provides evidence on the robustness of our result with respect to changes in the data set. To determine the magnitude of true state dependence under different methodological choices, four waves panel data have been applied: 2005,2009 ,2010 and 2011. The four waves Uganda household panel surveys are not conducted with equal time interval. There is a marked gap between 2005 and 2009 compared to the time gap between 2009 and 2010 or between 2010 and 2011. Intuitively, as the time gap is tightened, it becomes less feasible for individuals to change their observed compositions. For instance, poor or non-poor individuals in 2010 may not change their poverty status by 2011. On the other hand, several years have already passed between 2005 and 2009 and as a result, we expect high poverty entry and exit rates. The raw transition probabilities from these data suggest that the poverty persistence rate between 2005 and 2009 is lower than the persistence rate between 2010 and 2011. It is of interest to examine how the TSD effect is sensitive to changes in the panel series.

In doing so, I use data with equal distance between rounds, namely 2005,2009 and 2013 and each round has four years gap. The 2013 data have been officially released in the World Bank living standard measurement study recently in September 2016. The endogenous regression model has been re-estimated with the same set of exclusion restrictions and same set of explanatory variables so that one can see the impact of changes in data set. The exclusion restriction variables still satisfy the required properties. The 3 and four rounds of panel survey share many significant variables(results can be available upon request) albeit small difference. The three rounds panel qualitatively and quantitatively mimics the findings of the four waves panel in all aspects considered in the previous section.

It is of the paper's objective to estimate the share of true state dependence using the three rounds equal gap panel and compare it with an estimate from the four survey rounds. Table 9 offers the raw transition poverty persistence and entry probabilities for the whole observations present at t-1 as well as among observation presented at t-1 and t. The poverty persistence accounted for by the true state dependence varies from 49% among observations present at t and t-1 to 68.7% among observations present at t-1. The main conclusion is that TSD explains non-trivial portion of the poverty persistence, which holds irregardless of changes in methodological choices and data structure and the result is thus commendable.

Another way to look at the robustness check is by expanding the data set to include urban households. The data was collected in the same years as that of rural counterpart using the same instruments. Indeed, rural households are more poor compared to urban households. Urban households are mainly from the principal city of the country where poverty is less frequent. The sample size for urban households is small and one fourth of the total sampled households in 2005/06. Table 5 presents the summary tests for endogeneity of sample selection and validity of instruments using the four rounds survey for the national and rural sub-samples. Most of the explanatory variables in the endogenous switching regression have the same statistical importance in both national and rural sub-sample. The rural dummies (rural=1,urban=0) is negative and significant in the poverty transition and entry equations, suggesting that rural households are improving their poverty overtime. The TSD effect (0.175) using the national data is almost the same as the the TSD effect (0.187) using rural sub-sample and the share of TSD is 60.7% and 71.8% respectively. The substantial impact of past poverty on current poverty after accounting for observed and unobserved individual characteristics is a robust finding.

5. Conclusion

Recently, consumption dynamics and poverty persistence have received public and academic discourse. A better understanding of the poverty problem and its measurement can be achieved when cross section data is complemented by longitudinal data. A year to year change in poverty status resulting from changes in consumption is the most relevant and this study examines the degree of poverty persistence using the five waves panel household. The paper finds that individuals who were poor in the previous year, on average, have 26 percent higher probability of being poor in the current year compared to non-poor individuals in the previous year. For the first time, this paper distinguishes the heterogeneity and true state dependent effects of the observed poverty persistence in Uganda. The paper applies random effect dynamic probit models and endogenous switching regression method to determine the magnitude of true state dependence. Even after controlling for observed and unobserved differences in individual characteristics, past poverty significantly increases the probability of current poverty. This finding is robust under alternative assumptions and methodological choices. Yet, the magnitude of TSD varies between methods. TSD accounts for 23% of the observed persistence in poverty probability using the Wooldrige (2005) random effect dynamic probit where as its contribution becomes 71.8% using endogenous switching regression. There is actually a genuine state dependence effect in Uganda, which explains a non-trivial portion of the observed poverty persistence.

Whenever there exists a genuine effect from past poverty in increasing the risk of future poverty, it has an important policy implications. Short run policies are effective because they can affect current and future poverty, by limiting the possibility of developing current poverty onto persistent poverty. The policy objective is therefore to keep households from entering poverty in the first place because once poor, they are more likely to develop unfavorable attitudes such as loss of motivation, stigmatization,and demoralization resulting from loss of key factor inputs (land and oxen for rural household) which make future poverty more promising and permanent. Such short run policies may include creation of off-farm activities; providing subsidies in the form of agricultural inputs; introduction of risk mitigating and copying strategies and expanding credit service and insurance schemes to smooth consumption against adverse shocks. The risk management opportunities available to the households, inter alia, are income diversification, precautionary saving and asset as insurance.

By keeping households out of current poverty, policy makers can in principle break the cycle of poverty from becoming permanent. Nevertheless, it is only the informal risk copying opportunities that are often available to households living in poor African countries. Formal risk mitigating and copying strategies are very limited due to the absence of good governance and institutions. Using asset as insurance is constrained by the presence of risk and lumpiness. [5] Income diversification is less feasible because of entry constraint. Formal insurance and credit markets are incomplete and consumption loan is virtually insufficient or access to formal credit is rationed.

An important step for poverty reduction is to establish functioning institutions that mobilize resources for the benefit of the society at large, not to involve in rent-seeking activities. In other word, good governance is the key source of development. Political stability (or lack of violence) is one of the World wide governance indicators. In this study, civil unrest and political instability bring significant impediment to the formation of human and social capital. In the presence of civil strife, households are more likely to refrain from making investment on education, land improvements and non-farm activities. The paper finds that civil strife significantly reduces the chance of poverty exit as well as increases the probability of slipping into poverty. Drought is also a significant predictor of poverty risk. It increases the poverty persistence and entry probabilities. Being married increases the risk of poverty as they are more likely to persistent in poverty than those without. On the other hand, being educated and having TV-radio substantially reduce the poverty persistence probability. These vari-

[5] this has been reviewed by Dercon (2005) for Ethiopia

ables also decrease the propensity of entering poverty in the first place. In addition, having large proportion of adult male (15-64) in the household decreases the probability of falling into poverty.

The paper finds that households inflicted by past poverty are more likely to persistent in poverty than those without. Since the heterogeneity effect is significant (at least 27%), public intervention, of course long term in nature, is also recommended. In particular, investments on human capital and information technology are of paramount importance as suggested by the empirical finding in this paper. Education and having electronic devices such as mobile and TV-radio are significant determinants of poverty transition.

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Appendix Tables

Table 1. Comparison of consumption expenditure between parent and split off households in each year.

		National			Urban Households			Rural Households		
	Type	Obs	Mean	Median	Obs	Mean	Median	Obs	Mean	Median
2005 to 2009	Split	364	74708	48660	168	96890	64553	196	55696	43183
			(4535)			(7838)			(4689)	
	Parent	2566	59527	45332	582	95297	73995	1984	49035	40727
			(1115)			(3331)			(939)	
	Difference		15181	3328		1593	-9442		6661	2457
			(4670)	(2941)		(8517)	(6935)		(4782)	(2024)
	T-statistics		3	1		0	-1		1	1
2009 to 2010	Split	48	88669	56474	8	167507	125031	40	72901	54158
			(17275)			(73655)			(14092)	
	Parent	2608	64375	47501	581	100225	73500	2027	54099	42927
			(1423)			(3875)			(1374)	
	Difference		24294	8974		67282	51530		18802	11231
			(17334)	(5693)		(73757)	(81134)		(14159)	(4645)
	T-statistics		1	2		1	1		1	3
2010 to 2011	Split	190	78469	55995	33	77507	59045	157	78671	55684
			(5328)			(10292)			(6087)	
	Parent	2637	62854	46145	543	102991	71005	2094	52446	41281
			(1667)			(6845)			(1005)	
	Difference		15615	9849		-25484	-11961		26225	14402
			(5583)	(3581)		(12360)	(11595)		(6170)	(3747)
	T-statistics		3	3		-2	-1		4	4

Note: Note: standard errors of the mean and the difference are presented in the bracket The standard error for the median difference is also in bracket, obtained from quantile regression at the median

Table 2. Household level attrition across panel waves, excluding split off households

		National			Urban Households			Rural Households		
	Type	Obs	Mean	Median	Obs	Mean	Median	Obs	Mean	Median
2005 to 2009	Attrited	556	94890	66576	273	125904	87799	283	64972	50936
			(4388)			(7893)			(3164)	
	Non-attrited	2564	62678	48197	586	98675	72653	1978	52013	43751
			(1145)			(3963)			(758)	
	Difference		32212	18379		27228	15146		12959	7185
			(4535)	(2786)		(8832)	(5541)		(3254)	(2287)
	T-statistics		7	7		3	3		4	3
2009 to 2010	Attrited	238	79138	52618	91	126286	86250	147	49951	39707
			(5340)			(11628)			(2844)	
	Non-attrited	2326	57523	44673	490	89591	70877	1836	48965	40778
			(1094)			(3257)			(989)	
	Difference		21615	7945		36695	15372		987	-1071
			(5451)	(3820)		(12075)	(6311)		(3010)	(2835)
	T-statistics		4	2		3	2		0	-0
2010 to 2011	Attrited	141	76767	56992	49	97460	78026	147	49951	39707
			(5727)			(8941)			(2844)	
	Non-attrited	2185	61826	46088	461	97441	72097	1724	52303	42114
			(1533)			(4136)			(1517)	
	Difference		14941	10904		19	5929		-2352	-2407
			(5929)	(4772)		(9851)	(13792)		(3223)	(4328)
	T-statistics		3	2		0	0		-1	2

Table 3. Pooled summary statistics of household's and head's characteristics used for estimation (2005-2011)

	Whole sample		Rural sub-sample	
	Mean	SD	Mean	SD
Male household head	0.7100	0.4538	0.7189	0.4495
Marital status of head: Married	0.7353	0.4411	0.7484	0.4339
No schooling	0.1489	0.3560	0.1742	0.3792
Some primary school	0.5590	0.4965	0.6071	0.4884
Secondary school and above	0.2920	0.4547	0.2188	0.4134
Number of disables in the household	0.4601	0.7492	0.4920	0.7742
% of male members aged above 64 in the household	0.0227	0.1043	0.0263	0.1136
% of female members aged above 64 in the household	0.0263	0.1172	0.0282	0.1225
% male adult members aged 15-64 in the household	0.2629	0.2277	0.2496	0.2166
% female adult members aged 15-64 in the household	0.2622	0.1838	0.2481	0.1676
Number of unemployed	1.8778	1.9218	1.6979	1.7277
Number of paid workers in the household	0.4200	0.7288	0.3273	0.6491
Ownership of mobile	0.4466	0.4971	0.3739	0.4838
Ownership of TV radio	0.6735	0.4689	0.6327	0.4821
Access to all weather road	0.7900	0.4073	0.7614	0.4262
Civil strife	0.0922	0.2893	0.0995	0.2993
Drought	0.4267	0.4946	0.5024	0.5000
Mobility experience of the head	0.1554	0.3623	0.1330	0.3396
Father deceased	0.6618	0.4731	0.6580	0.4744
Mather deceased	0.4534	0.4978	0.4597	0.4984
Observations	10221		7849	

Note: Note: standard deviation (SD) for dummy variable is computed as $SD = (pq)^{0.5}$ where q is mean and p=1-q

Table 4. Raw transition probabilities for rural households with and without missing consumption: 2005 -2011

	Poverty transition for individuals >14			Transition for head of household		
Poverty status: year t-1	Poverty status: year t			Poverty status: year t		
	Poor	**Non-poor**	**Missing**	**Poor**	**Non-poor**	**Missing**
a) Whole sample-including attritors						
Poor	0,435 4	0,306 4	0,258 2	0,535 2	0,343 6	0,121 2
Non-poor	0,511 7	0,197 7	0,290 6	0,606 1	0,243 9	0,150 1
b) Balanced sub-sample						
Poor	0,586 906 6	0,413 093 4		0,608 993 9	0,396 1	
Non-poor	0,721 311 5	0,278 688 5		0,713 094 7	0,286 905 3	

Table 5. Correlation coefficients between unobservables in transition, retention and initial poverty equations, and exogeneity tests for retention and initial condition

	Rural		National	
	Coefficients	Standard error	Coefficients	Standard error
A. Correlation Coefficients				
Initial poverty status and retention:ρ_1	0.0549	0.0245	0.0246	0.0216
Poverty transition and retention:ρ_2	0.6115	0.1096	0.4633	0.1777
Poverty transition and initial poverty status:ρ_3	-0.2654	0.1097	-0.4063	0.0725
B. Wald test of exogeneity				
Exogeneity of panel attrition:$\rho_1 = \rho_2$	34.9282	0.0000	8.8534	0.0120
Exogeneity of initial condition:$\rho_1 = \rho_3$	11.5025	0.0032	32.6820	0.0000
Joint Exogeneity :$\rho_1 = \rho_2 = \rho_3$	51.8829	0.0000	53.9576	0.0000
C. Instrument Validity				
Exclusion of parental death from transition equation(d.f.=4)	0.8618	0.9300	1.1604	0.8846
Exclusion of parental death from initial condition(d.f.=2)	4.8483	0.0886	7.8494	0.0197
Exclusion of past mobility experience for more than 6 months at a time from poverty transition(d.f.=1)	2.6057	0.2718	3.5964	0.1656
Exclusion of past mobility experience for more than 6 months at a time from sample retention(d.f.=1)	6.4650	0.0110	7.8343	0.0051
Exclusion of both parental variables and mobility experience from transition equation(d.f.=6)	3.3180	0.7680	4.5293	0.6054
D. Absence of genuine state dependence				
(d.f.=15)	55.9660	0.0000	69.5420	0.0000

Table 6. Estimated coefficients for initial poverty, retention, poverty persistence and entry(rural)

	Retention	Intial Poverty	Poverty persistence	Poverty entry
Indvidual characterstics				
Sex(male=1)	0.0321	0.0493***	-0.0407	0.0528**
	(0.0279)	(0.0158)	(0.0299)	(0.0255)
Marital status: Married	0.8573***	0.0430	0.3025***	0.2108***
	(0.0339)	(0.0336)	(0.0754)	(0.0600)
Some primary school	-0.1050**	-0.1085**	-0.1864***	-0.1079*
	(0.0476)	(0.0433)	(0.0681)	(0.0623)
Secondary school and above	-0.1373**	-0.4559***	-0.3440***	-0.4334***
	(0.0561)	(0.0590)	(0.1084)	(0.0877)
Household characteristics				
Number of disabled members	0.0385*	0.0663*	0.0453	0.0420
	(0.0227)	(0.0341)	(0.0456)	(0.0434)
% older male members($>$ 64)	-0.0270	-0.1099***	-0.0900**	-0.0360
	(0.0190)	(0.0240)	(0.0377)	(0.0283)
% older female members($>$ 64)	0.0026	-0.0855***	-0.0322	-0.0709**
	(0.0187)	(0.0230)	(0.0341)	(0.0293)
% male adult members(15-65)	-0.0549***	-0.0650***	-0.0588***	-0.0675***
	(0.0100)	(0.0130)	(0.0219)	(0.0167)
% female adult members(15-65)	-0.0481***	-0.0858***	-0.0774***	-0.0762***
	(0.0129)	(0.0169)	(0.0284)	(0.0202)
Number of unemployed	-0.0429***	0.0597***	-0.0071	-0.0393**
	(0.0103)	(0.0139)	(0.0202)	(0.0175)
Ownership of mobile	0.3180***	-0.5356***		
	(0.0454)	(0.0587)		
Ownership of TV radio	-0.1174***	-0.5006***	-0.1750**	-0.2466***
	(0.0415)	(0.0515)	(0.0882)	(0.0769)
Access to all weather road	0.2187***	0.0486	-0.1028	-0.0757
	(0.0406)	(0.0510)	(0.0767)	(0.0654)
Civil Strife	0.1161*	0.3569***	0.4522***	0.3025***
	(0.0666)	(0.0852)	(0.1159)	(0.1164)
Drought	0.1158***	0.1081**	0.1239*	0.1171*
	(0.0375)	(0.0495)	(0.0741)	(0.0600)
Exclusion restriction				
Mobility experience of the head since 2001 till 2004)	-0.1879***			
	(0.0650)			
Father deceased		-0.0441		
		(0.0544)		
Mother deceased		0.1229**		
		(0.0536)		
Intercept	0.3478***	0.2997***	0.5520***	-0.3352**
	(0.0877)	(0.1060)	(0.1909)	(0.1697)

Note: Log-likelihood=-15194; Chi-square(d.f.=61) =1419 , P-value=0.000 Number of persons in the sample=6331 and number of person-wave observation=9884. Significance level: * 10%, ** 5%, *** 1%.

Table 7. Effect of heterogeneity and true state dependence in aggregate poverty persistence(rural)

	Transition probabilities		State dependence		Composition effect	
	Persistence (a)	Entry (b)	Aggregate(a-b)	GSD(c)	Heterogeneity (a-b-c)	GSD(%)
Whole sample	0.4695	0.2085	0.2609	0.1875	0.0735	71.8489
Balanced sample	0.5869	0.2787	0.3082	0.1958	0.1124	63.5307

Table 8. Dynamic panel data models: the Wooldrige's and Heckman's estimators for balanced and unbalanced data

	RE[1]	RE[2]	WCM[3]	WCM[4]	Heck[5]	Heck[6]
lagged poverty	0.4645***	0.5785***	0.2379***	0.2165***	0.4265 ***	0.4057***
	(0.0643)	(0.0737)	(0.0744)	(0.0729)	(0.0735)	(0.0703)
Some primary educ.	-0.0862	-0.0274	-0.1297	-0.1099	-0.1138	-0.0775
	(0.0725)	(0.0487)	(0.1092)	(0.1087)	(0.0713)	(0.0701)
Secondary & above	-0.4286***	-0.2551***	-0.2853***	-0.2643***	-0.4367***	-0.4017***
	(0.0949)	(0.0713)	(0.1041)	(0.1021)	(0.0953)	(0.0884)
Sex (male=1)	-0.0276	-0.0272	-0.0139	-0.0495		
	(0.0647)	(0.0427)	(0.0771)	(0.0744)		
Age	-0.0023	-0.0018	-0.0102			
	(0.0021)	(0.0014)	(0.0072)			
% male above 65	-0.0649***	-0.0430***	-0.1304***	-0.1318***	-0.0888***	-0.0872***
	(0.0229)	(0.0162)	(0.0652)	(0.0642)	(0.0209)	(0.0199)
% female above 65	-0.0836***	-0.0574***	-0.1157**	-0.1199**	-0.0991***	-0.0941***
	(0.0209)	(0.0150)	(0.0516)	(0.0504)	(0.0195)	(0.0188)
% male (15-65)	-0.0778***	-0.0562***	-0.0422**	-0.0418**	-0.0873***	-0.0906***
	(0.0130)	(0.0107)	(0.0254)	(0.0247)	(0.0132)	(0.0122)
% female (15-65)	-0.0851***	-0.0584***	-0.0456**	-0.0488**	-0.0967***	-0.0932***
	(0.0146)	(0.0120)	(0.0233)	(0.0231)	(0.0144)	(0.0138)
disable members	0.0726***	0.0482***	0.0654**	0.0781***	0.0724***	0.0841***
	(0.0276)	(0.0193)	(0.0301)	(0.0278)	(0.0273)	(0.0255)
off-farm working	-0.0918**	-0.0476	-0.0862**	-0.0766*	-0.1279***	-0.1277***
	(0.0417)	(0.0312)	(0.0450)	(0.0434)	(0.0428)	(0.0406)
unemployed	0.0748***	0.0475***	0.0841***	0.0886***	0.0738***	0.0751***
	(0.0143)	(0.0115)	(0.0200)	(0.0195)	(0.0144)	(0.0138)
Owned mobile	-0.4011***	-0.2501***	-0.3497***	-0.3820***	-0.4553***	-0.4872***
	(0.0524)	(0.0467)	(0.0570)	(0.0547)	(0.0535)	(0.0510)
Owned tv-radio	-0.3354***	-0.2353***	-0.1867**	-0.2297***	-0.4119***	-0.4179***
	(0.0518)	(0.0425)	(0.0738)	(0.0713)	(0.0527)	(0.0549)
All weather road	-0.1468**	-0.1004**	-0.1339**	-0.1340**	-0.1122**	-0.1200**
	(0.0579)	(0.0421)	(0.0614)	(0.0587)	(0.0581)	(0.0549)
initial poverty			0.2635***			
			(0.0709)			
initial poverty(1)				0.2791***		
				(0.0711)		
initial poverty(2)				0.6356***		
				(0.2121)		
Year 2010	0.0362	0.0776	0.0261	0.0157	0.0521	0.0299
	(0.0526)	(0.0491)	(0.0561)	(0.0536)	(0.0529)	(0.0502)
Year 2011	0.0592	0.1140**	0.0860	0.0609	0.0713	0.0482
	(0.0525)	(0.0423)	(0.0565)	(0.0526)	(0.0527)	(0.0500)
Eastern region	0.4951***	0.3860***	0.4340***	0.4297***		
	(0.0723)	(0.0578)	(0.0809)	(0.0783)		
Northern region	0.6345	0.4149***	0.5277***	0.5112***		
	(0.0767)	(0.0691)	(0.0845)	(0.0818)		
Western region	0.2704***	0.1763***	0.2860***	0.3144***		
	(0.0752)	(0.0542)	(0.0860)	(0.0818)		
Intercept (1)				0.7203***		
				(0.1795)		
Intercept (2)				-0.2042		
				(0.4533)		
Intercept	0.1828	-0.0495	0.7221***		0.5666***	0.3768***
	(0.1529)	(0.1180)	(0.1974)		(0.1188)	(0.1122)
θ					0.4960***	0.4321***
					(0.149)	(0.1412)
λ	0.1478	(-0.045 ,0.188 ,-0.231)	0.233	(0.274 ,0.215)	0.197	0.229
APE	0.1463	0.2	0.07	0.0611	0.1336	0.125
Number of Obs	6084	6084	6084	6920	6084	6920

Note: [1] refers Random Effect(RE) dynamic probit with exogenous initial condition. [2] is RE with free correlation of the composite errors. [3] is the Wooldridge Conditional Maximum likelihood(WCM) with endogenous initial condition. [4] is WCM where unbalancedness is correlated with unobserved individual specific heterogeneity.[5] is the Heckman estimator with endogenous initial condition. [6] is the Heckman estimator with unbalanced data. Estimates from initial poverty, are not reported for space reason. regional dummies is used as exclusion instruments and included only in initial poverty. Age and sex are insignificant in Heckman.

Table 9. Sensitivity checks: effects of heterogeneity and true state dependence

		Transition probabilities		State dependence		Composition effect	
		Persistence (a)	Entry (b)	Aggregate(a-b)	GSD(c)	Heterogeneity (a-b-c)	GSD(%)
National	Whole sample	0.4526	0.1636	0.289	0.1754	0.1136	60.69
	Balanced sample	0.5737	0.2306	0.3431	0.1900	0.1531	55.3741
Rural	Whole sample	0.7568	0.5862	0.1706	0.1172	0.0533	68.74
	Balanced sample	0.5423	0.2961	0.2463	0.1207	0.1256	49