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Essays on Poverty Issues: Microeconomic Evidence from African Countries

by

Seid Mohammed Yimer

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Program Coordinator:

Prof. Rita D'Ecclesia

Supervisor:

Prof. Pierluigi Montalbano

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Contents

Summary of the Thesis

The thesis consists of 5 self-contained but related essays on poverty issues, each of which is summarized below.

1 Estimating Utility Consistent Poverty Lines: Does poverty decrease in Uganda?

The starting point for poverty analysis is to find a common level of utility with which welfare of individuals can be assessed. The poverty line is the cost of obtaining a common level of utility defined over a bundle of consumption. The living standard of the household (welfare) is represented by real consumption. This paper provides an exhaustive study on how to construct utility consistent poverty lines so that welfare can be compared both inter-temporally and spatially. This paper tries to offer convincing arguments on the level and evolution of poverty using the four waves panel data drawn from Uganda. The study closely looks at other research works carried out in Uganda and attempts to place its contribution to the contemporary heated debates whether Uganda succeed in curbing poverty into a recommended level as stipulated in the Millennium Development Goal or not. The paper starts with background information about Uganda and then proceeds on technical issues of handing and processing the raw data from which spatially and inter-temporally utility consistent poverty lines are drawn.

After the cease of protracted civil war, Uganda has showed an impressive economic growth during the 1990's. Part of the growth is attributable to the implementation of economic reforms under the policy initiatives of structural adjustment program and consequently, the country can be taken as a good example in Sub-Saharan African for transforming itself into liberal economies. According to Uganda Bureau of Statistics (UBOS,2006) and Ssewanyana and Kasirye (2014),the official headcount ratio falls from 56 percent in 1992/93 to 20 percent in 2012/13. Based on stochastic poverty dominance approach, Ssewanyana and Ksirye (2012) and UBOS (2010) have shown that the official poverty headcount declines between 2005 and 2009 irregardless of the poverty line chosen. Using cross section data, it falls from 31.1 percent in 2005/06 to 24.5 % where as it declines from 28.5 to 24 % based on the panel data. In addition, all the four principal regions record a significant reduction in poverty level (UBOS,2010). On the contrary, Duponchel et al. (2014) argue that there is a uniform decline in GDP growth after 2005/06 . As suggested by Levine (2012), the poverty figures published by World Bank do not coincide with the poverty level reported by UBOS. He argues that poverty line set by Appleton et al.(1999)is too low and that the calculated poverty figures may not depict the true poverty level.

All these authors(UBOS, 2006,2010; and Ssewanyana and Ksirye,2012,2014) use the poverty line constructed by Appleton et al.(1999). The official poverty line is 16443 shilling per adult per month. Using the purchasing power parity exchange rate of 369 shillings to a dollar in 1993/94, the poverty line stands to be 44.56 dollar per adult equivalent a month. The line is equivalent to 34 dollar per capita per month and hence comparable with the "1 dollar a day" poverty line used for international poverty comparisons by the World Bank (Appleton et al,1999). Ssewanyana and Ksirye(2012) and UBOS(2010) use a 1 dollar poverty line to compute the official poverty figures. The sources of the inconsistency in the poverty figures are not well identified by the extant researches in Uganda. We start from the scratch to establish utility consistent poverty line using the four waves panel spanning 2005/06, 2009/10,2010/11 and 2011/2011. We believe that outdated food basket may not reflect the household's current consumption pattern. We follow the cost of basic need approach and thus, food poverty line is defined as the cost of achieving the minimum acceptable energy needs for an individual to stay productive and healthy. For Uganda, the minimum daily energy requirement per adult stands to be 3000 calories. As a starting point, it is of important to mention the stylized facts of the consumption patterns among Ugandan households.

Uganda has diverse dietary system. Matook is the most important dish for West and Central regions but not at all for North and East. The North gets significant portion of the diet from sorghum. That would not be a problem if the cost of obtaining a given amount of calorie is the same for all diets. Nevertheless, the cost of calorie differs significantly among food items. Matook is an inferior source of calorie where as sorghum is calorie efficient. In other word, matook is an expensive source of calorie while sorghum is a cheap source of energy. The cost of obtaining a given amount of food energy is larger for the West than for the North and ignoring regional food composition implies an increasing cost of living for the North. Constructing region specific poverty lines using region specific prices and region specific food bundle apparently seems a solution to this problem. However, multiple bundles by themselves do not solve the consistency problem. Recently, Arndt snd Simler (2010) develop a minimum cross entropy method to ensure consistency in welfare comparisons across space and time. We apply this method to establish poverty line bundles that are spatially and inter-temporally utility consistent.

Using a 2012/2013 national household survey, Van campenhout et al (2016) construct spatially utility consistent poverty lines for Uganda based on the cross entropy method suggested by Arndt and Simler (2010). However, our work differs from this recent paper in a number of ways. First, we use highly dis-aggregated food items in the basket, which is relevant. Cassava and sweet potatoes are the most important diets in Uganda. Cassava is of two types(cassava fresh and cassava dry/powder). Similarly, sweet potatoes has two varieties: sweet potatoes fresh and dry. These authors add up these varieties together. Aggregating or lumping would not be a problem if their prices were similar. Even in the same region, differences in the consumption patterns and prices between these varieties are quite substantial. Instead, we preserve these differences and hence they are part of the consumption basket. Second, it is not clear how many food items are in the consumption basket. They just describe the 5 food staples in Uganda and the consumption profiles of these bundles across regions. If they do not capture all consumption patterns of the Ugandan households, welfare comparison across space becomes perplexing. Appleton et al (1999) use 28 food items where as we use 34.

Third, the survey duration in all Uganda household survey is between 12 months and 18 months. This is a common problem to all of us. Consumption data is not collected in the same season of the survey period. Price variations across seasons within the survey are quite large, making welfare comparison less reliable unless seasonal inflation is removed from the nominal consumption. These authors do not consider this important issue. Using the laspeyres index approach, the default behavoir of the PLEASe code can consider temporal price changes within the survey. We modify the PLEASe computer software code in two ways. The literature offers different types of price indexing methods such as laspeyres index and the superlative price indexes(the Fisher ideal and the Tornqvist price indexes). Both theoretically and using data, the paper confirms that the conventional laspeyres index is inappropriate deflator.. First, we use Tornqvist price indexes in PLEASe code to construct temporal price index within the survey,which is used to deflate nominal consumption because laspeyres and Paasche are biased deflators . Second, the default behavior of the PLEASe code uses average prices to value consumption of own production. Instead, we use the median price as averages are susceptible to outliers.

Fourth, Van campenhout et al (2016) construct spatially consistent poverty lines. On the other hand, our poverty lines are both spatially and inter-temporally consistent. In addition, the objective of the thesis , besides constructing poverty lines that are consistent across space and time, is to show whether poverty decreases between 2005/06 and 2009/10 or not. These two are at least my contributions to the literature. As opposed to the official report, poverty headcount does not decrease as we move from 2005/06 to 2009/10. Instead, the thesis finds that there is an increase in the poverty headcount.

The thesis shows that methodological choices matter for poverty headcounts. Moreover, it is not only the differences in poverty lines that create wedge between the officially published poverty headcount and the poverty figures obtained using the new poverty lines. The official poverty headcount is underestimated simply because an implausibly large weight is attached to non-food component (0.72) and a small weight to food component (0.28). Both econometrically using Engle curve and triangular weighting approaches as well as from the observed consumption data, the thesis asserts that the share of non-food does not exceed 45%.

It is noted that 2005/06 is the base year. Food price inflation is substantially high compared to the non-food price inflation for the survey periods being considered (i.e. 2009/10 til 2011/12). Our calculated inflation rates are not significantly different from the inflation rates computed by OBS for our survey periods. Real consumption can be obtained by deflating the nominal consumption by the national price index, which is a weighted average of food and non-price index. The difference arises on the choice of the weights. They give less weight to food inflation and consequently, understates the national price index. This in turn overestimates the real consumption and thereby understates the non-base years poverty headcounts for any given poverty line. We show that poverty does not decline between 2005/06 and 2009/10.

In determining the proportion of people below the poverty line, the thesis involves in the following challenges. First, we ask how to construct the welfare measure itself at a given point in time. The guidance, relevance to developing countries, has already been well articulated in the existing literature by Hentschel and Lanjouw (1996), and Deaton and Zaidi (2002) and the thesis takes into account on this. Second, price data and their sources are useful. External price data (from national aggregates collected by OBS) and unit price data from households survey may give different poverty profiles. Approaches to organize the price data into a single index are diverse, yet identifying the limitations of the conventional method is important. Third, households' consumption patterns are heterogeneous across regions as well as overtime, calling for specificity. Regional poverty lines should capture the norms and consumption patterns specific to that region and yet, at the same time the poverty line bundles must ensure consistency of welfare comparisons over space and time. Finally, the unity of analysis chosen for consumption and poverty line must coincide. For instance, if we use consumption per person, then we need to have poverty line per person. An example inconsistency can be noted from Ssewanyana and Ksirye (2012) who use real consumption per adult and a 1 dollar poverty line per person to compute the headcount ratio.

The objective of the first chapter is twofold. First, we establish utility consistent poverty lines for each region and year. In the text, the food poverty lines and the national poverty lines are explicitly documented. I use these poverty lines throughout the thesis. They can be used by any other researchers from Uganda. Second, we show that the level of poverty headcount depends on assumptions and methodological choices. Yet, poverty profiles based on spatially and temporally utility consistent poverty lines are the preferred measure. By all standards, poverty headcounts ratio does not decrease as we move from 2005/06 to 2009/10. The official report indicates a decrease in poverty from 28.5% in 2005/06 to 24 % in 2009/10. Based on our preferred utility consistent poverty lines, the poverty headcounts increases from 22.6 percent in 2005/06 to 32 percent in 2009/10 and the difference is statistically significant. The policy implication is that Uganda government should revise and update the available poverty reduction strategies to bring changes in the national welfare improvement.

2 Measures and Determinants of Chronic Poverty: Panel Data Evidence from Uganda

Quantitative poverty analysis helps identify the target population most affected by extended duration in poverty. This paper decomposes aggregate poverty into chronic and transient poverty because the policy recommendation depends on whether poverty is chronic or transient. When poverty is mainly transient, provision of insurance markets is effective to stabilize consumption. If chronic poverty is more important, intervention in the form of increasing human and physical capital is a relevant policy choice. Removing any social, economic and political constraints may expedite the process of poverty alleviation. Several approaches are proposed in the literature to identify the chronic poor and determine the chronic poverty index. These approaches generally fall into two main branches: the spells and components approaches. According to the spells approach, the proportion of time in which real consumption below the poverty line has been used to classify a household as chronically poor. Of course, such discrete dichotomization of households into two classes (chronic or non-chronic),however, involves some degree of arbitrariness and also not sensitive to the depth of poverty.

In the components approach, the sequences of real consumption per adult has been changed into a permanent component and a transitory variation around it. As part of the component approach, the Jalan and Ravallion's (2000) method has been conventionally used in the existing literature. The time average of consumption has been compared with the poverty line to identify the chronic poor and this relies on the assumption of prefect consumption smoothing with complete credit market perhaps at prevailing zero interest rate. Using the four waves panel data from Uganda, the paper contributes to the existing literature by providing comprehensive empirical evidence on the relative importance of chronic poverty in Uganda based on Spell's and component approaches. The paper compares the chronic poverty estimates between the conventional and the recent proposed poverty measures in order to get useful insights about the persistence of poverty in Uganda.

Jalan and Ravallion's (JR ,2000) and Foster and Santos (FS,2013) decompose the aggregate inter-temporal poverty into chronic and transient components. Unlike JR, the later assumes an imperfect resource substitution across periods. The presence of fragile credit markets in tandem with highly unpredictable risks in rain-fed economy renders JR's assumption less appealing. The FS approach incorporates the degree of difficulties in transferring consumption between periods. Based on the Spell's approach, Foster (2009) proposes duration adjusted chronic poverty measures with no possibility of consumption substitution.

Another approach proposed by Duclos et al. (2010) assumes absence of resource substitution across time. They argue that there exists additional social cost resulting from two sources: consumption variability across time for the same household and unequal consumption distribution between poor households at a time. The costs of within time inequality in poverty gap as well as unequal poverty gap between households increase the total burden of poverty. Thus,the social cost of poverty is above the level of poverty had it been spread equally among the poor. The Equally-distributed Equivalent(EDE) poverty gap for Duclos et al. (2010) represents the poverty gap which, if assigned equally to all households and in all periods could generate the total poverty gap directly obtained from the data. Transient poverty is the cost of volatility in poverty gap overtime. Chronic poverty is the difference between inequality adjusted squared poverty gap and transient poverty. However, lack of population decomposability is the weakness of the EDE approach for chronic poverty measure. We can not,for instance,decompose the national poverty index into sub-components. Nevertheless,the approach is very relevant to determine the degree of chronic poverty relative to transient poverty at national level. Another duration sensitive inter-temporal poverty measure is also suggested by Quinn (2014). We compare and contrast the magnitude of chronic poverty based on Quinn (2014), JR (2000),FS (2013),Foster (2009) and EDE approaches.

It is noted that the objective of the Millennium development goal was to half the proportion of people below one dollar a day by 2015. This simple discretization ,however, neglects households experiencing deep and persistent poverty (Quinn,2014).

This study adds value to existing debate about the level of chronic poverty in Uganda. To the extent of my knowledge,the FS (2013) and EDE approaches are not applied by the previous researchers in Uganda. In particular, we have three unique contributions. First, previous researches in Uganda use the conventional JR approach to identify who are chronically poor or not. Based on this, they analyze the correlates of poverty. Yet, the thesis finds that the JR method underestimates the chronic poverty index, especially as poor receive more weight. Instead, I apply the FS approach for identification and aggregation of the poverty measure. Second, the thesis takes into account the determinants of chronic poverty from the aspect of consumption growth using fixed effect panel data, which is not carried out in Uganda. Third, we identify the type of households most affected by chronic poverty using both uni-dimensional consumption based poverty and multi-dimensional deprivation indicators. All the way, I consider alternative econometric specifications and extensively discuss how results are robust to these myriad assumptions. Results that are sensitive to methodological choices have to be viewed carefully about the relevance of that assumptions to a particular country and that choice is a normative judgment of the researcher. The paper provides a fresh evidence on identification and aggregation of chronic poverty chronic as well as the determinants of chronic poverty.

Having said this, I summarize the findings in the order below. All the different approaches agree in one common finding, which is that chronic poverty is pervasive in Uganda. The chronic poor contribute to inter-temporal poverty more than their population share in poor households, suggesting that they have large consumption fall relative to the poverty line. When we attach more weights to the poorest of the poor,the share of chronic poverty increases except in JR (2000), indicating that the traditional JR's (2000) method underestimates chronic poverty. The contribution of chronic poverty to aggregate poverty gap is 82% , 67% and 45% respectively using EDE , FS (2013) and JR approaches. The assumptions employed in FS method generally better emulate the characteristics of financial, economic and institutional constraints prevailed in Africa. Based on this method, we conclude that 67% of the total poverty gap ascribes to chronic poverty and the remaining 33% is explained by the level of transient poverty. Thus, poverty in Uganda is largely chronic.

The paper examines the level of chronic poverty across the four principal regions in the country. The thesis finds that chronic poverty is the highest in North and the least in Central region. It is about 10 times higher in North compared to Central. Chronic poverty is pervasive in the North and East. This finding holds intact irregardless of the approaches used to measure chronic poverty.

It is already identified who are chronic, transient and never poor households using the preferred FS approach. Another objective of the paper is to know the characteristics of the chronically poor households. To this end, the paper estimates two models: micro based consumption growth model and censored quantile regression. Using the real consumption growth in all four waves, we closely look at the determinants of of consumption growth between chronic poor and non-chronic poor (never poor and transient poor). Dercon et al.(2012) apply this model to Ethiopia. However, they never use information as an input, which is one of the predictors of consumption growth in this paper. We set up a micro based fixed effect consumption growth model that include lagged consumption, growth enhancing variables and shocks as explanatory variables(note that lagged consumption is instrumented). We find that ownership of TV-radio and access to electricity are key predictors of consumption growth. We also find that both chronic and non-chronic poor received the same marginal benefit from observed growth driving forces. The difference between chronic and non-chronic poor is in their fixed effects. The chronic poor have time invariant unobserved attributes that have negative impacts on their consumption growth while the non-chronic poor have positive average fixed effects. As a result, the consumption growth difference between chronic and non-chronic poor due to fixed effect is 33%

Using the 2005/06 household characteristics, the thesis applies censored quantile regression (using chronic poverty index) to identify the determinants of chronic poverty. The most important variables that reduce chronic poverty are: education of the household head, proportion of male and female adults members aged 15-65, ownership of TV-radio, access to all weather road and average land holding per capita. Land is an important asset for rural households. The predictors are robust to changes in methodological choices.

So far, the paper identifies the chronic poor and their correlates using uni-dimensional consumption based poverty measure. The limitation of this is that households may be constrained by multitude of factors, not only just by one dimension of deprivations. As a response, the paper considers three dimensions (consumption ,education , housing/safe water) and 7 indicators (consumption, school enrollment, educational achievement, shelter, overcrowding, toilet and access to safe water) to investigate the extent of multi-dimensional chronic poverty and the mechanisms affecting it. Households are classified into three groups depending on the number of dependents in the household. HH1 is a household division with small number of dependents (less than 2 children with age less than 14). HH2 type household has 2 to 4 dependents and HH3 type has at least 5 dependent members. The thesis finds that households with large dependents are the most affected both by multi-dimensional poverty and uni-dimensional consumption based poverty.

The level of multi-dimensional poverty is comparable between the three surveys, namely 2009/10, 2010/11 and 2011/12. Yet, it declines significantly in 2013/14. Based on the Shapley decomposition approach, which decomposes changes into demographic and within group effects (headcount plus intensity), the paper analyzes what accounts for the changes in poverty between 2009/10 and 2013/14 using the three types of households. HH1 households significantly reduce their headcount ratio and the number of dimensions in which they are poor where as HH3 do not. Policy makers in Uganda should target HH3 households as they are the most affected by multiple deprivations as well as characterized by a high level of inter-temporal poverty burden using uni-dimensional consumption based poverty. In addition, the paper finds that consumption poverty is a driver of changes in multidimensional poverty than other indicators. Consumption based poverty is persistent in Uganda.

Chapter two succinctly offers the relative importance of chronic poverty and the characteristics of households associated with high level of inter-temporal poverty burden. Yet, we cannot infer causality on the persistent of poverty using the current model settings. **Chapter three** examines the true causes of chronicity of poverty using dynamic probit model and switching regression model. Chronicity refers the degree of poverty persistence or recurring poverty events.

3 Poverty Persistence and True State Dependence in Uganda

The true causes of poverty persistence are not yet clear. Who is at a risk of becoming poor? Do poor and non-poor in the past have the same chance to fall into poverty at the current time?. What factors determine households' poverty transition probabilities?. An individual with low standard of living today is more likely to stay in that state in the future. Thus, poverty experience in the past may lead to a higher risk of becoming poor. This is called state dependent in the literature. It means that those who were poor in the past are more likely to remain poor than those who were not. There are 2 sources of persistent poverty: True state dependence (TSD), unobserved and observed heterogeneity. TSD is the effect of past poverty resulting from poverty dynamics or it is the result of poverty induced changing behaviors. Even after controlling for initial condition and household heterogeneity, being poor in previous period may lead to development of unfavorable attitude(laziness, lack of motivation, social exclusion, demoralization resulting from even one time loss in asset like oxen), which induce poverty persistence.

This paper quantifies the level of TSD in aggregate poverty persistence. The study applies the most advanced dynamic non-linear panel data which is quite useful to scrutinize the relative importance of the sources of poverty persistence. To the extent of my knowledge, this paper is the first in linking the data with poverty dynamics in Uganda using dynamic probit and endogenous switching regression models. It is the first in developing country to apply on the rural sample. It also uses the national sample to test the presence of TSD in Uganda. Investigating the impact of TV-radio on productivity of rural farmers is also an added value. Generally, previous studies in Sub- Saharan Africa use the balanced part of the household panel surveys. By doing so, most of the observations can be excluded if not observed in all survey rounds. This leads to substantial efficiency loss in particular when the sample size is small as is the case in Africa countries. On top of this, those who left out the sample may be systematically different from the average population, offering a sample selection which is endogenous. In other word, being unbalancedness may be correlated with unobserved heterogeneity. This paper fills this lacuna. The paper allows for the random effect probit model and endogenous switching regression to consider endogenous initial condition and sample retention using simulated maximum likelihood (SML) estimators.

It is worth to mention that estimating the random effect dynamic probit model is computer intensive compared to endogenous switching regression. The paper uses all individuals whose age exceeding 14 by year 2005/06 as a unit of analysis in the switching regression mode. The reason is that within the household, there is heterogeneity in education and marital status, which affect poverty. One can use the head of the household as a unit. This excludes, however, some households from the regression as the head status varies across time for several reasons. In Uganda household panel survey, sampling representativeness overtime is achieved by tracking all households members of the 2% randomly selected households in 2005/06. Thus, there are two types of households: splits off households and original households. Split offs are newly formed households by one or many members leaving the household that is assigned for further tracking in 2005/06. Original households include two types. The first is those assigned for further tracking in 2005 but no members leaving the households during other survey years. The second is those households that are not assigned for tracking purpose during 2005. This novelty of this data has been captured by considering individuals as a unit of analysis, which is not examined by other researchers in Uganda except that some explain it in a descriptive form. Individual characteristics and household level characteristics are controlled for in the regression.

The key research question the paper intends to answer is that whether there exists a true state dependence in Uganda or not, that is the true impact of past poverty on current poverty after controlling for observed and unobserved heterogeneity. Because the policy prescription differs with and without this effect. In the presence of TSD, short run policies are effective. The aim of the policy is to keep away individuals from entering into poverty in the first place because once they are a poverty membership, they are more likely to remain as poor in the future. They are more likely to develop unfavorable attitudes that make poverty permanent. It is not the scope of this paper to exactly identify the mechanisms or channels that are the likely reasons for the emergency of this attitude. However, the literature (see

Biewen,2014) identifies stigmatization is the most likely reason.

The thesis asks how the TSD effect is robust to methodological assumptions and data changes. From the perspective of methodologies: the issues of unbalanced panel, initial condition and endogenous sample attrition are important. First, we estimate the random effect dynamic probit models (the Heckman's 1981 and Wooldridge's 2005 versions) with endogenous initial condition. The paper uses observations available in all waves (balanced data). Second, the paper re-estimates these models with unbalanced data: observations presented in at least two waves and then assume that unbalancedness itself is endogenous, meaning that attrition is not random. The estimation results suggest that past poverty has a genuine impact on current poverty in both first and second cases because the coefficients associated to the lagged poverty in all models are significant at any reasonable confidence level. Consequently, the average partial effect of the lagged poverty has been calculated, which is the TSD effect. It means that by how much being poor in the past increases the risk of future poverty even after controlling for individuals difference in observed and unobserved heterogeneity. TSD is expressed as a share of observed poverty persistence (aggregate state dependence). TSD accounts for at least 23% of the observed poverty persistence. There may a possibility of feedback effect from past poverty , yet it is not the case in this paper as it has been discussed convincingly in the result section.

Third, the thesis estimates endogenous switching regression model which controls for endogenous initial condition and sample attrition. Since the lagged coefficient is not directly estimated, there is no feedback effect (if any) in the switching regression. This is a transition probability model where poverty entry, persistence probability, initial poverty and sample retention equations are estimated simultaneously. In this model, the impact of a given explanatory variable switches or varies depending on whether an individual is poor or not in the previous period. If all variables included in the model jointly show that there is no switching, then there is no true state dependence, which means that being poor in the past is not associated with current poverty after controlling for individuals difference in initial poverty. The null hypothesis of no true state dependence has been carried out and the test reveals that there is actually TSD. The estimated TSD stands to be 0.187%, implying that once controlling for observed and unobserved individual heterogeneity, those who were poor in the past, on average, have 18.7% more chances to be poor in the current period than those who were not.

The aggregate state dependence, which is obtained from the raw transition probability without controlling for heterogeneity, is 26 percent. It is the combined effects of TSD and individual heterogeneity. TSD accounts for about 72% (0.187/0.26) of the observed poverty persistence probability. It is worth to remind that the TSD effect is 23% and 48% respectively using the Wooldridge and Heckman random effects models that control for endogenous initial condition and sample retention. Whereas it is 72% in the endogenous switching regression. What is common in these findings is that the TSD effects are statistically significant. This is what the paper intends to show. The difference in the magnitude of TSD arises from the assumptions stipulated by the different models and slight variation in the number of controls. The paper compares this result with the existing literature in two ways. First, the results from random effect dynamic probit models (REDP) are compared with those who use REDP in developed countries and African countries. Unlike these studies, this paper computes the average partial effect, which is the share of TSD in overall poverty persistence. Nevertheless, the significance of the coefficient to lagged poverty, which is a measure for the presence of TSD, has been compared between different studies. Second, the result from switching regression is also compared with those who use this model for developed and developing countries. In both cases, our results are consistent with the findings in the existing literature.

TSD is significant in Uganda and thus, short run policies are effective. The policy instruments include creation of-farm activities, providing subsidies in the form of agricultural inputs and expanding credit service and other insurance schemes to smooth consumption against adverse shocks. They can break the cycle of poverty. Since heterogeneity effect is not small, long term intervention on human capital is also relevant.

This paper chooses the endogenous switching regression for the interpretation of the determinants of poverty persistence as it is less computer intensive and allows to include all individuals aged above 14 in the regression. It finds that access to tv-radio (news as input to increase productivity)is a significant predictor that affect both the transition probabilities and the steady state poverty. Being married and incidence of civil strife increases the propensity of being persistently poor. Being educated and having radio and TV reduce the likelihood of poverty persistence. They also decrease the propensity of entering poverty in the first place. Having large proportion of adult male (15-64) in the household also decreases the probability of falling into poverty.

The core objective of this paper was to determine the size of true state dependence. Factors that affect poverty transition were also studied as a second objective. However, the paper disregards the presence of measurement error in the consumption data. One can argue that some of the observed mobility are ascribed to measurement error and as a result,all the mobility into or out of poverty may not be the result of movements in true consumption. Instead, some of the observed mobility may be due to errors in the reported consumption (e.g. recall lapse). As a result, **Chapter 4** examines the extent of upward bias in the measured mobility that is due to measurement error. Chapter four quantifies the true observed state dependence(or true observed poverty persistence) as measurement error often understates the observed persistence.

4 Quantifying the Real Poverty Transition in Uganda

The term economic mobility has been extensively used in the poverty and employment literature. It is broadly defined as changes in economic welfare or changes inequality indices for a society. The poverty transition matrix is an important dimension of the measure of economic mobility of the poor, which is the focus of this paper. The error in consumption, however, affects the magnitudes and direction of the poverty transition parameters. This is not an exception to Uganda.

Using latent Markov model, Rendtel (1998) find that almost half of the observed poverty mobility in Germany is accounted for by measurement error, a finding closer to our upper limit (38.9%). Breen and Moisio (2004) apply a latent mover-stayer Markov model for 10 European countries. When measurement error is disregarded, they find that the observed poverty mobility can be overstated by between 25% and 50%. By combing a difference GMM and the minimum distance methods for controlling for measurement error, Lee et al. (2017) find that the observed poverty persistence (chronic poverty) in Korea is 56.5% and this has been raised to 68% based on an error-free simulated consumption. In the same vein, McGarry (1995) for USA finds that measurement error understates poverty persistence probabilities by 11%. Using instrumental variable method, Glewwe (2012) estimates the expenditure mobility for Vietnam based on 2 years panel data, not just poverty transition. He finds that between 15% and 30% of the measured consumption mobility is attributable to measurement error.

Policy design depends on whether poverty is transitory or persistent. In the presence of high mobility, short run policies that smooth consumption fluctuation is more effective because poverty is mostly transitory. In contrast, In presence of low consumption mobility, which in turn implies low poverty transition, poverty is more of permanent and long term intervention is a priority. However, the consumption expenditure from the household surveys is often contaminated with errors and these will lead to upward bias in consumption or poverty mobility. Identifying the true poverty transition is an empirical challenge. None of the previous studies in Uganda provide evidences for the extent measurement error in consumption and the size of true poverty mobility. The paper applies the first order Markov poverty transition model in random effect panel that controls for observed and unobserved individual specific heterogeneity, endogenous initial condition and measurement error. This is a model that combines the structural and the error components.

The paper finds that measurement error overstates the observed mobility in Uganda. The poverty persistence probability increases from 52% in the observed data to 61% in the true data, suggesting that measurement error understates persistence poverty by at least 9%(or 17% (0.09/0.52)[1] Since the poverty persistence rate is significant in Uganda(at least 61%), the policy priority is to increase the human capital and productive assets(e.g. land, oxen) of the poor. Poverty is largely chronic implies that targeting the poorest households through long- term policies help reduce permanent poverty. Another finding is that the effects of some of the observed individual characteristics on poverty transition are considerably attenuated due to measurement error (e.g land size and education).

The most important variables that affect poverty transitions are: land size per capita; ownership of mobile, having TV-radio, dependency ratio; proportion of female and male adult members. Education reduces the chances of transiting into poverty, yet it does not affect the mobility out of poverty. Land size is a crucial asset in reducing the probability of transiting into poverty as well as increasing the chances of poverty exit. Special provisions to the poor such as access to information technology and land are fundamental to reduce chronic poverty in Uganda.

Generally, there exists high level of poverty persistence in Uganda. One of the explanations as this chapter shows is that because they have low qualification or less observed and unobserved productive characteristics. However, besides individual characteristics, firms can play a role in wage settings which in turn affect consumption poverty and this aspect is ignored in most previous studies. Especially, if firms impose different wage premiums by gender for those who are already poor, this exacerbates the social cost of poverty. Though the evidences come from Ghana, another African country which is structurally similar to Uganda, the result can give a useful insight for policy makers in

[1] this is the lower limit because the true poverty persistence is 89% instead of 50% in the observed data when we consider the unequal space snap shot of the data. This is taken as the upper limit

Uganda. **Chapter 5** offers this empirical evidence.

5 Gender wage gap and poverty: Evidence from employer-employee data in Ghana

In order to link the study of gender wage gap to the poverty literature, we split individuals into two economy classes: female and male. We start with a plausible assumption that poverty is related with wages, especially in urban economy. Higher wages can be translated into higher consumption which in turn implies low poverty for a given reference standard of living. Of course, wages may not fully converted into current consumption as it is partly saved for smoothing future consumption. We ask why females are poor compared to males. Are females at the bottom of the wage distribution more disadvantaged than those at the upper end of the wage spectrum?. Existing literature suggests that women earn substantially low wages compared to men. This thesis aims to investigate the sources of wage inequality. Because developmental success requires the participation of all society, not just only males or females.

As discussed in the second chapter, consumption variability between poor households brings additional social cost which increases chronic poverty. Since individuals at lower quantiles of the wage distributions are closer to any reasonable poverty line, this paper closely looks at whether there is unequal wages between genders at these quantiles. If wage inequality is discovered, its social cost in terms of poverty is expected to be huge and such effect is illustrated in chapter 2 following Duclos et al.(2010). The paper finds that there is significant wage inequality between genders at the lower quantiles of the wage distributions. Policy makers should target the poorest of the poor. Using wage inequality decomposition method, the thesis identifies the sources of the wage gaps between genders. Decomposing distributions in many economic streams has received considerable importance in designing and implementing public policy. Policy intervention in labor demand and supply to affect income distribution in a society can be taken as an example where decomposition across the full range of wage distributions is required.

Once the link between wages and poverty is established, the econometric procedure and the main findings are indicated below. The main contribution of the paper is here. Several studies in African countries (Fafchamp et al. (2009) ; Nordman and Wolf,2009,2010; Van Biesebroeck,2011) examine the sources of gender wage gap using manufacturing firms. However, none of these studies analyze the role of firms' wage polices in gender wage gap across the entire wages distributions. The thesis fills this research gap by exactly quantifying the part of the gender wage gap that is accounted for by the firm fixed effects (i.e observed and unobserved firm heterogeneity) across the different points of the wages distributions. The use of matched employer- employee data to analyze gender wage gap is a recent research phenomenon possibly because of the paucity of this data for African countries.

Besides individual level characteristics to identify the sources of gender wage gap, the thesis sheds light on the demand side wage determinants using matched employee-employer data from Ghana manufacturing firms. The Re-centered Influence Function (RIF) approach has been used to decompose wage gap across quantiles of the wages distribution. Since there are many employees in the same firm, clustering and stratification are considered using the bootstrap methods of standard error(se) pair clustering because the within firm correlation may render biased standard errors unless otherwise corrected. I establish my own computer program in this exercise. Following Solon et al (2015), the thesis provides statistical evidence that weighting does not add value in the regression. Fafchamp et al. (2009) apply weights in their study of education wage gap and job sorting in African manufacturing firms and yet, the result is questionable on this ground.

This paper finds that gender wage gap at the 10 quantile is 2.5 larger than the gap at 90 quantile. The literature interprets this pattern as a sticky floor. The larger gap at the bottom quantile suggests that poor women are more disadvantaged than poor men and this calls for policy makers to pay attention to the poorest of the poor.

Gender sorting across firms is one of the reasons for the wage gap. Women are disproportionately segregated in low paying firms and this effect substantially varies across the wage distribution. 38.8% of the observed gender wage gap at 10^{th} quantiles is attributable to sorting effect where as it is 22.6% and 0% respectively at 50^{th} and 90^{th}. This clearly shows that poor women are sorted into low paying firms. Even after netting out sorting effect from the gender wage gap, firm fixed effect still explains significant portion of the gap. After controlling for individual level characteristics and sorting effect, firm characteristics (firm effect) accounts for between 44% and 69% of the adjusted gender wage gap, depending on the quantile being considered. This suggests that manufacturing firms in Ghana widen the observed gender wage gap and hence, firms wage policies indeed matter. The paper further analyzes as to what kind of firms increase the gap. Ghanaian owned firms, less labor intensive firms, those located in Cape coast, firms with low composition of managers, firms established long ago 1985 and those with low union density are more likely to intensify the gender wage gap. In other word, high union density, young firms, labor intensive firms, firms facing high competition (firms with low market power), firms with high mentors and supervisions and importing firms are those firms that reduce the earning differential between genders.

Another channel through which poor women are more disadvantaged is because they have low labor market experience compared to men. Other things being equal, after removing sorting effect from observed wages, 19% of the adjusted gender wage gap between women and men at $10th$ quantile is attributable to differences in their experience. In contrast, the adjusted gender wage gap due to experience is about 12% both at $50th$ and $75th$ quantiles. The policy implication is just to increase the labor market participation of poor women. Otherwise, the unequal wage between poor men and women entails significant social cost as shown by Duclos et al.(2010). Though the matched employer-employee data is ideal, the possibility of sample selection cannot be assessed based on this data, which is a limitation of the paper.

Introduction

Households observed in survey data from developing countries may experience changes in poverty in the course of their life time. Hence poverty is not static as it can change overtime. If it is static, a cross section data at a given point in time is sufficient and it is not necessary to extend the analysis of poverty into a dynamic perspective. In contrast, if there is substantial mobility into and out of poverty, the cross section data offers a misleading result because it is difficult to know the entire poverty burden for an individual identified as poor using a single snap shot of data. The individual may be temporarily pushed into poverty only in one period because of idiosyncratic or covariance shocks. Alternatively, the individual may be poor in his life cycle or in all periods considered in the survey. Cross section data does not identify the transitory poor from chronic poor even though the policy prescription is virtually different between the two. Instead, panel data is required to make this distinction as well as portrait the extent of poverty mobility in a more realistic manner.

In the literature, the poverty dynamics based on longitudinal data is different from poverty trend and static poverty. Static poverty relies on households survey carried out at a single period. Poverty trend uses a series of cross section data of several years in order to construct the poverty measures (headcount ratio, poverty gap and severity) one for each year and based on that, the development of poverty across years can be assessed easily. Nevertheless, it does not capture the economic mobility of individuals. If poverty trend remains the same, it does not imply zero poverty mobility. While the inter-temporal aggregate poverty does not change overtime, households can make substantial mobility into and out of poverty.

Instead, poverty dynamics captures the households' economic mobility using longitudinal data. In developing countries, a sizable of literature points out that households experience a great deal of poverty mobility overtime (Baulch and Hoddinott, 2000; Gibson and Glewwe, 2005; Yaqub, 2000). Consumption, rather than income as the latter is more prone to error, has been used as a welfare measure in these studies. Nevertheless, even the consumption variable can be measured with error in the household panel survey, which biases the movement into and out of poverty. This thesis extensively discusses the concepts, the poverty measurement methods, the problem of initial condition, the attrition and measurement error problems using the most up to date econometric methodologies by dividing the issues in self-contained essays in a comprehensive and coherent synthesis. To easily grasp the red-thread established in the thesis, the following 5 main research questions and hypothesis are formulated.

Does poverty actually decrease between 2005 and 2009?

To answer this question, a number of methodologies has been employed. Because several researchers can apply different assumptions and come to different answers although the validity of these assumptions is questionable, making the comparison to fully rely on the normative assessment of the researchers. The thesis first constructs spatial and inter-temporal utility consistent poverty lines, taking into account seasonal inflation within the same survey period. Price variations (at least quarterly) even within the same survey (12 till 18 months for a completion of a given survey) brings enormous impact on the intra-personnel welfare comparison, especially in economy having two or more main cropping seasons unless the within survey nominal consumption is corrected for seasonal inflation. The methods used to deflate consumption are also important. The conventional price deflator such as Laspeyres index and Paasche index respectively overstates and underestimates the actual inflation. The superlative index , which is used to adjust seasonal nominal consumption in the thesis, fills this gap by offering a geometric average of the Laspeyres and Paasche index.

In addition, it is important to have a careful look on the shares of food and non-food total consumption because the wrong weights induces a great deal of bias to answer whether poverty improves between 2005 and 2009 or not. The thesis incorporates within survey seasonal price inflation to construct spatial and inter-temporal utility consistent poverty lines. The more disaggregated food items are also included in the food basket to better emulate the actual consumption pattern of households. This is the preferred approach. Based on these poverty lines, the thesis shows whether poverty actually decreases or not. The results based on other approaches, for instance poverty lines that consider spatial variation but assumes fixed food basket overtime, have been compared with the preferred approach.

Does poverty in Uganda mostly chronic or transient?

Can the distinction between the two depend on methodological assumptions? Do the multi-dimensional chronic poor also appear to be chronically poor based on uni-dimensional consumption based poverty? The policy prescription depends on whether poverty is largely of permanent or transitory nature in a country. None of the previous researches in Sub-Saharan Africa apply the recent methodologies (e.g. Foster and Santos, 2013; Alkire et al, 2014) to the analysis of uni-dimensional and multi-dimensional chronic poverty. The downward bias on chronic poverty by the conventional chronic poverty measure has been revealed in the thesis, in particular as the poverty aversion parameter increases. Intuitively, there are two steps to construct inter-temporal chronic poverty index. The first is the identification stage, that asks who is chronically poor. Second, the aggregation index, that averages the inter-temporal poverty levels of all chronic poor households into a single index. Aggregate poverty is the inter-temporal poverty averaged over all individuals. The difference between aggregate and chronic poverty gives rise to transitory poverty.

The traditional and the recent approaches profoundly vary to identify who is chronically poor. Methodological assumptions indeed matter. Based on the preferred approach that reflects the structural constraints facing households, the thesis determines the extent of chronic poverty and the characteristics of the chronically or transiently poor households. As a task of the thesis, identifying the type of poverty that prevailed most using all waves of panel data is of course important. Yet, the real causes of chronic poverty cannot be established based on the regression models that use the initial period households characteristics. It is of important to decompose the observed poverty persistence into a part attributable to individual's heterogeneity and into a part due to the causal impact of past poverty using dynamic random effect probit or transition probability models.

How large is the observed aggregate state dependence that is accounted for by true state dependence?

The design of policy depends on whether poverty persistence is mainly explained by heterogeneity or state dependence. Even after controlling for individuals difference in observed and unobserved heterogeneity, there still exists poverty persistence attributable to state dependence, which is the effect of being poor in the past on current poverty. Few previous researches (Alem, 2015; Kedir et al, 2005) from developing countries apply the dynamic random effect probit model that controls for initial condition to determine whether the coefficient associated to lagged poverty is significant or not, which is a measure for the presence of state dependence. None of them compute its average partial effect and then decompose the aggregate poverty persistence into true state dependence and heterogeneity effects. None of them estimate this model in the presence of unbalanced data. This thesis fills this research gap. In addition, the paper also estimates endogenous switching regression model using all individuals in the panel aged above 14 by 2005, rather than taking the head of the household as a unit of analysis.

The model controls for initial condition, endogenous attrition, and observed individual, and household level characteristics and individual specific unobserved heterogeneity. In this case, the observed aggregate state dependence (i.e. observed poverty persistence) can be decomposed into two effects: heterogeneity and true state dependence effects, making comparison with dynamic random effect models feasible. Though, these models take into accounts several selection mechanisms, they are operating under the assumption of error free consumption. In practice, consumption in the household survey can be measured with error. Measurement error overestimates the observed mobility into and out of poverty or understates the observed poverty persistence.

How large is the real poverty transition?

Some of previous studies in developing countries estimate the dynamic panel (Glewwe,2012; Lee et al.,2017; Antman and Mckenzie,2007) using either GMM (does not need external instruments) or Instrumental variables to control for measurement error. Yet, these instruments are subject to criticisms. Instead, the thesis uses the mixed latent Markov model that has three model components: latent initial poverty, latent poverty transition and the measurement error component. It considers the latent consumption as missing. An important challenge in developing economies is that most of the panel data are collected in unequal gap intervals.

This may have an impact on the estimated poverty persistence. When the time interval between two adjust surveys is tightened, there is less mobility into and out of poverty. In contrast, when the gap is longer, substantial mobility is expected. Interestingly, the latent mixed Markov model permits the possibility of having irregular snap shot of measurement. The thesis applies the mixed latent Markov model in panel data for the first time in Sub-Saharan Africa to correct for the measurement error problem and other selection mechanism (initial condition, individual specific unobserved heterogeneity). It also estimates the model to take into account the irregular space in the panel data. The model produces the level of true poverty persistence rate, the true transition probabilities, and level of measurement error. These latent persistence and transition probabilities can be compared with the observed persistence and transition probabilities obtained from error ridden consumption. Since this model cannot decompose the true poverty persistence into heterogeneity and true state dependence effects, the thesis carefully exploits the information from endogenous switching regression and mixed latent Markov models to make a sound and dependable conclusion.

Do firms wage policies and gender sorting across firms decrease the social cost of poverty?

This is to examine whether there exists firm induced poverty or not. The analysis starts by assuming that ,on average, workers of the same sex composition in a give firm are treated symmetrically provided that they have the same productivity(observed and unobserved). Yet, a testable hypothesis is formulated, that is firms are discriminatory by gender in the sense that they offer higher wage premium for men than for women. Another hypothesis is that gender sorting across firms explain part of the wage gap between poor men and women. It has been observed that some firms are female dominant while others not. If there exists gender wage gap accounted for by gender segregation,a situation where women are sorted into low paying firms, that would not be a problem if firms are not discriminatory. Because segregation can be the result of employers' or workers preference, the policy priority in this case is to increase the productivity of these firms. Hence, higher wage for female dominant firms eventually tend to close the overall gender wage gap. Policy design becomes cumbersome if firms are detected as discriminatory.

Both gender sorting and discriminatory firms wage polices can increase wage inequality between genders. If these effects are detected among poor individuals, the social cost of poverty is higher than it would be had firms offered equal premium for comparable male and female. Thus, the objective of the thesis is to examine the extent of gender wage gap that is accounted for by gender sorting between poor mean and women. In addition, it is of interest to detect the gender earning gap attributable to firms wage polices across the income distributions of the poor. Workers whose income below the 40^{th} percentile of the wage distribution can be deemed as poor. The thesis gives special focus on the bottom wages distribution(at 10^{th} quantile).

The thesis is structured in 5 self-contained but related chapters. The first chapter estimates spatial and inter-temporal utility consistent poverty lines. They are taken as inputs for other chapters. In the first chapter, different methodologies are deployed to determine the poverty profiles at a given year and poverty changes overtime. The thesis concludes that the poverty profiles based on the the new poverty lines are more accurate as the latter depict the true consumption patterns of the poor in space and time. As opposed to the official report, the thesis shows that poverty does not decrease between 2005/06 and 2009/10. Instead there is an increase in poverty. The second chapter distinguishes between chronic and transient poverty. The paper asserts that the conventional Jallan and Ravallion (2000) method underestimates the level of chronic poverty. The thesis finds that poverty is largely chronic. The North takes the burden of chronic poverty. It extends the analysis of chronic poverty based on uni-dimensional consumption poverty into multi-dimensional chronic poverty. Consumption poverty still remains a predicament though multidimensional poverty declines between 2009 and 2013.

Chapter 3 decomposes the observed poverty persistence into heterogeneity and true state dependence effects. It finds that past poverty has a causal impact on current poverty. Chapter three assumes that consumption is error free. Chapter 4, instead, dispenses this assumption. It estimates the true observed poverty persistence and the true transition probabilities. The thesis finds that measurement error overestimates the observed poverty mobility into and out of poverty. It also understates the effects of observed control variables on the probability of making a particular poverty transition. Chapter 5 examines the sources of poverty from the demand side perspective.

The unexplained part of the wage gap can be exaggerated if the demand side determinants of individuals wage are ignored. It consists of the effects of individual unobserved attributes and workplace characteristics,which includes the sex composition in that place and the firms wage policies. The last chapter is devoted to isolate the effect of workplace characteristics from the unexplained part. It uses workers wage(wage earners data) and firm level characteristics. Though the evidence comes from Ghana, the implication of the result can be a lesson for other Sub-Saharan countries including Uganda. The unexplained part is decomposed into individual coefficient effect(difference in wage premium due to gender difference in unobserved productivity), gender sorting across firms, and firm wage policies. The main focus is on wage distribution of the poor as a low wage worker is more likely poor. Chapter two shows that unequal poverty gap between individuals induces additional social cost which is part of chronic poverty. Unequal poverty gap just reflects unequal consumption of the poor for a given poverty line. Chapter 5 discusses by how much firms increase unequal wage between genders by offering unequal premium for comparable poor men and women. Other thing equal, unequal wage between genders can also arise if women are disproportionately working in low paying firms. The thesis finds that the high proportion of women in less paying firms exacerbates the national level gender wage gap, in particular along the lower wage distribution. Firms wage policies also increase gender wage gap. This result implies that firms tend to increase chronic poverty,which comes from unequal wage between poor men and women.

The value added of the thesis can be fleshed out briefly as follow:

- It extensively reviews the existing poverty literature. It offers the theoretical underpinnings and concepts of chronic poverty and economic mobility. It discusses the empirical challenges on the identification of impact analysis.

- It provides a fresh and comprehensive empirical evidence on the determinants of poverty persistence using robust and advanced econometric methodologies. It also address the problem of measurement error in consumption, which has been left untapped by extant empirical poverty researches in African countries. There are 4 most common problems in the households panel survey. First, the survey duration is too long and seasonal inflation leads to misleading intra-personnel welfare comparisons. Second, there is unequal time interval between successive surveys. Third, attrition. Fourth , measurement error in consumption. The thesis addresses these empirical challenges.

- It presents the downside effects of ignoring the demand side determinants of individual wages. None of the previous studies in Sub-Saharan Africa examine the role of firms in narrowing or widening the wage inequality between genders across the different points of the income distributions. The thesis emphasis to determine the magnitude of gender wage gap accounted for by gender sorting and firms wage policies on the bottom wage distribution.

1 Estimating Utility Consistent Poverty Lines:Does poverty decrease in Uganda?

1.1 Introduction

After the cease of protracted civil war, Uganda has showed an impressive economic growth during the 1990's. Part of the growth is attributable to the implementation of economic reforms under the policy initiatives of structural adjustment program and consequently, the country can be taken as a good example in Sub-Saharan African for transforming itself into liberal economies. According to Uganda Bureau of Statistics (UBOS,2006) and Ssewanyana and Kasirye (2014),the official headcount ratio falls from 56 percent in 1992/93 to 20 percent in 2012/13. Based on stochastic poverty dominance approach, Ssewanyana and Ksirye (2012) and UBOS (2010) have shown that the official poverty headcount declines between 2005 and 2009 irregardless of the poverty line chosen. It falls from 31.1 percent in 2005/06 to 24.5 % in 2009. In addition, all the four principal regions record a significant reduction in poverty level (UBOS,2010). On the contrary, Duponchel et al. (2014) argue that there is a uniform decline in GDP growth after 2005/06 . As suggested by Levine (2012), the poverty figures published by World Bank do not coincide with the poverty level reported by UBOS. He argues that poverty line set by Appleton et al.(1999) is too low and that the calculated poverty figures may not depict the true poverty level. Previous researchers (Appleton,1999; Kikafunda et al,1992; Jamal,1998) construct absolute poverty lines without including the northern region because of the prolonged instability and war in this region. Thus,the poverty line is not nationally representative.

All these authors (UBOS, 2006,2010; and Ssewanyana and Ksirye,2012,2014) use the poverty line constructed by Appleton et al.(1999), which is a national poverty line that does not capture regional difference in prices,and food composition. In addition, the outdated food basket may not reflect the household's current consumption pattern. Because Uganda has a diverse dietary system.

Matook is the most important dish for West and Central regions but not at all for North and East. The North gets significant portion of the diet from sorghum. That would not be a problem if the cost of obtaining a given amount of calorie is the same for all diets. Nevertheless, the cost of calorie differs significantly among food items. Matook is an inferior source of calorie where as sorghum is calorie efficient. In other word, matook is an expensive source of calorie while sorghum is a cheap source of energy. The cost of obtaining a given amount of food energy is larger for the West than for the North and ignoring regional food composition implies an increasing cost of living for the North. Constructing region specific poverty lines using region specific prices and region specific food bundle apparently seems a solution to this problem. However, multiple bundles by themselves do not solve the consistency problem. Based on the cost of basic need approach, the paper uses the minimum cross entropy method to ensure consistency in welfare comparisons across space and time. It establishes poverty line bundles that are spatially and inter-temporally utility consistent.

Using a 2012/2013 national household survey, Van campenhout et al. (2016) construct spatially utility consistent poverty lines for Uganda based on the cross entropy method suggested by Arndt and Simler (2010). However, my paper differs from their work in a number of ways. First, unlike this paper, they use highly aggregated food items in the basket. Cassava and sweet potatoes are the most important diets in Uganda. Cassava is of two types (cassava fresh and cassava dry/powder). Similarly, sweet potatoes has two varieties: sweet potatoes fresh and dry. Beans is of two types: beans dry and beans fresh. These authors add up these varieties together. Aggregating or lumping would not be a problem if prices of a given variety were similar. Even in the same region, differences in the consumption patterns and prices between these varieties are quite substantial. Instead, this paper preserves these differences and hence they are part of the consumption basket. Second, they just use 5 food staples in Uganda. If all consumption patterns of the Ugandan households are not captured, welfare comparison across space becomes perplexing because the selected few bundles do not represent the consumption pattern of the poor Ugandan population. Appleton et al (1999) for Uganda and Gebremedhin and Whelan (2008) for Ethiopia respectively use 28 and 22 food items to establish poverty line. This paper uses 34 food items.

Third, the survey duration in all Uganda household survey is between 12 and 18 months. This is a common problem to all of us. Consumption data is not collected in the same season of the survey period. Price variations across seasons within the survey are quite large, making welfare comparison less reliable unless nominal consumption is corrected for seasonal price changes. These authors do not consider this important issue. In addition, the different methods to deflate nominal consumption do not give the same result. The conventional laspeyres and Paasche price index methods are biased deflators because they respectively overstates and understates the actual inflation. By giving weights to end and first period consumption ,the superlative price indexes(the Fisher ideal and the Tornqvist price indexes) instead are the best unbiased estimators of the price indexes, which are used to deflate within survey nominal consumption in this paper. Moreover, previous researchers in Uganda use average unit prices to value consumption of own production. Instead, this papers uses the median price as averages are susceptible to outliers.

Fourth, Van campenhout et al (2016) construct spatially consistent poverty lines using one period data. In contrast, I construct poverty lines that are both spatially and inter-temporally utility consistent. The objective of the current paper is two fold. the first is to construct poverty lines that are consistent across space and time. The second is to show whether poverty decreases between 2005/06 and 2009/10 or not. These two are at least my contributions to the existing literature.

The government of Uganda, using the same data we use, has showed improvement in living standards between 2005 and 2009. Using the whole set of the 4 waves panel data from 2005, 2009, 2010 and 2011, this paper examines whether the stipulated findings and claims put forward by the Uganda Bureau of statistics(UBOS) and Economic Policy Research Center(EPRC) are robust and dependable. This paper provides evidence on the heated debate whether poverty in Uganda decreases or not as we move from 2005/06 to 2009/10. This thesis finds that poverty headcount increases as one moves from 2005 to 2009 by about 9%. The paper is structured as follows. In section 2,the literature is presented. Section 3 presents the data source and describes the consumption pattern. Section 4 briefly offers the method on the construction of poverty line. Section 5 discusses the result on the level and evolution of poverty profiles across time. Section 6 offers the poverty dominance analysis. Section 7 concludes.

1.2 Literature

Since 1981,a year where peace was restored, the Uganda economy has registered an impressive annualized GDP growth rate of 6.8%. This rapid growth has been translated into substantial poverty reduction from 56% in early 1990's to 24.5% in 2009/10 (UBOS,2010; Kakande ,2010). Byekwaso (2010),however,question the rapid fall in the official poverty figures and argue that such estimates are not exactitude. The consumption expenditure used to measure poverty does not portray the source of income. While the contribution of agriculture to overall economy has declined by half and at the same time more than 72% of the population eke their income from it,the factors causing poverty reduction are ostensibly less clear. Income earned from agriculture is not re-invested on land improvements but siphoned out to the purchase of items such as iron sheet roofed houses and mattress which are nothing to do with productivity but are part of consumption at the expense of basic needs like food. It is unbelievable that the percentage of households eating 3000 calories per day has increased under the plight of diminishing asset base.

Some others go beyond the monetary poverty measure and apply the multi-dimensional poverty analysis in Uganda (Levine et al.,2014) using the Foster, Greer and Thorbcek's (FGT,1984) poverty measures. They find that 73% of the population were deprived in 2005/06, which stands in stark contrast to 31% official poverty figures based on monetary measures. Other authors such as Daniels and Nicholas (2015) also question the large decline in the official poverty figures. They use both the 2005/06 Uganda national household survey (UNHS) and the Demographic and Health Survey (DHS) to compare their estimates with official poverty estimates. The non-monetary indicators from DHS suggest a modest poverty decline((5%) from 35.8% in 1995 to 30.6% in 2009/10. Their finding stands in a sharp contrast with that of the decline in the official poverty figures(14.3%) from 38.8% in 2002/03 to 24.5% in 2009/10 in a very short period. Van Campenhout et al. (2016) use the 2012/13 household survey data and they find that 33% of households were poor while the official headcount was 19.47% for the same year.

Levine (2012) asks why the World Bank poverty estimates and UBOS official estimates show much discrepancy though both use consumption expenditure as a welfare measure. World Bank has organized survey data in group form of the same source as UBOS and put it in non-readily available meta data called PovcalNet [2] which is an online tool for poverty estimates. Levine(2012) uses both the micro data from UBOS and the World Bank meta data for the survey years 1993,2000, 2003 and 2006 and compares the poverty levels between the two sources using the national and International Poverty Lines (IPL). He argues the main reason for the difference point estimate between the UBOS and World Bank is that World Bank uses per capita consumption where as UBOS uses per adult consumption. The

[2] The Development Research Group of the World Bank (http://iresearch.worldbank.org/PovcalNet/) is in charge of developing this tool

World Bank's poverty level (51.5%) in 2005 is closer to his estimate ((49%)when consumption is expressed in per capita term. However, I argue that they use different poverty lines that partially explain the difference. A 1.25 dollar per capita IPL (expressed in 2005 prices) has been applied to World Bank data while the official poverty line is 1 dollar per capita(in 2005 PPP). In addition,World Bank did not revalue home consumption by the market price while UBOS did. Revaluation can significantly increase the consumption expenditure of rural households as they initially report using farm gate prices.

Appleton et al.(2003) use the national prices to value the regional food baskets. Though this enhances specificity,there is no guarantee that these baskets provide the same welfare. In addition, the consumption basket of the lower half of the poor was used to compute poverty line (Gebremedhin and Whelan ,2008; Appleton et al.,2003; Deaton,2003). For Indonesia, Ravallion and Bidani (1994) use the consumption patterns of the 15 percent poor. World Bank (1996) derive the food basket from the consumption pattern of 50% poor ranked according to their consumption per capita in Uganda. They find that the poverty line was sensitive to the initial judgment about the number of poor(Appleton et al.1999). Instead of using this arbitrary choice, this paper applies the iterative procedure suggested by Arndt and Simler (2010,2007). I initially use the consumption pattern of the half poor households. From prices and consumption facing the half poor, I estimate the poverty line which is used to calculate the population poverty headcounts for each spatial domain. Then, another basket is derived from the consumption pattern of the poor which is now anchored to the initially calculated poverty level in each spatial domain. This process is repeated until convergence occurs by which the headcount ratio (or the poverty line) in the last iteration does not change. The consumption basket from the last iteration is used for poverty analysis.

All previous studies in Uganda use cross section data collected by Uganda Bureau of Statistics. Both UBOS and World Bank collected four waves panel data with similar period as cross section ones. This data set is ideal because by linking the same observation overtime, a useful insights about the level and evolution of poverty can be recovered. This paper uses this panel data and contribute to the existing debate about the level of poverty in Uganda. Since the old basket may not reflect the current consumption pattern of the poor, the paper constructs spatial and inter-temporal utility consistent food poverty lines from regional baskets consisting of 34 food items using the cost of basic needs approach.

1.3 Data and consumption patterns

1.3.1 Data

This paper uses the four waves panel data spanning 2005/06, 2009/10 ,2010/11 and 2011/12 collected by the joint effort of Uganda Bureau of Statistics(here after denoted by UBOS) and World Bank. The data is part of the Living Standard Measurement Studies(LSMS) organized by World Bank team with the aim to create high quality panel data for African countries. The data is freely available at their website.[3]. The data is a multi-topic,nationally representative

[3]http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS

data designed to bolster especially the link between agriculture and poverty reduction. The survey starts with 3120 households in 2005/06 with the intention to resurveying them in subsequent rounds. The questionnaire was virtually similar across waves making comparisons more appealing.

The Uganda National panel Survey(UNPS) consists of several modules such as socioeconomic ,consumption, labor and agriculture. The consumption module consists of expenditure on food and non-food components. The recall period for food items is 7 days. Non-durable and semi-durable frequently purchased services such as medical expense,education,soap, rent ,fuel, expenses on transport and communication,expenses on phone services have relatively longer recall period. Households are asked to report expenses incurred on these goods and services during the last 30 days. The flow of services obtained from semi-durable goods purchased during the last year are also part of the consumption expenditure. Total consumption expenditure for each household is prepared after converting expenses from different recall periods into a month equivalent. Consumption expenditure per adult equivalent is our welfare measure used to analysis the poverty level.

There are two conventional methods to set poverty line. The first is to use a dollar per day per person line which has been introduced by the World Bank(1993) using the 1985 purchasing power parity exchange rates. This is rather quite arbitrary though it helps for international comparison of welfare and improvement in the standard of livings between nations. The second more alluring alternative is to estimate the cost of meeting basic needs as originally proposed by Ravallion and Bidani (1994).

The Cost of Basic Needs (CBN) approach used to construct the poverty line requires information on the daily energy needs for an individual to stay healthy and productive. There is no officially established daily energy requirement that can be used at all times and for all countries. The calorific requirement varies across countries, for instance it amounts to 2200 calories per day in Ethiopia and 2700 calories in Gambia (Taddesse and Dercon,1997) and Hanmer et al.,1997). In 1995 report,World Health Organization (WHO) defines standards regarding the amount of calories underlying the poverty line for sub-saharan African countries and the level of energy requirements, vary with intensity of work, age, sex, pregnancy and lactation(see table 6 in Appleton et al.1999 for Uganda).

Instead, this paper focuses on the moderate work and allow calorie needs to vary with age but not with sex composition. According to the WHO (1985) recommendation for Uganda, an adult man aged 18-30 who is engaged in a moderate work is deemed to consume 3000 calories per day. For the rest of the household group, the paper calculates the adult equivalent calorie consumption taking into account only differences in age composition. The WHO recommends 30 percent less calorie needs for a woman aged 18-30 compared to an adult man with the same age. However, females in sub-Saharan African are found on average to work more hours than men especially in rural areas (UNICEF, 1988) suggesting the need of comparable energy requirement for both sexes instead of launching large discrepancy of calorie demand between genders. As a result, the paper does not take sex difference to imply for gender specific energy requirement. The adult equivalence scale for a person in a given age and sex category is just equal to the ratio of the recommended energy intake of an individual at that age to the calorie needs (3000 k) of an adult male aged 18-30.

For the poverty analysis, we prepare the consumption per adult equivalent, not the consumption per capita. Following Deaton and Zaidi (2002),the standard approach to compute the equivalent household size is given by:

$E = (A + \sum_j \alpha_j K_j)^\theta$

where A is the number of adult members, K is the number of children in age class j , α is the adult equivalent scale for age class j and θ is the household economies of scale. Economies of scale has been observed in non-food expenditure such as expenditure on heating,light and dwelling. Housing consumption is the most significant part of total consumption in urban part of developing countries. The survey data contains imputed and rental rate from which information on housing expenditure is gleaned from. This data was not collected in most other household surveys conducted in African countries (Gebremedhin and Whelan,2008). Household members in sub-Saharan African often share a single dwelling and consequently the rental cost of housing per individual is low. When individual welfare is measured by the expenditure per person,it is likely that the individual may be classified as poor though the person is actually consuming the home service. Thus, welfare obtained from housing expense should be adjusted for household size.

Economies of scale in housing and other heating expense has been taken in this study by assuming θ to be less than one(θ=0.9 following Deaton and Zaidi,2002; Deaton and Paxson ,1998 for comparable context). The positive correlation of household size and poverty has become questionable and raised considerable debates because of the presence of size economies in the household consumption (Lanjouw and Ravallion,1995). It is obvious that the poor devote large fraction of budget on rival goods such as food. But,there exist some other goods such as water taps,firewood,clothing, cooking utensils and housing that allow possibilities for common use. As a result,the cost of living per person may be lower when household members live together than apart. It is of relevant in poverty study to consider both size economies as well as attaching weight for the child and adult consumption based on age (Lanjouw and Ravallion,1995).

Concerning expenditure on the other durable goods, we focus on the flow of services rather than taking the purchasing value of the good itself (Deaton and Zaidi,2002; Hentschel and Lanjouw,1996; Deaton,2003,1997). This requires data on depreciation rate and initial level of investment for goods such as car,machinery and other durable and semi-durable goods. However, Deaton and Zaidi (2002) estimate the user cost using only information from current replacement value and the year of purchase. Without using depreciation and user cost methods ,the current paper drives the flow services from survey itself. Respondents are asked the value of a given stock at the time of purchase. They are also asked to estimate the fraction of initial value consumed during the survey year and this gives us the flow of services that must be included in total consumption expenditure. All food and non-food expenditure with different recall periods are then converted and re-scaled into one month expenditure equivalent. Food expenditure is expressed per adult equivalence while non food expenditure is corrected for economies of scale. Total consumption expenditure comprises food and non-food expenditure.

The Unit value of a good is defined as the ratio of expenditure to the quantity consumed. The household survey data consists of both expenditure and physical quantity of food items consumed from which unit value is derived. It is assumed that expenditure and quantity data are measured correctly without error. The advantage of unit values over prices collected from shops and few urban markets is that they reflect actual transactions of households that include large and heterogeneous markets. However, all commodities do not have standard metric unit of measurement. For instance, when households were asked how much did they consume an item in the last 7 days,they used diverse units:some of them made it in metric units such as Kilogram and Litre while some others in non-metric local units such as heaps, bunches , bundles, clusters and several other local units.

Non-food items and services such as transportation are also reported in non-readily defined units. Since regions are diverse in terms of availability of staple food and access to transportation, it is of vital to compute region specific food price indexes. The survey includes 4 major regions(West, East ,North and Central). For each region, unit-values are calculated to derive the metric equivalent quantity using the market survey conversion factors and purchased items in standard units. Median price is computed by item, by region and year. Median unit value is less sensitive to outliers compared with average and is thus preferred to unit value to mute the effect of measurement errors.

1.3.2 Consumption and its pattern

The way consumption expenditure is adjusted for spatial and inter-temporal price difference has an important implication for the poverty analysis. In the survey, home consumption was initially reported at farm gate price while purchases are at market price. The first row of table 1 offers the official consumption expenditure as is reported initially. The consumption per adult after revaluing home consumption with the market price (row 5 in row B) is higher than the initial consumption per adult (row 4 in row A),suggesting that there exists significant difference between market price and farm gate price. This price gap could be ascribed to the presence of high transport margin and transaction costs.

The year 2005/06 is a base year(CPI=100). The current paper uses Tornqvist price index method as a way of computing CPI for other years in the survey. UBOS (2009,2013) uses the Laspeyres price index method to deflate nominal consumption. The current paper asks whether real per adult consumption decreases between 2005 and 2009 or not. As shown in row 7(row E), both the median and average real consumption per adult decrease as one moves from 2005 to 2009. For instance, the median real consumption per adult decreases from shillings 50721 in 2005 to shillings 45653 in 2009, representing an annualized average growth rate of -2.5%. The implication is that the decrease in consumption per adult across periods reflects a corresponding increase in poverty level for a given poverty line.

How large is the consumption difference due to different sources of weight (survey,or external)?. The food price indexes obtained from UBOS (2013,2009) are comparable with the food price indexes from the current survey,which is calculated based on Tornqvist method. I borrow their non-food price index just in this section. The difference is the magnitudes of food and non-food shares in total consumption between the current survey and external sources (UBOS). UBOS uses 0.272 and 0.728 respectively for food and non-food shares. On the other hand, the food and non-food shares from the current survey (i.e the observed shares in total consumption) are 0.62 and 0.38 respectively. The national CPI index is a weighted average of food and non-food price indexes. The national CPI from the respective sources are used to deflate nominal consumption. Th external sources (weights and price indexes) are applied to my current consumption data. The real consumption based on the borrowed UBOS shares is reported in row J while it is shown in row G for the current survey shares. The difference in real consumption between row J and G is 4713 shillings (66516-61803), suggesting that the borrowed UBOS shares overstate the real consumption in 2009 by 7 percent. The official food inflation is higher than non-food inflation. The borrowed UBOS shares give low weight to the high food inflation , which implies a low weighted CPI and consequently, a high real consumption in 2009.

1.3.3 The spatial and temporal composition of food items

There are two main reasons to construct region specific poverty lines to examine the poverty profiles across regions. First, there exists regional variations in the food baskets. As shown in table 3, Cassava fresh is an important source of calorie (17%) for all regions except in Central (6.5%). It is also the cheap source of calorie for all regions. Since matook has high inedible portion (i.e less retention rate),it is the most expensive source of calorie. Matook is ,however, the main diet in Central and Western regions (4% and 9%) compared with the North where its calorie contribution is almost zero. The calorie contribution of Matook to total calorie is 4 times larger in the central region compared to the East. Its price per calorie is,however, 2 times larger in Central than in the Eastern region. The calorie contribution of sweet potatoes fresh in the Central and Eastern regions is 22 % and 28 % respectively. It is also a calorie efficient and less expensive food item in the East(0.11 in table 3). Sorghum contributes 17.4 percent of the total calories consumption in the North. Its calorie share in the West and Central regions,however,is almost zero or negligible. Dodo is mainly consumed in Central and Eastern regions. Generally, Cassava is an important source of calories for all regions ranging from 20% in the Central to 32% in the North. Each food item has different calorie content as shown in table 2.

Second,the price per calorie for a food item as shown in table 3 is not the same across regions, implying a marked difference in price per unit in each location. Appleton (2003) disregards the presence of regional price difference. As indicated in table 3,the price per unit of Matook is almost twice higher in Central than in West. Thus, it is of relevant to use region specific prices and regional food baskets to consider spatial variation in poverty rates, which are important for resource allocation decision to alleviate poverty and promote balanced regional growth.

About 10 percent of the total calorie in the West comes from Matook, which is the most expensive source of calorie as it has high inedible portion and low calorie content. This may justify setting higher poverty line for the West. Yet, people living in this region may be culturally accustomed to eat matook and enjoy matook diet more than other types of food. Therefore, this paper considers both spatial variation in food prices as well as food basket compositions to derive palatable regional poverty lines.

Not only there exists spatial difference in food composition, but also changes in the consumption patterns overtime. Table 3 suggests that food consumption pattern certainly varies as one moves from 2005 to 2009. The West and

Central regions substantially increase the consumption of maize grains in response to its low inflation rate compared to the inflation rates of other main food staples in 2009. On the other hand, they reduce their consumption of cassava fresh. The North increases its consumption of cassava fresh in 2009 relative to 2005. The Eastern region reduces its consumption of sweet potatoes fresh from 28 % in 2005 to 14.7 % while its consumption of cassava dry doubled in 2009 (from 15.8 % to 30.7 %). Thus, it is important to capture both the spatial and temporal variations in households consumption patterns. The latter considers the consumers substitution effect. The food baskets need to be flexible across space and time. Time fixed basket has been used by the extant research in Uganda. The latter section studies the extent of poverty bias between the two choices.

This paper computes the superlative price indexes (Fisher's ideal and Tornqvist) and the conventional Laspeyres and Paasche price indexes. In this paper, the superlative price indexes give the same outcomes and that Tornqvist method has been applied to capture within survey temporal price changes based on the median unit values of 40 food items (details on this issue can be available upon request). Within the same survey period in 2005, inflation ranges from 2% to 23% depending on the choices of regions and quarters.

Price development is not uniform across space and time. Based on the Tornqvist price index, the overall inflation in 2009 (relative to 2005) ranges from 68% in the central and 97% in the West. Between 2005 and 2010, the average annual inflation does not exceed 25%. However,sporadic and unprecedented price spike emerges between 2010 and 2011. The annual inflation in this period (about 60%) is atleast twice of the annual inflation rate between the year 2009 and 2010. This suggests that using fixed national basket to construct poverty line is invalid because inflation patterns across time and space vary considerably.

1.4 Construction of the poverty Lines

The calorie content per kilogram for each food item in the basket is obtained from East and West African food composition tables (Charrondiere et al.,2012; West et al.1988). As indicated in table 2, part of the weight for some food items is lost during preparation and the nutritional value left after the inedible portion is deducted would give us the calories per kilogram, which is used to calculate the cost of the daily minimum acceptable energy needs of 3000 calories for an adult person aged 18-30(Appleton,1999). Poverty line is the cost of meeting 3000 calories per adult per day. This is computed from the poor households ranked according to their real consumption expenditure per adult using an iterative approach. Convergence occurs after 3 iterations for Uganda. This method allows us to exclude the food consumption profile of the rich as their basket may contain luxury items, which are not consumed by the poor.

The most staple food items in the basket are sweet potatoes fresh, matook, cassava fresh, cassava dry/flour ,maize flour beans dry, sorghum and dodo. For each region, more than 80 percent of the total calorie is derived from the 7 main staples (maize,dodo,cassava,sweet potatoes,sorghum, matook,and beans). As shown in table 3,the consumption pattern suggests that there is a region specific dominance by some kind of food staples (Appleton et al,1999). When preferences and relative prices vary across time or region, imposing a common bundle for all regions or periods leads to a poverty line that is typically larger than it should be (Arndt and Simler,2007).

To account for spatial and time heterogeneity in the consumption patterns, multiple food baskets ,each associated to the different periods and space can be used. The different bundles, one for each region or time, help reduce the possibility of imposing locally irrelevant food basket. Several recent researches (Tarp et al. 2002; Mukherjee and Benson 2003; Ravallion and Lokshin, 2006) apply region specific bundle as well as region specific prices to compare the cost of living or the poverty ranking across spaces. However,multiple bundles by themselves can not solve the consistency problem. Ravallion and Lokshin (2006) initially suggest a method of testing consistency of poverty line. They define a utility consistent poverty line as the minimum cost of the common utility (welfare) shared by the different groups in the population at prices facing each group. Andrt and Smiler (2010) propose a maximum entropy method to ensure consistency in the food poverty line bundles. Several authors apply this method in African countries (Van Campenhout et al.,2016; Pauw et al.2016).

Poverty lines should be consistent both across space and time. They should give the same standard of living (i.e consistency) and at the same time, they should reflect the local consumption pattern of the poor (i.e specificity). The underlying assumption is that consumers are rational in the sense that they prefer more to less. Thy maximize utility subject to a given expenditure.

Spatial consistency of the poverty line imply that a rational consumer chooses a bundle from his own spatial domain over another domains for some reasons. First, the other bundles may be expensive when valued with prices prevailed in his own domain. Second, though the other bundles are low cost,they do not provide the reference standard of living(welfare). The other bundles are, therefore, said to be spatially utility inconsistent. Concerning poverty line consistency overtime, it is certain that fixed bundle can provide the same well-being overtime provided that relative prices and preferences are unaltered overtime (Ravallion and Bidani,1994; Arndt and Simler,2010). Fixed bundle,however, can overstate inflation by disregarding consumers substitution. Time varying food baskets are required for a valid inter-personal welfare comparisons across periods. These food bundles should provide the same utility and at the same time, the cost of attaining the recent period bundle should not be larger than the cost of the previous year bundle evaluated at prices of recent time.

Following Arndt and Simler (2010), the paper estimates the poverty lines that are spatially and inter-temporally utility consistent and yet, are characterized by specificity by which the bundles reflect time varying consumer's preferences and the local circumstances and perception of what poverty constitutes. The idea is to minimize the budget share gap between the new consumption bundle (see equations in the appendix. details are in the authors' article) and original bundle subject to the fact that the new bundles should meet all the spatial and inter-temporal consistency restriction requirements as well as the reference standard of living (the total daily calorie needed per adult per day). These consistency restrictions that have to be met by the different bundles are called the revealed preference conditions in the literature (Ravallion and Lokshin,2006; Gibson and Rozelle, 1999 , Arndt and Simler,2007).

This paper uses four spatial domains (Central, East, North and West regions), which give 12 spatial revealed preference conditions at a given year (see table 4). CE is used only if the original bundles fail to meet the revealed preference conditions. A pairwise comparison between bundles is made to know whether consistency is achieved or not. Table 4 reports the spatial and inter-temporal revealed preference tests. The 4 X 4 matrix in the upper left hand corner in table 4 gives the spatial revealed preference tests. Given region i's prices in the column,the cost of obtaining region j's food bundle relative to the cost of acquiring region i's own bundle is indicated in the matrix. The off-diagonal elements with values less than 1 fail to meet the revealed preference conditions. Failure of revealed preference occurs in a given region when the costs of other bundles each valued at prices prevailed in this region are found to be less than the cost of its bundle evaluated with its own prices. A particular bundle in a given region is utility consistent only if the bundle passes both the spatial and temporal revealed preference conditions.

As shown in table 4, of the 12 pairwise comparisons of bundles, 8 of them meet the spatial revealed preference conditions. Consumers in the Central region prefer their own poverty line bundle even if they can afford to buy the Eastern bundle with only 78 percent of what they spend on their bundle. A cost minimizing rational consumer in the central region would have chosen the Eastern bundle had not it been yielding a low well-being (utility). Thus, the Eastern bundle is utility in consistent(is low cost but does not provide same well-being as the central bundle). From the 6 possible mutually consistent conditions, two of them are mutually consistent. Two different bundles ,say A and B ,are said to be mutually utility consistent when bundle A evaluated at region's B prices and bundle B evaluated at region's A prices pass the revealed preference conditions. Bundles from the West and Central in one hand and Bundles from North and East on the other hand are mutually consistent. Other studies by Ravallion and Lokshin (2006) for Russia, and Arndt and Simler (2010) for Mozambique respectively find only 1 and 11 percent mutually consistent bundles.

Temporal revealed preference tests are offered in the upper right corner in table 4. Column A gives the cost of the poverty bundle in 2005 and Column B offers the poverty line by valuing the 2009 bundle with 2005 prices. Valuing the fixed bundle with 2009 prices provides the poverty line as indicated in column C. Column D gives the cost of 2009 bundle valued at its own price. The underlying assumption is that consumers are rational and their choice must be consistent overtime. As shown in table 4, only 2 of the 8 possible comparisons are inconsistent with the temporal revealed preference conditions. The bundles from East and North are temporally utility consistent. Violation of temporal revealed preference occurs in West and Central regions suggesting a high quality bundle in 2009 relative to their bundle in 2005. They do have Superior quality food bundles(expensive bundles) which can overstate the poverty headcount unless the cross entropy method is used to achieve consistency.

Based on the computed new food bundles that are spatially and temporally utility consistent, food poverty headcounts (13%) substantially decreases in the West(13%) and Central regions(17.7%)because they have expensive or high quality bundle that overstates poverty in the original bundles without applying for CE. The poverty headcount almost remains unaltered in the Eastern and Northern regions with and without CE.

The next task revolves around the treatment of non-food requirement to estimate non-food poverty line. It is very difficult to itemize the level of non-food consumed and find out their corresponding prices as most of them are measured in non-standard units. One of the commonly used approach is to estimate the Engle curve relation as proposed by Ravallion and Bidani (1994)and Ravallion (1998).

A non-parametric triangular method is another approach to derive the non-food poverty line (Arndt et al.2015). A household's per adult consumption closer to the food poverty line receives a larger weight. According to Uganda Bureau of Statistics (UBS,2010), the official non-food share stands to be 72 %. Since this estimate seems to be quite large, this paper estimates the non-food share of the poor after having spatial and temporal utility consistent food poverty lines because incorrect shares can bias poverty figures. The non-food shares of the poor reported in figure 1 using both methods. As shown in figure 1, the non-food share never exceed 45% irregardless of the methods pursued.

1.5 The levels and patterns of poverty profile

Why do we use the new food basket from 2005/06 while we already have the 1993/94 basket? First, because the consumption patterns of the poor differ between the two baskets. Maize flour contributes to 6 % of the total calorie in 1993/1994 (Appleton,2003) while its contribution raises to 15% in 2005/06. The calorie contribution of matook at the national level was 12.2 % in 1993/94 while it is only 3.3 % in 2005/06. Only the consumption of cassava seems to be stable overtime, which is 22.8 and 27% respectively in 1993/94 and 2005/06).

Second, updating the old basket by the current survey prices or current purchasing power parity gives different poverty lines. When the 1993/94 food poverty line(11463 Ugandan shilling per adult per month) is updated by 2005/06 PPP, the food poverty lines becomes 23080 shillings per adult. When the 1993/94 food basket is valued with current survey prices, it becomes 25680 shilling per adult. On the other hand, when the new basket is valued with the current survey prices, the food poverty line becomes 22140 shilling per adult(see table 1). One can see that revaluing the old fixed bundle by the current price gives a higher cost of poverty as it ignores substitution effect.

Due to these reasons, this paper constructs utility consistent poverty lines that allow for changes in the consumption patterns across regions and overtime. There is shifts in the consumers taste overtime due to exposure to trade, globalization and new sets of information than otherwise available in the past. Spatial diversity is also pervasive in Uganda. The poverty headcounts based on the spatial and temporal utility consistent poverty lines are our preferred benchmark. By considering spatial and temporal heterogeneity in food consumption patterns and prices, this paper finds that poverty headcount does not decrease as opposed to official report by Ssewanyana and Kasirye (2013, 2012) and UBS(2010). The impact of other assumptions are compared to the benchmark. These include, impact of household composition, sources of price data, food and non-food shares, fixed or flexible food baskets.

Appleton et al.(1999) construct a national poverty line using the 1993/94 monitoring survey. The official poverty line in 1993/94 prices is 44.56 dollars per adult per month or 34 dollars per person per month. In other word, it is 1.485 dollar per adult per day or about 1 dollar per person per day. The official purchasing power exchange rate for one dollar in 2005/06 was 744 Uganda shillings. Ssewanyana and Kasirye (2013, 2012) apply the one dollar per person poverty line expressed in 2005/06 PPP on the four waves of Uganda panel household surveys. 2005/06 is considered as a base year(CPI=100). They deflate the consumption per adult by national CPI index, which is a weighted average of food and non-food CPI, where the weights are the food and non-food shares in consumption which are amounted to be 0.272 and 0.728 respectively.

i) Effect of Household Composition

Ssewanyana and Kasirye (2013, 2012) calculate the poverty headcount as the proportion of households whose consumption per adult fall below the one dollar per person. This biases the poverty figures because real consumption per adult is mistakenly combined with the poverty line per person. How much is the bias?. Their assumptions are applied to this current data to determine the magnitude of bias. In one hand, consumption per adult in 2005 has been compared with the poverty line per adult(1.485*744*30=33153 Ugandan shillings), which gives the population poverty headcounts to be 35%. On the other hand, the poverty headcount is calculated based on the consumption per adult and poverty line per person(1*744*30=22320 shillings). It estimates the headcount ratio to be 23%. The difference between the two is the bias, which is 12%.

The current survey consumption aggregate in both 2005 and 2009 is higher than the respective consumption aggregate from Ssewanyana and Kasirye (2012), implying lower poverty headcount in this paper for the same poverty line. Unfortunately, they do not clearly explain the components of the consumption aggregates. As a result, I cannot replicate their consumption aggregates (i.e their mean and median). The average household size(5.7) is the same for both of us. Since the questionnaire is identical overtime, the arithmetic difference in consumption does not affect the change in poverty. This systematic difference in averages between these two sources only affects the headcount ratio at a given period. Using their own official consumption per adult and poverty line per person (22320 shillings), they estimate the official headcount to be 28.5% in 2005/06. The 5.5% (28.5-23) difference in the poverty headcount is due to differences in the consumption aggregate. Since consumption aggregates differs between the official and ours, the impacts of different assumptions on poverty headcounts are assessed based on our consumption aggregate.

ii) Effect of Food and Non-food Shares

UBOS always sets the food and non-food shares in consumption to be 0.272 and 0.728 respectively. These shares are fixed overtime. On the other hand, food and non-food shares in consumption in this paper are observed to be 0.39 and 0.61 in 2005. This difference by itself alone biases the change in poverty between 2005 and 2009. As UBOS, this paper assumes that the observed shares are constant across time. The official food and non-food consumer price indexes are 169 and 134 respectively. The difference is on the weighted national CPI between the official (1.44) and this paper(1.56) just because of the difference in food share. Given the official poverty line per adult(33153 shillings per adult),the population poverty headcounts are estimated to be 35% in 2005 and 34%2009 using this paper's food share and consumption per adult. In contrast, the poverty headcounts become 35% and 29% in 2005 and 2009 respectively using the official food share and our consumption per adult. The official weights understate the poverty headcount in 2009 by 5%. The non-food share can not go beyond 45% in 2005/06(see my evidence in figure 1).

iii) Effect of Fixed National Basket

A single national basket without considering regional price difference and food composition has been used for the year 2005/06. The difference from the official poverty line is that we use a new basket from 2005/06 and also adjust consumption for within survey price changes. The poverty line is found to be 29733 Ugandan shillings as indicated in column 8 of table 5. The conventional method to estimate the poverty headcount for 2009 is to update the 2005 poverty line by the 2009 prices. These prices can be obtained from two sources.

a) Market based prices: UBOS (2009,2012,2013) constructs the official food and non-food CPI, which are 169 and 134 in 2009 respectively. This paper borrows the official CPI and food share to update the baseline poverty, which is applied to our consumption per adult. The poverty line stands to be 42221 shillings(29733*(1+0.42))in 2009/10. As shown in the third column of table 6, Poverty headcount decreases from 30% in 2005 to 23% in 2009.

While the poverty headcount based on our preferred method(benchmark) shows a 9% increase (from 22.6 to 32 % as indicated in the last column of table 6), this method reduces the poverty headcount by 7%. If the observed food share(0.61) from current survey is used in place of the official food share, the poverty headcount in 2009 stands to be 28%. Yet, the observed food share does not typically represent the food share of the poor. Using triangular weighting scheme, the food share of the poor is 0.75, which is the ratio of food poverty line to total poverty line in 2005. The non-food share is 1 minus food share. Based on this, the poverty headcount is estimated to be 29.3%.

In all cases, the poverty incidence decreases when the fixed basket is valued with the official prices. Indeed, the official prices and weights give the lowest poverty headcount (23%). As we move from the official food share(0.272) to the food share of the poor(0.75), the poverty headcount increases by 6% for the given official food and non-food price indexes. The official weight alone understates the poverty headcount in 2009 by 6%. Using their own consumption aggregates, official CPI and food shares, Ssewanyana and Kasirye (2012) calculate the official population poverty headcounts to be 24% in 2009, showing a decline in poverty by about 4.5 % relative to the 2005 official poverty headcount(28.5%). Using the current consumption aggregates, the official price index and food share, the population poverty headcount is estimated to be 23% in 2009, which also shows a reduction in poverty relative to 2005. Though poverty headcount actually increases by 9 percent, the official price indexes and food share reduce the poverty headcounts in 2009 by 4.5 % and 7% respectively based on the official and current consumption aggregates .

b) Survey based price.

The fixed national food basket from 2005/06 is valued with 2009/10 prices and this gives rise to the food poverty line in 2009. The non-food share of the poor is fixed overtime. It is the ratio of non-food poverty line to total poverty line, which is 0.25 in 2005/06. The updated total poverty line is the ratio of the food poverty line in 2009 to the constant food share. As one moves from 2005/06 to 2009/10, the poverty line inflation is 82%, which is substantially larger than the official inflation rate(42%). As indicated in the fourth column in table 6, poverty headcount increases from 30% in 2005 to 36% in 2009, which is 4% higher compared to preferred bench mark as given in the last column. This result suggests that (compared to a),the official food and non-food CPI are low compared to their values from the current survey. UBOS (2010) uses average retail market prices which may not reflect the pricing behavior of households. The non-food poverty line inflation revealed by the data is remarkably higher than the official report. Price sources matter. Note that poverty in this paper uses individuals(i.e household weight times household size)

iv) Effect of Spatial Prices and Food Composition

Prices and consumption patterns across regions are quite different in Uganda, offering a reason to estimate region specific food poverty lines. Multiple food bundles can certainly enhance specificity by capturing local perceptions and norms confined to that spatial domain and this help avoid imposing irrelevant consumption item in the construction of poverty line. Hence, we estimate food poverty line bundles that are spatially utility consistent for 2005. Instead of estimating temporally utility consistent poverty lines for 2009, we update the 2005 poverty lines by the consumer price indexes by assuming that the spatial food baskets are fixed overtime. Then we compare the poverty headcount differences between fixed spatial food baskets (columns 5 and 6) and flexible spatial food baskets(column 8). The fixed spatial food baskets have been used to update the poverty lines for 2009 using two sources of prices.

a) Market based prices: the region specific poverty lines in 2005 are updated by the national official CPI index(142)in 2009. An inflation rate of 42% is exogenously imposed though we do not know how this inflation is related to the 2005 food bundles. The poverty headcounts decrease from 22.6% in 2005 to 18% in 2009(see column 5 in table 6). This contradicts with the poverty headcount based on the preferred approach, which indicates an increase in poverty from 22.6% in 2005 to 32% in 2009(cf,column 8 in table 6).

b) Survey based prices:

The spatial utility consistent food bundles from 2005 are valued with their own 2009 survey prices. For each spatial domains, the food shares of the poor are also constant between 2005 and 2009. Total poverty lines are obtained by dividing the food poverty lines by their 2005 food shares. The poverty headcounts ratio increase from 22.6% in 2005 to 38.5% in 2009, which is higher than the preferred value(32%). By ignoring the substitution effect, fixed bundles overestimates inflation compared to the flexible bundles in the preferred method. Instead, if we use market based prices and current food weight, poverty headcount is 38.5%. Using official CPI and food share, it is 18%. Using official CPI and our estimated food share of the poor, headcount 24% in 2009. Official food share alone underestimates the poverty level by 6% where as official price indexes understates the 2009 headcount by 8%.

v) Effect of Spatial and Temporal Utility Consistent Food poverty Bundles

In this case, spatial food baskets vary overtime in response to changes in relative price and households' preference. The assumptions of fixed food basket and official CPI bias the changes in poverty headcounts. If relative prices of food in 2005/06 differ from relative prices in 2009/,the food consumption patterns can vary accordingly despite preferences remain unaltered. Because consumers often substitute the expensive foods item by the relatively cheap items to obtain an equivalent welfare with a minimum cost. When the food baskets are flexible across space and time(columns 7-8), the national poverty headcount is 6% lower compared to the poverty headcount based on food baskets that vary only across space(column 6). The fixed food baskets disregards consumers substitution, which in turn overstates inflation so as to yield upward bias on poverty headcount.

In column 7, food baskets are varying overtime. Yet, the spatial non-food shares are fixed between 2005 and 2009. Here,the paper assumes flexible food baskets across time and space as well as flexible non-food shares across time. Results based on these assumptions are the preferred choice of this paper(see column 8). The poverty impact of relaxing fixed non-food share is meager. It means that as long as the food poverty line bundles are consistent across space and time, the decision to use fixed or flexible non-food share does not make any difference on poverty headcounts. To conclude, the official poverty as computed by Ssewanyana and Kasirye (2012,2013,2014) declines by 4.5% where as our preferred method rather shows a 9% increase in the poverty headcount as one moves from 2005 to 2009.

vi) effect of food items aggregation

Uganda has 6 main food items such as matook, sorghum, maize, sweet potatoes, cassava and beans. The last four food items have two varieties. The relative price of varieties exhibit quite large variation. It is of interest to examine the differences in poverty headcounts between aggregated and dis-aggregated food items using the 2005 data. The spatial utility consistent poverty lines are separately estimated based on the 6 aggregated food staples and 10 dis-aggregated food items. Using the 6 aggregated food staples ,the poverty headcount has been computed as 32.8% where as it is 18.2% based on the 10 dis-aggregated food items. This large difference(14%) is the aggregation effect, which upward biases the headcounts ratio. Finally, the poverty headcount using the 34 food items(the preferred one as indicated in the last column in table 8) is compared with effect from 10 food items. The headcount ratio in the former is 22.6 where as it is 18.2 in the latter, suggesting that omitting food items from the basket understates the poverty headcount by about 4.4%. Hence ,this is a reason to include relevant consumption items in the basket to construct poverty lines consistent across space and time.

1.6 Poverty Dominance Analysis and tests

This research seeks to provide poverty dominance test on the changes in poverty. Poverty dominance occurs if poverty is lower overtime irrespective of the choice of the poverty line and choice of poverty measures.

Suppose $F(y)$ denotes the cumulative distribution function at different consumption level. It is written in the vertical y-axis while consumption denoted by y is written in the horizontal x-axis. At a given consumption level y, $F(y)$ gives the cumulative percentage of people whose consumption is below y. If y corresponds to the poverty line(z),then $F(z)$ tells us the proportion of people with consumption below the poverty line y.

We can take the maximum conceivable poverty line z_{max} and compare two distributions up to z_{max}. If one distribution dominates the distribution of another, meaning that the headcount ratio of the first is higher than the other up to z_{max}, one can say that stochastic dominance occurs and the former is said to be a dominating distribution. In the same analogous, the dominance test can be applied to the poverty gap poverty measures based on the Generalized Lornez curve(GL). If GL curve of the first distribution is every where above the GL curve of another distribution, then the poverty deficit curve(PD) of the first is every where below the poverty deficit curve of the second. Dominance refers less poverty gap. The poverty deficit curve plots the consumption per adult(up to z_{max})in the horizontal axis against the cumulative normalized poverty gap in the vertical axis.

The test results for poverty dominance analysis has been presented in figure 2 through figure 4 in appendix. As shown in figure 2, the FGT food poverty incidence for 2009 lies above the food poverty incidence curve for 2005 for all choices of the poverty lines. Figure 3 demonstrates that food poverty gap is always higher in 2009 than in 2005 regardless of the exact location of the poverty line. Not only the poverty incidence but also the poverty gap appears to be low in 2005 than in 2009. SseWanyana and Kasirye (2012, on page 12) find that the headcount ratio in 2009 was always lower than the headcount ratio in 2005 for all reasonable choice of poverty lines. Their finding is in sharp contrast with the finding established by our data. This paper finds that the poverty intensity curve in 2009 is every where above that of 2005 for all poverty lines considered confirming the presence of first order stochastic dominance in poverty deficit.

A problem of stochastic dominance, however, is the assumption of constant relative poverty line across the different multiples of poverty line in the x-axis (Dercon and Krishnan,1998). The conventional stochastic dominance test assumes that all individuals, irrespective of where they locate themselves in the income distribution, face the same price index at a give period. Instead, the price index has to vary across income distribution. The idea is to calculate an inflation rate that gives the same poverty level for the two periods at each cumulative proportion of population. For each cumulative percentage of households, the price deflator has to be computed ,which is ratio of the nominal expenditures of second period to the first period. This is the required/computed inflation that gives equal poverty level in the two periods at the given percentile. Finally,the actual inflation and the computed inflation would be compared to each other if poverty is consistently lower in one period or not.

Figure 4 provides required inflation that would have made the poverty incidence the same between any two periods at different percentage of consumption distribution. 2005 is the reference year. If the actual inflation index is found to be greater than the computed inflation,then poverty incidence has been virtually increased in the comparison period. The actual food CPI in 2009 is 166 which is higher than required inflation implied by the curve to have equal poverty level with 2005. This suggests that food poverty is actually higher in 2009 than in 2005 at all poverty lines.

1.7 Conclusion

This paper uses the four waves panel spanning the years 2005,2009, 2010 and 2011 to construct poverty line for Uganda. Previous researches in Uganda use the national poverty line constructed by Appleton et al (1999) and we believe that this food basket may not reflect the current consumption pattern. We divide the country into four main geographic regions: Central, East ,North and West. It is of important to study the poverty profiles across regions for efficient allocation of resources and balanced growth. The paper uses consumption expenditure as a measure of living standard. The precise choice of a poverty line is,however, contentious. Disparity in spatial food compositions and prices do not support use of a single basket and national price. People in the West obtain their calories from the consumption of Matook, which is not consumed in the North and East. Sorghum is mainly consumed by people living in the North. Differences in diets would not distort poverty measures if the cost of obtaining a given amount of calories is the same irrespective of the diets. However, price per calorie differs significantly among food products. Matook is the most expensive source of calories while sorghum is calorie efficient. The cost of obtaining a given amount of food energy is larger for the West than for the North. Other things constant, ignoring regional food composition implies increasing the cost of living in the North.

Spatially and temporally heterogeneous consumption bundles enhance specificity by capturing the local consumption patterns of the poor confined to that specific spatial domain and time. However,multiple bundles can induce consistency problem. Following Arndt and Simler's (2010), we estimate poverty line bundles that are spatially and inter-temporally utility consistent. Thus,inter-personal welfare comparisons across space and time are valid and consistent. We estimate the national poverty headcounts to be 22.6 and 32% respectively for 2005/06 and 2009/10. According to SseWanyana and Kasirye (2012), the official poverty headcounts are 28.5 and 23.9% respectively for same survey periods. We find that methodological choices for handling poverty lines, systematic difference on preparing the consumption data and CPI deflation played significant roles for poverty estimates at given survey year and across periods. The official national poverty line in 1993/94 prices was 1 dollar per person per day or 1.485 dollars per adult per day. UBOS (2010) and SseWanyana and Kasirye (2012) revalue the official line into 2005/06 prices using CPI and purchasing power parity respectively.

Using the 2005/06 as a base year,the 2009/10 nominal consumption is deflated by the national CPI index of 142. According to them, the official food CPI and non-food CPI indexes relative to 2005/06 are 169 and 134 respectively. The official food and non-food share in the aggregate consumption were 0.272 and 0.728. We apply the triangular weighting and engle curve relation to estimate the non-food share using the 2005/06 and 2009/10 panel household surveys and find that the estimated non-food share is actually lower than 45 percent. For the given official poverty line, the official poverty level is underestimated because of the low weight attached to food inflation index and thereby offering low overall CPI deflator. It is certainly incorrect to deflate food and non-food consumption by the same CPI index while both the magnitude of food inflation and food share are quite different from its non-food counterparts. In addition, care should be taken to express the poverty line and consumption in the same unit of analysis. SseWanyana and Kasirye (2012) use the 1 dollar a day per person poverty line and consumption per adult to estimate the poverty levels and this by itself reduces the poverty measures significantly.

The paper provides several methodologies to estimate poverty lines and actually finds that methodological choices matter. This study has two added value to the poverty literature in Uganda. First, it considers spatial and temporal differences in the food consumption patterns and prices for the poor Ugandan households and yet utility consistence poverty line bundles are achieved using a maximum entropy method. The paper finds that temporally utility consistent poverty bundles decrease the poverty headcount by 6 percent relative to the poverty headcount based on spatially consistent but fixed food bundles overtime, suggesting the importance of considering temporal heterogeneity(i.e permit consumers substitution effect) in tandem with spatial heterogeneity in food composition. In addition, we allow a more dis-aggregation of the main food staples so that the likely difference in the composition and prices is explored. Cassava, sweet potatoes ,and maize are each dis-aggregated into two distinct types.

Second, seasonality in the consumption and prices within a given survey period can make inter-personal welfare comparison problematic especially if the duration of the data collection is long. Prices are often low during crop harvesting relative to prices prevailed in other sub periods. For each region, the paper divides the the survey period into sub-periods and then prepare CPI by taking the first sub-period as a base. Instead of using the lasperyes price that has been used as a default in PLEASe computer code, we use the Tornqvist price index so that the method treats each sub-periods equally and thus,the CPI index appropriately incorporates the consumers substitution effect. In addition, the default PLEASe code gives the poverty line per capita. For the sake of flexibility and future use of our poverty line by others, we estimate and present the poverty lines both in per capita and per adult terms[4]. Based on our preferred utility consistent poverty line bundles, we find that the poverty headcounts increases from 22.6 percent in 2005/06 to 32 percent in 2009/10 and the difference is statistically significant. The policy implication is that Uganda government should revise and update the available poverty reduction strategies to brings changes in the national welfare improvement.

Appendix 1.I : The cross entropy method

Following andrt and Smiler(2010),the model to be estimated is provided in the appendix. The following constrained minimization problem is estimated: s^{orig} and s^{ent} represent the budget shares in the original and the endogenous new consumption bundles. i, r and t denote food item, spatial domain and time(2005 or 2009) respectively. cal is the calorie requirement

$$min_{q^t_{ir} s^{ent}_{ir}} \sum_i \sum_r s^{ent}_{ir} ln(\frac{s^{ent}_{ir}}{s^{orig}}) \tag{2}$$

Subject to

$$\sum_i p^t_{ir} q^t_{ir'} \geq \sum_i p^t_{ir} q^t_{ir} \quad \forall \quad r, r' \quad r \neq r' \tag{2a}$$

$$\sum_i p^t_{ir} q^{t-1}_{ir} \geq \sum_i p^t_{ir} q^t_{ir} \quad \forall \quad r \tag{2b}$$

$$\sum_i p^{t-1}_{ir} q^t_{ir} \geq \sum_i p^{t-1}_{ir} q^{t-1}_{ir} \quad \forall \quad r \tag{2c}$$

$$s^{ent}_{ir} \sum_{i'} p_{i'r} q_{i'r} = p_{ir} q_{ir} \quad \forall \quad i, r \tag{2d}$$

$$\sum_i cal pg_i q_{ir} = cal \quad \forall \quad r \tag{2e}$$

[4]Since the official poverty line was initially expressed in per adult scale, this paper uses the the poverty line per adult and consumption per adult to discuss and compare the poverty levels. Of course,the poverty line per capita and consumption per capita in our survey offers similar poverty estimates as that of using poverty line per adult and consumption per adult

Appendix 1.II regression tables and figures

Table 1.1: Consumption expenditure adjusted for market margins, spatial and inter-temporal price changes

	Monthly average consumption per adult				Monthly median consumption per adult			
	2005	2009	2010	2011	2005	2009	2010	2011
With region specific prices								
A)Home Consumption(HM) at farm gate price	58065	83255	91820	113073	38040	56775	61624	76452
B)Revaluing HM at market price	62678	90227	99912	122558	43535	65465	71655	88170
C) B is adjusted for regional price differences	70568	98515	104672	130670	51887	74116	77142	97671
D) B is adjusted for inflation	62678	56972	58857	59724	43535	39762	40262	40352
E) Considers inflation and spatial price changes	68418	61404	63620	63809	50721	45653	46835	46635
With national price								
F)Revaluing HM with national market price	65512	92849	100882	122685	46515	68057	73705	88501
G) F is adjusted for inflation	65512	61803	62648	60662	46515	44150	44776	42116
H) HM at farm gate price,then adjusted for inflation	58065	56030	56646	56543	38040	37341	37134	36780
National prices from UBS(external))								
I) HM at farm gate price,then adjusted for inflation	58065	59853	61025	62556	38040	40496	40471	41924
J) HM at market price,then adjusted for inflation	65512	66516	68037	67628	46515	48494	49373	48043

Note: The external national CPI is obtained from UBOS(2009,2013). We also estimate the national CPI and regional CPI from our surveys.

Table 1.2: Food basket used to establish food poverty line for 2005

Items	Quantity	Median price	Calories	Retention	Cal per day	Cost per day	Price per cal
sweet potatoes fresh	3.99	132.44	1160	.84	555.13	75.45	0.14
cassava fresh	2.10	151.73	1600	.84	402.41	45.43	0.11
matook	1.92	264.51	770	.5	105.42	72.43	0.69
cassava dry/flour	0.85	486.20	3400	1	413.38	59.11	0.14
maize flour	0.84	600.00	3540	1	426.05	72.21	0.17
beans dry	0.67	736.41	3300	.75	238.14	70.86	0.30
other vegetables	0.60	236.18	290	.75	18.49	20.08	1.09
dodo	0.42	317.53	1800	1	107.83	19.02	0.18
sorghum	0.32	525.00	3450	.9	140.58	23.77	0.17
fresh milk	0.23	486.20	640	1	21.02	15.97	0.76
maize grains	0.22	658.45	3470	.9	98.49	20.77	0.21
mangoes	0.19	354.04	600	.78	12.37	9.36	0.76
millet	0.16	736.41	3231	.65	49.34	17.30	0.35
tomatoes	0.14	650.00	200	.95	3.89	13.31	3.42
sugar	0.14	1 555.85	3750	1	75.02	31.13	0.41
irish potatoes	0.14	486.20	750	.85	12.43	9.48	0.76
sweet potatoes dry	0.14	242.08	3300	1	63.81	4.68	0.07
cabbages	0.13	181.50	230	.78	3.39	3.43	1.01
beans fresh	0.11	777.93	1040	.75	12.26	12.23	0.00
fresh fish	0.09	972.41	1030	.6	8.33	13.10	1.57
dry/smoked fish	0.09	1 333.33	3005	.7	26.43	16.75	0.63
ground nuts	0.09	1 504.98	2350	.93	27.19	18.72	0.69
rice	0.08	1 104.61	3600	1	39.25	12.04	0.31
sweet bananas	0.07	264.09	1160	.56	6.26	2.54	0.41
beef	0.06	2 333.78	2340	.8	16.09	20.06	1.25
onions	0.06	777.93	480	.8	3.13	6.34	2.03
cooking oil	0.05	2 338.74	8570	1	59.88	16.34	0.27
peas	0.04	972.41	820	.75	3.63	5.74	1.58
simsim	0.04	1 371.07	5930	1	33.22	7.68	0.23
meat	0.03	2 225.57	2340	.75	6.80	8.63	1.27
chicken	0.02	2 739.61	1460	.61	2.87	8.82	3.08
bread	0.02	1 104.61	2490	1	5.86	2.60	0.44
passion fruits	0.01	1 166.89	920	.75	0.63	1.07	1.69
eggs	0.01	2 092.07	1490	.88	0.95	1.52	1.60
total					3 000.00	22 140.00	

Note: quantity is offered in kilogram. Quantity represents the average consumption in a week.

Figure 1: The level of non-food share for the different values of estimated food poverty lines

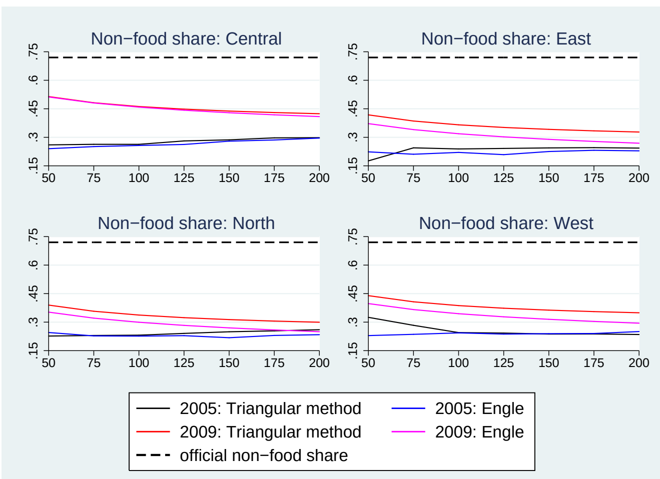


Table 1.3: Price per calorie and the percentage calorific contribution of some food items

	Share of total calories required				Price per calorie			
Items	Central	East	North	West	Central	East	North	West
2005								
Cassava Fresh	0.170	0.065	0.174	0.178	0.135	0.135	0.081	0.106
Maize grains	0.016	0.052	0.079	0.078	0.239	0.091	0.111	0.087
Sweet Potatoes fresh	0.220	0.281	0.046	0.193	0.220	0.110	0.186	0.136
Cassava dry/flour	0.028	0.158	0.151	0.102	0.150	0.112	0.152	0.141
Maize flour	0.216	0.144	0.111	0.094	0.171	0.155	0.177	0.167
Dodo	0.038	0.063	0.007	0.019	0.306	0.176	0.176	0.210
Sorgum	0.000	0.037	0.166	0.007	0.000	0.148	0.166	0.177
Beans dry	0.068	0.027	0.088	0.121	0.315	0.296	0.323	0.242
Matook	0.042	0.012	0.002	0.091	0.746	0.596	0.546	0.414
Sweet Potatoes dry	0.000	0.039	0.010	0.032	0.194	0.075	0.036	0.060
2009								
Cassava Fresh	0.128	0.066	0.265	0.091	0.346	0.294	0.169	0.271
Maize grains	0.171	0.029	0.115	0.183	0.148	0.136	0.196	0.120
Sweet Potatoes fresh	0.207	0.147	0.082	0.232	0.329	0.316	0.282	0.286
Cassava dry/flour	0.042	0.307	0.095	0.112	0.278	0.219	0.294	0.251

Table 1.4: Spatial and inter-temporal revealed preference tests for 2009

	Spatial revealed preference test				Temporal revealed preference			
Region specific bundles	Region specific prices							
	Central	East	North	West	A	B	C	D
Central	1.00	1.41	1.40	1.05	26775.40	31587.65	49477.89	53501.20
East	0.78	1.00	1.05	0.80	17033.68	17269.26	39937.62	37286.40
North	0.92	1.17	1.00	0.89	18843.12	18997.48	36574.64	35301.35
West	1.04	1.43	1.39	1.00	18490.85	21445.71	40485.50	45405.98
Revealed preference tests after entropy adjustment								
Central	1.00	1.10	1.11	1.01	26775.40	26805.06	49477.89	42267.43
East	1.00	1.00	1.09	1.00	17033.68	17834.05	39937.62	37229.34
North	1.16	1.17	1.00	1.07	18843.12	18997.48	36574.64	35301.35
West	1.14	1.19	1.29	1.00	18490.85	19828.38	40485.50	37618.52

Note: The 4 X 4 matrix in the upper left hand corner in table 4 shows that : given region i's prices in the column, the cost of obtaining region j's food bundle relative to the cost of region i's own bundle. The off-diagonal elements with values less than 1 represent failure of revealed preference conditions. In the upper right hand corner: letter A denotes the food poverty line in 2005(2005 bundle evaluated at 2005 prices). Letter B denotes the cost of 2009 bundle evaluated at 2005 prices. C represents the cost of 2005 bundle evaluated at 2009 prices. D offers the cost of 2009 bundle evaluated at 2009 prices. The 2005 bundle is the entropy adjusted bundle and the bundle is exogenous for 2009. For instance ,a bundle in central region is utility consistent if the cost of its own bundle is less than the cost of the bundle in other region evaluated at prices from central region and the cost of its 2009 bundle at 2009 prices must be less than the cost of the 2005 bundle at 2009 prices.

Figure 2: food poverty incidence stochastic dominance curve

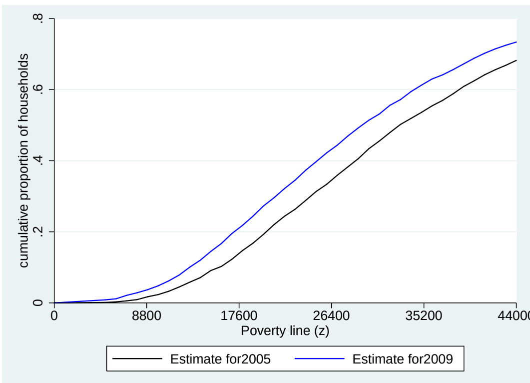


Table 1.5: Utility Consistent poverty lines and other types of poverty lines

	Utility consistent poverty lines				Official poverty lines		Using national and fixed basket	
	Per adult		Per-person		Per adult		Per adult	
	Food(1)	Total(2)	Food(3)	Total(4)	2005 PPP(5)	2005 CPI(6)	CPI(7)	survey price(8)
2005								
National					33176	30492	29733	29733
Central	26775	37164	21925	31449	33555	30840	30611	30611
East	17034	22232	13549	18373	32377	29757	29103	29103
North	18843	24357	14713	19815	31640	29081	29437	29437
West	18491	24451	15055	20304	32256	29646	29371	29371
2009								
National					47109	43298	42221	54241
Central	42267	55867	35062	48115	47648	43793	43468	55876
East	37229	48144	29763	39072	45975	42256	41327	53124
North	35302	45760	27981	37546	44929	41294	41800	53732
West	37619	49891	30337	41089	45803	42098	41707	53613
2010								
Central	44833	61757	43834	62233				
East	37340	47903	36244	48286				
North	37267	49684	36229	49062				
West	35668	45183	34795	46152				
2011								
Central	60760	84810	59571	85194				
East	49802	64441	48389	66671				
North	50162	63907	49223	64407				
West	49870	64752	48353	63260				

Note: Poverty line can be given in per adult or in per-capita terms. Poverty line per adult needs to be combined with consumption per adult. Alternatively, poverty line per person should follow consumption per capita. Appleton et al.(1999)initially constructed the poverty line using 1993/1994 monitoring survey and estimated the food and total poverty lines per adult to be 11463 and 16443 Ugandan shillings respectively. Since then,they were re-based into 2005 prices using PPP or CPI. Given a dollar PPP rates of 369 and 744.5 Ugandan shilling respectively in 1993 and 2005,column 5 gives the updated official poverty lines. Alternatively,the 1993/94 poverty lines can be updated by the 2005 official Consumer Price Index, which is 1.854 and this result is reported in column 6. In per capita term, the official poverty line was 34 dollars per month in 1993/94 prices,which is about 1 dollar per day per person and this line tends to be 25313 and 23265 Ugandan shillings when expressed in 2005 PPP and CPI respectively. Our poverty line per person based on a single basket using 2005 prices is 23757, which is almost the same as the official poverty line. Based on a national basket,the official poverty line expressed in CPI and our poverty lines are the same.

Figure 3: Food poverty deficit curve

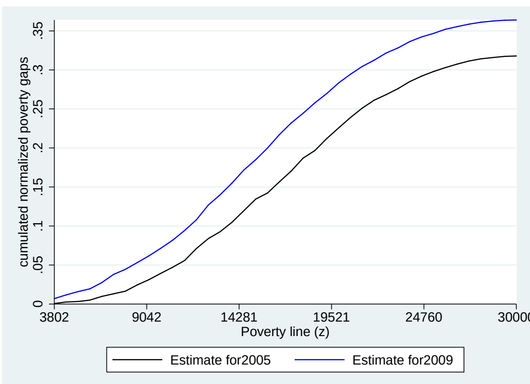
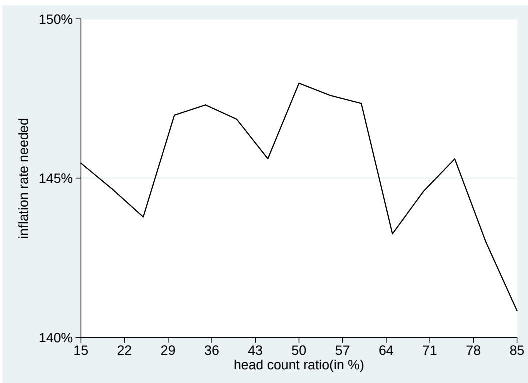


Table 1.6: Does poverty decrease across time? the different methods and the poverty headcounts

	Official headcount (1)	Single basket CPI(2)	Single basket survey prices(3)	multiple bundles CPI(4)	multiple bundles survey prices(5)	food baskets vary overtime(6)	non-food share vary overtime(7)
2005							
Central	0.192	0.117	0.117	0.195	0.195	0.195	0.195
East	0.374	0.442	0.442	0.195	0.195	0.195	0.195
North	0.527	0.588	0.588	0.443	0.443	0.443	0.443
West	0.190	0.255	0.255	0.148	0.148	0.148	0.148
Rural	0.324	0.366	0.366	0.266	0.266	0.266	0.266
Urban	0.870	0.093	0.093	0.099	0.099	0.099	0.099
National	0.285	0.300	0.300	0.226	0.226	0.226	0.226
2009							
Central	0.137	0.090	0.193	0.200	0.347	0.244	0.227
East	0.244	0.236	0.355	0.087	0.304	0.271	0.270
North	0.438	0.433	0.604	0.304	0.519	0.486	0.491
West	0.249	0.271	0.425	0.162	0.419	0.377	0.378
Rural	0.267	0.270	0.417	0.205	0.438	0.373	0.368
Urban	0.930	0.079	0.152	0.097	0.188	0.149	0.143
National	0.239	0.230	0.361	0.182	0.385	0.326	0.321

Note: The official estimates in column 1 is directly taken from SseWanyana and Kasirye(2012) on page 13. The official CPI index(142) in some columns is adapted from UBOS(2010,2009). This is used to increase the 2005/06 poverty line by 42 percent. The updated poverty line is combined with the 2009/10 nominal consumption per adult to estimate headcount ratio . All other estimates(except column 1 and CPI index) are my own calculations from the 2005/06 and 2009/10 survey data

Figure 4: Food Inflation needed for equal poverty between 2005 and 2009



2 Measures and Determinants of Chronic Poverty

2.1 Introduction

Uganda is a land locked country located in the east Africa with an estimated population of 37.58 million in 2013 and also one of the poorest country in the world with a per capita income of 572 USD in the same year. The Government has been implementing several economics reforms to stir the performance of the economy through liberalization of exchange rate and agricultural pricing. The country has virtually abolished taxes on export as well as the government's monopoly on tea and coffee exports and rather overhauled a marketing system where prices are determined by competition and market forces (World Bank,1993). Since Agriculture is the backbone of the Uganda economy, an incentive in favor of cash crops has been put in place to enhance the income of poor farmers who are engaged in producing these crops. In addition, the poor in rural areas require intervention in basic social services including access to education, health, rural feeder roads and agricultural extension and marketing. Uganda introduced the Poverty Eradication Action Plan(PEAP) in 1997 which had been revised in 2000 with the objective of poverty reduction through increasing off-farm activities, enhancing agricultural productivity and diversification of crop production.

As part of integrated national development project which has been launched in 2011,clustering in agriculture is considered to be a viable option available for the poor to exit poverty by adopting operational mechanisms for modernizing agriculture which ends up in prompting export competitiveness of the farmers. According to World Bank(2015),clustering of agriculture under the most promising and high value export crops such as flowers and upland rice can boost agricultural productivity and contribute to creation of value chain. Despite socioeconomic reforms have been put in place, rural poverty is an ongoing issue. This paper aims to investigate the magnitude of chronic poverty at country and regional levels. There is no single and universally accepted method to quantify the level of chronic poverty. It depends on the normative assessment of the poverty analysts because a given poverty measure can not satisfy all desirable properties or axioms of poverty (Porter and Quinn,2013). This paper has two contributions. First, it is the first study in Uganda to apply new methodologies to identify the chronically poor households and the total burden of poverty using the Uganda household panel data. Lawson et al.(2006) and Ssewanyana (2010)in Uganda answer the question who are chronically poor.

They did not, however,study the intensity of poverty. Lawson et al.(2006) first set up a probit model to identify the factors that make the household more likely to be poor in the first place using the first year survey. Second,they establish two probit models for the second year survey to examine the factors that make them poor conditional on the first year poverty status. They want to know whether the variables that affect initial poverty is different from the variables that affect changes in poverty. However,these three separated probit models entail substantial loss of information as well as more susceptible to measurement error. In addition, the sequential probit model can not be applied(or more cumbersome) when the panel dimension exceeds two periods. These two studies completely ignore the possibility of resource transfer. Though imperfect, households in developing countries can partially smooth consumption through borrowing from local money lenders, friends, relatives, safety net programs and storing grains. When chronic poverty is defined as low average well-beings (Foster and Santos,2013;Duclos et al,2010; Jalan and Ravallion,2000; Porter and Quinn,2013), which is the definition this paper adapts, the model treatment differs from the conventional spells approach.

Before analyzing the determinants of chronic or transitory poverty, it is important to identify the relative importance of these types of poverty in the first place. Following the spells approach, extant studies in Uganda use the concept of chronicity to indicate the situation of extended periods under poverty. However, the spells approach does not capture the entire burden of inter-temporal poverty. Unlike the studies in Uganda, this paper applies the permanent income standard approach, a method proposed by Foster and Santos,2013, which allows an imperfect inter-temporal resource compensation. This method helps us to distinguish the chronic poor from transient poor as well as the level of chronic poverty relative to transitory poverty. For each household, we can compute the chronic poverty index and the average level of transitory poverty. Finally, we establish a censored quantile regression method to investigate the determinants of chronic poverty. As a robustness check, the dependent variable is replaced by a discrete categorical variable which is suitable to apply multi-nominal logit. It is noteworthy to point out that the paper applies different chronic poverty measures to understand whether the relative importance of chronic poverty depends on the choices of the methods or not. We find that the burden of chronic poverty is higher than the burden of transitory poverty for the same proportion of chronic and transient poor and for the same proportion of time in which they are under poverty. This finding is robust to the methodological choices and assumptions. Hence poverty in Uganda is largely chronic.

If chronic poverty is pervasive, we then seek to identify their characteristics which make them in a state of low welfare across time compared to the other type of households. Do the chronic poor different from the non-chronic poor (include the never poor households as well) in their time varying characteristics that explain consumption growth after controlling for their unobserved heterogeneity?. We set up an empirical consumption growth model using fixed effect panel data. Analyzing the determinants of chronic poverty from this perspective is our second contribution. Previous studies in Uganda use two periods data and examine how the initial household characteristics explain the growth in welfare and this method,however, does not allow to disentangle the fixed effect component from time varying characteristics explaining growth. We find that there is no difference between chronic and non-chronic poor in-terms of returns to their time -varying characteristics. These variables include lagged consumption, access to all weather road,extension services,ownership of TV-radio(information is taken as a factor of production) and other time varying shocks including pests and burglary. Instead,they do have differences in their time invariant latent characteristics. On average,the chronic poor have unfavorable latent attributes that reduce their consumption growth while the non-chronic poor have growth promoting time-invariant unobserved characteristics. 33 percent of the consumption growth difference between the two is attributable to their fixed latent factors. After retrieving the fixed effect associated to each household, we run an OLS regression to show how initial household characteristics affect the fixed effect residual. We find that the same mechanisms affect the level of chronic poverty,or the probability of being chronically poor or the time fixed portion of consumption growth. The effects of these variables are robust as we move from the permanent income standard to the duration sensitive spells approach used to identify the chronic poor and the chronic index. Thus, the significant predictors of chronic poverty are education of household head,high proportion of female and male adult members in the household, average land size per capita, having TV-radio and monogamy martial status.

Another contribution of this paper is to examine how the determinants of chronic poverty vary as we move from uni-dimensional consumption based poverty to a perspective of multidimensional poverty measure. To extent of my knowledge, only Levin et al. (2014) compute the magnitude of multidimensional poverty headcount as well as identify the relative importance of the poverty dimensions using the Ugandan Demographic Health Survey (DHS) collected in 2000/01 and 2005/06. They consider three dimensions of deprivations ,namely education ,health and standard of living. We use the Ugandan national households panel survey spanning 2005/06,2009/10,2010/11,2011/12 and 2013/14, which is part of the Living Standards Measurement Studies (LSMS) conducted by Ugandan Bureau of statistics and the World Bank group(which is freely available at http://econ.worldbank.org).

This paper uses three dimensions such as education,housing and consumption and we find that consumption is the main contributor to multidimensional headcount. Levin et al. (2014) did not investigate the type of households with the highest burden of multidimensional poverty. Since they have cross section data, they also did not investigate the extent of multidimensional chronic poverty. Our paper provides an interesting insights on the correlates of multidimensional chronic poverty as well as on the drivers of changes in multidimensional poverty.

Households are classified into three groups depending on the number of dependents in the household. Children who are below 13 as well as those who are above 64 years old are considered to be dependents. The three distinct household types are: households having less than 2 dependents (HH1); households with 2-4 dependents (HH2) and households having dependents above 4 (HH3). The main finding is that households with more dependents (HH3) are more poor compared to households with small number of dependents(HH1). The evidence comes from consumption based poverty, static period by period multidimensional poverty headcount and longitudinal adjusted poverty headcount. The multi-dimensional adjusted headcount ratios for the years 2009,2010 and 2011 are indistinguishable and higher than poverty headcounts in 2005 and 2013.

It is of relevant to identify the mechanisms by which these households react to the improvement in multidimensional adjusted headcount ratio from 2009 to 2013. Based on the shapely decomposition on changes in multidimensional poverty, HH1 and HH2 are found to reduce their within group poverty incidence(mainly) and intensity. On the other hand, HH3 do not decrease their poverty headcount and intensity. They contribute to the improvement by decreasing their population share(called demographic shift). The poverty incidence indicates the proportion of households who are multi-dimensionally poor. The intensity of poverty is the the percentage of deprived dimensions by the multidimensional poor household. The multidimensional poor households do not decrease consumption poverty relative to other dimensions. We conclude that the within group effect((64%), which includes effects of poverty incidence(50%) and intensity((14%), is the main reason followed by demographic shifts(36%) for the improvement in the adjusted poverty headcount.

The paper is structured as follow. Sections two and three offer the literature and the data respectively. Section four presents the methods to distinguish the chronically poor from transient poor and the poverty measures. Section five offers the determinants of chronic poverty using two approaches: the consumption based uni-dimensional poverty measure and multidimensional poverty. Finally , section six concludes.

2.2 Literature

The growth experience of African countries is more diverse as well as volatile. Uganda had experienced versatile economic success in two periods: between 1961-1969 (with a 4% average growth rate in real GDP following its independence in 1962) and between 1989-2002. The growth performance between 1969 and 1987 was extremely low. The first growth period was followed by a period of war and civil strife and vehement authoritarian regime ,that disrupted the overall economy as well as the foundation of government' plan and objective. Real GDP per capita plummeted below its pre-independence level due to the highly debilitating civil strife. Thus ,the period was characterized by a negative growth rate in real GDP but with a small upheaval only in 1983 (André,2008). Peace was restored in Uganda in 1986 and the country has embarked economic growth since then though the new government who took power in 1986 was a no party system until 2006. The post conflict annualized growth rate in GDP was merely above 4% and the national poverty incidence had declined from 55.7% in 1992/1993 to 33.8% in 1999/2000 (Kappel et al,2005). But, poverty has risen to 38% in 2002/2003. Overall, the growth spurts in the period 1989 to 2002 was continuous and registering significant impact on household living standard. Nevertheless,GDP growth rates in 2000's were generally lower than the 1990's owing to recurrent drought, global financial crisis and high inflation pressure. During the 2000's, the highest positive growth rate was recorded in 2005/06 but then it continuously declines until 2011/2012 except a sheer small upheaval in 2009/2010. The official national poverty since 2005 has been decreasing in Uganda while others confirm that there is no substantial improvement in poverty and hence the result is mixed. It depends on the measurement of poverty as well as the assumptions adopted in the construction of the welfare measure. This paper recaps the literature on poverty to underpin the conceptualization and measurement of chronic and transitory types of poverty. The paper provides evidence from uni- dimensional as well as multi-dimensional poverty.

2.2.1 Uni-dimensional poverty

Recently, there are ample evidences and studies that contribute to the literature on uni-dimensional poverty dynamics which has by now three broad divisions. First, literature that models poverty transition probabilities (e.g. Cappellari and Jenkins, 2004). Second, literature that distinguishes the chronic poverty from transient component in the content of inter-temporal aggregate poverty (Foster, 2009; Foster and Santos,2013; Calvo and Dercon,2009; Porter and Quinn ,2013; Jalan and Ravallion ,2000; Hoy and Zheng ,2011; Gradin et al., 2011 ; Bossert et al., 2012; Duclos et al,2010; Quinn,2014). Third, literature that links poverty trap with asset based approach (Carter and Barret, 2006; Lybbert et al., 2004). Yet, the poverty dynamic literature that considers the multiple dimensions of well-being is at nascent stage (Apablaza and Yalonetzky, 2013; Alkire and Foster,2011; Nicholas and Ray 2011; Nicholas et al.,2013; Alkire et al.,2014). This section offers the literature on the consumption poverty dynamics while studies that investigate the multiple deprivations of well-being are provided in the next section. The choice of a particular poverty index depends on the extent to which it satisfies the axioms of poverty and the normative assessment of the poverty analysts appropriate for a specific setting and application. Each property affects the distribution of the poverty measure and thus, constitutes a basic desideratum for an aggregation method (Alkire et al.,2014). A well behaved poverty measure should satisfy a broad array of properties such as population decomposability, monotonicity, replication invariance, symmetry and transfer axiom.

The traditional poverty measures use a cross section of consumption data to examine the incidence of poverty and its intensity across the poor. However, they ignore the duration of poverty while persistent poverty might have precipitated and a long lasting detrimental impact on individual's outcome. This paper aims, therefore, to investigate the level and determinants of chronic poverty using panel data because it explicitly incorporates the time spent in poverty, which is crucial to know how individuals often experience poverty. It is well understood that analysis of poverty using a cross section data only at a point in time offers little insights on the evolution and persistence of poverty (Mckay and Lawson, 2003; Hoy and Zheng,2011; Rocio and Daniel,2015). To design and implement effective poverty reduction strategies, policy makers must have a deeper understanding on the causes of poverty, its distribution across time and different societal groups. It is important to know who are chronically poor and who are not because the chronic poor are more likely to remain in a high risk of perpetuating poverty in the absence of effective public intervention while those who are episodically poor are more likely to escape poverty without assistance (Hulme and Shepherd, 2003). Thus, the two distinct groups need different policy responses, targeting and social protection (Mckay and Lawson, 2003). The challenge here is that there is no universally accepted sets of criteria used to identify the chronically poor from its counterpart transiently poor.

Hulme and Shepherd (2003) define the chronic poor in this manner: those who are poor for an extended episodes of their life and are more likely to transfer their poverty to the next generation. Thus, chronic poverty refers the duration in poverty or a sort of persistent deprivation. When the poverty spells are longer, this may lead to asset depletion and social exclusion. This in turn increases the propensity to remain in same state of poverty or may further deepen the intensity of poverty. There are two main approaches available for identifying the chronically poor. The first is the components approach, which compares the average/permanent income with the poverty line (Jalan and Ravallion, 1998; Foster and Santos, 2013; Gaiha and Deolaiker ,1993, Duncan and Rogers,1991). Dunacn and Rogers (1991) estimated a fixed effect earning model to purge the effect of transitory variation from the permanent component. The intercept term gives the permanent income component while the residual term offers the transitory component. Using a fixed effect panel regression, Gaiha and Deolaiker (993) run consumption on household characteristics and, the predicted value was taken an estimate of the permanent income. Jalan and Ravallion (1998) define the permanent income as a simple inter-temporal average of resources through time. In all these alternative definitions, the chronic poor relegates to households whose permanent income falls below the poverty line. The chronic poverty measure under the permanent income/consumption approach, however, is not sensitive to the duration in poverty and the variation in consumption across periods (Foster, 2009; Quinn,2014).

The spells approach is the second method for measuring chronic poverty, which focuses on the time spent in poverty by comparing the period by period real consumption with that of a given absolute poverty line. This approach uses two distinct cut- offs namely the duration (the fraction of time spent in poverty) and the poverty line for identifying the chronically poor. By counting the number of spells of poverty facing the households, 3% households in rural Pakistan were found to be consumption poor in all five rounds of the panel survey (Baulch and McCulloh,2002). Using 9 years panel data sets in rural South India, Gaiha and Deolaiker find that 21.8% of households were consumption poor in each of the successive years. A critical issue for the spells approach that uses the length of time for which a person is poor is that information on consumption data is not available throughout an individual life(consumption is truncated in nature) and poverty outside the survey years is not known. Consumption is observed only in the survey periods under consideration. An individual may be poor immediately preceding the first survey year or poor immediately after the last survey year. In addition, in panel data with gaps, several spells of poverty may pass between the first and the last observations. A household who is poor in two different survey years does not imply the same poverty status to hold in all other years outside the current panel surveys. The duration cut off line in the spells approach is also arbitrary and as a result, the level of chronic poverty can be affected by the dimension of the panel. If the cut off line is 1, a person should be all times poor (consumption falls short of the poverty line in all survey periods) to be a chronically poor. Under this definition, however, the percentage of chronic poor is more likely to be low in the presence of long panel data.

In general, both approaches inevitably shared the fact that their poverty measures may be sensitive to the definition of the standard of living measure and the poverty line chosen (Mckay and Lawson, 2003). Measurement error in the welfare variable due to recall error or imputation of missing data brings another challenge to the quantification of the poverty dynamic using panel data. Dercon and Krishnan (2000) found that 50% of the households' observed mobility across the consumption quintile was attributable to measurement error. Correction to measurement error is not considered in several poverty literature. The main distinction between the spells and permanent income approaches discussed above is on the assumption of resource transferability across periods. In the spells approach, resources are not transferred across periods because resources available at any given year is assumed to be consumed during that year. On the other hand, the permanent approach uses a simple arithmetic average of resources by assuming a perfect substitution of resources overtime (Foster and Santos, 2013), suggesting that households can smooth consumption by borrowing or lending with zero interest rate. Collins et al.(2009) argue that the assumption of perfect resource substitutability is far from reality because poor households in developing countries face fragile capital and financial markets characterized by high interest rate spreads and high transaction cost of borrowing and lending making consumption smoothing problematic. Though Foster and Santos (2013) follow the permanent income approach, they suggest a new methodology that allows an imperfect degree of resource substitutability overtime. The general mean consumption, which is obtained from the Atikson's (1970) income standard function, averages the individual's consumption streams across time into a permanent consumption standard using a discounting parameter that reflects the degree of consumption volatility through time. When the permanent consumption is less than an exogenously given poverty line, an individual is identified as chronically poor.

Eventually, the permanent income has been applied into the Clark, Hemming and Ulph (1981) decomposable family of poverty measures to obtain the aggregate chronic poverty index (Foster and Santos, 2013). While the inter-temporal poverty measures suggested by Calvo and Dercon (2009) and Foster and Santos (2013) capture the entire burden of the poor, their estimates are less sensitive to the duration of poverty. Porter and Quinn (2014) argue that the cost of consumption fluctuation and the chronicity of well-being cannot be jointly captured in the inter-temporal poverty measures as they are incompatible in the trajectory ordering. They propose a poverty measure that is sensitive to duration but does not allow for compensation of resources. Though the chronic measure proposed by Porter and Quinn (2014) addresses the persistent poverty in the inter-temporal content, interpretation of the estimated parameter seems to be less obvious.

Duclos et al, (2010) suggest a chronic poverty measure that attaches more weight on the poorer individuals, suggesting that volatility has unprecedented negative effect on the well-being of poor households. Their poverty measure, however, does not satisfy the population decomposability axiom. This paper aims to apply the imperfect substitutability permanent income approach to examine the determinants of chronic poverty. According to the seminal contribution of Sen (1976), there are actually two distinct steps for measuring poverty. First, the identification step which sets the criteria for determining who is poor and who is not (Foster 2009). Second, the aggregation step organizes the data on the poor in a holistic manner to form an overall poverty index. The identification step asks whether the individual's resource is sufficient enough to exceed the consumption poverty line cut off. On the other hand, the aggregation step relies on the formation of an overall indicator of poverty using the three FGT poverty measures, namely the headcount, the poverty gap and squared poverty gap.

2.2.2 Multi-dimensional poverty

Chronic poverty has been extensively studied from the view point of the monetary dimension, partly because the consumption variable can fluctuate a lot in a short time relative to the non-monetary dimension. However, an individual can be dynamically constrained in a multiple factors and this may motivate the poverty analysts to consider the multi-dimensionality of chronic poverty. Multiple dimensions of deprivations should be taken into account in the measurement of chronic poverty (Hulme and McKay,2007; Roche,2013) because consumption poverty does not fully capture the multiple deprivations of poverty. Alkire et al. (2014) argue that high consumption level may not always imply better well-being in some non-monetary dimensions such as nutrition (i.e. stunting, body mass index); schooling and housing. A person with low consumption may be well off in housing facilities or nutritional indicators, suggesting that there may not be a trade-off between monetary and non-monetary dimensions. Thus, the multidimensional poverty index can give a useful policy insight on targeting a specific or multiple deprivations to improve the well-being of individuals. The aggregation of different indicators of deprivations into a single index helps understand the incidence of deprivations in the same individual. The paper adapts the Alkire Foster family of multi-dimensional method, specifically the Foster (2009) duration approach, to investigate the incidence and intensity of chronic poverty as well as identify the characteristics of households that reduce the burden of chronic poverty. The Alkire and Foster (2011), Alkire et al (2014) and Foster (2009) poverty measures are essentially parsimonious and more intuitive and easy to communicate the result. Their poverty measure satisfies the two important axioms of poverty useful for policy making: dimensional monotonicity and sub-group decomposability.

Dimensional monotonicity refers to changes in the poverty incidence when the already poor person is deprived in another dimension. The population decomposability property is used to characterize the sub-groups' contribution to the overall change in poverty across time and this property is crucial to prioritize a segment of population or a region that has a substantial impact on the entire poverty dynamics. The chronic multi-dimensional poverty measure proposed by Alkire et al. (2014) requires three sets of cut-offs: dimension specific deprivation cut -offs, multidimensional poverty cut-off and a duration cut-off. We set a poverty line for each available indicator of poverty that helps determine whether a person is deprived in that dimension or not. The multi-dimensional poverty cut off identifies a person as being poor by assessing the vector of his weighted deprivations. The union and intersection approaches have been suggested in the literature as two different methods of identification of the multi-dimensionally poor (Tsui, 2002; Bourguignon and Chakravarty, 2003). Based on a union approach, a person is said to be multidimensional poor at a given time if there exists at least one dimension in which a person is deprived. This method, however, does not help to target the poorest of the poor when the number of dimensions is large (Alkire and Foster, 2011).

On the other hand, it can be that a person is poor only if he/she is deprived in all dimensions. This renders the intersection approach. Instead of these two extreme classifications criterion, Alkire and Foster (2011) take an intermediate cut off k, which is the number of dimensions for a person to be considered multi-dimensionally poor. When k=1(at least poor in 1 dimension), the union approach holds while the intersection approach occurs when a person is poor in all dimensions(k=d, d refers number of a available dimensions). We can attach different positive weights to the indicators depending on their relative importance. For each survey period, we determine whether a person is poor or not by assessing the weighted deprivation score with the given multi-dimensional cut-offs k. We then count the number of years in which a person is multidimensional poor. After defining the duration cut-off, which is the proportion of time periods under poverty, we can identify the multidimensional chronic poor when the total number of periods under poverty is found to be at least the given duration cut off. From the view point of policy design, it is of important to sharpen our understanding on the determinants of multi-dimensional chronic poverty.

Though the conceptualization and the measurement of chronic poverty in a dynamic setting and multiple dimensions has been well established in the recent literature (Alkire et al.,2014, Apablaza and Yalonetzky,2013), the application of the method to panel data for African countries is very scanty (see Levin et al.,2014). The widely used method to analyze the determinants of changes in poverty overtime using the consumption poverty in these countries is that of the Datt and Ravallion's (1992) approach, which explains the change as the effect of growth and inequality components. However, this method ignores the multiple deprivation indicators and the decomposition is also path dependent. Recent studies by Roche (2013) and Rocio and Daniel (2015) incorporate the Shorrocks's (2013) shapley decomposition (1953) method into the Alkire and Foster dynamically multidimensional poverty measure. This method decomposes the change in poverty into two factors. The first is changes due to the within group poverty effect arising from changes in the incidence and intensity of poverty by a particular sub-group of population. The second is attributable to changes due to demographic shift, which illustrates how the distribution of sub-groups' population share contributed to changes in multi-dimensional poverty. To scrutinize the determinants of change in poverty, we mimic these recent studies to apply in the context of Uganda.

2.3 Data

To examine the level of chronic poverty as well its determinant, this paper uses the Uganda Panel household data collected by Uganda Bureau of Statistics(UBOS) and the World Bank group covering the period 2005/06, 2009/10, 2010/2011 and 2011/2012. The survey comprises a rich arrays of information on labor force, health,subjective well being, agricultural production ,asset, food and non-food expenditure. In this paper, we adjust total expenditure per adult per month to take into account spatial and inter-temporal price differences using the Tornqvist price index. Home consumption is now re-valued with market price. For each food item, the market price is the median price, obtained from households purchasing it using standard metric unit in a given region. Each household reports both the values and quantity consumed of each food item,which allows us to retrieve unit price.

Since large number of respondents are from rural households and their characteristics are different from their counterpart urban households, we choose rural households for a through analysis of determinants of chronic poverty. Table 1 shows the incidence of rural poverty over the four waves panel. 33% of the households are below the poverty line (34618 shilling using the 2005 prices) in 2005/06. In contrast, the headcount ratio stands to be 38.9% in 2009/10. The poverty incidences in 2010/11 and 2011/12 are indistinguishable(39.8%). As to the persistence of poverty, 10.7% of households are classified as poor in all four waves. The concept of chronic poverty refers the proportion of time spent in poverty. This counting approach,however, renders subjective judgment on the duration cut off used to dichotomize households into chronic and non-chronic poor. Non-chronic poor consists of transitory poor and never poor households. Kedir and Mckay (2005) define chronic poverty as those households with real consumption per adult below the poverty line in all survey rounds. In many other poverty literature, it is also defined as those slipping into poverty for atleast half of the total rounds (Foster,2009; Dercon et al. 2012). As shown in table 1, 71.3% of households have fallen into poverty atleast once in 4 rounds, ,suggesting a high risk of poverty.

As to the poverty profile by regions, 24% of households who reside in the North are poor in all four rounds, which is more than 7 times larger compared to the level of poverty persistence in West and Central regions (3% and 4.5% respectively). 44% of households in Central region are found to be non-poor in all waves whereas the never poor households in the West tends to be 37%. The highest and lowest poverty persistence are found respectively in North and Central regions irrespective of definition of chronic poverty pursued.

Table 2.1: Poverty status of households by regions(%)

	Central	%	**East**	%	**North**	%	**West**	%	**National**	%
Never poor	156	44.2	90	21.5	67	16.1	124	37.2	437	28.7
One period poor	105	29.7	105	25.1	63	15.1	98	29.4	371	24.4
Two period poor	50	14.2	118	28.2	101	24.3	63	18.9	332	21.8
Three period poor	26	7.4	71	16.9	85	20.4	37	11.1	219	14.4
Always poor	16	4.5	35	8.4	100	24	11	3.3	162	10.7

Note: For a given region,the table offers the percentage and the number of households under a given poverty status

2.4 Methods for measuring chronic and transient poverty

To decompose aggregate poverty into transient and chronic poverty,we adapt several approaches: The Jalan and Ravallion (1998,2000) method (here after denoted as JR); the Equally Distributed Equivalent (here after called EDE) poverty gap approach proposed by Duclos et al.(2010);Quinn (2014) and the approach proposed by Foster and Santos (2013). Since the JR approach is widely used the existing literature, it is taken as a reference to compare with other methods.

2.4.1 Jalan and Ravallion's (1998,2000) measure of chronic and transient components

Consider that a household's welfare overtime is denoted by $Y_i = Y_{i1} + Y_{i2} ... Y_{it}$. Household welfare is measured over a total period of T. The poverty index based on the conventional Foster Greer -Thorbeck(FGT) measure of poverty is given by:

$$P_{it} = (1 - Y_{it}/z)_+^\alpha \tag{1}$$

where z is the poverty line. α is a measure of poverty aversion. Precisely, it reflects the weight attached to the variability of loss of consumption. When $\alpha > 1$, the poverty index is more sensitive to the variability of consumption below the poverty line. We choose $\alpha = 2$ so that the index is more susceptible to the consumption distribution pattern of the poor. The poverty gap associated to household i at time t is given by $g_{it} = (1 - y_{it}/z)_{+}^{\alpha}$. The FGT index over N individuals and T time period is given by:

$$P_{\alpha}(g) = (NT)^{-1} \sum_{i=1}^{N} \sum_{j=1}^{T} g_{ij} \tag{2}$$

According to Jalan and Ravallion (1998), an estimate of permanent consumption is obtained as the household's mean consumption across T time periods. JR compared the estimated permanent consumption with the poverty line to identify the chronically poor. The level of chronic poverty for a household i is defined as a short fall of mean consumption from the poverty line. The aggregate chronic poverty index over all households is written as : $P_{\alpha}^{C}(g) = (N)^{-}1 \sum_{i=1}^{N} (1 - \overline{y_i}/z)^{\alpha} I(\overline{y_i} < z)$,where $\overline{y_i}$ is the average welfare of household i. Transient poverty is estimated as the difference between total poverty and chronic poverty. $P_{\alpha}^{T}(g) = P_{\alpha}(g) - P_{\alpha}^{C}(g)$

2.4.2 Foster and Santos's (2013) approach of poverty measure

Time is an important dimension to assign the poor in one of the two groups: chronically poor or transiently poor. But the approach to classify them into a specific category is a contentious issue. Two broad methods are distinguished in the poverty literature: a spells approach and a permanent income approach. According to the spells approach,the proportion of time periods spent in poverty determines whether the household is chronically poor or not. The permanent income approach (called component approach), in contrast, compares the poverty line with that of available resources a household owned overtime (Foster and Santos,2013; Jalan and Ravallion,1998;Duncan and Rogers,1991). These two methods differ significantly in their underlying assumption.

The spells approach assumes that a household's resource at a point in time determine his poverty status and resources are imperfect substitute and can not be transferred to other periods. The component approach stands in a sharp contrast and assumes that resources could be freely averaged up and they are effectively perfect substitute across time. Foster and Santos (2013)follow the component approach but explicitly consider the possibility of imperfect substitution across time. Their approach is similar with that of Duclos et al. (2010) as they use the concept of equally distributed equivalent income, a term they borrowed from Atkinson(1970). The idea is that variability in a household's resource overtime plummets the sample estimate of permanent income. Duclos et al (2010) also considers adverse effect of volatility of resources within the same household as well as between households. Nevertheless, lack of population decomposability is the shortcoming of this method. The work of Duclos et al (2010), Foster and Santos (2013) and Jalan and Ravallion (1998) fall under permanent income approach. Foster and Santos (2009) use the spells approach, which will be presented later.

Foster and Santos (2013) develop a new way of measuring chronic poverty based on a component approach and the

Atkinson's (1987) decomposable version of Clark Hemming and Ulph (1981)(here after referred to as CHU). The later is the static utility based poverty measure with diminishing marginal utility to reflect how hard to transfer resources overtime. There are two important steps to determine chronic poverty. The first is the identification stage: a method that help classify whether a household is chronically poor or not. In analogous to Jalan and Ravllion's approach to measuring poverty, Foster and Santos (here after called FS, 2013) make use of a permanent consumption approach in order to classify a household into chronic or transient poor. But the permanent consumption for FS is the general mean consumption which is defined as :

$$\mu_\beta(y_i) = \begin{cases} \left(\sum_{t=1}^{T} y_{it}^{\beta}/T\right)^{1/\beta} & \text{if } \beta \neq 0 \\ \prod_{t=1}^{T}(y_{it})^{1/T} & \text{if } \beta = 0 \end{cases}$$

β reflects the degree of consumption substitution between two periods. As β increases,the propensity of transferring resources from one period to another also increases. Specifically the elasticity of substitution is given by 1/(1- β) and it increases with β. The general mean ($\mu_\beta(y_i)$)is an increasing function of β. If $\beta = 1$, FS's formula for the general mean coincides with JR permanent consumption,reflecting perfect consumption smoothing. This might be implausible even in the perfect foresight world because some sort of costs are inevitable in resource transfer. $\beta = 0$ and $\beta = -1$ respectively denotes the case of geometric and harmonic mean. In line with FS and because of the fact that transferring resource is imperfect especially in developing countries, we choose $\beta < 1$, which according to Atkinson(1970), belongs to the family of equally distributed equivalent incomes. The cost of variability in consumption overtime is given by $(1-\beta)$. If the general mean is less than the poverty line, a household is identified to be chronically poor.

Nevertheless, based on FS, a household can be chronically poor even if the arithmetic mean is greater than the poverty line because volatility in consumption itself can generate costs or because transferring resource entails costs (such as cost of lending and borrowing, transaction costs,leakage occurring through exchange). Such costs are expected to be significant in fragile insurance and financial markets (Collins et al,2009). Consumption smoothing in bad year, a situation where real consumption falls below the poverty line due to co-variate or idiosyncratic shocks, is notoriously difficult. The available mechanisms that households use to smooth current consumption are more likely decreasing their future consumption substantially. Borrowing from local money lenders with a high interest rate is one of the options available to poor households in African countries. Yet, reimbursing it in a good time presses down the real consumption in that period. Selling land as a buffering against low current consumption is used by rural households but that deteriorates their income generating capacities in the future. Households coerced to sell oxen, a key factor of production in rural household but that would deplete core asset base which may have negative repercussion on future income. Generally, transferring resources between periods results in a high leakage costs. When consumption is very low in a particular year, it may have devastating long-run impact on health outcome (though not observed at that moment) or may lead to social exclusion and other possible effects (loss of motivation and incentives to work hard). A poverty analysis should give more weight to low consumption than high consumption. Low β gives more weight to low consumption than higher consumption.

let the general mean,$\mu_\beta(y_i)$ be denoted by y_i^*. If $y_i^* < z$, a household is said to be chronically poor and the vector of consumption is given by $y_{it}^* = y_{it}$. On the contrary, we set $y_{it}^* = z$ when $y_i^* \geq z$ (for the non-chronically poor). At a given point in time, the household utility depends on his consumption and inequality aversion parameter (β) and this is given by $U_\beta(y_{it}^*) = y_{it}^{*\beta}/\beta$. FS (2013) define chronic poverty for a particular household as a loss of utility, the decline in utility relative to the utility had real consumption been at the poverty line, obtained as the difference between utility at a poverty line and within time average utility. Once identification is carried out in the first stage,the level of chronic poverty is computed based on Clark, Hemming and Ulph (1981)or CHU class of poverty indexes(for $\beta \leq 1$ and $\beta \neq 0$) as follow:

$$C_\beta(y;z) = H(z)\frac{1}{N}\sum_{i=1}^{N}\left(U_\beta(z) - \frac{1}{T}\sum_{t=1}^{T}U_\beta(y_{it}^*)\right) \quad = \quad \frac{1}{N}\frac{1}{T}\frac{1}{\beta}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(1-(\frac{y_{it}^*}{z})^\beta\right) \tag{3}$$

Where H(z)is a normalization factor.[5]. Note that the level of chronic poverty for non-chronically poor is zero because the general mean consumption(y_i^*) is greater than or equal to the poverty line and thus, we set $y_{it}^* = z$ for all t. Eq(3) gives the aggregate chronic poverty index. Now ,we compute the total average poverty level as given in eq(2) by comparing the real consumption (y_{it}) of a household at a given year with a poverty line and then averaging first overtime for a give household and second,averaging the within time poverty over households. Generally,the average poverty measure is obtained by taking the period by period poverty status of the household. If $y_{it} < z$, the level of poverty may be written as $p_{it}^\beta = (1-(\frac{y_{it}}{z})^\beta)/\beta$. If $y_{it} > z$, then p_{it}^β will be zero. The aggregate poverty over N households and T time period is :

$$G_\beta(y;z) = \frac{1}{N}\frac{1}{T}\frac{1}{\beta}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(1-(\frac{y_{it}}{z})^\beta\right) \tag{4}$$

Transient poverty,denoted by $C_\beta^T(y;z)$, is the difference between average poverty($G_\beta(y;z)$) and chronic poverty($C_\beta(y;z)$)

Finally, following Foster (2009), the spells approach for chronic poverty has been adopted. Chronic poverty depends on the duration in poverty, which is the proportion of time a household is under poverty, and the poverty line. The fraction that delineates the chronic from non-chronic is an arbitrary duration cut-off line. Finally, aggregated chronic poverty index is constructed using those chronically poor.

But, according to Foster (2009), this is a crude measure of poverty and he rather introduces a duration adjusted chronic poverty index. The core premise is that repeated poverty has a large impact than episodic poverty. Unlike the cross section data, panel data reveals an important feature that allows us to discern whether poverty experienced by a household is a transitory phenomenon or the usual state of affairs (Jalan and Ravllion ,1998,2000; Foster,2009, Duclos et al,2010). We use the dual cut-off approach to identify the chronic poor: the poverty line z and another cut-off τ representing the minimum fraction of time spent in poverty to be a chronic membership. If consumption falls below the poverty line for a proportion of d and if d is greater than the target cut off point τ, then the household is said to

[5]it comes from the definition chronic poverty and U_β. $H(z) = 1$ when $\beta = 0$ and $H(z) = 1/(\beta U_\beta(z))$ when $\beta \leq 1$ and $\beta \neq 0$

be chronically poor. In the aggregation step, the average chronic poverty index is constructed. It is of important to remind that all the chronic poverty indexes adopted in this paper assumes that the sequences of poverty are valued equally. All spells are equally important and it does not matter when it occurs: the order of poverty is not important. Calvo and Dercon (2009), on the other hand, argue differently in the sense that the pattern of poverty matters in the calculation of chronic poverty. They incorporate a discounting factor by which the poor spells are compensated by the non-poor spells.

We are now turning to (after identification stage) an important question about the percentage of households in chronic poverty and also the magnitude of the their consumption short fall, which is precisely about their poverty gap indexes. To illustrate this with a hypothetical example, suppose that 4 households are observed each in 4 time periods. Given a poverty line z, two household are always poor, one household is never poor and another household is only two times poor out of a 4 window period. Given a duration cut off as $\tau = 0.68$, one can say that two households are chronically poor. Thus, 50% of households are chronically poor(H=0.5). But this measure of chronic poverty does not take into account the heterogeneity of the chronic poor in duration of poverty or it is not sensitive to the average years the chronically poor under poverty. Suppose a household who was always poor now receives a positive income shock in period 2 and becomes 3 times poor. The percentage of chronically poor is still not affected though there is an increment in the duration of poverty spells. This violates the time monotonicity axiom, a position that requires sensitivity of poverty index with respect to changes (decrease or increase) in the actual consumption of the chronic poor (Foster,2009).

A simple intuitive solution is just to find the total number of years slipped into poverty by all chronically poor households and divide that by the entire number of observations and the resulting figure is known as duration adjusted headcount ratio(K_1). The above example puts the fraction to be 0.437(K_1= 7/16) implying a decrease in headcount ratio as a result of improvements in one of the households welfare. The duration adjusted headcount ratio(K_1 can be written as H* D. D is the duration intensity, which is the average share of time spent in poverty by the chronically poor households. Let $d_i(\tau)$ is the fraction of time spent in poverty by a chronic poor household i. Averaging this over the chronic poor households gives the duration intensity(D= $d_1(\tau) + d_2(\tau).../Q$), where Q indicates the absolute number of chronically poor). Under the dual cut off points criteria, for a given z and τ, first we have to identify the chronic poor. Second, we calculate their duration adjusted FGT indexes. For example, the squared poverty gap index for the chronic poor households is obtained by taking the sum of their squared poverty gaps and then divide this by the entire set of observations in the sample. When $\tau = 0$, every spell of poverty is taken into consideration and the chronic poverty measure coincides with the total poverty because one time period in poverty is enough for the household to be chronically poor. All poverty is chronic and there is no transient poverty. Transient poverty is obtained as the difference between aggregate poverty and chronic poverty. Let $G_\alpha(y,z,0)$ be the FGT average poverty measure and let $G_\alpha(y,z,\tau)$ be a chronic poverty measure,the FGT index associated to transient poverty is given by:$G^T_\alpha(y,z,\tau) = G_\alpha(y,z,0) - G_\alpha(y,z,\tau)$. Where y and z respectively are real consumption per adult and poverty line .

2.4.3 EDE poverty gap approach

Duclos et al.(2010) argue that inequality in poverty gap among the poor induces additional social cost and the corresponding social cost of poverty is generally higher compared with the situation where ill-fare was spread equally across the poor population. This section just recaps the procedures used to estimate the components of poverty. Using my own data, the findings based on this approach will be compared with other methods in the result section. Let $\Gamma_\alpha(g)$ be the level of household ill-fare with stringent assumption that ill-fare is equally spread across households and period. $\Gamma_\alpha(g)$ is known as the Equally Distributed Equivalent(EDE) poverty gap which, under the above assertion, yields the same poverty measure as that of the total poverty generated by $P_\alpha(g)$.

$$\Gamma_\alpha(g) = P_\alpha(g)^{1/\alpha} \tag{5}$$

$\Gamma_1(g)$ is a measure of poverty that fails to take into account the social cost of having unequal poverty status among the poor. If all poor households lie at the same absolute distance from the poverty line meaning that if ill-fare were presumably spread equally across the entire poor households, we can say that $\Gamma_\alpha(g) = \Gamma_1(g)$. On the other hand, if the distribution of normalized poverty gap is markedly unequal for a given α, the poverty measure under this situation is larger than the level of poverty had it been equal spread to all poor households. Thus, the cost of inequality, which increases the social cost of poverty, is given by

$$C_\alpha(g) = \Gamma_\alpha(g) - \Gamma_1(g) \tag{6}$$

$C_\alpha(g)$ is additional cost of poverty that a social decision maker would like to bear in order to remove all inequality in poverty gaps. It includes the cost of inequality resulting from variability in poverty gaps between households as well as the variability in ill-fare across time for the same household. Total poverty measure ($\Gamma_\alpha(g)$) is the sum of the cost of inequality and the poverty level that prevails in the risk neutral world ($\Gamma_1(g)$). In the following, we decompose aggregate poverty into chronic and transient components based on the EDE approach. Consumption variability (or volatility in poverty gap as we use the same poverty line overtime) across periods for the same household generates transient cost of poverty. Let $\gamma_\alpha(g_i)$ represents variability adjusted EDE poverty measure for household i, which is written as:

$$\gamma_\alpha(g_i) = (T^{-1}\sum_{j=1}^{T} g_{ij}^{\alpha})^{1/\alpha} \tag{7}$$

For this particular household observed across time, the cost of variability in his/her ill-fare is:

$$\theta_\alpha(g_i) = \gamma_\alpha(g_i) - \gamma_1(g_i) \tag{8}$$

$\gamma_1(g_i)$ is the average poverty gap (with assumption of no cost of inequality). $\theta_\alpha(g_i)$ is the risk premium (transient poverty) by which a household is willing to increase his average ill-fare just to remove all fluctuations in his/her ill-fare across time. From eq(8), the aggregate transient poverty considering all households is:

$$\gamma_\alpha^T(g) = \theta_\alpha(g) = \gamma_\alpha(g) - \gamma_1(g)$$
$$\gamma_\alpha^T(g) = \gamma_\alpha(g) - \Gamma_1(g) \tag{9}$$

the cost of inequality between households is obtained as

$$C_\alpha^*(g) = \Gamma_\alpha(g) - \gamma_\alpha(g) \tag{10}$$

If we combine eq(7) and eq(8) to eliminate $\gamma_\alpha(g)$, the total EDE poverty gap will be:

$$\Gamma_\alpha(g) = \Gamma_1(g) + C_\alpha^*(g) + \gamma_\alpha^T(g) \tag{11}$$

The sum of the first two terms in eq(11) gives the level of chronic poverty while the last term gives the transient poverty. In addition, if we substitute eq(9) and eq(6) into eq(8), the total cost of inequality can be written as:

$$C_\alpha(g) = C_\alpha^*(g) + \gamma_\alpha^T(g) \tag{12}$$

The first term is the cost of inequality between households,and this is what the social decision maker(SDM) is willing to bear to remove all ill-fare inequalities among poor households. Similarly, the second term describes the level of poverty resulting from variability in ill-fares overtime. $C_\alpha(g)$ is the total cost of inequality that SDM is willing to suffer to discard all kinds of inequality in poverty gaps. Note that inequality costs are increasing function of α Finally, we have a panel data of four waves drawn from Uganda household panel survey spanning from 2005/06 to 2011/2012. The panel dimension is relatively modest. Nevertheless,four waves are large enough if we consider the fact that panel data in Africa is generally scant(for many reasons). Small number of time observations can actually create systematic bias between the sample estimate and the true unobserved poverty measure for each household (Duclos et al,2010)). They suggest statistical bias correction method for the problem of short panel.

2.4.4 Summary of the chronic poverty measures

Table 2 summarizes some of the inter-temporal poverty measures which are available in the literature of uni-dimensional consumption poverty. We use the following abbreviation for the sake of brevity: The Jalan and Ravallion(1998) as JR(1998); Foster and Santos(2013) as FS (2013); Foster (2009) as F (2009); Porter and Quinn(2013) as PQ (2013); Duclos et al.(2010) as D(2010) and Quinn (2014) as Q (2014). All the poverty measures displayed in the table satisfy some of the axioms of poverty such as continuity, weak monotonicity, strong monotonicity, weak focus ; focus, time symmetry and population decomposability.

If the poverty index remains unaffected due to changes in the well-being of non-poor person, then it meets the focus principle. From the perspective of inter-temporal poverty, the weak focus describes that the poverty measure should not change in response to changes in the well-being of the always non-poor person (those whose consumption is already above the poverty line in every period). Under strong focus, poverty remains unaltered when consumption in non-poor periods increases though the household was still poor for some other periods. This property does not meet by all the above methods except in F(2009). The weak monotonicity states that inter-temporal poverty should not increase when the well-being of an individual increases in any given period. The poverty measure is a weakly decreasing function of well-being in any time. Poverty should decrease when the well-being of the poor person improves. Yet,the increase in well-being by the never poor individual should not affect the poverty level. Strong monotonicity allows the poverty measures to be sensitive to changes in consumption at one point in time though the person is till poor after changes in well-being in that period. Only the headcount version of F(2009) that does not satisfy this property.

Inter-temporal intrapersonal transfer axiom elucidates that elevated consumption in one period can not fully compensate depressed consumption in another period. JR(1998) allows perfect compensation where as PQ (2013) and FS (2013) allow imperfect compensation. Foster (2009) does permit compensation only when the well-being is below the poverty line. Quinne (2014) does not allow compensation at all. Imperfect compensation assumes that transferring resource is more costy. A poor person having different consumption levels in two periods may want to transfer a certain amount from a period of low consumption to a period of high consumption. Though the average consumption is the same, the inter-temporal poverty level after transfer is higher than without because of the increased dispersion. Porter and Quinn (2013) argue that the resistance to compensation is higher at the lower levels of well-being. They define non-decreasing compensation to indicate that the marginal rate of compensation between two periods should not decrease as the well-beings increase in proportion.

An increasing compensation describes the property that the marginal rate of compensation should increase as poor person's consumption increase in proportion (i.e when consumption increases by the same factor in all periods, consumption smoothing is less difficult). All poverty measures satisfy decreasing compensation except Foster(2009) and Quinn (2014). Increasing compensation is achieved only by PQ (2013). Duration sensitivity is another central property of the inter-temporal poverty measure. Large number of poverty spells has large adverse effect than severe poverty observed in short periods. Duration sensitivity implies that poverty increases when transferring resources within periods with the effect of increasing the number of periods below poverty. According to Porter and Quinn (2013), inter-temporal transfer and duration sensitivity are incompatible properties. A person who is poor in both periods can transfer resources from one period to another and can be only one time poor at the expense of very low well-being in one period. The persistence of poverty is low. Yet, the depth of poverty is high which makes the person more poor according to the inter-temporal transfer axiom. Only the poverty measures suggested by Foster (2009) and Quinn (2014) are sensitive to poverty persistence while the other measures are not.

Lack of population docomposability is the main weakness of the poverty measures proposed by Duclos et al. (2010). We do not know who is chronically poor. The method provides only the aggregate chronic poverty index. The measure

Table 2.2: The Inter-temporal poverty measures proposed by different authors

	Total poverty	Chronic poverty measures
JR(1998)	$P(y,z)=\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\max\left[0,(1-\frac{y_{it}}{z})\right]\right)^2$	$C_{JR}(y,z)=\frac{1}{N}\sum_{i=1}^{N}\left(\max\left[0,\frac{1}{T}\sum_{t=1}^{T}(1-\frac{y_{it}}{z})\right]\right)^2$
FS(2013)	$P_{\beta}(y,z)=\begin{cases}\frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\max\left[0,\frac{1}{\beta}\left(1-(\frac{y_{it}}{z})^{\beta}\right)\right]\\ \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\max\left[0,\left(ln(z)-ln(y_{it})\right)\right]\end{cases}$	$C_{\beta}(y,z)=\begin{cases}\frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\max\left[0,\frac{1}{\beta}\sum_{t=1}^{T}\left(1-(\frac{y_{it}}{z})^{\beta}\right)\right] & \text{if} \quad \beta\leq 1;\beta\neq 0\\ \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\max\left[0,\sum_{t=1}^{T}\left(ln(z)-ln(y_{it})\right)\right] & \text{if} \quad \beta=0\end{cases}$
F(2009)	$P(y,z)=\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\max\left[0,(1-\frac{y_{it}}{z})\right]\right)^2$	$C_F(y,\tau)=\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(1-\frac{y_{it}}{z}\right)^2 I(y_{it}<z)I\left(\sum_{t=1}^{T}I(y_{it}<z)\geq\tau T\right)$
PQ(2013)	$P_{PQ}(y,z) = \frac{1}{(k+1)NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\max\left[0,\left(\left(\frac{z}{y_{it}}\right)^k + ln\left(\frac{z}{y_{it}}\right)-1\right)\right]$	$C_{PQ}(y,z)=\frac{1}{N}\sum_{i=1}^{N}\max\left[0,\frac{1}{(k+1)T}\sum_{t=1}^{T}\left(\left(\frac{z}{y_{it}}\right)^k+ln\left(\frac{z}{y_{it}}\right)-1\right)\right]$ for k ≥ 1
Q(2014)	$P(y,z)=\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\max\left[0,(1-\frac{y_{it}}{z})\right]\right)^2$	$C_Q(y,z)=\frac{1}{N}\sum_{i=1}^{N}\max\left[0,z-\frac{1}{2}\left(\left(\frac{1}{T}y_i'Ay_i\right)^{\frac{1}{2}}+\frac{1}{T}\sum_{t=1}^{T}y_{it}\right)\right]$
D(2010)	$P_D(y,z)=\left[P(y,z)\right]^{\frac{1}{2}}$	$C_D(y,z)=P_D(y,z)-(\frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{T}\sum_{t=1}^{T}\left(\max\left[0,(1-\frac{y_{it}}{z})\right]\right)^2\right]^{\frac{1}{2}}-P(y,z))$

is not sensitive to duration in poverty as well. It does not allow inter-temporal transfer when consumption is above the poverty line. Chronic poverty represents a low average well-being while the risk component belongs to transient poverty. They assume that unequal poverty gaps between households as well as within time for the same household give rise to additional social cost. Transient poverty is the cost of volatility in consumption across time. Chronic poverty is the sum of the poverty gap that prevails in the absence of unequal ill-fare and additional cost resulting from unequal poverty gaps between households. Inequality adjusted total poverty index is the sum of transient and chronic poverty.

Another version of the Jalan and Ravallion's (1998) method, which is denoted by JR2, allows imperfect substitution. Households whose consumption below the poverty line can smooth consumption. On the other hand, we assume that households do not save and transfer when income is above the poverty line. Thus, the average uncensored consumption in JR is now replaced by the average consumption censored at the poverty line in JR2 (Duclos et al.,2010). Let $y^{\cdot}_{ij}=min(y_{ij},z)$ be consumption censored at z in period j, the JR chronic poverty component in table 2 replaces y_{ij} with $y^{\cdot}_{ij}$. The total poverty index remains same but there is a trade-off between chronic and transient poverty.

Finally, it is noted that the average poverty in EDE is an increasing function of the inequality aversion parameter α (provided that $\alpha\geq 1$). This is in sharp contrast with the JR (or generally the FGT index) approach where poverty decreases with an increase in α.

2.5 Discussion of estimation results

2.5.1 Results based on uni-dimensional consumption poverty

2.5.1.1 Distinguishing the chronic poor from transient poor: how large is the level of chronic poverty?

In table 3, first, we provide the main findings from the different approaches used to measure chronic poverty. A detail step by step discussion is presented next.

Table 2.3: Chronic and transient poverty aspects in the inter-temporal poverty using different methods

	Population share	Poverty index		Composition of the poor		
Approach	% Chronic poor	Chronic(%)	Transient(%)	Chronic(%)	Transient (%)	Difference [a] (%)
JR (1998,2000)						
α=1	28.99	57	43	40.6	59.4	16.4
α=2	28.99	45.4	54.6	40.6	59.4	4.8
JR2						
α=2	35.37	64.9	35.1	49.6	50.4	15.3
Foster and Santos (2013)						
β=0	34.45	66.71	33.3	48.3	51.7	18.4
β=-1	40.63	78.22	21.78	56.9	43.1	21.3
Foster (2009)						
τ=0.5	46.88	91.12	8.88	65.7	34.3	25.4
τ=0.75	25.05	68.79	31.21	35.1	64.9	33.7
Porter and Quinn (2013)						
k=1	37.73	73.09	26.9	52.9	47.1	20.2
k=2	42.10	84.41	15.59	59	41	25.4
Quinn (2014)	25.44	67.01	32.99	35.7	64.3	31.3
Duclos et al.(2010)		81.6	18.4			

Note: [a] the percentage point by which the chronic poor contribute to total poverty more than their share in the poor households

Table 2.4: EDE Chronic and transient poverty measures with and without bias correction (alpha=2)

	without short panel correction		with short panel correction	
	Coef	**% contrib.**	**Coef**	**% contrib.**
Bias			0.0134	
			(0.0001)	
Average poverty	0.0513		0.0513	
	(0.0014)		(0.0014)	
Cost of inequality b/n indviduals	0.0669		0.0535	
	(0.0038)		(0.0455)	
Chronic	0.1848	81,5981	0.1714	75,6871
	(0.0038)		(0.0038)	
Transient	0.0417	18,4019	0.0551	24,3129
	(0.0021)		(0.0021)	
Total poverty	0.2265		0.2265	
	(0.0032)		(0.0032)	

We start to offer the standard JR (Jalan and Ravallion,1998) poverty decomposition method that assumes that high consumption in one period fully compensates the low consumption in other period. Chronic poverty occurs when the average well-being is below the poverty line. A household can be poor for several periods but an unprecedentedly large consumption in one period can put the mean above the poverty line and the household could be no longer a chronic member. This may render invalid poverty estimate especially if consumption is contaminated with error. Moreover, imperfection in financial and labor markets actually render the permanent income standard as unpalatable especially in African countries with a myriad of behavioral,economic and political constraints that hamper households to smooth consumption through borrowing or saving a windfall income. An alternative for original JR approach is to replace uncensored average consumption with mean consumption censored at the poverty line. The later assumes that excess resources in a good time are neither saved nor transferred into other period. There is no difference between JR2 and Foster (2009) when α =1 and $\tau = 1$.

Table 3 presents chronic and transient components based on both uncensored and censored average consumption. As expected, the JR approach exaggerates the contribution of transient poverty(54.6%) to overall poverty compared with the chronic share (45.4%). However, JR2 method based on censored average consumption virtually reverses the poverty ranking offered by JR. The contribution of chronic poverty raises to 64.9% while transitory poverty falls down(35.1%).

Based on the FS (2013) method (elasticity of substitution is 1 when $\beta = 0$), 66.7% of aggregate poverty severity is attributable to chronic poverty. The duration adjusted poverty measure proposed by Foster (2009) puts the share of chronic to 68.8%. The perfect resource substitution method by JR assigns the smallest share to chronic poverty(45%). When the simple arithmetic mean is replaced by the average consumption censored at the poverty line, JR2 gives higher chronic share (65%). According to Porter and Quinn (2013), the marginal rate compensation decrease as k increases. Compensation is less difficult at higher well-being than at lower consumption. The share of chronic poverty under this approach tends to be 84%. The duration sensitive poverty measure suggested by Quinn (2014) also indicates the fact that chronic poverty is pervasive compared to transient poverty. Finally, under the assumption of no consumption substitution across periods but variability in ill-fare triggers additional social cost, the share of chronic poverty in total poverty is 81.6% as shown in the last row. We conclude that the conventional JR approach understates chronic poverty. The percentage of households who experience poverty at least in one period is found to be 71.3%, suggesting that the transient poor households are in the range of $29-50\%$ depending on the poverty measure chosen. The chronic poor households are also in the range of 21%- 42% , where the lower and the upper limits correspond to the methods proposed by Foster(2009) and Porter and Quinn (2013)respectively.

We find that the intensity of poverty is higher for chronically poor than for transient poor, especially in the methods that do not allow inter-temporal resource transfers. The number of chronically poor households are about half of the transient poor households in Foster(2009) when τ is 0.75 and in Quinn (2014) and, yet 67% of the total poverty burden comes from these small number of chronic poor households. Households who are in a prolonged spells of poverty experience very low consumption in the periods in which they are poor. One third of the total poor households are poor only in 1 period but their contribution to total poverty is about 8%. Thus, chronically poor households are not only those who experience more spells of poverty , more importantly, they experience intense poverty that make it more persistent unless the government intervenes to improve living standard (i.e through increasing human capital and their key asset base)

The result based on EDE approach proposed by Duclos et al.(2010) has been presented in the last row of table 3. The result is also reported in table 4 to get insights of the sub-components of chronic poverty. The method examines the cost of volatility of consumption. Unequal poverty gaps between households lowers the average well-being and this is a social cost that increase chronic poverty . In addition, variability in poverty gaps across time generates transitory poverty. The term risk has been used to indicate the fluctuation of consumption by the poor households overtime, which constitutes the transitory poverty. It is the risk premium that a social decision maker would like to pay in order to remove within period consumption volatility. Consumption variability overtime for a given person contributes to transitory poverty unless the person is non-poor in all periods. In Foster and Santos (2013), on the other hand, a person whose consumption is below the poverty line in all years does not contribute to transitory poverty.

Table 4 presents the estimates of chronic and transient poverty indexes based on the EDE method with and without short panel bias correction. We find that chronic poverty is pervasive(81.6%) in EDE compared with the 45.4% in JR. Thus, EDE method confirms the importance of chronic poverty just like the component approach presented above. The transient poverty(18.4%) in EDE is interpreted as risk premium. The social decision maker(SDM) would like to spend 18% of total poverty gap to remove intra-household inequality in poverty gaps across periods. The JR approach strongly overstates transient poverty by about 36% compared with the EDE for the same parameter α. In the EDE case, chronic poverty is defined as a low average well being. The cost of inequality between households(0.0669) suggests that 36% of aggregate chronic poverty comes from unequal poverty gaps across households. This is the level by which SDM is willing to pay to remove inter-household inequality. This result implies that reduction of chronic poverty requires long term investment on education and health, in particular affecting the asset ownership of poor as well boosting the productive return to those resources. The result is robust to the dimension of panel data as the gain from bias correction is meager

Since the their methods does not permit disaggregation of the chronic poverty index(say by regions, or household characteristics), we follow FS (2013) and Foster (2009) to understand the mechanisms that affect chronic poverty. There are two sources of transient poverty under Foster and Santos (2013): from chronic poor as well as transient poor. Consider a chronically poor individual with the first period consumption below the poverty line but the second period consumption lies above the poverty line. On the basis of period by period static CHU poverty measure,the poverty level in the second period is zero as consumption is above the poverty line. The chronic poverty level in the second period is less than 0, implying that the excess resources in the second period lowers the overall chronic poverty. Since transient poverty is defined as the statics poverty measure minus chronic poverty, the transient poverty is now positive in the second period. This part of transient poverty comes from chronically poor. Not all transient poverty arises from transient poor but they may also come from chronically poor. A chronically poor households whose consumption below the poverty line in all periods does not contribute to transitory poverty..

To be transient poor,there must be at least one period in which consumption falls short of the poverty line. Otherwise, the household is a never poor household. A transient poor household has always zero level of chronic poverty. Households are generally classified into 3 mutually exclusive groups: chronic, transient and never poor. By linking observations across time using panel data, a chronically poor based on the first few waves can contribute to transient poverty in two ways when all waves are pooled together. First, by avoiding being chronically poor. The high consumption in the later years compensate the low consumption in the previous periods and the household can now be transient poor. Second,the household can still be chronically poor. Yet, the excess consumption in the later waves (that surpass the poverty line) can increase the general average consumption, which in turn reduces the overall level of chronic poverty. This ,however increases transient poverty(Foster and Santos,2013). A chronically poor household whose consumption above the poverty line for some periods contributes to transient poverty.

Table 5 presents the poverty estimates using the different inequality aversion parameters,β . Chronic poverty increases with a decrease in β. Smoothing consumption across times by moving resources between periods is often difficult because of high interest rate operating through informal local money lenders or presence of imperfect asset market as well as fragile insurance system in African countries. As β moves from 1 to minus 1, the percentage of chronically poor rises from 29 percent to 40.6 percent because some of the transient poor now become a chronic membership. This 11% increase is remarkably high compared with what Foster and Santos (2013) obtained (5%) using data drawn from Argentina, reflecting high inequality in the consumption distribution overtime in Uganda compared to Argentina. This indicates lack of consumption smoothing portfolios in Uganda. When β=1, JR (1998) and FS (2013) compute identical average poverty gap. This is our reference to compare the result with the other lower value parameters presented in the table. The aim is to examine the intensity of poverty between chronic and transient poor households. The base line estimate (when β=1) suggests that 40.6% of the poor households are chronically poor while 59.4% of the poor are transient poor. The contribution to the average poverty gap by the chronic poor is 57% where as it is 43% by the transient poor. This shows that the chronic poor contributes more than their population share in the poor households (by 17 percent more), implying that the consumption of the chronic poor is more depressed relative to the poverty line.

As β decreases, the chronic membership increases while the number of transient poor decreases. When β decreases from 1 to -1,57% of the poor are chronic membership where as the remaining 43% of the poor are transiently poor. The share of total poverty contributed by the chronic is 78% while the rest 22% is attributable to the transient poor. As we reduce the β from 1 to -1, the number of chronic poor increases by 17% where as their contribution to total poverty increases by 21%. The effect of decreasing β is almost to proportionately increase their chronic membership and their share to total poverty in the same way(as 4%) is small). The main finding is that the share of total poverty by the chronic poor is about 17% higher than their share in poor households irrespective of the value of β. Though β affects the composition of poor(chronic or transient),the importance of chronic poverty is always higher at a certain level. For instance, when β=0, the number of chronically poor (48%) is almost the same as the number of transient poor. However,the chronic poor contribute 16.7% more to total poverty compared to what the transient poor contribute.

We find that chronic poverty is most important than transient poverty. As β decreases, the chronic poor as well as their poverty index become large while the share of the transient poor gets small accordingly. The choice of β for a particular country requires a proper calibration, a topic not addressed here. This study gives, however, a useful insight on how Uganda households react to different plausible choices of β.

Table 6 presents the decomposition of chronic poverty by four main regions in Uganda and the region's contribution of chronic poverty to the aggregate chronic poverty. Chronic poverty largely prevails in the North and this region is the principal contributor to the overall chronic estimates. The population share of the north is 27% but they contribute 58% to overall chronic poverty and this bulk contribution remains robust irregardless of the choice of the inequality aversion parameter β. All regions have almost similar population share but their contribution to overall chronic poverty varies significantly between regions. With 23.3% population share, Central region is the least contributor ($about 8.7\%$) for all values of β. The North and East have almost the same population share but the north contributes about 2.5 times more (58%) compared to the East (22%). The East is the second largest contributor following the North. The regions can be ranked according to their highest contribution to overall chronic poverty estimates in descending order as follows: North ,East ,West and Central.

Table 7 offers the contribution of each year to overall chronic poverty. The first year of the panel (2005) is found to have the least chronic poverty compared with other periods irrespective of the value of β chosen. The year 2005 makes up about 14.5% of aggregate chronic poverty when β takes 1 and 16.4% when β becomes -1. However, the contribution of chronic poverty to overall chronic by the remaining years resembles the same. Each year (namely,2009,2010 and 2011) contributes in the order of 28% (for instance when β is 1) to the average chronic poverty. In addition, their contributions across the different values of β resembles similar.

This paper attempts to provide chronic poverty indexes under different assumptions about resource substitution across time. So far ,we assume imperfect substitution of resources as captured by β. In the following (cf tables 8-9),we assume that there is no transfer of resources across periods. The result presented in tables 6-7 was based on the permanent income standard that allows some form of resource substitution. After identifying the chronic poor, the depth of chronic poverty was analyzed. In tables 8, on the other hand, we adopt the spells approach of poverty measures with no possibility of transferring resources across time. The shortcoming of this assumption is that there is no clear reason why a person with huge resources at one period but whose consumption falls just below the poverty line in other periods would be classified as chronically poor (Foster,2009). The spells approach focus on the duration slipped into poverty by examining the period by period poverty status of the household. Dual cut off points namely duration cut off and poverty line are used to identify the chronically poor. Duration cut off is often arbitrary.

A cut off line τ equals to 0.5 identifies the household as chronically poor if the household is poor for atleast half of total periods observed in the panel. Another key concern here is that each period in poverty is valued equally. Earlier period in poverty has received the same weight as a recent period in poverty, which is a case of no discounting Ramsey model (1928). However, Dercon and Calvo (2009) argue that previous year poverty should receive greater weight than current period poverty. This is palatable when it comes to different age groups in the society. Early childhood poverty has devastating long term effect than poverty observed in later age as malnutrition at childhood has detrimental effect on later productivity. It also deteriorates individual's resilience in the presence of idiosyncratic and covariates shocks as well as the capacity to generate income. For this reason, more weight should have been placed on consumption obtained at earlier time using a method of discounting. But, this study does not consider discounting factor for poverty occurring at different periods. Because, the choice of the discount factor appears to be less obvious. It is convincing if micro founded endogenous saving model is estimated to calibrate the parameter, a research beyond the scope of this study.

Another concern is about the pattern of poverty. Is continuous spells of poverty (poverty occurring successively for few periods and then become non-poor for remaining periods) more preferable to intermittent poverty occurring in interval though total frequencies in poverty remains the same? Another perspective relegated to the fact that whether we should use more weight on chronically poor households who spend extended period in poverty? All these issues are not captured in this paper when we use the spell approach for chronic poverty.

Under the aforementioned assumptions (i.e no consumption transfer as well as attaching equal importance for the different periods in poverty), this paper provides an estimate of duration adjusted chronic poverty using the Uganda household panel. This helps compare the result with permanent consumption approach proposed by FS (2013). We believe that a comprehensive and full fledged analysis on poverty requires a careful understanding on different views and presumption proposed in recent poverty literature. Except Foster (2009), traditional measure of chronic poverty based on spells approach did not explicitly include the time spent in poverty in FGT indexes. As consumption of chronically poor increases, traditional measures were not sensitive to this change. This violates the monotonicity assumption which indicates that an improvement in the consumption of poor should reduce the measured level of chronic poverty. This paper then considers duration in poverty and offers duration adjusted chronic poverty estimates as presented in tables 7 and 8.

Table 8 offers duration adjusted chronic poverty FGT indices for the different cut off values,τ. Both duration adjusted and un-adjusted headcount ratios are offered in table 7. For each FGT poverty measures, the share of chronic poverty in total poverty index is reported in the last four rows of table 8 for the two values of τ: 0.5 and 0.75.

As the cut off line increases, more observations would be excluded from chronic membership and the level of chronic poverty decreases accordingly. The share of chronic and transient poverty from aggregate average poverty are portrayed in the last four rows of table 8. When $\tau \geq 0.25$,those who are slipping into poverty at least one time during the four survey periods are the chronic membership. In this case, all poverty is chronic poverty. 71.3% of households are poor for at least one period. These households are poor in 38.5% of the total time points in the sample(number of households X panel dimension(T) gives total observations). This is a duration adjusted poverty headcount. Intensity of poverty is the ratio of duration adjusted headcount to the simple headcount. The chronic poor,who are 71.3% of households, spend 54% of their time in poverty(0.385/0.713). They spend 38.5% of the total observations under poverty.

When $\tau \geq 1$, 10.6% of the households are chronically poor and they are the always poor households(i.e poor in all four waves). How large is the depth of poverty for the chronic poor compared with the transient poor? When $\tau = 1$, the number of time periods under poverty is 10.6% of the total observations in the sample. 34% of the total poverty gap comes from households who experience poverty in all four waves. On the other hand, 61% of households are transient poor and the number of periods in which they are under poverty is 28% of the total time observations ,which accounts for 66% of the total poverty gap. This suggests that the depth of poverty by the chronically poor is 23% higher compared to the poverty gap attributable by the transient poor.

When $\tau = 0.75$, those who are chronically poor spends 21.45% of the total time observations under poverty where as the transient poor spend 17% of the total observations in poverty. The chronically poor contribute 63.8% to the total poverty gap while the transient poor contribute the remaining 36.2%. The poverty gap obtained from the chronic poor exceeds by 18% compared to the poverty gap by the transient poor for the same proportion of time spent under poverty. Significant portion of poverty gap and severity originates from chronic poverty as the chronic poor involve large shortfall in their consumption relative to the poverty line. This finding is consistent with the result of FS's (2013) method discussed above. The chronically poor generally experience large fall in consumption in the periods in which they are poor. We conclude that poverty in Uganda is largely chronic which is robust to the choice of poverty measures. Another interesting finding is that as the poverty measures changes from poverty gap to squared poverty gap, the share of chronic poverty in total poverty severity also increases.

Table 9 offers the chronic poverty profiles of the 4 regions. Like the result presented in table 6, we show here that the north contributes much of the chronic poverty (e.g 73%) to the overall squared poverty gap followed by the East that makes up 14.3%. Central region with a population share of 23% contributes 7% to the total chronic poverty. The West shows comparable estimate with central region. For $\tau = 0.75$,the North and East respectively contribute 61.7% and 20% to total chronic severity index. Chronic poverty is largely confined to the North followed by the East.

Using the 2005 household characteristics, we can describe how these characteristics correlate with aggregated intertemporal poverty. Households who own TV-radio are 60 percent of total households and they account for 38% of the total poverty gap squared. Households who have access to all weather road, own TV-radio, having land size above the median and educated households contribute to total poverty less than their population share. Finally, we classify households into 3 groups depending on the composition of the household members. The first consists of households with number of dependents (presence of children below 13 and individuals aged above 64) between 0 and 1 inclusive (HH1). The second type is households with number of dependents between 2 and 4 (HH2). The third is households with dependents above 4 (HH3). HH1 contributes to poverty below its population share where as HH2 and HH3 contribute higher than their population share. This overall pattern suggests that dependency ratio,education,asset ownership (land size per capita, TV-radio),access to all weather road are determinants of future poverty.

2.5.1.2 Do chronic poor lack access to growth stimulating inputs?: evidence from consumption growth

What makes chronic poor to differ from non-chronic poor? What causes them to remain persistently poor overtime?. The four waves panel data consist of information that explain the development of real consumption between chronically and non-chronically poor households. There are supposedly growth stimulating factors that enhance households' productivity through a number of channels. For instance ,access to extension service, access to road, electricity , information technology (having ownership of radio, TV and mobile).

All households have access to some sort of road but the quality of the road varies greatly from supporting all-weather roads suitable for all vehicles to roads/paths that only allow foot traffic. Access to road reduces transport margins and facilitates the marketing of agricultural inputs and products. Access to road provides agricultural household a good incentive to produce even perishable vegetables as long as they have comparative advantages to do so compared with other regions. Thus, it allows regions to specialize in their most productive activities and trade their output/input with other regions or district and the gain from exchange may be tremendous. In addition, news can be considered as an important input for agricultural households. News related to weather forecast as well as news related to the daily market price (export ,import and domestic) of agricultural products can help households improve resource allocation or minimize the possible impacts of adverse shocks. The national TV and radio programs often supply these information on the daily basis. News obtained through TV-radio may have an impact on productivity in the same way as ownership of agricultural inputs such as seeds, fertilizer, and other machinery in affecting production.

From the perspective of macro -economics, access to capital stocks and technology (k_{it}) is the core determinants of growth. Now, we use the standard empirical growth model but viewed from the perspective of micro-economics growth regression using four waves panel data namely: 2005/06,2009/2010, 2010/2011 and 2011/2012. In fact, adopting micro-level growth regression is not a new topic in the growth literature. Dercon et al (2012) investigate consumption growth determinants in Ethiopia and find that access to extension service was a key predictor of growth. Moreover, they find that chronically poor are not different from non-chronic poor in terms of the returns to growth determinants such as access to roads and extension services. We are now motivated whether this finding can also hold for Uganda located in eastern Africa like Ethiopia by adopting a similar model as in Dercon et al (2012). However, we incorporate news (captured by ownership of TV and radio) as a factor of production in the growth regression which was not done at all in Dercon et al. (2012). We find that access to TV and radio is a significant and robust determinant of consumption growth in Uganda. Like Dercon et al (2012), the returns to these productive factors between chronic and non-chronic poor become indistinguishable. Instead, the chronic and non-chronic poor actually differ in their latent growth which is captured by the fixed effect component in the growth regression. We estimate the following fixed effect growth regression.

$$lny_{it} - lny_{i_{t-1}} = \alpha lny_{i_{t-1}} + \beta lnk_{i_{t-1}} + u_i + \varepsilon_{it}$$

where y_{it} denotes real consumption per adult while k_{it-1} indicates the capital stocks (access to roads, extension ,electricity and TV and radio) for a household i at t-1. In our data, the capital stocks are indeed time varying, a feature that allows identification in fixed effect regression. Each household is asked to state the number of TV and radio they own in the past before the interview date and a dummy variable is constructed (equals to one) if at least they have one in the household. A dummy for extension is also constructed based on the number of visit they received from extension agents in the last cropping season. The percentage of households having access to road,extension,electricity and TV-radio are found to be 78%, 37%, 3% and 63% respectively. Since the lagged dependent variable is included in the regression, this variable needs to be instrumented using external instruments such as lagged household size,lagged cultivatable land per adult and lagged livestock per adult. Due to the correlation between the last two instruments, one of them has to be left out from the first stage regression and the choice does not affect the final outcome. The first stage regression is reported in table 10 under the two definitions of instruments (i.e instrument 1 consists of household size and the proportion of cultivated plots per adult in acre while instrument 2 comprises household size and total live stocks per adult). Both instruments are significant predictors of past real consumption with the expected signs intact. We use instrument one for subsequent analysis as there is no quantitative difference from using instrument 2.

Dercon et al (2012) provide evidence for Ethiopia using the growth regression model based on spells approach ($\tau = 0.75$). But we provide evidence from both spells and permanent consumption approaches (based on Foster and Santos ,2013). In addition, we use system GMM for robustness check. Dercon et al (2012) did not use TV-radio and electricity as predictors of growth. We find that news obtained through TV-radio significantly affect productivity (cf,table 11). It must be noted that estimating the model after removing the consumption part associated to TV-radio from the total consumption expenditure yields a similar result(it will be available when needed).

Table 11 offers the determinants of consumption growth as well as the returns to these factors for chronic and non-chronic poor. The result in the second column suggests that access to TV radio and access to electricity are significant predictors of consumption growth. Those households who own TV-radio obtain 8.6% higher growth per year than those without. Given that 63% of households own TV-radio, the variable contributes about 5.5% to growth acceleration. Though electricity has substantial growth effect (21.8%), its contribution to growth acceleration is small (0.6%) because only few rural households (3%) have access to electricity in Uganda. Access to road influences growth (by about 5%) only after controlling for district level heterogeneity in unobserved time varying shocks which are captured by including the interaction between districts dummies and time dummies as shown in the fourth column. The sample households are splitted into 9 main districts in order to incorporate some of the observed and unobserved differences among districts. We allow for the impact of time dummies to vary across the 9 districts which is a more general version of macro-economic growth model as depicted in columns 4-5. Access to electricity, access to all weather road and ownership of TV-radio are important determinants of growth in real consumption per adult. Do the returns to these growth promoting factors vary between chronic and non-chronic poor?. The question can be succinctly answered by interacting growth stimulating variables with a dummy variable that show whether the household is chronically poor or not. We use two approaches to identify the chronic poor: the permanent income standard based on Foster and Santos (2013) and the spells approach by Foster (2009).

We assume that the allocation of input factors such as road , extension and electricity are random. If quality road is available in richer region or if extension is available in fertile land of the region, the result is more likely plagued with endogeneity bias. But, the use of panel data minimizes the bias as they are more likely to be constant in a given region. The use of regional dummies help circumvent the problem of initial condition by capturing region specific growth opportunities. Just to show that the result of the fixed effect regression is not spurious due to endogeniety, we estimate system GMM dynamic panel data (Arellano and Bond,1991; Arellano and Bover,1995) that use past changes as instrument for the current value. Our estimates look reasonable and robust(result is available up on request). Since system GMM does not allow to extract the fixed effect component under the current setting, we do not need to go further in applying and interpreting that result.

Columns 2-5 in table 11 presents the estimation results based on τ =0.75 and the last two columns use the the FS general mean standard for β =0 and β =0.5. Column 5 shows that none of the interaction terms are significant at 5% confidence level. This implies that chronic poor are also equally benefited from growth stimulating factors because the change in consumption growth resulting from a given percentage change in any of these factors remain the same for chronic and non-chronic poor. If these observed factors do not explain the growth difference between chronic and non-chronic people, what else explains the consumption growth?. We find that the latent factors explain their growth difference. Fixed effect is retrieved from the growth model in column 1 and the average fixed effects for chronic and non-chronic households are found to be -0.249 and 0.083 respectively. Other things remain constant, the fixed effect of the chronic poor lowers the annualized average real consumption growth by 24.9% while it explains 8.3% of the total growth for non-chronic households. The average growth difference between chronic and non-chronic poor due to their fixed effect becomes 33.2%. This difference is statistically different from zero at all reasonable confidence level.

With this significant growth gap (33.2%), consumption convergence between chronic and non-chronic poor is less likely to hold in the future unless government puts special attention on the chronic poor to enhance their time varying characteristics. Our estimate of 33.2% is found to be large compared with what Dercon et al (2012) find for Ethiopia (23%). Since the lagged value of the dependent variable is lower for Uganda(-0.508) compared to their estimate (-0.33), the steady state convergence is higher for Uganda than for Ethiopia. The negative coefficient for lagged real consumption implies that households with higher consumption in the past experience lower consumption growth or high past growth lowers current consumption. Thus, poor may have faster growth than rich just as stipulated by the hypothesis of conditional convergence between poor and rich countries in the macro growth regression. Nevertheless, the convergence in our micro evidence is much higher as given by the lagged coefficient(-0.508). The fixed effect significantly moves against this convergence and plummets the occurrence of faster convergence between chronic and non-chronic poor. How large is the difference in the steady state consumption due to fixed effect? . The latent growth difference (i.e. fixed effect) explains 65%((0.33/0.508)) of the total difference in steady state consumption between chronic and non-chronic poor. The result on the basis of this sample provides a fresh evidence for Uganda on the size of steady state consumption difference due to latent growth. Since panel data with longer time dimension is generally scant in Africa (Dercon et al 2012, Kedir and Macky,2005), our result has to be taken with cautious

Moreover, the correlation between fixed effect and the chronic dummy as well as between fixed effect and squared poverty gap is estimated to be -0.57 and -0.66 respectively. We proceed to run a robust OLS regression to examine the determinants of the latent growth itself. The explanatory variables are obtained by taking averages across time. Thus, all variables are collapsed into a cross section data. The result is reported in table 12. Access to road, average land holding per capita, education of the head of household and high proportion of adult members are associated positively with fixed effect and thus considered as drivers of latent growth. A 10% increase in village level access to road leads to a 5% increase in latent growth, which also implies a 8.9% permanent consumption difference. In addition,as we move from 25% to 75% in the district level distribution of distance to the principal city of the country(Kampala), the latent growth decreases by 3.7%

2.5.1.3 Other determinants of chronic poverty

This section presents the determinants of chronic poverty using different model specifications based on the 2005/06 households and community characteristics. Chronic poverty makes use of the spell approach ($\tau = 0.75$) and the permanent income standard approach ($\beta = 0$). Each model is estimated under these two settings so that one can understand whether the impact of a given variable depends on the particular definition pursued or not. Two models are specified: multi-nominal logit and censored quantile regression. We have 3 distinct households divisions: never poor, chronic poor and transient poor. What are the characteristics that affect chronic poverty but not transitory poverty? If the chronic and transitory poor do share some important characteristics, does the magnitude of the relative influence indistinguishable?. The average marginal effects of household characteristics based on multi-nominal logit (MNL) help determine whether the same underlying mechanisms derive both types of poverty or not. In MNL model, the categorical dependent variable consists of the nominal values that represent the three types of households (1 for chronic poor, 2 for transient poor and 3 for never poor households). To capture the heterogeneity effect within the same type of household, we augment the result with censored quantile regression (CQR) where the dependent variable is the level of chronic poverty. The squared poverty gap is zero for non-chronic poor household while it is a positive number for chronic poor obtained from the permanent income approach when $\beta = 0$.

We control both household and district level characteristics. The importance of household level characteristics remains unchanged with respect to using either the district dummies or packing the community level characteristic. Thus, the district characteristics are explicitly added as correlates of poverty in all columns in table 13. We find that the correlates of fixed effect and chronic poverty resembles the same for most of the variables. Access to road, average land holding per capita, education of head of household are significant determinants of chronic poverty. The coefficient of a given variable indicates the effect of that variable on the likelihood of being chronically or transitory poor relative to the never poor households. The average marginal effect (AME) represents the propensity of being chronic, transient or never poor in response to changes in a given variable and the sum of these marginal effects is zero.

We do not report the marginal effects for the never poor households in table 13 (yet,can be residual determined as the sum of AME should be zero). We find that households having TV-radio are more likely to be non-poor than being poor (chronically or transitory) compared with those without. Hence the variable reduces the propensity of being poor. The AME suggests that the probability of being chronically poor is 8.9 percentage points lower for those having TV-radio than those without. On average, the probability of being transitory poor is 3.8 percent lower for those having TV-radio than without for the same level of their individual and community level characteristics. Thus, households with TV-radio are 12.7 percent more likely to be non-poor than those without. The AME of this variable is significant and can be taken as an important policy variable to reduce the incidence of poverty in Uganda. Indeed, the relative importance of this variable in reducing chronic poverty is higher than transitory poverty.

Different distribution of land across community significantly affects chronic poverty but not transitory poverty. Chronic poor live in a district where the average land holding per person is small. Monogamy household head is 8.9% more likely to be chronically poor than unmarried individuals. This variable, however, has no effect on transitory poverty. To reduce chronic poverty, policy makers can target monogamy household heads' who are chronically poor. As shown in table 13, when the share of female adult members(15-64)in the household increases, the probability of being poor decreases. A 1 percent increase in the share of female adult members reduces the probability of being chronic poor by 0.3 percent and this estimate is statistically significant at all reasonable confidence level. The relative importance of this variable in reducing chronic poverty than transitory poverty is confirmed in the data. Community level characteristics are important correlates of poverty , implying that the distribution of poverty is location specific. We have 9 main districts in the sample. One can incorporate the district dummies in the regression in order to capture some observed and unobserved community level heterogeneity. Alternatively, we can take the average of the district level observed characteristics in place of the dummies. Both approaches (packing or unpacking) offer the same result. We report the result based on the latter. Districts having large proportion of working age household members, improved access to road and increased land size per person are less likely to be poor(chronically or transitory). If we increase the percentage of households who have access to road by 1 additional number, the probability of being chronically poor declines by 0.56 percent. This effect is significant though it is numerically low for the transient poor (0.37 percent).

The estimates under the two different poverty measures ($\beta = 0$ and $\tau = 1$) are highly comparable for all variables except the impact of male adult members and hence the result is not sensitive to the way chronic poverty is defined. In the absence of market information about what is actually happening to resource substitutability in a poor country like Uganda, the robustness of the estimation result to the different definitions increases the effectiveness of policy by relying on the significant correlates. The key correlates of chronic poverty are education of household head, access to TV-radio , access to all weather feeder road,monogamy marital status,high composition of adult members in the household and average land holding per capita.

In the final column, estimates from censored quantile regression that use the poverty index as a dependent variable are offered. The tobit model assumes normality and homoscedasticity in the distribution of poverty index. If this assumption is not supported by the data, however, the tobit estimates are inconsistent. On the other hand, Censored Quantile Regression(CQR) is more robust to non-normality and heteroscedasticity. Using stata software, we first test the null hypothesis of normality and homoscedasticity in tobit model specification. The null hypothesis is rejected[6]. We seek to estimate censored quantile regression which helps examine the sensitivity of poverty measures as we move from categorical dependent variable to continuous dependent variable. So as to give more weight to the poor, CQR is estimated at 70^{th} quantile. The interesting finding is that the same mechanism (set of variables) affects chronic poverty though different models are used to characterize the dependent variable, making the findings more dependable. The findings are suggestive of determinants of chronic poverty though causality can not be inferred from.

2.5.2 Results based on multi-dimensional poverty

2.5.2.1 Multi-dimensional deprivation indicators

We have also an interest to examine whether the predictors of chronic poverty have been changed as we move from a uni-dimensional consumption based poverty measure to a broader multi-dimensional deprivation indicators. Table 14 offers a summary of deprivation indicators for each year. In this section, we pool both rural and urban household sub-samples where the rural households comprise about two-third of the total population We use three dimensions: education, housing and access to water, and consumption. Our choice of poverty indicators is similar to Alkire et al.(2014) except for the consumption dimension. Heterogeneity of employment and availability of pension in rural Uganda are very limited and hence, these indicators are not informative and have little relevance to consider them as operational indicators under the consumption dimension. We have applied equal weights to each dimension. Each indicator under the given dimension has equal weights. For housing/water dimension, we use four indicators: overcrowding, availability of shelter, toilet and access to safe water. For education dimension, educational achievement and school attendance are indicators of deprivations. Except for consumption and school attendance indicators, the deprivation rates for all indicators are higher for 2005 than for the rest of years. The lowest deprivations in all respective indicators are available only for 2013.

2.5.2.2 Household characteristics and multi-dimensional chronic poverty

Table 15 presents the adjusted headcount ratio (M) using the cross section and longitudinal data based on the multi-dimensional cut off,which is 40%(i.e k=0.4). A person is poor if he/she is deprived in at least 40 percent of the total indicators. The headcount ratio (H) using cross section shows the proportion of multidimensional poor households or the percentage of chronic poor households based on longitudinal data. The intensity of poverty (A) shows the average share of weighted deprivations that the poor people experience. The adjusted headcount ratio is the product of H and A. The cross section adjusted headcount ratios are indistinguishable for the year 2009, 2010 and 2011. The levels of poverty in these years are higher than the poverty levels observed in the year 2005 and 2013. Both the intensity and incidence of poverty are lower in 2013 compared with the remaining years. The intensity of poverty almost remains constant across years. In 2005, for instance, the multidimensional poor are deprived in 67% of the total dimensions.

[6]the computed LM test value is 231 while the bootstrap critical value at 1% is 7.14

In 2013, only 25.8% of the households are poor in 64.5% of their dimensions. The main finding is that the intensity effect of poverty is higher compared to the poverty incidence, suggesting that the poor are deprived in a multiple dimensions. The last four columns in the table give the chronic poverty index based on the different duration cut-offs.

In the longitudinal case, the intensity of poverty uses the sub-sample of chronic poor and it is defined as the product of duration and deprivation intensity. The duration intensity represents the average share of time spent under poverty by the chronically poor, and deprivation intensity reflects the share of weighted deprivations under the periods in which they are poor. The time intersection method sets a duration intensity of 100 percent, in which all periods are under poverty for a chronic poor person. As shown in table 15, the time intersection method ($\tau = 1$) identifies 7.9% of the households as being chronically poor who are deprived in 77.6% of their dimensions. The headcount ratio (H) is lower than the intensity of poverty except in the time union approach ($\tau = 0.2$), indicating that the chronically poor experience deprivations in several periods and in a multiple dimensions. Under the time union approach ($\tau = 0.2$), 63.%of the households are chronically poor.

It is of interest to scrutinize the correlates of multidimensional chronic poverty. We classify households into three groups depending on the number of dependents in the household. We define dependents as those who are not economically active in the labour market and hence, children who are below 13 as well as those who are above 64 years old are considered to be dependents. The three distinct household types are: households having less than 2 dependents (HH1); households with 2-4 dependents (HH2) and households having dependents above 4 (HH3). The share of households belonging to each group is presented in table 15. The cross section data suggests that households with more dependents (HH3) experience the highest level of poverty. They are 19.4% of the total households but contribute to 28%of the total poverty. In addition, households with small number of dependents (HH1) are less poor compared to other household types. They constitute about one third of the total households, yet contribute only 17.6% to the adjusted headcount ratio in 2005. This pattern holds in other years too. In the last 4 columns, the longitudinal data presents the multi-dimensional chronically poor for the different duration cut-offs and for the given multi-dimensional poverty cu-off ($k = 40\%$). Using the population decomposability property of the poverty measure proposed by Alkire et al. (2014) and Foster (2009), the total burden of poverty is the weighted average of the sub-groups poverty.

Like the evidence from the cross section ones, multidimensional chronic poverty is also found to be the lowest among households having small number of children and older adult members (HH1). HH1 make up 12% of the households but represent 7.9% and 0.9% of the chronically poor when $\tau = 0.2$) and $\tau = 1$ respectively, implying that their share of chronic poverty is below their population share. As we move from the time union approach (a person is chronically poor if he is multi-dimensionally poor in at least 1 period) to an intersection method (a person must spent all years under poverty to be a chronic membership), chronic poverty does not come from HH1 class. Instead, it comes from HH3 household type. 50.2% of the chronic poor households are the HH3 households. Yet, HH3 represent 33.2% of the total households in the sample. They contribute to chronic poverty 17 percent more than their population share.

2.5.2.3 Drivers of multi-dimensional poverty between 2009 and 2013

A poverty analyst may be interested to know the evolution of poverty across the different sub-groups of households. It is also an interest to examine the change in chronic poverty between two periods but this requires a long panel data that can be splitted into two sub- periods with large gap in between them as well as sufficient observations per household in each sub-period (yet our data does not support this). Instead, our data can shed light on the pattern of poverty period by period as well as on the drivers of changes in poverty. The adjusted headcount ratios between 2009 and 2011 remain unchanged. Multi-dimensional poverty increases by about 2% as we move from 2005 to 2009. On the other hand, the adjusted headcount decreases by about 5.5% from 2009 to 2013 (see table 16) and this is statistically significant based on a t-test (available if needed). The proportion of poor people (H) decreases by 7.1% while the intensity of poverty (the share of weighted deprivations averaged over the poor households) slightly decreases by 2.7%, implying that poverty incidence is the main effect that drives the changes in poverty.

This effect can vary across the different household's characteristics and the full decomposition result based on the shapley method in the context of multi-dimensional poverty is presented in table 16. All household types improve their poverty between 2009 and 2013. Households with higher dependents (HH3) reduce their population share from 30.5% in 2009 to 20.2% in 2013 where as the adjusted poverty incidence increases slightly from 28.5% to 29.2%. Though the poverty headcount is still the highest in this household group, it is also the type of household that contributes most to the decline in total poverty, which is due to a significant shift in their demographic dynamics.

Households with number of dependents between 2-4 (HH2) have made significant contribution to the reduction of poverty following HH3. The difference between HH3 and HH2 is that the former reduce their population share with almost constant poverty level while the later decrease their poverty headcount significantly without altering their population share. The change in poverty (ΔM) is the combined effect of changes in poverty level (had the population share held constant) and changes in population share (had the poverty levels remained unchanged). In other word, ΔM is the sum of the within group effect and the demographic effect. The within group effect describes the changes in poverty levels had the population share of a given household type remained constant. HH1 and HH2 present substantial reduction in the headcount ratio. Thus, the within group effect generally explains 63.9% of the total improvement in poverty while the remaining 36% is attributable to the population shift. To reduce the aggregate poverty, policy makers should target the HH3 households to reduce their poverty incidence. The within group effect, which is the adjusted headcount ratio, is decomposed into the incidence effect (the share of poor households) and the intensity effect, which is the share of weighted deprivations that the poor household experience.

The change in poverty incidences explains 50% of the total change in the adjusted poverty headcount ratio (ΔM), which is the most important driver of improvements in poverty. As we move from 2009 to 2013, the proportion of poor households in HH1 and HH2 decreases substantially with the effect to explain 24% and 30% of the overall changes of poverty respectively. Except for households with number of dependents above 4 (HH3), the changes in incidence are admittedly higher than the intensity effect. HH3 household fare the worst as the changes in incidence increase, in particular given that they make up 20% of the population. These households only slightly improve the intensity of deprivation while marginally increase the poverty incidence (-4.3%). They reduce their population share significantly with almost holding their poverty level intact.

Finally, we disaggregate the intensity effect to determine the importance of each indicator. Educational achievement and school attendance are the most important indicators that help improve the intensity effect while consumption contributes to an increase in the intensity of multi-dimensionally poor households. Households with dependents 2-4 (HH2) increase their education and school enrollment at a faster rate compared to other sub-groups in the period studied whereas as consumption poverty rapidly increases among HH3 households.

Table 17 offers the sensitivity of the poverty incidence with respect to the choice of k and the duration cut-off. Based on the union approach, which identifies a person as being chronically poor if he is deprived in at least one dimension and in at least one period, 96.8% of the population is chronically poor. The intersection approach, in which a person is poor if deprived in all dimensions in all periods, renders the chronically poor to be less than 1 percent. Thus, the plausible values of k and τ should be in the range of$0.2 < k < 1$ and $0.2 < \tau < 1$ just to allow for sensitivity in the poverty estimates. In addition, it is of interest to distinguish the dimension that contributes most to the aggregate poverty. In the plausible range of the multidimensional poverty cut-offs k, the consumption dimension dominates the housing dimension except when τ =0.2. The education dimension contributes the least share to poverty. Thus, policy makers should pay special attention to curb down the consumption poverty in Uganda.

2.6 Conclusion

This study uses the Ugandan rural household panel survey spanning 2005/06,2009/2010,2010/2011, 2011/2012 and 2013/14 to examine the level of chronic poverty and its determinants. We find that poverty in Uganda is mainly chronic in nature. We investigate the level of chronic poverty under different approaches. Based on Jalan and Ravallion's(1998), which allows for perfect consumption susbtitutiability across periods, 45% of the squared poverty gap is explained by chronic poverty.

The spells approach proposed by Foster (2009) and the Equally Distributed Equivalent (EDE) poverty gap approach proposed by Duclos et al.(2010) do not allow inter-temporal resources transfers. Under EDE approach, variability in poverty gaps across households at given period and across periods for the same household brings additional social costs. Under the spells approach by Foster (2009), the duration in poverty has been used to classify a household as chronically poor or not. There are dual cut off lines : the poverty line and duration in poverty. The latter is arbitrary and we check all the possible values. We find that there is significant difference between duration adjusted poverty level and its un-adjusted counterpart. For a given duration cut off($\tau = 0.25$) and poverty line (34618 Uganda shilling), 71% of the households are chronically poor. The duration adjusted headcount ratio suggests that the chronic poor spends only 38% of the total time under poverty. When $\tau = 0.75$, the chronic poor who are 35% of the poor households explain 69% of the poverty severity index, reflecting their higher contribution to total poverty than their population share. On the other hand, the transient poor who are 65% of the total poor households contribute 31% to the aggregate poverty index. Chronic poverty is pervasive compared to transient poverty. The paper adopts several measures of poverty to examine whether this finding is robust to the methodological choices and assumptions. All the different approaches consistently affirm the largest burden of chronic poverty relative to transitory poverty.

Indeed, the conventional method proposed by Jalan and Ravallion(1998) underestimates the total burden of chronic poverty as we move from poverty gap to squared poverty gap measure. The chronic poor contribute to total poverty at least 15 percent higher than their population share depending on the poverty measures chosen. Methodologies that are sensitive to poverty persistence (e.g Quinn,2014;Foster,2009) offer higher weight to chronic poverty than methodologies that allow perfect or imperfect inter-temporal resource transfer(Foster and Santos,2013; Porter and Quinn,2013;Jalan and Ravallion,1998). Imperfect substitution implies higher consumption in one period can not fully compensate lower consumption in another period. When an elasticity of substitution equals 0.5 ($\beta = -1$), the chronic poor contribute 21 percentage points higher than their population share in the poor households. Based on the method proposed by Duclos et al.(2010), the contribution of chronic poverty to aggregate poverty gap is found to be 81.6% while the share of transient poverty is 18.4%. This suggests that poverty in Uganda is largely chronic. This is mainly due to the fact that the chronic poor involve large fall in consumption relative to the poverty line for equal absolute number chronic and transient poor or for the same proportion of time in which they are under poverty.

The financial markets (in particular the credit and insurance markets) fail to provide adequate services in African countries including Uganda, making perfect consumption smoothing a daunting task. In addition, massive economic constraints, political instability, weak institutions and malfunctioning labor markets still exist. Therefore, imposing some sort of imperfect inter-temporal compensation as suggested by Foster and Santos (2013) is more appealing. A poverty trajectory ordering can not simultaneously satisfy the axioms of duration sensitivity and inter-temporal resource transfer. Therefore, the choice of a particular poverty measure depends on the normative assessment of the poverty analysts, which includes inter-alia the openness of the economy, institutions and overall financial development of a given country. Thus, this paper makes use of the assumption of imperfect compensation (as Foster and Santos,2013) to identify the chronic poor, determine the level of chronic poverty and the mechanisms that drive chronic poverty using the uni-dimensional welfare measure. When $\beta = 0$, the method identifies almost equal proportion of chronic (48.3%) and transient poor(51.7%), yet the chronic poor explain 67% of the total poverty gap and the remaining 33% ascribes to transient poor.

It is of interest to examine the size of chronic poverty across the four principal regions in the country. We find that chronic poverty is the highest in the North and the Least in Central region. It is about 10 times higher in the North compared to Central. Chronic poverty is pervasive in the North and East. This finding holds true irregardless of the approaches used to measure chronic poverty.

Finally, the paper establishes the determinants of chronic poverty in Uganda using two conceptually related approaches. First, we ask if the consumption growth dynamics between chronic and non-chronic poor households can be explained by the differences in their time-varying characteristics after controlling for unobserved heterogeneity using fixed effect panel regression. The empirical model suggests that ownership of TV-radio ,access to electricity and improved access to all weather road are significant predictors of consumption growth. However, the marginal effect of a respective variable is the same for the chronic and non-chronic households. Instead, the time- invariant characteristics (individual fixed effect) explain much of the consumption growth difference between the two groups. We find that initial household characteristics such as distance to town ,village level land holding per capita, education of the head ,per capita land size are strongly related to latent consumption growth.

Second, we also ask how the initial household characteristics explain the inter-temporal poverty burden in Uganda. Using the index of chronic poverty as the dependent variable, we apply censored quantile regression. The most important variables that reduce the level of chronic poverty are: education of the household head, proportion of male and female adults members aged 15-65, ownership of TV-radio, access to all weather road and average land holding per capita. These variables are robust to changes in methodologies used to identify the chronic poor. The determinants of chronic poverty are also robust to changes in model specification such as using the multi-nominal logit. These correlates of poverty can be used as policy instruments to targeting and reducing chronic poverty in Uganda.

Focusing only on consumption poverty, by ignoring the fact a household can be constrained in a number multiple dimensions, may not help design policy instruments relevant to improve the overall welfare of the society unless the consumption poverty is found to be the most significant dimension compared to other types of deprivations. To this end, the paper considers three dimensions(consumption ,education , housing/safe water) and 7 indicators(consumption, school enrollment,educational achievement, shelter,overcrowding,toilet and access to safe water) to investigate the extent of multi-dimensional chronic poverty and the mechanisms affecting it. Households are classified into three groups depending on the number of dependents in the household. Children who are below 13 as well as those who are above 64 years old are considered to be dependents. The three distinct household types are: households having less than 2 dependents (HH1); households with 2-4 dependents (HH2) and households having dependents above 4 (HH3). Both the static and the dynamic poverty measures identify households with more dependents (HH3) as more poor compared to households with small number of dependents (HH1). HH1 are 12.5% of the total households and yet they contribute only 4.8% to the total multi-dimension chronic poverty headcount.

For the years 2009,2010 and 2011, about 33 % of households are multi-dimensionally poor. The consumption poor households are also 33 %. On the other hand, the multidimensional poverty headcounts in 2005 (30%) and in 2013 (25.9 %) are low compared to other survey years. The paper investigates the drivers of changes in poverty between 2009 and 2013. HH1 and HH2 households significantly reduce their multi-dimensional poverty headcounts. On the other hand, HH3 households do not improve their poverty incidence. As we move from 2009 to 2013, HH3 reduce their population share while keeping their poverty incidence remain intact. The within group effect, which is the combined effect of the decline in the absolute number of multi-dimensional poor (poverty incidence) and/or decline in the number of dimensions in which they are poor (intensity) for unchanging population share, is the main driver of improvement in the adjusted multidimensional poverty headcount. The incidence effect by HH1 and HH2 is the major factor explaining multi-dimensional poverty in Uganda. Poor households in Uganda do not reduce poverty due to low consumption. Hence the consumption poverty still remain an important challenge facing the Ugandan households. The policy implication is that government should target HH3 households and design a method to reduce their consumption poverty first and at most.

Appendix 2: Regression Tables

Table 2.5: Poverty estimates based on Foster and Santos(2013) for different Beta values

	β				
	1	0.5	0	–0.5	–1
Average poverty index	0.1179	0.1363	0.1608	0.1946	0.2433
Chronic poverty index	0.0672	0.0839	0.1073	0.1407	0.1903
Contribution by chronic poor index	0.5704	0.6155	0.6671	0.7232	0.7822
Transitory poverty index	0.0506	0.0524	0.0535	0.0539	0.0530
Population share of chronic poor	0.2899	0.3176	0.3445	0.3774	0.4063
Population share of transient poor	0.4227	0.3951	0.3682	0.3353	0.3064
Share of chronic out of total poor	0.4068	0.4456	0.4834	0.5295	0.5701

Table 2.6: Decomposition of chronic poverty by region based on different Beta parameter

	population share	β**=1**	**%**	β**=0.5**	**%**	β**=0**	**%**	β**=-0.5**	**%**	β**=-1**	**%**
Central	23.3	0.0251	8.7	0.0309	8.6	0.0402	8.7	0.0537	8.9	0.0744	9.1
East	27.5	0.0542	22.1	0.0679	22.3	0.0873	22.4	0.1141	22.3	0.1533	22.2
North	27.4	0.1431	58.3	0.1786	58.3	0.2275	58.1	0.2985	58.1	0.4046	58.3
West	21.9	0.0336	10.9	0.0419	10.9	0.0532	10.9	0.0692	10.8	0.0917	10.6

Table 2.7: decomposition of chronic poverty by year using different Beta parameter

	β**=1**	**%**	β**=0.5**	**%**	β**=0**	**%**	β**=-0.5**	**%**	β**=-1**	**%**
2005	0.0391	14.5	0.0478	14.2	0.0635	14.8	0.0852	15.1	0.1248	16.4
2009	0.0759	28.2	0.0934	27.8	0.1183	27.6	0.1566	27.8	0.2100	27.6
2010	0.0788	29.3	0.1012	30.2	0.1279	29.8	0.1670	29.7	0.2258	29.7
2011	0.0752	27.9	0.0932	27.8	0.1194	27.8	0.1540	27.4	0.2003	26.3

Table 2.8: FGT poverty chronic measures using different duration cut off lines(τ)

		Duration adjusted poverty level		
	Head count	**Head count**	**Poverty gap**	**Poverty severity**
τ=0.25	0.7127	0.3846	0.1179	0.0513
τ=0.5	0.4688	0.3236	0.1047	0.0467
τ=0.75	0.2505	0.2145	0.0752	0.0353
τ=1	0.1065	0.1065	0.0402	0.0201
Share of chronic(τ=0.5)	0.6577	0.8415	0.8877	0.9112
Share of transient(τ=0.5)	0.3423	0.1585	0.1123	0.0888
Share of chronic(τ=0.75)	0.3515	0.5577	0.6380	0.6879
Share of transient(τ=0.75)	0.6485	0.4423	0.3620	0.3121

Table 2.9: FGT duration adjusted chronic poverty: percent contribution by regions

		% contribution when τ=1			% contribution when τ=0.75		
	Pop.share(%)	**Head count**	**Pov. gap**	**Pov. severity**	**Head count**	**Pov. gap**	**Pov. severity**
Central	23.3	9.9	8.1	7.0	10.9	9.0	8.0
East	27.5	21.6	17.0	14.3	27.1	23.1	20.1
North	27.4	61.8	68.6	73.1	50.3	56.8	61.7
West	21.9	6.8	6.5	5.8	11.9	11.1	10.3
Total	100	100.0	100.0	100.0	100.0	100.0	100.0

Table 2.10: First stage regression of lagged log consumption (dependent variable) with instruments)

	Instruments 1:coef	instruments 2: coef
Number of adult equivallent	–0.0237***	–0.153***
	[0.0039]	[0.0157]
Cultivated land per adult	0.00435***	
	[0.0012]	
Log(total livestocks)		0.0871***
		[0.0073]
constant	10.73***	10.80***
	[0.0200]	[0.0240]
N	4563	4563

Table 2.11: Determinants of consumption growth: do they differ between chronic and non-chronic poor?

	Correlates of consumption growth	Interaction with chronic poverty	District X year effect	Poverty interacts with district, year	Interaction with Chronic poverty, $\beta = 0$	Interacts poverty, $\beta = 0.5$
Lagged(logconsumption)	–0.5087***	–0.5072***	–0.5016***	–0.4971***	–0.5089***	–0.5054***
	(0.0652)	(0.0668)	(0.0683)	(0.0687)	(0.0665)	(0.0668)
access to all-weather feeder road	0.0259	0.0407		0.0514*	0.0462*	0.0494*
	(0.0220)	(0.0262)		(0.0267)	(0.0277)	(0.0262)
Received extension service	0.0043	0.0039	0.0036		0.0014	0.0061
	(0.0039)	(0.0043)	(0.0041)		(0.0051)	(0.0050)
Ownership of TV and radio	0.0907***	0.0862***	0.0854***	0.0793***	0.1125***	0.0682**
	(0.0232)	(0.0295)	(0.0241)	(0.0291)	(0.0293)	(0.0303)
Affected by pest shock	0.0219	0.0145			0.0693	0.0019
	(0.0456)	(0.0453)			(0.0540)	(0.0468)
Faces burglary and theft	–0.0416	0.0076		0.0056	–0.0733	–0.0091
	(0.0416)	(0.0518)		(0.0523)	(0.0570)	(0.0512)
Access to electricity	0.2128**	0.2183***	0.1877**		0.2152*	0.2186***
	(0.0922)	(0.0744)	(0.0734)		(0.1158)	(0.0763)
Interacted with chronic poverty						
Access to all-weather feeder road		–0.0494		–0.0482	–0.0007	–0.0617
		(0.0478)		(0.0490)	(0.0004)	(0.0473)
Received extension service		0.0116			0.0001	–0.0102
		(0.0170)			(0.0001)	(0.0074)
Ownership of TV and radio		0.0106		0.0141	–0.0009*	0.0650
		(0.0515)		(0.0513)	(0.0005)	(0.0509)
Affected by pest shock		0.0198			–0.0014*	0.0990
		(0.0913)			(0.0008)	(0.0871)
Faces burglary and theft		–0.1663*		–0.1615*	0.0011	–0.0922
		(0.0963)		(0.0974)	(0.0008)	(0.0969)
Access to electricity		–0.1730			–0.0000	–0.1039
		(0.1595)			(0.0015)	(0.1649)

Standard errors are in bracket

** $p < 0.10$, ** $p < 0.51$, *** $p < 0.01$*

The specification test for column 1 shows that the Hansen J test for over identification is 0.42 with a corresponding p-value of 0.52. Thus, instruments are valid. At all critical value, we reject the null of weak instruments based on Cragg-Donald F statistic, which is 80"

Table 2.12: Correlates of the fixed effects of the consumption growth: what determines the latent growth?

Variables	**Coef**	**Robust standard errors**
Sex of head(male=1)	–0.0329**	(0.0156)
Education level of head	0.0182***	(0.0017)
Per capita land size	0.0003***	(0.0001)
Proportion of male:age > 65	0.0049***	(0.0012)
Proportion of female:age > 65	0.0051***	(0.0010)
Proportion male adult:15-65	0.0059***	(0.0008)
Proportion of female adult:15-65	0.0056***	(0.0008)
Proportion of boys: 5-14	0.0014*	(0.0008)
Proportion of girls: 5-14	0.0012	(0.0008)
Proportion of boys: 0-4	0.0033***	(0.0011)
Proportion of girls: 0-4	0.0022**	(0.0011)
Marital status:monogamy	–0.0048	(0.0153)
Marital status:polygamy	–0.0077	(0.0141)
District level characteristics		
Average size of male adults per hh	0.0007	(0.0009)
Average size of female adults per hh	0.0006	(0.0007)
All weather road acesss(%)	0.0049***	(0.0008)
Average land holding per capita	0.0003***	(0.0000)
Distance to town(km)	–0.0008*	(0.0004)
constant	–1.0570***	(0.1257)
Observations	1521	
Pseudo R^2	0.2936	

Table 2.13: Determinants of chronic poverty based on Multinomial logit and censored quantile regression

	τ=0.75				β=0		QREG
	Chronic		Transient		Chronic	Transient	Chronic
	Coeff	AME	Coeff	AME	Coeff	Coeff	Coeff
Sex of head(male=1)	-0.2802	-0.0402	-0.0190	0.0144	-0.0955	-0.0111	0.0234
	(0.2586)	(0.0351)	(0.2499)	(0.0356)	(0.2816)	(0.2494)	(0.0784)
Education level of head	-0.2073***	-0.0224***	-0.1206***	-0.0069**	-0.2679***	-0.1615***	-0.0846***
	(0.0252)	(0.0033)	(0.0220)	(0.0032)	(0.0254)	(0.0203)	(0.0086)
Per capita land size	-0.0099	0.0018	-0.0530	-0.0080	-0.0134	-0.0092	-0.0014
	(0.0144)	(0.0029)	(0.0373)	(0.0060)	(0.0125)	(0.0062)	(0.0014)
Proportion of male:age $>$ 65	-0.0166	-0.0019	-0.0082	-0.0003	-0.0219*	-0.0163	-0.0084***
	(0.0118)	(0.0015)	(0.0102)	(0.0015)	(0.0118)	(0.0104)	(0.0031)
Proportion of female:age $>$ 65	-0.0221**	-0.0017	-0.0248**	-0.0027*	-0.0322***	-0.0231**	-0.0115***
	(0.0106)	(0.0014)	(0.0108)	(0.0016)	(0.0114)	(0.0103)	(0.0039)
Proportion male adult:15-65	-0.0083	-0.0006	-0.0094	-0.0010	-0.0224***	-0.0163**	-0.0085***
	(0.0080)	(0.0011)	(0.0075)	(0.0011)	(0.0083)	(0.0073)	(0.0025)
Proportion of female adult	-0.0300***	-0.0029**	-0.0233***	-0.0020	-0.0368***	-0.0225***	-0.0099***
	(0.0087)	(0.0012)	(0.0081)	(0.0012)	(0.0090)	(0.0077)	(0.0026)
Proportion of boys: 5-14	0.0021	0.0007	-0.0074	-0.0013	-0.0068	-0.0093	0.0043*
	(0.0077)	(0.0010)	(0.0073)	(0.0011)	(0.0081)	(0.0071)	(0.0023)
Proportion of girls: 5-14	0.0018	0.0002	0.0011	0.0001	-0.0064	-0.0061	-0.0024
	(0.0083)	(0.0011)	(0.0078)	(0.0012)	(0.0087)	(0.0077)	(0.0024)
Proportion of boys: 0-4	0.0134	0.0016	0.0049	-0.0000	0.0044	-0.0020	0.0019
	(0.0097)	(0.0013)	(0.0091)	(0.0013)	(0.0102)	(0.0091)	(0.0028)
Proportion of girls: 0-4	0.0066	0.0007	0.0032	0.0001	0.0005	-0.0039	-0.0002
	(0.0095)	(0.0012)	(0.0089)	(0.0013)	(0.0100)	(0.0089)	(0.0029)
Marital status:monogamy	0.6817**	0.0891***	0.0953	-0.0248	0.6757**	0.1928	0.4966***
	(0.2673)	(0.0326)	(0.2475)	(0.0364)	(0.2768)	(0.2356)	(0.0886)
Marital status:polygamy	0.2589	0.0301	0.1279	0.0045	0.4491	0.3540	0.0444
	(0.2706)	(0.0369)	(0.2505)	(0.0371)	(0.2896)	(0.2516)	(0.0850)
Ownership of radio or TV	-0.8219***	-0.0891***	-0.5399***	-0.0386*	-0.8874***	-0.4264***	-0.3486***
	(0.1562)	(0.0219)	(0.1500)	(0.0233)	(0.1724)	(0.1590)	(0.0500)
District level characteristics							
Average size of female adults	-0.1075***	-0.0109***	-0.0745***	-0.0055***	-0.1036***	-0.0339**	-0.0393***
	(0.0135)	(0.0014)	(0.0132)	(0.0015)	(0.0171)	(0.0164)	(0.0022)
Average size of male adults	0.0916***	0.0091***	0.0665***	0.0052***	0.0933***	0.0333**	0.0238***
	(0.0133)	(0.0015)	(0.0126)	(0.0016)	(0.0158)	(0.0144)	(0.0029)
All weather road access	-0.0576***	-0.0056***	-0.0442***	-0.0037***	-0.0655***	-0.0328***	-0.0228***
	(0.0065)	(0.0008)	(0.0061)	(0.0008)	(0.0073)	(0.0068)	(0.0017)
Average land holding per capita	-0.0004**	-0.0000*	-0.0003*	-0.0000	-0.0003*	-0.0001	-0.0003***
	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0001)	(0.0001)
constant	5.9799***		4.2415***		8.0281***	4.6600***	4.2639***
	(1.4435)		(1.3871)		(1.6114)	(1.4973)	(0.4137)

Note: * 10%, ** 5%, *** 1%. τ=0.75 is used based on spells approach while β=0 indicates the general mean criteria from FS(2013). AME is the average marginal effect associated to each variable. We use multinominal logit for the first 7 columns. The last column applies the censored quantile regression(QREG)

Table 2.14: Multidimensional deprivation indicators for Uganda(2005-2013)

Dimension	Indicators	Deprived if:	Weight	% in deprivation 2005	2009	2010	2011	2013
Housing/water			1/3					
	Overcrowding	More than 2.5 persons per habitable bedroom	1/12	57	58	61	65	48
	Shelter	The housing materials are insufficient (i.e Dung or sand floor, mud wall or,unburnt bricks,thatch roofing)	1/12	60	57	57	54	56
	Toilet	There is inadequate sanitation facility such as bucket toilet,or uncovered pit latrine,covered pit latrine shared with other households(with or without slab)	1/12	58	49	49	51	48
	Water	a household does not have access to safe drinking water or the time to access takes more than 30 minutes	1/12	35	31	28	25	31
Education			1/3					
	Years of schooling	No household member has completed 6 years of schooling	1/6	31	29	26	25	21
	school attendance	Among the school age children in the household(6-17 years),at least one individual is not attending school	1/6	17	25	25	25	14
Consumption		The consumption per capita falls below the poverty line	1/3	28	33	32	33	28
	N			3119	2870	2601	2821	3117

Table 2.15: Multidimensional poverty measures based on cross-section and panel data(k=40%)

	Based on cross section 2005	2009	2010	2011	2013	Based on longitudinal $\tau = 0.2$	$\tau = 0.4$	$\tau = 0.6$	$\tau = 0.8$	$\tau = 1$
Headcount ratio(H)	29.91	33.03	32.53	32.79	25.86	63.40	43.70	29.58	17.13	7.98
Intensity(A)	67.04	67.19	66.51	66.07	64.50	46.84	54.17	60.59	68.87	77.65
Adjusted headcount ratio(M)	20.05	22.20	21.63	21.66	16.68	29.70	23.67	17.92	11.80	6.20
Indicators contribution to M										
Overcrowding	9.83	9.59	9.83	10.23	9.52	11.55	10.87	10.41	9.76	9.35
Shelter	10.58	10.11	10.20	10.16	10.56	13.26	12.27	11.52	10.63	10.00
Toilet	9.57	7.95	8.20	8.19	8.18	9.95	9.49	9.19	8.81	8.72
Access to safe water	5.41	4.68	3.95	3.25	3.96	5.21	4.64	4.31	3.96	3.78
Educ. achievement	13.22	12.98	12.47	11.04	10.16	13.44	13.77	13.92	14.87	15.48
School attendance	9.62	11.04	10.72	11.43	9.59	11.32	11.34	11.76	12.70	13.59
Consumption	41.78	43.64	44.61	45.70	48.03	35.27	37.62	38.89	39.26	39.07
Population share										
HH1	31.42	20.84	15.72	13.75	30.86	12.15	12.15	12.15	12.15	12.15
HH2	49.18	48.64	45.64	42.04	48.76	54.69	54.69	54.69	54.69	54.69
HH3	19.40	30.52	38.64	44.20	20.37	33.16	33.16	33.16	33.16	33.16
Contrib. by hhs division to M										
HH1	17.56	11.16	8.01	5.58	11.59	7.88	6.20	4.80	3.85	0.91
HH2	54.38	49.66	41.32	39.86	52.73	51.24	50.92	51.70	49.35	48.86
HH3	28.06	39.18	50.67	54.57	35.68	40.88	42.88	43.50	46.80	50.24

Note: HH1= households having number of dependents less than 2. HH2=households with number of dependents between 2 and 4 inclusive. HH3= households with number of dependents above 4. Dependents are those consisting of children aged less than 13 and older household members whose age exceeding 64.

Table 2.16: The Shapley decomposition of the variation in the multidimensional poverty(2009 and 2013)

	HH1	HH2	HH3	Total
Multi-dimensional poverty in 2009				
Mult.headcount(H)	18.73%	33.67%	41.78%	33.03%
Intensity of poverty(A)	63.47%	67.30%	68.19%	67.19%
Mult.dimensional poverty index(M)	11.89%	22.66%	28.49%	22.20%
Population share	20.84%	48.64%	30.52%	100.00%
Share of headcount(H)	11.81%	49.58%	38.61%	100.00%
Multi-dimensional poverty in 2013				
Mult.headcount(H)	10.40%	28.42%	43.15%	25.86%
Intensity of poverty(A)	60.25%	63.45%	67.70%	64.50%
Mult. poverty index(M)	6.26%	18.03%	29.21%	16.68%
Population share	30.86%	48.76%	20.37%	100.00%
Share of headcount(H)	12.41%	53.60%	34.00%	100.00%
Decomposing the variation in multidimensional poverty in 2009 and 2013				
% of contribution(Δ M)	9.86%	40.39%	49.75%	100.00%
Demographic effect	-16.49%	-0.46%	53.08%	36.13%
Within group effect	26.35%	40.85%	-3.33%	63.87%
Decomposing within group effect into incidence and intensity				
Incidence	24.15%	30.27%	-4.29%	50.14%
Intensity	2.19%	10.58%	0.96%	13.73%
The intensity component				
Overcrowding	-0.03%	1.27%	-0.12%	1.12%
Shelter	-0.67%	0.22%	0.47%	0.01%
Toilet	0.73%	-0.00%	-0.08%	0.66%
access to safe water	0.24%	1.09%	1.74%	3.08%
Educational achievement	2.04%	7.50%	2.33%	11.86%
School attendance	0.45%	2.95%	2.44%	5.83%
Consumption	-0.56%	-2.44%	-5.82%	-8.82%

Table 2.17: The adjusted headcount ratio(M)and Percentage contribution of the poverty indicators to M for different k and τ cut-offs

	$\tau = 0.2$				$\tau = 0.6$				$\tau = 0.8$			
	Hc	H	C	E	Hc	H	C	E	Hc	H	C	E
k=20%	96.85	45.1	30.61	24.29	83.38	43.9	31.28	24.82	73.94	43.22	31.67	25.11
k=40%	63.4	39.97	35.27	24.77	29.58	35.43	38.89	25.68	17.13	33.17	39.26	27.57
k=60%	54.1	38.8	35.73	25.47	20.06	34.18	38.46	27.36	11.71	32.35	38.39	29.26
k=80%	17.79	34.89	34.75	30.37	5.34	31.08	34.57	34.35	2.56	29.51	35.51	34.98
k=100%	4.69	32.76	33.49	33.75	0.15	31.62	34.19	34.19	0.07	32.2	33.9	33.9

Note: Hc is the headcount ratio. H represents housing(includes overcrowding,shelter and toilet) and access to safe water. C denotes consumption. E represents education, which includes educational achievement and school attendance

3 Poverty Persistence and True State Dependence in Uganda

3.1 Introduction

It is of important to ask why some people escape poverty while others remain in it for un-interrupted periods. 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. An individual with low standard of living today is more likely to stay in that state in the future. For some reasons such as health problem ,social exclusion, and lack of motivation, past experience in poverty may lead to a higher risk of becoming poor and this phenomenon is often referred to as state dependent in poverty. It is of important to identify who is at a risk of becoming poor. Analyzing the pattern of poverty persistence is more important for developing countries. Do the poor and non-poor in the past have the same chance to fall into poverty at the current time?. What characteristics make individuals to persist in poverty?. What factors determine their transition probabilities from different states in the past into the same poverty state today?. It is of interest to understand whether being in poverty today leads to higher future poverty compared to those who do not experience it today. This raises the question of whether poverty is state dependent or not. If those who were poor in the past are more likely to remain poor in the current time than those who were not ,then poverty may persist among the initially poor, which by itself may yield long lasting negative repercussion on their well being and future productivity.

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 such as education, access to infrastructure and roads, ownership of land,and access to information technology. Since the observed characteristics are available to the researcher, they are easily captured in the empirical setting. Households with low productive attributes are more likely experience repeated poverty spells than those with high productive characteristics. Persistent poverty can also emanate from individual specific unobserved attributes such as individuals ability ,risk attitude, rate of time preference, parental effects, motivation,laziness and health traits, which are unavailable to the researcher. Thus ,identifying the part of poverty persistence due to heterogeneity (both individual specific observed and unobserved heterogeneity) is of crucial in an effort to combat poverty and social exclusion. If the relative importance of heterogeneity is larger than the true state dependence, it is of relevant to alter those characteristics that drag individuals into a risk of poverty.

On the other hand, true state dependence in poverty arises after controlling for both observed and unobserved individual heterogeneity. A failure to address unobserved attributes leads to spurious state dependent. The objective of the paper is therefore to determine the amount of true state dependence in the overall poverty persistence. The overall persistent poverty consists of the true state dependence and heterogeneity effects. Each component has interesting insights from the view point of policy implication. If unobserved heterogeneity is found to be the main sources of persistent poverty, policies that address those characteristics will lead to better outcome. And short run policies aimed to alleviate poverty through cash transfer program including safety nets,and aid in the form of consumption goods such as wheat may not bring huge impacts on individual long term poverty status (Faye et al,2011).If persistent poverty is mainly explained by the true state dependent, short run policies would be most effective. Thus, policies that reduce current poverty will also reduce future poverty, leading to lower poverty in the steady state. 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).

Deininger and Okidi (2003) examine the link between growth and poverty reduction in Uganda and yet, they do not study the poverty transition dynamics. Azomahou and Yitbarek (2014) and 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 two commonly used approaches, however, require a balanced panel data. Observations that do not appear in all rounds will be omitted and estimation is only conducted on the balanced portion of the sample. This will lead to substantial loss of information if the attrition rate is significant. The balanced sample discards useful information leading to an efficiency loss. It may also have few common periods, as is true in the absence of long panel data, making estimation less appealing. This paper instead estimates the Wooldrige and the Heckman approaches for unbalanced panel using my own user defined programs. In evaluating the multivariate integrals, I use Geweke Hajivassilliou Kean(GHK) simulator instead of Gausian Hermite quadrature so that variation in the two models parameters due to the different ways of approximating the integrals are virtually removed. The GHK simulated maximum likelihood method is highly flexible to allow for changes to variance-covariance structure of the model. The efficiency gain in the model convergence and parameter stability is substantial even at a low halton draws.

The initial condition problem has been intensively studied (after the Heckman's (1981) ground breaking work for the first time to solve the problem of initial condition in dynamic non-linear panel data using the two step maximum likelihood estimator. If the initial distribution of poverty is not random, estimation of dynamic models using lagged poverty yields inconsistent estimates. Because the stochastic process of poverty actually started before we see the first period in the panel and thus the start of stochastic process does not coincide with initial period for which data is collected. Thus, we can not observe the entire history of the stochastic process for each household. A failure to take into account the initial condition problem results in a spurious state dependence due to its correlation with unobserved heterogeneity.

The paper contributes to the existing literature in three main ways. First,the paper improves the original Wooldrige (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 possibility of endogenous sample selection is also considered. Second, the simulated maximum likelihood estimator based on halton draws has been applied to both models. The built in software to estimate the Wooldridge model was only based on the quadrature approach that evaluate multi-dimensional integrals. Thus, the same GHK integral evaluator technique has been used in both models which help us compare the size of true state dependence in Uganda.

Third, we apply the endogenous switching regression model proposed by Cappeillari and Jenkins(2004) to analyze the poverty Dynamics in Uganda. The three models take into account the initial condition problem and endogenous sample retention. For a comprehensive evidence on poverty dynamics in Uganda, we estimate these three models. These models, as far as I understand, were not applied in Uganda. This paper deals with split off households and sample attrition. They are considered in the estimation of endogenous switching regression model. If a researcher chooses the head of a household as a unit of analysis, often used in several studies, other split off individuals are ignored. In stead, we include all individuals whose age above 14 in the first year panel so that the split off individuals as well as the characteristics of the household they join/form are being considered. For instance, the education levels of individual household members (than only choosing the head's education) can be important determinant of their poverty. The marital status of individual members may be important for the analysis of poverty risk (widow female my be different from divorced male member in their motivation and resilience). Though the focus of this study is on rural households for several good reasons (see in the main text), we also study the robustness of the result by pooling both rural and urban households. We take advantage of the availability of both rural and urban household panel data in Uganda.

The aggregate 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. True state dependent explains the larger portion of persistence poverty. Its contribution lies between 61%-72% depending on the samples being considered. We find 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 presents the theoretical and empirical literature related to the issue of poverty persistence. Section 3 offers the data. The methodology is portrayed in section 4. section 5 offers the discussion and interpretations of the estimated parameters based on the different methodological approaches. Section 6 concludes.

3.2 Related Literature

Persistence in economic phenomenon, which is defined as repeated spells of an event, has been studied since Heckman's ground break work in 1981. For instance, persistence in social benefit (Andren and Andren, 2013; Cappellari and Jenkins,2008) ; Unemployment persistence (Arulampalan et al.,2000; Hann,2005); low pay wage persistent (Cappellari and Jenkins,2008; Plum ,2014; Knabe and Plum,2013; Mosthaf,2014; Stewart and Swaffield,1999; Stewart,2007) and poverty persistence (Cappellari and Jenkins,2004,2002; Devicienti,2002; Poggi,2007; Biewen,2009; Assave et al,2006). Recently, the issue of poverty persistence has been recognized as a main social indicator in public and academic discussion. If the same individuals experience poverty year after year, this implies some sort of poverty persistence among these individuals.

There are two factors explaining why individuals experiencing poverty today are more likely to be poor in the future. First, these individuals may have low education, or low work experience and job propensity or unobserved factors such as unfavorable attitudes that make them at a risk of future poverty as long as these characteristics persist overtime. The second source of persistence arises if there exists a genuine causal link between past poverty and current poverty, which is called true state dependence. Biewen and Steffes (2010) attempt to directly identify the mechanisms that lead to the effect of true state dependence in the context of unemployment persistence and these factors were stigmatization and disincentive effect of unemployment insurance. The majority of research work focus, however, on determining the size of true state dependence after controlling for observed and unobserved individual characteristics (Cappellari and Jenkins,2004; Poggi,2007). State dependent effect reflects the situation that two individuals having identical attributes behave differently in the future only due to the fact that one of them is poor today.

There are two main approaches to study the poverty dynamics in the literature: the hazard or duration models and the transition probability models. The latter models are of three types: the basic models; lagged dependent variable models (such as dynamic random effect probit models and dynamic panel data models using system or difference GMM) and endogenous switching regression models. The basic models emphasis on the correlates of poverty mobility with no allowance for state dependence. The multi-nominal logit and sequential logit are the most applied models to examine the determinants of poverty transitions. The sequential logit model helps identifies the characteristics of households which trap them in poverty in a sequential step wise fashion, in particular the lock-in effect attributable by the initial household characteristics.

These models, however, reduce the continuous welfare measure into discrete categories, which result in a loss of information. In addition, the estimates are more sensitive to outliers among independent variables (Baulch and Dat, 2011). The pooled probit model (by pooling data overtime) can be used to reduce the discrete categories and increase sample size. An alternative to this discretization is to estimate a fixed effect panel regression using consumption as a dependent variable (Woolard and Klasen, 2005). All these models consider the initial condition as exogenous and they cannot distinguish the true state dependence from unobserved heterogeneity. There may be over-representation of poor individuals in the base year who are more likely to remain as poor in the future because they have persistent unobserved individual heterogeneity. Estimates based on this selected sample cannot represent the population poverty transition probabilities. The basic models assume that all differences among individual are encapsulated by their observed attributes and there is no poverty transition probability that can be ascribed to persistent unobserved heterogeneity (Cappellari and Jenkins,2008).

The lagged dependent variable approach has been extensively used for the analysis of poverty dynamics (Biewen,2009) ; social assistance dynamics (Cappellari and Jenkins,2008 and Andren and Andren,2013) and for unemployment dynamics (Arulampalam et al ,2000; Stewart,2007). This method controls for both observed and unobserved fixed individual heterogeneity and as a result the coefficient associated to the lagged dependent variable is taken as the effect of true state dependent. The standard random effect model assumes that initial poverty is uncorrelated with the time constant unobserved individual heterogeneity. Since this is a stringent assumption, Wooldrige (2005) and Heckman (1981a,1981b) apply the maximum likelihood estimators by simultaneously modeling both the initial period and dynamic equations so that the fixed individual specific error term is integrated out using either the quadrature or simulation method. The Heckman's estimator is computationally intensive while the Woodrige estimator can be obtained using standard built in xtprobit command in stata software. To integrate out the individual specific error, Orme (1997) also suggests a two step solution that can be easily implemented with the built in command xtprobit. Though this estimator is potentially fraught with heteroskedasticity, the monte-carlo evidence shows a better performance (Arulampalam and Stewart, 2009). All these estimators are developed for balanced samples. Indeed, the Orme and Wooldrige estimators can be potentially estimated for unbalanced data by assuming that sample selection is ignorable in the sense that unobservable affecting attritions are not correlated with unobservable determining current poverty status (Cappellari and Jenkins, 2008). This assumption, however, is ubiquitous. Extant researches in relaxing this restriction are scant and the current paper allows for correlation between unbalancedness and individual specific unobserved heterogeneity in the Wooldridge estimator.

The endogenous switching regression model is another transition probability model that allows for the impact of explanatory variables on the current poverty status to vary according to the poverty status of an individual in the previous round (Cappellari and Jenkins, 2004). The transition probability equations, the two possible endogenous sample selection equations (initial condition and sample attrition) and the correlations of individual specific unobservables affecting the transition, initial and retention equations are all jointly taken into consideration. After controlling for the initial condition and unobserved heterogeneity, the true state dependence effect (TSD) for an individual is obtained as the difference between the predicted probability of being poor at the current period conditional on being poor in the previous round and the predicted propensity of being poor at current time conditional on being non-poor in the previous time. Averaging this difference over all individuals gives the TSD effect.

Unlike the standard Wooldrige's and Heckman's estimators, endogenous switching estimators offer two added advantages. First, they allow for the possibility of endogenous sample attrition. Second, since the impact of a given variable switches depending on whether an individual was poor or not at t-1, one can identify household characteristics that reduce both poverty persistence and entry rates. Even after controlling for unobserved heterogeneity, the true state dependence effect is statistically significant (Cappellari and Jenkins, 2004; Biewen, 2009 and Poggi, 2007). Cappellari and Jenkins (2004), using the British Household panel data for the 1990's, show the genuine causal effect from past poverty on current poverty as TSD explains 59 percent of the poverty persistence in Britain. Using dynamic random effect probit model, Biewen (2009) concludes that about half of the poverty persistence in Germany is attributable to TSD even after controlling for observed and unobserved individual heterogeneity, indicating that experiencing poverty increases future poverty. However, Giardo et al (2006) find that all poverty persistence in Italy during the period 1995-2004 was only driven by unobserved heterogeneity. The TSD effect disappears after controlling for the initial period permanent income and the permanent component of a shock shaping the sequences of income.

Empirical works on the sources of poverty persistence in Sub-Saharan Africa are generally limited. In particular, there is no empirical work that disentangles the effect of unobserved heterogeneity from true state dependence in Uganda. Our paper fills this lacuna. There is a dearth of empirical evidence to show why individuals experiencing poverty today are more likely to face it again, in particular in the rural economy of Sub-Saharan Africa. Ethiopia has 6 waves urban household panel data (1994, 1995,1997,2000,2004 and 2009). However, there are differences in the questionnaires between the 1990's and 2000's, especially seasonal variations significantly affect the consumption variable as the duration and seasons in which the data are collected vary a lot.

Using the Ethiopian household panel data, few studies (Islam and Shimeles, 2007; Bigsten and Shimeles,2008,2011) apply the dynamic random probit model and find that TSD is a driving factor of poverty persistence. These studies, however, use the balanced portion of the data and the robustness of the findings are questionable if sample attrition is endogenous. Even in the absence of correlation between unbalancedness and unobserved heterogeneity, excluding some part of the sample results in a significant loss of information, which affects the efficiency of estimates. Based on the dynamic random effect probit model, Islam and Shimeles (2007) use only the first three waves of the data as they are not synchronized with the rest of the recent surveys and yet the short panel is another concern. Using only two waves of household level panel data from Kenya, Faye et al (2011) apply endogeneous switching regression and confirm the presence of strong true state dependence. Our paper attempts to use a relatively longer panel data using an endogenous switching regression and a dynamic random probit model that allows for endogeneous sample selection.

3.3 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. UBOS survey collected data from 7421 households having 42,111 individuals during the year 2005/06. 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. UBOS planned to conduct panel data since 2009/10. They intend to re-survey 3123 households in 2009/10 from the 2005/06 national household survey. The selection of 3123 households from 7421 households was done to be representative of all regions. UBOS was able to track 2888 households out of the targeted 3123 households in 2009/10, indicating a small attrition rate. Kristen(2014) constructs sampling weights for households tracked in

2009/10 because new households were entering into the sample (will be discussed later). Both surveys share similar questionnaire on consumption,education,labor ,household roster, perception on shocks,community infrastructure, and agriculture and are thus more comparable. 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. Actually, both UBOS and the World Bank group were participating in the collection of the panel data. The household panel survey is part of the living Standard Measurement Study- Integrated Survey on Agriculture(LSMS-ISA) project under the World bank Development research group which is funded by the grant from Bill and Melinda Gates foundation to collect panel data for Sub-Saharan African countries. The Uganda panel data consists of four waves: 2005/06, 2009/10,2010/11 and 2011/2012. In all surveys, a short recall period of 7 days was used for food and beverage expenditure while a recall period of 30 days was used for non-durable and less frequently purchased consumption items. A 1 year recall period(365 days) was used for semi-durable and durable consumption goods. In all waves, food expenditure comprises consumption from own production, purchases and free gifts. Purchases and free gifts were valued at current market price while consumption out of home production was valued at farm gate price. 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: how much the owner would like to rent for someone else or his willingness to pay for rent had it been owned by another person. Housing rent is the most important non-food consumption expenditure for urban household in African countries, yet it is not available, for instance, in Ethiopia household surveys. Respondents are directly asked about their monthly expenditure for rent or the imputed value. The share of other non-food consumption expenditure is quantitatively small(less than 30 percent). Some of the non-food consumption includes expenditure on clothing,education, heat and energy,health ,transportation ,electronic appliance and kitchen equipment.

Food expenditure is the largest portion of total expenditure in poor African countries including Uganda. Most of the rural households are autarky of food while some others are net sellers. In contrast, urban households are net buyers of food. Consumption out of own production is valued at farm gate prices while purchased food is valued at market price. 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. Thus, gifts,in kind receipts and quantity consumed from own production are re-valued with the market price. We have constructed real consumption expenditure per adult. Unlike the extant researches in Uganda (Duponchel et al.2014; Lawson et al.2006; Mckay and Lawson,2003;Ssewanyana and Kasirye,2012,2014) who use an outdated poverty line constructed by Appleton(1999,1996,2003), I use the poverty line constructed by myself, which is 34618 Ugandan shillings.

In order 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. This was acceptable for logistic and cost reasons as it is impossible to track all split off individuals from all households 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. It can be that all members may be completely disintegrated in the next round(due to death, external migration etc) and no member from the household could be reached by 2009/10. 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 irregardless of the age of the split off individuals.

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 representativness of the sample by reducing the attrition of the original household and its members for reasons of shifting into another location or permanently joining another household in another location. To elucidate with example, consider a household with husband and wife as the only members who live together in 2005/06 and this household was selected for split of tracking in the same year. They divorce and then live in a separate household in 2009/10. The parent household (eligible original household) is the one who resided in original place of resident as of 2005/06 or a household living closer to their 2005/06 dwelling or households not assigned for tracking in 2005. The other household would be designated as a split off household. As a second example, consider a household with 6 members in 2005/06. All the 6 members may not reside in the same dwelling in 2009/10. If a head of the household remains in the original place while all other five members are moving into another location, the head is the parent household and the other five members are under a split off household. The interesting point is that split off households would be tracked and interviewed in their new location. The the eligible parent household and the split offs obtained from 2005/06 should be visited in subsequent rounds of 2009/10,2010/11 and 2011/12.

Identifying the unit of analysis is an important step in using the panel households. The household is defined as a group of individuals who are residing in the same dwelling and sharing meals together for at least 6 months out of a year. Household head is a member of the household who manages or administers other household members because of his/her seniority (often older age) or education and superior knowledge. If 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 uses individuals in the household as a unit of analysis [7]. This allows us to include split off individuals in the regression. When an individual establishes/joins another household (through marriage,migration) by leaving his/her eligible original household, a new household identification number is issued but the personal id of the split off individual is not altered. This new split off household was also interviewed in the remaining surveys. As a result, many new households were entering the sample because split offs made by individuals were followed and interviewed in the next rounds in their new location.

In endogenous switching regression, we include all individuals whose age exceeding 14 in the year 2005/06. This allows us to include the characteristics of the split off and original households. Poverty is measured at household level as the members share the same meals and other resources. The heterogeneity of the household's members determines their poverty status: members' education level, sex and their age, number of employed and unemployed members in the household, and the proportion of female and male adult members. Incorporating 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, attrited households and original households in Uganda. Table 1 presents the average and the median real consumption per adult for split off and original households across years for the sub-sample of households (national,urban and rural). As defined above, split off households are newly established households by one or many household members leaving the eligible original household. It is of interest to examine how the welfare of the two household groups can be compared at each round of the panel. If the average consumption of the splits off is significantly different from the average consumption of the original, it lacks randomness and the selection process may induce endogeniety bias. Since mean is more sensitive to outliers, the test is complemented by the median measure. To test the null hypothesis that the two types of household are independent (have equal mean consumption), we assume that the mean is normally distributed. In that case there exists a formula to compute the standard errors of the means.

However, there is no established small sample formula to get the standard error of the sample median (Efron and Tibshirani,1993). The bootstrap method and quantile regression are available options to estimate the standard errors associated to median. We run median quantile regression to test if the two medians are statistically different from zero. Table 1 offers the test-statistics for the null of no difference in the means or medians between the two households. Rejecting the null means that the split off household has a better standard of living than the original household. As we move from 2005/ 06 to 2009/10, about 364 new split off households are formed. In 2009/10, it was possible to track 2566 households out of 3120 households in 2005/06. The splits have higher average consumption than the original households but their medians are not different at 5% significance level. The importance of the difference in average consumption disappears when the data is dis-aggregated by rural and urban households.

[7] Individuals whose age above 14 are included in the endogenous switching regression. For the Wooldridge and Heckmans' models, the head of the household is used because of high execution time

Table 3.1: 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

In 2010/11, the number of split off households are small(48). The survey was able to reach 2608 original households: those who remain in the same place as in 2009/10. The split off households in 2010/11 comes from the 2009/10 eligible original households.[8]

In the third panel survey (2010/11), there is no difference between the split off and the original households based on the national sample as well as the rural and urban sub-samples irregardless of the choice of the measure of central tendencies. 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. Another study in Uganda finds similar descriptive evidence (Duponchel et al.2014). Urban splits are not different from

[8]there are some possible reasons why they are small in 2010/2011. Look at the rule of assigning households for split off tracking: 20% of 3120 (about 624 households) are chosen for split of tracking from 2005/06 households. In every round when the survey is conducted, the enumerators try to reach all 3120 households and their member individuals. They want to track (e.g in 2009/10) all the 624 eligible original households who are assigned for further tracking of their members. If these households are available in their original place, the enumerators ask whether all members live together. For instance, if one member leave this household and join another household, the respondent is asked to give the location and address of the migrant(note that it can happen that two or more members may join different households and form multiple new split off households). Within that year, the enumerators should move to the new place and if they succeed, ask not only the migrant but also all other members in that household. This new household will be tracked in the next round. If all the 624 households are tracked and do not have split off members, there would be no new split of households. If they do have split off members but impossible to get the new location of the migrant, there would not be new households joining the sample. If some of the parent households out of 624 are completely disintegrated, no new household emerges . It could be that some of the 624 households may not want to cooperate in the survey though they are reached, the parent households are attrited and hence there is no information about the splits if any

urban original households. Rural splits are the better off households compared to rural original households. Previous studies in Uganda did not include split off households in the empirical estimation of chronic poverty determinants. The empirical specification of this paper includes individual splits and their household characteristics.

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.[9]. 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 percent. Households who are observed in both 2005/06 and 2009/10 stand to be 2564. 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.

Table 3.2: 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

Note: Note: non-attrited refers those households observed in the panel since the start of the survey (i.e 2005) till the last survey conducted. Attrited indicates those households that leave the sample in the last survey.

Since we have information about the expenditure of attrited households just before they leave the sample, we can test whether their median consumption is different from that of the non-attrited counterpart. In the first round, both the mean and median consumption of attrited households were significantly large compared to the mean and median consumption of the non-attrited households, suggesting that attrited households were wealthier to start with. In

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

all other waves, attrited households were generally better off. This shows the presence of systematic consumption patterns among the two types of households and thus, attrition is not random. Those who leave the sample may have different productive characteristics than the average population. After splitting the sample into rural and urban sub-samples, the attrition effect becomes modest. In 2005/06, there is a strong attrition affect for a national ,rural and urban sub-samples. This effect virtually evaporates in the next two waves (at 2009/10 and 2010/11) for rural households, implying that attrited households have experienced lower real consumption growth compared to those retained in the sample. With respect to attrition, urban households differ from rural households in two ways: first, the rate of attrition for urban households is always larger than the rate for rural counterpart. Second, attrited urban households have always higher average and median consumption than the non-attrited urban households. This effect is strong during 2005/06 and 2009/10. In addition, the variability among attrited households is higher.

Household level attrition is often different from individual level attrition. Household's head can be chosen to investigate the determinants of household level poverty. However, household members are heterogeneous in their education level, which can affect their common poverty. For instance, the head of the household may be less educated compared to his spouse. We include individuals and their characteristics to better explain the determinants of poverty dynamics. In addition, this setting permits to capture the attrition patterns of individuals. Since we may have several individuals included in the regression coming from the same household, we adopt clustering at household level in order to get robust standard error. The control variables are organized into 2 groups: individual and household level characteristics. The outcome variable is the poverty status of an individual. A household (i.e all the members) is said to be poor if the consumption per adult is less than the absolute poverty line, which is 34618 shilling per month. Table 3 presents the characteristics of both the household and the head of the household.

Our focus will be on rural households[10] because the livelihood of the majority of African population including Uganda depends on agriculture and resides in rural areas. Poverty reduction strategy should give priority to the majority in order to have a balanced, sustained and inclusive growth. The poverty transition rates and individual attrition rates are offered in table 4 for national and rural sub-samples. 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. To be consistent with empirical approach adopted, the poverty transition rates are constructed in such a way that 2005/06 and 2010/11 are the base years for the transition years 2009/2010 and 2011/2012 respectively. The transition probabilities are then pooled together. I use this approach following Nilsson(2012).

The transition probabilities in table 4 indicate the likelihood of being in a certain poverty state at t conditional on the poverty state at t-1. In the first part of table 4, all individuals observed at t-1 are presented (i.e includes attritors). The second panel in table 4 comprises individuals who are observed in both t-1 and t. As shown in the table, the

[10]large sample size is drawn from rural households. The rural sample is chosen than the national sample because agricultural land holding as a determinant of poverty is not available for most urban households. Low variability in land size per capita in urban households is a real concern. We also believe that TV-radio is more important for rural households as an input to production than for urban households. We want to know the impact of TV-radio on productivity of rural household

Table 3.3: 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

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 at t-1,on average, have 30.8% higher probability to be poor at t compared to those who were not poor at t-1. This is suggestive of high true state dependent effect of past poverty on current poverty. The 30.8% poverty persistence effect, which is taken as as a measure of aggregate state dependence in poverty, is the combined effect of household heterogeneity in observed and unobserved attributes and past poverty dynamics. The econometric method allows us to distinguish the contribution of heterogeneity and poverty dynamics (known as true state dependence) in the aggregate poverty persistence. The high poverty persistence rate may already exist before the date of the first interview, which is due to prolonged past poverty history or low composition effect. If that is the case, most of the poverty persistence would be ascribed to heterogeneity effect. After controlling for the determinants of initial poverty, the true state dependent effect will be obtained from inflows and outflows of poverty dynamics over the four waves.

The persistence rates for initially non-poor and poor are reported in table 4. On average, initially non-poor households have 72% chance to stay as non-poor or 27.9% chance to slipping into poverty every year. On the other hand, initially poor have 41% chance to exit poverty and 58.7% chances to remain as poor. Aggregate poverty persistence(30.8%) is obtained as the difference between the poverty persistence rate of the initially poor and the poverty entry rate of the initially non- poor.

The transition matrix using all individuals at t-1 is presented in table 4. We report the attrition of all individuals

Table 3.4: Raw transition probabilities for rural households with and without missing consumption: 2005 -2011

Poverty status: year t-1	Poverty transition for individuals >14			Transition for head of household		
	Poverty status: year t			Poverty status: year t		
	Poor	**Non-poor**	**Missing**	**Poor**	**Non-poor**	**Missing**
a) Whole sample-including attritors						
Poor	0.4354	0.3064	0.2582	0.5352	0.3436	0.1212
Non-poor	0.5117	0.1977	0.2906	0.6061	0.2439	0.1501
b) Balanced sub-sample						
Poor	0.5869	0.4131		0.6090	0.3961	
Non-poor	0.7213	0.2787		0.7131	0.2869	

(including splits off individuals) whose age exceed 14. 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 last round (t-1) have 25.8% chance to leave the sample in the next round(t) while the propensity to quit the sample by the initially non-poor is 29%. Initially richer individuals are more likely to leave the sample than initially poor though the difference in attrition is small(3%). Overall,both table 2 and 4 show that poor individuals are more likely to remain in the sample than non-poor individuals. This is also confirmed by the empirical analysis. Just focusing only the balanced part of the sample offers too pessimistic a view on poverty alleviation over the sample period.

Comparing table 4 with table 2, we find that attrition by individuals is higher than attrition by original households. Beginning from the first round, we use the household's identification number to examine its presence in the next round when the interest is to know household level attrition. If a parent household (eligible original household) at t-1 forms two new splits off households at t and none of the members of a parent household live in the original location, the parent household is considered as attrited though the members and their identification particulars of the parent household are available at t. Studying attrition based on individuals' personal identification can give a lower attrition rate than studying based on the household's (original) identification number. Since the original households who are eligible for further tracking spilt off members are generally small, however, individuals' attrition rate is higher than households' attrition. In table 4, attrition made by the head of the household is smaller than attrition made by all individuals aged above 14.

Table 5 offers the transition matrix by pooling rural and urban households. The aggregate poverty persistence rate now becomes 34%, implying that individuals residing in urban areas have a lower propensity to fall into poverty(23%) compared to the poverty entry rate of individuals from rural areas (27.9%). Based on the descriptive study, we can conclude that rich households are less likely to remain in the panel survey. The rate of attrition is higher for urban households than rural households. Rural poor and urban poor do have similar propensity to remain in the sample. Urban rich individuals attrited most in these 4 waves survey.

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Table 3.5: Raw transition probabilities for national sample with and without missing consumption: 2005 -2011 Poverty transition rates (in %)for individuals >14

Poverty status: year t-1	Poverty status: year t		
	Poor	**Non-poor**	**Missing**
a) Whole sample-including attritors			
Poor	0.4164	0.3094	0.2742
Non-poor	0.5169	0.1550	0.3281
b) Balanced sub-sample			
Poor	0.5737	0.4263	
Non-poor	0.7694	0.2306	

3.4 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 impose different assumptions depending on the nature of the data and state-of-the-art. We apply 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.

3.4.1 Endogeneous switching regression

It is of interest to look at the poverty status of an individual i overtime . 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). We use the Cappellari and Jenkin's (2002,2004) endogenous switching model to determine the level of poverty persistence and distinguish the heterogeneity effect from true state dependence effect of poverty persistence. This transition probability model takes into account multiple endogenous selection issue 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. After controlling for the two endogenous selection process namely initial condition and panel attrition, we can see how individuals' characteristics affect the poverty persistence and entry rates . The corresponding coefficients associated to these two process allow us to test the presence of true state dependence. 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 $P_{it-1} = I(P^*_{it-1} > 0)$. The latter is an indicator function that takes a value of 1 when the inequality is satisfied and zero otherwise. If the latent poverty propensity exceeds zero, which is often used as a critical threshold value, an individual is observed as poor ($P_{it-1} = 1$). 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 ($u_{it-1} = \mu_i$ + δ_{it-1}) is assumed to follow the standard normal distribution: $u_{it-1} \sim N(0,1)$

If an individual is available in two consecutive periods, t and t-1, with all the necessary information about consumption and main activity, then he is observed in the sample and assigned to take a value of 1. If an individual does not appear in both periods due to some reasons such as death,refusal and incomplete information, he is not retained in the sample and an indicator taking a value of 0 is attached. 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:

$$r^*_{it} = \phi' w_{it-1} + \eta_i + \varepsilon_{it} \tag{2}$$

It follows that $r_{it} = 1[r^*_{it} > 0]$. r_{it} is a binary indicator retention outcome that takes a value of 1 if $r^*_{it} > 0$ and zero otherwise. 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: $\omega_{it} \sim N(0,1)$. The individual's poverty status will be observed at t only if her latent retention propensity is higher than some critical threshold value (which is normalized to 0). equation(1) and equation(2) are called initial and retention equations respectively. The poverty transition probability is given by eq(3) below. The transition probability model presents the probability to remain as poor for those who were poor at t-1 and the probability of entering poverty for those who were not poor at t-1. 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. Depending on whether an individual was poor or not in the previous year, the parameters γ_1' and γ_2' can vary from each other. If γ_1' and γ_2' are equal, current poverty is not affected by the base year poverty status and this implies absence of true state dependence. γ_2' are parameters associated to factors that affect poverty entry rate while γ_1' are estimated coefficients obtained from poverty persistence determinants. Thus , equation 3 is referred to as equation for poverty transition. 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}. Of course, we apply exclusion restriction by looking for variables that should affect the initial poverty but not the transition probabilities (we report these variables in later section). The composite error term $\vartheta_{it} = \tau_i + \zeta_{it}$ is assumed to take a standard normal distribution: $\vartheta_{it} \sim N(0,1)$. τ_i is time invariant individual specific unobserved effect while ζ_{it} is idiosyncratic orthogonal white noise error. The three equations are estimated jointly using a multivariate probit. Since the model is non-linear, identification can be achieved without looking for exclusion restriction variables (Cappellari and Jenkin, 2004). Even if the functional form is non-linear, we find instrumental variables that affect the initial poverty equation and/or the retention equation but not the transition equation. We need variables that should be excluded from z_{it-1} but should be included in x_{it-1}. 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:

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

ρ_1 denotes the correlation between individual specific unobservables affecting initial poverty and retention while ρ_2 depicts the correlation of individual specific unobservables in the transition and retention equations. ρ_3 is the correlation between unobservables affecting transition and initial equations. When ρ_1 is positive,those who are initially poor are more likely to retain in the sample(i.e appear in two consecutive years) 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 while a negative sign implies that they are more likely to exit poverty compared to those non-poor initially. 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, both attrition and initial poverty are not endogeneous. So 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 in order to test the null hypothesis of exogenous initial poverty and sample attrition.

To construct the sample log-likelihood , the key idea is to determine all the possible choices available to the individual. There are 6 possible poverty regimes. An individual may fall into one of these regimes. If an individual appears in two consecutive years, there are 4 possible outcomes depending on his previous and current poverty status. The first case is that an individual may be persistently poor at the base year (t-1) and current year (t):$Pr(p_{it} = 1, p_{it-1} = 1, r_{it} = 1)$. The second is that an individual may fall into poverty at the current time, $Pr(p_{it} = 1, p_{it-1} = 0, r_{it} = 1)$ though she was not poor initially. The third case is that an individual may be non-poor in both initial and current periods: $Pr(p_{it} = 0, p_{it-1} = 0, r_{it} = 1)$. The fourth is that an individual was initially poor but escapes poverty at the current period: $Pr(p_{it} = 0, p_{it-1} = 1, r_{it} = 1)$. Finally,the remaining two possibilities arise when she was not observed in the sample in both periods. At the initial period, she is either poor ($Pr(p_{it-1} = 1, r_{it} = 0)$ or non-poor ($Pr(p_{it-1} = 0, r_{it} = 0)$. The three equations have binary indicators that take either 0 or 1. p_{it} is a binary indicator that shows whether an individual is poor or not conditional on the previous year poverty status. p_{it-1} is a binary poverty indicator at initial period. r_{it} is a binary retention indicator that show whether an individual is observed in two successive periods. The likelihood function summarizing all these 6 probability measures is given by :

$$L = \prod_{i=1}^{N} \Big(\Phi_1(\gamma_1' p_{it-1}, \phi' w_{it-1}, \beta' x_{it-1}; cov1)\Big)^{(p_{it})(p_{it-1})(r_{it})} \Big(\Phi_2(\gamma_2' p_{it-1}, \phi' w_{it-1}, -\beta' x_{it-1}; -\rho_1, \rho_2, -\rho_3)\Big)^{(p_{it})(1-p_{it-1})(r_{it})}$$
$$\Big(\Phi_3(-\gamma_2' p_{it-1}, \phi' w_{it-1}, -\beta' x_{it-1}; -(\rho_1, \rho_2, \rho_3)\Big)^{(1-p_{it})(1-p_{it-1})(r_{it})} \Big(\Phi_4(-\gamma_1' p_{it-1}, \phi' w_{it-1}, \beta' x_{it-1}; cov2)\Big)^{(1-p_{it})(p_{it-1})(r_{it})}$$
$$\Big(\Phi_5(-\phi' w_{it-1}, \beta' x_{it-1}; -\rho_1)\Big)^{(p_{it-1})(1-r_{it})} \Big(\Phi_6(-\phi' w_{it-1}, -\beta' x_{it-1}; \rho_1)\Big)^{(1-p_{it-1})(1-r_{it})} \quad (5)$$

where Φ_1 up to Φ_4 represent a trivariate normal cdf. Φ_5 and Φ_6 are bivariate normal cdf. Cov1 denotes ρ_1, ρ_2, ρ_3 while cov2 represents $\rho_1, -\rho_2, -\rho_3$. 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 base years for transitions into t and t+2. We adapt this approach following Nilsson (2012)[11]. Since we have many individuals on the same household at given time and we have also repeated observations for the same individual, we use the Pseudo Simulated Maximum Likelihood method(SML) for clustering the standard error (White,1982, Cappellari and Jenkins,2004; Nilsson,2012).

If we use a sign variable such as $k_i = 2p_{it} - 1, m_i = 2r_{it} - 1, q_i = 2p_{it-1} - 1$,then eq(5) can be re-written as in eq (6), which consists of three parts: the first is the likelihood for those individuals observed in two consecutive periods and are poor in the initial period. The second is for those who were not poor initially and also retained in the sample. The third part of the likelihood is for atriting individuals. For brevity,the trivariate normal cdf is represented by Φ_3 while the bivariate cdf is denoted by Φ_2

$$L = \prod_{i=1}^{N} \Big(\Phi_3(k_i\gamma_1' p_{it-1}, m_i\phi' w_{it-1}, q_i\beta' x_{it-1}; k_im_i\rho_1, k_iq_i\rho_2, m_iq_i\rho_3)\Big)^{(p_{it-1})(r_{it})}$$
$$\Big(\Phi_3(k_i\gamma_2' p_{it-1}, m_i\phi' w_{it-1}, q_i\beta' x_{it-1}; k_im_i\rho_1, k_iq_i\rho_2, m_iq_i\rho_3)\Big)^{(1-p_{it-1})(r_{it})} \Big(\Phi_2(m_i\phi' w_{it-1}, q_i\beta' x_{it-1} m_iq_i; \rho_1)\Big)^{(1-r_{it})} \quad (6)$$

This equation is the same as the equation defined in Cappeilari and Jenkins(2004). The multivariate normal cdf (Φ_3 and Φ_2) are evaluated using Geweke Hajivassiliou Kean (GHK)(Kean,1994) simulation method. Train(2003) provides the detail 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, we choose 100 halton draws. After taking the logarithmic of eq(6), the model computation is solved using simulated maximum likelihood(SML) method. Finally, the model helps to predict poverty persistence and entry rates which are of crucial to test the presence of genuine state dependence as well as to determine the level and its relative importance in aggregate poverty persistence(Arulampalam et al.2000, Cappeillari and Jenkins(2002,2004),Nilsson,2012). Poverty persistence($Persist_{it}$) and poverty entry rates($Entry_{it}$) are defined as

[11] I would like to thank Nilsson for his good explanation for the question I raise and also replied me very quickly.

transition probabilities conditional on the base period poverty status as follow:

$$Persist_{it} = prob(p_{it}|p_{it-1} = 1) = \frac{\Phi_2(\gamma_1' z_{it-1}, \beta' x_{it-1}; \rho_3)}{\Phi(\beta' x_{it-1})} \tag{7}$$

$$Entry_{it} = prob(p_{it}|p_{it-1} = 0) = \frac{\Phi_2(\gamma_2' z_{it-1}, -\beta' x_{it-1}; -\rho_3)}{\Phi(-\beta' x_{it-1})} \tag{8}$$

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 over all individuals gives rise to the size of true state dependence(TSD). TSD uses individual specific predicted probability and hence all individuals including those exit the sample are incorporated. This is because of the fact that explanatory variables are measured in t-1 and forecasts out of the sample can be applied for the attritors. Given their initial characteristics, we can predict their poverty persistence and entry probabilities. TSD is computed after controlling for individual heterogeneity (observed and unobserved). Poverty experience in the past, keeping other things constant, may lead to loss of motivation and stigmatization which trigger persistence poverty.[12]. TSD quantifies the pure effect of past poverty experience on persistence poverty and is given by:

$$TSD = \frac{1}{N}\sum_{i=1}^{N}(prob(p_{it} = 1|p_{it-1} = 1) - prob(p_{it} = 1|p_{it-1} = 0)) \tag{9}$$

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:

$$ASD = \frac{\sum_{i\in(p_{it-1}=1)} prob(p_{it} = 1|p_{it-1} = 1)}{\sum_{i=1}^{N} p_{it-1}} - \frac{\sum_{i\in(p_{it-1}=0)} prob(p_{it} = 1|p_{it-1} = 0)}{\sum_{i=1}^{N}(1 - p_{it-1})} \tag{10}$$

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.

3.4.2 Random effect dynamic probit model

In this model, we present an alternative model that complements 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). In order to examine the impact of previous period 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

[12]Two individuals with same qualification in the base year (productive features such as education,experience etc) except that one of them is poor,may have different poverty outcomes in the current time

is obtained. However, our households have existed as households 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 her past poverty history, which triggers her to develop unfavorable characteristics such as lack of motivation (which is unobserved to researcher). Thus, initial poverty can be correlated with unobserved heterogeneity and it is no longer exogenous. Cappeillari and Jenkins (2002,2004) and Stewart and Swaffield (1999) use the first order Markov chain which is called endogenous switching to tackle the initial condition problem. Wooldridge (2005) and Heckman (1981) propose correlated random effect model to the initial condition and then the coefficient associated to the lagged poverty is taken to be the true measure of state dependence (TSD). Arulampalam et al.(2000) apply the random effect probit model and interpret the lagged unemployment effect on current unemployment as a genuine state dependence. Of course, the issue of unemployment state dependence has been extensively carried out in advanced economies (see Hyslop,1999; Stewart,2005).

Both ESR and CRE approaches distinguish the impact of past poverty on poverty persistence from the impact of unobserved heterogeneity. What are the difference between correlated random effect model (CRE) and endogenous switching regression model(ESR)? CRE considers non-response or attrition as random and exogenous. While ESR treats attrition as non-random endogenous selection process. Thus, CRE uses the balanced portion of the panel data while ESR uses all samples including those exit the sample. After controlling for both observed and unobserved heterogeneity, the CRE method uses the dummy lagged poverty to capture the pure effect of past poverty on persistence poverty. After controlling for household heterogeneity, ESR assumes that the returns to individual characteristics are affected by whether an individual has experienced poverty in the past or not. If initially poor and non-poor individuals derive the same marginal returns ($\gamma_1 = \gamma_2$) after controlling for observed and unobserved heterogeneity, there is no genuine state dependence

There may be several reasons why being poor in the past leads to higher poverty persistence compared to those who were not. Though the poor and non-poor start with similar observed and unobserved characteristics, slipping into poverty may trigger the poor to develop unfavorable attitudes. For instance, poor individuals may be less motivated to work hard. The poor may be less patient to look for high paying jobs and rather they may accept low paying jobs immediately and end up with low marginal returns. The poor may be more risk averse and may engage in low return activities. Being in poverty by itself entails social exclusion and loss of dignity. This lack of confidence prohibits an individual from participating in social net works. Due to these reasons, the returns to observed characteristics switch depending on an individual is poor or not in the past, from which the true effect of past poverty on persistence is derived. The heterogeneity effect on poverty persistence arises from composition difference between poor and non-poor at the initial period.

To get a comprehensive understanding on poverty persistence, estimating the Wooldridge (2005) and Heckman (1981) complements our estimates from endogenous switching regression. As discussed above, the original CRE models (Wooldridge,2005;Heckman,1981) discard those individuals who are not observed in all survey waves. Now, we include the whole sample (including attritors) and update the CRE models to take into account the non-random retention.

Plum (2014) illustrates the application of simulated maximum likelihood for unbalanced data. However, he assumes that unbalancedness and unobserved heterogeneity are not correlated. Individuals who leave the sample (potentially non-randomly) may have peculiar unobserved characteristics compared to those observed across all waves. In this case, the estimated coefficients may be biased and inconsistent. Thus,it is plausible to consider the endogenous process where unbalancedness is correlated with initial poverty. Albarran et al. (2015) propose a method of incorporating unbalancedness in a dynamic non-linear random effect model and their method is adapted here. Our difference is that I use the GHK simulator based on simulated maximum likelihood (SML) method[13]. The SML method is computationally less intensive and model convergence is achieved with very low halton draws (Plum,2014; Cappellari and Jenkins,2004). Plum (2014) finds that parameter stability can occur even with less than 50 halton draws. So that all models used in this paper including endogenous switching model are estimated using simulated maximum likelihood. We briefly present on how to include unbalancedness in the Wooldridge and Heckman models.

let $S_i = (s_{i1}, ..., s_{iT})$ represents the unbalanced structure of the data for individual i. s_{it} is the selection indicator that takes a value of 1 when a person is observed at given time t and zero otherwise. When $s_{it} = 1$ for all i and t, the data is said to be balanced. It is therefore a special case of unbalanced data. t_i is defined to be the first period in which person i is observed. We define $T_i = \sum_{t=1}^{N} s_{it}$ as the number of periods person i is available in the panel with complete information. S_i consists of two main elements: the year an individual joins the panel(t_i) in the first time and the total number of survey rounds unit i is observed in the sample. For instance, the correlation between S_i and unobserved heterogeneity(η_i) can be through t_i or the total number of periods in the panel(T_i). Assume that half of total sample start at t-1 while the other half start at t,we can have two random unobserved parameters specific to each sub sample (provided that other things are equal).

There are three conditions under which the initial condition is endogeneous $(\eta_i/(p_{it_i}, X_i, S_i, \delta_{S_i}))$. The first is through the correlation between individual specific unobserved heterogeneity(η_i) and initial poverty(p_{it_i}). Based on the balanced portion of the data,the solution to this problem is addressed in the literature (Cappellari and Jenkins,2004; Wooldridge,2005;Heckman,1981). The second is due to the fact that different individuals join the sample at different time (t_i). Individuals can be grouped into sub-sample according to their starting time. The variance of distribution of the unobserved heterogeneity is assumed to be different across sub-samples and the random parameter(δ_{S_i}) is estimated for each sub-sample. Unless the process is not dynamic (i.e it is steady state since period t=0),different starting periods(t_i) may cause endogeneity. The third correlation between S_i and η_i arises when the total number of periods (T_i) differ across individuals. The specific period in which person i joins the sample is irrelevant. In deed, one can consider differences in T_i and t_i simultaneously. One can construct sub-samples based on different combinations of T_i and t_i. In our data, all individuals join the sample at the same time, t_i=1, where 1 corresponds to the year 2005/06 in our data and hence endogeneity does not not emerge because of the correlation between S_i and η_i through t_i. Rather, we examine the possibility of endogeneity through the correlation between S_i and η_i due to T_i. There exists different

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

parameters for each sub-panel. The joint density for the dynamic discrete model is given by:

$$Pr(s_{i1}p_{i1}, s_{i2}p_{i2}...s_{iT}p_{iT}|X_i, S_i) = \{\prod_{t=2}^{T_i} Pr(p_{it}|p_{it-1}, X_i, S_i)\}Pr(p_{i1}|X_i, S_i) \tag{11}$$

Assume that the conditional density of the first observation ($Pr(p_{i1}|X_i, S_i, \eta_i)$ follows a normal distribution, the joint probability in eq(11)can be re-written as:

$$Pr(s_{i1}p_{i1}, s_{i2}p_{i2}...s_{iT}p_{iT}|X_i, S_i) = \int_{\eta_i} \{\prod_{t=2}^{T_i} Pr(p_{it}|p_{it-1}, X_i, S_i, \eta_i)\}Pr(p_{i1}|X_i, S_i, \eta_i)f(\eta_i|X_i, S_i)d\eta_i \tag{12}$$

Heckman(1981) dispensed the assumption of independence between p_{i1} and η_i and proposed a linearized reduced form equation for the initial latent poverty propensity as:

$$p_{i1} = 1[p_{i1}^* = \delta_{S_i}z_{i0}^{'} + \theta_{S_i}\eta_i \geq u_{i1}] \tag{13}$$

where $z_{i0}^{'}$ is a vector of exogenous variables which are not correlated with u_{i1}. Both u_{it} for $t \geq 2$ and u_{i1} follow the same normal distribution($u_{it} \sim N(0,1)$). For $t \geq 2$,the random effect model implies equi-correlation of the composite error($v_{it} = u_{it} + \eta_i$) between any two different periods. Thus, the conditional density for the initial poverty is given by: $Pr(p_{i1} = 1|X_i, S_i, \eta_i) = \Phi(\delta_{S_i}z_{i0}^{'} + \theta_{S_i}\eta_i)$. The dynamic part for the remaining periods also follow similar parametric form as u_{it} for $t \geq 2$ is normal. It is written as: $Pr(p_{it} = 1|p_{it-1}, X_i, S_i, \eta_i) = \Phi(\gamma_{p_{it-1}} + \beta x_{it}^{'} + \eta_i)$. In the Heckman model,however,unbalancedness, S_i, is independent of individual specific unobserved heterogenity, η_i. It means that $Pr(p_{i1} = 1|X_i, S_i, \eta_i) = Pr(p_{i1} = 1|X_i, \eta_i) = \Phi(\delta z_{i0}^{'} + \theta\eta_i)$. Note that $z_0^{'}$ includes all $x's$ in the first period and additional exclusion restriction variables such as region dummies. Now, we present the updated version of the Heckman model that allows for correlation between S_i and η_i. The likelihood to be maximized is given as follow:

$$L = \prod_{i=1}^{N} \int_{\eta_i} [\Phi(\delta_{S_i}z_{i0}^{'} + \theta_{S_i}\eta_i)(2p_{i1} - 1)\{\prod_{t=2}^{T_i} \Phi(\gamma_{p_{it-1}} + \beta x_{it}^{'} + \eta_i)(2p_{it} - 1)]\}f(\eta_i|X_i, S_i)d\eta_i \tag{14}$$

Thus, the conditional density for individual effect becomes:$\eta_i|X_i, S_i = \eta_i|S_i \sim N(0, \sigma_{\eta S_i}^2)$. Eq(14) is estimated using simulated maximum likelihood as the integral is evaluated using GHK simulator. Wooldridge (2005)propose another estimator for the initial condition problem. Wooldridge re-formulate the first term of eq(11) using Bayes probability formula and using the assumption that p_{it} for $t \geq 2$ is uncorrelated with unobserved heterogeneity. Thus, for $t \geq 2$, it is possible to write as: $Pr(p_{it}|p_{it-1}, X_i, S_i) = Pr(p_{it}|p_{it-1}, X_i, S_i, \eta_i)f(\eta_i|p_{i1}, X_i, S_i)$.

Wooldridge (2005) specifies an approximation for the density of individual effect η_i conditional on the initial period poverty. According to him, $f(\eta_i|p_{i1}, X_i, S_i) = f(\eta_i|p_{i1}, X_i) \sim N(\alpha_1 p_{i1} + \alpha_1\overline{x_i}, \sigma_\eta^2)$. Instead, we include unbalanced observations in the estimation and dispense the assumption of independent between individual effect and unbalance-deness. As a result, the density of η_i conditional on the initial observation depends on different random parameters. Following Chamberlain(1984),the longitudinal averaged variables derived for each individual are included as additional regressors just to capture the correlation between explanatory variables and individual specific heterogeneity

(Rabe-Hesketh and Skrondal,2013). The joint density for observed sequences of the dependent variable in the updated version of Wooldridge is given by:

$$Pr(s_{i1}p_{i1}, s_{i2}p_{i2}...s_{iT}p_{iT}|X_i,S_i) = \int_{\eta_i} \{\prod_{t=2}^{T_i} Pr(p_{it}|p_{it-1},X_i,S_i,\eta_i)\}h(\eta_i|p_{i1},X_i,S_i)Pr(p_{i1}|X_i,S_i)d\eta_i \tag{15}$$

Since $Pr(p_{i1}|X_i,S_i)$ does not depend on η, we can omit it from eq(15). Since sample selection S_i is correlated with η_i, an approximation for the conditional density of individual effect is given by: $\eta_i|p_{i1},X_i,S_i \sim N(\alpha_{1S_i}p_{i1} + \alpha_{1S_i}\overline{x_i}, \sigma^2_{\eta S_i})$. Or this can be specified as: $\eta_i|S_i = \alpha_{1S_i}p_{i1} + \alpha_{1S_i}\overline{x_i} + a_i$ where a_i is a mean zero unobservable term uncorrelated with initial poverty. Specifically,the new individual effect is a normal random variable: $a =\sim N(0, \sigma^2_{\eta S_i})$. and its density function is $f(a) = \frac{1}{\sigma_{\eta S_i}}\phi(\frac{a}{\sigma_{\eta S_i}})$. For each sub panel constructed based on S, different random parameters(σ_η) are estimated. Finally, the likelihood function to be maximized is written as:

$$L = \prod_{i=1}^{N}\int_{\eta_i}\prod_{t=2}^{T_i}\Phi[(\gamma_{p_{it-1}} + \beta x'_{it} + \alpha_{1S_i}p_{i1} + \alpha_{1S_i}\overline{x_i} + a)(2p_{it}-1)]f(a)da \tag{16}$$

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, $corr(v_{it},v_{is}) = \lambda = \sigma^2_\eta/(\sigma^2_u + \sigma^2_\eta)$,for $t \geq 2$ and $t \neq s$. σ^2_u 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}):

$$\begin{aligned} s_{it} = pr(p_{it} = 1|p_{it-1} = 1, \beta x'_{it}) = \Phi[(\beta x'_{it} + \gamma) * (1-\lambda)^{0.5}] \\ e_{it} = pr(p_{it} = 1|p_{it-1} = 0, \beta x'_{it}) = \Phi[(\beta x'_{it}) * (1-\lambda)^{0.5}] \end{aligned} \tag{17}$$

$\frac{1}{(1-\lambda)^{0.5}}$ 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.

3.5 Estimation results and discussion

3.5.1 Testing the validity of joint estimation

We have estimated the random effect dynamic model and endogenous switching regression. We first offer and discuss the results of the latter model in order to investigate the relevance of estimating simultaneously the three tiers of the model as well as to examine the determinants of poverty persistence and entry rates. If all unobservable individual effects are uncorrelated, then one can estimate the probit model for initial, transition and retention equations independently. The validity of the model and the implication of the estimated coefficients on the dynamics of poverty will be discussed. In particular, the key objective is to disentangle the state dependence and heterogeneity effects from the aggregate poverty so that a specific policy issue can be recommended. To start with, the validity of exclusion restriction has been tested and reported in table 6. 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 , we use the binary variable that indicates whether the head of the household has lived another location for more than 6 months at a time since 2001 til 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 or changing the original place of residence for unintended period are 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, past experience of individual mobility can 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 condition 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 the majority of rural households rely on a single economic activity (i.e farming). Instead, we use whether the head had lost his parents (mother or father) or not as a predictor of initial poverty status.

Table 6 reports that the death of mother 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. We find that 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 in the initial poverty and retention equations. ρ_1 is positive and statistically significant suggesting that those who are poor at t-1 are more likely to be observed in two successive periods (i.e both at t-1 and t) compared to the non-poor individuals. The high attrition propensity of the non- poor may imply that the non-poor are actually less represented in the sample. This underestimates the national headcount ratio if the balanced data is used by ignoring unbalancedness. Using data drawn from urban households in Kenya, Faye et al.(2011) show that the poor have higher retention propensity compared to non-poor, a finding similar to our rural households from Uganda.

Cappellari and Jenkins (2002,2004) use urban household data from UK and rather find that initially poor households have lower retention propensity compared to initially non-poor households. From the perspective of rural studies, to the extent of my knowledge, this paper is the first to give empirical evidence on poverty transition and endogenous sample selection. Nevertheless, empirical evidence can vary from country to country and from rural to urban even within the same country. In particular, the majority of people in poor African countries resides in rural area and factors that affect their living standard are not the same as that of the urban counter part. A full-fledged evidence requires a separate analysis of urban and rural households on the main correlates of poverty and their selection mechanisms. However, due to small sample size for urban households in our data, we offer empirical results for the whole sample and rural households separately. Given the large sample size of rural households and our interest to find the causal impacts of some variables on rural poverty, a through discussion is devoted to rural households.

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. Even if individuals are not observed at t, the model can predict the poverty persistence and entry rates for those who are observed in $t-1$. Since ρ_1 is positive, poor households at $t-1$ are more likely to remain in the sample. In addition, the positive sign of ρ_2 suggests that non-attriting individuals have higher propensities to fall into poverty or remain as poor.

These two evidences suggest that sample attrition is not random because it affects both initial poverty and conditional current poverty. In other word, since ρ_1 and ρ_2 are both separately and jointly different from zero,the unobservable individual effect in the retention equation is significantly correlated with unobservables in both initial poverty and poverty transition. Thus, sample retention is endogenous and should not be ignored. 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 unobserved individual effects determining poverty transition. The sign of the coefficient implies that initially poor are more likely to escape poverty, indicating 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).

The exogeneity tests for initial condition and panel retention are offered in table 6. The 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 taken into account while modeling poverty dynamics and the three equations (initial,retention and poverty transition) should be estimated simultaneously.

3.5.2 Estimated parameters from endogenous switching regression

Table 7 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 7. The estimates for retention and initial condition are presented in column 1 and 2 respectively.

Concerning the impacts of explanatory variables on poverty transition, we find that variables that affect poverty persistence are also variables that affect poverty entry rates. 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 the extent by which 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 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. Having secondary and primary education increases the chance of being out of poverty and/or reduces the propensity of falling into poverty. Education is seen to be vital in the aim to fight against poverty. Education improves the poverty status of individuals by preventing them from entering into poverty or by offering them an opportunity to exit poverty. As part of human capital, education is deemed to be an important variable to reduce poverty (Schultz,1975)

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 7.

For a sustained economic growth, first and foremost, political stability must be a pre-requisite 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 war in Ethiopia since 1984 til 1991; in Rwanda in 1994 and in Sudan after 1983, displaced thousands from their home and also caused hunger and death. Civil conflicts also appeared in Uganda, especially in the northern part of Uganda since 1990's. 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, we use the civil strife information from 2001 as a predetermined variable to explain 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. Deininger (2003) finds that civil strife reduces investment and non agricultural economic activities because it affects individual's decisions to invest or not. We find that civil strife tends to increase the risk of being poor. The estimated parameter is positive and statistically significant in poverty transition and initial poverty equations suggesting that civil strife is a serious handicap that keeps households in poverty or causes them to fall into poverty. 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 poverty. Concerning the effect of age composition in the household, the proportions of male and female adult members (age 15-65) in the household have discernible impact in mitigating poverty. The household members in this age bracket are rather less dependent and economically more productive. This is intuitive in the sense that most of the rural activities are labor demanding that requires physical strength of individual members and as a result, the relatively young household members are more productive due to their physical fitness for such laborious jobs including ploughing agricultural land (preparing the soil for cultivation),planting trees used for terracing and sowing seeds and harvesting crops in the appropriate time . Our empirical result suggests that as the proportion of adult members increases, the propensity to fall into poverty decreases significantly. These variables are significant determinants of poverty persistence and entry rates.

Previous research in Uganda (e.g. Andrews et al.,2014) has tested the efficiency of intra-household allocation of female and male labor inputs in agricultural production. They use male headed household having one or more spouses. For each plot,the amount of the husband and wife's time spent are recorded where as the output is recorded for each crop. They assume that output per acre is the same for all household,which helps to derive time spent for each crop and plot. Using the 2005/06 Ugandan survey data, they calculate the marginal rate of technical substitution between the labor inputs by the husband and wife across different crops. They find that males are productive than females and hence optimal labor input requires that males should own female-controlled plots where as females should use male controlled plots. Instead, we study the impacts of the different age composition of intra-household members and their heterogeneous labor market status on household poverty.

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 though which productivity is affected. We argue that having TV-radio tends to 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 besides other factors of production like land, labor and capital. News about pre-prevention of adverse shocks can also be transmitted through public and non-public channels in order to create awareness for the society at large. Through radio and TV, the daily prices of some major agricultural products at different towns can be disseminated and help farmers to take advantage of lower marketing margin. Moreover,the transaction cost of selling agricultural output or buying agricultural input could be reduced substantially if farmers get reliable information through electronic devices such as tvradio and mobile. Our empirical result suggests that those who have TV-radio are less likely to entering poverty as well as are less likely to persist in poverty compared to those without. The fact that the consumption flow from TV and radio is itself included in the computation of total consumption expenditure does not affect the statistical and economic importance of the variable on household poverty. To start with, the share of expenditure ascribes to TV-radio in our data is meager.

To test the robustness of the result, we remove the part of the consumption flow associated to TV-radio from aggregate consumption expenditure and re-estimate the model to see the impact of owning this asset on poverty transition and initial poverty. We find that the sign and statistical significance of the estimated coefficient remains unaltered. Based on the result, we recommend public intervention to invest on information technology by expanding coverage and reliability of all state owned medias. Government should also encourage private investment on electronic devices such as TV-radio and mobile which help to enhance communication and exchange of ideas among rural households. TV-radio and mobile can serve as consumption and production good. 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.

The impact of covariates on initial poverty and retention are offered in table 7. 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 in transition probability model. In fact, several of our parameters are significant compared to the percentage of significant parameters established in their papers. They explain the possible reasons for this weak effect as follow. First ,accounting for the endogeneity of both initial condition and panel retention may affect the precision of estimates in the poverty transition. The other possible reason for the weak effect may be associated to the size of the sample used to estimate conditional current poverty. The poverty persistence is estimated based on those who were poor in the base year while the poverty entry uses the base year non-poor individuals. 38 percent of individuals are poor in the base year while the remaining 62 percent are non-poor.

We find that variables that affect poverty persistence and entry resemble the same. This finding looks appealing from the perspective of designing policy. Because these variables are important not only to reduce poverty but also prevent individuals from slipping into poverty in the first place. The key policy variables in this regard, as mentioned above, are education and increased access to news and information (ownership of radio and TV) and civil strife. By eliminating the root causes of civil strife, government can break the cycle of poverty.

As reported in table 7, 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 tvradio and mobile phone are crucial variables that decrease the propensity of being poor in the initial period. Low poverty risk in the base year is also observed among households having higher fraction of older members (above 64). This seems to be counter-intuitive as older people are not productive. However, land allocation and re-distribution in rural areas are based on age and some village specific traditions (e.g land inheritance from grand father/mother when they die). It is more likely that older people may hold more acres of land compared to young individuals.

Though we have variables that reduce the chance of initial poverty, there are also variables that increase the likelihood of initial poverty which inter alia include civil strife, drought,and number of children below 14. In deed, the unemployed variable,used to capture dependency ratio, includes not only children below 14 but also other household members aged above 14 such as pensioners,and other dependents who are not participating in any paid and unpaid economic activities. These household members may not have sufficient resources (labor,land,capital) to contribute to household production, making them less productive. Family planning policy should 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 and thereby poverty. We find that households who experience drought in 2001 are more likely to be poor than those without. Adverse weather shock is often a serious problem in rain feed agricultural economy. 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.

Concerning the determinants of panel retention, we find that those married and those with access to all weather road as well as to 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. Married individuals appear to have a higher chance to stay in the sample. Though there are other factors for non-response, permanent migration for the couples may be too costy due to the presence of gender specific work divisions in rural farming which imply that some plots are male-controlled while other plots are female controlled. The spouse is mostly housewife and taking care of children and spending the rest of her time on home production. The husband is spending large portion of his time on agricultural plot to cultivate,sow seeds and harvest crops. Rural-urban wage differential can make migration a natural choice and yet,couples may not be responsive.

Concerning the impact of mobile phone, the finding suggests that those who own mobile are more likely to remain in the 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 dependents 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. The result suggests that attrition overestimates the poverty persistence by about 2 percent,albeit the figure seems to be small. In other word, poverty persistence for those leaving the sample between t-1 and t is less than the population average persistence poverty.

Similarly, one can ask whether attrition underestimates the poverty entry rates or not. After computing the probability of falling into poverty conditional being non-poor at t-1 (using γ_2) for each individual, these predicted probabilities are averaged separately over the balanced sub sample or over the whole observations observed at t-1. The poverty entry rates are respectively found to be 0.205 and 0.16 for the balanced observations and entire observations that include attritors. By excluding attritors, the poverty entry and persistence rates are overestimated by about 4 and 2 percent respectively. The latter finding is consistent with Cappellari and Jenkins (2004) who find negligible impact of attritors on average poverty propensity.

3.5.3 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) is examined based on the null hypothesis of no differences in the estimated parameters obtained from poverty persistence and entry rate equations. When $\gamma_1 = \gamma_2$, there is no genuine state dependence. In this case, the difference between the poor and non-poor is just explained 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 6 in panel D). Table 8 presents the size of aggregate state dependence (ASD) ,true state dependence and heterogeneity effect. Note that ASD is computed based on eq(10) using raw poverty transition rates while the true state dependence (TSD) is derived from eq(9). Heterogeneity effect of persistence poverty is obtained as the difference between ASD and TSD. ASD is estimated to be 26.1% based on the whole observations at t-1.[14]. This implies that those who were poor at t-1 have 26.1% more chances to be poor at t compared to those who were non-poor at t-1.

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 individual 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

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

may have different future poverty outcome as the person who experiences poverty may develop unfavorable attitudes that lead to persistent poverty. True state dependence is obtained by removing the effect of heterogeneity from the aggregate state dependence, which is estimated to be 30.8%. On average, heterogeneity explains 27.2%(0.07/0.308) of the aggregate state dependence where as the part of poverty persistence ascribed to true state dependence (TSD or GSD is interchangeably used) is 71.8%(0.187/0.308) as shown in table 8. Using observations available both at t -1 and t, GSD and heterogeneity are estimated to be 19.6% and 11.2% respectively and their shares in aggregate state dependence stand to be 63.5% and 36.5%. Generally, attritors have below the population average poverty persistence rate, poverty entry rate and true state dependence. We conclude that TSD accounts for a substantial part of ASD and as a result 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 in the literature. Heterogeneity explains 50% of the aggregate state dependence in Biewen (2009) ; 40% in Cappellari and Jenkins (2004) and 22% − 24% in Nilsson (2012). These studies use urban households from advanced countries while we use rural household from poor African country, Uganda. Using urban household from Kenya, Faye et.al (2011) show that heterogeneity explains only 10% of the poverty persistence. Using urban households from Ethiopia, Azomahou and Yitbarek (2015) find that 75% of the poverty persistence was due to heterogeneity. Our finding from Uganda lies between the two extreme values obtained by Azomahou and Yitbarek (2015) and Faye et.al (2011). As shown in table 8, heterogeneity effect is 36.5% when calculated using sample respondents present at t-1 and t while it is 27.2% when calculated using all sample respondents available at t-1.

Alternatively, ASD can be computed based on the predicted probabilities of poverty entry and persistence. It is the difference between the predicted probability of poverty persistence averaged over those who were poor at t-1 and the predicted probability of poverty entry averaged over those who were non-poor at t-1. ASD is estimated to be 0.295 using the whole observations at t-1 and it is 0.301 when calculated using observations presented at t-1 and t. 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. In the latter case, the share of TSD in ASD has been estimated as 63.6% and 65% respectively for respondents presented at t-1 and respondents available both at t-1 and t. Using both attiting and non-attriting observations, the true state dependence explains 63.5%-71.8% of the aggregate poverty persistence in rural Uganda.

3.5.4 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, we also estimate the Wooldridge (2005) model to determine the level of TSD. The aim of this study is to establish whether there exists a genuine state dependence effect or not. Estimating different models under different assumption helps to understand the robustness of the TSD effect. We present the estimation results based on the standard Wooldridge (2005) model that uses the balanced sub-sample of the four waves as well as the results from this version of the model that allows for not only unbalanced data but also the correlation between unbalancedness and unobserved heterogeneity. Woodridge(2009) propose correlated random effect models for unbalanced data but that can not be directly applied for dynamic models. Using simulated maximum likelihood method, we estimate the Heckman and the Wooldidge models for unbalanced data. Eq(16)is estimated for the Wooldidge model while eq(14) is for the Heckman model. Instead of including all individuals aged above 14 in the model, which is the case in endogenous switching regression, the head of the household is taken as a unit of analysis in the Wooldrige (2005) and Heckman (1981) dynamic random effect models. This reduces the computational burden. Lagged poverty, household level characteristics and own characteristics of the head are included as explanatory variables.

We start with estimating the random effect probit(RE) model that assumes exogenous initial condition. This is reported in the second and third columns of table 9. The random effect model also assumes equicorrelation of error terms for different periods(say $u_t = \alpha + \varepsilon_t$, with $\alpha \sim N(0, \sigma_\alpha^2)$ and $\varepsilon \sim N(0, \sigma_\varepsilon^2 I_T)$. This leads to $cov(u_t, u_s) = \sigma_\alpha^2 + \sigma_\varepsilon^2$ if $t = s$ and σ_α^2 if $t \neq s$). u_t is the composite error while α is time invariant individual specific unobserved heterogeneity and ε_t is white noise error. We dispense the equi correlation assumption and rather allow the covariance structure to be unconstrained except that the variance at first period is normalized to be unity for identification. The estimated parameters are reported in the third column of table 9. The second column is a RE model under restricted covariance structure while the third columns 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.

Assuming exogenous initial condition in random effect probit model is, however, a strict assumption. Initial poverty may be endogenous unless the stochastic poverty process coincides with the year in which the first survey is conducted. The solution to initial condition problem was first proposed by Heckman (1981) and latter by Wooldridge (2005). Cappellari and Jenkins (2002,2004) propose an endogenous switching regression model for the similar problem and they allow for the possibility of endogenous panel retention which was considered as exogenous in original Heckman (1981) and Wooldridge (2005) models. All models (Heckman,1981; Wooldridge,2005 and Cappellari and Jenkins,2004) permit us to decompose aggregate poverty persistence into true state dependence (TSD) and heterogeneity effect. The coefficient associated to the lagged dependent variable is a measure of TSD in Heckman and Wooldrige models. For all models, the aggregate poverty persistence is obtained from eq(10). The fourth and fifth columns in table 9 offer the estimated parameters of the Wooldridge models respectively for the balanced data and unbalanced data.

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 9), 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 9, 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 average partial effect for the lagged coefficient, which is the natural measure of the size of genuine state dependence, is calculated based on equation(17) 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%. Both the Wooldrige and Heckman conventional random effect models consider the selection on unobservables, yet 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 does not significantly change the APE, which becomes 0.061 to the former. Based on the Heckman estimator, Stewart (2007) computes the average partial effect for the coefficient of lagged unemployment using the 6 waves British Household Panel Survey. They find a substantially low APE, which is 0.035. In their study of persistence in social assistance receipt in UK, Cappellari and Jenkins (2008) apply the Heckman estimator to calculate the APE of the lagged receipt to be 0.144. Depending on the different types of sample selections they consider, the APE falls to 0.037 which is consistent with the Stewart estimator. Though all these authors use different data for different use, we all apply the same methodology which helps us study persistence in economic phenomenon.

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. Given the aggregate state dependence effect of 45 percent in their data, they find that almost 50 percent (0.22/0.45) of the observed poverty persistence is accounted for by APE of the lagged poverty. Given the aggregate state dependence effect of 26 percent in our data, the APE accounts for 23% (0.61/0.26) of the poverty persistence. 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 have been controlled for using a simultaneous random effect model. Though not in a strict sense of causality,the APE in our paper is of suggestive of directional effect for the rural sub-sample even without jointly capturing the three process. The argument that past poverty can affect the risk of future employment has little relevance in the study of rural poverty for African countries as households are employed in a single farming activity. The current fertility decision is also more of exogenous in rural areas of the same continent and is less likely to be affected by the past poverty status of an individual.

Our intuitive understanding on this issue is supported by an empirical study by Kedir et al.(2005) for Ethiopia ,a country structurally similar to Uganda. Kedir et al. (2005) and Biewen (2009) use similar models except that the former use the 3 waves household panel surveys drawn from urban and rural Ethiopia and jointly model poverty and fertility. Kedir et al.(2005) find that lagged poverty has no significant effect on childbearing event in the rural sub-sample, suggesting no causal feedback effect from poverty onto childbearing. Our paper considers endogeneous attrition but not by Biewen (2009 and Kedir et al.(2005), which we believe is important as attritors are found to have below the population average poverty persistence probability in this study. Finally, it must be noted that there is no problem of endogeneity from lagged poverty in the case of endogenous switching regression. Though it controls for individual specific unobserved heterogeneity,however, its exactitude is not clear.

Our estimates of APE are generally larger than APE established by Stewart (2007) and Cappellari and Jenkins (2008) who use the Heckman estimator. Even after controlling for the observed and unobserved individual differences in characteristics, the risk of being in poverty in a year is noticeable (by about 13.4%) if poverty has been experienced in the previous year. Based on the Wooldrige model, past poverty is associated to 7 percentage points higher chance of current poverty. As shown in table 8, the raw transition probabilities of poverty persistence and entry are 46.96 and 20.85 percent respectively and the difference between the two (26.1%) is the aggregate state dependence. TSD accounts for 23% (0.061/0.261) of the aggregate persistence in poverty probability.

Arulampalam et al. (2000) calculate the APE for those younger than 25 and for those above 25. For young men, they find that 20% of the aggregate state dependence in unemployment dynamics is attributable to true state dependence. In their study of social assistance dynamic, Cappellari and Jenkins (2008) find that the share of TSD in the aggregate state dependence was 23% (0.144/0.63). Our finding in study of poverty persistence based on the Wooldrige model resembles the same with the findings of these authors in unemployment and social assistance dynamics. The Heckman estimator in our model, however ,gives larger share of TSD, which is 43.5% of the total poverty persistence probability. Though the magnitude of APE varies between the endogenous switching regression and random effect dynamic probit models, as is the case in other studies (Stewart,2007; Cappellari and Jenkins,2004,2008), this paper provides evidence for the presence of true state dependent effect in our data. We conclude 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 initial condition.

As we move from an estimator that uses the balanced sample to an estimator that uses the whole observations (attritors and non-attritors), the coefficient associated past poverty declines, suggesting that those who quit the sample have a lower poverty persistence. This is inline with what we find when estimating the endogenous switching regression model. We allow for the dependence structure between those who left out the sample and individual specific unobserved heterogeneity. For instance, those who present in three survey rounds might have different unobserved characteristics compared to those presented in all survey rounds (four waves in our case). For each sub-sample , the variance of unobserved heterogeneity (σ_η^2) has been estimated. These variances are significant suggesting that unbalancedness is correlated with unobserved heterogeneity and hence panel retention is an endogenous process, a finding consistent with the endogenous switching regression. The magnitude of state dependence , as measured by the average partial effect, stands to be 0.061. The APE effect in the case of unbalanced data is not significantly different from the APE effect from the balanced data.

Turning to the Heckman estimators in the last two columns, the parameter θ, which shows the strength of correlation between initial poverty and individual specific unobserved heterogeneity, is statistically significant. The effect of lagged poverty tends be indistinguishable between between balanced and unbalanced panels. Both the Wooldridge and Heckman estimators share many significant variables except that the proportion of paid household members engaged in off-farm activities is a significant predictor of current poverty in Heckman model but not in Wooldrige. 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 disable household members increase the risk of being poor.

3.5.5 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, we use the four waves panel data: 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 with 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 our 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, we choose the data with equal distance between rounds. We use 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. We re-estimate the endogenous regression model with the same set of exclusion restrictions and same set of explanatory variables[15] so that we can see the impact of changes in data set. The exclusion restriction variables are still significant in retention and initial poverty equations but not in the transition equations and this is what the instruments must satisfy and also holds in the four rounds survey. For instance, none of the parental background (death of mother and father) and past mobility experience in 2001 are individually or jointly significant in the transition equations. The 3 and four rounds of panel survey share many significant variables(the result is reported in table 11). Though small difference exists, the three rounds panel qualitatively and quantitatively mimics the findings of the four waves panel in all aspects we consider in the previous section.

It is of the paper's objective to estimate the share of true state dependence in this three rounds equal gap data and compare it with an estimate from the four survey rounds. Table 10 offers the raw transition poverty persistence and

[15]except that information on disable household members is not available in 2013

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. We conclude 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. Rural households are indeed 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 they are one fourth of the total sampled households in 2005/06. Table 6 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.

3.6 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 four waves panel household. We find 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. We decompose this aggregate poverty persistence into a part due to household heterogeneity in observed and unobserved characteristics and a part due to true state dependence.[16]

For the first time, this paper distinguishes the heterogeneity and true state dependent effects of the observed poverty persistence in Uganda. I apply the 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

[16]there are 2 possible reasons why an individual experience poverty permanently (Biewen,2014). The first could be that an individual may have durable characteristics that make him prone to poverty at a given time. Some of these characteristics are observed while others not (like motivation,laziness). The second reason for poverty persistence is true state dependence. Slipping into poverty in one period increases the propensity of being poor in the future. There is a direct dynamic effect from past poverty into future poverty even after controlling for observed and unobserved differences in individual characteristics. This may occur because of social exclusion, demoralization,and depreciation of human capital. The objective of this study is to determine the poverty persistence accounted for by true state dependence, not to identify the channels through which TSD arises.

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. This finding has been carefully compared with the findings of other authors who study economic persistence in different fields such as unemployment ,social assistance; low pay dynamics and poverty dynamics (see the discussion section). Our finding based on random effect model with endogenous initial condition is consistent with the findings from Arulampalam et al. (2000) and Cappellari and Jenkins (2008). Using endogenous switching regression method, several authors (Faye et al,2011; Cappellari and Jenkins,2004; Nillsson,2012) find that more than 50% of the observed poverty persistence is attributable to the effect of true state dependence. We conclude that 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. During time of low consumption, households often sell key productive assets (like oxen) or get credit from friends, relatives and extended family (like shared accommodation) as a response to smooth consumption. 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. [17] 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 maximize the personal gain or involve in rent-seeking activities. In other word, good governance is the key source of development. The World wide governance indicators that have been published in the World Bank website are of 6 types: rule of law; voice and accountability; control of corruption; regulatory quality; government effectiveness and political stability and lack of violence. In particular, civil unrest and political

[17] this has been reviewed by Dercon (2002,2005) for Ethiopia

instability bring significant impediment to the formation of human and social capital. In the presence of civil strife, households can refrain from making investment on education, land improvements and non-farm activities. Since we have household and community level information on the incidence of civil strife, our switching regression suggests 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. Having married increase the risk of poverty as we find that married individuals 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 variables 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.

As discussed above, we find that households inflicted by past poverty are more likely to persistent in poverty than those without. Part of this persistence ascribes to true state dependence and the other part is attributable to heterogeneity. Since the latter effect is atleast 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.

Appendix 3: Regression Tables

Table 3.6: 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 3.7: 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 3.8: 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 3.9: Dynamic panel data models: the Wooldrige's and Heckman's estimators for balanced and unbalanced data

	RE[1]	RE[2]	WCM[3]	WCM[4]	Heckman[5]	Heckman[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 education	-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 education	-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 between 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 between 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 members	-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 members	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 phone	-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***		

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Table 3.9 – continued from previous page

	RE	RE2	WCM	WCM2	Heckman	Heckman2
				(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

[1] is the standard random effect dynamic probit with exogenous initial condition [2] as is in 1, but dispenses the assumption of equi-correlation of the composite errors [3] is the Wooldridge conditional maximum likelihood with endogenous initial condition. It uses observations presented in all rounds [4] is as in 3, yet, it also includes observations appearing in three rounds. Here, unbalancedness is also assumed to be correlated with unobserved individual specific heterogeneity(u_i).

[5] is the Heckman estimator with endogenous initial condition using observations available in all rounds.

[6] is the Heckman estimator with endogenous initial condition, which uses observations available in three or four rounds. It assumes that unbalancedness is independent of u_i. I have re-estimated the model by relaxing this assumption and we find that APE (average partial effect of the lagged poverty) is the same as in 5 because the coefficients of the lagged poverty are indistinguishable. Since the computation time is extremely huge for the Hekcman estimators, I drop some of the variables such as age and sex, which are actually insignificant. Regional dummies are taken as exclusion restrictions and they are included only in the initial poverty equation. The estimates of the initial poverty equation are not reported here,just for space reason. In addition, the estimates of time averaged variables for the time varying ones,which include dependency ratio(or unemployed members)and TV-radio, are not reported though they are estimated in all models(in 1-6). The average does not include the first observation and the later is also included in the model (see Rabe-Hesketh, S., and A. Skrondal,2013). As in Chamberlain(1984), these variables may capture some of the correlation between explanatory variables and unobserved individual heterogeneity.

Table 3.10: 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 (2005-2011)	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 (2005,2009,2013)	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

Table 3.11: Sensitivity test using endogenous switching regression for rural households based on 2005,2009 and 2013 rounds.

	Retention	**Intial Poverty**	**Poverty persistence**	**Poverty entry**
Indvidual characterstics				
Sex(male=1)	0.2401***	0.0507*	–0.1031*	–0.0517
	(0.0234)	(0.0302)	(0.0538)	(0.0445)
Marital status: Married	0.4916***	0.0141	–0.2008***	–0.2957***
	(0.0248)	(0.0298)	(0.0608)	(0.0523)
Some primary school	0.0439	–0.1310***	–0.2542***	–0.0750
	(0.0336)	(0.0410)	(0.0673)	(0.0631)
Secondary school and above	0.1786***	–0.4531***	–0.4964***	–0.4237***
	(0.0405)	(0.0509)	(0.1063)	(0.0793)
% older male members($>$ 64)	–0.0723***	–0.0981***	–0.0297	0.0023
	(0.0171)	(0.0164)	(0.0340)	(0.0250)
% older female members($>$ 64)	0.0039	–0.1035***	–0.0292	–0.0540**
	(0.0142)	(0.0173)	(0.0372)	(0.0220)
% male adult members(15-65)	–0.0494***	–0.0672***	–0.0143	–0.0177
	(0.0076)	(0.0082)	(0.0174)	(0.0122)
% female adult members(15-65)	–0.0096	–0.0744***	–0.0591***	–0.0549***
	(0.0092)	(0.0102)	(0.0210)	(0.0143)
Number of unemployed	–0.0266***	0.0550***	0.0298*	–0.0008
	(0.0066)	(0.0071)	(0.0153)	(0.0149)
Ownership of mobile	–0.5492***	–0.5167***		
	(0.0315)	(0.0354)		
Ownership of TV radio	–0.0475*	–0.4748***	–0.2150***	–0.1310**
	(0.0272)	(0.0295)	(0.0788)	(0.0629)
Civil Strife	–0.0162	0.4430***	0.3676***	0.1434*
	(0.0369)	(0.0485)	(0.0883)	(0.0819)
Drought	0.0096	0.0770***	0.1066**	0.0858**
	(0.0218)	(0.0278)	(0.0500)	(0.0379)
Exclusion restriction				
Mobility experience of the head since 2001 till 2004)	–0.17**			
	(0.0484)			
Father deceased		0.0107		
		(0.0318)		
Mother deceased		0.1319***		
		(0.0325)		
Intercept	–0.0991*	0.3512***	1.1796***	0.8228***
	(0.0600)	(0.0705)	(0.1617)	(0.2725)

Note: Significance level: * 10%, ** 5%, *** 1%.

4 Quantifying The Real Poverty Transition in Uganda

4.1 Introduction

It is of interest in poverty literature to examine poverty as a longitudinal phenomenon in order to get useful insights underlying poverty dynamics as well as its importance to the development of social policy. All previous studies on poverty dynamics or consumption dynamics in Sub-Saharan Africa assume a direct correspondence between observed and true consumption expenditure by ignoring the possibility of having error ridden data in the consumption measure. This paper fills this lacuna by considering a separate treatment between a saturated structural model and a measurement model using the four waves panel data from rural households in Uganda. To avoid researcher induced errors in the consumption data, it has been carefully cleaned to fix possible errors using different techniques so that the data is of informative.

Some extant studies (Duncan and Hill, 1985; Cappellari and Jenkins,2004; Bound et al., 2001) argue that the impact of measurement errors on the average estimate is negligible even though there might be a high level of misreporting consumption at the individual level. This kind of argument is often used in many literature. Griliches and Hausman (1986) extensively discuss measurement error in panel data in the analysis of labor demand relationship but this approach is not suitable to analyze the poverty dynamics and the impact of measurement error on the transition into and out of poverty. Of course, the analysis of poverty dynamics based on observed data is not the only model that the data can support but there exists other alternative plausible model that permits to incorporate both the structural and measurement components (Breen and Moisio,2004; Pavlopoulos et al,2012; Rendtel et al.,1998).

These studies dispense the assumption of direct correspondence between measured poverty and true poverty. As a result ,it is possible to distinguish the amount of true changes in the data from spurious changes resulting from measurement error. The main contribution of this paper is to apply the existing Markov models for the first time in Uganda to examine the impact of measurement errors on poverty dynamics. Since we have unequal space data, the paper uses the latent class models, specifically the different versions of the Markov models. There may exist much mobility in and out of poverty but the true transition dynamics is not known unless we specify the three important models and estimate them simultaneously using the Expectation maximization (EM) and Baum – Welch Algorithm. The three model components are the initial condition, transition logit, and measurement error.

The thesis seeks to determine the extent of real mobility into or out of poverty because policy design depends on whether poverty is transitory or persistent. In the case of high mobility, policy that enhances consumption smoothing is relevant. In the presence of high immobility (i.e high poverty persistence), policies that increase the human capital and other productive assets of the poor are effective. This is the relevance of the study. In a simple probability transition matrix with a 2 X 2 dimension depicting two latent states (poor and non–poor), one can estimate the extent of true mobility or poverty persistence probabilities(as measured by the likelihood of a household to remain in that same state). The standard Markov considers the observed transition without considering errors in the data while the latent Markov models control for measurement error and depict the real transition. Our main research question is here : how large the poor is misclassified as non-poor? It is to quantify the percentage of households who are truly non-poor mis-classified as poor. This classification error in the measurement sub model arises from mis-classification in the consumption expenditure.

Another research question is to identify the determinants of true transition probability from having one state to another. The controls variables are education, land holding per adult, ownership of radio and TV, having mobile phone, and household composition. Does education help to increase the probability to transit from poor to non- poor state or does it keep individuals from slipping into non-favorable state from their favorable state? The paper finds that education, dependent ratio, ownership of mobile, ownership of TV-radio, adult members in the household and land size per adult are significant determinants of individual's poverty transition. This paper finds that measurement error actually exaggerates the mobility into or out of poverty. It overestimates the poverty persistence probabilities by at least 9%. Measurement error also attenuates the impacts of observed covariates on poverty transitions.

The organization of the paper is as follows. Literature on poverty dynamics, mobility and measurement error is presented in section 2. Section 3 and 4 respectively offer the data and the econometric methodology. Section 5 presents the estimation results and discussion. Section 6 concludes.

4.2 Literature

This section first discusses the theoretical underpinning of economic mobility and then illustrates the problems associated to empirical work on mobility. Analyzing the distribution of income or consumption expenditure at different points in time is more interesting than focusing on distribution at single point in time because long run outcome (inequality, poverty) is the object of concern. Inequality may be low using the long run-distribution of income than using the short run income because long run income is more likely distributed equally than its short run counterpart. Overtime, individuals can change their relative position in the short run distribution of income and this is the essence of economic mobility. If individuals who were at the lowest 25% of the income distribution several years ago are not located in that same position today, then poverty is not as such formidable to change.

High mobility implies more equitable distributions, which suggests that poverty is more of transitory than permanent. High mobility is characterized by having large consumption fluctuation (of poor and non-poor) from year to year, which reduces households welfare if they cannot smooth their consumption over those periods. In this case, the policy aim is to target the poor households in helping them smooth consumption by improving the operation of credit, and insurance and safety nets programs (Glewwe, 2012). In contrast, if mobility is low, individuals do not change their relative position in the initial period. In this case (the situation where poor remain poor and rich remain rich), poverty reduction policy should focus on increasing the human capital and productive asset (e.g. land) of the poor. Economic mobility is measured by comparing changes in the shares of consumption expenditure of individuals overtime and thus it refers to relative mobility. An economy that raises the consumption expenditures of all individuals by the same proportion does have zero mobility because the expenditure share, for each individual in the current period, does not change , which is that nobody changes his /her relative position in the consumption expenditure distribution (Shorrocks,1993).

Shorrocks (1993) summarizes the Atkinson-Bourguignon (1982) condition, which is an axiom that has to be satisfied by the relative mobility measure (presented in an intuitive example in Glewwe, 2012). Consider two persons in that the first is rich and the second is poor in both two periods. If the first person switches his income with a second person in one of the two periods, it happens that economic mobility increases. On the other hand, if the first switches his income with the second in both periods, there is no change in relative mobility because switching does not alter the distribution of income at a given period. The Atkinson-Bourguignon (1982) condition reflects the Pigou-Dalton transfer in the sense that the switch in the former equalizes the long run inter-temporal consumption whereas the transfer in the second just reduces inequality at a given point in time (Glewwe, 2012).

Several studies (Heise,1969; Gottschalk,1997; Baulch and Hoddinott,2000, Glewwe, 2012) estimate the extent of mobility using household panel survey on consumption expenditure. Mobility is defined as 1 minus the correlation of consumption/income overtime. Low correlation coefficient implies a higher degree of consumption fluctuation overtime and consequently a higher mobility into and out of poverty. However, the consumption data is more likely measured with error and this exaggerates the mobility rate. In the presence of measurement error, the true mobility is less than the measured mobility, obtained from the observed consumption expenditure. While Dragoset and Fields (2006) use the USA administrative employers record on earning to assess the extent of measurement error , this validation study is not relevant for the least developing economy with a large number of self-employed workers and even no good tracking for wage employees.

The consumption/ income dynamics that account for measurement error (using GMM or IV), has been estimated by few authors in the existing literature: for instance, Lee et al. (2017) for Korea; McGarry (1995) for USA; Fields et al. (2003) for Indonesia, South Africa, Spain and Venezuela: Antman and McKenzie (2007) for Mexico; and Gibson and Glewwe (2005) for Vietnam and Indonesia and Glewwe (2012) for Vietnam. Glewwe (2012) uses two years panel data and estimate the correlation coefficient of consumption expenditure between two periods with and without correcting for measurement error using instrumental variable method. He compares the measured mobility index (1-correlation coefficient) with that of the mobility index corrected for measurement error. He finds that at least 15% of the observed mobility is due to measurement error.

Gibson and Glewwe (2005) simulate error -free consumption expenditure under two alternative assumptions: 15% of the measured mobility is due to measurement error (lower estimate) and the upper estimate makes it 25%. According to them, households who remain in the same quintile increases from 40% in the reported data to 45% in the simulated data using the upper estimate. Though measurement error overstates the observed mobility, their result suggests that there still remains substantial mobility after correcting for measurement error. Glewwe's (2012) result based on body mass index as an instrument for lagged consumption is less appealing whereas the second measurement approach for IV requires more additional assumptions on the distribution of errors though it has the benefit of using the correlation of different components of expenditure as instruments instead of looking for external instruments. Of the several authors above, only few of them construct poverty transition matrix with and without the presence of measurement error in consumption data (McGarry ,1995; Gibson and Glewwe et al ,2005 and Lee et al. 2017).

Lee et al. (2017) first estimate a consumption dynamic model using difference GMM and then compute the residual term which contains time varying measurement error and random shock to consumption (white noise). These errors are assumed to be homoscedastic and normally distributed. The different lagged correlation structures of the residual term help identify the two variances associated to time-varying measurement error and white noise using minimum distance method to solve moment conditions. They simulate the error free consumption for the four periods (2002-2005) using all estimated parameters obtained from the dynamic equation including the variances of the two types of error. In the dynamic model, log of consumption lagged three periods and lagged measure of income satisfaction are used as internal and external instruments respectively and this drops two initial observations (year 2000 and 2001) from the dynamic equation. They simulate the error free initial values using a projection method. Finally, they compare the error free simulated consumption with that of the reported consumption expenditure in different ways such as by constructing poverty transition matrices and /or expenditure quintiles transition matrices. They find that time varying measurement error overestimates the observed poverty mobility into and out of poverty. The poverty persistence rate based on observed consumption increases from 56.5% to 68% using consumption that is corrected for error. Yet, the downward bias effect tends to be small when both types of measurement errors are controlled for (time vary and time invariant measurements errors offset each other)

In this paper, I follow a different approach than using GMM or IV methods that have been used by the above authors to correct for the downward bias effect of measurement error because the internal instruments used in difference GMM are contentious. The Markov model, that considers the true consumption as missing, has been applied to Uganda to study poverty transition rates with and without measurement error.

4.3 Data

The paper uses the four waves household panel spanning the period 2005, 2009, 2010 and 2011. The data is collected and organized by the Uganda bureau of statistics and World Bank group as part of the living standard measurement survey (LSM) and is available in http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH The data contains the household characteristics, price and marketing information, community level information, agricultural module and consumption expenditure of durable and non-durable goods. The data is very convenient for poverty analysis but it requires an in-depth understanding on how to use complex household survey.

4.4 Methodology

The latent Markov models, which allow for missing data in the dependent variable, have been implemented to distinguish between true and measured mobility. The likelihood function consists of the initial state probability, the probability of real transition from one state to another and the probability of classification error in the response variable.

The key task of this paper is to carry out both the discrete and continuous time Markov Models and determine the magnitude of measurement errors in the two cases. The Discrete time Markov model usually works for equally spaced panel data while the continuous Markov can be used for the unequal space panel data. This paper takes into account unobserved heterogeneity and this is an important aspect of the study. Except Pavlopoulos at al.(2012), previous studies apply non-parametric approach to consider population heterogeneity in the Markov model. A mover- stayer model is a special case of mixed latent Markov model where a stayer is assumed to be in the same state throughout the period and also having no error in their consumption expenditure. The current paper uses the parametric approach in the context of random effect panel data to control for unobserved heterogeneity in the analysis of poverty dynamics. Our first task is to determine the best model that fit the data using the model selection criteria.

In the following, the models have been succinctly elaborated briefly. To begin with, the mechanism by which measurement error enters into the model and the direction of bias it yields can be illustrated as follow. Following Pavlopoulos at al. (2012) and Bound et al. (2001), one my have a regression of the form : $y = \beta z + u$ where consumption y is measured with error, v($y = y* + v$). $y*$ is the true value of consumption. v is given by: $v = \delta y + v*$. v* is uncorrelated with u and z. In many literature, measurement error is said to be mean reverting (Rogers et al.,1993;Duncan and Hill,1985; Bound and Kruger,1991;Griliches,1986). It means that there is negative correlation between true consumption and measurement error. Based on this, we can re-write the regression as $y* = (1-\delta) * \beta z + \varepsilon$ where $\varepsilon = u(1-\delta) + v*$. This implies that measurement error has downward bias on the estimated parameter provided that the error is mean reverting (i.e. δ is negative). The true coefficient β^* ($\beta^* = 1-\delta) * \beta$) tends to be larger than β . In the studies of the returns to human capital variables, measurement error induces significant attenuation bias. Ashenfelter and Krueger (1994) find that returns to education increased from 8.4 percent in OLS to 11.6 percent in the error adjusted instrumental variable estimation.

In our application of poverty dynamics, any error in the reported household consumption affects the household's true poverty status as the discretization depends on the continuous consumption variable. Just in line with the idea of measured consumption and true consumption, we have also observed the dependent categorical variable (say Y) and true categorical variable X , which originates from discretizing the continuous variable. Thus, it is of interest to examine the likelihood that a household is mis-classified into a wrong state given his true state, which is known as classification error probability. For each two consecutive years, the real transition matrices based on the latent Markov

$$
\begin{tikzcd}
\cdots \arrow[r, "\varphi_0"] & x_{t-1} \arrow[r, "\varphi_1"] \arrow[d, "\eta"] & x_t \arrow[r, "\varphi_2"] \arrow[d, "\eta"] & x_{t+1} \arrow[r, "\varphi_3"] \arrow[d, "\eta"] & x_{t+2} \arrow[r] \arrow[d, "\eta"] & \cdots \\
& y_{t-1} & y_t & y_{t+1} & y_{t+2} &
\end{tikzcd}
$$

Figure 5: A graphical representation of latent markov

model are constructed following Va de pol and Langeheine (1990). The standard Markov model, which is a first order Markov process, has been rarely used in the estimation because of its four stringent assumptions. First, it assumes that the state occupied today (at t) depends only on the state occupied yesterday (t-1). The long past history is considered as irrelevant in determining the level of the current state. Second, it does not consider measurement error. Third, it takes transition probabilities as time homogeneous($Pr(X_t = x_t/X_{t-1} = x_{t-1}) = Pr(X_{t+1} = x_{t+1}/X_t = x_t)$). Fourth, it assumes a homogeneous population, which is that transition probability matrices are the same across the different household groups. On the other hand, the latent class Markov model dispenses the first two assumptions. It is a first order Markov process after the covariates have been controlled for. Given the covariates, the state occupied at t depends only on the state occupied at t-1 regardless of the whole past history.

$$(Pr(X_t/X_{t-1}, X_{t-2}...X_1, Z_t, Y_t) = Pr(X_t/X_{t-1}, Z_t) \tag{1}$$

Where X_t is the latent unobservable discrete Markov process whileY_t is the manifest or observed categorical response variable. Z_t is the observed explanatory variables and they are assumed error free. Under measurement error, the response variable is correlated (not perfect correlation) with its latent counterpart as follow.

$$(Pr(Y_t/X_{t-1}, X_{t-2}...X_1, Y_{t-1}, Y_{t-2}...Y_1)) = Pr(Y_t/X_t) \tag{2}$$

Y_t, the manifest variable at time t, is affected by the latent response variable X_t at current time. This is known as the independent classification error assumption (Pavlopoulos at al.,2012). Conditional on the true state, the errors that are made at different time points are uncorrelated. Serial correlation in measurement error is often small (Bound and Krueger,1991; Bound et al.,2001,lee et al.,2017). The real transition matrices between latent states in the latent Markov are time heterogeneous once controlling for time varying variables in eq(1). Z_t comprises both time varying and time invariant control variables. In this specification, a dummy is constructed for each time period in the panel and thus,time is a relevant control variable. A graphical representation of time heterogeneous latent Markov model is given in figure 1. The arrow indicates the impact of a state at a point in time on the state at the following time. The imperfect relationship between the observed poverty state and the true poverty state at each point in time is depicted by the downward arrows.

On the other hand, the mixture Markov models remove the assumption of homogeneous population. Thus, the mixture latent Markov models consider both population heterogeneity and measurement error problem. As shown in figure 2, there exists different transition patterns for each latent class $k = 1, 2, ..., K$ that reveals the actual transition probabilities

$$
\begin{tikzcd}
\cdots \arrow[r, "\varphi_0(k)"] & x_{t-1} \arrow[r, "\varphi_1(k)"] \arrow[d, "\eta"] & x_t \arrow[r, "\varphi_2(k)"] \arrow[d, "\eta"] & x_{t+1} \arrow[r, "\varphi_3(k)"] \arrow[d, "\eta"] & x_{t+2} \arrow[r] \arrow[d, "\eta"] & \cdots \\
 & y_{t-1} & y_t & y_{t+1} & y_{t+2} &
\end{tikzcd}
$$

Figure 6: A graphical representation of mixture latent markov

of a household . Besides the latent poverty states, we have unobserved class heterogeneity to which an individual belongs to. The advantage of the latent Markov model is that it incorporates both the transition probabilities and the measurement error parameters, making it so flexible to isolate the true mobility from a spurious one (Magidson et al.,2009; Hagenaars,1990). Let y_{it} denotes the manifest value of the dependent variable at time t for individual i. y_{it} is a binary variable with H=2 categories at least for our case in this paper. In our robustness check , y_{it} becomes a nominal variable with H=3 categories. The total number of time points is $T+1, 0 \leq t \leq T$,(which is 4 in this case). The observed response of individual i, denoted by y_i, contains $T+1$ time periods with its corresponding model probability $P(y_i$. The Latent Markov model contains $T+1$ latent variables , each having M categories. The number of latent poverty states is assumed to be equal to the number of observed poverty states(H=M=2). Let x_t denotes the values of the latent variable at time point t. An individual ,who is observed in $T+1$ time points and having a binary response at each point in time, may have $2^5 = 32$ response patterns. Using the Bayes probability formula and the first order Markov assumption, the joint distribution of all sequences of observed states for a household is give by:

$$P(y_i) = \sum_{x_0=1}^{M} \sum_{x_1=1}^{M} \ldots \sum_{x_T=1}^{M} P(x_0) \prod_{t=1}^{T} P(x_t|x_{t-1}) \prod_{t=0}^{T} P(y_{it}|x_t) \tag{3}$$

The unknown model probabilities to be estimated are the initial latent state probabilities ($P(x_0)$), the latent transition probabilities ($P(x_t|x_{t-1})$) and the measurement error probabilities, $P(y_{it}|x_t)$. For the purpose of identification, classification error parameters are time homogeneous. The probability of observing a state y_{it} conditional on the true state x_{it} is restricted to be constant overtime (Pavlopoulos et al,2012, Vermunt et al.1999, Magidson et al,2009). By aggregating across all individuals, the log-likelihood function to be maximized is given by:

$$logL = \sum_{i=1}^{N} lnP(y_i) \tag{4}$$

The standard maximum likelihood method cannot be used directly in the presence of missing data (i.e.x_t is missing for each individual at time t). Instead, the expectation maximization (EM) algorithm is employed. It has two steps to estimate the parameters of the model. The E-step of the EM algorithm involves computing the expected value of the complete data log-likelihood in order to fill in the missing data given observed data and parameter guess (Dempster et al,1977;Vermunt and Magidson,2008; Vermunt et al.,1999, Pavlopoulos et al.,2012). The missing data here refers to the unobserved class membership (latent state poor or non-poor) and the individual specific unobserved heterogeneity. In the M-step, the logistic regression model for the initial state, transition and measurement error probability is adopted by taking the posterior probabilities estimated in E- step as weights. Thus, the model parameters are updated in M-step by maximizing the expected value of the full data log-likelihood. The E and M steps interchange each other until convergence occurs.

However,for tractability and gain in speed in the presence of many time points, the variant of EM algorithm called Baum-Welch algorithm is implemented in Latent GOLD software[18] (Vermunt and Magidson,2013, 2016; Vermunt et al.1999). Following Pavlopaoulos et al.(2012), the unobserved heterogeneity in the context of random effect panel data is incorporated in the logistic regression model. This is because of the fact that transition probabilities from poor to non-poor or vis-versa may be affected by unobserved individual characteristics such as ability and motivation. Thus, the paper controls for both time varying and time invariant individual and household level characteristics in the Latent Markov model. Thus, covariates are allowed to affect the latent transition probabilities (Pavlopoulos et al. (2012). These transition probabilities are also time heterogeneous as we introduce time varying covariates in the model. Time is one of the key time varying variables in the model. From these period specific transition parameters, one can construct the overall transition parameters. On the other hand, the measurement error probabilities are time homogeneous and with this assumption, identification of all model parameters are palatable.

Based on multi-nominal logit model (or the logit regression model for binary response), the parameters of the model probabilities are :

$$P(x_0 = s) = \frac{exp(\alpha_s)}{\sum_{m=1}^{M} exp(\alpha_s)} \tag{5}$$

$$P(x_t = s|x_{t-1} = r, z_{it}) = \frac{exp(\alpha_{0rs} + \sum_{p=1}^{P} \alpha_{prs} z_{itp})}{\sum_{m=1}^{M} exp(\alpha_{0rm} + \sum_{p=1}^{P} \alpha_{prm} z_{itp})} \tag{6}$$

$$P(y_{it} = n|x_t = r) = \frac{exp(\beta_{nr})}{\sum_{h=1}^{H} exp(\beta_{hr})} \tag{7}$$

In $eq(5)$, it is possible to allow time invariant household characteristics such as gender and ethnicity in the model. But,in our model, we do not control for these variables. We allow for time varying covariates (z_{it}) in the transition probability model($eq(6)$). Of course, it is possible to incorporate time invariant explanatory variables in $eq(6)$. The variables included in $eq(6)$ are year (a year dummy is made for each year), education(educ),proportion of unemployed household members in the household(unemploy), the share of adult male(age 15-65) members in the household(propM), the share of female adult(age 15-65) in the household(propF), the number of disabled household member(disable),access to all weather road(road), ownership of Radio and TV(RTV), ownership of mobile(mob) and the size of land holding per adult equivalent(land). Finally, in measurement error probability model as shown in $eq(7)$, time varying covariates are not included as the classification error parameters are restricted to be time constant. To estimate classification error and latent transition probabilities,the total number of parametric restrictions tends to be $1+M+H$ (Magidson ,2009). The parameters of $eq(6)$ and $eq(7)$ can be estimated as follow after re-arranging these

[18]I use this software to estimate the models

two equations with respect to the probability to remain in the same state:

$$log\left(\frac{P(x_t = s|x_{t-1} = r)}{P(x_t = r|x_{t-1} = r)}\right) = \alpha_{0rs} + \alpha_{1rs}educ_{it} + \alpha_{2rs}propM_{it} + \alpha_{3rs}propF_{it}$$
$$+ \alpha_{4rs}RTV_{it} + \alpha_{5rs}mob_{it} + \alpha_{6rs}land_{it} + \alpha_{7rs}road_{it} + \alpha_{8rs}disable_{it} + alpha_{9rs}year_{it} \quad (8)$$

$$log\left(\frac{P(y_{it} = n|x_t = r)}{P(y_{it} = r|x_t = r)}\right) = \beta_{nr} \quad (9)$$

The coefficient of eq.(8) can be interpreted as the log odds of transiting from a state r to a state s rather than staying in the same state r. The probability of not making transition is the reference category. A positive sign shows an increase in the log odds ratio as a result of increases in that variable. Other thing constant, the negative sign indicates an inverse relation between the log odds ratio and a variable.

So far , the paper discusses the latent Markov model that assume a homogeneous population which is characterized by a single Markov chain. The Mixture latent Markov instead relax this assumption by taking into account population heterogeneity and split the population into different Markov chains in non-parametric way. The mover-stayer Markov model is a restricted version of the Mixture latent Markov where the population is splitted into two classes or chains: the Mover and Stayer. In the stayer chain, the transition probability from one state to another state is restricted to be zero. There is perfect correspondence between the observed response and the latent response in a stayer chain. On the other hand,in the mover chain, transitions are unrestricted and as a result,the measurement error model determines the extent of classification error probabilities. Following Pavlopoulos et al. (2012), the unobserved household heterogeneity can be addressed in parametric way akin to a random effect panel in logit regression.

Therefore, we estimate the mixed latent Markov model that captures both measurement error problem and individual specific unobserved heterogeneity using the 4 waves longitudinal data. let F_{1i} be individual specific unobserved heterogeneity in the initial state equation and F_{2i} denotes individual specific time invariant unobserved variable affecting transition probabilities. If there exists strong correlation between the two unobserved heterogeneity, it indicates the presence of sample selection in the base year, and hence the initial condition is endogenous. It means that having a particular poverty state in the initial year may not be random. If so, being in a particular poverty state in the initial year may affect the transition probabilities. The assumption that F_{1i} and F_{2i} are bi-variate normally distributed, however, should be tested. Following Pavlopoulos et al.(2009),the joint probability distribution for the random effect panel is specified as:

$$P(Y_i = y_i|Z_i) = \int\int \sum_{x_0=1}^{2} \sum_{x_1=1}^{2} \cdots \sum_{x_T=1}^{2} P(X_{i0} = x_0|F_{1i})$$
$$\prod_{t=1}^{T} P(X_{it} = x_t|X_{it-1} = x_{t-1}, Z_{it}, F_{2i}) \prod_{t=0}^{T} P(Y_{it} = y_{it}|X_{it} = x_t) f(F_{1i}, F_{2i}) dF_{1i} dF_{2i} \quad (10)$$

where $f(F_{1i}, F_{2i})$ is the joint density function of the two individual specific unobserved variables $F_{1i} and F_{2i}$. It is worth to mention that we estimate the different versions of the mixed latent Markov models in order to fix the best fit to our data. Thus, latent mixed Markov model which is supported by the data is presented above.

4.5 Estimation Results

4.5.1 Model comparisons

For the purpose of identifying the Markov model that fit the current data, 14 models are estimated in total. The models are generally classified into 3 groups. The first 4 sub-models under part A assume a single Markov chain for every one in the sample. The other models (under part B and C) are mixture models that consider the presence of heterogeneous population that requires specific transition matrices for each class of the population. In part B, as each individual constitutes a class, the number of chains is equal to the sample size in the first period because the transition probabilities are affected by individual specific unobserved heterogeneity. The unobserved heterogeneity varies across individuals but is constant overtime. The models under part C split the overall population into two latent classes. In model 13 and 14, we assume that one of the latent classes is a mover while the other is a stayer. All models except model 1 and 2 are time heterogeneous. Covariates are allowed to affect the transition probabilities.

Our survey data was not conducted in equal time interval. There is 4 years gap between the first year survey (2005) and the next year survey in a panel (2009). There is only one year gap in the last 3 consecutive survey years (2009,2010 and 2011). Consumption expenditure is adjusted for inflation and regional price difference that allow us to compare the development of real expenditure overtime. Poverty figures are computed using real expenditure and a poverty line(34618 shillings). Though the price effect is removed, this paper estimates both the continuous and discrete time latent Markov models are estimated. Because the presence of large time gap may yield low poverty persistence, which biases the true persistence than had all the survey years been equal space panel. There are two methods to address the unequal space data. The first is the continuous time Markov. Transition probabilities are function of transition intensity and the length of time interval (Crayen et al,2012). As in discrete time model, the estimation algorithm and the likelihood function resembles same.

Table 1 presents the log likelihood values(LL), the number of parameters estimated (par), and the Bayesian information criterion values (BIC) for the different version of estimated Markov models. Like Crayen et al.(2012), the continuous time model in our case also perform worse compared to the discrete models(see table 1). Except in the latent Markov (model 2),the likelihood value(LL) for continuous time Markov is lower than the discrete counterpart. The higher the LL value, the better the model fit. The second method to address unequal space is related to organizing the data in different forms. The simplest way, though not presented here, is to put missing value for missing time. By declaring that information is missing between surveys (i.e. missingness on fly), the Latent Gold can handle it.

Vermunt et al (2008), in their analysis of hard-drugs use in U.S, arrange the data structure to take into account the unequal space across panel waves. We adapt that approach and then proceed to treat the data as if it comes from the discrete time structure. At the first year of the survey (2005), we have 1521 household heads whose ages vary from

16 to 82. Age has been used as a time scale. Every one starts with age 16 and ends with age 88. It means that we have 73(T) time panel waves where age 16 corresponds to 1 and age 88 aligns to time period 73. For 6 panel waves, we have information for all dependent and independent variables, yet all other 67 time periods have missing values. For example, an individual who was 20 years old at the first measurement occasion (in 2005) will have 4 missing values before age 20 and 3 missing values between ages 21-23 and 60 missing values after age 26. This format of data is called sparse data and is part of the discrete time model. The total number of observations becomes 111033(1521*73) compared to had the data been equally spaced (1521*4=6084).

Another alternative is to estimate the discrete time (the 4 waves) by ignoring the unequal space and we call it non-sparse data. Bias from having irregular snapshots of measurement is less likely to occur on the measurement error model as it is time homogeneous. However, irregular measurement occasions can affect transition probabilities. Crayen et al. (2012) implement a discrete time model for their unequal space panel data. Yet, we estimate a discrete time model with and without considering the panel gap in the survey.

The model selection criterion (see table 1) ranks the fit of the different models as follow. Under part A in table 1, the latent Markov (model 2) that considers measurement error performs better than the simple Markov model (model 1). Moreover, adding covariates considerably improve the fit of the model. For instance, model 4 performs better than model 2. Model 3 is better than model 1. Other things being equal, a model that controls for covariates has shown a better fit. In the same vein, correcting for measurement error always improves fit irrespective of the type of data structure chosen. We conclude that correcting for measurement error and controlling for covariate yield substantial gain in the model fit (see model 4). Under part B and C, the models are time heterogeneous. Survey year as a nominal scale is an important time varying regressor.

Comparing model 3 with all other mixture models (model 5, model 7, model 9,model 11 and model 13) suggests that having different Markov chains is preferred to characterizing the whole population by a single transition matrix. This conclusion holds for all types of data constructs (except model 5). This implies that controlling for unobserved heterogeneity improves the model fit. After correcting for the measurement error problem, however, adding unobserved heterogeneity does not help improve the model fit for a sparse data. The latent Markov (model 4) is slightly better than any other mixed latent Markov models for sparse data. For non-sparse data, the BIC is higher in model 4 than in models 8 ,10 12 and 14 ,suggesting that the mixed latent Markov is better than the latent Markov. Model 8 is chosen for non-sparse data because the model fit improves after controlling for measurement error, observed characteristics, individual specific unobserved heterogeneity and endogenous initial condition. For sparse data, we also estimate model 8 from which the discussion follows. For all types of data, we just estimate model 4 for robustness check.

4.5.2 How large is the measurement error?

The key objective of the paper is to identify the level of measurement error in the household's consumption expenditure. Table 2 provides the classification error probabilities ($P(Y_{it} = y_{it} | X_{it} = x_t)$) based on model 4 (latent Markov).

The sparse and continuous time models consider the presence of irregular snapshots of measurement occasions (missing data in between 2005 and 2009) while the non-sparse data uses the four waves data by ignoring the unequal time interval. The last 3 consecutive panel waves (2009,2010 and 2011) form another group. Based on non-sparse data (households' head is the unit of analysis), the magnitude of measurement error for the poor is 22.2% , which is the percentage of poor individuals who are mis-classified as non-poor. Only 8.6% of the true non-poor individuals are mis-placed as poor or observed as poor in the data. The measurement error profile resembles similar across the different model specifications used to consider the unequal space interval in the survey years.

The main finding is that the consumption of the poor is most affected by measurement error. For the discrete and continuous time models in table 2, the measurement error probability for the poor is about 2.5 times larger compared with the error probability for the non-poor. Measurement error overstates the observed mobility and that bias is large for the consumption pattern below the poverty line (34618 shillings). This finding is consistent with Lee et al. (2017) and Gibson and Glewwe (2005) who find that measurement error magnifies mobility at lower quintiles of consumption expenditure. We all find that measurement error understates chronic poverty (i.e poverty persistence). The effects of measurement error between the 3 types of data structure vary based on model 4 as shown in table 2, 19% in the three years data ; 22.% in non-sparse and 25.4.% in the sparse data. Yet, the difference seems to be meager. Unlike model 4, model 8 controls for endogenous initial poverty and individual specific unobserved heterogeneity(see, table 3). This model is preferred to others according to the model fit criteria presented in table 1 for non-sparse data. Measurement error overstates the mobility out of poverty by 25.4% and 13.6% respectively in sparse and non-sparse data. As we move from model 4 to model 8, the error probabilities decline in non-sparse data where as they remain unaltered in the sparse data. Controlling for the confounding factors reduces the magnitude of measurement error in non-sparse data but not in sparse data.

The implication of the size of measurement error for transition probabilities is presented in table 4. The average transition probabilities without (from model 7) and with (from model 8) correcting for measurement error for both non-sparse and sparse data are offered in table 4. High measurement error implies large discrepancy between observed and actual transition probabilities. Both in sparse and non-sparse data, the poverty persistence probabilities are downward biased by measurement error, with biases estimated to be 38.9% (89.3% minus 50.4%) in sparse data and 9% (60.9% minus 52.3%) in non-sparse data. In other word, the real transition probabilities from a state of being poor into a state of being non-poor amounts to be only 10.7% while measured mobility out of poverty is 49.6%, implying that the latter is overstated by 38.9% due to measurement error. The key finding is that measurement error understates the observed poverty persistence by 38.9%. The observed mobility into poverty is understated by 12.2% and 4% in sparse and non-sparse data respectively. The main difference between sparse and non-sparse data comes from the choice between model 4 and model 8. After controlling for confounding factors such as initial condition and time constant unobserved heterogeneity in model 8, the size of measurement error significantly declines (from 22% to 13.6%) in the non-sparse data where as it does not change in sparse data.

Of course, even in model 4, ignoring the irregular measurement occasion understates the level of measurement error and thereby overstates the real transition probabilities. Thus, the effect of measurement error based on model 8 in non-sparse data should be taken as a lower limit while its effect in sparse data is deemed as upper limit. Using the lower limit, our finding is much closer to the findings established by Lee et al. (2017) for Korea and McGarry (1995) for USA. This means that measurement error understates poverty persistence probabilities by 11.5% for Korea and 11% and 9% respectively for USA and Uganda. Using latent Markov model, Rendtel et al. (1998) find that almost half of the observed poverty mobility in Germany is accounted for by measurement error, a finding closer to our upper limit (38.9%). Breen and Moisio (2004) apply a latent mover-stayer Markov model for 10 European countries. When measurement error is disregarded, they find that the observed poverty mobility can be overstated by between 25% and 50%. Using instrumental variable method, Glewwe (2012) estimates the expenditure mobiity for Vietnam based on 2 years panel data, not just poverty transition. He finds that between 15% and 30% of the measured consumption mobility is attributable to measurement error

4.5.3 Effects of Covariates on Poverty Transition

Table 5 illustrates how classification error in poverty measurement affects the impacts of the control variables in random effect panel regression. The estimated coefficients are compared with and without controlling for measurement error. The mixed latent Markov (model 8) that corrects measurement error and the mixed Markov (model 7)that disregard errors in data are estimated for both non-sparse and sparse data. The main covariates included in the model are education, household composition which comprises the percentage of unemployed member in the household, the fraction of handicapped/disabled members, members' age composition such as the share of female or male adults (age 15-65) in the household ,asset ownership (Mobile phone, TV and radio,landholding per adult),access to infrastructure (captured by the dummy variable called access to all weather road) and calender time.

Since access to road and disable variables are not significant in the model, we do not report the estimated coefficients in table 5 but are already part of the model variables. The unemployed variable broadly captures the intra-household labor market status. Partly, it captures the number of dependent children aged below 5 who are not in labor force as well as the retired household members. Partly, it includes unemployed and underemployed youth. Under-employment (several household members working on small acre of land) in agriculture can occur if the off-farm labor market is volatile and tightened to accommodate the surplus labour. Households with a high percentage of unemployed members are expected to be poor either due to large dependency ratio or law of diminishing return.

It is of important for rural poverty to investigate the age composition of the household members as the manual labor in rural areas is in itself more energy demanding. In rural area, a household member can participate in a number of diversified activities: own farm (crop cultivating, cattle raising) and off-farm activities. To maximize the overall benefit of the members, each adult household member can engage in in activities that make them more productive and thus, they are more likely to specialize depending on their skills (acquired or innate) and physical fitness. The more adult members (age 15-65) means that the more likely they are placed in jobs that fit them. Apriori, one can expect that as the fraction of adult members increases, poverty incidence may decline. The social cohesion in the form of social capital (e.g. through remittance) may help households to organize their assets into a large scale jobs and investments.

The role of asset ownership in poverty is also vital. Especially for rural households who simultaneously perform production and consumption decision, the role of information related to prices of agricultural products and weather condition is enormous. Rural radio and TV can reach wider rural areas and effectively supply information on several farming related activities, which include improved seeds, timely planting ,crop diversification, marketing agricultural inputs and output (Mohammed et al.,2010,Chapman et al.,2003; Nwaerondu and Thomson,1987; Nakabugu,2001). It is the most cost effective tool to educate farmers about modern crop cultivation, livestock raising, prevention and treatment of crop and animal diseases, minimizing the impact of negative shocks (climatic,inflation,natural disaster such as flooding, earthquake,storm,crop pests and diseases etc). Households who posses Radio and TV, and mobile phone are expected to be more productive and consequently, the poverty incidence can be lower. Finally, land size per-capita is expected to have negative association with poverty incidence.

In the standard logit or probit models for poverty analysis, the marginal effect of a given control variable describes the change in poverty persistence probabilities resulting from a change in that variable. It gives the likelihood of being in a certain state at a current time. In contrast, the transition logit model gives the variable's impact on the probability of making a particular type of transition from one state to another. We estimate the Markov transition logit model with and without controlling for measurement error. For instance, instead of modeling how education affects the probability of being poor, it is of interest to know how education affects the mobility into or out of poverty when consumption is measured with and without error. This method helps us to test whether measurement error underestimates the impact of control variables on poverty transition or not. The estimated results based on the mixed Markov (model 7) and the latent mixed Markov (model 8) are reported in table 5 for both types of data. Using the Hausman test (Hausman,1978), we find that the estimated coefficients between model 7 and 8 are significantly different from each other.

Column 4 in table 5 offers the estimated covariates effects from the mixed latent Markov after corrected for measurement error (model 8). As shown in table 5, education is a significant predictor that helps individuals not to fall into poverty in the first place in both columns 4 and 5. In the presence of measurement error (column 4), it also increases the chances of being non-poor (or reduces poverty persistence probability). Other thing being equal,on average, education reduces the risk of future poverty for individuals who were poor or non-poor in the previous period. Nevertheless, the variable is no longer significant on making transition out of poverty once controlling for the measurement error effect (column 5). Hence, measurement error overestimates the mobility effect of education.

As regard to the impact of unemployment variable (a good indicator of the number of dependents or underemployed members in the household), the probability of entering into poverty substantially increases in response to a rise in the dependency ratio. It also yields a big hindrance for households to transit from poor to non-poor state. As the percentage of unemployed household members increases, it puts a pressure on the household to be in a state of poverty and also prevents them to escape from that state. Thus it is of important for policy makers to curb the dependency ratio through inducing family management program as well as through creating a platform where the unemployed utilize their labor in off-farm activity. This may mitigate the vicious circle of poverty emanating from large fraction of dependent members in the household.

Ownership of mobile phone has a positive impact on making a transition from being poor into non-poor. The variable also prevents households from slipping into poverty from their favorable non-poverty state. In other word, it decreases the probability of entering into poverty as well as increases the propensity of escaping out of poverty. Ownership of mobile significantly reduces the incidence of current poverty irrespective of whether an individual was poor or not in the previous time.

Similarly, those who own TV-radio are more likely making a transition out of poverty than those without. Once non-poor today, they are also less likely slipping into poverty in the future. It also decreases the transition probability from non-poor into being poor. 63% of households own TV and radio while 38% own mobile phone. A simple descriptive analysis also confirms that those who own TV and radio have a higher average annualized consumption growth than those without. At the median consumption, those who own TV and radio appear to have 28.1% higher real consumption compared to those without. The empirical result accords with the descriptive statistics.

Concerning the impact of age composition, the high proportion of male adult members (age 15-65) significantly reduces the chance of making a transition into poverty. Similarly, the large proportion of female members enhances the transition out of poverty but decreases the transition into poverty. This may be explained by the fact that adult members are more likely to specialize in activities to which they are more productive. They may work on farm and non-farm activities. When their resources are combined together, they may have better chances to open new profitable activities or involve in a more risky but profitable business because of their shared risk. More working household members can be taken as a good collateral (by enhancing members' business confidence or better access to informal village based lenders)to launch new portfolio in presence of malfunctioning credit market. Alternatively,the poverty transition effect of large adult members can be viewed from their physical strength compared to households with large proportion of children under 15. Because rural jobs are often more energy demanding than urban jobs.

The impact of land size per adult depends on whether measurement error is corrected or not. It has significant impact on transition only in using error- free consumption. [19] Finally, unobserved heterogeneity has significant impact on transition probability except in latent Markov for sparse data. It is of important to mention that measurement error does not affect the statistical importance of control variables except for land size and education. Yet, the magnitudes of the estimated coefficients differ with and without controlling for measurement error. Columns 6 and 9, for each variable and types of data, give the percentage difference between coefficients obtained from mixed and latent mixed Markov models.

As expected, measurement error underestimates the covariate effects for all variables under scrutiny. For instance,

[19] We exclude land holding per adult in the sparse data estimation as it causes convergence problem.

in the sparse data, the effect of TV-radio on making a transition out of poverty is underestimated by 31% where as its effect in reducing the chances of transiting into poverty is underestimated by 56.9%. Educated households have strong inertia not to leave their non-poverty state. But, the education effect is attenuated by 47.6% with measurement error. Out of the 12 estimated parameters in the sparse data, 9 of the parameters have been experiencing downward attenuation bias due to measurement error. All estimated coefficients have exhibited downward bias in the non-sparse data. Therefore, measurement error reduces the impacts of covariates in making transitions into and out of poverty. Since measurement error is higher in sparse data, the downward bias effects are stronger in this data than using the regular snap shot of measurement occasions (non-sparse data). Yet, the conclusion of this paper does not differ whether we use sparse or non-sparse data. In both cases, we find that measurement error underestimates poverty persistence probabilities. In addition, it also understates the impacts of covariates in making poverty transitions.

4.5.4 Sensitivity of measurement error to changes in poverty line

Based on the four waves panel data, we estimate the absolute poverty line(34618 shillings) using a utility consistent approach. We re-estimate model 8 to examine the sensitivity of measurement error and the corresponding transition probabilities to the different definitions of poverty line. Our poverty line (34618) corresponds to 83% of the median real consumption per adult equivalent. Absolute poverty line is commonly used in developing countries while relative poverty line is more important for advanced countries(Foster,1994). Absolute poverty line is fixed overtime and does not take into account the real economics growth. On the other hand,relative poverty is defined as some percentages of standard of living in a given time. For the analysis of poverty dynamics in some European countries , Breen and Moisio (2004) use relative poverty line threshold set at 60% of the median income. In this paper, we do not use relative poverty lines due to the aforementioned reason that it is applied barley in developing world. For the sensitivity analysis, we affect the fixed poverty line to drop to some reasonable level and see its effect on poverty profile. We decrease the poverty line from 34618 to 24810, which is 60% of the median consumption per adult equivalent (shilling 41350). The median consumption is obtained after pooling all sample years together

Table 6 offers the estimation results for both poverty lines, which are shilling 34618 (83% of median consumption per adult) and shilling 24810 (60% of the median consumption). When the poverty lines are 34618 and 24810 ,the manifest overall poverty incidences become 37.8% and 18.7%. The poverty incidence declines by 50.5% in response to a 28.3% decline in the poverty line, suggesting that the consumption elasticity of poverty amounts to be 1.78. It is defined as the percentage reduction in poverty headcount associated with a 1 percent increase in the consumption per capita. Poverty incidence is highly responsive to changes in consumption/poverty line.

After correcting for measurement error, the true overall poverty incidence is found to be 37.9%. Measurement error slightly underestimates the overall true/latent poverty incidence when the poverty line is Shilling 34618. When the poverty line stands at 24810 instead, the true poverty incidence amounts to 22.2%, which is higher than the observed poverty headcount ratio (18.7%). The true consumption elasticity of poverty has been computed to be 1.39. As the poverty line decreases,the level of measurement error increases and the likelihood to classify the poor as non-poor is drastically escalated.

It is of interest to ask which segment of the poor population constitutes the largest measurement error. Table 7 split the poor population into two parts. Very poor are those whose consumption per adult is less than or equal to 50% of the median while the poor are those whose consumption lies between 50% and 83% of the median. Rendtel et al.(1988) use a more informative three state description of poverty in their investigation of poverty dynamics in Germany though they use mean income rather than the median which is often used to indicate standard of living.

As shown in table 7, we have three latent states associated with the three observed states: non-poor, poor and very poor. The Mixed latent Markov(Model 8) and the Mixed Markov (model 7) for the sparse data are estimated using the three latent/observed poverty states. Model 8 controls for measurement error while model 7 not. The extent of classification error and transition probabilities are reported in table 7. We find that households in the class 50%- 83% are identified to have the largest measurement error. 62.7% of the poor are mis-classified into another state(58.8% into non-poor and 3.9% into very poor). The overall classification error among the very poor tends to be 43.2%, where 42.1% of them are misplaced into poor state and 1% into non-poor state.

The right panel in table 7 offers the latent/true and observed transition probability, whose divergence is a consequence of measurement error. The observed transition is estimated from a mixed Markov model without controlling for measurement error. In line with the previous section (that uses binary poverty category), measurement error understates poverty persistence probabilities. The poverty persistence by the very poor individuals increases from 22.7% in the observed data to 57% in the true data. Thus, significant portion of the mobility into and out of poverty is attributable to measurement error.

4.6 Conclusion

This paper tries to scrutinize the size of measurement errors and the true poverty transition for Uganda using the 4 waves panel data spanning the period 2005,2009,2010 and 2011. The paper applies the first order Markov poverty transition model in random effect panel that controls for observed and unobserved individual specific heterogeneity, endogenous initial condition and measurement error. We find that measurement error overstates the observed mobility in Uganda. The poverty persistence probability increases from 52% in the observed data to 61% in the true data, suggesting that measurement error understates persistence poverty by at least 9%.[20] Since the poverty persistence rate is significant in Uganda (at least 61%), the policy priority is to increase the human capital and productive assets (e.g. land,oxen) of the poor.

Poverty is largely chronic implies that targeting the poorest households through long- term policies help reduce permanent poverty. Another finding is that the effects of some of the observed individual characteristics on poverty

[20]this is the lower limit because the true poverty persistence is 89% instead of 50% in the observed data when we consider the unequal space snap shot of the data. This is taken as the upper limit

transition are considerably attenuated due to measurement error (e.g land size and education). The most important variables that affect poverty transitions are: land size per capita; ownership of mobile, having TV-radio, dependency ratio; proportion of female and male adult members. Education reduces the chances of transiting into poverty, yet it does not affect the mobility out of poverty. Land size is a crucial asset in reducing the probability of transiting into poverty as well as increasing the chances of poverty exit. Special provisions to the poor such as access to information technology and land are fundamental to reduce chronic poverty in Uganda.

Appendix 4: Regression Tables

Table 4.1: Summary of model fit comparison

	Discrete time Markov						Continuous time Markov		
	Non-sparse			Sparse			4 waves(2005-2011)		
	LL	BIC	Npar	LL	BIC	Npar	LL	BIC	Npar
A) Homogenous population									
1)Standard Markov	−3859	7739	3	−3844	7711	3	−3906	7834	3
2)Latent Markov	−3781	7599	5	−3760	7557	5	−3780	7596	5
3)Markov with covariates	−3651	7500	27	−3563	7281	21	−3656	7496	25
4)Latent Markov with covariate	−3606	7424	29	−3501	7171	23	−3636	7469	27
B) Parametric: Unobserved Heterogeneity(UH)									
5)Mixed Markov ,exogenous initial condition	−3650	7506	28	−3540	7242	22			
6)Mixed latent Markov ,exogenous initial condition	−3606	7431	30	−3501	7178	24			
7)Mixed Markov ,endogenous initial condition	−3615	7442	29	−3540	7249	23			
8)Mixed latent Markov ,endogenous initial condition	−3588	7404	31	−3495	7173	25			
9)Mixed Markov , free corr. of UH b/n equations	−3615	7449	30	−3540	7257	24			
10)Mixed latent Markov , free corr. of UH	−3588	7411	32	−3501	7193	26			
C) Non-parametric: unobserved heterogeneity									
11)Mixed Marko	−3610	7446	31	−3530	7242	25			
12)Mixed latent Markov	−3582	7407	33	−3500	7197	27			
13)Mover-stayer mixed Markov	−3613	7439	29	−3541	7250	23			
14)Mover-stayer mixed latent Markov	−3588	7405	31	−3501	7185	25			

Note: LL represents value of log likelihood while BIC denotes the Bayesian information criteria. Npar shows the number of parameters estimated

Table 4.2: Size of measurement errors across data for the Latent Markov (model 4)

	Discrete time				Continuous time			
	Non-sparse		3 waves(2009-2011)		Sparse		4 waves(2005-2011)	
Latent state	Observed state		Observed state		Observed state		Observed state	
	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor
Non-poor	0.914	0.086	0.934	0.066	0.904	0.096	0.903	0.097
Poor	0.222	0.778	0.19	0.81	0.254	0.746	0.231	0.769

Table 4.3: The extent of measurement error for non-sparse and sparse data (model 8))

	Non-sparse		Sparse	
Latent state	Observed state		Observed state	
	Non-poor	Poor	Non-poor	Poor
Non-poor	0.94	0.06	0.904	0.096
Poor	0.136	0.864	0.254	0.746

Table 4.4: Observed and Latent Transition probabilities for the better fit(model 8)

	Non-sparse data				Sparse data			
State at t-1	Observed transition in t		Latent transition in t		Observed transition in t		Latent transition in t	
	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor
Non-poor	0.718	0.282	0.759	0.241	0.843	0.157	0.965	0.035
Poor	0.477	0.523	0.391	0.609	0.496	0.504	0.107	0.893

Table 4.5: Estimated parameters from mixed latent and mixed Markov models (model 7 and 8)

			Non-sparse data			Sparse data		
	Origin state	Destination	Mixed	Mixed Latent	Difference(%)	Mixed	Mixed Latent	Difference(%)
Education	Non-poor	Poor	-0.664	-0.889	25.361	-0.988	-1.883	47.550
			(0.145)	(0.281)		(0.138)	(0.273)	
	Poor	Non-poor	0.440	0.546	19.290	0.606	0.537	-12.729
			(0.193)	(0.313)		(0.191)	(0.378)	
Unemployed	Non-poor	Poor	0.115	0.130	11.283	0.114	0.335	65.937
			(0.029)	(0.052)		(0.024)	(0.051)	
	Poor	Non-poor	-0.213	-0.307	30.534	-0.155	-0.305	49.161
			(0.037)	(0.090)		(0.042)	(0.146)	
Ownership of mobile	Non-poor	Poor	-0.807	-1.277	36.811	-0.530	-2.032	73.909
			(0.127)	(0.289)		(0.101)	(0.538)	
	Poor	Non-poor	0.494	0.693	28.646	0.491	1.220	59.729
			(0.147)	(0.285)		(0.147)	(0.428)	
TV-radio	Non-poor	Poor	-0.674	-0.900	25.113	-0.655	-1.522	56.935
			(0.128)	(0.232)		(0.097)	(0.231)	
	Poor	Non-poor	0.803	1.258	36.199	0.783	1.134	30.957
			(0.135)	(0.382)		(0.141)	(0.416)	
% male adult	Non-poor	Poor	-0.010	-0.015	35.792	-0.012	-0.010	-21.799
			(0.003)	(0.005)		(0.002)	(0.005)	
	Poor	Non-poor	0.004	0.007	40.776	0.007	0.046	84.413
			(0.003)	(0.006)		(0.003)	(0.011)	
% female adult	Non-poor	Poor	-0.011	-0.018	35.737	-0.011	-0.011	-7.761
			(0.003)	(0.006)		(0.003)	(0.005)	
	Poor	Non-poor	0.008	0.016	45.561	0.014	0.059	75.910
			(0.004)	(0.007)		(0.004)	(0.013)	
Land holding	Non-poor	Poor	-0.019	-0.554	96.623			
			(0.014)	(0.139)				
	Poor	Non-poor	0.027	0.436	93.736			
			(0.020)	(0.134)				
Unobs. heterogeneity			-1.010	-1.335	24.310	-0.699	-0.000	
			(0.121)	(0.257)		(0.071)	(0.892)	

Note: Standard errors are offered in the parenthesis. The Coefficients associated to difference are significant at 1% and 5% significance level. The model includes year dummies,proportion of disable household members and access to road. But their estimates are not reported here. Year dummies are significant but not access to road and disable variables

Table 4.6: Sensitivity to different poverty lines

	Poverty line:80% of the median consumption		Poverty line:60% of the median consumption	
	Observed)	Latent	Observed	Latent
a) Sparse				
Non-poor	0.622	0.621	0.813	0.778
Poor	0.378	0.379	0.187	0.222
b) Non-sparse				
Non-poor	0.615	0.596	0.861	0.741
Poor	0.385	0.404	0.139	0.259

Table 4.7: Three scheme category of poverty states: reliability and transition probabilities from sparse data

	Extent of measurement error			Transition probabilities					
State at t-1	Observed Response			Observed			Latent		
	Non-poor	Poor	Very poor	Non-poor	Poor	Very poor	Non-poor	Poor	Very poor
Non-poor	0.945	0.055	0.0001	0.844	0.132	0.024	0.976	0.022	0.002
Poor	0.588	0.373	0.039	0.531	0.378	0.091	0.041	0.882	0.076
Very Poor	0.01	0.421	0.568	0.439	0.334	0.227	0.111	0.317	0.572

Note: Non-poor are those in the income bracket : $>=$ 83% of the median income. Poor refers the group: 50% -83%. Very poor indicates the class: $<=$ 50%.

Table 4.8: Real transition probabilities from the latent Markov (model 4)

	Discrete time				Continuous time			
	Non-sparse		3 waves(2009-2011)		Sparse		4 waves(2005-2011)	
Latent state at t-1	Latent state at t		Latent state at t		Latent state at t		Latent state at t	
	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor
Non-poor	0.805	0.195	0.79	0.21	0.965	0.035	0.826	0.174
Poor	0.292	0.708	0.255	0.745	0.107	0.893	0.27	0.73

5 Gender wage gap and poverty: Evidence from employer-employee data in Ghana

5.1 Introduction

Gender equality is instrumental for achieving developmental success and wage inequality is one of the important determinants of persistent gender inequality in Sub-Saharan African countries. The problem of gender inequality is overwhelmingly amplified in sub-Saharan African countries. Attempts to identify the size and determinants of the gender wage gap have been conducted in these countries using labor force surveys and matched employer-employee data. Yet evidence on the role firms wage policies in accounting for the gender wage gap is scarce

This paper[21] uses quantile regression that considers the full range of wage distributions to analyze the sources of the gender wage gap in Ghana manufacturing firms. The matched employer-employee data that we use in this study is well suited for providing appropriate empirical insights and evidence regarding labor market discrimination. The demand and supply side determinants of individual wages are taken together to analyze gender wage gap using quantile regression. The paper contributes to the existing literature in four different ways.

First, we use an extended version of the quantile regression decomposition method, which is called Re-centered Influence Function (RIF), as this method has a number of attractive features. One attractive feature is that RIF allows for clustering and stratification. We use the bootstrap standard errors (se) pairs clustering method in RIF quantile regression to produce reliable standard errors for inference. Moreover, RIF is robust to outliers and heteroscedasticity. In addition, it allows us to examine the effect of covariates on unconditional quantiles and as a result, the contribution of each explanatory variable to the gender wage gap can be retrieved at each quantile of interest. The RIF decomposition method is more flexible if one has an interest in knowing the percentage of the gender wage gap explained, for instance, by education at a given quantile.

Second, analyzing the impact of observed and unobserved firm characteristics on the gender wage gap across the entire wage distribution , to the extent of our knowledge, not yet explored in Ghana. We identify the size of firm fixed effect in gender wage gap across quantiles of the wage distribution. Further, we study the characteristics of firms that reduce the within firm gender wage gap. In doing so, the problem of stratification and clustering has been corrected, which otherwise inflates the standard error (see the discussion on the data)

Third, we take into account the problem of detailed decomposition following Yun (2005). The original Oaxaca and Blinder (1973) method and the RIF decomposition methods were sensitive to this problem because the impact of a

[21] I wrote this gender wage gap paper while I was a visiting PhD student at Copenhagen University for 1 year since May 1,2014 till June 1,2015. Prof. Mette Gørtz was supervising me on this topic. My principal advisor Prof. Montalbano also has offered interesting insights and directions on this topic

categorical variable (e.g. no education, some education, etc.) on the gender wage gap depends on the choice of the reference group. Yun (2005) proposes a method to solve the problem of identification in detailed wage decomposition proposed by Oaxaca and Blinder (1973). We extend Yun's (2005) method in the RIF decomposition so that our result is not sensitive to the choice of reference group for dummy variables. Our fourth contribution is to provide statistical evidence on whether sample weights for causal inference should be used or not. We follow Solon, Haider and Wooldridge (2015) and Winship and Radbill (1994) as they explain the situation when to use weighting for estimation.

We find that gender segregation into low paying firms accounts for significant portion of the gender wage gap at the bottom of the wage distribution. Poor women are sorting into low paying firms. Not only sorting across firms affecting the gap, but also firm wage policies in Ghana increase gender wage gap. The remainder of the paper is organized as follows. Related literature is presented in section 2. Section 3 provides the data. The econometric methodology is presented in section 4. Section 5 discusses the estimation results, and section 6 concludes.

5.2 Related Literature

Decomposing the gender wage gap at the mean has been used conventionally in the existing literature (Oaxaca and Blinder ,1973). Recently, however, decomposing wages across the entire distributions has received more attention when designing and implementing public policy on labor demand and supply. Both individual and firm characteristics, indicated by workplace characteristics, can influence individual wages. Employer–employee data, which consists of both individual and firm level information, is ideal for the analysis of wage differentials between genders. The application of employer-employee data in sub-Saharan Africa is limited (Fafchamps et al., 2009; Nordman and Wolff, 2009, 2010). The gender impact on wages has been empirically examined by Fafchamps et al. (2009), who provide comparative evidence in a few African countries using survey data from manufacturing firms.

Yet, they do not apply quantile regression and hence, firm effects across the quantiles are not calculated. A very related article to our work comes from Nordman and Wolf (2009), who use a matched employer-employee data collected in 2005 as part of RPED surveys for Madagascar and Mauritius. The questionnaires and sample design are generally the same for all RPED data (see our data section), except that we use the RPED data from Ghana. They identify the total firm effect using the Meng's (2004) approach, which is essentially a regression at the mean.

The standard quantile regression method proposed by Machado and Mata's (2005) cannot be used to identify the size of firm effect across quantiles because detailed decomposition is impossible using this method. To the extent of my knowledge, there are three different approaches proposed in the literature that allow for detailed decomposition using quantile regression: the Re-entered Influence Function by Firpo et al. 2009 and Fortin et al., 2011 ; sequential wage decomposition by Antonczyk et al. (2010) and another method by Heinze and Wolf (2010). Our paper applies the Re-centered Influence function for quantile regression. The standard quantile regression methods proposed by Machado and Mata (2005) and Melly (2005,2006) do not allow for clustering the standard error.

Understanding that we all have the RPED data with the same sampling design, the efficiency of the estimators in the Nordman and Wolf (2009) decomposition is questionable. We apply clustered bootstrap standard error in the RIF decomposition. We build our own software program that allows for the different types of clustering the standard error in RIF. Using fixed effect regression at the mean, Nordman and Wolf (2009) find that there is no firm effect in gender wage gap in both countries. Nordman and Wolf (2010) apply a similar method using RPED data for Morocco. They find glass ceiling effect in Morocco, gender wage gap is higher at the top quantiles than at lower quantiles. Fafchamp et al. (2009) apply clustering and weighting to quantify the level of the unexplained wage gap between genders for eleven African countries using RPED data. However, their weight is questionable according to Solon, Haider and Wooldridge (2015). In an OLS specification that controls for individual characteristics, they re-estimate the model with and without firm fixed effect. They find effect of both education and gender sorting across firms.

However, the assumption of equal returns to the same observable attributes of male and female is restrictive. In addition, the assumption of constant gender wage gap across distributions does not hold in many literature (Albrecht et al.,2003; Mata and Mechado, 2005). Similarly, Nordman et al. (2011) analyze the size and sources of gender and ethnic wage gap in 7 west African cities using urban household survey data conducted in 2001 to 2002. This data has information on employment status of individuals (unemployed and un-employed) that allows for correcting for the possibility of sample selection. They identify three sectors: public ,private formal and informal. First, they apply the multi-nominal logit model to determine the probability of employment in a given sector for male ,female and pooled sample separately. Second, they estimate 6 wage models distinguished by gender and sectors , in which the selection correcting inverse mills ratio derived from multi-nominal logit is added as additional covariate. They use the pooled wage structure rather than the male wage structure as a competitive norm. Using all the estimated parameters, they decompose the wage gap into sectoral earning gaps and gender difference in the distribution of workers across sectors. This is essentially an accounting approach which does not account the role of firms in wage determination.

They find that more than 60%, depending on the cities considered, of the gender wage gap is accounted for by within-sector difference in earning. Less than 40 % is due to disproportionate distribution of genders across sectors and that the sectoral location is in favor of males. An interesting study emerges from Van Biesebroeck (2011) who compares wages directly with productivity using RPED , a data similar to ours in sampling design, collected in 1991 and 1995 for three African countries , namely Kenya , Tanzania and Zimbabwe. They find that equality strongly holds in Zimbabwe, but not at all in Tanzania. Examining whether wage equals productivity by gender at a plant level in Ghana seems a complementing evidence in the future. Several previous studies use individual level characteristics to identify the sources of gender wage gap in Sub-Saharan Africa based on distributional analysis or at the mean while they fail to disentangle the wage gap explained by firm characteristics across quantiles

5.3 Data

As part of the regional program for enterprise development (RPED), data for Ghana manufacturing firms were collected by the Center for the Study of African Economies (CSAE) at Oxford University in collaboration with the Ghana Statistical Office and University of Legon. We choose the manufacturing firms for the analysis of the gender wage gap because most of them are privately owned having a profit maximizing motive. Private firms are more likely to pay workers according to their marginal productivity compared to publicly owned firms. The public sector in Africa is characterized by over-staffing and nepotism, and thus wage rewards do not intrinsically reflect the true returns to productive characteristics (Fafchamps et al.,2009). Those who are defending the politics of the current regime are more advantaged in terms of job promotion and entitlement to new senior positions as well as unfettered access to the country's resources .

The employer–employee data consists of information for both workers and firms spanning 1992-2003 in 7 main waves. We use 6 waves, omitting year 1992. The survey is conducted in 1992, 1993, 1994, 1996, 1998, 2000 and 2003. Worker data were collected during the time firms were surveyed, making the data rich and more informative for comprehensive analysis of gender wage differentials in the country. Workers data started in 1992, while firm data in 1991. Having a one year lag between workers' wages and firm level characteristics may reduce the possible endogeneity bias in the individual earnings specification (Fafchamps et al., 2009) because firm characteristics are pre-determined variables. The data covers all types of firm size (small and large) and all locations in a country, and thus the sample is representative of manufacturing firms in Ghana. Firms were asked to provide information about their previous year performance such as sales, wage bills, profits, production, number of total workers, investment in building and equipment and ownership structure of firms. We have seen consistency in the main questions asked during the course of survey. Concerning workers data, the survey consists of information on wages, education, labor market . The data set is a panel for firms, but does not track workers overtime.

The matched employer-employee data helps controlling for firm heterogeneity in the process of wage determination. Most previous studies have emphasized supply side determinants of wages such as education and experience and give less attention to demand side factors, probably due to the paucity of data in developing countries in general and in Africa in particular. Individuals are asked about the hours worked in a week and the usual pay period and earnings. This information has been used to compute the hourly wages of the respondents. The GDP deflator has been used to convert the nominal hourly earnings to real wages. The hourly real wage is the dependent variable.

Table 1 recaps the development of real earnings and the gender wage gap. The average wage for males is higher than the average wage for females in all years. The gender wage gap, expressed as percentage of the female wage, peaks and troughs respectively in 1993 and 1996, but remains stable for the rest of the period. This pattern suggests that the country has done little in eliminating gender disparity in earnings even though international donors, domestic private and government actors have in the same period put in place a myriad of reforms including universal access to basic education, equal pay for equal work, legislation aiming at promoting gender equality in the wealth distribution and access to credit, health and public utilities.

Using GDP deflators (year 1995 as base line for purchasing power parity), the nominal earnings are converted into real earnings . A comparison of the earnings gap across time by quantiles suggests that, except in 2003, the wage gap is highest among disadvantaged men and women. At the 10th quantile, for instance, female wage is 52% and 50% of male wage in 1993 and 1996 respectively. Based on the median values, the gender wage gap as the percentage of female wage is small in 2003 suggesting a high income inequality among males. Hourly average real earnings for female and male is respectively, Ghanaian cedi 873 (0.276 dollars) and 1150 (0.364 dollars) (averaged over the entire period).

Table 2 offers information on establishment and individual level workforce composition and their labor market attributes used in the empirical earning specification. Hence, both demand and supply side determinants of the wage settings are fully covered. Individual characteristics include human capital variables (level of education, worker experience, and on-the-job training), marital status, and the seven occupational categories.

Table 5.1: Development of real earnings from 1993 to 2003 for women and men

	1993	1994	1996	1998	2000	2003	overall
Male average wage	257.99	302.48	664.91	1292.02	1894.03	3485.34	1150
Female average wage	168.06	225.54	537.63	944.69	1376.38	2680.49	873
Difference of means	89.93	76.94	127.28	347.33	517.65	804.85	277
Pay gap as % female wage	0.5351	0.3411	0.2367	0.3676	0.3760	0.3003	31.7
Ratio of female wage to male wage at different wage spectrum							
Q10	0.5236	0.6667	0.4940	0.5445	0.5177	0.8696	
Q25	0.5563	0.6508	0.7012	0.5556	0.6475	0.9162	
Q50	0.7554	0.7625	0.7306	0.6797	0.7703	0.9511	
Q75	0.7908	0.8448	0.7828	0.7469	0.5902	0.8672	
Q90	0.5968	0.7011	0.7870	0.7059	0.7887	0.7980	
Median values							
Median male wage	192.52	227.39	455.47	858.85	1193.58	2463.43	
Median female wage	145.43	173.38	332.75	583.74	919.45	2342.99	
Wage gap as % female wage	0.324	0.312	0.369	0.471	0.298	0.052	

Establishment characteristics include sales per employee, female proportion, firm size, union density, firm ownership, location and sectors. Summary statistics for weighted and un-weighted data is offered in table 2. The matched employer-employee data has information on actual experience of workers which is computed as the sum of experience at the current firm (tenure) and previous experiences obtained outside the current firm. Obtaining the actual labor market experience of a worker from the data is more relevant than using potential experience(age 6–years of education). Potential experience is a crude measure of labor market experience because it often overestimates the actual experience if a person faces prolonged and intermittent layoff from the labor market for some reasons such as war or unemployment, which are more likely in African countries. Women have quite low market experience (9 years) compared to men (14 years). This may be due to the fact that they are more involved in home production, caring for older parents and children, protracted detachment from the labor market owing to frequent child bearing and pregnancy. The gender education gap, however, is fairly meager (1 year), suggesting that Ghana has been promoting female education in the last two decades, almost achieving one of the key objectives of the millennium development agenda.

Table 2 shows the relative distribution of men and women across occupation and sectors and highlights the size of gender segregation in employment. About 29 percent of women and 10 percent of men have been placed in sales and commercial jobs. Women are working disproportionately (46%) in the food and bakery sector, whereas men (67%) are segregated in the metal, wood and furniture sub-sectors. Females are employed in small firms having average employment size of 88 workers. The average firm size is 115 workers in male working places. Women are also working in firms with less union coverage compared to union coverage in male working places. The female proportion is constructed as the ratio of female workers to total workers in a given firm. In a sample of firms that hire at least one female, on average, 40 percent of the total work force are female workers. Knowing that women represent on average 18 percent in manufacturing, the female proportion variable illustrates that women to a larger extent are disproportionately placed in certain types of firms.

The sample is initially designed to interview approximately 200 manufacturing firms using random sampling, and firms which were unavailable or dropped out would be replaced by new firms to maintain the representativeness of the data at the firm level. The sampling design made it possible to interview up to 10 workers from each firm if size allows. However, this sampling technique offers workers unequal chances of being sampled when firm size varies remarkably. About 10 individuals were interviewed from each firm suggesting that large firms are underrepresented (Fafchamps et al., 2009), suggesting that individuals in all firms do not have equal probability of selection. This calls for use of weighting.

In the presence of homoscedastic errors, Solon, Haider and Wooldridge (2015) demonstrate that weighting gave rise to heteroscedasticity. Thus, testing rather than assuming heteroscedasticity is important. Their main advice is to bear in mind carefully what we are weighting for and then apply relevant diagnostic tests that help identify the correct estimation method. We provide three empirical pieces of evidence with respect to the decision to apply weights or not in our regression (detailed procedures and results are available upon request). First, following DuMouchel and Duncan (1983) and Winship and Radbill (1994), the earnings specification is estimated using OLS and weighted least square. Second, we apply the Breusch Pagan test for the null hypothesis of homoscedastic errors. Third, the weight variable interacts with all covariates in the earnings function, and the OLS model is re-estimated using these additional variables. All these methods suggest that weighting does not add any information and thus, the paper concludes that weighting is unnecessary.

Firm level variables are used to predict individual earnings. As individuals in the same firm may share similar observed and unobserved characteristics, two sources of within-firm correlations may emerge: within-firm correlations in the error terms and correlations between observed covariates. We pooled observations across survey waves and pooling makes the results more robust to shocks affecting the economy and also attenuates the problems of sample selection.

The paper addresses the possible within-firm correlations in the disturbance terms which otherwise inflate the sta-

Table 5.2: Descriptive summary for establishment and individual characteristics by gender

	Unweighted statistics			Weighted statistics		
Variables	Full	Male	Female	Full	Male	Female
Individual level characteristic						
Real hourly logwage	6.3653	6.4293	6.0801	6.6572	6.6685	6.5522
Education level	11.1160	11.2025	10.7303	11.3973	11.3969	11.4012
Experience	13.4867	14.4278	9.2937	15.0894	15.5069	11.1822
Experience square(1/100)	2.8432	3.1532	1.4619	3.2746	3.4285	1.8349
age	36.4125	37.4927	31.5995	38.4068	38.8698	34.0736
Age square(1/100)	14.4648	15.2792	10.8365	15.7412	16.1098	12.2914
On jobtraining (yes =1)	0.4109	0.4093	0.4180	0.3453	0.3454	0.3440
Married (married=1)	0.6889	0.7334	0.4906	0.7987	0.8287	0.5183
Famile ties to manger	0.1071	0.0947	0.1627	0.0398	0.0381	0.0556
Production worker	0.5921	0.6005	0.5545	0.3450	0.3438	0.3571
Professional workers	0.0801	0.0843	0.0613	0.1120	0.1135	0.0981
Manager/propritor	0.0486	0.0539	0.0250	0.0266	0.0273	0.0203
masters	0.1145	0.1126	0.1227	0.0240	0.0227	0.0357
Sales/commericial worker	0.1351	0.0992	0.2954	0.0497	0.0346	0.1912
supervisors	0.1087	0.1244	0.0388	0.0320	0.0344	0.0100
Firm level characteristics						
Technicians	0.1051	0.1261	0.0113	0.1007	0.1113	0.0017
Union(fraction of employee)	48.8091	51.8393	35.3079	74.8028	75.9469	64.0962
Female proportion	0.1426	0.0907	0.3738	0.0859	0.0644	0.2875
Sales per employee	3.6155	3.6208	3.5919	5.0891	5.0207	5.7289
Firm age	0.4010	0.4138	0.3442	0.3666	0.3572	0.4552
Investment in equipment	0.5877	0.5961	0.5507	0.7345	0.7371	0.7108
Total employees /firm size	3.9376	4.0160	3.5883	5.2944	5.3319	4.9428
Owned by Ghana	0.0268	0.0301	0.0125	0.0558	0.0613	0.0048
Owned by foreign	0.0344	0.0362	0.0263	0.0731	0.0637	0.1608
Metal/machinery	0.2955	0.3264	0.1577	0.2680	0.2826	0.1307
Textile/garments	0.1360	0.1225	0.1965	0.1242	0.1206	0.1584
Wood/furniture	0.3239	0.3545	0.1877	0.3890	0.4065	0.2260
Beverage/drinking	0.0108	0.0110	0.0100	0.0239	0.0233	0.0294
Firm Location:Takoradi	0.0964	0.1034	0.0651	0.2342	0.2543	0.0457
Firm location:Kumasi	0.2482	0.2576	0.2065	0.1436	0.1438	0.1420
Firm location : Cape coast	0.0202	0.0202	0.0200	0.0128	0.0134	0.0070
Sex(female=1)	0.1833					
N	4.359	3.560	799	4.359	3.560	799

tistical significance of the estimated parameters (Cameron et al., 2008; Mackinnon and Webb, 2013). We apply the standard error pair cluster bootstrap method for RIF quantile regression wage decomposition. To the extent of my knowledge, there is no stand alone built in computer program used to cluster the standard error in RIF wage decomposition. By clustering the standard error, we can make the findings more reliable for practical policy recommendation.

5.4 Decomposition method based on quantile regression

Detailed decomposition is not possible in the quantile regression wage decomposition method as originally proposed by Mechado and Meta (2005). Firpo, Fortin and Lemieux (hereafter called FFL, 2009) have proposed the detailed decomposition method, which is called Re-centered Influence Function (RIF). This method is similar to Oaxaca and Blinder (denoted by OB) (1973) decomposition method, but now estimation is based on quantiles of the unconditional wage distributions rather than on the mean. The underlying departure from the standard regression is that the outcome variable is now replaced by the re-centered influence function of the statistics of interest (Fortin et al., 2011). The dependent variable is replaced by the proportion for each quantile of interest. Thus, decomposing proportions is easier than decomposing quantiles.

Let τ represents the percentile that lies between 0 and 1. Suppose Y denotes the unconditional log hourly wage. Q_τ is the τ^{th} quantile of Y. $f_\tau(Q_\tau)$ is the Epanechnikov kernel density estimator of the unconditional distribution of Y where the density is evaluated at each percentiles of Y. The Kernel function assigns greater weight to the nearest neighbors and less weight to the more distant neighbors. Following FFL, the Influence function $IF(Y,Q_\tau)$ is given by $I\left\{Y > Q_\tau\right\}/f_\tau(Q_\tau)$, where $I\left\{\right\}$ is an indicator function indicating whether the dependent variable, is greater than or equal to the Q_τ.

Define c_τ=$Q_\tau + \frac{\tau-1}{f_\tau(Q_\tau)}$. $RIF(Y,Q_\tau)$ is equal to $= c_\tau + IF(Y,Q_\tau)$ and can be represented as :

$RIF(Y,Q_\tau) = Q_\tau + \frac{\tau-1+I(Y>Q_\tau)}{f_\tau(Q_\tau)}$

The indicator function, $I(Y > Q_\tau)$ resembles the linear probability model so that regressing the indicator on a set of regressors is just a distributional regression. By considering $RIF(Y,Q_\tau)$ as a dependent variable, one can carry out the standard regression by regressing the outcome variable on covariates to obtain the estimated coefficients for each male and female sub samples separately. Finally, the OB type decomposition is carried out at the unconditional quantile function.

The presence of firm level data allows us to disentangle the firms' impact from unobserved individual characteristics on the gender pay gap and it requires, however, at least two male and two female workers in a given firm (Meng, 2004). The idea is that two individuals (say male and female) employed in a particular firm share the same firm characteristics: they may work in an exporting firm or in a firm that disproportionately hires females. Even after controlling for individual characteristics, a firm may pay higher wages for females than for males.

Thus, it is of important to control for the firm fixed effect and then disentangle gender wage gap accounted for by firm heterogeneity. After computing the gender wage gap attributable to firm fixed effect, we ask why different firms pay different wages for men and women even after netting out the wage gap attributable to the observed and unobserved individual characteristics. What are the characteristics (wage policies) of firms that reduce the within-firm gender wage gap?. Does firm effect vary across the wage distribution? To answer these questions, we first estimate the within-firm gender wage gap following Meng (2004). Our approach, however, differs from Meng (2004). He uses fixed effect OLS model. This paper uses fixed effect quantile regression and then apply the RIF wage decomposition method. Meng (2004) does not compute the standard errors of estimated coefficients. This paper offers the clustered bootstrap standard error. In addition, this paper controls for time dummies and examine their effect on the gender wage. Perceptions towards female and male may vary overtime. With a tendency of increasing globalization, gender bias may decline overtime. Just for ease of understanding (for readers), I just drop the quantiles of interest in presenting the equations here . The earnings model is estimated separately for male and female workers as follow.

$$w_{ij}^{m} = \eta^{m} + \alpha^{m} + \beta^{m} x_{ij}^{m} + \gamma_{j}^{m} + \varepsilon_{ij}^{m} \tag{1}$$

$$w_{ij}^{f} = \eta^{f} + \alpha^{f} + \beta^{f} x_{ij}^{f} + \gamma_{j}^{f} + \varepsilon_{ij}^{f} \tag{2}$$

β^f and β^m are vectors of estimated regression coefficients for individual characteristics at a given quantiles of theta for the observed characteristics of females and males respectively.

γ_j captures the wage premium associated to firm's j characteristics (observed and unobserved). The wage premium for female and male workers hired in firm j is given by γ_j^f and γ_j^m respectively. They are also called firm fixed effect. x_{ij}^f and x_{ij}^m capture individual specific characteristics of each gender in firm j respectively . The third term denotes the coefficient effect, the wage gap resulting from differential treatment for comparable male and female observed individual characteristics. In the same vein, the fourth term is the coefficient/ price effect, capturing the differential firm wage polices with respect to gender. Other things being constant, the fourth term illustrates the gender difference in firms premium. We pool the data overtime and time is a control variable. The year dummies are represented by η^f and η^m in female and male sub-samples respectively. ε_{ij} is an idiosyncratic white noise error term.

Given the competitive male wage coefficients, the counter-factual female wage, $RIF(\overline{w}_f, Q_{m,\tau}) = \beta_\tau^m \overline{x}_f' + \eta_\tau^m + \gamma_{j,\tau}^m$,represents the wage level female would receive had she been rewarded the male premium at firm j , the price the market pays for observed male attributes but retained her own characteristics. The firm fixed effect would be zero if male and female enjoy the same firm premium. The raw gender wage gap is decomposed into 4 parts: a part due to differential individual endowments; a part due to unexplained factors; a part due to gender difference in the firm premium ; a part due to time effect. The wage decomposition equation can be written as follow:

$$RIF(\overline{w}_m, Q_{m,\tau}) - RIF(\overline{w}_f, Q_{f,\tau}) = \overline{x}_f'(\beta_\tau^m - \beta_\tau^f) + \beta_\tau^m(\overline{x}_m' - \overline{x}_f') + (\eta_\tau^m - \eta_\tau^f) + (\gamma_{j,\tau}^m - \eta_{j,\tau}^f) \tag{3}$$

The first and second terms represent the coefficient and endowment effects respectively. The third is the time effect and the last term represents the firm effect (differences in firm premia between genders).

5.5 Estimation results

5.5.1 Effects of gender sorting and firms wage policies

One caveat is that women may self-select into labor markets based on their expected wage, implying that those entering the labor market may have different characteristics compared to the average characteristics of the whole female population in the country. Properly accounting for this problem would require individual level data for both individuals in wage employment and non-wage employment (self–employed and non-employed individuals). The manufacturing survey contains earnings information only on salary employed individuals and we do not have data on unemployed persons and their characteristics and unable to address the potential sample selection. This is the limitation of the paper. However, RPED data have been extensively used for the same topic in African countries as discussed in the literature.

Estimation result is reported in table 3. As the dependent variable is in log wage, results have been reported in logarithmic scale, which can be transformed back into the original scale in level. At the 10^{th} quantile ,the log of wage difference (log(male wage)-log(female wage)) is 0.52, which mean that females' wage is 59% of males' wage ($e^{-0.52} = 0.59$). Similarly, females' wage is about 65 percent of males' wage at 25^{th} and 75^{th} quantiles. Females earn 81 % of males' wage at 90^{th} quantile. Women earn about two thirds of men's wage except at the 90^{th} quantile.

The gender wage gap at the 10^{th} quantile is 2.5 times larger compared to the gender wage gap at 90^{th} quantile. Gender wage gap declines across quantiles except at 50^{th} quantile. The widening gap at the bottom of the wage distributions implies that poor women are more disadvantaged than poor men. They are less endowed with human capital, and also disproportionately segregated in less paying firms. Firm premium is in favor of males (discrimination by employers)

The positive sign for the firm effect suggests the presence of a positive correlation between firms' wage policies and the gender wage gap. Firm effect explains more than 50 percent of the gender wage gap. Women receive low firm premia irrespective of their location in the wage distributions. Hence, manufacturing firms in Ghana do not make a substantial effort to mitigate gender difference in wages, rather increase the gap. Time effect (5 %) is found to be insignificant. The log wage difference between men and women due to observed individual compositions is lower at the 10th decile (0.099) but higher at the 90th (0.2355). The raw gender wage gap is found to be higher at the bottom decile than at the top decile, suggesting evidence of a sticky floor effect. Poor women are more disadvantaged than men.

Nevertheless, the firm effect in table 3 may be due to segregation effect, which is gender sorting across firms by employers, rather than firms wage policies. It may be due to labor market segmentation in the sense that females are disproportionately placed in low paying firms. We remove sorting effect and re-estimate the model. First, we estimate the wage model for each gender using a full set of individual, observable establishment characteristics and the proportion of female employees in a firm. Second, individual earning is adjusted for by the effect of female proportion. Using the adjusted individual wage as a dependent variable, the earning function is re-estimated using individual characteristics and firm fixed effect. The result is displayed in table 4. The gender wage gap (in log) at the mean decreases from 0.44 to 0.358 or falls from 35.6% ($1 - e^{-0.44}$) to 30%($1 - e^{-0.358}$) of the male wage. Thus, gender wage gap accounted for by just the pure effect of gender sorting is about 18.6% (0.44-0.358)/0.44) at the mean. Yet, the effect varies substantially across quantiles. Wage gap decreases from 0.5218 to 0.3195 at 10^{th} quantile after removing the effect of female proportion(or sorting effect). It decreases from 0.4366 to 0.3324 at 25^{th} quantile and from 0.5382 to 0.4166 at 50^{th} quantile. It also falls from 0.4374 to 0.344 at 75^{th} quantile. In contrast, it does not decrease at 90^{th} quantile. Putting these into perspective, gender sorting accounts for 38.8%, 23.8%, 22.6% , 21% and 0 of the observed gender wage gap respectively at 10^{th} ,25^{th} , 50^{th} ,75^{th} , and 90^{th} quantiles. The result suggests that gender sorting is pervasive for poor women. It is one of the main reasons for gender wage gap.

The remaining gender wage gap (i.e adjusted gender wage gap) after deducting the effect of gender sorting is further decomposed into firm effect, time effect , individual endowment and coefficient effects as shown in table 4. Firm effect captures the firms' wage policies, which include observed (such as firm size, exporting firm, wage bargain, firm ownership and location etc) and unobserved firm specific characteristics. Even after controlling for female segregation, firm effect is still substantial across the entire wage distributions, suggesting that firms' wage policies actually increase the gender wage gap in Ghana manufacturing firms. This paper concludes that firm attributes (observed and unobserved establishment characteristics) explain between 44% and 69% of the adjusted gender wage gap , depending on the quantile being considered. In other word, firm effects are between 33% and 58 % of the observed gender wage gap, where the lower and the upper bounds correspond to the 10^{th} and 90^{th} quantiles respectively. Firm effects and gender sorting explain the largest portion of the observed gender wage gap. Both explain the largest portion, between 58 and 71.8 percent respectively at 90^{th} and 10^{th} quantiles, of the observed gender wage gap.

The unexplained gender wage gap disappears after controlling for firm fixed effect except at higher quantiles. We have noted that once controlling for the firm effect, the returns to education decline in both female and male earning models, suggesting that high paying firms attract educated individuals. In this case, this finding is consistent with Fafchamps et al. (2009) who find that African manufacturing firms actually value education.

Table 5 reports the detailed decomposition result based on table 4. Note that the Oaxaca decomposition based on OLS should be used only as a benchmark, not the final model of interest. The contributions of the control variables to the total gender wage gap are presented in table 5. The difference in labor market experience between male and female is an important contributor to the gender wage gap. After controlling for firm heterogeneity, education and experience explain 20% , 14% and 19 % of the adjusted gender wag gap respectively at the 10^{th}, 50^{th} and 75^{th} quantiles. Out of this, the effect of labor market experience is substantial (about 80%). Women's low labor market experience still remains a serious impediment to wage equality. Females are not fully integrated in the labor market. In particular, poor women have low labor market experiences compared to men. Gender difference in experience accounts for 19% of the adjusted gender wage gap at 10^{th} quantile.

5.5.2 Firms' wage policies: what kind of firms reduce within-firm gender pay gaps?

We ask what causes firms to pay different premia for women and men. γ_j^m and γ_j^f are firm fixed effects respectively for males and females at firm j (retrieved from eq(1)and eq(2)). Individually, γ_j^m and γ_j^f are not zero. The within-firm gender wage gap, which is given by $\gamma_j^m - \gamma_j^f$, is statistically different from zero. We take the within-firm gender pay gap as the dependent variable ($\gamma_j^m - \gamma_j^f$) and regress it on the observed firm characteristics .

The estimation results are reported in table 6. We find that observed firm characteristics explain 44.7 percent (R-squared=0.4468) of the within-firm gender earning differential, which is considerably large compared to the finding established in Meng and Meurs (2004) for Australian labor market (0.068) and for France (0.039). Thus, the data plausibly fits the model.

Table 6 allows us to test some hypotheses and contentious thoughts and ideas which have been widely asserted in economics of discrimination and labor economics in the last couple of decades. Becker (1957) and Arrow (1973) describe discrimination as something related to personal prejudice against a specific group. They argue that discrimination in a competitive environment brings considerably large costs to discriminatory employers because non-discriminatory firms can get cheap labor and consequently derive the discriminatory firms out of market. Expensive workers are retained in the discriminatory firms, not just by their better productivity but by personal taste of employers. Two dummy variables have been included in the model as a measure of market competition facing a firm. The first is a dummy variable indicating whether a firm declares itself under high a competition or not.

Firms were asked whether the rise in the number of competitors was the major concern or not. The second variable represents the percentage of raw materials imported from abroad. We expect that the higher import contents in firms' product, the more likely they are to engage in tough competition. Consequently, a firm facing world competition is more likely to pay its workers their marginal product and thus act in a less discriminatory way. The estimation result is reported in table 6. As expected, strongly import dependent firms are more involved in narrowing the gender wage gap. Competition in product markets is seen to be a panacea against employers' personal taste and prejudice in labor market. This finding is in line with a recent study by Black and Brainerd (2004) who find a negative relationship between globalization and employment discrimination, using increased volume of import as an indicator of high market competition. As shown in table 6, firms that involve in a high competition are less discriminatory.

We look at the impact of the percentage of workers under union membership on the gender wage gap. Firms with a high union density reduce within-firm gender pay gap. This reflects the importance of labor market institutions in wage determination. Decentralized wage bargaining system brings unwanted prejudice. The imperfect information hypothesis is another relevant aspect in the discrimination literature. Firms having reliable information about workers' productivity are less likely to discriminate than those with little or no information concerning objective measures of worker performance and productivity. Lack of accurate information about worker productivity is another source of the gender wage gap (Arnott and Stiglitz,1985). Two variables have been incorporated as additional covariates to account for the role of information on gender wage gap. One variable is the share of labor costs in the aggregate costs and another variable is the share of managers in total workers in a given firm.

Worker productivity in labor intensive firms can be measured easily and thus remuneration is determined based on their objective performance. As expected, labor intensive firms narrow within-firm gender pay gap (see table 6). Had firms not been labor intensive, then the raw gender wage gap would have been about 8% higher. Similarly, the coefficient associated to the share of managers is negative and statistically significant suggesting that firms with high supervision do have better information on workers' productivity and are less likely to discriminate between genders.

Firm ownership is also crucial in the determination of wage. The positive and significant impact of domestic ownership suggests that Ghanaian owned firms are more discriminatory than other types of ownership. Finally, we have seen no industry effect except that textile/garment activity reduces the within-firm gender pay gap. In addition, strategic location of business is deemed to be an important determinant of within-firm gender premia. Firms located at the Cape coast have a higher within-gender wage gap. Firms that expect improved access to credit raises the gender earnings gap.

According to Becker's (1971) personal taste hypothesis, firms that hire more women are more likely to have less prejudice against women and may have equal pay policy . To test this hypothesis, the proportion of women in total employment is incorporated in the regression model. The variable has maintained the expected sign but is statistically insignificant. In general, union density, young firms, labor intensive firms, firms facing high competition(firms with low market power),firms with high mentors and supervisions and importing firms are those that strive to reduce the earning differential between genders. On the other hand, fully domestic owned firms escalate gender wage gap. Finally, we must note that the estimation result reflect association, no causal interpretation should be enshrined in.

5.6 Conclusion

This study investigates the role of individual and establishment characteristics in determining the gender wage gap across the entire wage distribution in Ghana. The study emphasis on why poor women are more disadvantaged than their male counterparts. Controlling for these two types of characteristics offers new insights regarding the sources of the gender wage gap. Workplace characteristics as demand side determinants of individual wages have received modest attention in gender pay gap analysis in the past, although they are believed to affect wages through a number of channels such as knowledge spillovers and peer effects. We find that the gender pay gap is not constant across the wages distribution and the decomposition is therefore carried out across the entire wages distribution using the re-centered influence quantile regression approach. The wage gap is decomposed into 4 components: firm effect, time effect, individual endowment and coefficient effects. Poor women earn 59% of the men's wage at 10 quantile. The gender wage gap at the bottom of income distribution is 2.5 times larger than the gender wage gap at the top quantile. The larger gap at the bottom quantile suggests that poor women are more disadvantaged than poor men. The widening gap at the bottom of the wage distributions implies that wage differentials are driven by different mechanisms for the high and low income workers. The main sources of gender wage gap for the low earning workers are segregation into low paying firms and low labor market experience. Gender sorting across firms accounts for 38.8% of the observed gender wage gap at 10^{th} quantile where as 12% of the gap is attributable to gender difference in experience.

Even after deducting the pure effect of gender based labor market segmentation from the observed wage gap, observed and unobserved firm specific characteristics explain a significant portion of the gender wage gap. Firm wage polices actually increase the gender wage gap in Ghana. After controlling for gender differences in observed and unobserved individual characteristics, there exist firms that reduce gender wage gap. Firms that reduce the within-firm gender wage gap include those having centralized wage bargaining, young firms, labor intensive firms, firms facing high competition (firms with low market power), firms with high mentors and supervisions and importing firms. On the other hand, fully domestically owned firms escalate the earnings differential between genders. Firms wage policies matter for the gender wage gap.

By disproportionately sorting into low paying firms, poor women earn low wage. They have also a record of low experience, making them to earn less. This calls for policy makers to pay attention to the poorest of the poor through a number of policy avenues, especially targeting those observed characteristics. During the later stage of pregnancy, women usually quit their job as there is inadequate sick leave with pay in most African countries. The maternity leave is also inadequate. They have less chance to return to their job after child birth. Intervention to promote their earning should be in place by increasing the poor women's labor market participation and mitigate the constraints facing women during pregnancy, and maternity leave. It is one way to decrease poverty as well as the social cost of poverty. Poor women are also disproportionately working in less paying firms, which are often small and inefficient. Another way of decreasing poverty is therefore to increase the capacity and productivity of those firms, in particular the female dominant firms that hire poor women. Introducing better management system (e.g skill enhancements through training within and between firms) as well as access to credit are important policy instruments to promote the competitiveness of the female dominant but inefficient firms. These findings and policy recommendations may also apply to Uganda, as most of the Sub-Saharan African countries are structurally similar (in terms of labor market and governance measures).

Appendix 5: Regression Tables

Table 5.3: Wage differential between gender: decomposition result

	Oaxaca	Q10	Q25	Q50	Q75	Q90
Characteristics effect	0.1464***	0.0995**	0.1125***	0.1166***	0.1707***	0.2355***
	(0.0361)	(0.0453)	(0.0368)	(0.0429)	(0.0538)	(0.0637)
Coefficient effect	–0.0144	0.0599	0.0714	0.1464***	–0.1119	–0.2580**
	(0.0351)	(0.1013)	(0.0665)	(0.0606)	(0.0821)	(0.0969)
Firm effect	0.2635***	0.3128**	0.2050**	0.2456***	0.3269***	0.1637**
	(0.0585)	(0.1271)	(0.0809)	(0.0673)	(0.0812)	(0.0825)
Time effect	0.0446	0.0495	0.0477	0.0295	0.0517	0.0694
	(0.0403)	(0.0478)	(0.0463)	(0.0553)	(0.0494)	(0.0543)
Wage gap	0.4402***	0.5218***	0.4366***	0.5382***	0.4374***	0.2108**
	(0.110)	(0.1474)	(0.0947)	(0.0785)	(0.1001)	(0.0958)

Note: Significance level: * 10%, ** 5%, *** 1% . For the quantiles and Oaxaca, the clustered bootstrap standard errors are in the bracket . 999 replications used

Table 5.4: The within-gender wage gap after removing the effect of female proportion

	Without firm effect	With firm effect					
	Oaxaca	Oaxaca	Q10	Q25	Q50	Q75	Q90
Characteristics effect	0.1937	0.1458	0.1257	0.1178	0.1103	0.1754	0.2296
Coefficient effect	0.1283	–0.0160	–0.0476	0.0094	0.0547	–0.1235	–0.1959
Firm effect		0.1829	0.1761	0.1459	0.2230	0.2390	0.1226
Time effect	0.0295	0.0452	0.0654	0.0592	0.0285	0.0532	0.0631
Wage gap	0.3579	0.3579	0.3195	0.3324	0.4166	0.3440	0.2194

Table 5.5: The contribution of the composition effect to the total gender wage gap (%)

	education	experience	training	occupation	other	overall
OLS	4.41	6.10	–0.35	13.99	16.71	40.86
Q10	0.88	18.93	2.75	5.60	11.31	39.47
Q20	2.17	11.03	1.04	7.23	17.86	39.32
Q30	1.19	12.38	0.94	7.44	12.03	33.98
Q40	2.59	7.79	–0.59	0.20	18.78	28.77
Q50	2.78	11.53	–1.03	7.52	6.02	26.82
Q60	2.90	11.34	–1.29	9.33	7.97	30.25
Q70	5.20	16.42	–2.29	15.75	6.70	41.78
Q75	6.87	12.46	–1.13	25.96	6.99	51.15

Table 5.6: The effect of observed firm characteristics on within-firm earning premium

Variables	Coefficients	Standard error
Fraction of workers covered in labor union(union density)	–0.0030***	0.0011
Female proportion	–0.2133	0.1997
Sales per worker	–0.0030	0.0081
Business established after 1985	–0.3487***	0.0887
Investment in equipment and plant	–0.1064	0.1258
Firm size	–0.0282	0.0402
Firm facing strong competition	–0.1645	0.1160
Labor intensive firms	–0.8077**	0.4106
Percentages of raw material imported	–0.0038**	0.0015
Share of managers in total workers	–2.1815***	0.6354
expect improved credit availability/no credit constraint	0.2276**	0.1148
Ghanian ownership	0.4263***	0.1394
Foreign ownership	–0.1268	0.2248
Metal/machinery	–0.0269	0.1219
Textile/garments	–0.2572**	0.1170
Wood/furniture	–0.1344	0.1249
Beverage/drinking	0.0711	0.1828
Business Location: Takoradi	–0.0859	0.1241
Business Location :Kumasi	–0.0999	0.1029
Business Location :Cape coast	0.1676**	0.0822
Constant	1.2383***	0.2123
R squared	0.4468	

Note: Significance level: * 10%, ** 5%, *** 1%. Other in the table represents marital status, and whether the manager is a relative of the worker.

Conclusion and Policy recommendation

By comparing the fixed standard of living with that of the amount of resources (consumption) commanded by a person at a point in time, one can classify whether a person is poor or not because knowing the proportion people falling below the poverty line is of an interest by donors and policy makers. The empirical challenge is on how to construct poverty line bundles that are utility consistent because they should reflect the consumption patterns and local perceptions of households living in different regions and time-varying preferences ((specificity to region and time). The thesis constructs poverty lines that are spatially and inter-temporally utility consistent for Uganda and apply them to assess the extent of changes in poverty across periods and analysis of poverty dynamics. It finds that the official poverty headcount ratios are always lower than the poverty headcounts computed based on our utility consistent poverty lines. The official report by Uganda Bureau of statistics suggests a reduction of poverty as one moves from 2005/06 to 2009/10. Yet, this claim is not supported at all in this study though we all have the same set of raw consumption data. Instead, there is an increase in poverty. The thesis shows that methodological choices matter to the magnitude of poverty level and its change. Our recommendation for policy makers in Uganda is to revise their poverty reduction strategies in a way to have a practical impact on poverty alleviation. Using the utility consistent poverty line as an input, the thesis goes deep into a number of relevant topics step by step: identifying the type of poverty that prevails most in Uganda; the causal impact of past poverty and the true level of poverty persistence.

The availability of longitudinal data helps distinguish the chronically poor from the transitory poor. Poverty in Uganda is largely chronic, not just because the absolute number of chronic poor is higher than the absolute number of transitory poor, rather it is due to the fact that the chronic poor involve large drop in consumption relative to the poverty line. Their contribution to the poverty gap is more than their population share in the poor households. Analyzing the distribution of chronic poverty by regions suggests that the North is the most affected by chronic poverty followed by the East. In addition, households having large number of dependency ratio (having at least 4 children aged under 14) are the most constrained by consumption poverty as well as other multiple deprivation indicators. Of the three dimensions of deprivation indicators (consumption, education, housing), consumption poverty does not improve overtime in Uganda.

This type of analysis belongs to one strand of the literature that characterizes the poverty overtime into a composite index. The inter-temporal poverty measure is decomposed into chronic and transient components. In this strand of the literature, it is difficult to empirically identify the mechanisms affecting chronic or transient poverty because of the confounding individual specific unobserved heterogeneity. Another strand of the literature focuses on poverty dynamics, which is the movement into and out of poverty by each individual at different points in time. With the presence of longitudinal data, one can model the poverty dynamics of individuals so as to determine the magnitude of economic mobility and the mechanisms determining the degree of poverty persistence.

The thesis applies the poverty transition dynamic model ,called endogenous switching regression, that decomposes the observed poverty persistence into two effects: true state dependence and heterogeneity effects (observed and unobserved). Even after controlling for differences in individuals observed and unobserved heterogeneity, endogenous initial condition and attrition, substantial portion of (between 49 and 71%) the observed poverty persistence is accounted for by the pure effect of past poverty (True state dependence). TSD is resulting from the poverty induced changing behavior of individuals. In the presence of TSD, short run policies are effective. Of course, the observed poverty persistence in itself can be biased with measurement error. An ideal approach is to directly estimate this model with the possibility of correcting for measurement error in consumption. This is beyond the current topic and be a potential direction for future research. Nevertheless, the Markov poverty transition probability model helps determine the magnitude of the true poverty persistence though it does not allow to decompose the latter into two effects. Like the endogenous switching regression model, the mixed latent Markov model controls for individual specific unobserved heterogeneity, observed individual characteristics and endogenous initial condition. The difference is that it also controls for measurement error. The model has two main components: the structural component (latent/true transition probabilities and initial state) and the measurement error component.

The thesis finds that the true poverty persistence is at least 61% instead of the 52% observed from data, suggesting that measurement error understates the observed poverty persistence by at least 9%. Measurement error also attenuates the impacts of covariates on making transition from one state to another. To formulate the policy implication of poverty persistence, the thesis combines the information obtained from mixed latent Markov model with that of the endogenous switching regression, as the latter decomposes the poverty persistence into TSD and heterogeneity effects. Clearly, the poverty in Uganda is largely persistent, not transitory.

When TSD dominates the poverty persistence, the policy priority is to keep individuals not to fall into poverty in the first place. The thesis recommends the poverty reduction policy design to be done in this order. First, government should target those households whose consumption is slightly above the poverty line using short run policies. These households are not chronically poor but whose inter-temporal general mean consumption (using the most flexible approach by Foster and Santos (2013) that gives more weight to low consumption than higher consumption) is marginally above the poverty line because they are at a risk of falling into poverty. Once they slipping into poverty, they are less likely to exit because of the presence of poverty induced changing behavior effect (TSD) in the country. Further research, if necessary, can be carried out to know the most important poverty induced changing behaviors in Uganda (like stigmatization, social exclusion, demoralization, lack of motivation as done by Biewen, 2014). The short run policies that can be used to avoid the risk of falling future consumption include access to credit, crop and health insurances, precautionary savings and strengthening social capital (extended family ties and support, village based risk sharing).

Second, since the magnitude of true poverty persistence is already high, policy makers should target those households at the bottom end of the consumption distribution, which is to target the poorest of the poor through long term polices. When we say poverty is mostly persistence, on average, individuals experience high probability of recurrently being a poverty membership. As we move from poverty gap to squared poverty gap poverty measures, the thesis finds that the share of chronic poverty significantly increases irrespective of the methodological choices used for inter-temporal poverty aggregation. This implies that those who are at bottom of the consumption distributions bear most of the inter-temporal poverty burden. These long term policies include intervention in the form of increasing their human capital and asset bases. Safety net and food for work programs can be available to the very poor so as to ameliorate the persistently low consumption. In particular, land is an important asset for rural households and increasing the return to land is a promising way out of poverty. The paper finds that land size per capita reduces the chances of slipping into poverty as well as increases the propensity of poverty exit. Besides increasing land access to the poor, an interaction between land and information can increase the return to land. Mobile phone and TV-radio are significant predictors of poverty. Even after removing the part of expenses associated to TV-radio and mobile phone from the consumption components, the finding suggests that households who own mobile phone and TV-radio are always less poor compared to those without.

About 63% of households own TV-radio in their home. Given their poverty reducing role as stipulated in this thesis, how to increase the supply of these assets to the bottom poor households is a policy concern. At national scale, increasing investment on information and communication industry as well as privatizing the sector may enhance competitiveness, which can offer incentives for users. The very poor can be privileged in the form of subsidy and access to credit to own these electronic assets because the information can be an input in production as well as marketing (besides their consumption role). Finally, the latent mixed Markov model in this thesis offers the impacts of covariates after controlling for measurement error, which can be used for policy consideration. Dependency ratio, education, ownership of electronic assets (mobile phone and TV-radio), land size per adult and high proportion of adult members are the most important variables that affect the poverty transition probabilities. Family planning lessons and off-farm employment opportunity should be given due attention in the poverty reduction plan. In the survey, we have information regarding how civil strife before 2001 affected households economy (at least four year long before the start of the first survey). In the poverty dynamic models, those who were affected by the incidence of civil strife are more likely remain poor or falling into poverty. Building better performing institutions that ensure good governance must be part of the poverty reduction strategy plan of the Ugandan government. In short, the thesis recommends to target those who are very poor and those who are marginally above the poverty line using long and short term policy interventions respectively.

Another lesson emerges from the analysis of gender wage gap using employer-employee data from Ghana. Considering both the demand and supply side determinants of individuals wage gives useful policy insights. The finding suggests that poor women are disproportionately sorted into low paying firms. This exacerbates the cost of poverty by increasing wage inequality between poor men and women. These firms are female dominant but unproductive. Hence, policy makers should give attention to increase the productivity of these firms by increasing access to credit and building better managerial systems, which include on-job training between as well as within firms. Eventually, they would increase female's wage and this helps close the wage inequality.

In addition, the thesis finds that firms wage polices widen the gender wage gap. Some of the firms that reduces differential wage premium between genders include firms that are labor intensive, those having centralized wage bargaining, young firms, firms with high mentors and supervisions and firms facing high competition. Finally, poor women are more disadvantaged because they have low labor market experience, which explains at least 12% of the observed gender wage gap at bottom wage distribution(10^{th} quantile). Intervention to promote their earning should be in place by increasing the poor women's labor market participation and mitigate the constraints facing women during pregnancy, and maternity leave. These findings suggests that policy intervention to increase the productivity of female dominant firms as well as women's labor market involvement is required to reduce the national level poverty.

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