Poverty persistence and informal risk management: Micro evidence from urban Ethiopia

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Abstract

We study poverty dynamics in urban Ethiopia with an emphasis on the effect of idiosyncratic shocks and informal risk management strategies. We used a unique panel data spanning a decade. Our results show the adverse impact of uninsured idiosyncratic shocks on welfare. We find unemployment of household head propel households to persistent poverty. We also observe poor households using ineffective risk management strategies which have negative consequences on welfare than their non-poor counterparts. We also confirm the existence of strong poverty state dependence which is mainly driven by households' heterogeneity. The overall results of our study suggest that public insurance programs that support poor households during 'bad times' may improve welfare by providing consumption insurance. Indeed, policies focusing on household heterogeneities such as exposure to risk, lack of education, personal skills and capacities, would have long lasting effect.

Key words: Poverty persistence, idiosyncratic shock, endogenous switching model
JEL Classification: D14; I32; O12

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1 Introduction

Understanding why people remain poor is immediate consequential research issue in developing world. There exist large body of literature that analyzed poverty in developing countries particularly static poverty analysis.[1] There is now however a consensus that static poverty analysis has limited explanatory power of poverty determinants and can lead policy makers to focus on the symptom of poverty rather than the main causes of poverty (Cappellari and Jenkins, 2002; Addison et al., 2009).

With the availability of panel data in developing countries, poverty dynamics literature is growing. A good survey of poverty dynamics literature in developing countries is given in Baulch and Hoddinott (2000), McKay and Lawson (2003), Dercon and Shapiro (2007) and Baulch (2011). All the reviews pointed out that the literature is far from complete. About half of the studies examine a few hundred households, about 40% used a data set that only have two waves and about 10% analyze urban poverty dynamics. Most importantly, though risk[2] and non-random panel attrition turn up in many of narratives of poverty dynamic studies, the literature omit them largely (Dercon and Shapiro, 2007); a lacuna towards which this study contributes to.

Among many other factors, shocks like unemployment, sickness, death, theft, drought and political strife creates large income and consumption variation over time. Barrientos (2007) reviews the existing literature and concludes that there exist increasing evidence that uninsured shocks raise poverty incidence. Nonetheless, the long term effect of shocks to propel households into persistent poverty remains unknown. There are two consequences of shock. First, there is impact of shock on welfare. Alderman et al. (2006) in rural Zimbabwe found children affected by the civil war and drought shocks in 1970s and 1980s incurred a loss of about 14% of their lifetime income. Second, there is a behavioral change; households that face uninsured risk may push themselves towards low risk and low return activities or asset portfolios. Asset poor rural India households, for instance, allocate large proportion of their land to safe traditional varieties of rice and castor than high yield but high risk crops (Morduch, 1995). Household decision to hold non-productive asset or use low return variety of seed doesn't only means forgone current income but also a higher chance that a household is poor in the long run. Being able to smooth income or consumption variations overtime despite the existence of shocks therefore reflects an important dimension of welfare. And, an essential part of poverty analysis requires understanding the pattern of risk exposure and risk management strategies employed by households.

de Neubourg (2002) explains how household smooth consumption in a framework of a 'Welfare Pentagon' representing five core institutions namely: family, markets, social networks, membership institutions and public authorities. Households use institutions in Welfare Pentagon to generate income and smooth consumption. Credit and insurance markets are however mostly absent in most developing countries including our case study, Ethiopia. According to AfDB (2011), less than 10% of Ethiopian households have access to formal credit and insurance. 80%

[1] An analysis that measures living conditions at point in time or compares poverty indicators of a given year with past years ignoring household trajectories over time.

[2] There exists different risk definition. Here we follow the World Bank definition, risk is an event that trigger decline in well-being and shocks as a manifestation of the risk (World Bank, 2001). We use shock and risk interchangeably.

of the global population has no access to comprehensive social protection (UN, 2012a). Social network, family and membership institution (in general informal risk management channels) are thus more prevalent than other Welfare Pentagon institutions in developing countries.

Carter (1997) argues that it is rational for households to partake in some form of informal risk sharing arrangements with their neighbors, friends and families in the absence of insurance and social protection. Morduch (1999) looks at these coping strategies as effective instruments to reduce current poverty while Dercon (2005) argues exposure to uninsured risk may force household to hold less-productive assets for the purpose of consumption smoothing. There is more empirical literature related to informal risk sharing with a particular emphasis on rural developing economies. Deaton (1990), Fafchamps and Lund (2003), Ayalew (2003), Skoufias and Quisumbing (2005) and Santos and Barrett (2011) are among other. Almost all studies examined whether households consumption allocations replicate the Pareto-efficient full risk pooling outcomes in a rural context. The findings reveal that the estimated response of consumption to income shocks is small but significant, suggesting a rejection of full insurance.

The existing literature provides plausible explanations on rural poverty dynamics and how rural poor households manage risk in the absence of public and market institutions. However, there is a dearth of empirical evidence to show how uninsured shocks and household risk management strategies affect poverty dynamics among the rapidly expanding urban population in developing countries.[3] Due to open world assumption that poverty is rural phenomenon, poor urban were generally neglected by both researchers and development programs until recently. Bigsten and Shimeles (2004), Kedir and McKay (2005), Islam and Shimeles (2006) and Faye et al. (2011) are few exceptions that analyze poverty dynamics in urban Sub-Saharan Africa excluding South Africa. Despite the fact that uninsured shocks are common in the region and households developed sophisticated informal risk management mechanisms to reduce the consequence of shocks on welfare, none of these studies look at their impact. Thus, our study seeks at filling these gaps using a decade long panel data from urban Ethiopia.

Rural and urban distinction is important in studying risk and risk management. For instance, while rural households are more vulnerable to weather shocks (like drought, variability of rainfall or flood) and need support to cope with fluctuations in food production, the urban poor are more vulnerable to income shocks (like unemployment, loss of productive day due to illness or loss of income due to death of breadwinner) and need support to cope with fluctuations in food prices. Proximity and occupational similarity to some extent mitigate information asymmetry in rural areas which facilitate mutual risk sharing arrangements when households face idiosyncratic shocks. Urban households on the other hand are engaged in different economic activities which increase information asymmetry that deters it. Given the idiosyncratic nature of shocks, one can expect informal risk management mechanisms to protect households from the effect of shocks in urban areas. However, it is not possible to conclude a priori (Cox and Jimenez, 1998).

Using rich urban household panel data and more rigorous econometrics specification than previously applied to this topic in developing country, we study the impact of idiosyncratic shocks and informal risk management strategies on urban poverty dynamics. Understanding the effect of shocks and shock management mechanisms on poverty dynamics provides useful insight in

[3]The proportion of Africans living in urban areas increased from 15% in 1950 to 39% in 2010 and the proportion is expected to reach 50% by 2030.

designing poverty reduction policies. If the existing informal risk management strategies found to be effective to deal with the consequence of shocks households are facing, introducing a public insurance scheme simply crowd out the existing mechanisms. On the other hand, if it only provide protection to better-off households, targeted public insurance to the poor enhance net gain to society. The study also substantially contributes to the on-going debate whether poor households can insure themselves against consequence of idiosyncratic shocks in the absence of market and public institutions by providing evidence in urban setting of least developing country for the first time. We employed two 'poverty transition' econometric models; the random effect dynamic probit model and the endogenous switching model. One of the key findings of this empirical work is that urban households don't succeed to enjoy full insurance like their rural counterparts. Economic shock, unemployment of household head, have a positive effect on poverty persistence. We also find that poor households use ineffective risk management strategies which have negative consequence on welfare than their non-poor counterparts. Having access to international remittance decrease the probability of poverty persistence. Similar result is found to Peruvian households; during macro-economic shock households with access to international remittance are better off (Glewwe and Hall, 1998). However, it worth to mention that only 17% of poor households have access to international remittance in our sample. On the other hand, the most dominant informal risk management mechanisms used by poor household (gift and local remittance) have a positive effect on poverty entry probability. Finally, consistent with Bigsten and Shimeles (2004), we find strong state dependence of Ethiopian urban poverty mainly driven by households' heterogeneity.

The remainder of the paper proceeds as follows. The next section takes stock of the literature on risk, risk management and their impact on welfare. Section 3 describes the data and variables used. Section 4 outlines the estimation strategy. We discuss the estimation results and its policy implication in Section 5. Section 6 concludes the study.

2 Risk and welfare: Insights from the literature

Designing effective anti-poverty policies in developing world motivated a series of studies that aimed at a theoretical conceptualization, measuring and addressing poverty and risk empirically. This section provides a selective literature review on risk typology, how risk management mechanisms operate in developing countries and what are the related economic implications on welfare.

2.1 Risk typology

The literature on risk is both broad and extensive; there exists a difference in its definition. de Guzman (2003) defines risk as a probability that an individual or a household incurs a loss in the future. Clarke (1999), Alwang et al.(2001) and Cardona (2003) among others, define it as the possibility that adverse effects will occur. From a policy point of view knowing only the probability of an event occurring does not suffice, knowing the value of the loss, for instance, in terms of adverse movements in incomes or consumption of households is equally important (Modena and Gilbert, 2012). As outlined in the introduction, here we adopt the definition of the World Bank and define risk as an event that trigger decline in well-being and shocks as a manifestation of the risk (World Bank, 2001). The definition is chosen because it includes both the probability and effect of uncertainty on household well-being.

One way to understand risks better is through a typology of risks. Risks can be classified based on scope (micro, meso and macro) or by the specific nature of the events such as natural, political, social or economic (World Bank, 2001). Risk may occur at micro level affecting a specific individual or a household -'idiosyncratic' shock. Risks can also occur at macro level affecting an entire nation or certain community -'covariant' shock. No clear demarcation often occurs; as most risks may comprise both (Dercon, 2005). The extent to which a risk is covariant or idiosyncratic highly depends on the underlying causes or the nature of the events. Understanding the nature of a shock has also implication on the ability of household to cope with its consequences. For example, when a family head loses her job due to illness, it is an idiosyncratic shock. Or this can be a covariant, if loss of her job is a result of the economic crisis that leads to mass employee layoff. Empirical evidence suggests that idiosyncratic risk may be as important and even dominate covariate risk in most developing countries (Townsend, 1995; Deaton, 1997; Morduch, 2006 and Azam and Imai, 2012).

2.2 Risk management

Although risky events are exogenous households employ a portfolio of mechanisms to smooth consumption. In de Neubourg Welfare Pentagon's paradigm, household generate income and smooth consumption using five core institutions: family, markets, social networks, membership institutions and public authorities. Indeed having access to one institution of the welfare pentagon (e.g. financial market) means households may not have to rely on others (e.g. membership institutions) for the purpose of consumption smoothing. For instance, in the absence of old age pension schemes, remittance from family members has been seen as a substitute for formal pensions (Sana and Massey, 2000).

Credit and insurance markets are mostly absent or incomplete in most developing countries including our case study - Ethiopia; less than 10% of households have access to formal credit and insurance (AfDB, 2011). When households have limited or no access to financial markets, they may find it hard to save or use assets to smooth consumption (Fafchamps et al., 1998; Zimmerman and Carter, 2003; Berloffa and Modena, 2013). On the same line among the world total population, less than 20% have access to formal social policy programs (UN, 2012a). This implies that households in developing countries depend primarily on their own strategies and informal risk sharing networks to mitigate the myriad sources of risk they face.

Risk can be shared within a household (Dercon and Krishnan, 2003; Mazzocco, 2004, 2012), or can be spread across different households. In the latter, unit of risk-pooling is very context specific. Evidence of risk sharing among extended families has been found by Foster (1993) and Witoelar (2005), friends and relatives by Fafchamps and Lund (2003), ethnic groups by Grimard (1997) or community by Townsend (1994). Any of two households or individuals are said to share risk if they employ state-contingent transfer to increase the expected utility of both by reducing the effect of shock at least in one (Townsend, 1994).

Anthropological literature captured the existence of a variety of informal risk sharing mechanisms in Ethiopia that are driven by tradition and 'reciprocity' (Hailu and Northcut, 2012). Sahlins (1972) makes a distinction between 'generalized reciprocity' and 'balanced-reciprocity'. The first refers to transactions that are purely altruistic; assistance among members of a closely-knit social group which is typical of free gifts. Extended families have provided this type of protection in the country for long. For instance, among the Arsi Oromo, relatives living in other areas transferred grains to drought victim families or the victims migrate temporarily to their families who are residing in other areas (Hailu and Northcut, 2012). Similarly, during drought times individuals and households could depend on transfers from members of the extended family. The second, 'balanced reciprocity' involves direct reciprocation in which the material transaction is as important as the social aspect. The traditional and dominant risk sharing mechanisms in Ethiopia such as 'Iddir' and 'Eqqub' are good example of balanced reciprocity risk sharing mechanisms.[4]

Access to informal risk management mechanisms is not homogeneous to all households, however. Access, for instance, is determined by household resource endowments (such as social, human, financial and physical resources). Households also differ in consumption preference, risk exposure and risk 'appetite' which determines their capacity to produce and accumulate wealth in the market. Together with initial wealth distribution and corresponding consumption distribution, household adapt different consumption smoothing strategies based on available options. In the wealth distribution some households are poor; they don't have enough resource to satisfy the requirement of welfare pentagon institutions to insure both current and future consumption. The position of a household in wealth and income distribution therefore affects household consumption smoothing behavior (Notten, 2008). Therefore, being able to smooth consumption and income despite the existence of uninsured risks reflects an important dimension of well-being.

2.3 Risk, risk management and welfare

In the developing world an uninsured risk is ubiquitous. Low income households still face manifold uninsured risks (Baulch and Hoddinott, 2000; Word Bank, 2001; Dercon, 2002). Between 1999 and 2004, 25% and 29% of Ethiopian rural households reported losses of income due to drought and illness, respectively. There are two effect of risk. First, there is impact of shock on welfare. Rainfall shock is found to have a persistent effect on consumption growth of rural Ethiopian households (Dercon et al., 2005). Deininger et al. (2003), report arrival of a foster child to household results in low capital formation in Uganda. In rural Zimbabwe, children affected by the civil war and drought shocks in 1970s and 1980s incurred a loss of around 14% of their lifetime income (Alderman et al., 2006). Second, there is a behavioral change; households that face uninsured risk may push themselves towards low risk activities or asset portfolios with low return. Exposure to risk may induce households to hold non-productive assets for the purpose of consumption buffering (Dercon, 2005). Asset poor rural Indian households allocate large proportion of their land to safe traditional varieties of rice and castor than high yield but high risk crops (Morduch, 1995). Household decision to hold non-productive asset or to use low

[4] Iddir is a voluntary association that usually formed among friends, colleagues and neighbors to provides resources necessary to carry out funeral rituals. Eqqub is a voluntary association that regularly pools fund and rotates among members.

return variety of seed not only means forgone current income but also a higher chance that a household remain poor. This implies that risk management decisions of a household have both short and long-term implication which may result in poverty entry and poverty persistence.

Based on the aforementioned literature this study investigates the effects of self-reported idiosyncratic household head shocks and informal risk management strategies of urban households on poverty dynamics. We focus on self-reported idiosyncratic household head shock and distinguish *economic shocks* (unemployment) and *health shocks* (illness and disability). We purposely select shocks that impose cost to specific household in terms of lost income, reduced consumption and destruction of human capital. With regard to informal risk management strategies we include remittance (local and international); credit from informal sources; gifts (cash and in-kind); membership in 'Eqqub' and 'Iddir'. The next section elaborates in detail the data used in the study.

3 Data

This paper takes advantage of a unique longitudinal dataset, the Ethiopian Urban Household Survey (EUHS), collected by Addis Ababa University in collaboration with Departments of Economics of Gòteborg University and Michigan State University. The survey covers 1,500 households in seven major cities of the country (Mekele, Dessie, Bahir Dar, Dire Dawa, Addis Ababa, Awassa and Jimma) in five waves (1994, 1995, 1997, 2000 and 2004). The period covered by the data is characterized by major macroeconomic and political changes in the country. The period between 1994 and 1997 is characterized by peace, recovery from the long civil war and good weather; between 1997 and 2000 the country experienced drought, sharp decline in international coffee price and war with Eritrea.[5] Between 2000 and 2004 the economy resurged from the 1999/00 crises and experienced a moderate growth.

3.1 Sampling

The sampling frame of the survey includes all the cities with inhabitants greater than 100,000. Cultural diversity, major economic activity and administrative importance of cities are additional criteria to select sample cities.[6] The predetermined sample-size (1,500 households) was allocated to the selected cities and districts, in proportion to their residents. Households were then selected by systematic sampling from half of the 'kebeles', the lowest administrative units in the country, in each districts (wereda) using the official registration of residences available at kebeles. This sampling frame misses the homeless, residents of collectives and rural-urban migrants with no permanent resident address and registration at kebeles. Addis Ababa, Dire Dawa and Awassa contributed 60%, 8% and 5% of sample households, respectively. The other remaining four cities

[5]Coffee plays a vital role in the country economy; In 2009/10 it accounted for 36% and 43% of total and agriculture exports, respectively (MoFED, 2008).

[6]Mekele and Dessie represent the northern part of the country often affected by drought. Bahir Dar is a representative city of cereal producing part of the country while Dire Dawa is a major trading center. The capital and the largest city of all, Addis Ababa, represents very diverse population. The administrative centre of the south, Awassa, represents high production of 'enset'(false banana). Last, Jimma represents major coffee producing areas.

contributed 7% of the sample households each. The surveys were conducted over four successive weeks during a month considered to represent average conditions.

The database provides a rich array of information on household food and non-food expenditure; income by source; private transfers; consumption habits; employment; education; demographics; credit; health; anthropometrics; dwelling conditions and subjective evaluation of welfare. The sample used for the empirical analysis here is restricted to data from 2^{nd} to 5^{th} rounds (four waves) of EUHS. The time dimension of our panel is long enough to allow estimating poverty transition than similar poverty dynamic studies in Sub-Saharan Africa. It is important to mention panel attrition of our data: 11% from 1995 to 1997, 10% from 1997 to 2000, and 14% from 2000 to 2004. The observed attrition is selectively related to our outcome variables of interests, poverty status of households. We test this more formally under context and poverty transition pattern section of the study (see Section 3.2).

Analysis of the welfare impact of shocks and risk management strategies of household draws from the micro-economic theory of utility maximization. According to this theory, the objective of individuals and hence a household is to maximize utility subject to a budget constraint. Although utility is not directly observable, it is a construct representing household welfare. Traditionally either income or consumption is used to measure material (monetary) welfare. For developing countries, consumption is viewed as a better approximate to 'money-metric utility' than income (see Ravallion, 1992; Deaton and Grosh, 2000 for detailed discussion). Hence, we used household consumption to proxy household utility level. Our consumption definition is comprehensive that includes food and non-food components. Food consumption includes the value of food purchased from the market and in-house prepared food. The non-food component includes expenditures on clothing, energy, education, kitchen equipment, contributions, health, education, transportation and other non-durable items. Real total consumption then is divided by 'adult equivalent' to determine real per adult equivalent household consumption. We used a calorie based equivalence scales developed by Dercon and Krishnan (1998) for the country (see Table 10 of the Appendix).

Household is our unit of analysis. A household is defined as poor, if adult equivalent consumption of a household is lower than absolute poverty line of the country, which is defined by Ministry of Finance and Economic Development (MoFED) in 1995/96. It is worth mentioning how the poverty line is constructed. The poverty line is estimated following the cost-of-basic-needs approach in two stage. First, food poverty line estimated using the average quantities of a bundle of food basket most frequently consumed by households in the lower half of the expenditure distribution. Second, the non-food component of the poverty line was estimated by dividing the food poverty line by the average food-share of households that are below the minimum calorie-intake (MoFED, 2008).

Table 1 presents the descriptive statistics of variables used for analysis. We have two types of variables: the outcome variable (poverty status of households based on the country poverty line and real household per adult equivalent consumption) and the determinants of poverty status of households, control variables. We have gathered the controls into four main categories: household characteristics, household head characteristics, head shocks and household informal risk management strategies. We also include three exclusion restriction variables for selection equations of endogenous switching model (see Section 4.1 and 5.1 for detail discussion). The definition of all variables are summarized in Table 11 of the Appendix.

Table 1: Summary statistics of variables used in estimation

	Mean	SD*	Min	Max
Female household head	0.393			
Age in years	49.250	13.446	13	99
Household size	6.508	2.974	1	28
Number of family members aged between 0 and 14	1.789	1.578	0	10
Number of family members aged 64+	0.210	0.453	0	3
Married household head**	0.581			
Number of employee in the household	1.707	1.230	0	12
Number of unemployed in the household	0.629	1.038	0	10
Own account worker**	0.258			
Public sector employee	0.064			
Private sector employee	0.085			
NGO employee	0.025			
Casual worker	0.068			
Civil servant	0.144			
Pensioner	0.138			
Others	0.217			
No schooling**	0.326			
Primary schooling	0.248			
Junior Secondary Schooling	0.099			
Secondary schooling	0.174			
Tertiary schooling	0.153			
Unemployment	0.046			
Sickness	0.126			
Disability	0.148			
New family members joined the household in 1994	0.317	0.560	0	2
Family members left the household in 1994	0.049	0.268	0	4
Local remittance	0.097			
International remittance	0.086			
Iddir	0.780			
Received credit from informal sources	0.168			
Equup	0.195			
Gift	0.081			
Informal loan	0.168			
Real Total monthly food and non food Expenditure	761.963	928.745	0	13649.3
Observations	5,540			

EUHS, wave 2 to 5 (four waves) - Unbalanced Panel.

* SD of dummy variables can be calculated using $(pq)^{1/2}$ where p is the mean and $q = (1 - p)$

** Symbolizes a reference group.

3.2 Context and poverty transition patterns

Poverty reduction is central policy agenda of Ethiopian Government since it came to power in 1991. The country has implemented three Poverty Reduction Strategy Programmes (PRSPs). The first PRSP, Sustainable Development and Poverty Reduction Programme, lasted for three years (2002/03 to 2004/05), while its successor, the Plan for Accelerated and Sustained Development to End Poverty, was implemented between 2005/06 and 2009/10 and the current PRSP, Growth and Transformation Plan, runs from 2010/11 to 2014/15 (MoFED, 2010). The last two

Strategies are Millennium Development Goals (MDG) based plans that integrate the MDG in to national development policies and aim to reduce and eradicate poverty. Despite this, poverty remains to be pervasive and persistent in the country. In 2004/05, the number of people living below the poverty line of the country is estimated to be 35% and 39% for urban and rural area, respectively (MoFED, 2008).

Rural poverty reduction is the priority of all the poverty reduction strategies which is understandable for a country like Ethiopia whose economy mainly depends on small agriculture and 85% of the population resides in rural areas. Similar to other sub-Saharan Africa country's rapid urbanization is a growing phenomenon in the country, however. For the period between 1994 and 2007 Ethiopian urban population grew by 4.3% and more than half of this growth is attributed to rural - urban migration (CSA, 2010). This event is accompanied by more poor people living in urban areas than before, a process considered as the "urbanization of poverty" in the literature (Ravallion, 2002). For instance, between 1995 and 2004 the headcount index in rural areas declined by 17% while it increases by 6% in urban areas suggesting that the country overall poverty reduction did not bear much of its fruit for the expanding urban population (MoFED, 2008).[7]

Table 2: Poverty transition rates (in %), with and without missing, 1995-2004

Poverty status, year $t-1$	Poverty status, year t		
	Not poor	Poor	Missing
(a)Balanced Panel at t			
Not poor	75	25	
Poor	41	59	
All	60	40	
(b)All households (Unbalanced Panel)			
Not poor	50	16	34
Poor	33	49	18
All	43	30	27

Panel (a) sample size =611 households.
Panel (b) sample size =1,366 households.

Table 2 shows the raw poverty transition matrix of our panel households for the period between 1995 and 2004. The transition probabilities gives the propensity of households of being poor or non-poor at t conditional on the poverty status of households at $t-1$. Panel (a) shows the transition matrix for households that are observed in all waves - balanced panel. The table illustrates the chance of being poor in a given year highly differs depending on poverty status of the household in the previous year. Household that were poor and non-poor at $t-1$ have 59% and 25% chance to stay in poverty and to enter in to poverty at t, respectively. There is also a high persistence rate of both states. Non-poor households at $t-1$ have 75% of chance to stay in the same state at t. Similarly, households that were poor at $t-1$ have 59% probability to be poor at t. Further, the table shows lower transition probabilities for poor households to become non-poor than non-poor households to enter into poverty. The chance of getting out of poverty

[7]In fact, the policy choices during the the structural adjustment program of the country in 1992/93 like privatization of state-owned enterprises that led to mass employee layoff, lifting of subsidies on basic goods and tax reform are partly responsible for the worsening poverty situation in urban areas (Tadesse, 1996).

at t for those who were poor at $t-1$ is 41% while the probability of entering into poverty for non-poor households at $t-1$ is 25%. The probability of being poor for households that were poor in the previous year was about 34% points higher than the poverty rate for non-poor households in the previous year. This figure measures 'aggregate' poverty dependance without controlling for observed and unobserved household heterogeneity. The rate of persistence in the same state thus could arise either due to over representation of household that are likely to remain poor or non-poor among those who were poor and non-poor at $t-1$ (endogenous selection of households over time) or true state dependance of states over time. During our estimation, we address this problem by controlling for observed and unobserved determinants of initial poverty status of a household.

Panel (b) shows the transition matrix constructed using for all households in our dataset - unbalanced panel. The 'missing' column of the table shows the issue of endogeneity of household retention in the panel. Indeed, the column shows household probability to stay in the panel substantially differs by poverty status of the household at $t-1$. The attrition propensity of non-poor household (34%) is almost twice of poor household attrition propensity (18%). This might suggest that retention of households in our panel is non-random phenomena. This calls for specification of household retention mechanism and joint estimation with poverty transition equation if one needs consistent estimates. Therefore, we specify a model that takes in to account a non-random household attrition jointly with the initial conditions and poverty transition. We shall employe poverty transition model that uses sample data with observations of six different types: each one corresponding to each of the six cells panel (b) of Table 2 and incorporates household heterogeneity. We will get back to this in detail in Section 4.

Figures 1 and 2 are a reconstruction of all flows into and out of poverty over the decade under discussion. The figures show three interesting results. First, it gives an exact idea of the complexity of poverty transitions than what it displayed in Table 2. Second, the chart confirms that poverty frontiers go far beyond the category of the poor covered by one cross-section (one wave) analysis. For instance, the poverty rate in 2004 was 42% while 76% of households experience poverty at least once over the period under consideration. Finally, the figure shows that 37% of households do not change poverty status between 1995 and 2004. 24% of households held their non-poor status while 13% of poor households stays in poverty.

Figure 1: Flow into and out of poverty of poor households in 1995. Balanced EUHS, Waves 2 to 5 (4 waves), P=Poor, NP = Non-poor.

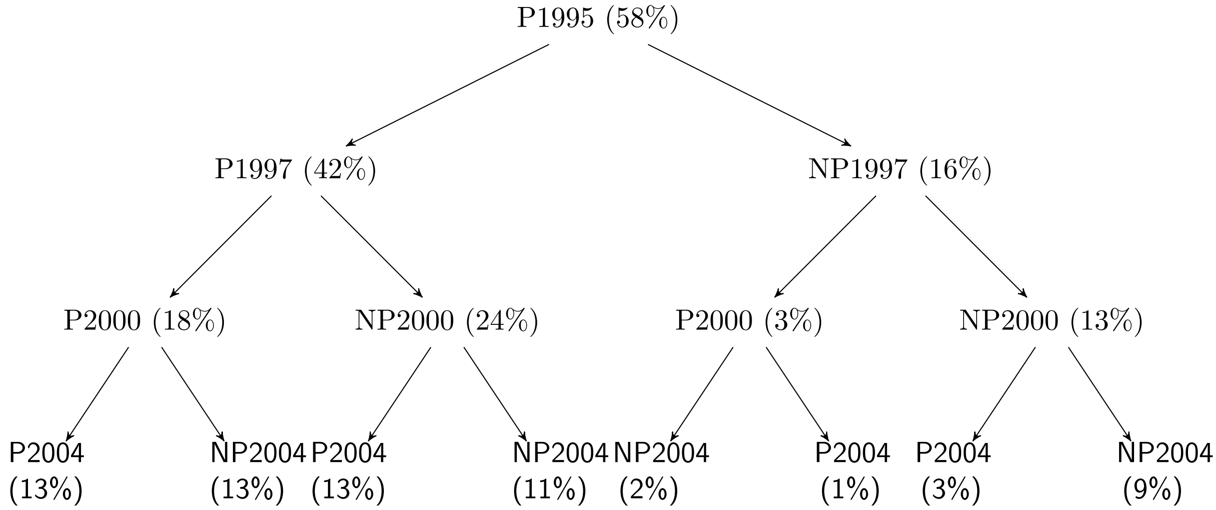

Figure 2: Flow into and out of poverty for Non-poor households in 1995. Balanced EUHS, Waves 2 to 5 (4 waves), P=Poor, NP = Non-poor.

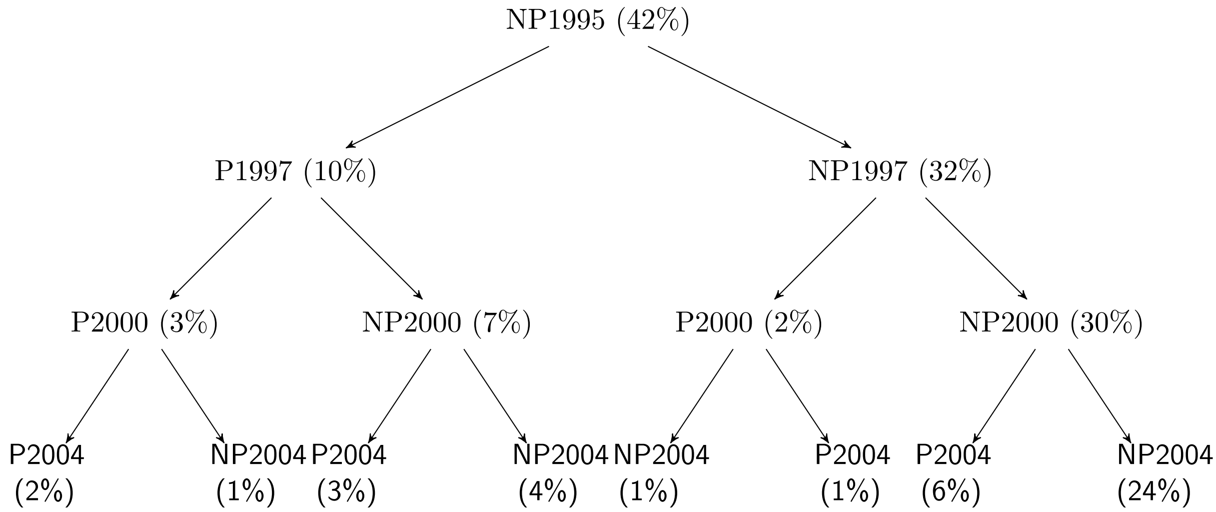

Table 3, shows self-reported idiosyncratic head shocks for the period between 1995 and 2004. The most common shock is head disability faced by 15% of households followed by head illness (13%) and head unemployment (5%). Head unemployment is more prevalent in poor households than their non-poor counterparts while head sickness and disability are more common in non-poor households.

Table 4 presents the different risk sharing mechanisms of households for the same period. 'iddir' and 'eqqub' are the dominant risk sharing mechanisms used by 78% and 19% of households, respectively. When we look at the mechanisms by poverty status of households, loan from informal sources is the main mechanisms for poor households while non-poor households predominately have access to international remittance. Overall, the table shows that access to informal risk share mechanisms is not homogeneous across households. Non-poor households have a better access to all mechanisms than their poor counterparts. For instance, 83% of non-poor households have access to international remittances while only 17% of poor households

Table 3: Incidence of self-reported shocks by poverty status, 1995-2004

Shocks	Poor	Non-poor (in %)	Total
Head illness	44.76	55.24	12.62
Head Unemployment	51.79	48.21	4.64
Head disability	44.07	55.93	14.78
Sample size	1,366 households		

EUHS, wave 2 to 5 (4 waves)-Unbalanced Panel.

have access to it. The same is true when we consider the dominant mechanism, 'iddir'. 40% and 60% of poor and non-poor households have access to 'iddir', respectively. This suggests that poor households don't have enough resources to cover the cost of migration and generally other available mechanisms to deal with the consequence of shocks.

Table 4: Informal risk sharing mechanisms, 1995-2004

Mechanisms	Poor	Non-poor (in %)	Total
Local remittance	42.31	57.69	9.66
International remittance	17.23	82.77	8.61
Gift	47.95	52.05	8.06
Iddir	40.15	59.85	77.98
Equip	32.68	67.32	19.47
Loan from informal sources	45.99	54.01	16.85
Sample size	1,366 households		

EUHS, wave 2 to 5 (4 waves)-Unbalanced Panel.

Table 5 summarizes the purpose of transfer from informal risk sharing mechanisms under investigation for households who have access. The table shows that the primary purpose of all transfers except transfer from 'equip' is consumption. 41% and 40% of households who are a member of 'equip' used the transfer to cover ceremonial expenses including wedding and consumption, respectively. This indeed may indicate that the main purpose of the transfer from the informal risk sharing mechanisms identified here is consumption smoothing. The absence of public and market institutions to back up households during 'bad' times propel households to depend on their informal networks to manage the consequence of shocks is supported by our data.

Table 5: Purpose of transfer from informal risk sharing mechanisms, 1995-2004

Purpose	International remittance	Local remittance	Gift	Eqqub	Informal loan
Consumption (Food and non-food)	79.73	85.63	79.90	39.35	54.25
Business expense	2.70	1.25	0.99	2.42	19.23
Saving	0.90	2.50	-	0.32	6.48
Asset	3.60	1.25	2.73	16.61	11.34
Debt payment	0.90	1.25	-	-	0.40
Ceremonial expenses	4.95	7.50	6.20	40.65	7.09
others	7.21	0.63	10.17	0.65	1.21
Sample size	1,366 households				

EUHS, wave 2 to 5 (4 waves)-Unbalanced Panel.

4 Estimation strategy

One of the main reasons for studying poverty dynamics is to identify households who are most likely to remain poor and understand why poverty persists among the identified sub-section of a society. As discussed in the previous section, poverty may persist due to materialization of risks (covariant or idiosyncratic) that erodes human and physical capital of households. Household may also experience extended poverty because of their specific characteristics (observed or unobserved heterogeneity) that prevent them from escaping poverty. Low human capital (for instance, low education) and lack of ability or motivation to work are good examples of observed and unobserved heterogeneity, respectively. Further, poverty may persist due to behavioral change that follows the experience of poverty in the past. In the literature, this is called 'genuine state dependence of poverty'. Therefore, empirical models of poverty dynamics need to control for effects of households heterogeneity (both observed and unobserved) and genuine state dependence to understand the effect of shocks on poverty dynamics.

In the literature three types of model have usually been used to study poverty dynamics namely: the 'component' approach, the 'spell' approach and the 'transition' approach. The first and the most commonly estimated model has been the component approach that is due to Jalan and Ravallion (1998). The approach decomposes a households poverty measure, mostly the squared poverty gap, into a permanent component measuring chronic poverty and transitory component measuring transient poverty. Chronically poor are identified as households whose intertemporal average consumption or income lies below the poverty line. The transitory component of poverty is the difference between total and chronic poverty using the same poverty indicator. The determinants of poverty dynamics are then explained by observed characteristics of households using censored regression models (Jalan and Ravallion, 1998). However, the approach has a shortcoming of not explaining the true causes of both type of poverty. Using intertemporal average of income or consumption for aggregation of welfare over time implicitly assumes poverty spells of households can be compensated by non-poverty spells in the following years. This assumption is unrealistic for most developing countries where financial markets and public schemes are largely absent. Moreover, identification of chronic poor doesn't take it to account time spent in poverty.

The second most used approach is the 'spell' approach (e.g., Bane and Ellwood, 1986; Stevens, 1994 and Devicienti, 2011). This approach analyzes duration of poverty spells and the probability of ending poverty or non-poverty spell. Chronic poor households are identified by the duration spent below the poverty using a 'duration cut-off'. In contrary to the component approach 'spell' approach analyzes the true dynamics of poverty over time. The approach models household characteristics along with the probability of exiting poverty for households that started poverty spell at t and are at the risk of exiting poverty at $t+1$ without considering multiple episodes of poverty. 'Duration models' which build on spell approach on the other hand take into account multiple episodes of poverty and unobserved heterogeneity of households. Spell approach have a potential to tests the effect of household heterogeneity and state dependence on poverty persistence. However, the possibility of poverty spells may have already begun in the first observation of the panel (left censure) or still be underway in the last observation (right censure) requires additional remedies during estimation. If censoring time is independent of poverty duration right censored data doesn't impose a problem; the censoring process can be modeled jointly with poverty transitions. On the other hand, left censored data are problematic. In the literature left censored data are mostly discarded (see for example Bane and Ellwood, 1986; Bigsten and Shimeles, 2008 and Devicienti, 2011) which reduces the amount of data that can be used for the estimation hence understates persistence of poverty. Tackling this requires a long time span data which is not currently the case in most developing countries.

The third, the most recent approach, is to model transition of probability using first-order Markov model of poverty persistence and entry rates. This approach consist of 'Random Effect Dynamic Probit' and 'Endogenous Switching' Models. The later is due to Cappellari and Jenkins (2002, 2004) that is built on Stewart and Swaffield (1999). In both models, only first order dynamics is modeled. This makes the poverty dynamics simpler than spell or duration models. Both models control for initial condition bias[8], household heterogeneity and state dependence. The choice between the two models mainly depends on the assumption on how previous poverty affects current poverty transition probabilities. If we assume previous poverty affects current poverty transition probabilities through a change in household characteristics, endogenous switching model is more appropriate. Otherwise, one may consider random effect dynamic probit model particularly if intercept effect exists. An endogenous switching model has an advantage of controlling for non-random panel attrition which is a characteristic of our dataset while dynamic probit model allows to control serial correlation. Thus, the models complement each other and using both models leads to more comprehensive poverty dynamics analysis.

In this study, we use both models to investigate urban Ethiopian poverty dynamics with an emphasis on the effect idiosyncratic shocks and informal risk management strategies of households. To our knowledge the models are rarely used to study poverty dynamics in developing countries. Bigsten and Shimeles (2008) used random effect dynamic probit model to study state dependency of poverty in Ethiopia. Since the purpose of their study was mainly to investigate the dynamics of poverty in urban and rural Ethiopia, they didn't investigate the effect of shocks and shock management strategies and they didn't control for non-random panel attrition that exist in the EUHS. Endogenous switching model is used by Faye et al. (2011) to study poverty

[8]The stochastic process generating households poverty experiences doesn't necessary start with the first wave of the panel.

in Nairobi slums. However, they used only four year's panel (with only two waves) which is short to undertake poverty dynamics analysis and they didn't analyze the effect of poverty dynamics determinants we are interested in. The following section discuss both estimation strategies one after the other.

4.1 Endogenous switching model

Endogeneous switching models poverty transitions between two consecutive years (waves), $t-1$ and t using a trivariate probit model. There are four parts of the model. First, the determination of poverty status at t. Second, the determination of household retention between $t-1$ and t. Third, the determination of poverty status at $t-1$ in order to account for the initial conditions problem. Forth, the correlations between the unobservables affecting all the three processes. The combination of all the four parts characterizes the determinants of poverty persistence and poverty entry rates.

Let households can be characterized by a latent poverty propensity p^*_{it-1} at $t-1$, of the following form:

$$p^*_{it-1} = \boldsymbol{\beta}'\mathbf{x}_{it-1} + u_{it-1} \tag{1}$$

Let's call Eq. (1) initial poverty status equation for brevity, where $i = 1, \cdots, N$ indexes households and $t = 1, \cdots, T$ time span, $\mathbf{x}_{it-1}$ is a vector of controls describing i's household characteristics, $\boldsymbol{\beta}$ is a vector of parameters to be estimated and the error term $u_{it-1} = \delta_i + \mu_{it-1}$ (the sum of an household-specific effect and an orthogonal white noise error) follows the standard normal distribution ($u_{it-1} \sim N(0,1)$). p^*_{it-1} is the latent dependent variable and p_{it-1} is the observed counterpart defined as,

$$p_{it-1} = \mathbf{1}_{[p^*_{it-1}>0]} \tag{2}$$

where $\mathbf{1}_{[]}$ denotes the indicator function which takes on the value 1 if the corresponding latent variable is positive, and 0 otherwise. Assume r^*_{it} to be a $i's$ latent propensity of household retention between two consecutive waves and summarized by the relationship below:

$$r^*_{it} = \boldsymbol{\gamma}'\mathbf{w}_{it-1} + \varepsilon_{it} \tag{3}$$

where the error term $\varepsilon_{it} = \eta_i + \vartheta_{it}$ (the sum of an household-specific effect η_i plus an orthogonal white noise error ϑ_{it}) follows a normal distribution $\varepsilon_{it} \sim N(0,1)$. $\boldsymbol{\gamma}$ is a vector of parameters to be estimated and $\mathbf{w}_{it-1}$ is a vector of controls describing i's household characteristics. If i's latent retention propensity is less than some critical threshold (normalized to 0), then household is not observed at t, and hence household's poverty transition status is not also observable. Let r_{it} be a binary indicator of households retention between t and $t-1$ which is defined as follows

$$r_{it} = \mathbf{1}_{[r^*_{it}>0]} \tag{4}$$

We call (3) retention equation. The third component of the model is the specification for poverty status at t: from now onwards we call this poverty transition equation for simplicity. Assume the latent propensity of poverty be summarized by:

$$p_{it}^{*} = \left[(p_{it-1})\lambda_1' + (1 - p_{it-1})\lambda_2'\right] \mathbf{z}_{it-1} + \epsilon_{it} \tag{5}$$

where λ_1', λ_2' are parameter vectors to be estimated and $\mathbf{z}_{it-1}$ denotes vector of controls, and the error term $\epsilon_{it} = \tau_i + \xi_{it}$ (the sum of an household specific effect τ_i plus an orthogonal white noise error ξ_{it}) follows a normal distribution $\xi_{it} \sim N(0, 1)$. Let's define the relation

$$p_{it} = \mathbf{1}_{[p_{it}^{*}>0]} \tag{6}$$

Note that p_{it} is only observed if we observe the households at t and $t-1$ or when $r_{it} = 1$. Given this, poverty transition equation re-specified as:

$$(p_{it}|p_{it-1}, r_{it} = 1) = \mathbf{1}_{\left[\{(p_{it-1})\lambda_1' + (1-p_{it-1})\lambda_2'\}\mathbf{z}_{it-1} + \epsilon_{it} < \kappa_t\right]} \tag{7}$$

This specification indicates that p_{it} is conditional not only on p_{it-1} but also $r_{it} = 1$. Hence, the model enables the impact of explanatory variables to 'switch' or differ based on whether the household was poor at $t-1$ ($p_{it-1} = 1$) or not ($p_{it} = 0$). Hence, the specification provides estimates of the poverty entry and persistence rate determinants. The model can be estimated jointly using multivariate probit regression. In order to identify the model however, execution restriction variables (instrument variables) are required for initial poverty equation (Eq.1) and retention equation (Eq.3). In other words, we need variables that affect initial poverty and retention of households but not poverty transition i.e. variables entering the $\mathbf{x}_{it-1}$ or $\mathbf{w}_{it-1}$ vectors but not in $\mathbf{z}_{it-1}$. If we assume a non-linear functional form, it is possible to estimate the model without including instrumental variables in the two exclusion equations. However, it is better to avoid the non-linearity assumption by including instrumental variables in retention and initial condition equations. We will discuss the instrument variables used in this study in Section 5.1.

The joint distribution of the error terms u_{it-1}, ε_{it} and ϵ_{it} is trivariate standard normal, and characterize unrestricted (and estimable) correlations across the three equations above: initial poverty status equation, retention equation and poverty transition equation. These three correlations are:

$$\begin{aligned}
\rho_1 &\equiv \text{correlation between unobserved characteristics affecting } p_{it-1} \text{ and } r_{it} \text{ or } \mathrm{cov}(\delta_i, \eta_i) \\
\rho_2 &\equiv \text{correlation between unobserved factors affecting } (p_{it}|p_{it-1}, r_{it}) \text{ and } r_{it} \text{ or } \mathrm{cov}(\delta_i, \tau_i) \\
\rho_3 &\equiv \text{correlation between unobserved factors affecting } r_{it} \text{ and } p_{it-1} \text{ or } \mathrm{cov}(\eta_i, \tau_i)
\end{aligned}$$

Thus, the distribution of unobserved households' heterogeneity is parameterized via the cross-equation correlations. A positive sign of ρ_1 indicates that households who were more likely to be initially poor are more likely to remain in the panel of the subsequent waves compared to initially non-poor households, and vice versa. A positive (resp. negative) sign of ρ_2, correlation between the unobserved factors affecting initial poverty status (Eq.1) and poverty transition (Eq.5), indicates poverty is more likely to persist among households who were initially poor compared to the non-poor. Positive ρ_3 (resp.negative) indicates households that are observed in two successive waves were more (resp. less) likely to remain poor or to fall into poverty compared to households that drop out from the panel.

Depending on whether household i has been observed consecutively in $t-1$ at t and on poverty status at $t-1$, the likelihood function consists of three parts: $(p_{it-1} = 1 \wedge r_{it} = 1)$, $(p_{it-1} = 0 \wedge r_{it} = 1)$ and $r_{it} = 1$. Formally, it involves the join estimation of Eqs.(2), (4) and (7) which leads to:

$$\begin{aligned}\mathscr{L} = \prod_{i=1}^{N}\prod_{t=2}^{T} & \Big[\int_{-\boldsymbol{\lambda}_1'\mathbf{z}_{it-1}}^{\infty} \int_{-\boldsymbol{\gamma}'\mathbf{w}_{it-1}}^{\infty} \int_{-\boldsymbol{\beta}'\mathbf{x}_{it-1}}^{\infty} \varphi_3(\epsilon_{it}, \varepsilon_{it}, u_{it-1}) \mathrm{d}\epsilon_{it}\mathrm{d}\varepsilon_{it}\mathrm{d}u_{it-1} \Big]^{(p_{it-1})r_{it}} \\ & \Big[\int_{-\infty}^{-\boldsymbol{\lambda}_2'\mathbf{z}_{it-1}} \int_{-\boldsymbol{\gamma}'\mathbf{w}_{it-1}}^{\infty} \int_{-\boldsymbol{\beta}'\mathbf{x}_{it-1}}^{\infty} \varphi_3(\epsilon_{it}, \varepsilon_{it}, u_{it-1}) \mathrm{d}\epsilon_{it}\mathrm{d}\varepsilon_{it}\mathrm{d}u_{it-1} \Big]^{(1-p_{it-1})r_{it}} \\ & \Big[\int_{-\infty}^{-\boldsymbol{\gamma}'\mathbf{w}_{it-1}} \int_{-\boldsymbol{\beta}'\mathbf{x}_{it-1}}^{\infty} \varphi_2(\varepsilon_{it}, u_{it-1}) \mathrm{d}\varepsilon_{it}\mathrm{d}u_{it-1} \Big]^{(1-r_{it})}\end{aligned} \tag{8}$$

where φ_3 and φ_2 denote respectively normal trivariate and bivariate density functions. Given the assumptions on the joint distribution of the errors terms and the related correlation coefficients ρ_1, ρ_1 and ρ_3, and using the symmetry property of the normal distribution, we can derive the final expression of the likelihood function as:

$$\begin{aligned}\mathscr{L} = \prod_{i=1}^{N}\prod_{t=2}^{T} & \Big[\Phi_3\big(\zeta_i\lambda_1'\mathbf{z}_{it-1}, \psi_i\boldsymbol{\gamma}'\mathbf{w}_{it-1}, \omega_i\boldsymbol{\beta}'\mathbf{x}_{it-1}; \zeta_i\psi_i\rho_3, \zeta_i\omega_i\rho_2, \psi_i\omega_i\rho_1\big) \Big]^{(p_{it-1})r_{it}} \\ & \Big[\Phi_3\big(\zeta_i\lambda_2'\mathbf{z}_{it-1}, \psi_i\boldsymbol{\gamma}'\mathbf{w}_{it-1}, \omega_i\boldsymbol{\beta}'\mathbf{x}_{it-1}; \zeta_i\psi_i\rho_3, \zeta_i\omega_i\rho_2, \psi_i\omega_i\rho_1\big) \Big]^{(1-p_{it-1})r_{it}} \\ & \Big[\Phi_2\big(\psi_i\boldsymbol{\gamma}'\mathbf{w}_{it-1}, \omega_i\boldsymbol{\beta}'\mathbf{x}_{it-1}; \psi_i\omega_i\rho_1\big) \Big]^{(1-r_{it})}\end{aligned} \tag{9}$$

where $\zeta_i = 2p_{it} - 1$, $\psi_i = 2r_{it-1} - 1$, $\omega_i = 2p_{it-1} - 1$; Φ_3 and Φ_2 are respectively the trivariate and bivariate cumulative normal distribution. To obtain the ML estimates of the model, we can maximize the log-likelihood $\ln \mathscr{L}$ using standard numerical techniques (e.g. Newton-Raphson). However, the estimation requires the evaluation of Φ_3 with simulation methods. We use the multivariate approach of Cappellari and Jenkins (2004) which is based on the Geweke-Hajivassiliou-Keane (GHK) simulator.

Other things being equal, if the first correlation (ρ_1) and the third correlation (ρ_3) are equal to zero, panel attrition is random and joint estimation of retention equation (Eq.(3) can be ignored; the model reduces to a bivariate model. If the second correlation (ρ_2) and the first correlation (ρ_1) are equal to zero, the initial condition can be ignored as well and past poverty experience can be treated as exogenous. Finally, if $\rho_1 = \rho_2 = \rho_3 = 0$ both initial poverty and sample attrition are exogenous and the model reduces to a univariate probit model (Cappellari and Jenkins 2002, 2004).

Following Arulampalam et al. (2000), the model also allows to test the existence of genuine poverty dependence based on ($\lambda_1 = \lambda_2$). Further, it allows predicting poverty persistence rate (the probability of being poor at t, conditional on being poor at $t-1$) and poverty entry rate (probability of being poor at t, conditional on being non-poor at $t-1$) using the whole sample, including households who exited the sample. The rates are defined as conditional probabilities as follows:

$$\mathscr{P}_{it} = \mathbb{P}(p_{it} = 1 | p_{it-1} = 1) = \frac{\Phi_2\left(\lambda_1' \mathbf{z}_{it-1}, \boldsymbol{\beta}' \mathbf{x}_{it-1}; \rho_2\right)}{\Phi\left(\boldsymbol{\beta}' \mathbf{x}_{it-1}\right)} \tag{10}$$

$$\mathscr{E}_{it} = \mathbb{P}(p_{it} = 1 | p_{it-1} = 0) = \frac{\Phi_2\left(\lambda_2' \mathbf{z}_{it-1}, -\boldsymbol{\beta}' \mathbf{x}_{it-1}; -\rho_2\right)}{\Phi\left(-\boldsymbol{\beta}' \mathbf{x}_{it-1}\right)} \tag{11}$$

where $\mathscr{P}_{it}$ is poverty persistence rate and $\mathscr{E}_{it}$ is poverty entry rate. Φ_2 and Φ are the cumulative functions of the bivariate and the univariate standard normal distribution. It is also possible to compute the aggregate state dependence, hereafter ASD, using these predicted transitions rates. It is the difference between the average probability of being poor at time t for households that were poor at $t-1$ and the probability of being poor at t for those non-poor households at $t-1$. The model also allows to quantify the magnitude of genuine poverty dependance (GSD). GSD is the difference between predicted probabilities of being poor at t conditional on the two states at $t-1$. It is quantified as follows:

$$\text{GSD} = \frac{1}{N} \sum_{i=1}^{N} \Big[\mathbb{P}(p_{it} = 1 | p_{it-1} = 1) - \mathbb{P}(p_{it} = 1 | p_{it-1} = 0) \Big] \tag{12}$$

GSD measure is based on households' specific probabilities; hence, it controls for households' heterogeneity in contrary to ASD which we calculate in Table 2. As discussed earlier, ASD comprises both household heterogeneity and sate dependence effects. As a result, we can asses the heterogeneity effect by differencing ASD and GDS.

4.2 Random effect dynamic probit model

An alternative approach to capture the underlying causes of poverty persistence and effect of shocks and household risk management mechanisms is to use random effect dynamic probit model. We specify the latent poverty propensity as follows:

$$p^*_{it} = \boldsymbol{\gamma} p_{it-1} + \boldsymbol{\beta} \mathbf{x}'_{it} + u_{it}, \qquad i = 1, \cdots, N; \; t = 2, \cdots, T \tag{13}$$

where $\mathbf{x}_{it}$ is a vector of controls describing i's household characteristics, $\boldsymbol{\beta}$ is a vector of parameters to be estimated and the error term $u_{it} = \alpha_i + \mu_{it}$ (the sum of an individual-specific effect and an orthogonal white noise error) follows the standard normal distribution ($u_{it} \sim N(0, 1)$). p^*_{it} is the latent poverty propensity and p_{it} is the observed counterpart defined as

$$p_{it} = \mathbf{1}_{[p^*_{it} > 0]} \tag{14}$$

where $\mathbf{1}_{[]}$ denotes the indicator function which takes on the value 1 if the corresponding latent poverty propensity is positive and 0 otherwise. N is taken to be large, but T is small and regarded as fixed, so that asymptotic are on N alone.

In the literature there are few studies (see Biewen, 2004; Cappellari and Jenkins, 2004; Bigsten and Shimeles, 2008) that link the current state of poverty using a first-order auto-regressive structure of the dependent variable, and few control for serial correlation in the error components (see Bigsten and Shimeles, 2008). Here we used a dynamic probit model that controls for state dependence, unobserved heterogeneity and serial correlation given by Eqs.(15) and (16).

$$\mathbb{P}\big(p_{i0}|x_{i0}, \alpha_i\big) = \mathbf{1}_{[\boldsymbol{\beta}_0 \mathbf{x}_{i0} + u_{i0} > 0]} \tag{15}$$

$$\mathbb{P}\big(p_{it}|x_{it}, \alpha_i, p_{i0}, \cdots, p_{it-1}\big) = \mathbf{1}_{[\boldsymbol{\gamma} p_{it-1} + \boldsymbol{\beta} \mathbf{x}'_{it} + u_{it} > 0]} \tag{16}$$

with $u_{it} = \alpha_i + \mu_{it}$, $\mu_{it} = \rho\mu_{it-1} + \upsilon_{it}$, $\upsilon_{it} \sim N(0, \sigma_\nu^2)$ and orthogonal to α_i, and $Corr(u_{i0}, u_{it}) = \rho_t t = 1, 2, \cdots, T$ and where $\mathbb{P}(\cdot)$ is the conditional probability of falling in to poverty, $\mathbf{x}_{it}$ is a vector of controls describing i's household characteristics, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, the parameter $\boldsymbol{\gamma}$ represents the genuine state dependence of poverty. α_i represents unobserved determinants of poverty that are time invariant for a given household such as innate ability and motivation to work of household members. And finally, μ_{it} are the idiosyncratic error term which is serially correlated overtime.

Estimation of Eqs.(15) and (16) requires an assumption about the initial observations, p_{i0}, in particular about its relationship with time invariant unobserved determinants of poverty for a given household (α_i). The assumption that leads to the simplest form of model for estimation is to take the initial conditions, p_{i0}, to be exogenous. However, even if the start of the stochastic process generating households poverty experiences coincides with the start of the observation period for each households and we observe the entire poverty history of every households, which is not generally the case, the assumption of independence between p_{i0} and α_i is flawed. For example, lack of both physical and human capital can contribute to the risk of being poor at time $t = 0$. Further, there is a high chance that poverty experience of households at $t = 0$ could related to household members specific factor like low work motivation or lack of abilities.

A better alternative is specifying a linearized reduced-form equation for the initial value of the latent poverty propensity for Eq.(15) proposed by Heckman (1981a) as follows:

$$p_{i0}^* = \mathbf{z}'_{i0}\pi + \eta_i \tag{17}$$

where $\mathbf{z}_{i0}$ is a vector of exogenous instruments and η_i is correlated to α_i, but uncorrelated with u_{it} for $t \geq 2$. Using an orthogonal projection, we can specify it as follows:

$$\eta_i = \theta\alpha_i + u_{i0}, \quad \theta > 0 \tag{18}$$

with α_i and u_{i0} assumed to be uncorrelated. If u_{i0} assumed to satisfy the same distributional assumption as u_{it} for $t = 2, \cdots, T$ or any change in error variance will also be captured in θ, the linearized reduced form for the latent variable for the initial period is therefore specified as Eq.(19)

$$p_{i0}^* = \mathbf{z}_{i0}'\pi + \theta\alpha_i + u_{i0} \tag{19}$$

where $\mathbf{z}$ includes initial period variables $\mathbf{x}$ (vector of controls describing i's household characteristics) as instruments. Thus, the joint probability of the observed binary sequence for a household i given α_i assuming serially independent u_{i0} in the Heckman approach is as follows:

$$\Phi\Big\{ \left(\mathbf{z}_{i0}'\pi + \theta\alpha_i\right)(2p_{i0} - 1) \Big\} \prod_{t=2}^{T} \Phi\Big\{ (\gamma p_{it-1} + \boldsymbol{\beta}\mathbf{x}_{it}' + \alpha_i)(2p_{it-1}) \Big\} \tag{20}$$

For a random sample of households, the likelihood to be maximized is then given by:

$$\prod_{i=1}^{N} \int_{\alpha^*} \left[\Phi\Big\{ (\mathbf{z}_{i0}'\pi + \theta\sigma_\alpha\alpha^*)(2p_{i0} - 1) \Big\} \prod_{t=2}^{T} \Phi\Big\{ (\gamma p_{it-1} + \boldsymbol{\beta}\mathbf{x}_{it}' + \theta\sigma_\alpha\alpha^*)(2p_{it} - 1) \Big\} \right] \mathrm{d}G(\alpha^*) \tag{21}$$

where G is the distribution function of $\alpha^* = \frac{\alpha}{\sigma_\alpha}$. Given normalization, $\sigma_\alpha = \sqrt{\frac{\lambda}{(1-\lambda)}}$. Following Butler and Moffitt(1982), the integral over α^* can be evaluated using Gaussian-Hermite quadrature given α is normally distributed. The estimation gets complicated when we allow serial correlation between the error terms which needs the likelihood function of random effect binary dynamic model evolution of T- dimensional integrals of normal density functions. This can be estimated with the maximum simulated likelihood method.

5 Results

We present the results in three stages. First, we discuss the validity of our estimation strategy looking at the correlations between unobservable and the associated exogeneity tests of initial conditions and panel retention. Second, we discuss the effects of the explanatory variables on probability of poverty persistence and probability of poverty entry. The implications of the model for poverty state dependence and household heterogeneity follows. Third, we discuss our estimates using dynamic probit model that account for initial condition and auto-correlated errors.

5.1 Testing validity of estimation strategy

In order to assess the endogeneity of initial conditions and panel retention, we tested for the separate and joint significance of the correlation coefficients associated with each of the two selection equations namely: retention and initial condition equations (see Eqs. 1 and 3). Panel (a) of Table 6 reports the estimates of the cross-equation correlations between the unobserved characteristics. The correlation between unobserved household specific factors determining base year poverty status and panel retention (ρ_1) is positive and statistically significant, indicating households that were initially poor remain in the sample of the subsequent waves than initially non-poor households. This confirms our earlier finding from the raw transition matrix that non-poor households have higher chance to dropout from the panel than their poor counterparts (see Table 2). This selective dropout of non-poor households during subsequent waves might potentially lead to under representation of non-poor households in the balanced panel data as compared to the whole sample. The result implies that estimation which ignores the sample retention mechanism or simply uses the balanced panel data would likely yield biased results. The correlation between conditional current poverty status of a household and unbservables affecting initial poverty (ρ_2) is negative and statistically significant. Since ρ_2 measures the correlation between unobservables affecting initial poverty status and poverty transition propensity, the negative sign can be interpreted as an example of Galtonian regression towards the mean (Stewart and Swaffield, 1999). Finally, the correlation between unobservables affecting panel retention and conditional current poverty status of a household meaning poverty transition (ρ_3) is positive and significant. This indicates that households that are observed in two successive periods are more likely to remain poor or fall into poverty compared to households that dropout from the sample.

We report the exogeneity tests in panel (b) of Table 6. As discussed in the previous section, by testing the joint significance of $\rho_1 = \rho_2$, it is possible to test the exogeneity of initial conditions. Our test result strongly reject this hypothesis. Similarly, exogeneity of panel retention can be tested by joint significance of $\rho_1 = \rho_3$ again the joint significance is significantly different from zero. Finally, all the three correlation coefficient were jointly significant with a p-value of less than 1%.

We created dummy variables for arrival and departure of family member at the first wave of our data (1994) as exclusion (instrument) variables to the initial condition equation. This is inline with the recommendation of Heckman (1981b) to use prior labor market information to instrument initial conditions in labor market outcomes studies. Similarly, the retention equation is instrumented by a dummy variable summarizing the enumeration status of a household in 1994.[9]

Panel (c) of Table 6 shows the validity of the instruments in the two selection equations (Eqs. 1 and 3). We follow Cappellari and Jenkins (2004), and undertook Wald test for the relevance of our instruments both separately and jointly. Our test results shows that change in membership status of a household during base year (new family members join the household or existing family members left the household) could be excluded from poverty transition equation both jointly and separately, the joint excludability is more evident. The p-values for the separate Wald test were 0.057, 0.1 and 0.034 for the joint test (see Table 6). With regard to retention equation instrument, retention status of a households between the first (1994) and the last wave (2004), the p-value was 0.095 confirming its validity. Further, all the exclusion variables were found to be statistically significant in the two selection equations (Eqs. 1 and 3) at 10% significance level. Thus, the validity of used instruments was supported by our data.

In sum, all the tests we undertook confirms the model fitted our data and the necessity of simultaneous estimation of the three equations namely; initial condition (Eq.1), retention (Eq.3) and poverty transition (Eq.7) equations to get unbiased results.

[9] This instrument variable is similar to what is used by Cappellari and Jenkins (2002, 2004) and Faye et al. (2011).

Table 6: Estimated correlation coef. and statistics tests

Parameters	Coef.	Std. Err.
(a) Correlation coef.		
$\rho_1 = \text{cov}(\delta_i, \eta_i)$: initial poverty status, retention	0.112^{**}	0.056
$\rho_2 = \text{cov}(\delta_i, \tau_i)$: initial poverty status, poverty transition	-0.387^{***}	0.055
$\rho_3 = \text{cov}(\eta_i, \tau_i)$: retention, poverty transition	0.356^{***}	0.054
Parameters	Chi-2	P-Value
(b) Exogeneity Wald tests		
Exogeneity of initial conditions: $\rho_1 = \rho_2 = 0$	72.68	0.000
Exogeneity of sample retention: $\rho_1 = \rho_3 = 0$	59.71	0.000
Joint exogeneity: $\rho_1 = \rho_2 = \rho_3 = 0$	891.84	0.000
(c) Instruments validity		
Inclusion of 'New family members joined the household in 1994' in initial condition equation (d.o.f=1)	3.62	0.057
Inclusion of 'Family members left the household in 1994' in initial condition equation (d.o.f=1)	2.71	0.100
Inclusion of 'Enumeration in 1994' in retention equation (d.o.f=1)	2.78	0.095
Joint inclusion of exclusion variables in initial condition equation (d.o.f=2)	6.74	0.034
(d) Test of state dependence		
Null hypothesis: no state dependence, $\gamma_1 = \gamma_2$ (d.o.f=28)	135.11	0.000

5.2 Endogenous switching estimates: Effects of shocks and IRMS

Table 7 presents the effect of control variables on poverty transition probabilities which is given in Eq.7. We report two sets of estimates based on poverty status of a household at $t-1$. The first set reports the effect of control variables (z) on probability of poverty persistence (Eq.10) for households that were poor at t, where the probability of the conditioning event (being poor) in the base year is held constant. Similarly, the second set reports the parameter estimates (λ_2) in the poverty entry equation (E q.11) for households that were non-poor at $t-1$.

The estimation results show only limited number of covariates have estimated coefficients that are significantly different from zero. This is inline with similar studies such as Cappellari and Jenkins (2004) and Faye et al. (2011). From the household characteristics, larger households are more likely to experience higher probability of poverty persistence. On the other hand, we found strong evidence supporting Schultz (1975) hypothesis that education have a positive effect to reduces poverty. Head education is substantially correlated with lower probability of poverty persistence but not poverty entry. Attending junior secondary, secondary or tertiary schooling by the head of the household reduce the probability of falling in to persistence poverty than the corresponding reference of household head with no education. It thus suggests that education is a good persistence poverty reduction leverage in urban Ethiopia. Older household heads are as well less likely to be persistently poor indicating the role of life cycle to accumulate asset (both physical and human). The working sector of household head also make difference in terms of poverty persistence but not poverty entry. Being a casual worker and a pensioner significantly increase the chance of remaining poor, as compared to being own account employee. The later reflects the limited nature of pension scheme in the country. Until recently, only government employees were covered by the pension scheme and the scheme provides small amount of payment to the beneficiaries (Asaminew, 2010).[10] With respect to the probability of entering poverty, a significant difference appears when Non Governmental employees (NGO) are compared with own account employees. The former have a higher probability of entering into poverty indicating the temporary nature of NGO employment in the country.

Turning into our main poverty covariates, shocks, unemployment have a strong positive effect on propensity to remain poor while its effect is not apparent immediately. This shows the unsustainable nature of existing (informal) consumption smoothing mechanisms to protect households in the long run. Here it is important to mention that there is no provision of unemployment benefit under Ethiopian labour laws. Hence, households primarily depend on their own strategies to mitigate the myriad of losing a job. In terms of household informal risk management strategies, access to international remittance reduces the propensity to poverty persistence, while it does not significantly affect the probability of entering poverty. This may indicate the time lag between experiencing a shock and getting transfer from family and friends residing abroad. Glewwe and Hall (1998) found similar result in Peru, during macro-economic shock households with access to international remittance are better off. Our result also shows the long term impact of international remittance to reduce the probability of staying in poverty. However, it is worth to recall that only 17% of poor households have access to international remittance while

[10]Government of Ethiopia put in place a new proclamation (Private Organization Employees Pension Proclamation 715/2011) that enables employees of private companies and non-governmental organizations (NGOs) to participate in the national pension scheme.

83% of non-poor households have access to it (see Table 4). On the contrary, the most dominant risk management strategies employed by poor households either have a positive effect on poverty entry probability or don't have any effect on both poverty persistence and poverty entry at all. For instance, the coefficient of receiving local remittance and gifts have a positive and significant effect on poverty entry probability. While 47% and 42% of poor households use gift and local remittance, respectively. This might indicate the 'reciprocity' nature of theses transfers that creates a pressure on poor households. The second dominant IRSM of poor households, loan from informal sources, do not have effect neither on the probability of poverty entry nor on poverty persistence.

Table 7: Multivariate Probit model: Poverty transition

	Poverty persistence		Poverty entry	
Variable	Coef.	Std. Err.	Coef.	Std. Err.
Household characteristics				
Number of employees in the household	-0.079	0.016	-0.090	0.067
Number of unemployed in the household	0.057	0.058	0.048	0.063
Household size	0.118***	0.034	-0.023	0.033
Number of family members aged between 0 and 14	0.07	0.047	0.051	0.047
Number of family members aged 64+	0.126	0.126	-0.128	0.134
Head of household characteristics				
Age	-0.012**	0.005	0.005	0.006
Sex:Female	0.181	0.163	0.016	0.167
Marital status: Married	0.037	0.150	-0.053	0.151
Education level:				
Primary schooling	-0.209	0.128	0.127	0.130
Junior Secondary Schooling	-0.513***	0.188	0.020	0.192
Secondary schooling	-0.870***	0.169	0.182	0.173
Tertiary schooling	-1.551***	0.213	-0.262	0.217
Head employment type:				
Public sector employee	0.164	0.181	0.064	0.183
Private sector employee	-0.296	0.221	-0.046	0.214
NGO employee	-0.493	0.350	0.583**	0.284
Casual worker	0.530***	0.200	-0.355	0.217
Civil servant	0.016	0.161	-0.162	0.167
Pensioner	0.375 **	0.160	-0.108	0.164
Others (unpaid family worker, housewife etc)	-0.243	0.177	-0.250	0.185
Head Shocks				
Unemployment	0.728***	0.274	0.097	0.259
Sickness	0.102	0.142	0.044	0.141
Disability	-0.015	0.143	-0.137	0.141
Household informal risk management strategies				
Local remittance	-0.059	0.154	0.319**	0.150
International remittance	-0.677***	0.239	-0.024	0.207
Gift	0.248	0.174	0.268*	0.157
Iddir	-0.161	0.116	0.073	0.117
Equup	-0.184	0.115	-0.014	0.116
Informal loan	0.031	0.109	0.070	0.105
Intercept	0.141	0.359	-0.769**	0.362
Log likelihood		-1797.000		
χ_2(d.o.f)		359.15 (106)		
P-value		0.000		

Continued on next page...

Table 7 – continued

Variable	Poverty persistence Coef.	Std. Err.	Poverty entry Coef.	Std. Err.
# Observations		837		

The standard errors are robust
Household is defined in the period when it is first observed (in 1994) and remains the same

Significance levels: ∗ : 10% ∗∗ : 5% ∗ ∗ ∗ : 1%

The estimates for initial poverty status and retention equations are provided in Table 8. The overview of the results indicates that more covariates are significantly different from zero in the initial poverty status equation in contrast to the poverty transition equation. We note being larger households, having either casual worker or pensioner head increase the probability of being poor in the base period. Conversely, having educated head including primary schooling and access to international remittance significantly reduces the propensity to be poor in the initial period. With regard to retention equation, having more number of household members involved in income generating activity induces higher probability of staying in the panel. This could be a plausible argument in light of the possibilities that families with more number of employees will find it difficult to move and find better opportunities simultaneously compared with those with a small number of employed members. Households heads with only primary educations, being a housewife or unpaid family worker likely reduces chances to move out and hence higher chance to remain in the panel. This confirms our result in the transition matrix in Section 3 which suggests that better off households are more mobile than poor households (see Table 2).

Table 8: Multivariate Probit model: Selection equations

Variable	Initial condition Coef.	Std. Err.	Retention Coef.	Std. Err.
Household characteristics				
Number of employee in the household	-0.102	0.063	0.149***	0.057
Number of unemployed in the household	0.074	0.062	0.043	0.058
Household size	0.126***	0.037	-0.036	0.032
Number of family members aged between 0 and 14	0.061	0.048	0.032	0.045
Number of family members aged 64+	-0.168	0.128	-0.030	0.121
Head of household characteristics				
Age	-0.011**	0.005	-0.008	0.005
Sex:Female	-0.118	0.153	0.273*	0.147
Marital status: Married	-0.186	0.142	0.151	0.137
Education level:				
Primary schooling	-0.365***	0.135	0.296 **	0.125
Junior Secondary Schooling	-0.535***	0.193	0.117	0.179
Secondary schooling	0.909***	0.169	0.130	0.163
Tertiary schooling	-1.338***	0.210	-0.235	0.190
Head employment type:				
Public sector employee	-0.093	0.184	-0.012	0.175

Continued on next page...

Table 8 – continued

Variable	Initial condition Coef.	Std. Err.	Retention Coef.	Std. Err.
Private sector employee	-0.307	0.223	-0.077	0.210
NGO employee	-0.405	0.314	0.012	0.295
Casual worker	0.397*	0.229	-0.014	0.193
Civil servant	-0.124	0.159	-0.172	0.155
Pensioner	0.340**	0.159	-0.113	0.153
Others (unpaid family worker, housewife etc)	0.004	0.189	0.246*	0.143
Head Shocks				
Unemployment	0.376	0.272		
Sickness	0.094	0.145		
Disability	0.132	0.140		
Household informal risk management strategies				
Local remittance	-0.098	0.154		
International remittance	-1.099***	0.234		
Gift	0.137	0.174		
Iddir	-0.170	0.116		
Equip	-0.141	0.116		
Informal loan	-0.040	0.109		
Exclusion restriction				
New family members joined the household in 1994	-0.133*	0.070		
Family members left the household in 1994	-0.185*	0.113		
Enumerated in 1994			0.145*	0.087
Intercept	0.689*	0.353	-0.140	0.334

ρ_1 : initial condition - retention 0.112**(0.056)

Significance levels: $*$: 10% $**$: 5% $***$: 1%

5.3 State dependence and household heterogeneity

Our result in Table 7 showed that observed characteristics of households have a different impact on poverty probabilities based of household's poverty status at $t-1$. This result already suggests the existence of Genuine State Dependence (GSD) of poverty. Formally, we checked the existence of GSD by testing the null hypothesis H_0: $(\lambda_1 = \lambda_2)$ (see Section 4.1). Panel (d) of Table 6 presents the test results. The test strongly rejects the null hypothesis confirming the existence of genuine state dependence of poverty in urban Ethiopian. This implies that past experience of poverty inflicts an adverse behavioral and physical impact on households that leads to downward shift in preference and loss of motivation and hence poverty persistence. Our result is inline with previous study (Bigsten and Shimeles, 2008) that used the same data set that we are using. Further, using the predicted probability of poverty entry and persistence we estimate ASD to be 44%. This estimate is 10% point higher than what we have estimated using a raw transition matrix in Table 2. Recall that our estimate in Table 2 doesn't take into account household heterogeneity. Furthermore, we quantify the GSD as 0.11 using Eq.(10). From these it is possible to conclude that poverty is strongly state dependent in urban Ethiopia and the line share (75%) of the state dependence arise from households heterogeneity.

Overall, our results using endogenous switching model suggest that policies that reduce the consequence of shocks like unemployment insurance will have a decisive effect to reduce both poverty entry and poverty persistence. Thus, public insurance schemes that target the disadvantage groups like households with unemployed head or uneducated head are important complements to growth enhancing policies to deal with long term poverty reduction in the country.

5.4 Random effect dynamic probit model: Effects of shocks and IRMS

Table 9 reports estimates using random effect dynamic model. This framework models poverty status of a household as a function of observed household characteristics and lag of the dependent variable (see Eq. 16). The table presents two sets of parameter estimates. The first set reports the effect of explanatory variables on probability of falling into poverty assuming initial condition is exogenous. As we discussed in Section 4.2, this assumption is strong. The result is presented here for comparison purpose only. The second set presents estimates of a model that controls for initial condition bias, household heterogeneity and serially correlated error terms. From the Wald chi-square, we can see that overall both models are significant at 1%. However, the log likelihood shows the model that controls initial condition, household heterogeneity and serial correlation fits best the data.

The estimation result shows more number of covariates have significant estimated coefficients than estimates we found using endogenous switching model. This is not surprising result since the endogenous switching models poverty propensities (poverty entry and poverty persistence) conditional on poverty status of households at $t-1$ rather than current poverty propensities which is the case in the random effect dynamic probit model. It is also plausible to attribute the weaker effect of covariates in poverty transition equation of the endogenous switching model to the effect of endogenity of panel attrition being accounted for.[11]

Larger households, households with higher number of unemployed and children between age 0 and 14 have a higher chance of falling in to poverty. Consistent with the results from the endogenous switching model, education played a significant role in reducing the probability of being poor. In terms of head occupation, being a public sector employee increase the probability of entering into poverty compared with own account employees. This could be due to the fact that public employees in the country earns less than other sectors employees. One of the striking features of the result here again is head unemployment and disability have a positive effect on the probability of falling in to poverty. With regard to informal risk sharing mechanisms, membership in equup, iddir and access to international remittance reduce the probability of entering into poverty. However, the top three dominant informal risk sharing mechanisms of poor households namely; local remittance, loan from informal sources and gift don't have any effect at all confirming the fact that the mechanisms have limited role to reduce current poverty as well. Inline with endogenous switching model, the dynamic probit model also predicts the presence of strong state dependence on the evolution of poverty in urban Ethiopia. The positive and significant effect of lagged dependent variable (lagged poverty status of a household) asserts the fact that even after controlling household heterogeneity and autocorrelation in the random error term the probability of falling into poverty in the current period is highly correlated with being poor in the past.[12]

[11]Note that the random effect dynamic probit model only uses balanced panel data, attri households are dropped out from the estimation.

[12]Note that the coefficient of the lag dependent variable increases significantly once we control for initial

Table 9: Random effect dynamic panel data model

Variable	RE with exogenous initial condition Coef.	Std. Err.	RE with endogenous initial condition and auto-correlated error term Coef.	Std. Err.
Lag poor	0.826***	0.083	1.043***	0.140
Household characteristics				
Number of employees in the household	-0.005	0.038	0.013	0.047
Number of unemployed in the household	0.088*	0.042	0.105**	0.053
Household size	0.041	0.025	0.062**	0.031
Number of family members aged between 0 and 14	0.178***	0.037	0.127**	0.047
Number of family members aged 64+	0.198*	0.037	0.205	0.131
New family members joined the household in 1994	-0.082	0.058	-0.107	0.077
Family members left the household in 1994	0.049	0.035	0.042	0.043
Head of household characteristics				
Age	-0.003	0.005	-0.006	0.006
Sex:Female	0.142	0.099	0.183	0.118
Education level:				
Primary schooling	-0.420***	0.109	-0,490***	0.138
Junior Secondary Schooling	-0.495***	0.155	-0.349**	0.177
Secondary schooling	-0.700***	0.144	-0.616***	0.175
Tertiary schooling	-0.805***	0.158	-0.652***	0.193
Head employment type:				
Public sector employee	0.260	0.171	0.409**	0.203
Private sector employee	-0.271*	0.164	-0.341*	0.208
NGO employee	0.091	0.279	0.283	0.320
Casual worker	0.222	0.139	0.284	0.208
Civil servant	0.229	0.173	0.348**	0.158
Pensioner	0.113	0.134	0.194	0.169
Others (unpaid family worker, housewife etc)	-0.099	0.125	0.043	0.164
Head Shocks*				
Unemployment	0.417**	0.179	0.452**	0.209
Sickness	-0.001	0.134	-0.173	0.183
Disability	0.216*	0.124	0.318**	0.174
Household informal risk management strategies				
Local remittance	-0.132	0.130	-0.178	0.160
International remittance	0.604***	0.148	-0.769***	0.202
Gift	0.021	0.150	0.094	0.189
Iddir	-0.349***	0.111	-0.440**	0.144
Equup	-0.392***	0.103	-0.299**	0.124
Informal loan	-0.109	0.119	-0.031	0.150
Intercept	-0.523*	0.297	-0.753	0.370
AR1			-0.4281***	
Log likelihood	-704.198		-560.777	
χ_2(d.o.f)	30(326.80)		30(219.29)	
P-value	0.000		0.000	
# Observations	2,444		2,444	

Household is defined in the period when it is first observed (in 1994) and remains the same

* All the shock variables are one wave lag

Significance levels: $*$: 10% $**$: 5% $***$: 1%

condition and the persistence of error components.

6 Conclusion

The study provides a thorough investigation of urban poverty dynamics in Ethiopian with an emphasis on the effect of idiosyncratic shocks and informal risk management strategies. We used a unique panel data collected for a decade from seven major cities of Ethiopia. We address three main research questions. One, what is the nature of poverty transitions experienced by urban Ethiopian households? Two, do idiosyncratic shocks have an effect on poverty persistence? Three, what is the impact of idiosyncratic shocks and informal risk management strategies on poverty dynamics? Providing answers to these questions is crucial for designing effective poverty alleviation policies in urban settlement where uninsured risk is ubiquitous and insurance market and safety nets to deal with the consequence of uninsured risk are largely absent.

We employed two 'poverty transition' econometric models: endogenous switching model and random effect dynamic probit model. The endogenous switching model accounts for initial conditions, non-random attrition, and unobserved heterogeneity. Our results show that both initial conditions and panel retention are indeed endogenous processes during poverty transitions estimation, implying both should be estimated simultaneously with poverty transition in order to get unbiased results. Our findings provide clear evidence on the adverse impact of uninsured risk on welfare. We found unemployment of household head propel the households to persistent poverty. On the other hand, access to international remittance and better education reduces the probability of remaining poor. Our estimation also confirms the fact that, in the absence of public insurance and market, poor household are forced to use ineffective risk management strategies which have a negative consequence on welfare. We note gift and local remittance that are predominately used by poor households increases the probability of entering into poverty.

Results of the random effect dynamic probit model (that accounts for initial condition bias, household heterogeneity and serially correlated errors) confirms most of the findings of endognenous switching model. Although we found more number of covariates have significant estimated coefficients than estimates of endogenous switching model. It is plausible to attribute the weaker effect of covariates in endogenous switching model to the endogenity of non-random panel attrition being accounted for.

The paper makes a substantive contribution to the knowledge base on understanding poverty dynamics and the main factors underlying poverty transitions using a decade urban panel data. Our study has three novel contributions. First, we bring a new applied evidence from one of the poorest country in SSA to bear on the on-going debate whether poor households can insure themselves against the consequence of *idiosyncratic shocks* in the absence of market and public institutions. Second, we confirm that uninsured shock indeed lead to persistence poverty. Third, we showed that in the absence of market and public institutions poor households use ineffective risk management strategies that have a negative consequence on welfare than their non-poor counterparts. Finally, we showed that there is a true state dependence in urban Ethiopia and the lion share of the state dependence is associated with household heterogeneity.

Our results imply that putting in place public insurance programs to the poor will have a positive effect on society welfare. Moreover, poverty reduction programs that aim to prevent households not to fall into poverty not only have a short run effect but also helps to reduce future poverty. Indeed, policies focusing on household heterogeneities such as exposure to risk, lack of education, personal skills and capacities, would have long lasting effect.

However, one caveat of our shock variables should be mentioned. Our shock variables are limited to the experience of a given shock. The data set we used doesn't quantify the amount of loss in income or consumption due to experience of shocks. A future research therefore involves examining the actual loss of household due to the materialization of risk and its effect on poverty dynamics. Doing so will not only document what kinds of shocks are associated with poverty entry and poverty persistence but also provides a clear picture on the extent to which shocks have a negative welfare effects.

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Table 10: Table Appendix (A1). Calorie based equivalence scales

Age in years	men	women
0-1	0.33	0.33
1-2	0.46	0.46
2-3	0.54	0.54
3-5	0.62	0.62
5-7	0.74	0.70
7-10	0.84	0.72
10-12	0.88	0.78
12-14	0.96	0.84
14-16	1.06	0.86
16-18	1.14	0.86
18-30	1.04	0.80
30-60	1.00	0.82
60 +	0.84	0.74

Source: Dercon and Krishnan (1998).

Table 11: Table Appendix (A2). Definition of variables

Variable name	Definition	Nature
Household characteristics		
Number of employees in the household	Number of household members involved in income generating activity	Continuous
Number of unemployed in the household	Number of household members who are looking for work but unable to find	Continuous
Household size	Number of family members	Continuous
Number of family members aged between 0 and 14	Number of family members whose age is between 0 and 14	Continuous
Number of family members aged 64+	Number of family members whose age is above 64	Continuous
Characteristics of household head		
Age	Age of head	Continuous
Sex	Sex of head	Dummy (female=1)
Marital status	Marital status of household head	Dummy (Married=1)
Education level	Highest educational status of head	Dummy (Ref. No schooling)
Head employment type	Household head employment type	Dummy (Ref. Own account worker)
Head shocks		
Unemployment	Household head is looking for work but unable to find	Dummy (yes=1)
Sickness	Household head suffered from illness during the last 4 weeks	Dummy (yes=1)
Disability	Household head is disabled	Dummy (yes=1)
Household informal risk management strategies		
Local remittance	Household received local remittance in the last 12 months	Dummy (yes=1)

Continued on next page...

Table 11 – continued

Variable name	Definition	Nature
International remittance	Household received remittance from abroad in the last 12 months	Dummy (yes=1)
Gift	Household received cash or in-kind gift from abroad in the last 12 months	Dummy (yes=1)
Iddir	Household is a member of iddir	Dummy (yes=1)
Equb	Household is a member of equb	Dummy (yes=1)
Informal loan	Household received a loan from money lender or friend or relative during the last twelve months	Dummy (yes=1)
Exclusion restriction		
New family members joined the household in 1994	Number of household members that join the household in 1994	Continuous
Family members left the household in 1994	Number of household members that left the household in 1994	Continuous
Enumerated in 1994	Household was enumerated in the first wave of the panel (1994)	Dummy (yes=1)