



**UNITED NATIONS
UNIVERSITY**

UNU-MERIT

Working Paper Series

#2015-006

**Poverty persistence and informal risk management:
Micro evidence from urban Ethiopia
Théophile T. Azomahou and Eleni A. Yitbarek**

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)

email: info@merit.unu.edu | website: <http://www.merit.unu.edu>

Maastricht Graduate School of Governance (MGSOG)

email: info-governance@maastrichtuniversity.nl | website: <http://mgsog.merit.unu.edu>

Keizer Karelplein 19, 6211 TC Maastricht, The Netherlands

Tel: (31) (43) 388 4400, Fax: (31) (43) 388 4499

UNU-MERIT Working Papers

ISSN 1871-9872

**Maastricht Economic and social Research Institute on Innovation and Technology,
UNU-MERIT**

**Maastricht Graduate School of Governance
MGSoG**

UNU-MERIT Working Papers intend to disseminate preliminary results of research carried out at UNU-MERIT and MGSoG to stimulate discussion on the issues raised.

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

Théophile T. Azomahou^a and Eleni A. Yitbarek^{b*}

^(a)United Nations University (UNU-MERIT) and Maastricht University
Keizer Karelplein 19, 6211 TC Maastricht, the Netherlands

^(b)United Nations University (UNU-MERIT) and Maastricht University
Keizer Karelplein 19, 6211 TC Maastricht, the Netherlands

February 16, 2015

Abstract

Two factors that have received limited attention in poverty dynamic studies are the role of risk in causing poverty mobility and attrition bias. Controlling for the attrition bias, 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 propels 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. Further, we find 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, could have long lasting effects.

Key words: Poverty persistence, idiosyncratic shock, endogenous switching model

JEL Classification: D14; I32; O12

*Corresponding Author: E.A. Yitbarek, Tel. +31 433 884 441, Fax +31 433 884 499, e-mail: e.yitbarek@maastrichtuniversity.nl; T.T. Azomahou (azomahou@merit.unu.edu).

1 Introduction

Understanding why people remain poor is an immediate consequential research issue in developing world. A large body of existing literature analyzed poverty in developing countries, in particular using static poverty analysis.¹ There is now 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 growing availability of panel data in developing countries, the literature on poverty dynamics is growing. Good surveys of this literature in developing countries are given in Baulch and Hoddinott (2000), McKay and Lawson (2003), Dercon and Shapiro (2007) and Baulch (2011). All reviews pointed out that the literature is far from complete. About half of the studies examine a few hundred households, about 40% consisting of only two waves and about 10% analyze urban poverty dynamics. Most importantly, though risk² and non-random panel attrition turn up in many of narratives of dynamic poverty studies, the literature omit them largely (Dercon and Shapiro, 2007); a lacuna towards which this study contributes.

Among many other factors, shocks like unemployment, sickness, death, theft, drought and political strife create large variations in income and consumption over time. Barrientos (2007) reviews the existing literature and concludes that there exist increasing evidence that uninsured shocks raise the incidence of poverty. Nonetheless, the long term effects of shocks propelling households into persistent poverty remain unknown. There are two likely consequences of shock. First, there is the direct impact of a shock on welfare. Alderman et al. (2006) in rural Zimbabwe found children affected by the civil war and drought in the 1970s and 1980s incurred a loss of about 14% of their lifetime income. Second, there is an indirect behavioral change; households that face uninsured risks may confine to low risk and low return activities or asset portfolios. For instance, asset poor rural Indian households, allocate a large proportion of their land to safe traditional varieties of rice and castor rather than high yield but high risk crops (Morduch, 1995). Household decisions to hold non-productive assets or use low return seed varieties do not only mean 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 is an important dimension of welfare. Therefore, 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 households 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 these institutions to generate income and smooth consumption over the life cycle. However, credit and insurance markets are mostly absent in developing countries including our case study (Ethiopia). According to the AfDB (2011) estimates, less than 10% of Ethiopian households have access to formal credit and

¹An 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.

²There 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.

insurance. 80% of the global population has no access to comprehensive social protection (UN, 2012a). Social network, family and membership institutions (i.e. informal risk management channels) are more prevalent in developing countries than other Welfare Pentagon institutions.

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) considers these coping strategies as effective instruments to reduce current poverty, while Dercon (2005) argues exposure to uninsured risk may force households to hold less productive assets for the purpose of consumption smoothing. There is more empirical literature on informal risk sharing with a particular emphasis on rural developing economies (see for instance Deaton (1990), Fafchamps and Lund (2003), Ayalew (2003), Skoufias and Quisumbing (2005) and Santos and Barrett (2011)). Almost all studies examine 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 the full insurance hypothesis.

The existing literature provides several plausible explanations for 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 showing 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 a rural phenomenon, until recently poor urban areas were generally neglected both by researchers and development programs. Excluding south Africa, Bigsten and Shimeles (2004), Kedir and McKay (2005), Islam and Shimeles (2006) and Faye et al. (2011) are exceptions analyzing poverty dynamics in urban Sub-Saharan 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 on poverty dynamics. Our study fills this gap using a decade long panel data from urban Ethiopia.

Distinguishing between rural and urban settings is important in studying risk and risk management. 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 a productive day due to illness or loss of income due to death of the breadwinner) and need support to cope with fluctuations in food prices. Proximity and occupational similarity to some extent mitigate information asymmetries 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 asymmetries that deters informal risk sharing arrangements. Given the idiosyncratic nature of shocks, one can expect informal risk management mechanisms exist to protect households from the effect of shocks in urban areas. However, it is not possible to make this conclusion a priori (Cox and Jimenez, 1998).

We study the impact of idiosyncratic shocks and informal risk management strategies on urban poverty dynamics using a large panel of urban households and more rigorous econometric specifications than previously applied to this topic in developing countries. Understanding the

³The 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.

effect of shocks and shock management mechanisms on poverty dynamics provides useful insights into the design of poverty reduction policies. If the existing informal risk management strategies are found to be effective in dealing with the consequences of shocks households are facing then introducing a public insurance scheme will crowd out the existing mechanisms. On the other hand, if this only provide protection to better-off households, targeted public insurance to the poor can enhance their lives and will be a net gain to society. By providing evidence in urban setting of a least developing country for the first time, the study also contributes to the on-going debate on whether poor households can insure themselves against the consequences of idiosyncratic shocks in the absence of market and public institutions.

The study contributes to the existing literature in the following ways. First, using endogenous switching model we are able to control for the attrition in our sample. As a result, unlike other studies that uses the data we are using, the estimates presented in this study do not suffer from sample selection bias caused by limiting the analysis to balanced panel (see Section 3.2 for detail discussion). Second, using two ‘poverty transition’ models; a dynamic random effect probit model and endogenous switching model, we study the impact of idiosyncratic shocks on urban poverty dynamics. To the best of our knowledge, there exist no other similar study in urban sub-saharan Africa. Finally, the role of informal risk management strategies to insure urban households against the consequence of shocks remains largely unexplored. In this paper we attempt to fill this void in the literature and provide an evidence using data from urban Ethiopia.

There are several key findings. First, urban households do not succeed in fully insuring themselves against the consequences of idiosyncratic shocks. Economic shock, unemployment of the household head, have a positive effect on poverty persistence. This result is in line with previous studies that reject the existence of the full insurance in rural village (see for instance Dercon and Krishnan, 2000; Ayalew, 2003; Skoufas and Quisumbing, 2005; Santos and Barrett, 2011). Second, poor households use more ineffective risk management strategies which have negative consequence on welfare than their non-poor counterparts. The most dominant informal risk management mechanisms used by poor household (gift and local remittance) have a positive effect on the probability of entering to poverty. On the other hand, having access to international remittance decreases the probability of poverty persistence. A similar result was found to Peruvian households; during a macro-economic shock, households with access to international remittance are better off (Glewwe and Hall, 1998). However, it worth to mention that in our sample only 17% of poor households have access to international remittance. Third, we find strong evidence supporting Schultz (1975) hypothesis that education plays a vital role to reduces poverty. The working sector of household head also makes difference in terms of poverty persistence. Such result is also consistent with similar findings (see Bigsten and Shimeles, 2004; Kedir and McKay, 2005). Finally, consistent with Bigsten and Shimeles (2004), we find strong state dependence of urban poverty in Ethiopian mainly driven by household 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.

2 Risk and welfare: Insights from the literature

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

2.1 Risk typology

The literature on risk is both broad and extensive, but defines risk in various ways. 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 triggers 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 the 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 implications on the ability of household to cope with its consequences. For example, a family head losing her job due to illness is an idiosyncratic shock. Or it is a covariant, if the loss of her job is a result of an economic crisis that results in mass layoffs. Empirical evidence suggests that idiosyncratic risk may be at least as important, or 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’s Welfare Pentagon paradigm, households generate income and smooth consumption using five core institutions: family, markets, social networks, membership institutions and public authorities. Indeed having access to any 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. In 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; Berloff and Modena, 2013). Similarly, 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 of risks 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, the unit of risk-pooling is very context specific. Evidence of risk sharing among extended families has been found by Foster (1993) and Witoelar (2005), among friends and relatives by Fafchamps and Lund (2003), among ethnic groups by Grimard (1997) and within communities by Townsend (1994). Any two households or individuals are said to share risk if they employ state-contingent transfers to increase the expected utility of both by reducing the effect of a shock in at least in one (Townsend, 1994).

The anthropological literature documents the existence of a variety of informal risk sharing mechanisms in Ethiopia that are driven by tradition and ‘reciprocity’ (Hailu and Northcut, 2012). Sahlin (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, typically 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’- a voluntary association that usually formed among friends, colleagues and neighbors to provides resources necessary to carry out funeral rituals and ‘Eqqub’- a voluntary association that regularly pools fund and rotates among members are good example of balanced reciprocity risk sharing mechanisms.

Access to informal risk management mechanisms is not homogeneous to all households. Access is determined by household resource endowments (such as social, human, financial and physical resources). Households also differ in terms of consumption preferences, risk exposure and risk ‘appetite’, which determines their capacity to produce and accumulate wealth in the market. Together with the initial wealth distribution and corresponding consumption distribution, households adopt different consumption smoothing strategies based on the available options. Some households are poor; and don’t have enough resources to satisfy the requirements of welfare pentagon institutions to insure both current and future consumption. The position of a household in the 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

Uninsured risks are ubiquitous in the developing world. 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 effects of risk. First, there is the impact of a shock on welfare. Rainfall shocks are found to have a persistent effects on consumption growth of rural Ethiopian households (Dercon et al., 2005). Deininger et al. (2003) report that the arrival of a foster child to household results in low capital formation in Uganda. In rural Zimbabwe, children affected by civil war and drought shocks in the 1970s and 1980s incurred a loss of around 14% of 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 rather than high yield but high risk crops (Morduch, 1995). A household's decision to hold non-productive assets or to use low return seed variety not only means forgone current income but also a higher chance that the household will remain poor. This implies that risk management decisions of a household have both short and long-term implications which may result in poverty entry and poverty persistence.

Based on the 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 shock and distinguish between *economic shocks* (unemployment) and *health shocks* (illness and disability). With regard to informal risk management strategies we include remittance (local and international), credit from informal sources, gifts (cash and in-kind) and membership in 'Eqqub' and 'Iddir'.

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 the Departments of Economics of Göteborg 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) over five waves (1994, 1995, 1997, 2000 and 2004). The period covered by the data is characterized by major macroeconomic and political changes. The period between 1994 and 1997 is characterized by peace, recovery from the long civil war and good weather whereas between 1997 and 2000 the country experienced drought, a sharp decline in international coffee prices and a war with Eritrea.⁴ Between 2000 and 2004 the economy recovered from the 1999/00 crises and experienced moderate growth.

⁴Coffee 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).

3.1 Sampling

The sampling frame of the survey includes all cities with more than 100,000 inhabitants. Cultural diversity, major economic activity and administrative importance of cities are additional criteria to select sample cities.⁵ 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 unit in the country, in each districts (wereda) using the official registration of residences available at the 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 contributed 7% of the sample 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. Here the sample used for the empirical analysis is restricted to data from the 2nd to 5th round (four waves) of the EUHS. The time dimension of our panel is long enough to allow estimating poverty transition than similar studies of poverty dynamic in Sub-Saharan Africa. It is important to mention panel attrition of the data. Attrition is 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 (the poverty status of households). We test this relationship more formally in Section 3.2.

Every analysis of the welfare impact of shocks and risk management strategies of households draws on the micro-economic theory of utility maximization. According to standard 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 approximation of ‘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 in that it includes both food and non-food components. Food consumption includes the value of food purchased from markets and prepared food in-house. 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 equivalents’ to determine real per adult equivalent household consumption. We used the calorie based equivalence scales developed by Dercon and Krishnan (1998) for the country (see Table 10 of the Appendix).

Our unit of analysis is a household.⁶ A household is defined as poor, if adult equivalent

⁵Mekele 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.

⁶Household is defined in the period when it is first observed and remains the same.

consumption is lower than the absolute poverty line of the country, which is defined by Ministry of Finance and Economic Development (MoFED) in 1995/96. The poverty line is estimated following the cost-of-basic-needs approach in two stages. First, the food poverty line is 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 is 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 determinants of the poverty status of households (control variables). We grouped the controls into four main categories: household characteristics, household head characteristics, head shocks and household informal risk management strategies. We also needed additional variables to test the exclusion restrictions in the selection equations of the endogenous switching model (see Section 4.1 and 5.1). The definitions of all variables are summarized in Table 11 of the Appendix.

3.2 Context and poverty transition patterns

Poverty reduction is a central policy of the 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 MDGs into national development policy and aim to reduce and eradicate poverty. Despite this, poverty remains pervasive and persistent in the country. In 2004/05, the number of people living below the poverty line is estimated to be 35% and 39% for urban and rural area, respectively (MoFED, 2008).

Rural poverty reduction is a priority of all three 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 countries, rapid urbanization is a growing phenomenon. 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 in the literature as an “urbanization of poverty” (Ravallion, 2002). For instance, between 1995 and 2004 the headcount index in rural areas declined by 17% while it increased by 6% in urban areas suggesting that the country overall poverty reduction did not bear much of the fruits of an expanding urban population (MoFED, 2008).⁷

Table 2 shows the raw poverty transition matrix for the period between 1995 and 2004. The transition probabilities give the propensity of households of being poor or non-poor at t

⁷In 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).

Table 1: Summary statistics of variables used in estimation

	Mean	St.Dev.*	Min.	Max.
Female household head	0.393			
Age in years	49.250	13.446	13	99
Household size	6.508	2.974	1	28
Family members aged between 0 and 14	1.789	1.578	0	10
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 members joined the household in 1994	0.317	0.560	0	2
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			
Equip	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.

* Min., Max. and St.Dev. for dummy variables are not included.

** Symbolizes a reference group.

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.

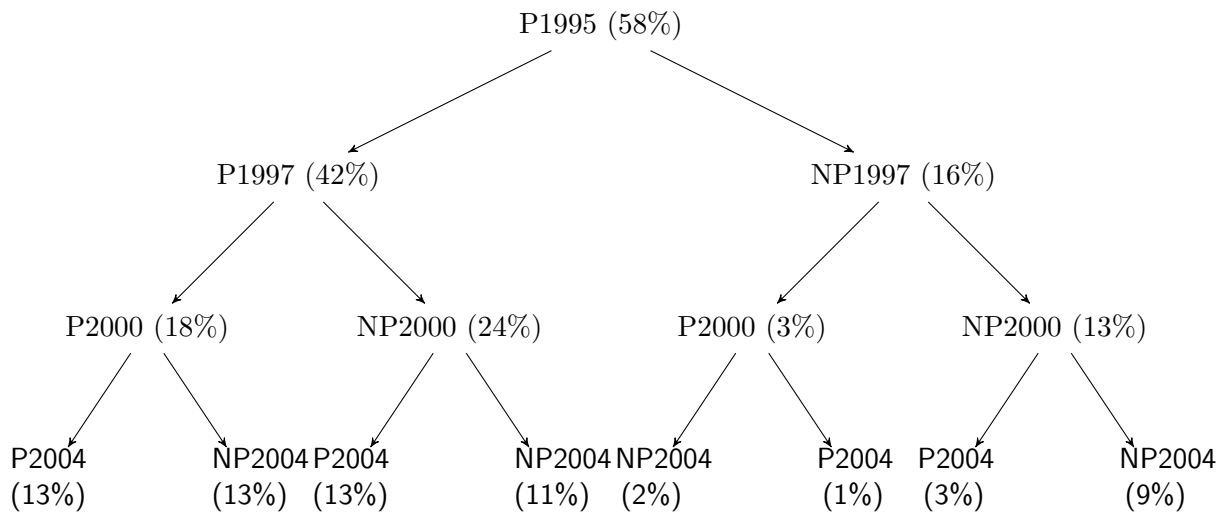
conditional on the poverty status at $t - 1$. Panel (a) shows the transition matrix for households that are observed in all waves (the balanced panel). The table illustrates the chance of being poor in a given year differs depending on poverty status of the household in the previous year. Households 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 a 75% of chance of staying in the same state at t . Similarly, households that were poor at $t - 1$ have a 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 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 twice that of poor households (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 the poverty transition equation for consistent estimates. Therefore, we specify a model that takes into account a non-random household attrition jointly with the initial conditions and poverty transition. We shall employ a 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.

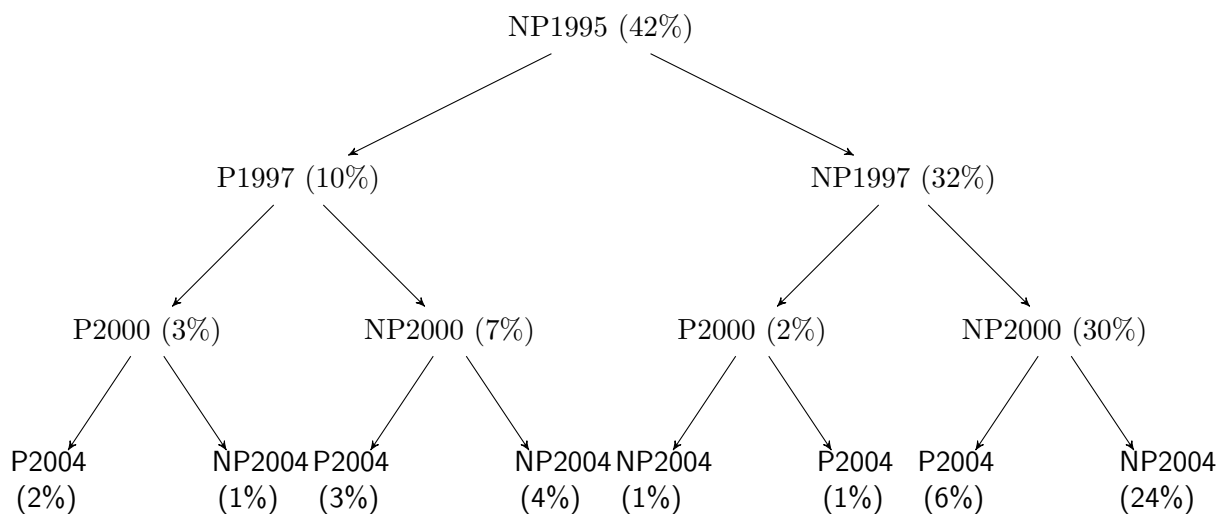
Figures 1 and 2 are a reconstruction of all flows into and out of poverty over the decade under discussion. The figures reveal two interesting results. First, the chart confirms that poverty frontiers go far beyond the category of the poor covered by one cross-section (one wave) analysis. For instance, the poverty rate in 2004 was 42% while 76% of households experience poverty at least once over the period under consideration. Second, 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 household head shocks for the period between

1995 and 2004. The most common shock is disability (15% of households) followed by illness (13%) and unemployment (5%). Unemployment of household head is more prevalent in poor households than their non-poor counterparts while sickness and disability are more common in non-poor households.

Table 3: Incidence of self-reported shocks by poverty status-(in %), 1995-2004

Shocks	Poor	Non-poor	Total
Head illness(a)	44.76	55.24	12.62
Head Unemployment (b)	51.79	48.21	4.64
Head disability (c)	44.07	55.93	14.78
Sample size	1,366 households		
a) suffered from any illness in the last 4 weeks.			
b) looking for a job but unable to find any in the last 12 months.			
c) suffered from any disability or major chronic health problem.			

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

Table 4 presents the different risk sharing mechanisms of households for the same period. ‘iddir’ and ‘equip’ 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, loans from informal sources is the main mechanism for poor households while non-poor households predominately use their access to international remittances. 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 mechanism than their poor counterparts. For instance, 83% of non-poor households have access to international remittances compared to only 17% of poor households. The same is true when we consider the dominant mechanism. 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-(in %), 1995-2004

Mechanisms	Poor	Non-poor	Total
Local remittance(a)	42.31	57.69	9.66
International remittance(a)	17.23	82.77	8.61
Gift(a)	47.95	52.05	8.06
Iddir(b)	40.15	59.85	77.98
Equip(b)	32.68	67.32	19.47
Loan from informal sources(a)	45.99	54.01	16.85
Sample size	1,366 households		
a) received transfer in the last 12 months.			
b)At least one household member is a member in the last 12 months.			

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

Table 5 summarizes the purpose of transfers from informal risk sharing mechanisms for households who actually have access. The table shows that the primary purpose of all transfers, except ‘equip’ is consumption. 41% and 40% of households who are a member of ‘equip’ used the

transfer to cover ceremonial expenses including weddings and consumption, respectively. This may indicate that the main purpose of the transfer from informal risk sharing mechanisms 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. A view that finds support in 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. As discussed in the previous section, poverty may persist due to materialization of risks (covariate or idiosyncratic) that erode the human and physical capital of households. Households 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 a 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 the effects of households heterogeneity (both observed and unobserved) and genuine state dependence to understand the effect of shocks on poverty dynamics.

Three types of models have usually been used to study poverty dynamics in the literature namely: the ‘component’ approach, the ‘spell’ approach, and the ‘transition’ approach. The first and the most commonly estimated model is the component approach due to Jalan and Ravallion (1998). The approach decomposes a household poverty measure, mostly the squared poverty gap, into a permanent component measuring chronic poverty and transitory component measuring transient poverty. The chronic poor are identified as all households whose intertemporal average consumption or income lies below the poverty line. The transitory component of poverty is the difference between total poverty 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 the shortcoming of not explaining the true causes of both types of poverty. Using the intertemporal average of income or consumption to aggregate welfare over time implicitly assumes that poverty spells 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, this type of identification of the chronic poor doesn't take the time spent in poverty into account.

The second most used approach is the 'spell' approach (e.g., Bane and Ellwood, 1986; Stevens, 1994 and Devicienti, 2011). This approach analyzes the 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 line using a 'duration cut-off'. In contrary to the component approach, the '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 a 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 can take into account multiple episodes of poverty and household-level unobserved heterogeneity. Spell approaches have a potential to test the effect of household heterogeneity and state dependence on poverty persistence. However, a poverty spell may have already begun before the first observation of the panel (left censoring) or still be underway in the last observation (right censoring) requires additional remedies during estimation. If censoring is independent of the duration, then right censoring doesn't pose a problem; the censoring process can be modeled jointly with poverty transitions. Left censored data are problematic. The literature usually discards left censored data (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 and understates poverty persistence. Tackling this issue requires more data currently unavailable in most developing countries.

The third, and most recent approach, is to model poverty transition using first-order Markov process. This approach consist of 'Dynamic Random Effects Probit' and 'Endogenous Switching' models. The latter is due to Cappellari and Jenkins (2002, 2004) who build on Stewart and Swaffield (1999). In both models, only first order dynamics are modeled. This makes the poverty dynamics simpler than spell or duration models. Both models control for initial condition bias, household heterogeneity and state dependence.⁸ 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 dynamic random effects probit models, particularly if intercept effects exists. An endogenous switching model has the advantage of controlling for non-random panel attrition which is a characteristic of our data while dynamic probit models allow correcting for a serial correlation. Thus, the models complement each other and using both models leads to a more comprehensive analysis of poverty dynamics.

In this study, we use both models to investigate urban Ethiopian poverty dynamics with

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

an emphasis on the effects of idiosyncratic shocks and informal risk management strategies of households. To our knowledge these models are rarely used to study poverty dynamics in developing countries. Bigsten and Shimeles (2008) used dynamic random effects probit models 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 models are used by Faye et al. (2011) to study poverty 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 discusses both estimation strategies.

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 be characterized by a latent poverty propensity p_{it-1}^* at $t - 1$, of the following form:

$$p_{it-1}^* = \beta' \mathbf{x}_{it-1} + u_{it-1} \quad (1)$$

Let's call Eq. (1) the initial poverty status equation, where $i = 1, \dots, N$ indexes households and $t = 1, \dots, T_i$ time span, \mathbf{x}_{it-1} is a vector of controls describing i 's household characteristics, β 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,

$$p_{it-1} = \mathbf{1}_{[p_{it-1}^* > 0]} \quad (2)$$

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:

$$r_{it}^* = \gamma' \mathbf{w}_{it-1} + \varepsilon_{it} \quad (3)$$

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 $\varepsilon_{it} \sim N(0, 1)$. γ 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

$$r_{it} = \mathbf{1}_{[r_{it}^* > 0]} \quad (4)$$

We call (3) retention equation. The third component of the model is the specification for

poverty status at t , which we call ‘poverty transition equation’. Assume the latent propensity of poverty be summarized by:

$$p_{it}^* = [(p_{it-1})\lambda'_1 + (1 - p_{it-1})\lambda'_2] \mathbf{z}_{it-1} + \epsilon_{it} \quad (5)$$

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

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

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

$$(p_{it}|p_{it-1}, r_{it} = 1) = \mathbf{1}_{[(p_{it-1})\lambda'_1 + (1-p_{it-1})\lambda'_2] \mathbf{z}_{it-1} + \epsilon_{it} < \kappa_t} \quad (7)$$

This specification indicates that p_{it} is conditional not only on p_{it-1} but also $r_{it} = 1$. Hence, the model allows the impact of the 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. However, in order to identify the model exclusion restrictions (instrumental variables) are required for the initial poverty equation (Eq.1) and the retention equation (Eq.3). In other words, we need variables that affect the initial poverty and the retention of households but not poverty transitions i.e. variables entering the \mathbf{x}_{it-1} or \mathbf{w}_{it-1} vectors but not \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 the retention and the initial condition equations. We discuss the instruments used in this study in Section 5.1.

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

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

Thus, the distribution of the unobserved households level 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. A Positive (negative) ρ_3 indicates households that are observed in two successive waves were more (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 joint estimation of Eqs.(2), (4) and (7) which leads to:

$$\mathcal{L} = \prod_{i=1}^N \prod_{t=2}^{T_i} \left[\int_{-\lambda_1' \mathbf{z}_{it-1}}^{\infty} \int_{-\gamma' \mathbf{w}_{it-1}}^{\infty} \int_{-\beta' \mathbf{x}_{it-1}}^{\infty} \varphi_3(\epsilon_{it}, \varepsilon_{it}, u_{it-1}) d\epsilon_{it} d\varepsilon_{it} du_{it-1} \right]^{(p_{it-1})r_{it}} \left[\int_{-\infty}^{-\lambda_2' \mathbf{z}_{it-1}} \int_{-\gamma' \mathbf{w}_{it-1}}^{\infty} \int_{-\beta' \mathbf{x}_{it-1}}^{\infty} \varphi_3(\epsilon_{it}, \varepsilon_{it}, u_{it-1}) d\epsilon_{it} d\varepsilon_{it} du_{it-1} \right]^{(1-p_{it-1})r_{it}} \left[\int_{-\infty}^{-\gamma' \mathbf{w}_{it-1}} \int_{-\beta' \mathbf{x}_{it-1}}^{\infty} \varphi_2(\varepsilon_{it}, u_{it-1}) d\varepsilon_{it} du_{it-1} \right]^{(1-r_{it})} \quad (8)$$

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:

$$\mathcal{L} = \prod_{i=1}^N \prod_{t=2}^{T_i} \left[\Phi_3(\zeta_i \lambda_1' \mathbf{z}_{it-1}, \psi_i \gamma' \mathbf{w}_{it-1}, \omega_i \beta' \mathbf{x}_{it-1}; \zeta_i \psi_i \rho_3, \zeta_i \omega_i \rho_2, \psi_i \omega_i \rho_1) \right]^{(p_{it-1})r_{it}} \left[\Phi_3(\zeta_i \lambda_2' \mathbf{z}_{it-1}, \psi_i \gamma' \mathbf{w}_{it-1}, \omega_i \beta' \mathbf{x}_{it-1}; \zeta_i \psi_i \rho_3, \zeta_i \omega_i \rho_2, \psi_i \omega_i \rho_1) \right]^{(1-p_{it-1})r_{it}} \left[\Phi_2(\psi_i \gamma' \mathbf{w}_{it-1}, \omega_i \beta' \mathbf{x}_{it-1}; \psi_i \omega_i \rho_1) \right]^{(1-r_{it})} \quad (9)$$

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 $\ln \mathcal{L}$ 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 the 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, then 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 testing for the existence of genuine poverty dependence based on ($\lambda_1 = \lambda_2$). Further, it allows predicting the rate of poverty persistence (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:

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

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

where \mathcal{P}_{it} is poverty persistence rate and \mathcal{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 dependence (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:

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

The GSD measure is based on household specific probabilities. Hence, it controls for household heterogeneity in contrary to the ASD which we calculate in Table 2. As discussed earlier, ASD comprises both household heterogeneity and state dependence effects. As a result, we can assess the heterogeneity effect by taking the difference between ASD and GSD.

4.2 Dynamic random effect probit model

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

$$p_{it}^* = \gamma p_{it-1} + \beta \mathbf{x}_{it}' + u_{it}, \quad i = 1, \dots, N; t = 2, \dots, T \quad (13)$$

where \mathbf{x}_{it} is a vector of controls describing i 's household characteristics, β 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

$$p_{it} = \mathbf{1}_{[p_{it}^* > 0]} \quad (14)$$

where $\mathbf{1}_{[\cdot]}$ 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 asymptotics 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 autoregressive 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).

$$\mathbb{P}(p_{i0} | x_{i0}, \alpha_i) = \mathbf{1}_{[\beta_0 \mathbf{x}_{i0} + u_{i0} > 0]} \quad (15)$$

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

with $u_{it} = \alpha_i + \mu_{it}$, $\mu_{it} = \rho \mu_{it-1} + v_{it}$, $v_{it} \sim N(0, \sigma_v^2)$ and orthogonal to α_i , and $\text{Corr}(u_{i0}, u_{it}) = \rho^t$, $t = 1, 2, \dots, T$ 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, β is a vector of parameters to be estimated, the parameter γ 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 terms which may be serially correlated over time.

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 model 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.

Heckman (1981a) propose a better alternative to specify a linearized reduced-form equation for the initial value of the latent poverty propensity of Eq.(15)as follows:

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

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:

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

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

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

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:

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

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

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

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 need the likelihood function of dynamic random effects model evolution of T - dimensional integrals of normal density functions. This can be estimated with the maximum simulated likelihood.

5 Results

We present the results in three stages. First, we discuss the validity of our estimation strategy by 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 unobservables 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). This actually means, unobservables that increase the probability to be non-poor initially also decreases the probability of being poor currently. If the initial conditions are ignored and estimation of poverty entry probability is done on a sample with a conditional poverty propensity lower than the relevant population, poverty entry rates will be underestimated. On the other hand, if we estimate poverty persistence probability on a sample with a conditional poverty propensity higher than the relevant population, poverty persistence will be overestimated. 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.

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 (Eq.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

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

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 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 these 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.

¹⁰Government 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.

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

Table 7: Multivariate Probit model: Poverty transition

Variable	Poverty persistence		Poverty entry	
	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
Family members aged between 0 and 14	0.07	0.047	0.051	0.047
Family members aged 64+	0.126	0.126	-0.128	0.134
Head characteristics				
Age	-0.012**	0.005	0.005	0.006
Sex:Female	0.181	0.163	0.016	0.167
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	-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
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
Equip	-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		
# 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). It is plausible to argue that shocks are also important factors that could affect household mobility and hence retention of households in the panel.¹¹The last panel in Table 8 shows our result of the retention equations after including the shock variables.¹² Indeed, head illness reduces retention propensity in our sample. The possible explanation could be a migration of sick head to live with relative seeking family care. This is consistent with Vearey (2012) findings in South Africa, where return migration (internally and international) in times of sickness, particularly HIV/AIDS, to rural sending household for care.¹³

Table 8: Multivariate Probit model: Selection equations

Variable	Initial condition		Retention		Retention	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Household characteristics						
Number of employee in the household	-0.102	0.063	0.149***	0.057	0.153***	0.057
Number of unemployed in the household	0.074	0.062	0.043	0.058	0.038	0.058
Household size	0.126***	0.037	-0.036	0.032	-0.039	0.032
Family members aged between 0 and 14	0.061	0.048	0.032	0.045	0.031	0.045
Family members aged 64+	-0.168	0.128	-0.030	0.121	-0.0434	0.122
Head characteristics						
Age	-0.011**	0.005	-0.008	0.005	-0.007	0.005
Sex:Female	-0.118	0.153	0.273*	0.147	0.286*	0.151
Education level:						
Primary schooling	-0.365***	0.135	0.296 **	0.125	0.284***	0.126
Junior Secondary Schooling	-0.535***	0.193	0.117	0.179	0.097	0.178
Secondary schooling	0.909***	0.169	0.130	0.163	0.120	0.164
Tertiary schooling	-1.338***	0.210	-0.235	0.190	-0.258	0.190
Head employment type:						
Public sector employee	-0.093	0.184	-0.012	0.175	0.002	0.177
Private sector employee	-0.307	0.223	-0.077	0.210	-0.072	0.208
NGO employee	-0.405	0.314	0.012	0.295	0.036	0.292
Casual worker	0.397*	0.229	-0.014	0.193	-0.014	0.193
Civil servant	-0.124	0.159	-0.172	0.155	-0.155	0.156
Pensioner	0.340**	0.159	-0.113	0.153	-0.102	0.153
Others	0.004	0.189	0.246*	0.143	0.226	0.171
Head shocks						
Unemployment	0.376	0.272			0.098	0.244

Continued on next page...

¹¹We thank Christopher Udry for his suggestion on this.

¹²Estimates on poverty transition equations are available from the authors upon request, including the shock variables does not affect our main findings reported in the previous section.

¹³Given weak social ties to people in urban settings, the role of IRSM on panel retention is insignificant. Therefore, we exclude these variables from our estimation in retention equation, including them does not affect our main findings. Result are available from the authors upon request.

Table 8 – continued

Variable	Initial condition		Retention		Retention	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Sickness	0.094	0.145			-0.267*	0.140
Disability	0.132	0.140			-0.024	0.138
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 members joined in 1994	-0.133*	0.070				
Members left the household in 1994	-0.185*	0.113				
Enumerated in 1994			0.145*	0.087	0.147	0.0871
Intercept	0.689*	0.353	-0.140	0.334	-0.131	0.339

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 three sets of parameter estimates. The first set reports the effect of explanatory variables on the probability of falling in to poverty assuming initial condition is exogenous, but allowing households specific effects. As we discussed in Section 4.2, this assumption is implausible. The result is presented here for comparison purpose only. The second set presents estimates of a model that control for initial condition bias and household heterogeneity. In the last column, we present the estimates of the model that controls for serially correlated error terms in addition to initial condition bias and household heterogeneity. When we compare the model with serially correlated error terms (column C) to the result of the model without correlated error terms (column B), the coefficient of the lag dependent variable almost doubles. This result is not surprising since $AR1 < 0$. The coefficient of other regressors decline slightly in absolute value when autocorrelation is introduced. However, the hypothesis of no autocorrelation is strongly rejected. The transformed parameter $AR1$ has a Z ratio of -3.93 and hence gives a Wald $\chi^2(1)$ test statistic of 31.2. Therefore, the model that accounts for initial condition, household heterogeneity and serial correlation fits the data best.

The estimation results shows that a larger number of covariates has significant coefficients compared to the endogenous switching model. This is not surprising 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 dynamic random effects probit model. It is also plausible to attribute the weaker effect of covariates in the poverty transition equation of the endogenous switching model to the effect of endogeneity of panel attrition being accounted for.¹⁴

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 increases the probability of entering into poverty compared to own account employees. This could be due to the fact that public sector employees in the country earn less than other employees. One of the striking feature of the results here again is head unemployment and disability have a positive effect on the probability of falling into poverty. With regard to informal risk sharing mechanisms, membership in Equip, Iddir and access to international remittances reduce the probability of entering into poverty. However, the top three dominant informal risk sharing mechanisms of poor households namely, local remittance, loans from informal sources and gifts don't have any effect at all. This confirms the fact that these mechanisms plays a limited role in reducing current poverty as well. In line with endogenous switching model, the dynamic probit model also predicts the presence of strong state dependence. The positive effect of lagged dependent variable implies that falling into poverty in the currently is highly correlated poverty in the past.

¹⁴Note that the random effect dynamic probit model only uses balanced panel data, attri-households are dropped out from the estimation. When we estimate endogenous switching model ignoring the retention equation, household size, having more number of children between age 0 and 14, having more number of unemployed family members, membership in equip and receiving a gift were strongly significant in the poverty transition equations.

Table 9: Random effect dynamic panel data model

Variable	RE with exogenous initial condition		RE with endogenous initial condition		RE with endogenous initial condition and auto-correlated error term	
	(A)		(B)		(C)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Lag poor	0.826***	0.083	0.646***	0.130	1.043***	0.140
Household characteristics						
Number of employees in the household	-0.005	0.038	0.039	0.051	0.013	0.047
Number of unemployed in the household	0.088**	0.042	0.127**	0.058	0.105**	0.053
Household size	0.041	0.025	0.071**	0.034	0.063**	0.031
Members aged between 0 and 14	0.178***	0.037	0.172***	0.050	0.127***	0.047
Members aged 64+	0.212**	0.105	0.275*	0.145	0.205	0.131
New members joined the household in 1994	-0.082	0.058	-0.137	0.081	-0.107	0.077
Members left the household in 1994	0.049	0.035	0.021	0.045	0.042	0.043
Head characteristics						
Age	-0.003	0.005	-0.009	0.007	-0.006	0.006
Sex:Female	0.142	0.099	0.200	0.136	0.183	0.118
Education level:						
Primary schooling	-0.420***	0.109	-0.516***	0.152	-0.490***	0.138
Junior Secondary Schooling	-0.495***	0.155	-0.406***	0.195	-0.349**	0.177
Secondary schooling	-0.700***	0.144	-0.733***	0.192	-0.616***	0.175
Tertiary schooling	-0.805***	0.158	-0.784***	0.207	-0.652***	0.193
Head employment type:						
Public sector employee	0.260	0.171	0.450***	0.221	0.409**	0.203
Private sector employee	-0.271*	0.164	-0.382*	0.224	-0.341*	0.208
NGO employee	0.091	0.279	0.273	0.352	0.283	0.320
Casual worker	0.222	0.139	0.201	0.237	0.284	0.208
Civil servant	0.229	0.173	0.327*	0.177	0.348**	0.158
Pensioner	0.113	0.134	0.246	0.186	0.194	0.169
Others (unpaid family worker, housewife etc)	-0.099	0.125	0.048	0.177	0.043	0.164
Head shocks*						

Continued on next page...

Table 9 – continued

Variable	RE1		RE2		RE3	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Unemployment	0.417**	0.179	0.500**	0.234	0.452**	0.209
Sickness	-0.001	0.134	-0.154	0.193	-0.173	0.183
Disability	0.216*	0.125	0.332**	0.184	0.318*	0.174
Informal risk management strategies						
Local remittance	-0.132	0.130	0.168	0.171	-0.179	0.160
International remittance	0.604***	0.148	-0.823***	0.211	-0.769***	0.202
Gift	0.021	0.150	0.155	0.201	0.094	0.189
Iddir	-0.349***	0.111	0.493***	0.153	-0.441***	0.144
Equip	-0.392***	0.103	-0.254**	0.132	-0.299**	0.124
Informal loan	-0.109	0.119	-0.043	0.157	-0.031	0.150
Intercept	-0.523*	0.297	-0.532	0.414	-0.753*	0.370
AR1					-0.4281***	
Log likelihood	-704.198		-567.130		-560.777	
χ_2 (d.o.f)	30(326.80)		30(158.52)		30(219.29)	
P-value	0.000		0.000		0.000	
# Observations	2,444		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%

6 Conclusion

The study provides a thorough investigation of urban poverty dynamics in Ethiopia 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’ models: an endogenous switching model and a dynamic random effects 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 propels households into persistent poverty. On the other hand, access to international remittances and better education reduce the probability of remaining poor. Our estimation also confirms that, in the absence of public insurance and market, poor household are forced to use ineffective risk management strategies which have negative consequence on welfare. Gifts and local remittances, mechanisms predominately used by poor households, increase the probability of entering into poverty.

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

The paper makes contribution to the understanding of poverty dynamics and the main factors underlying poverty transitions. 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 true state dependence in urban Ethiopia and the lion share of 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 social welfare. Moreover, poverty reduction programs that aim to prevent households from falling into poverty not only have a short run effect but also help to reduce future poverty. Indeed, policies focusing on household heterogeneities such as exposure to risk, lack of education, personal skills and capacities, could have long lasting effects.

However, one caveat is worth mentioning. 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 shocks. Future research should examine the actual loss for households 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 provide a clear picture on the extent to which shocks have a negative welfare effects.

Acknowledgements. We are deeply indebted to Richard Bluhm, Christopher Udry, Franziska Gassmann and Yesuf Awel for very constructive suggestions. We would also like to thank the participants at the Annual Bank Conference on Africa (ABCA), Paris, held on June 23-24, 2014 and participants at the 9th Annual Conference of the African Econometric Society and the 12th International Conference on the Ethiopian Economy, Addis Ababa, held on July 16-18, 2014 for very useful comments on earlier versions of the paper. This research was supported by UNU-MERIT. All views expressed as well as any errors are our own.

References

- ADDISON, T., D. HULME, AND R. KANBUR (2009): "Poverty Dynamics," *Poverty Dynamics: Interdisciplinary Perspectives: Interdisciplinary Perspectives*, p. 3.
- AFDB (2011): "Federal democratic republic of Ethiopia country strategy paper 2011-2015," country strategy paper, AfDB.
- ALDERMAN, H., J. HODDINOTT, AND B. KINSEY (2006): "Long term consequences of early childhood malnutrition," *Oxford Economic Papers*, 58(3), 450–474.
- ALWANG, J., P. B. SIEGEL, AND S. L. JORGENSEN (2001): "Vulnerability: a view from different disciplines," Discussion paper, Social protection discussion paper series.
- ARULAMPALAM, W., A. L. BOOTH, AND M. P. TAYLOR (2000): "Unemployment persistence," *Oxford Economic Papers*, 52(1), 24–50.
- ASAMINEW, E. (2010): "Adopting Private Pension System in Ethiopia," in *THE AFRICAN SYMPOSIUM*, p. 7.
- AYALEW, D. (2003): *Risk-sharing networks among households in rural Ethiopia*. University of Oxford, Centre for the Study of African Economies.
- AZAM, M. S., AND K. S. IMAI (2012): "Measuring Households' Vulnerability to Idiosyncratic and Covariate Shocks—the case of Bangladesh," *Research Institute for Economics and Business Administration, Kobe University, Japan. (Discussion Paper Series)*.
- BANE, M. J., AND D. T. ELLWOOD (1986): "Slipping into and out of Poverty: The Dynamics of Spells," *Journal of Human Resources*, pp. 1–23.

- BARRIENTOS, A. (2007): “Does vulnerability create poverty traps?,” *Chronic Poverty Research Centre Working Paper*, (76).
- BAULCH, AND HODDINOTT (2000): “Economic mobility and poverty dynamics in developing countries,” *Journal of Development Studies*, 36(6), 1–24.
- BAULCH, B. (2011): “Household panel data sets in developing and transition countries,” Chronic poverty reports, CPRC.
- BERLOFFA, G., AND F. MODENA (2013): “Income shocks, coping strategies, and consumption smoothing: An application to Indonesian data,” *Journal of Asian Economics*, 24, 158–171.
- BIEWEN, M. (2004): “Measuring state dependence in individual poverty status: are there feedback effects to employment decisions and household composition?,” Discussion paper, IZA Discussion paper series.
- BIGSTEN, A., AND A. SHIMELES (2004): *Dynamics of poverty in Ethiopia*, no. 2004/39. Research Paper, UNU-WIDER, United Nations University (UNU).
- (2008): “Poverty transition and persistence in Ethiopia: 1994-2004,” *World Development*, 36(9), 1559–1584.
- BUTLER, J. S., AND R. MOFFITT (1982): “A computationally efficient quadrature procedure for the one-factor multinomial probit model,” *Econometrica*, 50(3), 761–64.
- CAPPELLARI, L., AND S. P. JENKINS (2002): “Who stays poor? Who becomes poor? Evidence from the British household panel survey,” *Economic Journal*, 112(478), C60–C67.
- (2004): “Modelling low income transitions,” *Journal of Applied Econometrics*, 19(5), 593–610.
- CARDONA, O. D. (2003): “The need for rethinking the concepts of vulnerability and risk from a holistic perspective: a necessary review and criticism for effective risk management,” *Mapping vulnerability: Disasters, Development and People*, p. 17.
- CARTER, M. R. (1997): “Environment, technology, and the social articulation of risk in West African agriculture,” *Economic Development and Cultural Change*, 45(3), 557–590.
- CLARKE, L. (1999): *Mission improbable: Using fantasy documents to tame disaster*. University of Chicago Press.
- COX, D., AND E. JIMENEZ (1998): “Risk sharing and private transfers: What about urban households?,” *Economic Development and Cultural Change*, 46(3), 621–637.
- CSA (2010): “Population and Housing Census Report-Country,” Discussion paper, Central Statistical Agency, Federal Democratic Republic of Ethiopia , Addis Ababa.
- DE GUZMAN, E. M. (2003): “Towards total disaster risk management approach,” *United Nations Office for the Coordination of Humanitarian Affairs, Asian Disaster Response Unit*.

- DE NEUBOURG, C. (2002): “The welfare pentagon and the social management of risks,” *Social Security in the Global Village*, 8.
- DEATON, AND GROSH (2000): “Consumption,” in *Designing Household Survey Questionnaires for Developing Countries: Lessons from 15 Years of the Living Standards Measurement Study, Volume 1*, ed. by M. Grosh, and P. Glewwe. World Bank, Washington, DC.
- DEATON, A. (1990): “On Risk, Insurance and Intra-Village Consumption Smoothing,” *Preliminary Draft, Research Program in Development Studies. Princeton University*.
- (1997): *The analysis of household surveys: a microeconomic approach to development policy*. World Bank Publications.
- DEININGER, K., M. GARCIA, AND K. SUBBARAO (2003): “AIDS-induced orphanhood as a systemic shock: Magnitude, impact, and program interventions in Africa,” *World Development*, 31(7), 1201–1220.
- DERCON, S. (2002): “Income risk, coping strategies, and safety nets,” *The World Bank Research Observer*, 17(2), 141–166.
- (2005): “Risk, Insurance, and Poverty: A Review,” *Insurance Against Poverty*, p. 9.
- DERCON, S., J. HODDINOTT, AND T. WOLDEHANNA (2005): “Shocks and consumption in 15 Ethiopian villages, 1999-2004,” *Journal of African Economies*, 14(4), 559–585.
- DERCON, S., AND P. KRISHNAN (1998): *Changes in poverty in rural Ethiopia 1989-1995: measurement, robustness tests and decomposition*. Centre for the Study of African Economies, Institute of Economics and Statistics, University of Oxford.
- (2000): “Vulnerability, seasonality and poverty in Ethiopia,” *The Journal of Development Studies*, 36(6), 25–53.
- (2003): “Risk sharing and public transfers*,” *Economic Journal*, 113(486), C86–C94.
- DERCON, S., AND J. S. SHAPIRO (2007): “Moving On, Staying Behind, Getting Lost: Lessons on poverty mobility from longitudinal data,” .
- DEVICIENTI, F. (2011): “Estimating poverty persistence in Britain,” *Empirical Economics*, 40(3), 657–686.
- FAFCHAMPS, M., AND S. LUND (2003): “Risk-sharing networks in rural Philippines,” *Journal of Development Economics*, 71(2), 261–287.
- FAFCHAMPS, M., C. UDRY, AND K. CZUKAS (1998): “Drought and saving in West Africa: are livestock a buffer stock?,” *Journal of Development Economics*, 55(2), 273–305.
- FAYE, O., N. ISLAM, AND E. ZULU (2011): “Poverty Dynamics in Nairobi Slums: Testing for True State Dependence and Heterogeneity Effects,” *CEPS/INSTEAD Working Paper*, (2011-56).

- FOSTER, A. D. (1993): “Household partition in rural Bangladesh,” *Population Studies*, 47(1), 97–114.
- GLEWWE, P., AND G. HALL (1998): “Are some groups more vulnerable to macroeconomic shocks than others? Hypothesis tests based on panel data from Peru,” *Journal of Development Economics*, 56(1), 181–206.
- GRIMARD, F. (1997): “Household consumption smoothing through ethnic ties: evidence from Cote d’Ivoire,” *Journal of Development Economics*, 53(2), 391–422.
- HAILU, D., AND T. NORTHCUT (2012): “Ethiopia’s social protection landscape: Its surface and underlying structures,” *International Social Work*.
- HECKMAN, J. J. (1981a): “The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process and Some Monte Carlo Evidence” in C. F. Manski and D. McFadden, eds., *Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, Cambridge, MA, 179, 195.
- HECKMAN, J. J. (1981b): “Statistical models for discrete panel data,” in *Structural Analysis of Discrete Data with Econometric Applications*, ed. by C. F. Manski, D. McFadden, et al. MIT Press, Cambridge, MA.
- ISLAM, N., AND A. SHIMELES (2006): “Poverty dynamics in Ethiopia: State dependence and transitory shocks,” *Essays on Labour Supply and Poverty: A Microeconomic Application*. Department of Economics, Göteborg University.
- JALAN, J., AND M. RAVALLION (1998): *Determinants of transient and chronic poverty: evidence from rural China*. Citeseer.
- KEDIR, A. M., AND A. MCKAY (2005): “Chronic poverty in urban Ethiopia: Panel data evidence,” *International Planning Studies*, 10(1), 49–67.
- MAZZOCCO, M. (2004): “Saving, risk sharing, and preferences for risk,” *American Economic Review*, 94(4), 1169–1182.
- (2012): “Testing efficient risk sharing with heterogeneous risk preferences,” *American Economic Review*, 102(1), 428–468.
- MCKAY, A., AND D. LAWSON (2003): “Assessing the extent and nature of chronic poverty in low income countries: issues and evidence,” *World Development*, 31(3), 425–439.
- MODENA, F., AND C. L. GILBERT (2012): “Household Responses to Economic and Demographic Shocks: Marginal Logit Analysis using Indonesian Data,” *Journal of Development Studies*, 48(9), 1306–1322.
- MOFED (2008): “Dynamics of Growth and Poverty in Ethiopia,” Discussion paper, Ministry of Finance and Economic Development.

- MoFED (2010): “Growth and Transformation Plan (GTP) 2010/11-2014/15,” Discussion paper, Ministry of Finance and Economic Development, Federal Democratic Republic of Ethiopia, Addis Ababa.
- MORDUCH, J. (1995): “Income smoothing and consumption smoothing,” *Journal of Economic Perspectives*, 9(3), 103–114.
- (1999): “Between the state and the market: Can informal insurance patch the safety net?,” *The World Bank Research Observer*, 14(2), 187–207.
- (2006): “Micro-insurance: the next revolution?,” *Understanding poverty*, pp. 337–56.
- NOTTEN, G. (2008): “Measuring and Managing Poverty Risks,” Ph.D. thesis, Maastricht Graduate School of Governance, Maastricht, the Netherlands.
- RAVALLION, M. (1992): “Poverty Comparisons—A Guide to Concepts and Methods; World-bank,” *Living Standards Measurement Study Working Paper*, (88).
- (2002): “On the urbanization of poverty,” *Journal of Development Economics*, 68(2), 435–442.
- SAHLINS, M. D. (1972): *Stone age economics*. Transaction Publishers.
- SANA, M., AND D. S. MASSEY (2000): “Seeking Social Security: An Alternative Motivation for Mexico-US Migration,” *International Migration*, 38(5), 3–24.
- SANTOS, P., AND C. B. BARRETT (2011): “Persistent poverty and informal credit,” *Journal of Development Economics*, 96(2), 337–347.
- SCHULTZ, T. (1975): “Human capital and disequilibrium,” *Journal of Economic Literature*, 13, 827–846.
- SKOUFIAS, E., AND A. R. QUISUMBING (2005): “Consumption insurance and vulnerability to poverty: A synthesis of the evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia,” *European Journal of Development Research*, 17(1), 24–58.
- STEVENS, A. H. (1994): “The dynamics of poverty spells: updating Bane and Ellwood,” *American Economic Review*, 84(2), 34–37.
- STEWART, M. B., AND J. K. SWAFFIELD (1999): “Low pay dynamics and transition probabilities,” *Economica*, 66(261), 23–42.
- TADESSE, M. (1996): “Food consumption and poverty in urban Ethiopia: A preliminary assessment,” in *proceedings of the Fifth Annual Conference on the Ethiopian Economy*, Bereket Kebede and Mekonnen Tadesse (eds.), Addis Ababa, Ethiopian Economic Association.
- TOWNSEND, R. M. (1994): “Risk and insurance in village India,” *Econometrica*, pp. 539–591.
- (1995): “Financial systems in Northern Thai villages,” *Quarterly Journal of Economics*, 110(4), 1011–1046.

- UNITED NATIONS (2012a): “Social protection: A development priority in the post-2015 UN development agenda,” Discussion paper, United Nations.
- (2012b): “World Urbanization Prospects: The 2011 Revision,” Discussion paper, Department of Economic and Social Affairs, Population Division.
- VEAREY, J. (2012): “Learning from HIV: exploring migration and health in South Africa,” *Global public health*, 7(1), 58–70.
- WITOELAR, F. (2005): “Inter-household Allocations within Extended Households: Evidence from the Indonesia Family Life Survey,” Discussion paper, Center Discussion Paper no, 912, Economic Growth Center, Yale University.
- WORLD BANK (2001): “World development report 2000/2001: attacking poverty,” *New York, Oxford University Press*, table, 19, 311.
- ZIMMERMAN, F. J., AND M. R. CARTER (2003): “Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints,” *Journal of Development Economics*, 71(2), 233–260.

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
Family members aged between 0 and 14	Number of family members whose age is between 0 and 14	Continuous
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)
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)
Informal risk management strategies		
Local remittance	Household received local remittance in the last 12 months	Dummy (yes=1)
International remittance	Household received remittance from abroad	

Continued on next page...

Table 11 – continued

Variable name	Definition	Nature
	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 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)

The UNU-MERIT WORKING Paper Series

- 2015-01 *How does firms' perceived competition affect technological innovation in Luxembourg?* by Wladimir Raymond and Tatiana Plotnikova
- 2015-02 *The effect of supplementation with locally available foods on stunting. A review of theory and evidence* by Mutinta Nseluke Hambayi, Wim Groot and Nyasha Tirivayi
- 2015-03 *Ethnic divisions, political institutions and the duration of declines: A political economy theory of delayed recovery* Richard Bluhm and Kaj Thomsson
- 2015-04 *Offshoring of medium-skill jobs, polarization, and productivity effect: Implications for wages and low-skill unemployment* by Ehsan Vallizadeh, Joan Muysken and Thomas Ziese
- 2015-05 *Risk preference or financial literacy? Behavioural experiment on index insurance demand* by Yesuf M. Awel and Théophile T. Azomahou
- 2015-06 *Poverty persistence and informal risk management: Micro evidence from urban Ethiopia* by Théophile T. Azomahou and Eleni A. Yitbarek