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Poverty Persistence and Intra-Household Heterogeneity in Occupations: Evidence from Urban Ethiopia*

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Abstract

Previous studies of poverty in developing countries have to a great extent focused on the characteristics of the household head and used these as proxies for the underlying ability of the household to generate income. This paper uses five rounds of panel data to investigate the persistence of poverty in urban Ethiopia with a particular focus on the role of intra-household heterogeneity in occupations. Dynamic probit and system GMM regression results suggest that international remittances and labor market status of non-head household members are important determinants of households' poverty status. Results also show that controlling for these variables and the initial conditions problem encountered in non-linear dynamic probit models reduces the magnitude of estimated poverty persistence significantly for urban Ethiopia. These findings have important implications for identifying the poor and formulating effective poverty reduction and targeting strategies.

JEL Classification: I32, R11, R20, .

Keywords: Urban Ethiopia, poverty persistence, dynamic probit, system GMM, labor market status.

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1 Introduction

This paper uses panel data on urban households in Ethiopia to study the determinants and persistence of poverty. Most previous studies of poverty and poverty dynamics in Sub-Saharan Africa have focused on rural areas.[1] While important, the results and insights generated by these studies do not necessarily carry over to the urban context. For example, as discussed by Alem and Söderbom (2012), urban households may be more vulnerable than rural households to high food prices because there is little food production in urban areas. On the other hand, labor market opportunities are likely to be more diverse in urban than in rural areas, implying that urban households are less dependent on the developments in a single sector. Because the range of occupations available in urban areas is relatively wide (at least compared to rural areas), it may be important to consider intra-household heterogeneity in labor market status when studying urban poverty. Previous studies of poverty have typically focused on the characteristics of the household head and used these as proxies for the underlying ability of the household to generate income. This may be appropriate in a rural context, where family members typically work on the farm. In urban areas of developing countries, however, a focus solely on the characteristics of the household head may be too narrow. For instance, it could be that a household head is an uneducated housewife but has educated and working children residing in the same house. In this paper, I use detailed data on the occupations of all household members to investigate the effect on poverty of intra-household heterogeneity in jobs. I also study the effects of remittances, which have become an important component of urban households' income over the last decade.

Much of the recent literature on poverty has focused on the dynamics of poverty. A household may fall into poverty for many reasons, and the factors that caused poverty incidence in the first place may impact the speed at which the household can find a pathway out of poverty. The literature makes an important distinction between transient and chronic poverty, where chronic poverty is of course the more serious state. In this paper, I assume that chronic poverty depends on education and unobserved time-invariant factors specific to the household. On the other hand, transient poverty is persistent but not permanent. This type of poverty may arise due to state dependence, i.e., that poverty today has a causal effect on the likelihood of poverty tomorrow. If the state dependence is strong, falling into poverty is likely to have adverse effects on future welfare. However, exploiting the panel dimension in the data and using a robust dynamic probit model that controls for a full set of household variables and the initial conditions problem encountered in such models, I estimate the marginal effect of state dependence to be moderately low in urban Ethiopia.

Earlier studies analyzing the dynamics of poverty in urban Ethiopia are relatively few. Bigsten

[1] See, e.g., Dercon & Krishnan (1998), Dercon (2004), Dercon et al. (2005), Harrower & Hoddinott (2005), Barrett et al. (2006), Dercon (2006), Dercon (2008), Beegle et al. (2008), and Litchfield & McGregor (2008).

et al. (2003) used data on urban and rural households to investigate the impact of economic growth on poverty and showed that education and occupational status of heads, dependency ratio and geographical location are important determinants of poverty in urban areas. A similar analysis of the correlates of chronic urban poverty was made by Keddir and McKay (2005) using data for 1995-1997. They find that high dependency ratios, low levels of education, lack of asset ownership, insecurity in employment, and unemployment of household heads are important correlates of chronic poverty. However, these papers do not focus on the dynamics of poverty and state dependence, or on the effects of the labor market status of household members.

Using rural and urban household data, Bigsten and Shimeles (2008) investigate poverty transitions and persistence in Ethiopia. Their results indicate that households move frequently in and out of poverty with a speed which varies between male and female headed households, and that urban households have a higher degree of poverty persistence than rural households. They also find that poverty is closely related to household demographic characteristics and household head variables such as occupational status. Bigsten and Shimeles do not, however, investigate the relationship between poverty and the labor market status of household members. I show that not controlling for these variables appears to overestimate the magnitude of poverty persistence. Moreover, the last year covered in their study is 2004, whereas my data span the period 1994-2009. Given the dramatic food price inflation in 2008 and the rapid economic growth in the country, expanding the analysis to include this period is quite important. Finally, none of these previous studies look at the effects of remittances, which have recently increased by an unprecedented level in urban Ethiopia. I show that poverty rates would have been higher by at least 3.5 percentage points without the part of consumption augmented by international remittances.

The econometric techniques used in the present paper are robust enough to address the research questions. Poverty is modeled using a dynamic probit allowing for state dependence and unobserved time-invariant heterogeneity in the underlying likelihood of poverty across households. I use the most recent and advanced dynamic probit model - Wooldridge's conditional maximum likelihood estimator - to investigate the persistence of poverty and the role of intra-household heterogeneity in occupations. I also check robustness of my results using Heckman's two-step dynamic probit model, the linear dynamic system GMM estimator developed by Arellano and Bover (1995) and Blundel and Bond (1997), and using alternative definitions of poverty. Regression results suggest that, controlling for the initial conditions problem encountered in non-linear dynamic models, labor market status of all household members, and the full set of household-level variables significantly reduces the magnitude of the coefficient of poverty persistence in urban Ethiopia. The paper's findings have important implications for identifying the poor and formulation of policies and interventions aimed at reducing poverty.

The remainder of the paper is structured as follows. Section 2 motivates and outlines the empirical strategy applied in the paper. Section 3 discusses the data and provides descriptive statistics. Section 4 presents estimation results from dynamic probit and system GMM models. Finally, Section 5 concludes the paper.

2 Empirical Strategy

2.1 Modeling Poverty Dynamics

One of the main questions when determining poverty status and analyzing poverty dynamics is whether to treat poverty status and transitions as changes in a continuous money metric welfare measure (such as income or consumption) or a discrete variable (Baulch 2011). The former involves modeling money metric welfare indicators or their change directly, using a fixed or random effects estimation technique (as in Bigsten et al., 2003; Dercon, 2004; Dercon and Porter, 2011; May et al., 2011). The fixed effect is the most robust panel data technique; it enables estimation by taking care of time-invariant unobserved individual heterogeneity that is likely to be correlated with the explanatory variables. The random-effects approach is based on a strong assumption of orthogonality, which is very often unlikely to hold (Wooldridge, 2010). However, the fixed effect doesn't allow one to link changes in the welfare variable to poverty transitions; in some cases, this can be handled by controlling initial poverty status, which can also be interacted with other explanatory variables, and through interquantile regressions (Baulch, 2011).

Modeling poverty status and dynamics using a discrete indicator of welfare, on the other hand, involves construction of a cut-off level of income - the poverty line - which is deemed to be the minimum level of income needed to cover the cost of a consumption bundle considered adequate for basic needs, and classifying those whose income falls below it as poor. Correlates of poverty can therefore be examined using a binary model (such as the probit/logit). In order to study poverty dynamics in developing countries, however, a number of studies (e.g., Bigsten et al., 2003; Keddir and McKay, 2005; Quisumbing, 2011; Dercon and Porter, 2011) used the multinomial logit (MNL) model. This model involves constructing a polytomous variable for both those who are out of poverty and those who remain in poverty and examining their correlates. The main limitation of the discrete choice models, including the MNL, bivariate poverty probits, and logits, is the loss of information in converting a continuous variable to two or three discrete categories (Ravallion, 1996). In addition, consistent estimation of the parameters of the MNL model hinges on a strong assumption of Independence of Irrelevant Alternatives (IIA). One could overcome the limitation of this model by using other models which relax the IIA assumption, such as the sequential model (Baulch and Vu, 2011), ordered logit (or probit), and stereotype logistic models (Baulch, 2011).

Other more robust models of poverty transitions when there are a large number of rounds of panel data includes Markov chains and hazard models, which have been used to model poverty transitions using the British household panel survey (Cappeliari and Jenkins, 2002; Devicienti 2001; Jenkins and Rigg, 2001 cited in Baulch, 2011), and the US Panel Study of Income Dynamics (Bane and Elwood, 1986; Stevens, 1999). This method allows for detailed analysis of poverty dynamics through estimation of hazard rates for re-entry into and exit from poverty. The use of this method in developing countries has, however, been very limited due to its requirement of a large number of rounds of panel data, which are still difficult to find in developing counties.[2] Because the method involves using discrete categories of poverty status, it is subject to criticism, as is the case for the the discrete choice models discussed above (Baulch, 2011). Dynamic probit models, which are used in this paper and presented in detail in the next sub-section, are a class of discrete choice models where current poverty is modeled as a function of poverty in the previous period.

Baulch (2011) argues that, while one could use either a discrete or continuous variable based analysis of poverty, it is difficult to claim that one is better than the other, and each approach has its own advantages and limitations, depending on the data available and the research problem one is interested in. With the aim of providing robustness in the alternative modelling approaches, in this paper, I investigate the persistence and correlates of poverty using a robust dynamic probit model (a discrete choice model) and Arellano and Bover (1995)'s, and Blundell and Bond (1998)'s system GMM estimator (a continuous dependent variable model), which takes care of endogeneity of some of the correlates of poverty by using their lags as valid instruments.

2.2 State Dependence and Other Correlates of Poverty

The main rationale behind modeling poverty using a dynamic probit model is the presence of state dependence. There is a large amount of evidence in several countries (mainly OECD countries) that an individual or a household that is experiencing a poverty spell today is much more likely to experience it again in the future (Duncan et al., 1993; Oxley et al., 2000; Mejer and Linden, 2000; OECD, 2001; Giraldo et al., 2006, and Biewen, 2009). Ahmed et al., (2007) identify at least seven major causes of persistent poverty in the context of developing countries: (i) slow growth, inequality and conflict, which limit the propensity of diversifying livelihood to escape poverty; (ii) adverse ecology and remoteness of villages; (iii) the prevalence of shocks (adverse events) which often exert long-term impacts on uninsured households; (iv) poor health and disability, which not only drain households' resources but also limit their members' ability to work and earn income; (v) the inheritance of poverty; (vi) lack of assets and inability to invest in education, which could help

[2]See Baulch and McCulloch (2003) for applications in rural Pakistan, and Bigsten and Shimeles (2008) for applications in rural and urban Ethiopia.

households come out of poverty; and (vii) exclusion of some groups from access to resources, which perpetuates their poverty.[3]

Thus, a current state of poverty is modeled as a function of poverty in the previous period. In addition, unobserved household or individual characteristics that make specific groups prone to poverty should be accounted for while modeling poverty. These unobservables can be factors such as individual motivation, parental effects, rate of time preference, and risk aversion parameters. Because the outcome probability (poverty in this case) is hypothesized to depend on the outcome in the previous period (poverty in previous period), I use a dynamic probit model specified as

$$p_{it}^{*} = \gamma p_{it-1} + x_{it}'\beta + \alpha_i + u_{it} \tag{1}$$

($i = 1, ..., N; t = 2, ..., T$), where p_{it}^{*} is a latent dependent variable; p_{it} is the observed binary outcome variable defined as

$$p_{it} = 1[p_{it}^{*} \geq 0], \quad t = 2, ..., T, \tag{2}$$

x_{it} represents a vector of explanatory variables; α_i is a term capturing unobserved household heterogeneity; and u_{it} is a normally distributed error term with mean zero and variance normalized to one. The subscripts i and t refer to households and time periods respectively. It is assumed that N is large but T is small, which implies that asymptotics depend on N alone. In addition, in the standard random effects probit model, it is assumed that, conditional on x_{it}, α_i is normally distributed with mean zero and variance σ_{α}^{2}, and independent of u_{it} and x_{it}.

Under the above assumptions, the probability that individual i is poor at time t, given α_i, is specified as

$$P[p_{it}|x_{it}, p_{it-1}, \alpha_i] = \Phi[(\gamma p_{it-1} + x_{it}'\beta + \alpha_i)(2p_{it} - 1)], \tag{3}$$

where Φ is the cumulative distribution function of the standard normal distribution.

The presence of both the past value of the dependent variable and an unobserved individual heterogeneity term in equation (4) will result in what is called the "initial conditions problem." This problem arises because the start of the initial panel wave does not coincide with the start of the stochastic process generating households' poverty experiences. The households in my data existed as households before the initial panel wave and had already been at risk of poverty. Thus, a household observed to be in a state of poverty in the initial period may be there because of an earlier history of poverty, or because of some observed and/or unobserved characteristics affecting its poverty status. Consequently, estimating equation (4) using the standard random effects probit, which assumes that the initial state of poverty is exogenous, will result in inconsistent estimates. In

[3] See Biewen (2009) for possible reasons for poverty persistence in the context of industrialized countries.

order to take care of the problem and estimate the equation consistently, the unobserved individual heterogeneity term should be integrated out.

Heckman (1981) - who is the first to address the initial conditions problem - suggested a two-step maximum likelihood estimator, which involves specification of a linearised reduced-form equation for the initial value of the latent variable; the equation includes exogenous instruments and initial values of the explanatory variables. The reduced-form equation can then be introduced in the likelihood function of each individual/household and the integral in the likelihood function can be evaluated using the Gauss-Hermite quadrature (Butler and Moffitt, 1982) to estimate the parameters of the model in a consistent manner. Due to its huge computational cost, however, the use of this estimator in applied research has been limited.

Another approach to deal with the initial conditions problem in non-linear dynamic panel data models is the Wooldridge conditional maximum likelihood (WCML) estimator proposed by Wooldridge (2005). The WCML starts by stating the joint density for the observed sequence of the dependent variable $(p_2, p_3, ..., p_T|p_1)$ as $(p_T, p_{T-1}, ..., p_2|p_1, x, \alpha)$. By specifying an approximation for the density of the unobserved individual heterogeneity term α_i, conditional on the initial period value of the dependent variable p_1, Wooldridge integrates out α_i from the equation and suggests the specification

$$\alpha_i|p_{i1}, z_i \sim N(\zeta_0 + \zeta_1 p_{i1} + z_i'\zeta, \sigma_a^2) \tag{4}$$

where

$$\alpha_i = \zeta_0 + \zeta_1 p_{i1} + z_i'\zeta + a_i \tag{5}$$

Equation (8) alleviates the correlation between the initial value of the dependent variable and the unobservable (p_{i1} and α_i) and results in a new unobservable term a_i that is uncorrelated with the initial observation p_{i1}.

Substituting equation (8) into equation (1) gives

$$Pr(p_{it} = 1|a_i, p_{i1}) = \Phi[(x_{it}'\beta + \gamma p_{it-1} + \zeta_0 + \zeta_1 p_{i1} + z_i'\zeta + a_i] \qquad t = 2, ..., T. \tag{6}$$

Consequently, the likelihood function for household i is given by

$$L_i = \int \{\prod_{t=2}^{T} \Phi[(x_{it}'\beta + \gamma p_{it-1} + \zeta_0 + \zeta_1 p_{i1} + z_i'\zeta + a)(2p_{it} - 1)]\} g^*(a) da, \tag{7}$$

where $g^*(a)$ is the normal probability density function of the new unobservable term a_i introduced in equation (7). By incorporating a set of time dummies interacted with the initial value of the dependent variable, the WCML estimator like Heckman's estimator can be generalized to allow for the initial condition error to be freely correlated with the errors in the other periods. One other appealing feature of this estimator is the fact that it controls for period specific versions of the x variables, which also allows for correlation between x_{it} and α_i, following Mundlak's (1978) approach. I primarily use results from this estimator to analyze the persistence of poverty in urban Ethiopia. Estimating Wooldridge's estimator is straightforward in standard econometric software, for example, by using the *xtprobit* command in Stata.

It is plausible to argue that one or more of the explanatory variables in the probability of poverty model - for example, the remittance and occupational characteristics of household members - could be endogenous. Giles and Murtazashvili (2012) point out that when one or more of the explanatory variables is endogenous, the impact of the endogenous variable and the lagged poverty variable on the likelihood of poverty can be significantly biased. Consequently, these authors propose a "Control Function Approach" based on a two-step procedure to estimate a dynamic probit model with endogenous explanatory variables. In the first stage, a reduced form equation of the endogenous variable as a function of an exogenous instrumental variable and other exogenous variables of the model is estimated using OLS. In the second stage, the residuals obtained from the first stage are used as regressors along with other exogenous variables to estimate the dynamic probability of poverty model. However, estimation of the dynamic probit model using the this approach hinges on availability of an external instrumental variable.

Using a continuous dependent variable to capture welfare - such as income or consumption expenditure - one can alternatively apply a linear dynamic model and address endogeneity of an explanatory variable(s). Furthermore, the linear model would provide more information on the magnitude of the impact of the explanatory variables given it is continuous, a key limitation of the discrete choice models presented above.

A general dynamic model of consumption consistent with economic theory for household i at time t can be specified as:

$$c_{it} = \gamma c_{it-1} + x'_{it}\beta + \alpha_i + u_{it} \tag{8}$$

The standard linear panel data models cannot be used to estimate the parameters of equation (8) consistently. The lagged value c_{it-1} is positively correlated with u_{it} because it is correlated with the unobserved heterogeneity term α_i, and thus the pooled OLS estimator of the lagged dependent variable would be biased upward and inconsistent. The within (fixed effects) estimator can address the correlation between α_i and x_{it} but not between c_{it-1} and u_{it}. This problem arises because the within-transformation of the lagged dependent variable is correlated with the error. Consequently, it creates a large-sample bias in the parameter estimate of the coefficient of c_{it-1}, which is not alleviated even by increasing the number of individual units. A similar problem affects the random-effects model because the unobserved individual heterogeneity term α_i enters every value of the dependent variable c_{it} by assumption. Hence, the lagged dependent variable cannot be independent of the composite error process.

Writing equation [8] in first differences yields,

$$(c_{it} - c_{it-1}) = \gamma(c_{it-1} - c_{it-2}) + \beta(x'_{it} - x'_{it-1}) + (u_{it} - u_{it-1}) \tag{9}$$

or

$$\Delta c_{it} = \gamma \Delta c_{it-1} + \Delta x'_{it}\beta + \Delta u_{it} \tag{10}$$

The individual effect term is removed. However there is still correlation between the differenced lagged dependent variable and the disturbance process (the former contains c_{it-1} and the latter contains u_{it-1}). One can solve this problem and estimate the model using instruments for the lagged dependent variable from the second and third lags of the dependent variable (either in the form of differences or lagged levels). If the random disturbance term u_{it} is i.i.d., those lags of c will be highly correlated with the lagged dependent variable (and its difference) but uncorrelated with the composite error process, satisfying the key requirements of a good instrument. The resulting estimator is referred as the Anderson and Hsiao (1981) two-stage estimator (Wooldridge, 2010).

However, Arellano and Bond (1991) show that when $T > 3$, and with no serial correlation in the random error terms, a more-efficient IV estimator can be obtained by estimating [10] using more lags as instruments in a Generalised Method of Moments framework. This gives rise to what is known in the literature as the Arellano and Bond or Difference GMM estimator. Later on, Arellano and Bover (1995) and Blundell and Bond (1998) suggested a more advanced estimator - known as system GMM estimator - which estimates the parameters using a two-equation model (the level equation and a differenced equation) in an Instrumental Variable set up. By using lags and differences of of the lags as instruments for the endogenous explanatory variables (including the lagged dependent variable), one can deal with endogeneity without externatl instruments in this model. Validity of the instruments can be verified using Sargan's Overidentification Test. In this paper, I use this estimator to check for robustness of my findings from the dynamic probit model.

3 Data and Descriptive Statistics

3.1 Data

This study uses five rounds of the Ethiopian Urban Socioeconomic Survey (EUSS) - a panel data set collected in 1994, 1997, 2000, 2004, and 2008/09.[4] The first four waves were collected by

[4]Data was collected in 1995 as well. However, because the dynamic probit model is sensitive to the spacing of the data collection points, I excluded data collected in 1995 in order to maintain fairly even spacing between rounds.

the Department of Economics of Addis Ababa University in collaboration with the Department of Economics, the University of Gothenburg. Originally, it covered seven major cities in Ethiopia - the capital Addis Ababa, Awassa, Bahir Dar, Dessie, Dire Dawa, Jimma, and Mekelle, which were believed to represent the major socioeconomic characteristics of the Ethiopian urban population. About 1,500 households were included and each city was represented in proportion to population. Once the sample size for each city was set, the allocated sample size was distributed over all woredas (districts) in each urban center. Households were then selected randomly from half of the kebeles (the lowest administrative units) in each woreda, using the registration for residences available at the urban administrative units.[5],[6]

I conducted a sixth round survey from a sub-sample of the original sample covering four cities - Addis Ababa, Awassa, Dessie, and Mekelle - and comprising 709 households in late 2008 and early 2009.[7] The cities were selected carefully in order to represent major urban areas of the country and the original sample. All panel households were surveyed in three of the cities, but not in Addis Ababa, which constituted about 60 percent of the original sample. About 350 of the original households in Addis Ababa were selected following the sampling procedure discussed in the preceding paragraph. Out of the total of 709 households surveyed in the sixth round, 128 are new households randomly included in the survey. These new households were surveyed based on the concern that the panel households might have become atypical since they were incorporated in the sample in 1994 and thus no longer very well representative of the Ethiopian urban population. No significant difference was found between the new and the panel households in welfare measured by consumption expenditure, conditional on observable household characteristics (Alem and Söderbom, 2012). The analysis includes a total of 366 households that were surveyed in all rounds since 1994. The dataset is comprehensive and addresses household living conditions, including income, expenditure, demographics, health, educational status, occupation, production activities, asset ownership, and other variables on the household and individual levels. In addition, new sections on shocks and coping mechanisms, government support, and institutions were included in the 2008/09 survey.

To measure poverty, I followed the conventional approach for developing countries and used consumption expenditure on a monthly and weekly basis as reported by the households. The definition of consumption used in the analysis is comprehensive and incorporates both food and non-food components. Food consumption includes the value of food purchased from the market and food obtained in the form of gifts or aid. The non-food component includes expenditures on clothing, energy, education, kitchen equipment, contributions, health, education, and transportation. The cost of basic needs (CBN) approach (Ravallion and Bidani, 1994) was used to estimate poverty

[5]Refer to AAU & UG (1995) for details on sampling design.

[6]While tracking original households, unfortunately, household splits were not followed.

[7]Households in the other cities were not surveyed due to resource constraints.

lines. It consists of two steps: first the food poverty lines are estimated and then they are adjusted to account for basic non-food consumption. I therefore estimated the food poverty line for each city in each round by valuing a basket of food items that yield a minimum energy requirement of 2,200 kcal of energy per person per day, as stipulated by the World Health Organization (WHO). This basket of goods was borrowed from earlier studies on urban poverty in Ethiopia (Dercon and Tadesse, 1999; Tadesse, 1999; Gebremedihin and Whelan, 2005).

In order to estimate the non-food component of the poverty line, I followed Ravallion and Bidani (1994) and divided the food poverty line in each city by the average food share of households deemed to be below the food poverty line. I then used the poverty line of one of the cities (the capital, Addis Ababa)[8] in the initial period (1994) as a reference and divided all the other cities' poverty lines by the poverty line of the reference city, which yielded price deflators for the nominal expenditures of households in the different cities.[9] I then used these deflators to convert nominal household consumption to real values, adjusting for spatial and temporal price differences. [10] A household has been classified as poor if its real consumption per adult equivalent unit was below the poverty line of Addis in the initial period, which was 78.66 Ethiopian birr per month.[11], [12]

The number of households belonging to the sample formed back in 1994 declined over time due to attrition. In 2004, about 407 of the 1097 original households (representing 37 percent) in the four cities were not surveyed.[13] In addition, the number of panel households surveyed in the latest round has been reduced due to resource constraints. It is therefore reasonable to be concerned about bias

[8]Addis Ababa has been chosen because of the fact that about 60 percent of the households in the sample are located there. Moreover, the city contains diverse cultures and socioeconomic groups, which makes it a good representative of other cities when it comes to patterns of household consumption.

[9]Ravallion (1998) provides a detailed discussion on the use of poverty lines as deflators.

[10]I use poverty lines constructed from the survey rather than the ones constructed by the Ministry of Finance and Economic Development of Ethiopia for valid reasons: i) the ministry's poverty line, which was constructed in 1995/96 (see MoFED, 2012) is too general and was constructed to analyze poverty in both urban and rural areas, which may have different consumption patterns, while I use a basket of goods anchored in the lowest 40 percent of the distribution in urban Ethiopia, which makes poverty comparison in urban Ethiopia relatively easy; ii) to analyse poverty in 2010/11 and adjust consumption for spatial and temporal price differences, the national poverty line was deflated using the national and regional consumer price indices, which are too aggregated and general, while I use price data in the respective cities to adjust for spatial and temporal price differences; and iii) with the basket of goods and poverty lines I used, it is relatively straightforward to compare poverty figures over time with earlier studies (e.g., Dercon and Tadesse, 1999; Tadesse, 1999; Gebremedihin and Whelan, 2005) who analyzed poverty in urban Ethiopia using the data set I use in this paper.

[11]Following the standard practice, I used adult equivalent units constructed by Dercon and Krishnan (1998) for Ethiopia to adjust for household size and composition.

[12]One Ethiopian birr was about USD 0.20 in 1994.

[13]A large part of the attrition in the survey seems to have been a result of poor tracking. For instance, it is possible to see original panel households not surveyed in one wave but tracked and surveyed in subsequent years. For the dynamic probit analysis a balanced panel of the data containing 366 households observed in all waves is used.

in the estimation results as a result of attrition. I attempt to check for attrition bias using attrition probits (Fitzgerald et al., 1998) and a BGLW test (Becketti et al., 1988). Attrition probits consist of estimates of binary-choice models for the determinants of attrition in later periods as a function of base year characteristics. The BGLW test, on the other hand, involves investigating the effect of future attrition on the initial period's outcome variable. Two sets of the two tests (attrition probits and BGLW test) are performed - one for attrition during 1994-2004, and another for 2004-2009.

Attrition probits presented in table A.1 in the appendix show that during 1994-2004, households that were headed by males and by self-employed individuals had a higher correlation with future attrition. It can also be seen that having a higher number of private sector employee members and more children had a higher correlation with attrition in the future, although the coefficients are statistically significant only at the ten percent level. The attrition probit regression for the 2004 -2009 period on the other hand, shows that only being headed by a casual worker was correlated with attrition in 2009. Residing in the capital, Addis had a negative correlation with future attrition in the first period but a negative correlation in the latter period. The positive coefficient for Addis in the 2004 - 2009 round is not surprising given, the fact that a large proportion of the households absent from the 2009 survey were from Addis.

Table A.2 and A.3 in the appendix present regression results investigating the effect of future attrition on base year consumption variables for the period 1994-2004 and 2004-2009 respectively. Separate regressions are estimated for households who were in the sample in future rounds, and for the total sample in the initial years. For the period 1994-2004, the impact of being headed by an individual with secondary education is different (at five percent) between the total and nonattriting samples. For the 2004-2009 period, only the impact of being headed by an individual who had completed primary schooling and the number of unemployed household members are different between the two groups at the ten percent level, while there is no difference on the impact of the rest of the variables. Overall, one can conclude that attrition in the sample would be less likely to bias results from the sample of remaining households.[14]

3.2 Descriptive Statistics

The evolution of poverty in urban Ethiopia is presented in Table 1. The upper panel of the table shows the headcount index for the study period for the unbalanced panel, including mean values, and standard errors, whereas the lower panel shows the same figures in the same period for the panel households that have been observed in all rounds. It can be seen that the poverty incidence, as measured by the headcount index in adult equivalent units, was about 43 percent in 1994 but

[14] In addition, I performed Wald tests for the joint significance of the differences in all slope coefficients and intercepts and did not reject the hypothesis of equality of the coefficients from the two samples.

then declined consistently and reached about 27 percent in 2009. The poverty figure in 2009 - the period in which the country experienced rapid change in its economic setup - appears to be close to the Ethiopian government's statistics, which indicates a 26 percent urban poverty rate in 2010 (MoFED, 2012).

Table 1 here

Table 2 presents descriptive statistics of socioeconomic variables for households. These are used as explanatory variables in the poverty probability model by poverty status. It can be seen that the proportion of households that have never been poor is about 29 percent, while 8.5 percent have always been poor (the chronic poor). Hence, most poor households experience poverty for a short period of time, which makes the analysis of poverty dynamics important. Some important trends can also be noted from the rest of the descriptive statistics. As expected, real consumption in adult equivalent terms declines with the severity of poverty, with the "never poor" households having the highest consumption while the "always poor" exhibit the lowest level. There are more female headed households in the "always poor" category than in the "never poor" category, probably indicating the vulnerability of female headed households to poverty in a poor setting like urban Ethiopia. Education and international remittance variables show distinct differences between households who have never been poor and those who have always been poor. For instance, only 6 percent of the heads in the "always poor" category have completed secondary level schooling, while the figure is about 30 percent for the "never poor". Similarly, 20 percent of the household heads in the "never poor" category have completed a tertiary level education, whereas the figure for the "always poor" is only 1 percent. This provides some evidence on the strong negative relationship between education and poverty status in urban Ethiopia.

Table 2 here

One can also note that the poverty status of households varies with the value of international remittances received by households. On average, the "never poor" households received about 875.79 birr/year in real terms from international remittances during the period analyzed, while the figure was only 31.88 birr for the chronic poor.[15] The growing role of international remittances in urban Ethiopia is clearly evident from table 3 as well. The proportion of households that received international remittances in 1994 for example was only 3.6 percent, while it reached 31.8 percent in 2009. A significant jump in the flow of remittances from foreign sources was observed from 2004 to 2009.[16] One can finally note that there has not only been an increase in the number of households receiving international remittances, but also in the mean value of remittances received over the past 15 years.

[15] Remittances are expressed in real terms using 1994 prices.

[16] Table 3 shows the flow of international remittances only in the form of cash. The reported values could be much higher if in-kind remittances were included.

Table 3 here

The differences in labor market status of both heads and other members of the household (which are the focus of this paper) are also clearly evident from table 2. Twenty-seven percent of the household heads who have never been poor are either civil or public sector employees, whereas for the "always poor" the figure is only 8 percent. Only 6 percent of the heads of the "never poor" households are casual workers, while 18 percent of those of the "always poor" households depend on casual work to earn a living. There are also clear differences in terms of labor market status and demographic characteristics of other household members. "Never poor" households have on average 0.35 individuals working as civil/public sector employees, whereas those in the "always poor" category have only 0.09 individuals in this sector of activity. There are more casual worker household members (0.34) among the "always poor" than among the "never poor" households (0.05). Similar differences are noticeable in the case of household demographic variables. All these facts imply a close association between poverty status of households and the characteristics of household heads and other household members.

4 Results

Table 4 presents marginal effects for a model of the probability of being poor as given by equation (1). Column [1] presents marginal effects from a random effects probit model, which takes care of unobserved household heterogeneity but treats initial conditions as exogenous. Column [2] shows marginal effects from a dynamic probit model - Wooldridge's conditional maximum likelihood estimator (WCML) - which takes care of the initial conditions problem in addition to unobserved household heterogeneity.[17] Both models control for time and city fixed effects and the WCML estimator uses the time varying x variables in the z vector. One can see from the table that the marginal effect of the state dependence parameter declines from 0.22 to 0.08 once I control for the initial conditions problem. This indicates that a households which has been poor in any period has only an 8 percent higher probability of being poor in the next period, unlike the estimate from the random effects probit, which indicates a 22 percent higher probability of bing in poverty. The initial state of poverty (poverty in 1994) is not only statistically significant at one percent in the WCML estimator but is also larger than the coefficient of the lagged dependent variable, providing strong evidence in favor of controlling for endogeneity of initial conditions.

Table 4 here

Marginal effects from Wooldridge's conditional maximum likelihood regression results presented

[17]The marginal effects of the dummy variables represent the increase in the probability of poverty due to a change from zero to one in the dummy explanatory variables. While for continuous variables, it represents the change in the probability of poverty due to a one unit change in the continuous variable.

in table 4 column [2] show that other household members' occupation and demographic characteristics are important determinants of poverty status in urban Ethiopia. Households with more own-account workers, casual workers, unemployed members, out-of-the-labor-force members, and/or child members are prone to poverty. This reflects the adverse welfare impact of depending on volatile sources of income in the labor market, of being unable to have an income-generating job, and of having more dependent members. The positive association with poverty of being an own-account worker head (although the coefficient is not statistically significant) contradicts the negative association of the variable when it comes to other household members. A significant proportion of own-account worker household members in urban Ethiopia are engaged in low paying and unstable jobs. For instance, in 2009, 67 percent were engaged in activities such as petty trading and preparing and selling food and drinks. Hence, it may not be surprising that members engaged in such low-paying jobs would be likely to be in consumption poverty. However, the fact that own-account worker heads have a lower likelihood of being in poverty may indicate that it is those individuals with promising business activities that choose to form a family and become heads. This finding implies that simply taking the labor market status of an individual as an indicator may not be informative and that heterogeneity, even in a given type of occupation, should be considered in analyzing poverty.

Results also reveal the strong and important role of international remittances in affecting the likelihood of being in poverty. A one percent increase in the flow of international remittances reduces the probability of being in poverty by 1.5 percent. In order to further investigate the role of international remittances, I computed poverty head counts, excluding the amount of international remittances reported to have been used to finance consumption by households. The descriptive statistics presented in table 5 indicate that poverty would have been higher without international remittances. In the year 2009, for instance, when the country experienced rapid economic growth, poverty in adult equivalent terms would have been 34 percent, which would have been higher by about 3.5 percentage points compared to poverty figures with international remittances. It is, however, important to notice that this exercise of investigating the role of international remittances would not be free of limitations, such as the likely differences between international recipient and non-recipient households, measurement error in reporting on how remittances have been used, etc., which make inference of a causal relationship difficult. Nevertheless, the figures provide relatively reliable clues about the important and increasing role of international remittances in the livelihoods of households in urban Ethiopia. These findings are in line with descriptive statistics presented in table 3, which indicate the rapid growth of international remittances, both in value and the proportion of recipient households over time.

Table 5 here

The paper's findings have important implications for the analysis of urban poverty and poverty persistence. The important role of labor market status of other household members and international remittances implies that it is important to consider these variables - not only those of household heads' - when designing anti-poverty policies. It is striking to find that the coefficient of the poverty persistence variable significantly declined once I controlled for these important variables and the initial conditions problem using a robust dynamic probit model. Previous studies (e.g., Bigsten & Shimeles, 2008) did not control for these variables and found a significantly higher coefficient for the state dependence variable using a simulation-based dynamic probit estimator. The findings of this paper therefore imply that targeting these observable characteristics of households in anti-poverty interventions would be welfare enhancing. For instance, policies that ensure skill and stable job creation and those that protect household income variability would reduce poverty significantly.

Consistent with previous findings of poverty studies in SSA, which primarily consider household heads' characteristics, the regression results in the current paper confirm the importance of socio-economic characteristics of heads. Households headed by educated heads are less likely to be in poverty, with tertiary level of education having the largest marginal effect (0.21). This probably indicates the increasing returns of higher education in urban Ethiopia. One also notes a negative association between poverty and being headed by a non-working employer head. In fact, this variable has the largest marginal effect of all the coefficients I controlled for. Controlling for the whole set of determinants of poverty, households headed by an individual who is an employer have a 34 percent lower probability of being in poverty.[18] Being headed by a civil/public sector employee head also reduces the probability of being in poverty. This may be due to the fact that workers in this sector earn a stable stream of income and have a relatively better opportunity for saving and credit, at least compared to casual workers, and own-account workers on small businesses in urban Ethiopia.

Robustness Checks

As a robustness exercise, I also estimated Heckman's dynamic probit estimator.[19] In the Heckman model, I addressed the initial conditions problem by making use of the initial period equation, including three exogenous geographical location variables and the full set of period-specific versions of the time-varying explanatory variables as described in the empirical strategy section. Similarly here, the Heckman estimator yielded a significantly lower coefficient for the state dependence parameter compared to the random effects probit model but was slightly higher than the Wooldridge model.

[18]There were very few observations for employer members other than heads which made controlling for "employer members" in the regressions problematic.

[19]Results are available from the author up on request.

As mentioned in section 2, it is reasonable to argue that the main variables of interest - occupational characteristics of household members and remittances - could be endogenous, and this may bias the coefficient of the variable that measures poverty persistence. In order to address endogeneity of these variables, I took advantage of the long panel data at hand and estimated a linear model of poverty (where the dependent variable is the log of real consumption expenditure in adult equivalent units) using the Arellano and Bover (1995), and Blundell and Bond (1998) System GMM estimator. This estimator uses lagged values and differences in the lagged values of the endogenous variables as valid instruments to estimate the impact of the endogenous variables on the dependent variable. Two versions of the model are estimated and presented in table 6: one in which only lagged consumption is treated as endogenous, and another one in which lagged consumption, remittances, and labor market status of members are treated as endogenous. Regression results reveal that the impact of most of the variables of interest (including that of the lagged dependent variable) changed very little after controlling for endogeneity of the main variables.[20] Furthermore, the impact of most of the variables remained consistent with those obtained from Wooldridge's conditional maximum likelihood estimator.[21] One can, however, note that household head variables are not significant in the linear dynamic models, probably because these variables changed very little over time.

Table 6 here

As a final robustness check, I estimated the dynamic poverty probability model by moving the poverty line up and down by 10 percent to see the possible impact of measurement error on the main findings. Reassuringly, the results remained robust to this adjustment.[22]

5 Conclusions

Using one of the few rich panel data sets in Sub-Saharan Africa spanning 15 years - the Ethiopian Urban Socioeconomic survey - this paper investigated the persistence of poverty in urban Ethiopia and the role of intra-household heterogeneity in poverty. Dynamic probit results from Wooldridge's conditional maximum likelihood estimator suggest that there is a statistically strong state dependence in poverty in urban Ethiopia. However, the magnitude of the state dependence coefficient declines significantly once I control for the role of the complete sets of household income diversification activities and the initial conditions problem encountered in such non-linear dynamic panel data models. A household which has been poor in any period has only an 8 percent higher probability

[20]Controlling for endogeneity of the remittance and labor market status of household members actually reduced the coefficient of the lagged consumption variable by only about 1.2 percentage points.

[21]The null hypothesis that the population moment conditions are correct is not rejected at the commonly accepted 5 percent level of significance.

[22]Regression results are available upon request.

of being poor next period. Heckman's dynamic probit and a linear dynamic system GMM model have also been estimated to check for robustness of the results from the Wooldridge model.

The paper takes a more comprehensive view of the household than most previous studies, allowing poverty to depend on the occupational and demographic characteristics of all household members. Regression results suggest that households with a higher number of own-account workers, casual workers, unemployed members, out-of-the-labor-force members, and child members are more likely to be in poverty. This reinforces the facts that, dependence on unsustainable sources of income in the labor market, inability to have a job that generates income, and a higher number of dependent household members expose households to consumption poverty. These results imply that it may be important to consider occupational and demographic characteristics of all household members when designing poverty reduction and targeting policies. I also find that remittances play significant roles in determining poverty status in urban Ethiopia, and that poverty would have been higher by about 3.5 percentage points without the part of consumption augmented by international remittances.

I also find strong impacts of the characteristics of household heads, which is in line with previous studies. Being headed by an educated household head reduced the probability of being in poverty. However, the impact of education differs based on the level of education, with tertiary education having the largest impact and primary education having the lowest impact on being out of poverty. This finding most likely indicates the increasing returns to higher education in a growing economy. In this context, previous studies (e.g., Bigsten and Shimeles, 2008), which controlled for only completing primary schooling, may have underestimated the impact of education and overestimated the state dependence coefficient. The paper also documents the important role of labor market status of household heads. Compared to households headed by out-of-the-labor-force individuals, being headed by a non-working employer has the largest marginal effect in reducing the likelihood of being in poverty.

Some key policy implications follow from the findings of the paper. The finding that previous history of poverty matters for current state of poverty implies that policies aimed at reducing volatility in income of households and those aimed at supporting households stricken by shocks would have significant impact on reducing poverty. Because labor market status and demographic characteristics of all household members are important determinants of the likelihood of being in poverty, poverty reduction and targeting strategies will be more effective if they take these household characteristics into consideration to identify and support the poor. For instance, policies aimed at focusing on skill and job creation for the unemployed and casual workers and those that support children in schools located in low income areas could be welfare enhancing. Given that the persistently poor lack the required resources to invest in human and other productive capital important to generate income in an urban environment, it would be particularly important to support these groups with tailored packages of interventions, say, through human capital enhancing interventions and micro-finance supports to make them competitive in a rapidly growing urban environment. Tackling transient poverty, on the other hand, would require short term interventions during times of shocks, e.g., provision of access to subsidized food items during food price shocks (Alem and Söderbom, 2012). Finally, because remittances from international sources play an increasingly positive role in poverty reduction, it would to be useful for policy makers to investigate the mechanisms through which these remittances flow into the country and to design policies that encourage the flow, which could in the long-run be combined with appropriate redistribution mechanisms. However, given the fact that the findings of the paper are based on only 366 households - although observed over a 15 year period of time - I acknowledge that these policy implications have to be taken with caution.

Additional lessons can be learned from future research in relation to the underlying reasons for the reduction in poverty in recent years and the impacts of education, international remittances, and labor market access on poverty. The 2004-2009 period was characterized by rapid economic growth, but also by double digit inflation, which had a significant negative impact on the welfare of households in urban Ethiopia (Alem and Söderbom, 2012). During the same period, the proportion of households receiving remittances from abroad and food items from relatives/friends increased by 141 and 163 percent, respectively. This poses the important question of whether the poverty reduction in urban Ethiopia has been driven by economic growth or by the households' own efforts to diversify income. Future research can shed light on these and other issues related to the question of which sections of the community take advantage of a rapidly changing economic environment to escape poverty. Furthermore, the rapidly expanding panel data sets such as the South African National Panel of Income Dynamics, and the national panel surveys of Tanzania, and Uganda, which have both rural and urban components, could be used to increase the knowledge of poverty dynamics and labor market issues in the rapidly expanding urban areas of Africa.

References

Addis Ababa University (AAU) & the University of Gothenburg (UG), (1995). Report on the 1994 Socio-economic survey of major urban centers in Ethiopia.

Ahmed, A.U., Hill, R.V., Smith, L.C., Wiesmann, D.M., and Frankenberger, T. (2007). The world's most deprived: characteristics, and causes of extreme poverty and hunger, 2020 Discussion Paper No. 43.

Alem, Y. & Söderbom, M. (2012). Household-level consumption in Urban Ethiopia: The effects of a large food price shock. *World Development*, 40(1), 146-162.

Arellano, M., & Bond, S. R. (1991). Some Specification Tests for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, *Review of Economic Studies* 58, 277-298.

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental Variables Estimation of Error-Component Models, *Journal of Econometrics* 68, 29-51.

Arulampalam, W., & Stewart, M. (2009). Simplified implementation of the Heckman estimator of the dynamic probit model and a comparison with alternative estimators. *Oxford bulletin of economics and statistics*, 71(5), 659-681.

Bane, M.J., & Ellwood, D., (1986). Slipping into and out of poverty: the dynamics of spells. *The Journal of Human Resources*, 21(1), 1-23.

Barrett, C. B., Carter, M. R., & Little, P. D. (2006). Understanding and reducing persistent poverty in Africa: Introduction to a special issue. *Journal of Development Studies*, 42(2), 167-177.

Baulch, B. (2011). Overview: poverty dynamics and persistence in Asia and Africa. In: Why poverty persists: Poverty dynamics in Asia and Africa, ed. Baulch, B., 1-28. Cheltenham, UK: Edward Elgar Press.

Baulch, B., & McCulloch, N. (2003). Being poor and becoming poor: poverty status and poverty transitions in rural Pakistan. *Journal of African and Asian Studies*, 37(2), 168-85.

Baulch, B. & Vu, H. D. (2011). Poverty dynamics in Vietnam, 2002 to 2006. In: Why poverty persists: Poverty dynamics in Asia and Africa, ed. Baulch, B., 1-28. Cheltenham, UK: Edward Elgar Press.

Beegle, K., De Weerdt, J., & Dercon, S. (2008). Adult mortality and consumption growth in the age of HIV/AIDS. *Economic Development and Cultural Change*, 56(2), 299-326.

Becketti, S., Gould, W., Lillard, L. & Welch, F. (1988). The panel study of income dynamics after fourteen years: an evaluation. *Journal of Labor Economics*, 6(4), 472-492.

Biewen, M. (2009). Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition. *Journal of Applied Econometrics,* 24(7), 1095-1116.

Bigsten, A., Kebede, B., Shimeles, A., & Taddesse, M. (2003). Growth and poverty reduction in Ethiopia: Evidence from household panel surveys. *World Development*, 31(1), 87-106.

Bigsten, A., & Shimeles, A. (2008). Poverty transition and persistence in Ethiopia. *World Development*, 36(9), 1559-1584.

Blundell, R., & Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics* 87, 115-144.

Butler, J. S., & R. Moffitt. (1982). A computationally efficient quadrature procedure for the one-factor multinomial probit model. *Econometrica*, 50(3), 761-764.

Cappelari, L., & Jenkins, S. P. (2002). Who stays poor? Who becomes poor? Evidence from the British household panel data. *Economic Journal*, 112, C60-C67.

Chamberlain, G. (1984). Panel data. In Handbook of Econometrics, ed. Z. Griliches and M. Intrilligator, vol. 2, 1254-1318. Amsterdam: North Holland.

Davicienti, F. (2001). Poverty persistence in Britain: A multivariate analysis using the BHPS, 1991-1997. *Journal of Economics*, Supplement, 9, 1-34.

Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics*, 74(2), 306-329.

Dercon, S. (2006). Economic reform, growth, and the poor: Evidence from rural Ethiopia. *Journal of Development Economics*, 81(1), 1-24.

Dercon, S. (2008). Fate and fear: Risk and its consequences in Africa. *Journal of African Economies*, 17(2), 97-927.

Dercon S. & Krishnan, P. (1998). *Changes in poverty in rural Ethiopia 1989-1995: Measurement, robustness tests and decomposition.* CSAE working paper series, 1998-7.

Dercon, S. & Porter, C. (2011). A poor life? Chronic poverty and downward mobility in rural Ethiopia, 1994 to 2004. In: Why poverty persists: Poverty dynamics in Asia and Africa, ed. Baulch, B., 65-95. Cheltenham, UK: Edward Elgar Press.

Dercon, S., & Tadesse, M. (1999). A comparison of poverty in rural and urban Ethiopia. *Ethiopian Journal of Economics*, 8, 83-98.

Dercon, S., Hoddinott, J., & Woldehanna, T. (2005). Shocks and consumption in 15 Ethiopian villages: 1999-2004. *Journal of African Economies*, 14(4), 559-585.

Duncan, G.J., Gustafsson, B., Hauser, R., Schmauss, G., Messinger, H., Muffels, R., Nolan, B., & Ray, J.C. (1993). Poverty dynamics in eight countries. *Journal of Population Economics*, 6(3), 215-234.

Fitzgerald, J., Gottschalk, P., & Moffitt, R. (1998). An analysis of sample attrition in panel data. *The Journal of Human Resources*, 33(2), 251-299.

Gebremedhin, T.A. & Whelan, S. (2005). *Prices and Poverty in Urban Ethiopia*. Working Paper No. 5, School of Economics and Political Science, University of Sydney.

Giles, J. & Murtazashvili, I. (2012) *A control function approach to estimating dynamic probit models with endongenous regressors, with an application to the study of poverty persistence in China*. IZA Discussion Paper 668.

Giraldo, A., Rettore, E., & Trivellato, U. (2006). The persistence of poverty: true state dependence or unobserved heterogeneity? Some evidence from the Italian Survey on Household Income and Wealth. Paper Prepared for the 27th General Conference of the international association for research in income and Wealth Stockholm, Sweden. August 18-24, 2002

Harrower, S. & Hoddinott, J. (2005). Consumption smoothing in Zone Lacustre, Mali. *Journal of African Economies*, 14(4), 489-519.

Heckman, J. J. (1981). The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process. In Structural Analysis of Discrete Data and Econometric Applications, ed. C.F. Manski & D.L. McFadden, 114-178. Cambridge, MA: MIT Press.

Kedir, A. M., & McKay, A. (2005). Chronic poverty in urban Ethiopia: Panel data evidence. *International Planning Studies*, 10(1), 49-67.

Litchfield, J., & McGregor, T. (2008). *Poverty in Kagera, Tanzania: Characteristics, causes and constraints*. PRUS working paper no. 42.

May, J., Woolard, I., and Baulch, B. (2011). Poverty traps and structural poverty in South Africa: reassessing the evidence from KwaZulu-Natal, 1993 to 2004. In: Why poverty persists:

Poverty dynamics in Asia and Africa, ed. Baulch, B., 187-218. Cheltenham, UK: Edward Elgar Press.

Mejer, L., & Linden (2000). Persistent income poverty and social exclusion in the European Union. Statistics in Focus, Population and Social Conditions, Theme 3, 13/2000.

Ministry of Finance and Economic Development (MoFED) (2012). Ethiopia's Progress Towards Eradicating Poverty: An Interim Report on Poverty Analysis Study (2010/11).

Mundlak, Y. (1978). On the pooling of time-series and cross-sectional data. *Econometrica*, 46(1), 69-85.

OECD (2001). Employment outlook, Chapter 2, OECD, Paris.

Oxley, H., Dang, T. & Antolin (2000). *Poverty dynamics in six OECD countries. OECD Economic Studies*, No. 30, 2000/I, 7-52.

Quisumbing, A. R. (2011). Poverty transitions, shocks and consumption in rural Bangladesh, 1996-97 to 2006-07. In: Why poverty persists: Poverty dynamics in Asia and Africa, ed. Baulch, B., 29-64. Cheltenham, UK: Edward Elgar Press.

Ravallion, M. & Bidani, B. (1994). How robust is a poverty profile?. *The world Bank Economic Review*, 8(1), 75-102.

Ravallion, M. (1996). Issues in measuring and modeling poverty. *The Economic Journal*, 106, 1328-1343.

Ravallion, M. (1998). *Poverty lines in theory and practice.* LSMS working paper No. 133.

Stevens, A. H. (1999). The dynamics of poverty spells: Updating Bane and Ellwood. *Journal of Human Resources*, 34(3), 557-588..

Tadesse, M. (1999). Determinants and dynamics of poverty in urban Ethiopia. *Ethiopian Journal of Economics*, 8(1), 61-82.

Wooldridge, J.M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, 20, 39-54.

Wooldridge, J. (2010). *The econometrics of cross-sectional and panel data* (2nd ed.). MIT: MIT Press.

Table 1: Trends in poverty headcounts: 1994-2009* (%)

All households				
Year	City	Obs	Mean	SE
1994	Addis	854	0.453	0.017
	Other Cities	249	0.365	0.031
	All Cities	1103	0.433	0.015
1997	Addis	826	0.390	0.017
	Other Cities	227	0.396	0.033
	All Cities	1053	0.391	0.015
2000	Addis	848	0.356	0.016
	Other Cities	259	0.270	0.028
	All Cities	1107	0.336	0.014
2004	Addis	830	0.324	0.016
	Other Cities	288	0.295	0.027
	All Cities	1118	0.317	0.014
2009	Addis	421	0.311	0.023
	Other Cities	288	0.219	0.024
	All Cities	709	0.274	0.017
Panel households				
	City	Obs	Mean	SE
1994	Addis	292	0.476	0.029
	Other Cities	74	0.378	0.057
	All Cities	366	0.456	0.026
1997	Addis	292	0.421	0.029
	Other Cities	74	0.351	0.056
	All Cities	366	0.407	0.026
2000	Addis	292	0.390	0.029
	Other Cities	74	0.297	0.053
	All Cities	366	0.372	0.025
2004	Addis	292	0.370	0.028
	Other Cities	74	0.257	0.051
	All Cities	366	0.347	0.025
2009	Addis	292	0.329	0.028
	Other Cities	74	0.216	0.048
	All Cities	366	0.306	0.024

Notes: *Adjusted for adult equivalent units.

Table 2: Descriptive statistics of major variables by poverty status 1994-2009

Variable	Never Poor	Poor once	Poor twice	Poor 3 times	Poor 4 times	Always poor
%*	29.04	18.63	15.62	15.62	12. 60	8.49
Real consumption per adult equivalent units	244.38	169.30	135.05	94.25	79.64	47.13
Age of head	51.14	52.33	50.17	50.85	50.50	50.97
Head, male (%)*	68.72	51.04	55.16	43.71	47.45	52.24
Head, primary schooling completed (%)*	27.18	30.15	33.55	32.57	46.27	36.73
Head, jun-sec schooling completed (%)*	12.05	15.52	19.03	18.29	11.37	8.57
Head, secondary schooling completed (%)*	29.74	25.67	18.06	14	9.41	6.12
Head, tertiary schooling completed (%)*	20.00	5.67	7.42	2.00	1.18	0.82
Head, employer (%)*	2.31	3.28	0.65	0.86	0.39	0.00
Head, own-account worker (%)*	20.26	25.97	29.35	25.71	22.75	28.57
Head, civil/public servant (%)*	26.67	17.61	10.97	14.57	11.37	8.16
Head, private sector employee (%)*	5.90	8.06	8.71	6.86	9.80	9.80
Head, casual worker (%)*	6.41	4.48	11.61	12.29	14.51	17.55
No. of own-account worker members	0.15	0.19	0.15	0.16	0.24	0.29
No. of civil/public servant members	0.35	0.37	0.25	0.25	0.24	0.09
No. of private sector employee members	0.47	0.31	0.37	0.33	0.32	0.28
No. of casual worker members	0.05	0.11	0.13	0.20	0.29	0.34
No. of unemployed members	0.50	0.55	0.63	0.79	0.72	0.58
No. of out of labor force members	1.39	1.53	1.62	1.45	1.77	1.67
No. of children	1.45	1.49	1.66	1.82	2.19	2.83
No. of elderly	0.07	0.05	0.10	0.09	0.07	0.07
Real value of remittances from abroad	875.79	554.39	383.47	215.27	104.76	31.88
Resides in Addis (%)*	79.49	70.15	74.19	87.14	86.27	83.67
Resides in Awassa (%)*	6.41	10.45	8.06	7.14	5.88	6.12
Resides in Dessie (%)*	1.28	4.48	6.45	2.86	1.96	4.08
Resides in Mekelle (%)*	12.82	14.93	11.29	2.86	5.88	6.12

Notes: * denotes dummy variables.

Table 3: Trends in international remittances - panel households (%)

Year	HHs	(%)	Mean RETB
1994	13	3.56	85.04
1997	23	6.30	222.26
2000	40	10.96	486.08
2004	48	13.15	425.16
2009	116	31.78	801.16

Notes: RETB - Real Ethiopian Birr in 1994 prices.

Table 4: Determinants of poverty - marginal effects from dynamic probit regressions

	[1]		[2]	
	[ME-REPR]		[ME-WCML]	
Variable	Coeff.	SE	Coeff.	SE
Lagged poverty	0.216***	0.020	0.084**	0.035
Age of head	-0.003	0.004	0.005	0.006
Age of head squared/100	0.002	0.004	-0.004	0.005
Head Male	-0.045*	0.025	-0.027	0.028
Head primary schooling completed	-0.061**	0.029	-0.03	0.029
Head jun-sec schooling completed	-0.085**	0.037	-0.061*	0.038
Head secondary schooling completed	-0.131***	0.037	-0.091**	0.038
Head tertiary schooling completed	-0.273***	0.0650	-0.207***	0.069
Head-Employer	-0.425**	0.169	-0.344**	0.166
Head-Own-account worker	-0.038	0.029	-0.027	0.030
Head-civil/public servant	-0.086**	0.039	-0.074*	0.039
Head Private sector employee	0.015	0.043	0.024	0.044
Head-casual worker	0.002	0.041	-0.001	0.042
No. Of own-account worker members	0.055***	0.018	0.050**	0.023
No. Of civil/public servant members	-0.025	0.020	0.015	0.025
No. Of private sector employee members	-0.011	0.015	0.016	0.019
No. Of casual worker members	0.105***	0.021	0.070***	0.025
No. Of unemployed members	0.047***	0.011	0.061***	0.014
No. Of out of labor force members	0.040***	0.008	0.068***	0.011
No. Of children	0.054***	0.007	0.057***	0.011
No. Of elderly	0.031	0.039	0.034	0.051
Log of real value of remittances from abroad	-0.024***	0.005	-0.015***	0.006
Resides in Addis	0.075***	0.028	0.069**	0.032
Year 2000	0.023	0.032	-0.002	0.032
Year 2004	0.017	0.032	-0.011	0.033
Year 2009	0.039	0.035	-0.02	0.039
Initial poverty status (1994)	-	-	0.122***	0.031

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$.

ME-REPR represents marginal effects from the standard random effects estimator,

ME-WCML denotes marginal effects from the Wooldridge Conditional Maximum Likelihood Estimator.

Table 5: Trends in poverty headcounts excluding international remittances (%)

City	1994	1997	2000	2004	2009
Addis	47.84	44.52	41.20	40.20	36.21
Awassa	46.43	35.71	42.86	25.00	28.57
Dessie	46.15	46.15	53.85	46.15	30.77
Mekelle	28.57	28.57	17.14	22.86	20.00
Overall	45.89	42.44	39.52	37.67	33.95

Notes: Adjusted for adult equivalent units.

Table 6: Determinants of poverty - Dynamic System GMM Regression Results

	[1]		[2]	
	[SYS1]		[SYS2]	
Variable	Coeff.	SE	Coeff.	SE
Lagged log of real consumption per aeu	0.130**	0.061	0.118**	0.045
Age of head	-0.007	0.014	-0.006	0.013
Age of head squared/100	0.004	0.013	0.004	0.012
Head Male	0.016	0.081	0.052	0.082
Head primary schooling completed	0.046	0.063	0.097	0.063
Head jun-sec schooling completed	-0.076	0.087	-0.017	0.080
Head secondary schooling completed	0.033	0.077	0.071	0.074
Head tertiary schooling completed	0.064	0.107	0.072	0.115
Head employer	0.345	0.268	0.099	0.235
Head own-account worker	0.119	0.078	0.093	0.079
Head-civil/public servant	0.040	0.087	0.083	0.100
Head Private sector employee	0.130	0.089	0.144	0.092
Head casual worker	0.179	0.126	0.150	0.122
No. Of own-account worker members	-0.075*	0.042	-0.055	0.051
No. Of civil/public servant members	-0.080*	0.048	-0.008	0.045
No. Of private sector employee members	-0.064**	0.029	-0.040	0.032
No. Of casual worker members	-0.114***	0.043	-0.104**	0.043
No. Of unemployed members	-0.129***	0.026	-0.113***	0.024
No. Of out of labor force members	-0.141***	0.021	-0.135***	0.021
No. Of children	-0.162***	0.021	-0.144***	0.020
No. Of elderly	-0.024	0.119	-0.045	0.136
Log of real value of remittances from abroad	0.030***	0.009	0.034***	0.008
City Fixed Effects	Yes		Yes	
Year Fixed Effects	Yes		Yes	
AR(1)	0.000		0.000	
AR(2)	0.112		0.231	
Sargan	0.001		0.082	
Observations	1463		1463	

SYS1: System GMM estimaror - only lagged dependent variable endogenous.

SYS2: System GMM estimaror - lagged dependent variable, international remittances, and labor market variables endogenous.

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A1: Ever out Attrition Probits 1994 - 2004 & 2004 - 2009

	[1994-2004]		[2004-2009]	
	Coeff.	SE	Coeff.	SE
Log real consumption per aeu	0.005	0.058	0.061	0.062
Age of head	-0.01	0.02	-0.016	0.016
Age of head sq.	0.008	0.019	0.016	0.016
Head, male	0.254**	0.104	-0.001	0.095
Head, primary schooling completed	-0.177	0.111	0.088	0.109
Head, jun-sec schooling completed	-0.183	0.158	0.002	0.144
Head, secondary schooling completed	-0.366*	0.171	0.172	0.145
Head, tertiary schooling completed	0.148	0.195	0.192	0.18
Head, employer	0.476	0.282	0.022	0.354
Head, own-account worker	0.240**	0.115	-0.016	0.112
Head, civil/public servant	0.105	0.133	-0.019	0.134
Head, private sector employee	0.175	0.195	0.113	0.151
Head, casual worker	0.177	0.147	0.410**	0.159
No. of own-account worker members	-0.071	0.092	-0.065	0.088
No. of civil/public servant members	-0.103	0.066	-0.055	0.067
No. of private sector employee members	0.133*	0.069	-0.018	0.054
No. of casual worker members	-0.137	0.099	-0.035	0.08
No. of unemployed members	-0.023	0.04	-0.01	0.039
No. of out of labor force members	-0.024	0.033	0.006	0.033
No. of children	-0.072*	0.025	0.002	0.031
No. of elderly	-0.057	0.113	0.302	0.194
Log real remittances from abroad	-0.012	0.026	-0.008	0.015
Resides in Addis	-0.721**	0.097	0.960***	0.099
Intercept	0.565	0.586	-0.746	0.518
Pseudo R-squared	0.068	-	0.088	
Sample Size	1100		1118	
Number ever out	417		549	
Log-likelihood	-674.010		-706.376	

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$.

Table A2: Testing for the attrition bias 1994 -2004, log consumption regressions

	[Total]		[Present in 2004]		[Difference]	
	Coef	SE	Coef	SE	Coef	SE
Age of head	0.015	0.010	0.027**	0.012	-0.03	0.023
Age of head sq.	-0.013	0.011	-0.020*	0.012	0.016	0.021
Head, male	-0.004	0.054	0.065	0.066	-0.201*	0.114
Head, primary schooling completed	0.179***	0.058	0.259***	0.072	-0.189	0.121
Head, jun-sec schooling completed	0.394***	0.082	0.516***	0.102	-0.316*	0.171
Head, secondary schooling completed	0.552***	0.088	0.741***	0.108	-0.471**	0.185
Head, tertiary schooling completed	0.898***	0.1	0.967***	0.13	-0.175	0.205
Head, employer	0.613***	0.147	0.705***	0.207	-0.058	0.298
Head, own-account worker	0.144**	0.06	0.126*	0.075	0.057	0.125
Head, civil/public servant	0.065	0.069	0.093*	0.084	-0.020	0.147
Head, private sector employee	0.141	0.102	0.018	0.124	0.369*	0.215
Head, casual worker	-0.123*	0.077	-0.185*	0.092	0.176	0.164
No. of own-account worker members	-0.052	0.046	-0.044**	0.051	-0.030	0.116
No. of civil/public servant members	0.090***	0.032	0.094**	0.036	-0.014	0.075
No. of private sector employee members	0.177***	0.036	0.192**	0.05	-0.019	0.073
No. of casual worker members	-0.220***	0.05	-0.186**	0.058	-0.093	0.109
No. of unemployed members	-0.119***	0.021	-0.115**	0.025	0.0004	0.043
No. of out of labor force members	-0.052***	0.017	-0.074**	0.021	0.056	0.036
No. of children	-0.123***	0.013	-0.118***	0.016	-0.014	0.027
No. of elderly	-0.062	0.059	-0.050*	0.073	-0.001	0.124
Log real remittances from abroad	0.011	0.013	0.001**	0.016	0.029	0.028
Resides in Addis	-0.121**	0.052	-0.109*	0.074	-0.026	0.108
Intercept	4.239***	0.277	3.713	0.343	-0.527	0.349
Sample size	1097		690			
R-squared	0.308		0.32			
F-statistic	21.8		14.25			

Table A3: Testing for the attrition bias 2004 -2009, log consumption regressions

	[Total]		[Present in 2009]		[Difference]	
	Coef	SE	Coef	SE	Coef	SE
Age of head	0.007	0.008	0.012	0.012	-0.006	0.016
Age of head sq.	-0.002	0.008	-0.010	0.012	0.009	0.016
Head, male	0.027	0.046	-0.002	0.067	0.062	0.094
Head, primary schooling completed	0.133**	0.053	0.228***	0.075	-0.206*	0.108
Head, jun-sec schooling completed	0.353***	0.069	0.315***	0.096	0.056	0.140
Head, secondary schooling completed	0.515***	0.069	0.490***	0.102	0.032	0.141
Head, tertiary schooling completed	0.727***	0.086	0.829***	0.128	-0.193	0.174
Head, employer	0.289*	0.171	0.376	0.252	-0.201	0.346
Head, own-account worker	0.048	0.055	0.097	0.075	-0.110	0.111
Head, civil/public servant	-0.023	0.065	-0.023	0.093	-0.026	0.132
Head, private sector employee	-0.045	0.074	-0.009	0.111	-0.092	0.150
Head, casual worker	-0.174**	0.076	-0.273**	0.123	0.127	0.158
No. of own-account worker members	0.002	0.043	-0.030	0.060	0.061	0.087
No. of civil/public servant members	0.058*	0.033	0.035	0.048	0.039	0.067
No. of private sector employee members	0.024	0.027	-0.019	0.039	0.081	0.055
No. of casual worker members	-0.191***	0.039	-0.183***	0.059	-0.017	0.079
No. of unemployed members	-0.125***	0.019	-0.085***	0.028	-0.069*	0.038
No. of out of labor force members	-0.100***	0.016	-0.112***	0.022	0.029	0.032
No. of children	-0.112***	0.015	-0.122***	0.021	0.016	0.030
No. of elderly	-0.223***	0.093	-0.310**	0.152	0.123	0.193
Log real remittances from abroad	0.046***	0.007	0.052***	0.011	-0.013	0.015
Resides in Addis	-0.023	0.046	-0.051	0.060	0.042	0.106
Intercept	4.578***	0.214	4.545***	0.317	-0.033	0.315
Sample size	1118		569			
R-squared	0.303		0.289			
F-statistic	21.59		9.87			