Poverty dynamics in Ethiopia: state dependence and transitory shocks

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Abstract

This paper focuses on the persistency of poverty in rural and urban households in Ethiopia by estimating dynamic probit models. Unobserved heterogeneity, first order state dependence and serially correlated error component are allowed for The dynamic probit model of poverty that controlled for household heterogeneity and serial correlation performed better in explaining the dynamics of poverty in Ethiopia.. In rural areas, the effect of controlling for heterogeneity and serial correlation was typically in increasing the coefficient of the true state dependence by almost one fold. The statistical significance of some of the observed determinants of poverty remained unchanged. In urban areas controlling for transitory shocks brought out more strongly the effects of differences in towns of residence on the incidence of poverty, while it reduced the importance of such exogenous household attributes as ethnicity, age and family-background. Transitory shocks also contributed to poverty persistence in two additional ways. First, the persistence of urban poverty increased dramatically once we controlled for transitory shocks. Secondly, intrinsic risk of falling into poverty also declined substantially. That is, if not for transitory shocks, only a tiny fraction of the urban population would be at risk of falling into poverty.

Key words: Poverty persistency, state dependence, unobserved heterogeneity

1 Introduction

Existing studies (see Bane and Ellwood, 1986; Stevens, 1994) on the dynamics of poverty commonly use a spell approach to compute the underlying probabilities as functions of the number of durations in a particular spell. This approach, although powerful in capturing the effects of duration in poverty or out of poverty, it does not provide explicitly the magnitude of previous states on the risk of being poor in the present state, which provides an opportunity to estimate state dependency of the motion of poverty. That is, if the risk of entering into poverty is dependent on being in poverty in the previous period, after controlling for unobserved individual effects and serially correlated error components, then, it implies that there is much to be gained from policy interventions that reduce poverty in the current period on the evolution of poverty in subsequent periods. This suggests for the need to actually quantify the true state dependency of the poverty evolution and its contribution to the risk of being in poverty or not. This paper contributes to the literature on poverty dynamics by estimating an econometric model of poverty dynamics that explicitly takes into account the effect of the lag dependent variable, unobserved heterogeneity and serially correlated error components.

The rest of the paper is organized as follows: section 2 describes the data and variables, section 3 provides the methodological framework, discusses the underlying econometric model and methods of estimation, section 4 discuss the results, and Section 5 draws conclusion.

2 Data and variables

A panel data set covering rural and urban households of four waves in the period 1994-2000 was used in the analysis. The data set originally consisted of approximately 3000 households, equally divided between rural and urban households. The nature of the data, the sampling methods involved in collecting it, and other features are discussed in detail in Bigsten et al. (2005). It is one of the few longitudinal data sets available for Africa. The data covers households' livelihood, including asset-accumulation, labour market participation as well as health and education and other aspects of household level economic activities.

To measure poverty, we used consumption expenditure reported by respondents based on their recollections of their expenses in the recent past. The components of consumption expenditure are selected carefully to allow some room for comparisons between rural and urban households. The consumption-baskets include food as well as clothing, footwear, personal care, educational fees, household utensils, and other non-durable items.

Major food expenses among households in Ethiopia are difficult to measure, particularly in rural areas, because of problems related with measurement units, prices, and quality. The consumption period could be a week or a month depending on the nature of the food item, the household budget cycle, and consumption habits. Own-consumption is the dominant source of food consumption in rural Ethiopia, particularly with regard to vegetables, fruits, spices and stimulants like coffee and chat. Cereal, which makes up the bulk of food consumption, is increasingly obtained from markets as farmers swap high cash-value cereals such as *teff* for lower-value ones, such as maize and sorghum. Even so, food in rural areas is derived from own sources, which makes valuation difficult. The situation is better in the urban setting, where the bulk of consumption items are obtained from markets and measurement problems are less.

The poverty-line, to identify the poor population, was computed as follows; The major food items frequently used by the poor were first picked to be included in the poverty line 'basket'. The calorie content of these items was evaluated and their quantities scaled so as to give 2,200 calorie per day; the minimum level nutritionists require an adult person must consume to subsist in Ethiopia. The cost of purchasing such a bundle would be computed using market prices and constitutes the food poverty line. Taking the average food-share at the poverty line made adjustment for non-food items. Using the estimated poverty lines in each year for all the sites we adjusted consumption expenditure for all households by using the poverty line of one of the sites as price deflator. Thus, consumption expenditure was adjusted for temporal and spatial price differences. The poor were thus defined as those unable to meet the cost of buying the minimum consumption basket. In this study, we use the household as our unit of analysis, so that poverty dynamics is studied at the level of a household. Differences in individual attributes are adjusted using adult-equivalence scales in consumption.

The variables that we use to analyse poverty dynamics for households in rural areas are: household demographics (household size, sex of the head of the household, age of the head of the household, mean age in the household), dummy for major crops raised (coffe, chat and teff), wealth variables (cash values of durables, size of land, number of oxen owned) and quadratic terms to capture economies of scale and experience in farming. Table 1 (in appendix) provides a list of variables that we used for the analysis, particularly in reporting regression tables.

For households in urban areas, apart from demographic and educational variables, we used occupational categories, city of residence, the educational and occupational background.

Our main interest is the dynamics of poverty. Table 1 gives a broad picture of the dynamics. In rural areas, about 7 percent of the households can be classified as poor throughout the period. In urban areas, the corresponding share is around 15 percent. In rural areas almost 21 percent of the households have not been in any year, while in urban areas this share is 39 percent. The rest of the households have spent at least one period outside of poverty. Thus, in rural areas, poverty tends to be less persistent as compared to urban areas. Also, we observe that in both areas, the proportion of households who remained poor through out the period was quite low.

Tables 2a and 2b report demographic and other characteristics of the household stratified by the number of times in poverty. A visual inspection of these two tables shows some interesting things. For instance, in both rural and urban areas, poverty is persistent among households whose head are relatively older, have larger members, have little education, little asset, or engaged in self-employment etc. suggesting the structural nature of poverty. Although these correlates of poverty are also interrelated, they also point at the existence of some unobserved characteristics of the household that for instance allows for the co-existence of low ownership of land, oxen and asset at old age with a large family. Thus, it is useful and important to address unobserved household heterogeneity as a possible source of endogeneity of determinants of poverty dynamics. Finally, the dynamics of poverty can also be affected by unobserved random shocks that could persist over time and are common to all households. This could be caused by a number of factors such as drought, price shocks, policy changes and structural factors. Controlling for these factors brings out the true state dependence of the dynamics of poverty that provides a proper structure to the time-path of poverty irrespective of individual characteristics and persistent random shocks.

3 A Model of Poverty Dynamics

In the literature, poverty persistence is estimated in several ways. Some use variance-component models (Lillard and Willis, 1978, Abowd and Card, 1989; Baker, 1997; Cappelari, 2000); others use non-parametric transition probability distributions, such as life-cycle tables, and parametric hazard functions (Bane and Ellwood, 1986; Stevens, 1994, 1999, Antolin, et al 1999; Devicienti, 2001, 2003; Hansen and Wahlberg, 2004, Biewen 2003). What is common in these approaches is the effort to capture the effect of past history of poverty on current and future risk of being in poverty. In almost all cases, past history of poverty is found to be an important determinant of current or future poverty. The problem however with this finding is that it does not distinguish all three possible sources of poverty persistence over time. For example, the first source of poverty persistence is unobserved individual characteristics, such as ability, motivation, mental and physical disabilities, that pre-dispose some more than others to stay in or out of poverty for long time The second source of poverty persistence is the effect of timevarying shocks that are not specific to individuals, such as price fluctuations, natural calamities, general economic stagnation or slow-down, etc. The third is the behavioural and preference shifts that may be associated with the fact of being in poverty at least once in the past. This implies that regardless of household characteristics, once a household slips into poverty, it could trigger physical and other dispositions that allow poverty to persist over time. In the first case, poverty is driven by unobserved household attributes that may not change over time. In the second case, the events leading to poverty are correlated over time. In the last case, poverty is truly state dependent so that alleviating current poverty can lead to reduction of poverty in future too. Identifying and quantifying these causes of poverty dynamics is very important for policy purposes.

To capture the underlying causes of poverty persistence, we specify a general model of poverty as follows:

$$P_{it} = \Phi(P_{it-1}, Z_{it}, \alpha_i) \quad (1)$$

where P_{it} is equal to 1 if the i^{th} household is poor at time t and zero otherwise. The vector Z_{it} captures covariates of poverty and α_i controls for unobserved heterogeneity to each household. True state dependence in poverty dynamics is exists if current poverty is significantly correlated with lagged poverty.

In most applications that use parametric hazard functions, be it proportional or logistic, the state dependence is routinely captured by a dummy variable of duration in poverty (for exit probabilities) or out of poverty (for re-entry probabilities). For example, with a logistic specification, a typical model of poverty dynamics is specified as follows:

$$h_{it}(d) = \frac{\exp[\alpha(d) + X_{it}^{'}\beta)]}{1 + \exp[\alpha(d) + X_{it}^{'}\beta]} \quad (2)$$

where h_{it} (d) is the probability that a household *i* leaves the poverty state at duration *d*, given that it has remained in poverty up to *d-1*. Discrete intervals are commonly used to capture the duration dependence of the hazard rate of exiting or re-entering poverty. This specification combines into one the three sources of poverty persistence if the model is estimated without controlling for unobserved household characteristics. In this case, duration dependence is reported to be much stronger. Most studies do adjust for unobserved household characteristics through a joint maximum likelihood estimation of exit and re-entry rates where the hazard rates depend on spell-specific unobserved heterogeneity (e.g. Meghir and Whitehouse, 1997; Stevens, 1999; Devicienti, 2003; and Hansen and Wahlberg, 2004). Under this condition, a number of studies found that the effect of duration in or out of poverty has little role in determining poverty persistence[1]. There are few studies (Biewen 2004, Cappelari and Jenkins, 2004) that attempt to link current state of poverty with its lag, and to our knowledge none that control for serial correlation in the error components. With this limitation in mind, the empirical model used here is a dynamic probit model which controls for state dependence, unobserved heterogeneity and serial correlation -

$$P_{i0} = 1\{\beta_0 X_{i0} + u_{i0} > 0\} \quad (3)$$

$$P_{it} = 1\{\gamma P_{it-1} + \beta X_{it} + u_{it} > 0\} \qquad (i = 1,..., N; t = 1,.....T) \quad (4)$$

$$u_{it} = \alpha_i + \varepsilon_{it}$$

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + v_{it},$$

$v_{it} \sim N(0, \sigma_v^2)$ orthogonal to α_i. $Corr(u_{i0,} u_{it}) = \rho_t$ t=1, 2,…, T

[1] see Devicienti, 2003 for review of the evidence

The approach to modelling the dynamics of individual poverty status considered in this paper is a dynamic random effects probit model where P_{it} denotes the poverty status of individual i=1,2,…,N. X_{it} is a vector of observable characteristics. β is a set of associated parameters to be estimated. The parameter γ represents the true sate dependence that refers to a situation in which the experience of poverty causes a subsequently higher risk of continuing to be poor. α_i represents for all unobserved determinants of poverty that are time invariant for a given household. In the poverty context these might be factors such as intelligence, ability, motivation or general attitude of household members. And finally ε_{it} represents the idiosyncratic error term which is serially correlated over time.

However, in dynamic model, the individual's poverty status in the initial period may be correlated with the factors captured by unobserved determinants of poverty (α_i).For example low intelligence or a lack of abilities will contribute to the risk of being poor at time t=0. To address this issue, we follow Heckman (1981) suggestion and approximate the initial conditions using static probit model (for equation 3). In order to empirically implement the model, we need to specify the stochastic nature of unobserved heterogeneity. For this, we choose a latent class specification which allows for unobserved heterogeneity (α_i), first order state dependence (γ) and serial correlation (ρ) overtime. We follow the Heckman and Singer (1984) approach in which only the constant term varies across the classes. It is assumed that there exists M different set of unobserved determinants of poverty (α_i) each observed with probability π_m (where π_m>0 and $\sum \pi_m$ =1, m=1,2,…M). This specification allows the arbitrary correlation between initial and other periods. It is straightforward to estimate the model with maximum likelihood techniques. However for correlated disturbances the likelihood function of the above dynamic probit model requires the evolution of T-dimensional integrals of normal density functions. Under such circumstances, simulation based estimation (MSL) as proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others, can be used (Lee, 1997). In this case we use simulated maximum likelihood method (for more details see Lee 1997, Hyslop 1999, Islam 2005) and a standard approach to simulation draw has been applied.

4 Results

Based on the econometric model fully specified in section 3, we report results on the nature of poverty dynamics in Ethiopia. We start with a simple static probit model that sets the binary variable of being in poverty or not as functions of several regressors. We then compare it respectively with a model that controls for unobserved household heterogeneity, state dependence and serial correlation. We report the results separately for rural and urban households.

Table 3 provides probit estimates for the probability of falling into poverty with and without controlling for unobserved household heterogeneity in Column 1 and 2 respectively, and dynamic effects with and without controlling for serial correlation in Column 3 and 4 respectively. The key variables used to determine the probability of falling into poverty are the age of the head of the household and its square, which essentially capture life-cycle effects on household welfare such as experience, family formation, asset accumulation, and other inter-generational differences. Mean age within the household and its square is used to measure overall dependency in the household, which affects directly the probability of falling into poverty. The larger the number of dependents (the lower mean age of the household), the higher could be the probability of falling into poverty, and vice versa. The square term captures the effect of having elderly dependents. We have size of the household, education of the wife, agricultural systems, types of major crops cultivated, distance to the nearest market, total value of household asset, size of land and its interaction with household size as potential determinants of poverty.

Column 1 shows the result for simple probit (pooled) model. As expected, the probability of poverty increases with the number of household's size and the coefficient is 0.088. Coffee and Chat are two most important exported cash crops in Ethiopia. The estimated results show that the mean probability of coffee producing households being poor is -0.06 and that of for chat producing households is -0.31. This implies that as exportable crops coffee and Chat has significant role in the alleviation of poverty in Ethiopia. The results show that the coefficient of off-farm employment is statistically significant and positive, which means that off-farm employment is associated with a higher probability of poverty. The results also show that the land size is highly correlated (negatively) with the probability of being in poverty. It is noteworthy that good access to markets has also significant effects.

Column 2 contains the estimated results of latent class probit model which allows for household specific unobserved heterogeneity. The estimated distribution of unobserved heterogeneity (shown at the bottom) indicates that there are two types of households each observed with probability. The estimated probability (0.35) of type 1 households indicates that about 35 percent households have relatively **higher risk of being poor** due to permanent unobserved heterogeneity[2]. The majority, 65 percent, of the households belongs to the type 2 where the households have a relatively lower risk of being poor.

Columns 3 report the results from the dynamic model where the first order state dependence SD(1) (lag dependent variable) is included in the list of explanatory variables discussed above. The model allows the correlation between unobserved heterogeneity of initial and other periods. The result is quite interesting. The estimated lag dependent effect (true state dependence) is significant and the coefficient is 0.33. It suggests that even after controlling for observed and unobserved household specific characteristics, past experience was connected to a higher future poverty risk. This means that the households who experienced poverty during the preceding year have a higher risk of staying in poverty than the household who was not poor the previous year. In comparison to the results for the static random effects model in column 2, these results show the addition of lag dependent variable has a significant effect on covariates. For example the estimated coefficients for chat have decline 52%. It is also observe that there is a dramatic improvement in the fit of the model, as measured by the log likelihood, if the dynamic is modelled.

Column 4 contains the results of latent class probit specification which allows for unobserved heterogeneity, first order state dependence SD (1) and first order serial

[2]This is because the estimated value (1.81) of support point for type 1 household is higher than the estimated value (0.97) of type 2 household.

correlation AR(1) in the error components. The results show that the estimated serial correlation coefficient AR (1) is negative and statistically significant, with a magnitude of about -0.19[3].The result indicates that even after controlling for unobserved heterogeneity and first order state dependence SD(1), there is a negative transitory shock in poverty persistency which persist longer than one year but deteriorate in effect over time.[4]

Similar latent class probit regression is applied for the urban households in Table 4. As was the case with the rural sample household's size is positively related with poverty. The results show that the wife primary education is negative and statistically significant in all specifications. This suggests that if the wife has completed primary education, that will significantly decrease the chance of the household falling into poverty.

The model (column 3 Table 4) that allows household specific heterogeneity and first order state dependence SD (1) show almost the same pattern as for the rural sample. However the estimated proportion of type 1 households is 35 percentages and the proportion of type 2 households is 65 percentages. The results show that including first order state dependence has very little effect on unobserved heterogeneity (There is a little change of the estimated unobserved heterogeneity if the lag dependent variable is allowed). It is also observed that the proportion of type 1 in rural households is 26 percent lower than the proportion of type 1 households in urban households.

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[3] This confirms the negative transitory shocks in other studies. For example, Chay and Hyslop (1998) estimate dynamic models of welfare and labor force participation and find that the estimated AR(1) coefficient is always negative and statistically significant except for the exogenous initial condition models.

[4] The issue about transitory shock is discussed in Lillard and Willis (1978).

Again, the model (column 4 Table 4) which allows household specific unobserved heterogeneity, first order state dependence SD(1) and first order auto regressive error components AR(1) shows that the addition of transitory component of the error has significant effect on the model. The model found a statistically significant effect of transitory components in poverty persistency and the coefficient AR(1) is -0.45. However, the effect of transitory shocks in poverty persistency in urban households is stronger than that of in rural households. The results show that the estimated effects of the covariates and heterogeneity distribution are very sensitive to AR (1). The estimated proportion of type 1 households is now 4 percent and the estimated value of support point for type 1 household is -1,192 which is relatively higher than the other (type 1) support point (-1,923). This implies that type 1 (4 percent) households has stronger heterogeneity effect than the type 2 household (96 percent). The result also show a substantial increase in the estimated state dependence when first order autoregressive error components AR (1) is allowed. The estimated true state dependence is 1.49 which is almost three times larger (in magnitudes) than the model without AR (1). The model also shows that the degree of true state dependence is 60 percent lower in rural households than the urban households. This implies that the poverty in urban households is more persistent than the rural households.

5 Conclusion

This study focuses on the persistence of poverty in Ethiopia. We consider latent class probit models which allow for three components that generate serial persistence in poverty: a permanent household specific effect to control for unobserved heterogeneity, a serially correlated error component and state dependence components to control for the effects of previous poverty status on the current poverty status. According to Heckman (1981) the former two is termed as “spurious” state dependence where the source of persistence is unobserved. The last one is termed as true “state” or structural state dependence where the past experience has an actual behavioural effect. The empirical results for both rural and urban areas show that each of these components is statistically significant in characterising the dynamics of poverty in Ethiopia. The results show that the urban household display a greater degree of true state dependence than the rural households. This indicates that an urban household that experienced poverty during the preceding year has higher risk (almost twice) of staying in poverty than a rural household. Our result also shows that the majority of the households in rural area belong to the type 2 heterogeneity group where the households have a relatively lower risk of being poor due to permanent unobserved heterogeneity. However this proportion in urban area is quite high. Furthermore the effect of transitory shocks in poverty persistency appears to be stronger among urban households than rural households.

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Table 1: Percentage of Households by Poverty Status: 1994-2000

Poverty Status	Rural	Urban
Always poor	7.3	15.4
Once poor	28.9	20.4
Twice Poor	23.0	18.3
Thrice Poor	20.0	16.0
Never Poor	20.8	39.4

Source: Bigsten and Shimeles (2005)

Table 2a: Descriptive Statistics for Selected Variables by the Number of Times in Poverty During 1994-2000: Rural Households

Variable	Never Poor	Once Poor	Twice Poor	Three Times poor	Always Poor
Household size (numbers)	4.9	5.8	6.4	6.9	8.3
Age of head of household (years)	44	46	47	47	48
Female headed households (%)	23	22	18	22	16
Household head with primary education. (%)	12	10	7	7	3
Wife completed primary school (%)	4	2	2	1	1
Land size (hectare)	1.1	0.9	.7	0.7	0.5
Asset value(birr)	225	173	152	87	92
Off-farm employment (%)	24	38	39	45	29
No of oxen owned	2	1.7	1.4	1.1	0.78

Source: Bigsten and Shimeles (2005)

Table 2b: Descriptive Statistics for Selected Variables by the Number of Times in Poverty During 1994-2000: Urban Households

Variable	Never Poor	Once Poor	Twice Poor	Three Times poor	Always Poor
Household size (no)	5.7	6.3	6.6	6.9	7.6
Age of head of households(years)	47	49	50	48	51
Female headed households (%)	40	44	46	39	43
Head of household with primary educ. (%)	60	44	30	27	20
Wife with primary education (%)	33	21	16	12	8
Private business (%)	3	2	2	0.0	0.0
Own account employee (%)	19	17	15	12	16
Civil servant (%)	21	15	11	9	9
Public sector employee (%)	9	7	5	6	5
Private sector employee (%)	6	5	5	3	3
Casual worker (%)	4	6	7	14	32
Unemployed (%)	4	4	7	4	9
Resides in the capital (%)	68	71	79	78	87

Source: Bigsten and Shimeles (2005)

Table 3: Estimated probit effect (Rural areas).

	Simple Probit (1)		Latent Class Probit (2)		Latent Class Dynamic SD(1) Probit (3)		Latent Class Dynamic SD(1)+AR(1) Probit (4)	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
Const	1.044	12.23	-	-	-	-	-	-
Hhsize	0.088	16.33	0.092	9.94	0.100	13.11	0.099	10.50
Teff	0.011	0.87	-0.002	-0.08	-0.012	-0.58	-0.003	-0.06
Coffee	-0.130	-5.85	-0.171	-3.51	-0.012	-0.45	0.007	0.10
Chat	-0.647	-10.12	-0.692	-7.58	-0.387	-4.48	-0.323	-4.17
Landsize	-0.105	-8.44	-0.124	-5.16	-0.068	-4.47	-0.063	-2.14
Oxen	-0.016	-1.99	-0.013	-0.76	-0.005	-0.21	-0.005	-0.27
Off-farm	0.166	9.87	0.184	3.95	0.151	3.21	0.129	3.18
Market	-0.004	-7.42	-0.005	-6.12	-0.002	-3.11	-0.002	-2.81
Grozone	-0.412	-10.26	-0.464	-7.58	-0.512	-1.24	-0.463	-7.97
Wifeprim	-0.396	-5.18	-0.392	-2.61	-0.211	-1.49	-0.176	-1.30
Meanage	-0.018	-2.68	-0.023	-3.48	-0.010	-1.61	-0.006	-0.76
Agehhh	0.005	1.69	0.006	0.89	-0.003	-0.61	-0.005	-0.69
Meanage2	0.011	1.33	0.018	2.14	0.007	0.97	0.005	0.45
Agehhh2	0.001	0.25	0.001	0.16	0.008	1.51	0.008	1.23
Assetval	-0.064	-13.65	-0.064	-8.25	-0.058	-5.26	-0.057	-7.32
Land*Hhsize	-0.003	-1.308	-0.002	-0.77	-0.006	-2.65	-0.006	-1.69
LagP	-	-	-	-	0.331	8.54	0.598	6.64
AR(1)	-	-	-	-	-	-	**-0.188**	3.55
Type 1	-	-	**1.807**	9.50	**1.149**	7.74	**0.788**	2.74
Type 2	-	-	**0.968**	5.03	**0.858**	6.39	**0.596**	2.34
Pr Type 1	-	-	**0.35**	**-**	**0.26**	**-**	**0.26**	-
Pr Type 2	-	-	**0.65**	**-**	**0.74**	**-**	**0.74**	-
Log Likelihood	2956.59	-	2933.88	-	2826.82	-	2822.59	-

Notes: The estimated coefficients of initial year of corresponding specifications are not reported.

Table 4: Estimated probit effect (Urban areas)

	Simple Probit (1)		Latent Class Probit (2)		Latent Class Dynamic SD(1) Probit (3)		Latent Class Dynamic SD(1)+AR(1) Probit (4)	
	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio	Coeff	t-ratio
Constant	-0.330	-1.13	-	-	-	-	-	-
Hhsize	0.113	10.73	0.143	9.86	0.139	14.04	0.113	12.17
Hhhfem	0.169	3.10	0.260	3.20	0.171	6.29	0.099	3.45
Addis	0.143	0.89	0.114	0.39	0.144	4.54	0.123	3.29
Awasa	-0.019	-0.09	-0.088	-0.26	0.038	0.70	0.096	1.59
Bahadar	-0.408	-1.50	-0.551	-1.08	-0.051	-0.67	0.113	0.88
Dessie	0.192	0.94	0.093	0.25	0.416	3.89	0.447	3.79
Iredawa	-0.101	-0.55	-0.209	-0.65	0.167	2.59	0.294	3.99
Jimma	0.140	0.79	0.127	0.41	0.267	3.67	0.352	4.78
Amhara	-0.141	-1.54	-0.202	-1.37	-0.136	-3.72	-0.070	-2.12
Oromo	-0.139	-1.42	-0.231	-1.48	-0.132	-4.21	-0.098	-2.46
Tigrawi	-0.626	-4.16	-0.880	-3.29	-0.529	-6.95	-0.273	-3.46
Gurage	-0.066	-0.63	-0.112	-0.70	-0.113	-2.49	-0.122	-2.24
Wifeprime	-0.465	-6.84	-0.516	-5.41	-0.388	-7.31	-0.265	-5.07
Unemp	0.522	4.72	0.609	4.23	0.489	4.37	0.323	3.54
Fedn	-0.220	-1.65	-0.215	-0.96	-0.112	-2.48	-0.088	-1.59
Ffarmer	0.072	0.95	0.116	0.92	0.089	3.60	0.005	0.15
Fgempl	-0.530	-4.04	-0.667	-3.18	-0.486	-3.96	-0.364	-3.35
Fsempl	-0.427	-3.87	-0.465	-2.55	-0.319	-4.38	-0.233	-3.37
Meanage	-0.036	-3.56	-0.029	-1.82	-0.019	-2.86	-0.011	-1.37
Meanage2	0.034	2.54	0.024	1.11	0.019	2.18	0.015	1.28
Agehhh	0.003	0.40	0.009	0.77	-0.003	-0.70	-0.009	-1.46
Agehhh2	0.004	0.50	0.001	0.02	0.007	1.48	0.009	1.44
Avalue	-0.005	-11.15	-0.004	-23.87	-0.003	-7.17	-0.003	-6.28
LagP	-	-	-	-	0.543	10.77	**1.490**	18.76
AR(1)	-	-	-	-	-	-	**-0.452**	-12.39
Type 1	-	-	0.053	0.11	-0.470	-11.57	-1.192	-6.08
Type 2	-	-	-1.37	-2.78	-1.329	-5.11	-1.923	-9.39
Pr Type 1	-	-	**0.38**	-	**0.35**	-	**0.04**	-
Pr Type 2	-	-	0.62	-	0.65	-	0.96	-
Log Likelihood	1828.77	-	1739.42	-	1693.56	-	1662.76	-

Notes: The estimated coefficients of initial year of corresponding specifications are not reported.

Appendix Table (1): Definition of Variables used in the study

Variable definition	Explanation
Rural Households	
Household Characteristics	
Hhsize	Household size
Agehhh	Age of head of the household
Agehhh2	Squared age of the head of the household
Meanage	Mean age of the household
Meanage2	Squared mean age of the household
Wifeprime	Dummy for a wife completing primary school
Landsz	Land size
Assetval	Value of household assets (durables)
Oxen	Number of oxen owned
Types of crops planted	
Teff	Dummy if major crop grown is teff
Coffee	Dummy if major crop grown is coffee
Chat	Dummy if major crop grown is chat
Other means of income	
Offfarm	Off farm income
Regional variables	
Market	Access to local market
Urban Households	
Household Characteristics	
Hhsize	Household size
Agehhh	Age of head of household
Agehhh2	Squared age of head of household
Meanage	Mean age in the household
Meanage2	Squared mean age in the household
Hhhfem	Dummy if household head is female
Hhhprime	Dummy if household head completed primary school
Wifeprime	Dummy if wife completed primary school
Avalue	Value of household assets (durables)
Occupation	
Fedn	Father of household head has primary education
Ffarmer	Father of household head is farmer
Fgempl	Father of household head is government employed
Fsempl	Father of household head is self employed
Unemp	Household head is unemployed
Regional Dummies	
Addis	
Awasa	
Bahadar	
Dessie	
Iredawa	
Jimma	
Amhara	
Oromo	
Tigrawi	
Gurage	