ELSEVIER
www.elsevier.com/locate/worlddev

World Development Vol. 36, No. 9, pp. 1559–1584, 2008

0305-750X/$ - see front matter

doi:10.1016/j.worlddev.2007.09.002

Poverty Transition and Persistence in Ethiopia: 1994–2004

ARNE BIGSTEN and ABEBE SHIMELES *
University of Gothenburg, Sweden

Summary. — This study analyzes the persistence of poverty in both rural and urban areas in Ethiopia during 1994–2004. The key finding is that households move frequently in and out of poverty but the difficulty of exiting from poverty, like the chance of avoiding slipping back, increases with the time spent in that state and varies considerably between male- and female-headed households. Our results imply that it is important to design anti-poverty policies both to hinder households from slipping into extreme poverty and to minimize the length of the poverty spell for households once they have fallen into it.

Key words — poverty persistence, hazard models, state dependence, Ethiopia

1. INTRODUCTION

Despite moderate *per capita* growth in the last decade, Ethiopia's vulnerability to income and asset shocks remained entrenched. Both urban and rural household incomes fluctuate strongly and since there is very limited scope for insurance, household consumption and poverty vary considerably over time. Households try to deal with income risks in different ways. First, risk has an *ex ante* impact on household behavior, where uninsured risk makes them avoid profitable but risky activities and to pursue those that are less risky and engage in asset diversification. Second, there is an *ex post* impact of negative shocks that households seek to handle with various coping strategies. These may include self-insurance via precautionary savings or the use of various risk-sharing arrangements. The lack of insurance also means that human and physical assets may be lost and this reduces future growth (Biewen, 2004). Thus, the incidence of poverty could be reduced very significantly if policies to deal with shocks could be put in place. One needs to have policies to reduce risks and mitigate its consequences at the core of growth and poverty reduction efforts (Dercon, 2007).

While sustained growth is central to the reduction of poverty in countries such as Ethiopia (Bigsten & Shimeles, 2007), the possibility that poverty spells caused by short-lived shocks may persist is clearly a cause for concern. Safety nets that keep households out of poverty would have significant poverty reducing as well as growth-enhancing effects (Barrett, Carter, & Little, 2006; Baulch & Hoddinott, 2000). Therefore, it is important for policy makers to understand the time-varying and individual-specific determinants of households' poverty transitions (Devicienti & Gualtieri, 2006). This paper contributes to our understanding of poverty persistence and transition in a very poor African economy during the decade 1994–2004 by focusing on the prospects of exiting poverty for households that started a poverty spell

* This paper is the result of work that started in 1994, so the people who should be thanked are too numerous to be mentioned. Still, we would like to thank Stefan Dercon and Erik Thorbecke for comments of earlier versions of this paper and seminar participants at seminars at University of Gothenburg, a PEGnet conference in Berlin, and a conference in and Addis Ababa organized by the AERC. We would also like to thank the editor of the journal, two anonymous referees, Mark Stewart and Francesco Devicienti for very helpful comments. Finally, financial support from SAREC and the AERC is gratefully acknowledged Final revision accepted: September 3, 2007.

and correspondingly of re-entering poverty for those that started a spell out of poverty.

The dynamics of income-poverty has generally been assessed in three ways: the spells approach focusing on probabilities of ending poverty or a non-poverty spell (e.g., Bane & Ellwood, 1986; Devicienti, 2003; Stevens, 1999), statistical methods that model income or consumption with complex lag structure of the error terms (e.g., Lillard & Willis, 1978), and approaches that separate the chronic from transient component of poverty (Hulme & Shepherd, 2003; Jalan & Ravallion, 2000; Rodgers & Rodgers, 1991).

Studies of poverty dynamics in a less developed country context emerged quite recently (e.g., Aliber, 2003; Baulch & Hoddinott, 2000; Carter & Barrett, 2006; Carter & May, 2001; Deininger & Okidi, 2003; Grootaert & Kanbur, 1995; Haddad & Ahmed, 2003; Krishna, 2004; Sen, 2003). Most studies of the dynamics of poverty focus on the mobility across a given income threshold or poverty line, and attempt to distinguish chronic from transient poverty. [1] Ethiopia, being one of the few countries in Africa where longitudinal data on household welfare are available, poverty dynamics has been investigated in some previous work. Dercon (2004) and Dercon *et al.* (2005) show that rural households in Ethiopia are affected by a large number of shocks of different types such as drought (most importantly) but also death and serious illness, price shocks on inputs and output, crop pests, and crime. Dercon and Krishnan (2000) explore short-term vulnerability of rural households in Ethiopia finding that poverty rates were very similar over three surveys in 18 months, although consumption variability and transitions in and out of poverty was high. Bigsten, Kebede, Shimeles, and Taddesse (2003) and Bigsten and Shimeles (2005) report poverty transition and mobility for the period 1994–97 covering rural as well as urban areas. Dercon (2006) analyzes poverty changes in rural Ethiopia during 1989–95, and finds that shocks led to changes in the returns to land, labor, human capital, and location. This suggests that alongside the short-run poverty impact there are serious negative growth implications of shocks in Ethiopia.

This paper examines poverty dynamics in Ethiopia using the spells approach, which is a powerful tool in examining the persistence of poverty, on a panel data set that covers 10 years (1994–2004) in five waves. The period under study is characterized by fast changing circumstances, from peace, stability, and a favorable macroeconomic environment during 1994–97, to widespread drought, terms of trade shocks, political instability and war with Eritrea during 1998–2000, and an overall recovery during 2001–04. Also, the country has suffered from the spread of HIV/AIDs, which has caused considerable loss of human lives and disruption of livelihoods. These events have shaped the fortunes of households and affected their mobility across the survival threshold. During the decade under discussion, the Ethiopian economy had an average *per capita* GDP growth rate of about 2% but with large swings (see Figure 1).

Our results indicate that extreme poverty declined during the decade, more markedly in rural than in urban areas, and the changes in poverty do reflect the changing economic fortunes of Ethiopia. Overall, a very large segment of the sample population in the panel (about 70%) was affected by poverty at least once during the decade under study, showing that poverty is widespread in Ethiopia. The key result from the non-parametric analysis of poverty spells is that once a household slips into poverty, the probability of exiting from it is very low. The probability of exiting diminishes further as the spell in poverty increases. The risk that an initially poor household would re-enter into poverty after a single spell out of poverty is relatively low. Rural households had a higher probability of ending a spell of poverty and a lower probability of falling back than households in urban areas, suggesting that poverty is more persistent in urban than in rural areas. Male-headed households in rural areas tend to have a higher probability of ending a poverty spell and at the same time a higher risk of slipping back into poverty. In urban areas, male-headed households had more or less an equal chance of escaping poverty, but a much higher risk of slipping back into poverty than female-headed households.

This paper also estimates a model of poverty dynamics that decomposes poverty persistence due to unobserved household heterogeneity and true state dependence after controlling for transitory shocks that may also include measurement errors. Also the results from this exercise indicate strong state dependence of poverty in rural as well as urban areas.

The next section presents the methods used to capture poverty transitions and persistence, Section 3 describes the data and presents descriptive statistics on the evolution of long-

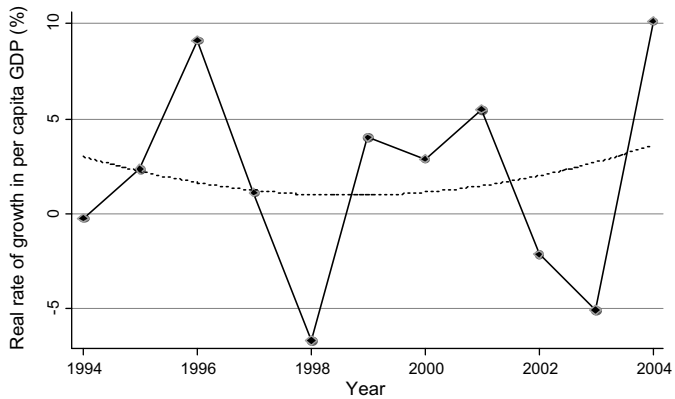

Figure 1. *Per capita GDP growth rate of Ethiopia: 1994–2004. Source: WDI (2007).*

term poverty, Section 4 provides exit and re-entry rates and its determinants using non-parametric and parametric approaches, and Section 5 summarizes and draws conclusions.

2. METHODOLOGY

(a) *Methods for analysing poverty spells and their determinants*

The standard approach to analyze poverty spells (e.g., Bane & Ellwood, 1986; Stevens, 1994, 1996) is to compute the probabilities of exiting and re-entering poverty given certain states and other characteristics of households, using either non-parametric or parametric methods. The probabilities can be considered as random variables with known distributions (see Antolin, Dang, & Oxley, 1999). Survival analysis based on duration data of poverty spells attempts to provide estimates for such important questions as what are the fraction of the population that remain poor after "*t*" periods (a measure of poverty persistence)? Of those that remain poor in each period, what percentage escapes poverty (exit or hazard rate)? How can multiple events or spells be taken into account, etc.? Some of the methodological challenges in addressing these issues revolve around the censoring of the duration data. That is to say in most cases only partial information is available on poverty or non-poverty spells for each household. Typically one faces a situation where a poverty spell might have already begun for a household long before it came under observation for the first time (left-censoring), or some households may end a poverty spell after the last observation period (right-censoring). Also, interval censoring can arise in a situation where we cannot observe the precise time a household escaped or re-entered poverty. Often, as is the case here, the event of exiting poverty or re-entering is observed in the interval of two rounds, during which period any number of unobserved transitions in and out of poverty might have occurred, creating perhaps a problem of aggregation bias. In the case of left-censored poverty spells, most studies prefer to ignore them (e.g., Bane & Ellwood, 1986; Devicienti, 2003; Stevens, 1999), as it is not straightforward to accommodate them in the estimation, though they play an important role (see for example Iceland, 1997). Right-censored observations are easily accommodated in the standard survival functions such as the one used in this study. Regarding the issue of interval censoring, previous studies have shown that the aggregation bias due to lack of information on the precise time of exit or re-entry and other episodes that may have occurred in between rounds are minimal, thus no effort is made here to address them (e.g., Bergstrom & Edin, 1992).

There are non-parametric and parametric methods commonly used in survival analysis to capture poverty persistence. Non-parametric methods are quite powerful in estimating the probabilities of exiting or re-entering poverty without assuming any functional form on the distribution of the spells (Kaplan & Meier, 1958). We report two hazard rates, one for the probability of exiting poverty at successive durations of the poverty spell and another for the probability of re-entering poverty at

successive durations of the non-poverty spell. Exit rates relate to a cohort of households that have just started a spell of poverty and thus are "at risk" of exit thereafter. That is to say, a poverty spell begins at period t for those households who were observed to be non-poor up until $t-1$. In this regard, those that fail to escape poverty create a right-censored observation, as the spell would continue at the year of the last observation (in our case 2004). Similarly, re-entry rates refer to the cohort of households that have just started a non-poverty spell at period t, having been poor until $t-1$ and are "at risk" of re-entering poverty (see e.g., Bane & Ellwood, 1986; Devicienti, 2003; Stevens, 1999 for detailed discussion of exit and re-entry rates).

Given this definition, the observations relevant for estimating the exit and re-entry rates are spells that occur in wave 2 or later due to the exclusion of left-censored observations.

We used the non-parametric Kaplan–Meier [2] method to estimate the probability of new-poor surviving as poor or of newly non-poor surviving as non-poor. The survivor function $S(t)$ is defined as the probability of survival past time t (or equivalently the probability of failing after t). Suppose our observation is generated within a discrete-time interval $t_1, \ldots, t_k$; then the number of distinct failure times observed in the data (or the product limit estimate) is given by

$$\hat{S}(t) = \prod_{j|t_j \leqslant t} \left(\frac{n_j - d_j}{n_j} \right), \tag{1}$$

where n_j is the number of individuals at risk at time j, and d_j is the number of failures at time t_j. The product is overall observed failure times less than or equal to t. The Kaplan–Meier estimator readily accommodates right-censored observations through n_j since households that failed to end a poverty or non-poverty spell in each period contribute to it. The standard error of Eqn. (1) can be approximated by

$$SD(\hat{S}(t)) = \hat{S}(t)^2 \sum_{t_i, t} \frac{d_i}{n_i(n_i - d_i)}. \tag{2}$$

The hazard rate, $h(t)$, for ending a poverty or non-poverty spell at period t can be computed easily from (1)

$$h(t) = \left\{ \begin{array}{ll} 1 - S(t)^{\wedge} & \text{if } t = 1, \\ \frac{\hat{S}(t) - \hat{S}(t-1)}{\hat{S}(t)} & \text{if } t > 1. \end{array} \right\} \tag{3}$$

Eqn. (3) is the basis for computing exit and re-entry rates reported in this paper.

The parametric method, on the other hand, models the distribution of spell durations via the probabilities of ending a spell. [3] Suppose we are interested in modeling the duration of poverty for household i which entered at t_0, [4] then we can define a dummy $\delta_i = 1$ to distinguish households which completed the spell (exited out of poverty) from those who continued in the poverty spell, $\delta_i = 0$ at the end of the period (months, years or rounds in our case). The percentage that completed a spell is the event-rate (or "hazard rate") for that period and corresponds to a "survivor-rate," which indicates the percentage continuing in poverty at that point. Formally, a discrete-time hazard rate h_{it} can be defined as

$$h_i(t) = pr(T_i = t / T_i \geqslant t; X_{it}), \tag{4}$$

where T_i is the time when poverty spell ended, and X_{it} refers to a vector of household characteristics and other variables. The overall probability of ending a spell at $T_i = t$ is given by the product of the probabilities that the spell has not ended from $t = t_0$ until $t-1$ and that it has ended at time t. Similarly, the probability of ending the spell at $T_i > t$ is given by the joint probability poverty that has not ended up to t, that is, [5]

$$\begin{aligned} prob(T_i = t) &= h_{it} \prod_{k=1}^{t-1} 1 - h_{ik}, \\ prob(T_i \succ t) &= \prod_{k=1}^{t} (1 - h_{ik}). \end{aligned} \tag{5}$$

One of the most frequently used parametric models is the proportional hazard model given by

$$h(t|x_{ij}) = h_0 \exp(x_{ij}\beta_x), \tag{6}$$

where h_0 is the baseline exit (or re-entry) rate and X_{ij} is the vector of variables believed to influence the hazard. It is possible to control for unobserved household heterogeneity [6] by adding a multiplicative random error term [7] into Eqn. (6) so that the instantaneous hazard rate becomes

$$h(t|x_j) = h_0 \varepsilon_j \exp(x_j \beta_x) = h_0 \exp[X_j \beta + \log(\varepsilon_j)]. \tag{7}$$

The underlying log-likelihood function for Eqn. (7) is a generalized linear model of the binomial family with complementary log–log

link (Jenkins, 1995). One of the features of the proportional hazard models is that individual hazard rates depend on the covariates, with the baseline hazard function remaining the same for all.

The other common way to specify the distribution of the hazard rate is the logistic structure. In this setup, the dependence of the hazard upon duration in spell t is explicitly emphasized, thus giving a flexible formulation compared to the proportional hazard models. In most applications, however, the logistic specification turns out to be very similar with the proportional hazard model the reason being that the former approximates the latter as the hazard rates become smaller (Jenkins, 1995). Thus, we report only results based on the proportional hazard model with and without controlling for the effects of unobserved household characteristics, which play an important role in creating biases on the role spell duration plays on the probability of exit (re-entry) from (into) poverty. For instance there are a number of unobserved characteristics, such as motivation, social networks, membership to solidarity groups, good health, and political affiliation by household heads and its members that facilitate or impede the end of a poverty or non-poverty spell, which if not controlled, can bias upwards the effect of spell duration on the probability of exiting poverty, and vice versa for re-entry rates.

(b) *Sources of poverty persistence: state dependence, transitory shocks and unobserved household heterogeneity*

One of the important reasons for studying poverty dynamics is to capture the interplay between a household's past history in poverty and its persistence. We may broadly identify three sources of poverty persistence. [8] A household may experience extended poverty because of either transitory shocks that induce a general slowdown in economic activities, or persistent unobserved characteristics that are disadvantageous for escaping poverty, or the tendency of poverty to propagate itself due to a number of behavioral responses induced by the past history of poverty, commonly referred to as true state dependence of poverty persistence or "scarring effect" in the literature of poverty dynamics where past poverty results in depreciation of human and physical capital stock, that may potentially spark a poverty spiral. Thus, empirical models of poverty dynamics need to control for effects of unobserved heterogeneity and transitory shocks to obtain the measure of true state dependence.

Though the non-parametric Kaplan–Meir survival function provides consistent estimates of hazard rates, [9] as well as the degree of duration dependence, it does not distinguish the many possible sources of persistence. Similarly, the parametric models, logistic as well as proportional hazard models, even though they allow for the estimation of factors that contribute to ending a particular spell, including the effect of the duration of the spell itself, are less suitable to explicitly model true state dependence (see e.g., Cappelari & Jenkins, 2002; Devicienti, 2003).

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

$$P_{it} = \phi(P_{it-1}, X_{it}, \alpha_i) \tag{8}$$

$(i = 1, \ldots, N;\ t = 2, \ldots, T)$, where P_{it} is equal to 1 if the ith household is poor at time t and zero otherwise. The vector X_{it} captures covariates of poverty and α_i controls for the unobserved heterogeneity of each household. True state dependence in poverty dynamics exists if current poverty is significantly correlated with lagged poverty.

There are few studies (Biewen, 2004; Cappellari & Jenkins, 2004) that attempt to link the current state of poverty using a first-order auto-regressive structure of the dependent variable, and most do not control for serial correlation in the error components. The empirical model used here is a dynamic probit model, which controls for state dependence, unobserved heterogeneity and serial correlation given by Eqns. (9) and (10).

$$P(P_{i0}|X_{io}, \alpha_i) = \left\{ \begin{array}{ll} 1 & \text{if } \beta_0 X_{i0} + u_{i0} > 0 \\ 0 & \text{else} \end{array} \right\}, \tag{9}$$

$$\begin{aligned} &P(P_{it}|X_{it}, \alpha_i, P_{io}, \ldots, P_{it-1}) \\ &\quad = \left\{ \begin{array}{ll} 1 & \text{if } \gamma P_{it-1} + \beta_i X_{it} + u_{it} > 0 \\ 0 & \text{else} \end{array} \right\} \\ &\qquad (i = 1, \ldots, N;\ t = 2, \ldots, T), \end{aligned} \tag{10}$$

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

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

$$v_{it} \sim N(0, \sigma_v^2) \text{ and orthogonal to } \alpha_i,$$

$$Corr(u_{i0,} u_{it}) = \rho_t t = 1, 2, \ldots, T,$$

where $P(\cdot)$ is the conditional probability of falling into poverty, β is a vector of associated

parameters to be estimated, the parameter γ represents the true state dependence that refers to a situation in which the experience of poverty causes a subsequently higher risk of continuing to be poor, sometimes also referred to as a measure of a poverty trap (Chay *et al.*, 1998) and α_i represents unobserved determinants of poverty that are time invariant for a given household. In the poverty context these might be factors such as innate ability, motivation or general attitude of household members. And finally ε_{it} represents the idiosyncratic error term, which is serially correlated over time.

The key estimation problem of the dynamic poverty model laid out in (9) and (10) is that the individual's poverty status in the initial period may be correlated with the factors captured by unobserved determinants of poverty (α_i). [10] For example, low motivation, lack of abilities, physical constitution, parental background, or social networks can contribute to the risk of being poor at time $t = 0$. The easiest approach to estimate Eqns. (9) and (10) would be to treat initial conditions or poverty states as exogenously given. This assumption, however, is flawed since it considers initial state of poverty uncorrelated either with unobserved household or individual characteristics, or with observed correlates of poverty. A better alternative is to allow the initial condition to be random, such as Heckman (1981) suggestion of approximating the initial conditions using a static probit model (for Eqn. (9)). That is

$$P_{i0} = \beta_0 X_{i0} + u_{i0}, \qquad u_{i0} = \theta\alpha_i + \varepsilon_{i0} \tag{11}$$

($\theta > 0$), with α_i and ε_{i0} assumed to be uncorrelated. If α_i is treated as normally distributed, then the likelihood function underlying (9) and (10) can be evaluated using Gaussian–Hermite quadrature. An alternative would be to use discrete approximations of the unobserved heterogeneity that varies across a group of individuals with known probabilities. [11] The estimation of Eqns. (9) and (10) gets complicated when serial correlation of the error terms is allowed for. In that case the likelihood function of the dynamic probit model requires the evolution of T-dimensional integrals of normal density functions that can be estimated with the Maximum Simulated Likelihood method (MSL). [12] We report results based on MSL for rural and urban dynamic poverty model for the period 1994–2004.

3. DATA AND DESCRIPTIVE STATISTICS

Data from 1500 rural and 1500 urban households were collected in 1994, 1995, 1997, 2000 and 2004 by the Department of Economics, Addis Ababa University, in collaboration with University of Oxford (rural) and University of Gothenburg (urban) covering household living conditions including income, expenditure, demographics, health and education status, occupation, production-activities, asset-ownership, and other variables.

Stratified sampling was used to take agro-ecological diversities into account, and to include all the major towns. 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 were selected carefully to allow 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.

The common problem in using consumption expenditure for poverty analysis is that of measurement errors. The major source of errors could come from problems associated with accurate reporting during data collection, which in general has to do with the level of disaggregation of consumption baskets. The finer the consumption breakdown, the better the accuracy of measurement (e.g., Deaton, 1997). In our case, the consumption breakdown is as detailed as one possibly could make it, and has been held constant to allow inter-temporal comparisons. In computing consumption expenditures, we used quantities reported for each commodity by respondents and per unit prices from the nearby market. A notable problem in this exercise was the different measurement units applied by especially farmers residing in different villages. Major food expenses among households in Ethiopia are difficult to measure, particularly in rural areas, because of problems related to 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*. [13] Cereals, which make up the bulk of food consumption,

are 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. To address this issue, we used carefully constructed conversion factors for all types of commodities that are comparable across households.

There may also be other sources of error that are systematic across households (say better educated households could be relatively good at keeping records of their regular expenses compared to less educated ones), or across survey periods (seasonality effects). So, consumption expenditure is not immune to measurement error even in the best-administered surveys. There are no readily available means, like alternative data sources, [14] to deal with the effects of measurement errors on our basic estimates of poverty persistence. Nevertheless, we employed a model of consumption expenditure as functions of exogenous household and community characteristics, along with unobserved heterogeneity, to predict consumption expenditure for each household as part of our effort to address measurement error. Its general form follows that of Datt and Joliffe (2005)

$$\ln c_{it} = \alpha + \sum_{k}^{K} \beta_k X_{kit} + \sum_{i} \sum_{k} \gamma_k X_{kit} X_{jit} + u_i + \varepsilon_{it}, \tag{12}$$

where c_{it} is real consumption expenditure in adult equivalent by household i at period t, X is a vector of exogenous explanatory variables with vectors of β and γ coefficients, u_i captures unobserved time-invariant household-specific effects, commonly interpreted as a measure of permanent consumption (Dercon & Krishnan, 2000), and ε_{it} is white noise. We employed a fixed-effects method to estimate Eqn. (12) to handle the potential problem of endogeneity due to correlation between u_i and the regressors. For households in rural areas, to predict consumption expenditure per adult equivalent we used explanatory variables such as household demographics (size, composition, and educational levels), dummy for farming systems, size of *per capita* land owned, number of oxen, access to market, rainfall shocks and dummies for survey rounds. For urban areas, household demographics, occupation of the head of the household, parental background of the head of the household, ethnic background of the head, and dummies for town of residence, survey round, etc. We note that consumption expenditure predicted for each household on the basis of (12) addresses not only measurement error, but also changes in consumption due to random shocks. Thus, one would expect limited mobility across the poverty threshold based on this measure.

We report poverty persistence based on two poverty lines, as well as consumption expenditure predicted for each household on the basis of Eqn. (12). The first is the absolute poverty line, which was computed as follows: [15] 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 were scaled so as to give 2,200 calories per day: the minimum level nutritionists require an adult person to subsist in Ethiopia. The cost of purchasing such a bundle was computed using market prices and constitutes the food poverty line. By using the average food-share at the poverty line we 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 are studied at the level of a household. An adjustment is then made for differences in household composition using adult-equivalence scales in consumption. The second poverty line is the relative poverty line, which is set at two-thirds of mean consumption expenditure. [16]

Table 1 shows the evolution of poverty [17] and income distribution over the decade 1994–2004 based on the absolute poverty line. The table shows that absolute poverty declined consistently among panel households in both rural and urban areas during 1994–97 and then increased until 2000 and again declined until 2004. The initial improvements could be due to good weather, strong policy reform and the general economic recovery (see Bigsten *et al.*, 2003). Inequality in consumption also declined in rural areas until 1997 so that the decline in

Table 1. *Poverty trends in Ethiopia: 1994–2004*

Type of welfare (poverty) measure	1994	1995	1997	2000	2004
Rural areas (N = 1250)					
Headcount ratio, *per capita*	56 (1.4)	49 (1.4)	39 (1.3)	50 (1.6)	43 (1.52)
Headcount ratio, per adult equivalent	48 (0.014)	40 (0.014)	29 (0.014)	41 (0.014)	32 (0.016)
Poverty Gap ratio, *per capita*	25.05 (0.51)	21.3 (0.49)	16.5 (0.48)	21.7 (0.49)	16 (0.45)
Poverty Gap ratio, per adult equivalent	21.0 (0.50)	16.0 (0.48)	10 (0.46)	14.0 (0.50)	11 (0.46)
Squared Poverty Gap ratio, *per capita*	16.7 (0.53)	13.3 (0.48)	8.8 (0.41)	13.68 (0.48)	8.0 (0.43)
Squared Poverty Gap ratio, per adult equivalent	13.1 (0.5)	10.2 (0.44)	6.02 (0.34)	10.2 (0.44)	6.0 (0.42)
Gini Coefficient, *per capita*	48 (0.8)*	46 (1.4)*	39 (1.6)*	47 (1.4)*	44 (1.0)*
Gini Coefficient, per adult equivalent	49 (0.8)*	49 (1.3)*	41 (1.6)*	51 (2.0)*	45 (1.1)*
Urban areas (N = 950)					
Headcount ratio, *per capita*	41.0 (0.16)	39.0 (0.161)	33.6 (0.15)	45.2 (0.016)	40.0 (0.012)
Headcount ratio, per adult equivalent	34.0 (0.015)	32.0 (0.014)	27.0 (0.014)	39.0 (0.02)	36.0 (0.015)
Poverty Gap ratio, *per capita*	17.86 (0.56)	16.9 (0.570)	15.7 (0.57)	18.83 (0.58)	16.0 (0.46)
Poverty Gap ratio, per adult equivalent	13.0 (0.21)	11.4 (0.20)	9.6 (0.19)	14.5 (0.24)	12.0 (0.20)
Squared Poverty Gap ratio, *per capita*	9.78 (0.49)	9.02 (0.47)	7.8 (0.44)	10.8 (0.51)	7.7 (0.43)
Squared Poverty Gap ratio, per adult equivalent	6.5 (0.45)	5.6 (0.42)	4.7 (0.39)	7.5 (0.48)	5.6 (0.46)
Gini Coefficient, *per capita*	44 (1.4)*	43 (1.4)*	46 (1.5)*	48 (8.0)*	44 (1.2)*
Gini Coefficient, per adult equivalent	43 (1.3)*	42 (1.0)*	46 (2.0)*	49 (2.3)*	45 (1.1)*

Source: Authors' computations, standard errors in parentheses.
* Bootstrapped standard errors.

poverty was due to both growth and a better distribution of income. In urban areas, poverty declined until 1997 even though income inequality increased. In both areas, poverty rose sharply in 2000 as a consequence of both a decline in *per capita* income and a rise in income inequality. In 2004, the trend in poverty was reversed again due to a modest rise in real *per capita* consumption as well as decline in inequality, especially in urban areas.

It is interesting to note that the extent of average deprivation (measured by P_1) declined in both rural and urban areas, indicating that poor households have increasingly been concentrated around the poverty line over time so that the burden of reducing poverty has fallen somewhat.

Table 2 shows the distribution of rural and urban sample households by the number of times in poverty. Among the five survey waves, only about 4% of rural households and 2.2% of urban households were poor every time. Then extreme poverty is more chronic in rural areas than in urban areas. The fact that over a decade only a fraction of the panel population was "always poor" indicates that over a long-term period, poverty is typically a transitory phenomenon that requires a detailed analysis on what determines the transitional dynamics (see Section 4).

Table 2. *Percentage of households by poverty status: 1994–2004*

Poverty status	Rural	Urban
Never poor	21.39	40.66
Once poor	25.73	25.41
Twice poor	20.59	15.29
Thrice poor	17.50	10.24
Four times poor	10.62	6.18
Always poor	4.16	2.23
Chronic poverty	26.0	25.0

Source: Authors' computations.

On the other hand, only 21% of the rural sample was never poor, compared to 41% of the urban sample. This may be due to higher variability of incomes in rural areas than in urban areas because of the dependence of agricultural incomes on weather and fluctuating output prices. Alternatively the larger fluctuations in consumption in rural areas may be due to the lack of consumption smoothing possibilities.

Tables 3a and 3b report descriptive statistics (means) for the rural and urban samples by the number of times in poverty. Rural households (Table 3a) were consistently poor more often as their size and age of the household head increased, while they had less land and fewer oxen. Their crop-sales and asset-values were

Table 3a. *Descriptive statistics for rural households by poverty status 1994–2004*

	Never poor	Poor once	Poor twice	Poor three or four times	Always poor
Household size	6.1	6.2	6.5	7.2	7.6
Age of head	44.0	46.0	47.0	47.0	48.0
Female head (%)	23.0	22.0	18.0	22.0	16.0
Head completed primary school (%)	12.0	10.0	7.0	7.0	3.0
Wife completed primary school (%)	4.0	2.0	2.0	1.0	1.0
Land size (hectare)	2.0	1.7	1.6	1.0	0.7
No. of oxen owned	2.0	1.7	1.4	1.1	0.8
Crop sale (birr per year)	334	387	289	215	120
Asset value (birr)	301	201	183	115	175
Off-farm employment (%)	30.0	38	39	45	29
No. of oxen owned	1.8	1.4	1.3	1.1	0.6

Source: Authors' computations.

Table 3b. *Descriptive statistics for urban households by poverty status 1994–2004*

	Never poor	Poor once	Poor twice	Poor three or four times	Always poor
Household size	5.8	6.6	6.6	7.3	7.8
Age of head	47.0	49.0	50.0	50.0	51.0
Female head (%)	35.0	38.0	46.0	41.0	44.0
Head completed primary school (%)	62.0	44.0	32.0	24.0	19.0
Wife completed primary school (%)	34.0	21.0	16.0	13.0	9.0
Private business employer (%)	2.0	3.0	1.3	0.0	0.0
Own account employee (%)	16.0	17.0	17.0	12.0	16.0
Civil servant (%)	21.0	13.0	13.0	10.0	6.0
Public sector employee (%)	8.0	8.0	7.0	4.0	6.0
Private sector employee (%)	6.0	6.0	4.0	3.0	7.0
Casual worker (%)	3.0	4.0	7.0	11.0	9.0
Unemployed (%)	4.0	4.0	4.0	7.0	14.0
Resides in Addis Ababa (%)	57.0	61.0	62.0	74.0	83.0

Source: Authors' computations.

also generally less. It was also consistently less likely that the head and/or the wife had completed primary school. With some anomalies, households who were poor more often were also more likely to have heads engaged in off-farm employment, but (perhaps less surprisingly) less likely to have female heads.

Following the discussion above, in the rural as well as urban areas, the proximate correlates of household consumption expenditure used to estimate the parametric models are household demographics, like size and composition of the household, the level of human and physical capital, and proxies for exogenous shocks such as rainfall and unemployment. Within this broad classification of the covariates of poverty transitions, for rural areas, we identified total number of people in the household in each period, mean age of the household (to capture composition) as well as the sex of the head of the household.

In addition, the education of the wife, in contrast to that of the head (see also Bigsten & Shimeles, 2005), turns out to be an important factor in the status, and overall welfare of rural households. Given that farming is the key source of livelihood in rural Ethiopia, we included dummies for different farming systems (cereal growing areas, cash-crop-growing areas, and *enset*-root crop-growing areas) to capture the underlying differences in climate and farming methods. Furthermore, household physical assets were proxied by the total size of land owned and the number of oxen owned. We also included in the model exogenous factors such as access to markets and rainfall shocks [18] as possible factors affecting mobility into and out of poverty. We have used these variables

in the context of both ending a spell of poverty and exiting it, and also ending a spell out of poverty and re-entering it. For households in urban areas, the variables determining exit or re-entry into poverty are basic demographic indicators, occupational structure, and region of residence, exogenous shocks such as unemployment and to a certain extent the ethnic background of the head of the household.

4. POVERTY TRANSITIONS AND PERSISTENCE

(a) *Transition probabilities and "survival functions"*

Table 4 shows transition probabilities by poverty status for the rural and urban households in the sample. Following the first survey, the possible transitions are either that a household that had been poor could remain poor or become non-poor, or a household that had been non-poor could remain non-poor or become poor. The transition probabilities depend on the total number of households in the sample and distributions of households in or out of poverty. Of all the possible transitions (regardless of the initial states) the probability of a household becoming poor in any one of the survey waves in rural areas was 36%, while in urban areas it was 30%. In rural areas, of those that started poor in the initial period, 49% remained poor, whereas of those that started non-poor 73% remained non-poor. So, there was substantial persistence of poverty and non-poverty.

In urban areas, the probability that a poor household in the initial period would remain poor was around 54%, higher than for rural households. In addition, 21% of urban households that had been non-poor in 1994 were poor in 2004, suggesting a higher degree of non-poverty persistence compared to rural households. From Table 4 we also see that mobility in and out of poverty is more extensive in the rural than in the urban areas. Rural households thus experience larger swings in consumption than urban households, indicating higher probability of poverty transition in rural than in urban areas. Tables A.1 and A.2 in Appendix A give a finer breakdown of transition probabilities by decile, but the picture is essentially the same. The high level of churning observed particularly among rural households during the decade could be explained largely by the effects of short-lived shocks and the response by households to recover from them. [19] An obvious limitation of the simple transition probabilities reported in Table 4 is the underlying assumption that repeated experiences in and out of poverty are assumed to be uncorrelated. To get a better measure of poverty transition as well as persistence, it is important to apply survival analysis for poverty spells that start and end during the period under investigation by focussing on a specific pattern of the poverty history of households. As described in Section 2, a typical household may experience a spell of poverty, non-poverty or both over a certain period. For poverty spell to set in, it would have to be preceded by a non-poverty status and vice versa for a non-poverty spell. Households that experience a poverty spell would exit and those that experience a non-poverty spell would re-enter poverty once the spell ends.

Tables 5a and 5b report estimates of poverty exit and re-entry rates for rural and urban households using the Kaplan–Meier estimator (Eqns. (1) and (3)) based on absolute and relative poverty lines (Columns 2 and 3) and consumption expenditure predicted from an econometric model, but using an absolute poverty line (Column 4).

We note that the survival and exit (re-entry) rates reported in Tables 5a, 5b, 6a, 6b, 7a and 7b refer to the round in which the "*d*" spell has started. In our case, the first spell starts in round 2 and ends in round 5 so that the maximum duration of a spell before it ends is three rounds. It follows that exit (re-entry) rates corresponding to "wave 1" refer to the beginning of the spell (round 2) so that there will be no household escaping (re-entering) poverty, and that for "wave 4" refer to the probability of ending a spell in round 5. It is clear for both

Table 4. *Transition probabilities by poverty status in adult equivalents: 1994–2004*

Poverty status	Poor	Non-poor	Total
Rural			
Poor	49.0	51.0	100
Non-poor	27.0	73.0	100
Total	36.0	64.0	100
Urban			
Poor	54.0	46.0	100
Non-poor	21.0	79.0	100
Total	30.0	70.0	100

Source: Authors' computations.

Table 5a. *Rural survival function, poverty exit and re-entry rates using the Kaplan–Meier estimator*

Number of waves since start of poverty spell	Absolute poverty		Relative poverty		Predicted poverty	
	Survivor's function	Exit rates	Survivor's function	Exit rates	Survivor's function	Exit rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.6125 (0.0176)	0.3875 (0.0224)	0.5329 (0.0181)	0.4671 (0.0248)	0.717 (0.0206)	0.283 (0.01)
3	0.4397 (0.0231)	0.2822 (0.0374)	0.3357 (0.0181)	0.37 (0.0336)	0.6136 (0.0226)	0.1442 (0.0123)
4	0.3058 (0.0339)	0.3043 (0.0813)	0.2048 (0.0187)	0.3898 (0.0575)	0.3917 (0.024)	0.3617 (0.0132)
Number of waves since start of non-poverty spell	Survivor's function	Re-entry rate	Survivor's function	Re-entry rate	Survivor's function	Re-entry rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.6567 (0.0205)	0.3433 (0.0253)	0.812 (0.0119)	0.188 (0.0132)	0.8913 (0.01)	0.1087 (0.0106)
3	0.4438 (0.0227)	0.3242 (0.0333)	0.6438 (0.0148)	0.2072 (0.0158)	0.8304 (0.0123)	0.0683 (0.0094)
4	0.3582 (0.0235)	0.1929 (0.0371)	0.5461 (0.0161)	0.1518 (0.0172)	0.8029 (0.0132)	0.0331 (0.0069)

Source: Authors' computations. Terms in brackets are standard errors.

Table 5b. *Urban survival function, poverty exit and re-entry rates using the Kaplan–Meier estimator*

Number of waves since start of poverty spell	Absolute poverty		Relative poverty		Predicted poverty	
	Survivor's function	Exit rates	Survivor's function	Exit rates	Survivor's function	Exit rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.7183 (0.0183)	0.2817 (0.0215)	0.7174 (0.0192)	0.2826 (0.0226)	0.8928 (0.016)	0.1072 (0.017)
3	0.5657 (0.0229)	0.2125 (0.0279)	0.5175 (0.0242)	0.2786 (0.0326)	0.8326 (0.02)	0.0674 (0.0155)
4	0.488 (0.0261)	0.1374 (0.0324)	0.4007 (0.027)	0.2258 (0.0427)	0.8013 (0.0225)	0.0376 (0.0142)
Number of waves since start of non-poverty spell	Survivor's function	Re-entry rate	Survivor's function	Re-entry rate	Survivor's function	Re-entry rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.6667 (0.0236)	0.3333 (0.0289)	0.6568 (0.0365)	0.3432 (0.0451)	0.9383 (0.0088)	0.0617 (0.0091)
3	0.4794 (0.0281)	0.2809 (0.0397)	0.4926 (0.0404)	0.25 (0.0521)	0.8402 (0.0136)	0.1046 (0.0124)
4	0.3934 (0.0311)	0.1795 (0.048)	0.4168 (0.0445)	0.1538 (0.0628)	0.8124 (0.0145)	0.0332 (0.0076)

Source: Authors' computations. Terms in brackets are standard errors.

rural and urban areas that the longer they were in poverty, the harder it was to get out (lower exit rates over time) and the longer they were out of poverty the less likely they were to re-enter (low re-entry rates over time); in other words, negative duration dependence. For instance, in rural areas the probability for a household to escape absolute poverty after spending one round in poverty was 39%, while for urban areas it was much lower, estimated at 28%. The longer the time spent in poverty, the harder it was to escape poverty, with some non-linearity indicated in the case of rural households. The probability of ending a poverty spell after two or three rounds more or less remained the same for rural households (28% and 30%, respectively). In the case of urban households, the exit rates out of poverty declined consistently

Table 6a. *Rural survival function, poverty exit and re-entry rates using the Kaplan–Meier estimator for male-headed households*

Number of waves since start of poverty spell	Absolute poverty		Relative poverty		Predicted poverty	
	Survivor's function	Exit rates	Survivor's function	Exit rates	Survivor's function	Exit rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.5419 (0.02)	0.4563 (0.0272)	0.5104 (0.0208)	0.4905 (0.0292)	0.717 (0.0236)	0.283 0.0279
3	0.3763 (0.0202)	0.3056 (0.0326)	0.3185 (0.0205)	0.376 (0.0394)	0.6136 (0.0254)	0.1442 (0.0216)
4	0.2474 (0.0217)	0.3426 (0.0563)	0.1911 (0.0205)	0.4 (0.0667)	0.3917 (0.0274)	0.3617 (0.0435)
Likelihood-ratio test of homogeneity (*p*-value)		0.07*		0.0029**		0.822
Number of waves since start of non-poverty spell	Survivor's function	Re-entry rate	Survivor's function	Re-entry rate	Survivor's function	Re-entry rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.6256 0.0245	0.3744 0.031	0.796 (0.0142)	0.204 (0.0159)	0.883 (0.0121)	0.117 (0.0129)
3	0.414 0.0263	0.3382 0.0407	0.6084 (0.0174)	0.2357 (0.0196)	0.8072 (0.0153)	0.0859 (0.0124)
4	0.3412 0.0273	0.1758 0.044	0.5148 (0.0187)	0.1538 (0.0206)	0.7797 (0.0161)	0.0341 (0.0083)
Likelihood-ratio test of homogeneity (*p*-value)	0.0682*			0.214		0.391

Source: Authors' computations. Terms in brackets are standard errors.
* Significant at 10%.
** Significant at 1%.

Table 6b. *Rural survival function, poverty exit and re-entry rates using the Kaplan–Meier estimator for female-headed households*

Number of waves since start of poverty spell	Absolute poverty		Relative poverty		Predicted poverty	
	Survivor's function	Exit rates	Survivor's function	Exit rates	Survivor's function	Exit rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.6263 (0.0351)	0.3802 (0.035)	0.6033 (0.0361)	0.3934 (0.0464)	0.7315 (0.0426)	0.2685 (0.0499)
3	0.4549 (0.0383)	0.2737 (0.0381)	0.3903 (0.039)	0.3529 (0.0644)	0.5536 (0.0487)	0.2432 (0.0573)
4	0.2582 (0.043)	0.4324 (0.0426)	0.2509 (0.0433)	0.3571 (0.1129)	0.3416 (0.0494)	0.383 (0.0903)
Number of waves since start of non-poverty spell	Survivor's function	Re-entry rate	Survivor's function	Re-entry rate	Survivor's function	Re-entry rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.7397 (0.0363)	0.2603 (0.0422)	0.8587 (0.021)	0.1413 (0.0226)	0.9129 (0.0174)	.0871 (0.0182)
3	0.5236 (0.044)	0.2921 (0.0573)	0.7475 (0.0265)	0.1295 (0.024)	0.8918 (0.0193)	0.023 (0.0306)
4	0.4036 (0.0464)	0.2292 (0.0691)	0.6372 (0.0314)	0.1477 (0.0315)	0.8645 (0.0217)	0.0306 (0.00125)

Source: Authors' computations. Terms in brackets are standard errors.

Table 7a. *Urban survival function, poverty exit, and re-entry rates using the Kaplan–Meier estimator for female-headed households*

Number of waves since start of poverty spell	Absolute poverty		Relative poverty		Predicted overty	
	Survivor's function	Exit rates	Survivor's function	Exit rates	Survivor's function	Exit rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.7163 (0.0252)	0.2862 (0.0314)	0.7154 (0.028)	0.2819 (0.033)	0.875 (0.0255)	0.119 (0.0266)
3	0.5762 (0.0265)	0.1955 (0.0383)	0.5512 (0.0347)	0.2295 (0.0434)	0.8256 (0.0301)	0.0565 (0.0213)
4	0.5391 (0.0354)	0.0645 (0.0323)	0.4651 (0.0385)	0.1563 (0.0494)	0.7934 (0.0342)	0.039 (0.0225)
Likelihood-ratio test of homogeneity (*p*-value)		0.6106		0.924		0.326
Number of waves since start of non-poverty spell	Survivor's function	Re-entry rate	Survivor's function	Re-entry rate	Survivor's function	Re-entry rates
1						
2	0.7419 (0.0321)	0.262 (0.0374)	0.7317 (0.0489)	0.2593 (0.0566)	0.9386 (0.0116)	0.0614 (0.0145)
3	0.5525 (0.041)	0.2553 (0.0521)	0.5452 (0.0576)	0.2549 (0.0707)	0.8252 (0.0173)	0.1208 (0.0213)
4	0.4564 (0.0459)	0.1739 (0.0615)	0.4543 (0.0635)	0.1667 (0.0833)	0.7955 (0.024)	0.036 (0.0127)
Likelihood-ratio test of homogeneity (*p*-value)		0.062*		0.001**		0.867

Source: Authors' computations. Terms in brackets are standard errors.
* Significant at 10%.
** Significant at 1%.

Table 7b. *Urban survival function, poverty exit and re-entry rates using the Kaplan–Meier estimator for male-headed households*

Number of waves since start of poverty spell	Absolute poverty		Relative poverty		Predicted poverty	
	Survivor's function	Exit rates	Survivor's function	Exit rates	Survivor's function	Exit rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.7299 (0.0252)	0.2677 (0.0294)	0.7292 (0.0262)	0.2734 (0.0308)	0.9073 (0.0203)	0.0976 (0.0218)
3	0.5631 (0.0324)	0.2286 (0.0404)	0.4948 (0.0338)	0.3214 (0.0479)	0.8384 (0.0268)	0.0759 (0.0219)
4	0.4678 (0.0375)	0.1692.051	0.3688 (0.0385)	0.2545 (0.068)	0.8076 (0.0299)	0.0367 (0.0183)
Number of waves since start of non-poverty spell	Survivor's function	Re-entry rate	Survivor's function	Re-entry rate	Survivor's function	Re-entry rates
1	1 (.)	. (.)	1 (.)	. (.)	1 (.)	. (.)
2	0.5591 (0.0515)	0.4348 (0.0687)	0.593 (0.053)	0.4138 (0.069)	0.9368 (0.0116)	0.0632 (0.0119)
3	0.3328 (0.0523)	0.4048 (0.0982)	0.4448 (0.0568)	0.25 (0.0791	0.8459 (0.0173)	0.097 (0.0155)
4	0.2288 (0.0527)	0.3125 (0.1398)	0.3763 (0.0655)	0.1538 (0.1088)	0.8182 (0.0187)	0.0327 (0.0099)

Source: Authors' computations. Terms in brackets are standard errors.

with the duration of the spell reaching 14% for absolute poverty after three rounds in poverty. Rural and urban areas exhibit a similar pattern with regard to the probability of re-entering into poverty following a spell of non-poverty. For absolute poverty, in both rural and urban areas, the probability that a household would slip back into poverty after spending one round out of poverty was 34% and 33%, respectively. The chance of slipping back into poverty declines faster for rural than urban households. How sensitive are these probabilities to the definition of poverty one adopts and issues of measurement errors and random shocks?

Tables 5a and 5b report estimates of exit and re-entry rates for relative poverty and consumption expenditure predicted from an econometric model. In general, exit rates tended to increase significantly for rural households (47%) while re-entry rates declined markedly (19%) when a relative poverty line was used to define poverty. The situation in urban areas more or less remained unaffected by the definition of poverty. One reason could be that for urban households the absolute poverty line used in the analysis was very close to the relative poverty line. The effect of adjusting consumption expenditure for possible measurement errors and random shocks on the exit and re-entry rates is substantial. In rural areas, exit rates declined to 28%, and in urban areas to 11% after a household spent one round in poverty. Likewise, re-entry rates also declined markedly. This suggests that consumption expenditure predicted on the basis of key household and community characteristics, including unobserved factors, largely capture the long-term features of transition into and out of poverty.

In general, however, the figures for Ethiopia show extreme persistence of poverty, whichever way poverty is measured. If we ignore the second round, the spacing between each interview would be about three years. If all waves were considered, staying out of poverty from one round to the next would involve a period of at least two years in our data set. Thus, one would expect higher exit and lower re-entry rates if poverty in general were inherently a transitory, disequilibrium state. The low exit and re-entry rates in general send a mixed message. It would be harder to both get out of poverty once fallen into and re-enter once escaped from poverty. Thus preventing the inflows as well as encouraging the outflows can lead to a sustainable decline in poverty.

The same exercise was repeated in rural and urban areas by partitioning the sample into female-headed and male-headed households to see if such differences would affect poverty persistence. [20] The results are reported in Table 6a for male-headed and in Table 6b for female-headed households in rural areas. Tables 7a and 7b provide, respectively, for female- and male-headed households in urban areas.

The sex of the head of the household does matter in rural areas as far as exiting poverty is concerned. Male-headed households tend to have a higher probability of ending a poverty spell than female-headed households. For example, while male-headed households have a 46% chance of escaping absolute poverty after one round (approximately two years), the figure for female-headed household is lower (38%). In urban areas, both male- and female-headed households have fairly similar chances of escaping poverty. With regard to re-entry male-headed households have a 10 percentage point higher chance of re-entering poverty in rural areas and a 17 percentage point higher chance in urban areas. This suggests that female-headed households tend to do better in maintaining a non-poverty spell than their male counterparts. Much of the re-entry rates exhibited in our sample could be driven by factors that are specifically disadvantageous for male-headed households. On the other hand, the persistence of undifferentiated poverty exit rates in urban areas indicates that factors that impede or facilitate escaping poverty work equally across the sexes of the heads of families.

The exit and re-entry rates reported in Tables 5a, 5b, 6a, 6b, 7a, and 7b can be used to obtain the distribution of households that spent "*d*" rounds out of four in poverty in single or multiple spells, which is a measure of poverty persistence. Table 8 provides the percentage of households that spent "*d*" rounds consecutively in poverty (single spell) or at different intervals (multiple spell). Overall, 63% of rural and 60% of urban households had spent at least one round out of four in poverty during 1995–2004 and escaped thereafter. This suggests that a significant proportion of rural and urban households in Ethiopia have had short stays (though in terms of years this would be approximately three years) in poverty during the period under investigation. When we take into account repeated spells, then, the percentage of people that had a short stay in poverty declines significantly, more in rural than in urban areas. For longer durations, the single spell

Table 8. *Distribution of the "number of rounds in poverty out of four rounds" for households starting a poverty spell in round 2*

Number of rounds in poverty	Hazard rates			
	Rural areas		*Urban areas*	
	Single spell	Multiple spell	Single spell	Multiple spell
1	63.35	38.83	60.35	44.15
2	23.64	31.92	22.79	25.34
3	8.86	21.00	10.93	18.37
4	4.15	8.25	5.93	12.14
	100	100	100	100
Mean number of rounds in poverty spell ("mean years")	1.5 (3)			1.62 (3.2)

Source: Authors' computations.

underestimates the persistence of poverty. Evidently a large percentage of households that started a poverty spell in 1995 or later managed to exit in 2004, though a significant minority (4% in rural and 6% in urban) continued to be trapped in it. On average, a typical household that fell in rural or urban areas would spend three or more years in poverty before escaping from it.

In general, the non-parametric estimates of poverty transition and persistence demonstrate that in Ethiopia, in both rural and urban areas, it is hard to exit poverty once a household slips into it and it is equally difficult to re-enter after escaping from it. The distribution of poverty across spells also suggests that a majority would have slipped into and out of poverty during the study period, more than 61% in rural and 56% in urban areas.

(b) *Correlates of poverty-exit and re-entry*

We report and discuss in this section estimates based on the proportional hazard models with and without unobserved heterogeneity as specified in Eqns. (6) and (7) for both the hazard rate of exiting and re-entering poverty. In their simpler form, the hazard models assume that spells in two alternating states for the same individual are uncorrelated. As a result, the spells in poverty and out of poverty can be estimated separately for the same individual. This can be true in the absence of unobserved household attributes and characteristics that may pre-dispose some more than others to be in one state rather than in another (see e.g., Devicienti, 2001). In our case, the shortness of the panel does not allow much of multiple spells, especially if the observations at the beginning of the survey are not considered (are left-censored).

Still, we address the issue of unobserved individual heterogeneity within the proportional hazard model using Jenkins' (2000) specification of a multiplicative error term capturing each individual household's unobserved characteristics. We report in Tables 9–12 estimates of the proportional hazard model without unobserved household heterogeneity (Model 1), and the same model that incorporates unobserved household heterogeneity (Model 2). Except for re-entry rates in rural areas, the likelihood-ratio test indicates that controlling for unobserved household-specific factors is necessary.

Table 9 reports coefficients (and the corresponding p-values) for exiting poverty. In both specifications, the duration of the spell of poverty itself had a statistically significant negative effect on the probability of exiting poverty. The absolute value of the coefficient has not changed much between the two specifications, though heterogeneity matters as indicated by the significant likelihood-ratio test reported. This negative dependence of exit rates on the duration of poverty spells is a common feature observed in similar studies (e.g., Devicienti, 2003, for UK, and Hansen & Walhlberg, 2004, for Sweden).

Other covariates with a significant role in facilitating exit out of poverty are farming systems, better access to markets (infrastructure), wealth indicators such as number of oxen owned and household durables. For instance, *teff* and coffee-growing areas tend to be associated with better opportunities for ending a spell of poverty. Producing enset had a significant negative effect in the first model, though far

Table 9. *Covariates of exiting poverty spell in rural areas*

	Proportional hazards		Proportional hazard with heterogeneity	
	Coefficient	*p*-Value	Coefficient	*p*-Value
Log of duration	−4.91	0.00***	−4.83	0.00***
Demographics				
Household size	−0.13	0.00***	−0.48	0.00***
Female head	−0.05	0.64	−0.29	0.56
Mean age of the household	−0.01	0.23	−0.03	0.07*
Head completed primary school	0.154	0.461	0.34	0.20
Wife completed primary school	0.04	0.87*	1.4	0.20
Farming systems				
Teff	−0.09	0.43	1.05	0.04**
Coffee	0.39	0.07	2.67	0.03**
Chat	0.48	0.00***	−1.4	0.17
Enset	−0.44	0.03**	−0.96	0.75
Wealth				
Asset value (birr)	0.00	0.12	0.00	0.05**
Land size (hectare)	0.06	0.02**	0.141	0.38
No. of oxen owned	0.09	0.04**	0.46	0.02**
Access to markets				
Population/distance to nearest town	0.00003	0.03**	0.00002	0.03**
Exogenous shock				
Rain variability (mm)	−0.02	0.00***	−0.03	0.08*
Change in rain (mm)	0.0023	0.26	−0.04	0.00***
Likelihood-ratio test of model 1 *versus* model 2	0.000***			

Source: Authors' computations.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

from significant when heterogeneity was controlled for in the proportional hazard model. On the other hand, factors such as larger household size, high dependency rate in the household, and high variability in rainfall (rainfall shocks) tend to make it harder to escape from poverty.

With respect to re-entering into poverty, while most variables tend to show expected signs (see Table 10), they are not statistically significant as they were in the case of exiting from poverty. Household size, farming systems, land ownership, and rainfall variability (shock) seem to be significant factors associated with the hazard of re-entering into poverty. Generally, households that started out with a larger family size, low asset accumulation, and that reside in sites with high rainfall variability tend to have a higher chance of slipping into poverty after a spell out of poverty. The time spent out of poverty is negatively related to the probability of re-entering into poverty (or the time spent in poverty is positively related to the probability of re-entering into poverty).

In urban areas, Table 11 reports that the duration of the spell in poverty had a statistically significant negative effect on the chance of getting out of it, as did household size, whereas "head completed primary school" had a statistically significant and positive effect in the first model, though not significant in the second. Some other occupations also had significantly positive effects in both the models though not as large effects as private business. In the second model, casual worker had a statistically significant, fairly large positive effect. Residence in Addis, Dire Dawa and Mekele also had significant and positive effects in both models with especially large coefficients in the second model.

Table 10. *Covariates of re-entering rural poverty*

	Proportional hazards		Proportional hazard with heterogeneity	
	Coefficient	*p*-Value	Coefficient	*p*-Value
Log of duration	1.83	0.00***	1.13	0.00***
Demographics				
Household size	0.12	0.00***	0.21	0.01***
Female head	−0.14	0.36	−0.24	0.45
Mean age of the household	−0.000	0.99	−0.001	0.92
Wife completed primary school[a]	−0.93	0.20	−2.35	0.14
Farming systems				
Teff	−0.20	0.16	−0.56	0.25
Coffee	−0.45	0.09*	1.17	0.09*
Chat	−0.61	0.10*	−0.53	0.54
Enset	0.38	0.05**	−1.22	0.99
Wealth				
Asset value (birr)	−0.0004	0.33	−0.01	0.00***
Land size (hectare)	−0.20	0.16	−0.14	0.14
No. of oxen owned	0.050	0.46	0.20	0.17
Access to markets				
Population/distance to nearest town	−0.00002	0.41	0.00002	0.65
Exogenous shock				
Rain variability (mm)	0.03	0.00***	0.06	0.00***
Change in rain (mm)	0.00	0.56	−0.05	0.32
Likelihood-ratio test of model 1 *versus* model 2	0.458			

Source: Authors' computations.
[a] Education of head dropped due to collinearity.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

As might be expected, being unemployed or a casual laborer are occupational categories for which exiting out of poverty is difficult and if they do so they are vulnerable to re-entry into poverty. Ethnic background seems to play little role if at all in affecting poverty mobility.

Table 12 reports the results for re-entering urban poverty, which are similar though again with less significance. Head completed primary school again had highly significant negative effects (on re-entering poverty) in both specifications. None of the other results are nearly so clear and consistent.

(c) *State dependence and correlates of exiting or entering poverty*

Based on the econometric model specified in Section (b), we report results on the nature of poverty dynamics in Ethiopia in Tables 13 and 14. We start with a dynamic random-effects model that sets the binary variable of being in poverty or not as functions of several observed regressors and its one period lag on the assumption that the initial conditions are exogenously determined. [21] Admittedly, this model simplifies the determination of initial states as well as assumes that the unobserved household characteristics are independent of the other observed regressors, thus, the coefficients estimated are inconsistent for reasons discussed in Section (b). We still report the results in order to compare with models that deal with the initial condition using observed and unobserved characteristics of the household and report the magnitude of the bias. The second model controls for initial condition and also allows for endogeneity of the unobserved error terms with respect to the regressors. The last model in addition to initial condition and unobserved heterogeneity also controls for serially correlated error terms. The last two models

Table 11. *Covariates of exiting urban poverty spell*

	Proportional hazards		Proportional hazard with heterogeneity	
	Coefficient	*p*-Value	Coefficient	*p*-Value
Log of duration	−1.6	0.00***	−1.69	0.00***
Demographics				
Household size	−0.09	0.00***	−0.2	0.00***
Female head	0.050	0.37	−0.10	0.72
Age of head	0.008	0.15	0.010	0.18
Mean age of household	0.003	0.70	0.002	0.19
Head completed primary school	0.60	0.00***	0.560	0.02**
Wife completed primary school	0.023	0.15	−0.070	0.82
Occupation of head				
Private business employer	1.40	0.00***	0.99	0.23
Own account worker	0.31	0.07**	0.45	0.23
Civil servant	0.47	0.02**	0.23	0.58
Public sector employee	0.040	0.19	−0.290	0.63
Private sector employee	0.50	0.05**	0.61	0.22
Casual worker	0.15	0.60	1.20	0.01***
Residence				
Addis Ababa	0.58	0.02**	9.08	0.00***
Awasa	−0.01	0.98	−4.90	0.99
Bahir Dar	0.21	0.72	8.5	0.00***
Dessie	−0.00	0.99	7.60	0.00***
Dire Dawa	0.85	0.01***	9.00	0.00***
Mekele	0.92	0.02**	19.80	0.00***
Exogenous shocks				
Unemployment	−0.4	0.21	−0.29	−0.49
Ethnic background				
Amhara	0.19	0.79	0.11	0.44
Oromo	−0.08	0.60	0.27	0.44
Tigrawi	−0.14	0.60	−9.8	0.04**
Gurage	0.20	0.29	0.28	0.48
Likelihood-ratio test of model 1 *versus* model 2	0.000***			

Source: Authors' computations.
* Significant at 10%.
** Significant at 5%
*** Significant at 1%.

control for unobserved household heterogeneity based on Heckman's (1981) suggestion for dealing with the initial condition problem. We report the results separately for rural and urban households.

Consistent with the results in the preceding sections, the dynamic probit model also depicted the presence of state dependence on the evolution of poverty in Ethiopia based on the three models. In rural as well as urban areas, the coefficient of the lagged dependent variable turned out to be positive and statistically significant. That is, controlling for observable household and community characteristics, the probability of falling into poverty in the current period is highly correlated with being in poverty in the past. Similarly, other covariates showed statistically significant effects on the probability of falling into poverty or escaping poverty.

The higher the size of a household, the higher the probability of falling into poverty, but relatively larger households tend to benefit from scale economies, perhaps from both consumption and production effects. Assets, both land and oxen, improve considerably the chance of

Table 12. *Covariates for re-entering poverty spell for urban households*

	Proportional hazards		Proportional hazard with heterogeneity	
	Coefficient	*p*-Value	Coefficient	*p*-Value
Log of duration	−0.14	0.13	9.9	0.00***
Demographics				
Household size	0.08	0.00***	0.01	0.23
Female head	−0.01	0.12	−0.09	0.72
Age of head	0.00	0.65	0.00	0.92
Mean age of household	−0.01	0.17	−0.00	0.63
Head completed primary school	−0.46	0.00***	−0.19	0.40
Wife completed primary school	−0.19	0.19	−0.65	0.02**
Occupation of head				
Private business employer	−0.68	0.09*	−0.45	0.70
Own account worker	−0.19	0.16*	−0.17	0.57
Civil servant	−0.18	0.25**	0.16	0.70
Public sector employee	0.52	0.01***	−0.22	0.64
Private sector employee	0.19	0.39	−0.113	0.81
Casual worker	0.31	0.03**	−0.23	0.52
Addis Ababa	−0.43	0.01***	0.76	0.18
Awasa	−0.11	0.64	1.2	0.08*
Bahir Dar	−0.49	0.13	1.06	0.21
Dessie	0.38	0.18	0.67	0.39
Dire Dawa	−0.27	0.34	0.81	0.24
Mekele*	−0.07	0.84	−1.08	0.13
Exogenous shocks				
Unemployment	0.49	0.01***	−0.01	0.98
Ethnic background				
Amhara	−0.13	0.20	−0.52	0.35
Oromo	−0.05	0.64	−0.38	0.29
Tigrawi	−0.76	0.01***	−0.52	0.35
Gurage	−0.25	0.36	−0.09	0.79
Likelihood-ratio test of model 1 *versus* model 2	0.000***			

Source: Authors' computations.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

exiting poverty, but with diminishing returns in the case of land. Other community characteristics, such as access to markets, agro-ecological zones, and farming systems, used in this model as determining initial condition, turned out to be important determinants of poverty exit or entry. We also note that the model that controls for unobserved heterogeneity and serial correlation led some important variables, such as dependency in the household, to be statistically significant coefficients in affecting poverty transitions.

Similarly in urban areas, households' demographic characteristics and occupation of the head of the household played a significant role in facilitating exit from poverty. Except for casual employment, all other occupations are associated with high probability of exiting poverty.

One of the striking features of the results in both rural and urban areas is that the coefficient of the lagged dependent variable rose significantly once we controlled for the persistence of the error component, sometimes also referred to as transitory shocks. The implication is that the true state dependence would have been understated due to the effects of transitory shocks, including measurement errors. As can be seen from the values of the log-likelihood, of the three, the model that controls for serial

Table 13. *Maximum simulated likelihood estimator of dynamic random-effects probit model of poverty persistence: rural areas, 1994–2004*

	Random-effects model with initial conditions assumed exogenous	Maximum likelihood estimator with initial conditions assumed endogenous, without auto-correlated error term	Maximum simulated likelihood estimator with endogenous initial conditions and auto-correlated error term
Lagged poverty	0.519 (0.000)***	0.346 (0.000)***	0.908 (0.000)***
Household size	0.158 (0.000)***	0.168 (0.000)***	0.143 (0.000)***
(Household size)^2	−0.004 (0.000)***	−0.002 (0.002)**	−0.004 (0.000)***
Age of head	0.001 (0.304)	0.0115 (0.322)	0.0008 (0.641)
Mean age	0.16 (0.16)	0.0132 (0.163)	0.015 (0.000)***
(Mean age)^2	−0.0002 (0.091)	0.0132 (0.132)	−0.0002 (0.049)**
Off-farm	−0.007 (0.866)	−0.016 (0.713)	−0.025 (0.507)
Number of oxen	−0.109 (0.000)***	−0.114 (0.000)***	−0.103 (0.000)***
Land size (household)	−0.123 (0.000)***	−0.138 (0.000)***	−0.110 (0.000)***
Land size (household)^2	0.002 (0.000)***	0.002 (0.000)***	0.001 (0.000)***
Constant	−1.36 (0.000)***	−0.669 (0.05)**	−0.17 (0.382)
AR1			−0.361 (0.000)***
Number of observations	6250	6250	6250
Log-likelihood	−3392	−3197	−3173

Source: Authors' computations. Terms in brackets are *p*-values.
** Significant at 5%.
*** Significant at 1%.

Table 14. *Maximum simulated likelihood estimator of dynamic random-effects probit model of poverty persistence: urban areas, 1994–2004*

	Random-effects model with initial conditions assumed exogenous	Maximum likelihood estimator without auto-correlated error term	Maximum simulated likelihood estimator with auto-correlated error term
Lagged poverty	0.601 (0.000)***	0.371 (0.002)**	0.809 (0.000)***
Household size	0.136 (0.000)***	0.139 (0.000)***	0.123 (0.015)**
Age of head	−0.003 (0.251)	−0.0032 (0.298)	−0.004 (0.196)
Mean age	−0.004 (0.329)	−0.0035 (0.468)	−0.0026 (0.550)
Head is female	0.066 (0.392)	−0.0035 (0.996)	0.004 (0.960)
Head completed primary	−0.312 (0.000)***	−0.361 (0.000)***	−0.320 (0.000)***
Wife completed primary	−0.352 (0.000)***	−0.303 (0.002)**	−0.260 (0.000)***
Head is in private business	−1.25 (0.000)***	−0.965 (0.001)***	−0.834 (0.000)***
Head is self-employed	−0.172 (0.000)***	−0.311 (0.002)**	−0.264 (0.000)***
Head is civil servant	−0.323 (0.000)***	−0.34 (0.003)**	−0.287 (0.000)***
Head is in public sector	−0.139 (0.320)	−0.171 (0.228)	−0.131 (0.308)
Head is in private sector	−0.035 (0.812)	−0.372 (0.022)**	−0.354 (0.017)**
Head is casual worker	0.324 (0.009)	0.1836 (0.161)	0.173 (0.142)
Addis	0.06 (0.392)	−0.060 (0.390)	−0.086 (0.180)
Constant	−1.16 (0.000)***	−1.02 (0.000)***	−1.05 (0.000)***
AR1			−0.227 (0.002)**
Number of observations	4750	4750	4750
Log-likelihood	−1972	−1871	−1868

Source: Authors' computations. Terms in brackets are *p*-values.
** Significant at 5%.
*** Significant at 1%.

correlation is a better fit for the dynamic poverty model. In addition, in all cases the coefficient of the serially correlated term is statistically significant, and it is also less than unity, implying that transitory shocks dissipate over time. Given that serial correlation of the error term is an important means of reducing the effects of measurement error (see e.g., Devicienti, 2003) on coefficients, we can interpret our result to imply that poverty is strongly state dependent if measurement error is controlled for. Part of the serial correlation also can be due to the overall positive transitory shocks, such as lessening of hunger, relatively improving living condition and better infrastructure, and improved donor response to deal with severe droughts and other adversities.

Nevertheless, the key message is that the existence of true state dependence of poverty, in both rural and urban areas, shows the effect of the past history of poverty in determining its future path. This implies that efforts to protect households from falling into poverty are an important complement to growth-enhancing policies in dealing with long-term poverty in Ethiopia. Thus, effective anti-poverty programs targeted at the currently poor, including insurance schemes, income-generating schemes, and other interventions that reduce future income uncertainty need attention. Furthermore, in the context of linear-probability model for instance, the long-term effect of the covariates on poverty turns out to be very large when the coefficient of the lagged dependent variable becomes significantly different from zero. This can be seen easily by noting that in steady state (or in the long-term) $P_{it} = P_{it-1}$, so that the marginal effects of the covariates of poverty would be adjusted by the state-dependent coefficient such that it is equal to $\frac{\beta_i}{1-\gamma}$ (see also Chay *et al.*, 1998). If $\gamma = 0$, then, variations in the correlates of poverty are fully translated so that short-term and long-term impacts remain the same. On the other hand, if $\gamma \neq 0$, then, differences in household demographics, and other endowments can have large long-term impacts on poverty as is the case here.

5. SUMMARY AND CONCLUSIONS

This paper has examined the persistence of poverty in Ethiopia for the decade 1994–2004 using a panel data set collected in five waves in rural and urban areas of Ethiopia. The decade under study was characterized by rapid economic and political reforms and daunting tasks of country building on the one hand, while dealing with shocks, such as drought, diseases, and war on the other. Ethiopia is also one of the poorest countries in the world, so the analysis of poverty persistence and understanding of its underlying causes are important for policy purposes.

We employed non-parametric and parametric methods to analyze poverty spells and persistence. Our results suggest that absolute poverty declined during 1994–97, then increased strongly up to 2000 and declined again in 2004. This finding is consistent with the major events that took place in the country: peace and stability, reform and economic recovery during 1994–97, then, drought, war with Eritrea and political instability during 1997–2000, and finally recovery in the period 2001–04, though the country experienced a major drought in 2003. Households in rural areas seem to have seen more rapid improvements than urban households during the decade under study, with poverty declining by more than ten percentage points. However, there were reversals of fortunes in some years for rural households. Our description of chronic poverty showed that only a minority in both rural and urban areas escaped poverty during the entire decade, indicating that a significant proportion of the population had been in poverty at least once in the decade under study, 72% in rural and 60% in urban areas. This generally indicates a society exposed to extreme poverty.

The results from analysis of poverty and non-poverty spells show that it is hard to exit poverty once a household falls into poverty, while it is easier to maintain a non-poverty status once a household has escaped poverty. For instance in rural areas, the probability of a household to escape absolute poverty after spending one round in poverty is around 39%, and for urban areas this figure is considerably less, standing at 28%. The longer the spell in poverty or out of poverty, the harder it becomes to exit or re-enter. This strong negative duration dependence is the hallmark of poverty persistence in Ethiopia. Our finding suggests that in general urban areas seem to experience greater degree of poverty persistence compared to rural areas. In general, it is harder to exit and easier to re-enter poverty in urban than in rural areas, which is interesting in its own right.

The results of exit and re-entry rates are sensitive to a certain degree to the choice of the poverty line, adjustment of consumption

expenditure for measurement error and other random shocks, as well as the characteristics of the initial group. In the case of relative poverty lines (defined as two-third of the mean), exit rates tended to be higher and re-entry rates much lower in rural areas. In urban areas, hazard rates for exiting or re-entering poverty being remained more or less unchanged with the definition of poverty adopted. When consumption expenditure generated from an econometric model was used for each household, both exit and re-entry rates declined dramatically, which is not surprising as the predicted consumption controls for random shocks as well as potential measurement errors. In rural areas, male-headed households have a much higher chance of ending a poverty spell, as well as slipping back into poverty. Female-headed households tend to maintain their non-poverty status, though they find it hard to end a poverty spell. In urban areas, both male- and female-headed households have similar probability of ending a poverty spell, though male-headed households tend to slip back into poverty after a spell out of poverty.

With regard to parametric estimation of hazard rates, we used two proportional hazard models, one controlling for unobserved individual heterogeneity using a set of household and community characteristics. The overall evidence suggests that unobserved heterogeneity matters for the probability of escaping or re-entering poverty in both rural and urban areas. Overall, the results indicate that exiting or re-entering poverty depends strongly on the duration of the spell in both rural and urban areas. Controlling for unobserved heterogeneity generally led to slightly lower value of the coefficient of the spell duration. Among the explanatory variables, in rural areas, the size of the household, primary education of the head or wife, access to markets and changes in rainfall levels and variability were statistically significant in either facilitating exit or preventing re-entry into poverty. In urban areas, household size, education level of the head, town of residence, and to a certain degree ethnic background tended to affect both exit and re-entry rates.

We also attempted to explicitly estimate a dynamic model of poverty by controlling for unobserved heterogeneity as well as serial correlation in an effort to capture the true state dependence of poverty evolution. Our results indicate that in Ethiopia current poverty is driven by the past history in poverty. The strong path dependence has important policy implications. Policies to reduce risks and mitigate its consequences are important for both short-term poverty reduction and long-term growth. Transitory poverty could be avoided or reduced if better safety nets were provided, but there may be problems of implementing them effectively in practice. So a major part of the policy response to the risky environment should be to strengthen the asset base of poor households, to provide mechanisms they can use to manage and cope with risk, combined with an effective and credible *ex post* support system. This would make it possible for the poor to maintain and expand their asset base and to engage in more risky but more profitable activities.

So it is important and potentially very rewarding to try to reduce transitory poverty in Ethiopia, but we must also keep in mind that there are also a large group of chronically poor, which are worse off than the transitory poor. This suggests that there is a strong case for a growth process that is broadly shared in the Ethiopian context, if the reduction of poverty in the long-term is the overarching policy objective.

NOTES

1. See surveys in Baulch and Hoddinott (2000), Hulme and Shepherd (2003), McKay and Lawson (2003), and Yaqub (2003).

2. See Kaplan and Meier (1958).

3. We draw heavily on Jenkins (1995) and Stevens (1999) to discuss the parametric approach to modeling exit and re-entry rates.

4. The same analogy applies for re-entry. So we restrict the discussion to the modeling of exiting from poverty.

5. See Jenkins (1995) for the details on the derivation of Eqn. (2).

6. Jenkins (2000) developed an algorithm that can be run in STATA to estimate a proportional hazard model with unobserved household heterogeneity and we report some of the results below.

7. ε is a Gamma distributed random error term with unit mean and variance.

8. See for example Hsiao (2004) for a general discussion of persistence in the context of dynamic discrete models.

9. See Wooldridge (2002).

10. In linear-probability models there are a number of transformation strategies whereby the unobserved effect can be isolated. In fully parameterized non-linear models such as probit density functions there are no known transformation techniques available to address the problem of initial conditions (see Wooldridge (2005) for useful discussion and an alternative to Heckman (1981) approach).

11. See Islam and Shimeles (2006) for an application of discrete approximation on Ethiopian data set.

12. See Stewart (2006) for a STATA program to estimate dynamic random-effects model with auto-correlated error terms using maximum simulated likelihood estimator with a normally distributed unobserved individual-specific error term.

13. *Chat is a* stimulant leaf commonly used in Ethiopia and neighboring countries.

14. See for example, Dercon and Krishnan (2000) discuss in some detail the problem of measurement error in poverty analysis in the same data context. They suggest the use of a consumption model to predict consumption expenditure and compare the result with the actual one. Following Bane and Ellwood (1986), we dropped cases of household consumption growth less than 20% of the poverty line to minimize spurious transitions that could be due to measurement error.

15. The poverty line is based on the Cost of Basic Needs approach to arrive at a minimum amount needed to secure the most basic items for mere survival (see Ravallion & Bidani, 1994 for details).

16. See Ravallion (1998).

17. We use the Foster, Greer, and Thorbecke (1984) class of poverty indices to report poverty trends.

18. To capture rainfall shocks (variability), we used standard deviation of volume of rainfall from its historical trend for the 15 villages in rural sites. Generally higher variance should be bad for farming. We used changes in rainfall during the survey period as an additional variable to pick up short-term impacts.

19. We also computed the transition matrix-based consumption figures predicted from a consumption model that accounts for endogeneity of some of the regressors. The result remained unchanged, except for the poorest and richest deciles (see Appendix Table A.3). Most households that had started out in a given decile, moved over the decade to another. Shimeles (2006) examined the role that shocks play in affecting consumption dynamics in both rural and urban areas. The result indicates that consumption dynamics in Ethiopia exhibits large movement around the steady state consumption. However, since households recover from shocks at different times, consumption dynamics exhibits non-linearity, which could explain the substantial movement across deciles.

20. We report likelihood-ratio tests for the significance of the differences in exit and re-entry rates between female- and male-headed households for the absolute poverty.

21. In other words, this is the standard random-effects model estimated with exogenous initial conditions and independence of covariates with unobserved heterogeneity (in STATA, it is estimated by the **xtprobit** command).

REFERENCES

Aliber, M. (2003). Chronic poverty in South Africa: Incidence, causes and policies. *World Development, 31*(3), 473–490.

Antolin, P., Dang, T. T., & Oxley, H. (1999). Poverty dynamics in four OECD countries. OECD Working Paper No. 212.

Bane, M. J., & Ellwood, D. T. (1986). Slipping into and out of poverty: The dynamics of Spells. *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., & Hoddinott, J. (2000). Economic mobility and poverty dynamics in developing countries. *Journal of Development Studies, 36*(6), 1–24.

Bergstrom, R., & Edin, P. A. (1992). Time aggregation and the distributional shape of unemployment duration. *Journal of Applied Econometrics, 5*, 609–624.

Biewen, M. (2004). Measuring state dependence in individual poverty status: Are there feedback effects

to employment decisions and household composition? IZA DP No. 1138, Institute for the Study of Labour.

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. (2005), Poverty and income distribution in Ethiopia: 1994–2000. Department of Economics, Göteborg University, mimeo.

Bigsten, A., & Shimeles, A. (2007). Can Africa reduce poverty by half by 2015? *Development Policy Review, 25*(2), 147–166.

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

Cappellari, L., & Jenkins, S. P. (2004). Modelling low income transitions. *Journal of Applied Econometrics, 19*, 593–610.

Carter, M., & Barrett, C. (2006). The economics of poverty traps and persistence of poverty: An asset-based approach. *Journal of Development Studies, 42*(2), 178–199.

Carter, M., & May, J. (2001). One kind of freedom: Poverty dynamics in post-apartheid South Africa. *World Development, 29*(12), 1987–2006.

Chay, K., & Hyslop, D. (1998). Identification and estimation of dynamic binary response panel data models: Empirical evidence using alternative approaches, mimeo.

Datt, G., & Joliffe, D. (2005). Poverty in Egypt: Modelling and simulations. *Economic and Cultural Development, 53*(2), 320–327.

Deaton, A. (1997). *The analysis of household surveys: A micro-econometric approach to development policy*. Washington, DC: The John Hopkins University Press for the World Bank.

Deininger, K., & Okidi, J. (2003). Growth and poverty reduction in Uganda, 1992–2000: Panel data evidence. *Development Policy Review, 21*(4), 481–509.

Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics, 74*(2), 309–329.

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

Dercon, S. (2007). Fate and fear: Risk and its consequences in Africa. ESRC Global Poverty Research Group, GPRG-WPS-074, Oxford.

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

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality, and poverty in Ethiopia. *Journal of Development Studies, 36*(6), 25–53.

Devicienti, F. (2001). Poverty persistence in Britain: A multivariate analysis using the British Household Panel Survey, 1991–1997. *Journal of Economics, 9*(supplement), 1–34.

Devicienti, F. (2003). Estimating poverty persistence in Britain. Working Paper Series No. 1, Centre for Employment Studies, Rome, mimeo.

Devicienti, F., & Gualtieri, V. (2006). The dynamics and persistence of poverty in Italy, mimeo.

Foster, J., Greer, J., & Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica, 52*(3), 761–766.

Grootaert, C., & Kanbur, R. (1995). The lucky few amidst economic decline: Distributional change in Cote d'Ivoire as seen through Panel Data Sets, 1985–88. *Journal of Development Studies, 31*(4), 603–619.

Haddad, L., & Ahmed, A. (2003). Chronic and transitory poverty: Evidence from Egypt 1997–99. *World Development, 31*(1), 71–85.

Hansen, J., & Walhlberg, R. (2004). Poverty persistence in Sweden. Discussion Paper 1209, Institute for the Study of Labour (IZA), Bonn.

Heckman, J. J. (1981). Statistical models for discrete panel data. In C. F. Manski, & D. McFadden (Eds.), *Structural analysis of discrete panel data with econometric applications* (pp. 114–178). MIT Press.

Hsiao, C. (2004). *Analysis of panel data*. Cambridge University Press.

Hulme, D., & Shepherd, A. (2003). Conceptualising chronic poverty. *World Development, 31*(3), 403–423.

Iceland, J. (1997). The dynamics of poverty spells and issues of left-censoring. Population Studies Centre Research Report Series No. 97-378, University of Michigan.

Islam, N., & Shimeles, A. (2006). Poverty dynamics in Ethiopia: State dependence and transitory shocks, Göteborg University, mimeo.

Jalan, J., & Ravallion, M. (2000). Is transient poverty different? Evidence from rural China. *Journal of Development Studies, 36*(6), 850–875.

Jenkins, S. (1995). Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics, 57*(1), 129–138.

Jenkins, S. (2000). Estimation of discrete time (grouped duration data) proportional hazards models: Pgmhaz. University of Essex, mimeo.

Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of American Statistical Association, 53*, 448–457.

Krishna, A. (2004). Escaping poverty and becoming poor: Who gains, who loses and why? *World Development, 32*(1), 121–136.

Lillard, L. A., & Willis, R. J. (1978). Dynamic aspects of earning mobility. *Econometrica, 46*, 985–1012.

McKay, A., & Lawson, D. (2003). Assessing the extent and nature of chronic poverty in low income countries: Issues and evidence. *World Development, 31*(3), 425–439.

Ravallion, M. (1998). Poverty lines in theory and practice. Living Standard Measurement Study, Working Paper No. 33, World Bank.

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

Rodgers, J., & Rodgers, J. (1991). Measuring the Intensity of poverty among sub-populations: Applications to the US. *Journal of Human Resources, 21*(2), 338–359.
Sen, B. (2003). Drivers of escape and descent: Changing household fortunes in rural. *Bangladesh World Development, 31*(3), 513–534.
Shimeles, A. (2006). *Consumption smoothing, income and asset shocks in Ethiopia*. mimeo: University of Gothenburg.
Stevens, A. H. (1994). The dynamics of poverty spells: Updating Bane and Ellwood. *American Economic Review, 84*, 34–37.
Stevens, A. H. (1996). Climbing out of poverty, falling back in. NBER Working Paper 5390.
Stevens, A. H. (1999). The dynamics of poverty spells: Updating Bane and Ellwood. *Journal of Human Resources, 34*(3), 557–588.
Stewart, M. (2006). Maximum simulated likelihood estimation of random effects dynamic probit models with auto-correlated errors. *STATA Journal, 6*(2), 256–272.
Wooldridge, J. M. (2002). *Econometric analysis of cross-section and panel data*. Cambridge, MA: The MIT Press.
Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, non-linear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics, 20*(1), 39–54.
World Development Indicators (2007). CD-ROM, World Bank, Washington, DC.
Yaqub, S. (2003). Chronic poverty. Scrutinizing patterns, correlates and explorations. CPRC Working paper 21, IDPM, University of Manchester.

APPENDIX A

See Tables A.1, A.2 and A.3.

Table A.1. *Rural transition probabilities by actual expenditure decile: 1994–2004*

Decile	1	2	3	4	5	6	7	8	9	10
Poorest	**18.74**	15.72	12.04	11.2	7.94	6.72	8.76	8.76	5.3	3.67
2	11.3	**17.55**	11.92	15.27	11.3	9.41	5.86	7.53	6.28	5.44
3	12.31	14.24	**9.03**	7.99	12.31	11.23	8.64	5.4	7.99	7.34
4	9.17	10.43	12.23	**10.74**	10.51	10.07	10.29	10.51	7.38	6.94
5	7.38	10.95	9.49	11.86	**12.08**	10.29	10.74	11.63	9.17	6.26
6	5.44	9.06	10.87	10.88	9.98	**11.79**	12.24	10.43	12.47	9.98
7	4.87	7.45	8.87	10.21	9.98	11.14	**12.99**	12.06	12.3	12.06
8	7.94	5.38	10.0	7.94	9.75	10.88	10.88	**13.61**	12.47	12.7
9	4.49	3.06	8.16	8.76	12.36	12.58	11.01	9.89	**14.61**	16.63
Richest	2.61	6.72	7.51	8.79	8.31	10.45	11.64	14.01	16.15	**20.43**

Table A.2. *Urban transition probabilities by actual expenditure decile: 1994–2004*

Decile	1	2	3	4	5	6	7	8	9	10
Poorest	**37.08**	21.25	17.50	9.17	5.00	3.75	2.08	2.92	0.42	0.83
2	18.50	**23.23**	17.32	13.78	10.24	5.51	6.30	2.36	1.57	1.18
3	21.62	15.32	**14.86**	9.91	12.16	6.76	7.21	4.95	5.86	1.35
4	8.63	12.94	15.29	**14.90**	13.73	11.37	9.41	6.67	2.75	4.31
5	4.12	8.23	9.05	16.87	**17.70**	12.76	10.29	9.05	7.00	4.94
6	5.56	7.26	8.55	6.84	15.61	**18.80**	11.54	10.26	10.68	4.70
7	2.08	3.75	7-92	12.50	8.33	16.67	**17.92**	12.92	11.67	6.25
8	3.27	4.49	2.86	8.57	7.35	10.61	15.92	**18.78**	19.59	8.57
9	1.22	1.22	1.22	6.53	4.08	8.16	13.88	16.73	**24.90**	22.04
Richest	0.42	1.26	1.26	3.78	3.78	6.30	5.88	15.55	16.81	**44.95**

Table A.3. *Rural transition probabilities by predicted expenditure decile: 1994–2004*

Decile	1	2	3	4	5	6	7	8	9	10
Poorest	**56.47**	29.75	9.64	23.63	0.28	1.1	0	0.28	0	0
2	15.25	**25.51**	29.62	19.06	8.5	0.59	1.17	0.29	0	0
3	2.59	22.48	**20.75**	23.63	17.87	9.22	3.17	0.29	0	0
4	1.15	8.07	18.44	**17.58**	22.77	20.46	8.36	1.44	1.73	0
5	0	1.79	11.94	14.63	**13.13**	22.99	20.3	12.54	2.09	0.6
6	0	1.47	3.53	13.82	12.35	**12.06**	25.59	21.18	8.53	1.47
7	0	0.55	1.1	3.31	15.47	16.02	**16.02**	24.59	20.44	2.49
8	0	0.3	0.3	0.89	5.62	15.38	18.05	**17.16**	31.07	11.24
9	0	0	0	0.83	1.1	4.7	8.84	24.31	**27.62**	32.6
Richest	0	0	0.28	0.28	0.28	0.85	2.25	8.17	19.72	**68.17**