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Editorial Note

Explaining the depth and magnitude of poverty is very difficult task as it is a result of multi-dimensional socio-economic factors such as population pressure and characteristics, low productivity, structural bottlenecks, dependency on nature (like rainfall) etc. A simple aggregate measure of poverty, such as the headcount ratio, does not tell us much about the dynamics of poverty among the society. Therefore, this edition will look at the dynamics of poverty using different methods of analysis.

The first topic tries to analysis the state of poverty, income distribution and its determinants and geographical dispersion of poverty. The second topic examines poverty persistence, chronic poverty and vulnerability that demand different types of interventions where persistence poverty requires long term interventions in terms of investment and structural reforms while transitory poverty requires temporary interventions that enable to absorb shocks. The third topic has given due emphasis to the persistence of poverty in the urbane and rural settings.

The Ethiopian Economic Association (EEA) believes that the analysis of the dynamics of poverty in Ethiopian presented in this special issue of *Ethiopian Journal of Economics* will provide important inputs that are of both academic and policy interest. We also believe that the readers will learn much from this special issue about the different aspects of poverty.

POVERTY AND INCOME DISTRIBUTION IN ETHIOPIA: 1994-2000[1]

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Abstract

Poverty and income distribution in Ethiopia were analyzed for the period 1994-2000 based on a panel data-set. The period under study is characterised by fast changing circumstances, from peace, economic reform and recovery during 1992-1997, then deteriorating into all-out war with Eritrea, severe drought and political instability during 1998-2000. The paper examines the evolution of poverty and income distribution in this setting, with a focus on the decomposition of poverty and inequality into proximate determinants. The potential effects of policy changes on poverty were also simulated and the results are reported.

1. Introduction

This paper analyzes the state of poverty and income distribution in Ethiopia for the period 1994-2000 using a panel data set collected in five waves for rural households and four waves for urban households.[4] The availability of such a data set is unique for Africa and has made it possible to undertake high quality poverty research in Ethiopia. Previous contributions are Dercon and Krishna (1998, 2000), Dercon (2000, 2001, 2005), Bigsten, Kebede, Shimeles, Taddesse (2003), Bigsten and Shimeles (2004) and Bigsten, Kebede and Shimeles (2005).

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Poverty in Ethiopia is widespread, in both rural and urban areas, and driven in many ways by deep seated structural factors. Thus, monitoring changes in the pattern of poverty over time has significant policy implications as the country struggles against hunger and diseases.

The paper updates existing poverty-studies by including the 2000 survey, which was administered in the wake of widespread drought, a serious political rift that nearly paralyzed the government, and a large scale border-war with Eritrea,. The previous surveys (1994-1997) had been conducted during a period of peace, strong policy stance, and recovery.

Most studies on the evolution of poverty report components of changes due to the effects of growth and redistribution, as well as by sub-groups. This study also uses regression-based decompositions to better understand the link between policy and poverty. In line with Datt and Joliffe (2005) and Dercon (2005) it focuses on the roles of unobserved individual effects and random shocks in influencing the changes in poverty. This paper analyses income distribution in Ethiopia in some detail to provide insights into its determinants. This is important as pro-poor growth strategies are debated in the African context, though little is known about what determines income distribution. The paper also attempts to simulate the implications of some potential policy interventions on poverty and income distribution by estimating poverty using observable individual and household characteristics as well as community features.

The next section reviews issues of poverty measurement. Section 3 gives an overview changes in poverty and income distribution in Ethiopia for the period 1994-2000. It decomposes poverty by household occupational groups, farming systems, and regions of residence to get a sense of the dispersion of poverty. Section 4 investigates how robust the reported poverty trends are by using non-parametric kernel density functions and the distribution-free stochastic dominance criterion. Section 5 analyzes poverty and income distribution in terms of observable and unobservable household characteristics and random shocks. Policy simulations are then reported on the basis of the model-based decompositions and their implications discussed. Section 6 summarizes and draws conclusions.

2. Poverty measurement: Identification and aggregation

The literature on measuring poverty has evolved rapidly over the last thirty years. Sen's (1976) seminal work laid the ground for an axiomatic approach to the measurement of poverty, which led to a large literature that provided a basis for welfare-theoretic measures of poverty. The earliest and perhaps the most popular measure of poverty is the headcount ratio that simply takes the ratio of the poor, however, defined to the total population in a community. The most common way of defining the poor is as those people who lack income sufficient for a minimum standard of living, called the poverty-line, which may be relative or absolute in magnitude. Later on, the poverty-gap or the total income shortfall relative to what would be required to eradicate poverty was suggested. We may formally state these poverty measures by considering an income distribution structure given by the vector $Y = (y_1, y_2 \ldots, y_n)$, so that $y_1 < y_2, \ldots < y_n$. y_i represents the income of individual *i* in the community. If z represents the poverty-line, then, H can be written as:

$$H = q/n \tag{1}$$

Where, q represents the number of people with income no higher than the poverty line z and n represents the total number of individuals in the community. In the same manner, we may express the poverty gap as follows:

$$IG = \sum_{i=1}^{q} (z - y_i), \tag{2}$$

Sen (1976) argued that H and IG lack desirable properties stated in his monotonicity and transfer axioms[5]. H remains invariant to any changes in the income of individuals below the poverty-line that is it does not respond to the relative deprivation of the poor, and IG is insensitive to income transfers among the poor. These deficiencies of H and IG motivated Sen to suggest what he called the "basic equation to measure poverty" defined as:

$$S(z, y) = A(z, y) \sum_{i=1}^{q} (z - y_i) v_i (z, y), \tag{3}$$

where S(z, y) is the aggregate income-gap of people whose income is no more than z, $v_i(z,y)$ is a non-negative weight given to the individual i , and A(z,y) is a normalizing factor.

Sen, then, considered the general poverty index defined as:

[5] In the context of poverty measurement, monotonicity refers to a situation where other things constant, an increase in income of a poor person, however small, should reduce the measure of poverty. In the case of headcount ratio, such an increase would lead to a reduction of poverty as long as it permits the poor person to cross the poverty line.

$$P(z,Y) = \text{Max } S(z,y), \qquad \textbf{(4)}$$

that is, the maximum aggregate income-gap of the poor in the community. Invoking a rank preserving welfare-criterion and the desirable properties of monotonicity, transfer and normalization, Sen, then, suggested a specific poverty index defined as:

$$S(z,y) = H(I-(1-I)G_p), \qquad \textbf{(5)}$$

where $$I = \sum_{i=1}^{q}(z-y_i)/z$$

is the average income gap and G_p is the Gini index among the poor. Sen thus tried to capture who the poor are (H), their average deprivation (I) and their relative deprivation to one another (G_p). This poverty index led to a large body of literature in the measurement of poverty.

Subsequent developments in the measurement of poverty followed two approaches. Thon (1979, 1983), Takayama (1979), Kakwani (1980), Foster et al (1984), Foster and Shorrocks (1991) pursued Sen's axiomatic approach to derive a poverty measure that satisfied certain desirable properties. Blackobry and Donaldson (1980), Clark et al (1982) and Chakravarty (1983) used the notion of social welfare function and the underlying concept of "equally distributed income" to obtain an index of poverty along Atkinson's (1970) inequality index.[6]
In this study we use the most common current measure of poverty index suggested by Foster et al. (1984), which meets most of the desirable properties discussed above.[7] The index is defined as:

$$p(z,y) = 1/n \sum_{i=1}^{q} \frac{(z-y_i)^{\alpha}}{z} \qquad \textbf{(6)}$$

where $\alpha \geq 0$

where α shows the weight the researcher is giving to the poorest of the poor. If α =0, then p (z, y) reduces to H, whereas if α =1 it reduces to the average income-gap. A higher value for α indicates increased concern for the poorest. Ravallion (1992) suggested that H measures the prevalence of poverty, I its intensity, and an indicator with α =2 its severity.

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[6] Vaughan (1986), Pyatt (1987) and Lewis and Ulph (1988), tried to endogenize the determination of the poverty line within the context of utility maximization. In application, such demand functions as the Linear Expenditure System provides convenient structure to obtain the poverty line without resorting to minimum calories. This approach has been rarely used in poverty studies. See Shimeles (1993) for an application to Ethiopian data.
[7] For further discussion see chapter 3 in Bigsten et al (2005).

Once an aggregate measure of welfare, in this case consumption expenditure is computed, the next step is to generate a poverty line to identify the poor. As indicated earlier, there is controversy surrounding the notion of a poverty line, mainly about the definition of poverty itself. People often tend to view their standard of living in comparison to others in their vicinity. Thus, they define poverty in relative terms which makes identification of the poor difficult. To avoid this, one can construct a poverty line that can be used as an instrument of comparison among households and sub-groups.

One of the most frequently used methods of constructing an *absolute* poverty-line is the cost-of-basic-needs approach popularized by Ravallion and Bidani (1991). The major food items frequently used by the poor are first picked to be included in the poverty line 'basket'. The minimum combined calorie requirement of an adult in Ethiopia is computed to be about 2200 calories per day. The cost of purchasing such a bundle would be computed using market prices and constitutes the food poverty line. Adjustment for non-food items can be done in various ways. Some researchers prefer to use the Engle's function to generate the food share. Others use the average food-share at the poverty line, as in this study. The difference in the methods selected is discussed in Ravallion and Bidani (1994). Section 4 discusses in detail the robustness of our results to changes in the poverty-line using distribution-free statistical criteria. Using the estimated poverty-lines in each year for all the sites, both urban and rural, we adjusted consumption expenditure for all households by using the poverty line of one of the sites as a price deflator. Thus, consumption expenditure was adjusted for temporal and spatial price differences. We also adjusted total household consumption expenditure for household size and composition so that we report poverty rates in per capita and per adult equivalent terms[8]

3. Evolution of poverty and income distribution in Ethiopia: 1994-2000

3.1 Background

In May 1991, the bloodiest and longest civil war in Africa came to an end and a new geographic, political and economic order emerged. Eritrea broke away, leaving Ethiopia, as the largest land-locked country in Sub-Saharan Africa. The introduction of an ethnic-based political system led to the enlargement of the state, and market-oriented economic reforms were introduced to foster private sector development. Private investment increased substantially. Privately owned banks, insurance companies and large and medium scale manufacturing industries, construction firms, hotels, colleges, and hospitals

[8] Details of the national food consumption basket are given in Annex Table 1, and that of the computation of the food and non-food poverty lines is given in Bigsten et al. (2005). Our adult-equivalent scales are based on Dercon's (2001) for rural and Taddesse's (1999) for urban areas.

emerged. Price deregulation helped farmers to sell their produce in the open market, a privilege they had been denied for nearly two decades.

The combined effects of rapid transformation in the political and economic sphere led to increased incomes. Between 1994 and1997, GDP in Ethiopia increased by about 7.2% per year (see Table 1). Agriculture showed a surprising recovery with a record growth rate of 14.7% in 1995/96, mainly due to good weather and widespread application of fertilisers (IMF, 2002). Growth in industry was also rapid.

However, in 1997/98, Ethiopia was hit by the worst drought since 1984, with 13 million people depending on food aid, and an unresolved border conflict with Eritrea erupted into full-scale war. In its aftermath during 1999/2000, a major rift erupted within the leadership of the party in power. In 1999/2000 drought again hit much of the Southern part of the country, which is, mainly a cash crop producing area. A sharp decline in the world-price of coffee further aggravated the situation there. Despite these factors, GDP declined only in the severe drought season of 1997/98, whereas during the two years of border conflict with Eritrea it grew robustly. Real GDP grew at an average rate of 3.3% in this period (see also Table 2) despite these political and economic shocks. However, much of the growth in GDP during this period came from expansion in “other services” (Table 1).

Table 1: Basic macroeconomic indicators for Ethiopia: 1993/4-1999/2000

Items	93/94	94/95	95/96	96/97	97/98	98/99	99/00
GDP (% growth)	1.6	6.2	10.6	4.7	-1.4	6.0	5.4
Agriculture (% growth)	-3.6	3.4	14.7	3.4	-11.2	3.8	2.2
Industry (% growth)	7.0	8.1	5.4	2.8	6.3	8.6	1.8
Distributive Services (% growth)	6.2	6.4	9.0	7.7	5.3	7.7	9.5
Other Services (% growth)	8.9	11.0	5.9	6.4	13.3	9.9	10.5
Private investment (%GDP)	8.0	9.0	11.6	10.8	10.6	8.4	9.9
Public investment (% of GDP)	7.1	7.5	7.5	8.3	7.6	7.9	5.3
Prices (% change)	11.0	13.4	0.9	-6.4	3.6	3.9	4.2
Terms of Trade (% change)	10.0	33.8	-22.1	10.5	18.1	-15.9	-33.9
Price of coffee+	2.17	3.50	2.80	2.88	3.5	2.78	2.25
Price of chat+	8.11	6.68	6.73	7.46	6.7	6.62	4.84

Source: IMF Country Reports: Various years. + Millions of Birr per thousand metric tons.

Aggregate price-increases have been modest except for 1993-1995 due to prudent monetary policy. But this national figure hides substantial regional differences. Particularly areas growing coffee and *chat* (key export crops) were severely affected as a result of large price declines in 1999/2000 (Table 1). Ethiopia’s overall terms of trade showed a large deterioration between 1998 and 2000 mainly due to the sharp decline in the world price of coffee.

Ethiopia's macroeconomic policy performance improved between 1992 and 1997 (Table 2) due to reforms in government finance, price deregulations, and market liberalizations as part of the country's agreement to implement Structural Adjustment Programs spearheaded by the IMF and the World Bank. The stabilization measures reduced the fiscal deficit, the exchange rate was aligned with external trade conditions, and inflation was put under control, which, essentially, led to a more stable macroeconomic environment. The overall policy-stance indicator, based on Demery and Squire (1996), essentially summarizes performance in fiscal, monetary and exchange rate policies.[9] The values obtained clearly track the major events in Ethiopia in 1990 decade.

After the remarkable progress in Ethiopia during 1992-1997, the country reversed course in 1998-2000 as we have seen.

Table 2: Changes in key macroeconomic variables in Ethiopia: 1992-2000

Policy Categories	1992-1994	1995-1997	1997-2000
Fiscal Policies			
Gov't deficit (% of GDP)	-9.50	-7.07	-10.03
Gov't revenue (% of GDP)	12.27	18.00	16.43
Monetary Policies			
Seignorage (annual % change)	5.62	-0.55	2.97
Inflation (annual % change)	10.73	2.63	5.43
Exchange Rate policies			
Real exchange rate (annual change)	20.77	-1.77	0.73
Black market premium (ratio of black market rate to official exchange rate)	96.30	15.77	5.07
Overall policy stance	0.55*	0.911**	-0.5***
Average per capita GDP growth+	1.13	4.7	0.83
Average GDP growth rate	3.33	7.12	3.33

Source: Computed based on Bigsten Kebede, Shimeles and Taddesse (2003), National Bank of Ethiopia (www.nbe.org), IMF (2005), WDI (2002);
Compared to 1989-1992, ** compared to 1992-1994, * compared to 1994-1997, + population growth is average of the decade based on data from IMF(1999), WDI(2002)*

Given this background, the question that this section of the paper attempts to address is what happened to poverty and to what extent it can be explained in terms of the events described above.

[9] Demery and Squire (1996) used the policy stance measures to link Structural Adjustment Programs implemented in Africa with poverty outcomes. They also discuss in detail the scores they assigned to changes in each of the policy variables and the weights used to aggregate them into a single policy stance index. We have updated the policy stance indicators used in Bigsten et al (2003) to assess Ethiopia's policy performance during 1998-2000. We use this index here to summarize the evolution of Ethiopian macroeconomic policies in the 1990s.

3.2 Data and estimation

A panel data set covering rural and urban households of four waves in the period 1994-2000 was used in the analysis.[10] The data-set originally consisted of approximately 3000 households, equally divided between rural and urban households. The nature of the data, the sampling methods involved in collecting it, and other features are discussed in detail in Bigsten et al. (2005). It is one of the few longitudinal data sets available for Africa. The data covers households' livelihood, including asset-accumulation, labour market participation as well as health and education and other aspects of household level economic activities.

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

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

The result as shown in Table 3 is that poverty declined consistently among panel households in both rural and urban areas from 1994-1997 and increased sharply in 2000 (Table 3). As discussed earlier, the initial improvements could be due to good weather, strong policy reform and general recovery. Inequality in consumption also declined in rural areas until 1997 so that the decline in poverty was due to both growth and better distribution of income. In urban areas, poverty declined until 1997 even as income inequality increased. In both areas, poverty rose sharply in 2000 as a

[10] The rural panel has two sets in 1994 and one set in 1989 for fewer villages.

consequence of both decline in per capita income and a rise in income-inequality.[11] Likewise, other measures of poverty, such as the poverty gap and the squared poverty gap that measure respectively average and relative deprivation also followed similar pattern over the study period. When we look at the normalized measures of poverty gap[12], in rural as well as urban areas, it hovered around 42% through out the study period suggesting that average deprivation is much more widespread than is suggested by the standard measures.

Table 3: Evolution of poverty and inequality in Ethiopia: 1994-2000 (%)

Type of Welfare (Poverty) Measure	1994	1995	1997	2000
Rural Areas (N=1216):				
Headcount ratio , per capita	56	49	39	50
	(0.014)	(0.014)	(0.013)	(0.016)
Headcount ratio, per adult equivalent	48	40	29	41
	(.014)	(.014)	(.014)	(.014)
Poverty Gap ratio, per capita	25.05	21.3	16.5	21.7
	(0.51)	(0.49)	(0.48)	(0.49)
Poverty Gap ratio, per adult equivalent	21.0	16.0	10	14.0
	(0.50)	(0.48)	(0.46)	(0.50)
Squared Poverty Gap ratio-per capita	16.7	13.3	8.8	13.68
	(0.53)	(0.48)	(0.41)	(0.48)
Squared Poverty Gap ratio, per adult equiv.	13.1	10.2	6.02	10.2
	(0.5)	(0.44)	(0.34)	(0.44)
Gini Coefficient, per capita	48	46	39	47
	(.8)*	(1.4)*	(1.6)	(1.4)*
Gini Coefficient, per adult equivalent	49	49	41	51
	(.8)*	(1.3)*	(1.6)*	(2.0)*
Urban Areas(N=927):				
Headcount ratio, per capita	41.0	39.0	33.6	45.2
	(0.16)	(0.161)	(0.15)	(.016)
Headcount ratio, per adult equivalent	34.0	32.0	27.0	39.0
	(.015)	(.014)	(.014)	(.02)
Poverty Gap ratio , per capita	17.86	16.9	15.7	18.83
	(0.56)	(0.570)	(0.57)	(0.58)
Poverty Gap ratio, per adult equivalent	13.0	11.4	9.6	14.5
	(0.21)	(0.20)	(0.19)	(0.24)
Squared Poverty Gap ratio , per capita	9.78	9.02	7.8	10.8
	(0.49)	(0.47)	(0.44)	(0.51)
Squared Poverty Gap ratio, per adult equiv.	6.5	5.6	4.7	7.5
	(0.45)	(0.42)	(0.39)	(0.48)
Gini Coefficient, per capita	44	43	46	48
	(1.4)*	(1.4)*	(1.5)*	(8.0)
Gini Coefficient, per adult equivalent	43	42	46	49
	(1.3)*	(1.0)*	(2.0)*	(2.3)*

Source: Authors' computation from Ethiopian Household Panel Data Set.
Terms in bracket are standard errors. * Bootstrap standard errors.

[11] The poverty figures reported in Table 3 have been revised to reflect more appropriately price differences across regions and time and also shares of the basic non-food component. As a result, the figures for rural areas are substantially different from our previous report in Bigsten et al (2003). Figures for urban areas remained unchanged. Otherwise, the trend in both poverty and inequality are the same with our previous result.

[12] The maximum value the poverty gap or squared poverty gap take is the headcount ratio. Dividing by the headcount estimated values of poverty gap and squared poverty gap provide estimate of how widespread for instance average deprivation or severity of poverty is in a society.

The levels and trend of poverty reported in Table (3) is more or less consistent with figures reported by the government based on nationally representative household budget surveys. For instance, the Ministry of Finance and Economic Development (2001) reported that in 1995 rural poverty was 48% and slightly declined to 46% in 2000. On the other hand, urban poverty increased from 33% in 1995 to 37% in 2000. The statistically insignificance of the decline in rural poverty and the rise in urban poverty between 1995 and 2000 as reported by the government is very close to what is reported in Table (3).

To get a better sense of how growth and distribution affected poverty, we use decompositions of the change in poverty into growth and changes in distribution components sometimes known as the Datt-Ravallion decomposition (Datt and Ravallion, 1992), which is based on parameterized Lorenz function estimations (Table 4). This decomposition is based on the fact that if an underlying parametric distribution of income can be estimated, then, one can derive from it a large class of poverty indices suggested in the literature. Between two periods, one can then calculate change in poverty due to growth alone, by holding distribution constant, and vice versa. The decomposition will not be exact since the actual distributions used to compare the changes in two periods can be different, in which case there will be a residual to take into account of this fact.[13]

We used the DAD-software for distributive analysis by Duclos et al (2004) to compute the contributions of economic growth, income inequality (redistribution) as well as the residual (Table 4). The sum of the three components is more or less equal to the changes in headcount ratios for the corresponding periods.

Table 4: The Datt-Ravallion decomposition of poverty into redistribution and growth

	1994-97	1997-2000
Rural Areas		
Growth	-7.8	0.9
Redistribution	-7.2	10.8
Residual	-2.2	-1.6
Urban Areas		
Growth	-10.8	8.5
Redistribution	4.4	2.9
Residual	-0.9	0.1

Source: authors' computations

[13] The residual thus can be interpreted as the difference between the growth component evaluated at the terminal and initial Lorenz functions, or equivalently as the difference between the distribution components evaluated at the means of the initial and terminal period (see Datt and Ravallion, 1992).

Clearly, rural poverty declined from 1994 to 1997 due to a nearly-equal combination of growth and changes in distribution. Urban poverty, on the other hand, would have fallen further were it not for adverse changes in distribution. For the period 1997-2000, rural poverty increased mostly due to an increase in inequality. Urban poverty on the other hand increased mostly due to shrinking per capita consumption expenditure. Thus, as we have seen earlier, strong growth at first led to much-reduced poverty in both rural and urban areas, but, later, faltering growth (especially in urban areas) and adverse distribution changes (especially in rural areas) reversed much of the rural gain and more than reversed the urban gain.

3.3 Profile of poverty

Real per capita consumption expenditure increased considerably in rural areas between 1994 and 2000 though it was slightly lower than in 1997 (Table 5). In urban areas, consumption also grew until 1997, but in 2000 it was far back down towards its 1994 level.

Table 5: Trends in real monthly consumption expenditure: 1994-2000, mean values, Birr

Variables (mean values)	1994	1995	1997	2000
Rural Areas				
Total per capita	80.0	92.0	96.0	93.0
Total per adult equivalent	100	118	125	121
Food per capita	66.3	78.9	86.6	84.1
Food per adult equivalent	83	102	113	110
Non-food per capita	13.4	12.9	9.4	9.2
Non-food per adult equivalent	17	16	12	11
Share of food expenditure in per capita	80.0	83.0	88.0	84.0
Share of food per adult equivalent	79	82.0	88.0	83.0
Urban Areas				
Total per capita	98.6	104.2	124.4	107.0
Total per adult equivalent	113.0	121.0	146.0	118.0
Food per capita	70.0	67.4	78.0	85.0
Food per adult equivalent	81.0	78.0	92.0	96.0
Non-food per capita	28.6	36.8	46.5	28.8
Non-food per adult equivalent	32.0	43.0	54.0	22.0
Share of food expenditure in total per capita	76.4	66.2	66.0	76.0
Share of food per adult equivalent in total adult equivalent	0.72	0.64	0.63	0.83

Source: Authors' computations

Poverty is determined to a large extent by characteristics that define the endowments and potentials of households and communities. Differences in the size and composition of households, and in the human and physical capital they possess affect income and consumption patterns. In rural areas these characteristics include the types of crops cultivated, the amount and fertility of land, as well as community characteristics such as access to markets and farming systems.

Table 6 shows the percentage of rural households in poverty during 1994-2000 according to these characteristics. In general, more female headed households were in poverty than male-headed ones, except in 2000. Households where the head had not completed primary school were more likely to be poor, whereas households where the wife had completed primary school were the least likely to be in poverty. Land-poor households were much poorer than land-rich households. Those near to town were generally less likely to be poor, as one might expect, though remoteness seems to have been less of a hindrance in 2000 than in 1994. Contrary to what one might imagine, households in enset and cash-crop growing areas were consistently more likely to be in poverty than those in cereal-growing areas, and those probabilities seem to have diverged. From 1994-1997, households in both areas did substantially better, but after that drought was severe in the *enset*, chat and coffee-growing regions of Ethiopia. In addition, the price of coffee and chat declined considerably, accounting for those divergences.

Table 6: Rural poverty profile: headcount ratio

Category	1994		1995		1997		2000	
Sex of the Head	**Pc***	**Pae****	**Pc***	**Pae****	**Pc***	**Pae****	**Pc***	**Pae****
Household Head is Female	65.4	56	51.0	41	41.2	33	46.0	35
Household Head is Male	54.6	46	48.5	40	39.0	29	55.0	43
Schooling								
Head completed primary	48	38	35	28	31	21	59	48
Head not completed primary	58	49	50	42	40	28	49	38
Wife completed primary	24.0	20	24.0	16	32.0	28	39.0	33
Wife not completed primary	57.4	49	49.5	41	39.6	29	53	41
Farming Systems								
Cereal Growing Areas	54	45	44	32	37	26	35	37
Enset growing areas	64	55	69	61	44	37	85	78
Land Holdings[14]								
"Land-poor"	58	49	65	59	46	34	71	64
"Land-rich "	40	29	36	26	27	17	31	22
Remoteness[15]								
Village is remote to town	74.5	63	48.7	41	38.0	30	57.0	46
Village is near to town	49.5	42	49.1	40	40.2	26	50.8	39
Off-farm Engagement								
Head is in off-farm activities	55.0	45	46.0	38	39.0	28	50.6	43
Head not in off-farm activities	60.5	53	54.0	45	40.0	30	56.2	43

Source: Authors' computation. * Real consumption per capita. ** Real consumption per adult equivalent

[14] Land rich and land poor refer to the top and bottom quintiles, respectively.
[15] Remoteness is defined as the ratio of population in nearest town to distance to the market. Remoteness measures market access.

Table 7: Urban poverty profile, headcount ratio

Category	1994		1995		1997		2000	
Sex of the Head	**Pc***	**Pae****	**Pc***	**Pae****	**Pc***	**Pae****	**Pc***	**Pae****
Head is Female	47	38	42	35	36	29	47	40
Head is Male	37	30	37	30	32	26	42	36
Occupation of the Head								
Private Employer	27	17	13	7	7	7	36	28
Own-account worker	37	30	39	33	33	29	46	33
Civil servant	31	23	20	12	19	17	45	31
Public Sector Employee	20	17	29	22	32	17	40	30
Private Sector Employee	24	23	28	25	*28*	*20*	44	28
Casual Worker	67	57	63	57	53	45	66	55
Unemployed	53	44	56	49	49	40	69	51
Residence of the Household								
Addis Ababa	57	40	53	36	46	30	54	38
Awasa	47	24	42	29	34	21	63	45
Bahir Dar	33	11	35	15	35	16	54	33
Dessie	55	35	48	31	59	31	71	48
Dire Dawa	29	13	43	24	43	23	63	41
Jimma	55	29	38	20	52	27	73	54
Mekele	51	23	53	30	47	16	42	14
Education								
Head completed primary	25	18	23	18	20	16	32	26
Head not completed primary	52	43	50	41	43	34	54	46

Source: Authors' computations. * Real consumption per capita. ** Real consumption per adult equivalent

The profile of poverty in urban areas is mixed in many ways. As in the rural areas, female-headed households were more likely to be in poverty than male-headed ones. However, while the proportion of female-households in poverty remained constant from 1994-2000, the proportion of male-headed households increased substantially. Similarly, households where the head had not completed primary school were more likely to be in poverty, and the proportion of such households was slightly higher in 2000 than in 1994; but the proportion of households in poverty where the head had completed primary school, while lower, had increased more from 1994 to 2000. Nevertheless, the level of education of the household head correlated with a bigger difference in poverty rates in the urban than in the rural sample. Every occupational category except the household-heads who were casual workers had substantially higher poverty-rates in 2000 than in 1994. Nevertheless, casual-worker heads may have had other sources of income (more on this in section 4). Public- and private-sector employees had the lowest rates of poverty in 1994, followed by business owners. By 1997, the business-owner rate had fallen almost to zero, however, while for public- and private-sector employees it had risen substantially, and rose further by 2000. At that point, business owners again had a substantial probability of being in poverty, only slightly lower than the four middle categories.

Poverty rates in Addis Ababa fell slightly from 1994 to 2000, while those in Mekele fell much more. Rates for all other towns increased substantially, with Jimma and Dessie having the highest, followed by Awassa and Dire Dawa.

Table 8 reports a more subjective assessment of living standards by the urban panel households. Consistent with the results just reported, the proportion of urban households reporting themselves as "poor" fell from 1994 to 1997 and then remained unchanged in 2000, while the percentages reporting themselves as "middle-income" or "rich" increased slightly. Nevertheless, overall rates of poverty seem consistent with the earlier results. It is hard to reconcile large and growing number reporting deterioration in 1997 and 2000 with falling rates of self-reported poverty, however. The numbers reporting improvement also grew from 1997 to 2000, but were substantially smaller.

Table 8: Household's perception of recent changes in their standard of living

	1994	**1997**	**2000**
How do you rate your wellbeing?			
Poor	56.9	52.9	52.2
Middle income	41.1	44.0	44.4
Rich	2.0	2.9	3.3
Has your welfare changed compared to past visits?			
Remained the same	15.2	47.7	30.8
Deteriorated	71.3	36.9	42.1
Improved	10.7	15.3	24.9

Source: author's computations.

In general, the rise in poverty in 2000, as reported in the surveys, was the result of fall in per capita income as well as sharp rise in income inequality suggesting the existence of complex factors at work here. The next section attempts to provide insight as how robust our findings are with respect to the determination of the poverty line.

4. Robustness of poverty estimates

4.1. An overview of the distribution-free dominance criterion for poverty comparison:[16]

Looking at the literature on the measurement of poverty that has emerged since the pioneering work of Sen (1973), it is not difficult to see the immediate and strong influence of the literature on the measurement of inequality, which itself owed a great deal to the classic work of Atkinson (1970), in creating some of the analytical constructs that link the statistical measures of income inequality and their welfare-theoretic interpretations with regard to poverty (see Haggenars 1987).

Atkinson (1970) integrated the notion of social welfare functions that meet certain regularity conditions in the comparison of situations with such popular statistical summary measures of income distribution as the Lorenz curve and the Gini-coefficient. Thus, Atkinson, invoking the "stochastic dominance" concept popular in the finance literature, showed that if two income distributions have the same mean and if one of the distributions Lorenz dominates the other, then social welfare (which is quasi-concave in income) in that distribution is higher than in the other[17]. Sen (1973) demonstrated that, if two distributions have unequal means, then Lorenz dominance does not offer any welfare inference. But Rothcild and Stiglitz (1973) argued that, when means are unequal, economic welfare can still be compared on the basis of the income received by some group of the poorest people. Sapsonic (1983) proved this proposition, so that rank dominance of absolute incomes is sufficient and necessary to generate welfare dominance, irrespective of the level of mean income.

Rank dominance utilises efficiency criteria alone between distributions, since dominance is implied if income of individuals in each decile of one distribution is higher than those in the corresponding decile in the distribution being compared, regardless of the level of inequality within each distribution. To get around this problem of focussing only on efficiency considerations, Shorrocks (1983) and Kakwani (1984) came up with a partial comparison of economic welfare on the basis of rank orders in the underlying Lorenz ordinates of any income distribution regardless of the means. This came to be known as ordering on the basis of a Generalised Lorenz curve (a Lorenz curve scaled by mean income of the population) with relative concern for equity. Thus, rank dominance, where the cumulative income of one Lorenz curve lies above that of another for all ordinates of the Lorenz curve, is

[16] This section draws heavily from Bigsten, Kebede, Shimeles (2005).
[17] "Social welfare" is the conventional term for "aggregate economic welfare" and will be used here with that meaning.

equivalent to first-degree stochastic dominance as in the finance literature, where expected returns on different investment opportunities are ranked.

The application of rank dominance to income distribution was facilitated by the development and simplifications of distribution-free test procedures in Beach and Davidson (1983), Beach and Richmond (1985) and Beach et al. (1994). Following this, Bishop et al. (1991) and others applied rank dominance to the comparison of welfare on the basis of the ordinates of Lorenz curves. The application to poverty was self-evident. Atkinson (1987) and Foster and Shorrocks (1988) proved that for all additive poverty indices, that is for those based on a utilitarian social welfare function, the dominance of a distribution over a given range of poverty lines is equivalent to the poverty ordering implied by the poverty indices. Bishop et al (1992) applied stochastic dominance testing to poverty comparison for selected countries with a promising potential for future application.

The stochastic dominance test criterion may be described formally as follows:
Suppose *F (**y**)* is distribution function or cumulative density function of income *f (**y**)* (so that $F\ (\mathbf{y}) = \int f\mathbf{y}$ where ***y*** is a vector of household income arranged in ascending order such that $y_1 < y_2 <,..,< y_n$, The inverse distribution function or quintile function, $y(p){:}\inf\{\ F(y) \geq p\},\ p\varepsilon[0,1],$ yields individuals' incomes in increasing order, where *p* is income percentiles. Following Sapsonik (1981), if W_p then denotes a class of anonymous, increasing welfare functions, then, for two distributions, X and Y, we have the following theorem:

X > R Y (i.e. X rank-dominates Y) $\;\mathit{iff}\ w(X) > w(Y)\ \ \forall w\varepsilon\, W_p.$

That is, distribution X rank-dominates distribution Y iff $x(p) \geq y(p)\ \forall\ p\varepsilon[0,1]$. If $\forall\ p\varepsilon\ [0,1]\ X(p) = Y(P)$, then X and Y have the same income distribution and standard of living. If X(p)>Y(p) for some p, and X(p)<Y(p) for some p, the distributions are non-comparable and cannot be ordered using rank dominance criterion.

Atkinson (1987) and Foster and Shorrocks (1988) showed as a corollaries that: a) Rank dominance of one distribution for all z (a range of poverty lines), implies that the headcount ratio is higher for that distribution ; and b) rank-dominance implies higher order-dominance including dominance for additive poverty indices, such as the P_α class defined as $P_\alpha = \int\{z - f(y)/z\}^\alpha$ dy, where f(y) is the density function of the income distribution, and α is distributive parameter (see Foster et al. 1984). Rank dominance is thus sufficient, but, not necessary for higher order dominance, but, the reverse is not true.

Following Beach and Davidson (1983), the statistics necessary for dominance testing are quite straightforward. Consider individual incomes, y_i in ascending order and divided into p decile groups with upper boundaries, p_1=.1, p_2=.2,., p_{10}=1. If the mean and variance of the distribution exist and are finite, an income decile, ξ_p, corresponding to abscissa p $(0 \leq p \leq .1)$ on a Lorenz curve is defined implicitly by $F(\xi_p)$, where F is monotonic. Thus, corresponding to a set of k-1 abscissas, 0<p1<p2<…<pk-1, there is a set of k-1 population income deciles, $\xi_{p1}<\xi_{p2}<,..,<\xi_{pk-1}$, and a set of k cumulative means, $\gamma_i \equiv E(Y \mid Y \leq \xi_{pi})$, for incomes less than or equal to ξ_{pi}. We can also define the conditional means, $\mu_i=E(y \mid \xi_{pi-1} <Y< \xi_{pi})$. The test for dominance is based on these estimators.

Until Beach and Davidson (1983), inference based on the ordinates of the Lorenz curve had to rely on parameterised Lorenz functions, which are not adequate to undertake the joint (mean income and distribution) dominance test. But Beach and Davidson (1983) proved that the above ordinates of the Lorenz curve are asymptotically normal with mean zero and a variance-covariance matrix $\Omega=(w_{ij})$, where: $w_{ij} = p_i [\lambda_i^2 +(1\text{-}p j)(\xi_{pi}\text{-}Y_i) (\xi_{pj}\text{-} Y_j) + (\xi_{pi}\text{-}Yi) (Y_{j\text{-}}Y_i)$ is the asymptotic variance of the k cumulative means. Beach, et al (1994) showed that a statistical test based on the conditional mean of the Lorenz ordinates can be constructed to test dominance between two Lorenz curves using the statistical test for mean difference. The test statistics for large samples can be written as: $T_i = (\mu_{i1}\text{-}\mu_{i2})/\{\sqrt{}(\text{var} (\mu_{i1})/N1+\text{var}(\mu_{i2})/N2\}$, where T_i can be treated as a t-ratio. The null-hypothesis is that the corresponding deciles have equal conditional means. If this is true for the entire range of the distribution, then, the two distributions are said to have equal welfare ranking whatever the level of the poverty line is. If there is a crossing, then a further criterion can be considered. Bishop et al. (1989, 1991) showed that if two distributions cross, and the crossing is statistically significant, then, ranking the two distributions according to some social welfare functions will not be possible Dominance exists if all other deciles have equal means and if there is statistically significant dominance in at least one of them. If there are two ordinates with different signs which are statistically significant, then, dominance cannot be determined. In applying the dominance test for Ethiopia we follow Davidson and Duclos (2000), where the distributions being compared are not strictly independent since the income distribution in one period is conditional on the distribution in previous period, and vice versa following the panel nature of the data.

4.2. Poverty comparisons based on semi-parametric kernel densities and non-parametric dominance-criterion.

Figure 1 and 2 show for rural and urban areas the entire distribution kernel density estimates of log of real per adult equivalent consumption expenditure.[18] The vertical axis stands for the proportion of households with a given level of consumption expenditure in adult equivalent. The kernel density function is essentially a smoothed-out histogram. Also in constructing the frequency distribution each observation is weighted depending on its distance from the mid-point in each interval. The function that determines the weights is called the kernel and the sums of the weighted values are called kernel-densities.

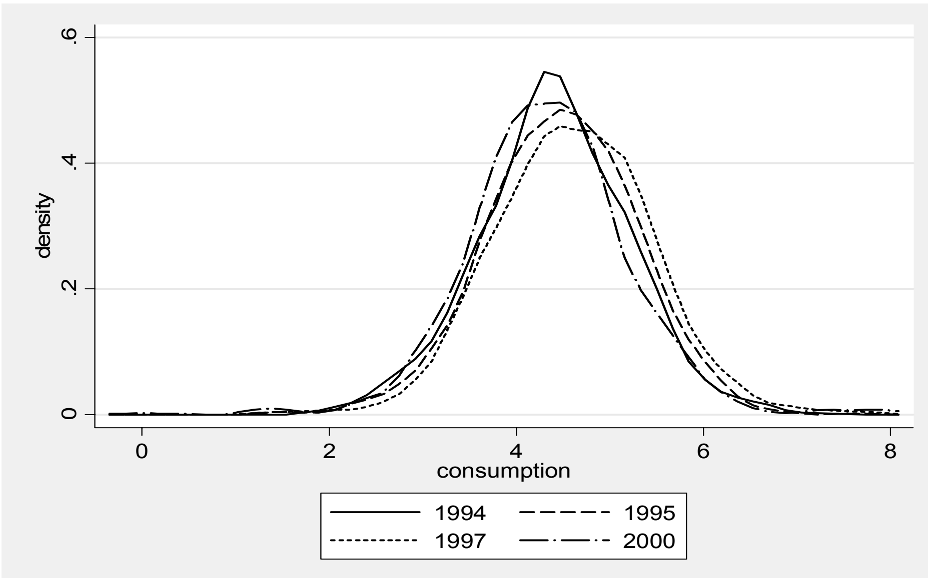
Figure 1: kernel density estimates for rural households: 1994-2000

Figures 1 and 2 illustrate how consumption expenditure and its distribution changed over the period. For both rural and urban households the 1997 distribution had clearly shifted to the right indicating higher average consumption. For rural households, the distribution also clearly clusters around the mean with narrower tails and higher top indicating greater equality.

[18] Kernel density is an extension of a histogram routinely used to construct the frequency distribution of a given data. Kernel density is a powerful tool to approximate a density function, such as for instance the distribution of income, using income data from individuals. Like a histogram, the data are divided into intervals or groups which may overlap and frequency distribution is set up for observations that fall within that interval.

Thus, as we have seen in Section 3, poverty had decreased as a result of both growth and more egalitarian distribution. The rural kernel density pattern for 2000 is both lower and had reverted to the left with wider tails, all indicating greater poverty again.

Figure 2: Kernel density estimates for urban HHs: 1994-2000



For urban households, the kernel-density diagram illustrates worsening distribution after 1997, with the 2000 distribution centred even to the left of 1994, which was the most equal of the three as evidenced by the narrow high. There was less poverty in 1997 as the distribution shifted right and became even less equal. By 2000, however, the distribution not only shifted to the left of 1994, but became even less equal than 1997. A clear picture that emerges from Figure 2 is that poverty increased in 2000 regardless of where we draw the poverty line up to a log income level of 4.2 (or Birr 100), which is higher than the absolute poverty line by 65%.

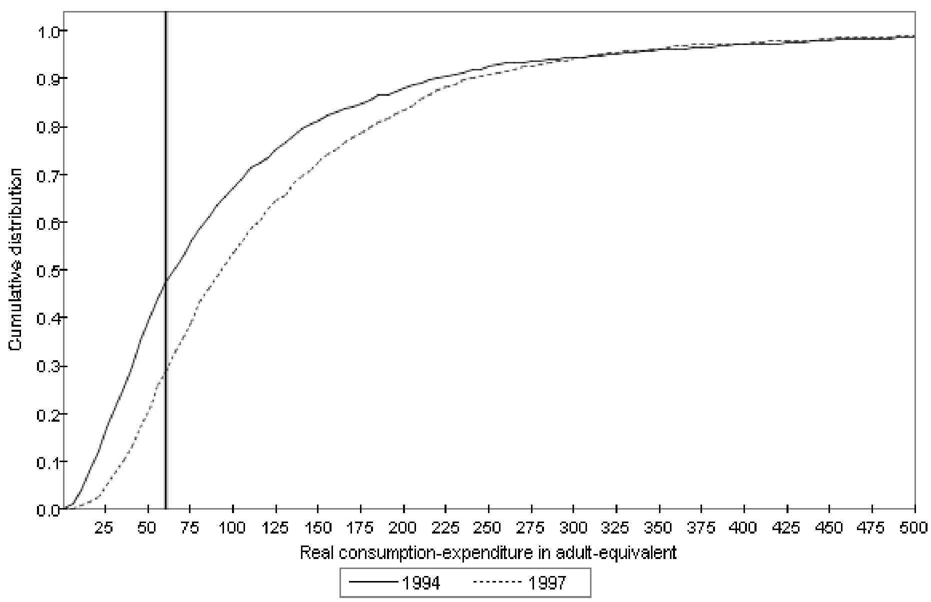
It is important to look further at the profile of poverty across households and communities to get a further sense of how changes in underlying household and community characteristics influenced poverty and how potential policy changes might alleviate it. The rest of the paper focuses on these issues.

The robustness of our result on poverty trends could be further examined using the distribution-free dominance method reviewed in Section 4.1. We compared two distributions at a time using the stochastic-dominance criteria discussed earlier

(Figures 3-6). Thus, we evaluated which headcount ratio of two periods was higher for a range of poverty lines where no statistically significant crossing occurred. Given our panel-data, we needed to take into account sample dependence between the distributions over time. We used DAD-software for distributive analysis (Duclos et al. 2003) which computes the level of income at which any crossing occurs, and whether it is statistically significant. The figures have real per capita consumption expenditure on the horizontal axis, and the cumulative percentage of household with at least that level of expenditure on the vertical axis. The distribution to the right or below has fewer people with lower expenditures and thus less poverty (headcount ratio).

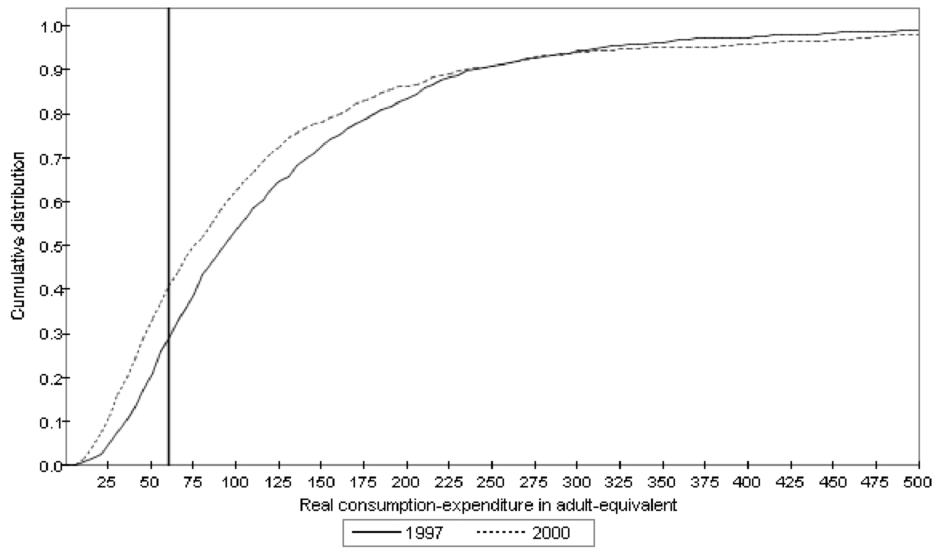
The headcount ratio for 1997 was lower than that for 1997 (Figure 3) up to Birr 208, which is more than three times the poverty-line used, and double the mean income (consumption) that prevailed in 1994. Crossings at higher levels (Birr 221, 227 and 223) are thus irrelevant for our purposes and changing the poverty line within any reasonable range would not change the poverty comparison between the two periods. There was clearly less rural poverty in 1997.

Figure 3: Poverty dominance in rural areas, 1994-1997



The headcount ratio for 1997 was also lower than that for 2000 (Figure 4) up to Birr 190, again far above any reasonable poverty-line so that rural poverty had unambiguously increased again in 2000.

Figure 4: Poverty dominance in rural areas, 1997-2000



The cumulative headcount ratios for the urban panel did not cross even at high levels, either in the 1994-1997 comparison (Figure 5) or in the 1997-2000 comparison (1997-2000). And, in the rural areas, the headcount ratio for 1997 was lower than that of 1994 (Figure 3) and also lower than that of 2000 (Figure 4) so that poverty clearly fell from 1994-1997, and rose again in 2000.

Figure 5: Poverty dominance in urban areas, 1997-2000

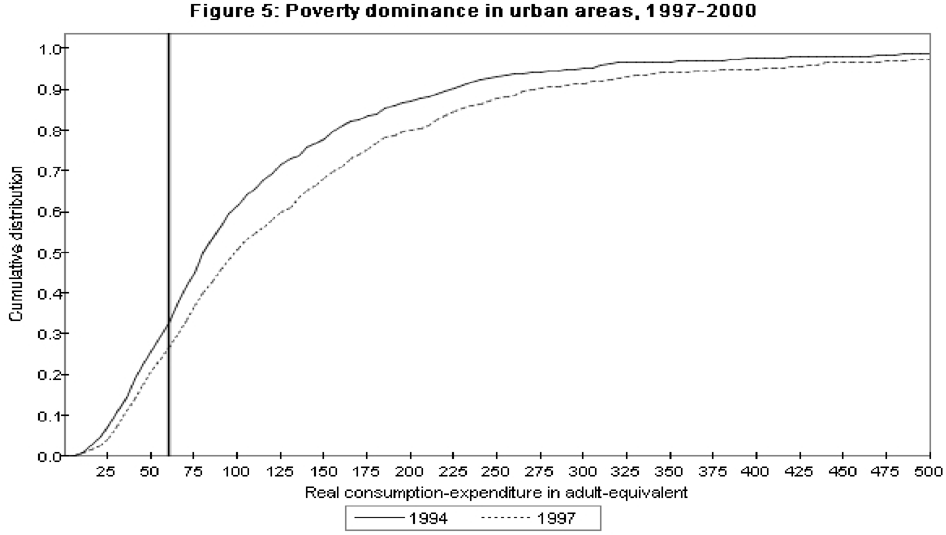
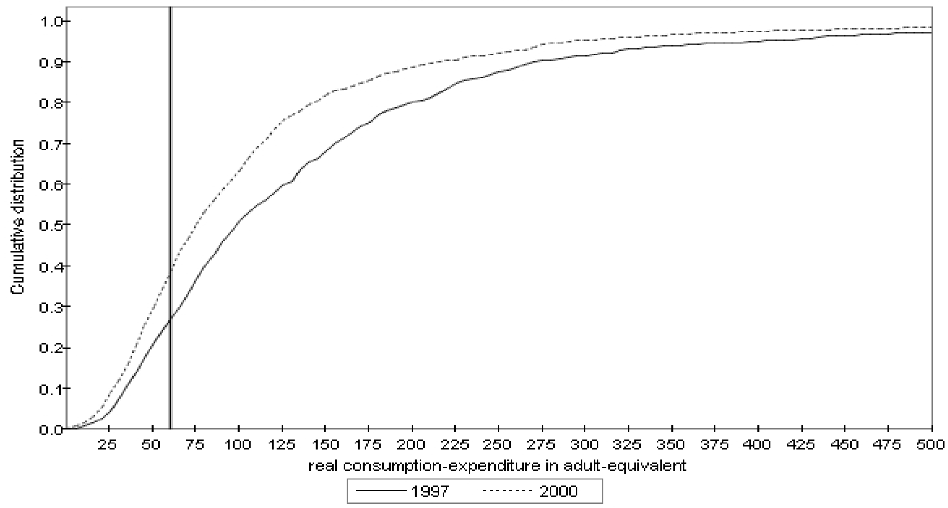
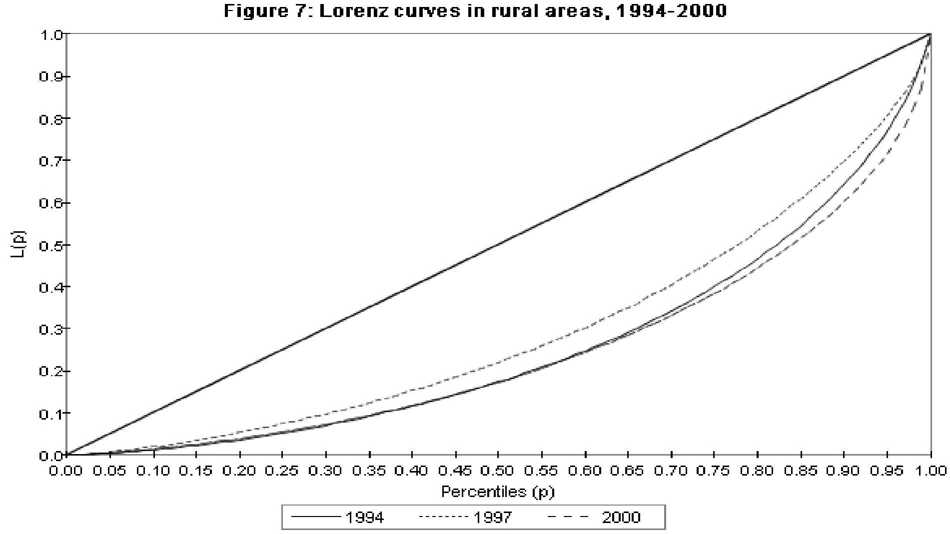


Figure 6: Poverty dominance in urban areas, 1997-2000



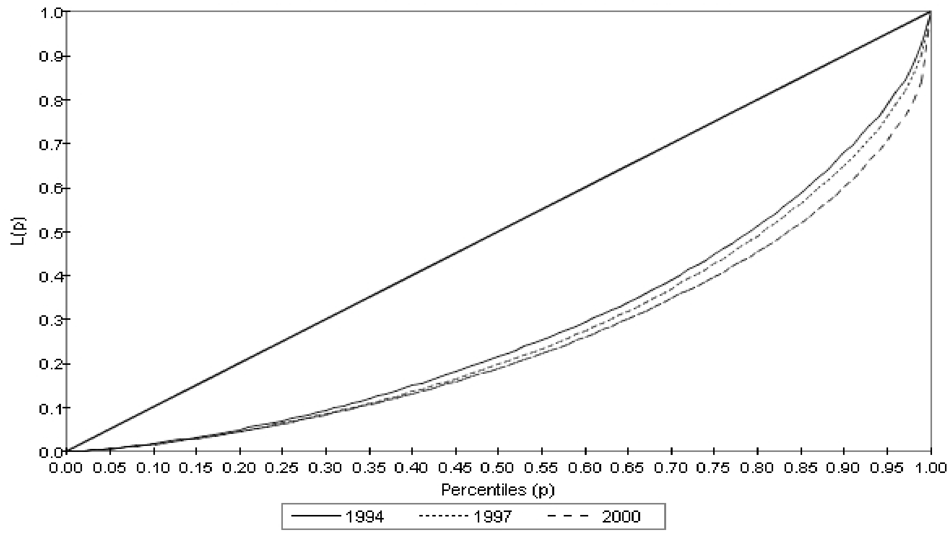
Since income inequality has become an important issue in our discussion of poverty in Ethiopia, Figures 7 and 8 illustrate for rural and urban households its evolution over time by using Lorenz curves. It can be seen that income inequality in rural areas was lowest in 1997 as compared to both 1994 and 2000. The rise in income inequality in 2000 was due mainly to faster consumption growth among the top 20 percent. The share of the bottom 15% more or less remained unchanged throughout the period.

Figure 7: Lorenz curves in rural areas, 1994-2000



On the other hand, in urban areas, inequality increased consistently from 1994, but, with the share of the bottom 30 percent remaining unchanged. With per capita consumption remaining more or less unchanged during 1997-2000, the increase in poverty was due to decline in the shares of people within the 40^{th}-50^{th} percentile.

Figure 8: Lorenz curves in urban areas, 1994-2000



5. Modelling poverty and inequality: Decompositions and simulations

5.1. Determinants of poverty

There is a large literature dealing with the decomposition of poverty and income inequality mainly in order to understand the factors that determine them. Many follow Foster and Shorrocks (1991) in sub-group decomposition, and others follow Kakwani (1990) and Datt and Ravallion (1992) in decomposing into growth and inequality components.

Sub-group decomposition is essentially the same as profiling poverty to evaluate its extent in various sub-groups and where it is concentrated. For example, decompositions by economic sectors reveal their shares in overall poverty. We also saw rough decomposition into growth and inequality components in Section 3.

There is an emerging trend to use model-based (regression-based) decomposition to identify factors responsible for the overall change in poverty and income distribution. Recently popularized in the literature on inequality-decomposition (Morduch and Sicular, 2002) this approach utilizes the collinearity between household or community characteristics and income (consumption) to determine their contributions to inequality. Dercon (2001, 2005) and Datt and Jolliffe (2005) use this technique for analysing poverty. Determining the contributions of household and community characteristics to changes in poverty could provide a better basis for policy formulation. It also suggests the possibility of simulating the impact of changes in some policy-variables on poverty. However the method is not without shortcomings. One difficulty is how to construct a model of consumption expenditure based on some theoretical framework. Otherwise, consumption expenditure is simply a linear (monotonic) transformation of the variables in the model so that the causation is not determinable, and that is the primary purpose of modelling poverty.[19] One cannot simply use the coefficients of the 'covariates' of consumption expenditure for simulation purposes. In practice, researchers use the Mincerian earning model (e.g Datt and Jolliffee, 2005) or a variation of the human capital theory to obtain reduced forms of determinants of consumption. Or in the case of agricultural households, a profit maximization model can be used to establish behavioural responses as well as clear direction of causation (e.g. Dercon, 2005).

Another, perhaps more challenging problem is that even if it is possible to set up a reduced form econometric equation representing some theoretical model, most variables obtained from household budget surveys suffer from problems of endogenity which affect the distribution of the error term with respect to explanatory variables. Unobserved factors, such as fertility-choices, as well as consumption-habits and preferences influenced by cultural, ethnic and religious practices, etc., can influence some of the explanatory variables. As a result, unbiased and efficient estimates of parameters can be obtained only if we treat these unobserved individual-effects as fixed (Baltagi et al. 2003). In the case of consumption expenditure, separating the effects of unobserved household-specific characteristics from the purely random variation is necessary to use the model for prediction or simulation. Poverty measures based on consumption data suffer from a number of sampling and other measurement errors, as well as from other types of extreme values. But, with panel data it is possible to decompose consumption variations into unobserved time invariant household-specific characteristics, and other time-varying observed characteristics plus the random residual. Thus, it is possible to get an idea of the sources of variations in poverty over time, apart from the distribution and growth-components.

[19] For a discussion of this issue see for example, Ravallion (1996)

Following Datt and Jolliffe (2005) we set log of consumption expenditure per adult equivalent as a linear function of a set of household characteristics, as well as a set of community characteristics also thought to determine income and expenditure. We make use of the panel nature of the data to control for possible endogenity between unobserved individual specific factors and observed ones thought to be determinants of consumption. In addition, we specified a flexible functional form that controls for interaction effects of closely-correlated determinants of consumption-expenditure as well as for scale effects of such variables as household size, land etc., which are especially relevant in the rural setting. The resulting specification is:

$$\ln c_{it} = \alpha + \sum_{k}^{K} \beta_k X_{kit} + \sum_{i} \sum_{k} \gamma_k X_{kit} X_{jit} + u_i + \varepsilon_{it} \tag{7}$$

with the following assumption on the distribution of the error terms:

$Eu_i = 0$, $Eu_i^{\,2} = \sigma_u^{\,2}$,

$E\varepsilon_{it} = 0$ $E\varepsilon_{it}^{\,2} = \sigma^2{}_{\varepsilon}$

$Cov(X_{kit}, \varepsilon_{it}) = 0$

$Cov(X_{kit}, u_i) \neq 0 \quad for \quad some \quad k$

From equation (7) consumption expenditure is assumed to be a linear function of k exogenous variables (X_{kit}) plus a non-linear component (the third term) that captures curvatures as well as interactions among the household and community characteristics correlated with consumption expenditure. The error terms were assumed to be identically and independently distributed with constant variance. The first error-component captures unobserved time-invariant household-specific determinants of consumption (occasionally considered as a proxy for permanent income)[20] and the second term is the random term.

We used the following demographic variables in rural areas: household size and composition, mean age of the household and age of the head of the household. But household decisions on size and composition, whether to have more children for example, are presumably dependent on complex factors, including income and thus consumption itself. We can think of a number of theoretical arguments why they need to be included on the right hand side of the consumption model, not the least is the broader framework of the human capital theory. More problematic could be household size which is also already included in the left-hand side to normalize household consumption into per

[20] See for example, Decron and Krishinan (2000)

capita consumption[21]. The other important variables in rural areas are amount of land holdings, and number of oxen owned, which are production inputs. We also included the value of household asset which in some way affects consumption smoothing. Finally, besides interaction terms, a number of exogenous factors, such as access to market, crops raised, rain-fall were included. Dummies for each survey period were also added to control for seasonality and other unobserved time-varying effects.

Analogously, the explanatory variables selected to estimate the consumption model for urban areas are as follows: demographic variables, occupational categories, residence in the capital, asset values, rate of "unemployment"[22] and ethnic background which fundamentally shape household fortune at some point in time. We included squared values of household size to control for scale-effects and interactions between age of the household and completion of primary school.

Treating the individual effects as random requires the assumption that all explanatory variables are exogenous, in which case the random-effects estimation method provides efficient parameter estimates. We used Hausman's (1978) specification test to decide whether or not to treat the individual effects as fixed (possibility of endogenity of some of the regressors) or random (exogenity of the regressors). The Hausman specification test compares an estimator say θ_1 known to be consistent (in this case the fixed-effects estimates) with an estimator θ_2 believed to be efficient (the random-effects estimate). If the assumption holds, both estimators should be consistent, and thus, no systematic difference need be observed. If there is systematic difference, then, we have to consider the possibility that the assumptions of the exogenity of the regressors in the random-effects model are questionable.

The results reported in Appendix Tables 2.1 and 2.2 show that the fixed effects and random effects model are distinct as shown by the significantly high value of the χ^2 tests. That is, the assumption that the random-effects model is efficient and consistent is not confirmed. This leaves us with the fixed-effects model to get consistent parameter estimates. It is not possible to get estimates of the time-invariant determinants of consumption expenditure, however. To get around this problem, we used instrumental variables to get consistent estimates of the parameters time-varying determinants.

[21] Note however also that the relationship between household size and per capita consumption expenditure is non-linear (see also Datt and Jolliffe, 2005 for more detail).
[22] We defined unemployment rate for each household as ratio of the unemployed (those not currently working) to those in the 15-64 age bracket. We recognize that such a definition is a crude measure of unemployment, but, we included it here on the belief that it may shade some light on the incidence of poverty.

The Hausman-Taylor (Hausman and Taylor, 1981) instrumental variable method was applied, which essentially uses as instruments both time-varying and time-invariant explanatory variables assumed not to be correlated with the unobserved household-specific random effects. Accordingly, we classified the explanatory variables into those as purely exogenous with respect to any unobserved individual-specific characteristics (called X_1 and Z_1) or possibly correlated with them (called X_2 and Z_2). Each group included both time-varying (X_1 and X_2) and individual-specific time-invariant (Z_1 and Z_2) characteristics. A variation of (7) using the above notations can then be re-written as:

$$\ln c_{it} = X_{1it}\beta_1 + X_{2it}\beta_2 + Z_{1i}\delta_1 + Z_{2i}\delta_2 + \mu_i + \varepsilon_{it} \quad \textbf{(8)}$$

Since X_2 and Z_2 are assumed possibly correlated with μ_i the standard random-effects estimation or maximum likelihood methods would probably result in inconsistent estimates. But, one could get consistent estimates X_1 and X_2 using a fixed-effects estimation method which essentially eliminates μ_i by taking a first difference of equation (8). The coefficients of Z_1 and Z_2 as well will be eliminated by the differencing, however, so that they remain unidentified. Hausman and Taylor (1981) suggested proceeding with the fixed-effects regression of (8) to obtain consistent estimates of β_1 and β_2. Using these, it is possible to generate the within-residuals for each household. In the next step, δ_1 and δ_2 are estimated by regressing the within-residual on Z_1 and Z_2 using X_1 and X_2 as instruments[23].

The question of identifying the endogenous explanatory variables is not always clear. Some researchers use an *adhoc* procedure of comparing the correlation between the unobserved household specific error components, u_i with explanatory variables and pick those with high correlation value as endogenous. [24]. In our case, we considered those variables within the confines of household choice or decision, such as the size of households, size of land, oxen, asset values, occupations, unemployment, etc, as being correlated with unobserved household characteristics. Demographic variables such as age, sex, farming systems, ethnic background, etc, could be considered as strictly exogenous variables. Next, we undertook the Hausman (1978) specification test if the choice of our instruments were valid by comparing the Fixed-effects model with the Hausman-Taylor random effects model. The P-values for rural areas and urban areas were 0.17 and 0.92 respectively for urban and rural areas, both of which indicated that the two specifications are equivalent.

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[23] To use this method, it is necessary that the number of variables in X_1 should be at least as many as those in Z_2.

[24] See for example, Mc Pherson and Trumbull (2003, 2004) in applying this procedure. It is important to note that higher correlation of an exogenous variable with individual effects does not necessarily imply that the variable is endogenous. It could very well be due to measurement error.

Tables 9 and 10 show respectively, the estimated coefficients of determinants of real consumption expenditure per adult equivalent for rural and urban households based on the three specifications: fixed-effects, random-effects and the Hausman-Taylor random effects estimator. Overall, we observe that for some variables, the three estimation methods had their coefficients increased in the instrumental method approach (for instance, for coffee and chat producing areas, and age of the household), while in other cases the coefficients of some variables became insignificant (for example, for off-farm employment). Finally we also note that the share of the unobserved household-specific effect error term in total residual was very low in the random-effects model while in the two other cases it was much higher. The difference is of interest because it provides a sense of how much of the variation in the unobserved component of consumption is due to unobserved household characteristics, which indicate permanent or long-term difference, or transitory random shocks, including measurement errors.

It is easy to see that among the time-varying explanatory variables in rural areas, coefficients for household size, and its square, size of land, number of oxen, household durables, and the interaction terms between size of land and household size, and size of land and number of oxen remained significant in the consumption model. The signs of the coefficients in most cases are consistent with what one would normally expect. For instance, consumption declined with household size and increased with its square, echoing the scale-effect frequently referred in household consumption analysis. Also, consumption also increased with the size of land per capita, number of oxen owned and the accumulation of household assets. Among the interaction terms, the coefficient for oxen and land is interesting. It indicates that households with low size of per capita land tend to own more oxen. This may sound strange under normal circumstances. But, it can be interpreted as a result of the imperfect or near non-existence of land market in Ethiopia. Farmers with small size of land can expand their livelihood easily by acquiring more oxen and enter into a share-cropping arrangement with relatively land-rich households.

Table 9: Fixed-Effects (FE), Random Effects (RE) and Hausman-Taylor (HT) Estimate of Rural Consumption Expenditure per adult equivalent

	FE	RE	HT
Constant	0.77772	0.237	0.74344
	(1.76)	(-0.56)	(1.7)
Household size	-0.22133	-0.13137	-0.20185
	(7.84)**	(8.45)**	(7.71)**
Household size squared	0.00478	0.00331	0.005
	(3.64)**	(4.67)**	(4.07)**
Female headed households	-0.1392	0.03095	-0.06729
	(-0.8)	(-0.39)	(-0.5)
Mean age of the household	-0.00057	0.00295	0.00156
	(-0.17)	(-1.57)	(-0.54)
Age of household head	-0.01761	-0.00348	-0.00527
	(4.19)**	(2.77)**	(2.02)*
Household head completed primary	0.21612	0.04112	0.22642
	(1.9)	(0.79)	(2.15)*
Dummy for wife with at least primary education	0.49608	0.55569	0.45283
	(1.57)	(2.44)*	(1.52)
Per capita size of land in hectares	0.38873	0.50454	0.34095
	(2.77)**	(4.64)**	(2.56)*
(Per capita size of land in hectares)^2	-0.06551	-0.10151	-0.04901
	(-1.58)	(2.95)**	(-1.24)
Number oxen owned (bulls, oxen and young bulls)	0.04531	0.06598	0.04767
	(2.59)**	(4.76)**	(2.87)**
Total current value of household assets	0.00013	0.00035	0.00015
	(2.18)*	(7.45)**	(2.68)**
Population of nearest town divided by the distance in kms from the site (access to market)	0	0.00003	0.00009
	(.)	(7.16)**	(4.11)**
Farming systems (dummy for enset growing area)	0	0.24069	0.01656
	(.)	(5.41)**	(0.13)
Dummy for households which harvested coffee during last season	0	0.1332	0.18286
	(.)	(2.59)**	(2.67)**
Dummy for households which harvested teff last season	0	-0.0355	0.10036
	(.)	(-1.1)	(-1.28)
Dummy for household which harvested chat last season	0	0.43251	0.53581
	(.)	(7.89)**	(6.90)**
Off-farm employment	0	-0.09492	-0.01677
	(.)	(3.15)**	(-0.05)
Rainfall in mm for stations near survey site	0.00459	0.00322	0.00353
	(10.03)**	(8.94)**	(9.42)**
Interaction between HH-size and head being female	-0.01326	-0.02281	-0.01445
	(-0.66)	(1.99)*	(-0.86)
Interaction between HH-size and education of wife	-0.07844	-0.07355	-0.06431
	(-1.66)	(2.07)*	(-1.44)
Interaction between HH-size and land	0.00355	0.00261	0.00464
	(2.10)*	(1.92)	(2.93)**
Interaction between oxen ownership and size of land	-0.08097	-0.0886	-0.09753
	(2.39)*	(3.00)**	(3.05)**
Dummy for 1995	0.01935	0.03125	0.03778
	(0.66)	(1.1)	(1.36)
Dummy for 1997	0.40321	0.2939	0.35049
	(12.34)**	(10.12)**	(11.96)**
Fraction of variance due to u_i	0.44	0.14	0.36
Wald chi(24)		1030	638

Source: authors' computations, HH-Household Head
Terms in bracket are t-values, ** significant at 1%, * significant at 5%

Table 10: Fixed Effects (FE), Random Effects (RE) and Hausman-Taylor Random-Effects (HT) Model of Urban Consumption Expenditure: 1994-2000

	FE	RE	HT
Constant	5.74483	4.75697	5.14499
	(22.50)**	(26.87)**	(21.58)**
Household size	-0.21342	-0.19089	-0.20798
	(8.31)**	(10.31)**	(8.67)**
Household size squared	0.00607	0.00734	0.00586
	(3.94)**	(6.32)**	(3.99)**
Female headed households	-0.19112	-0.06705	-0.20177
	(2.77)**	(-1.78)	(4.23)**
Mean age	-0.00618	0.02122	-0.00642
	(-0.6)	(2.92)**	(-0.72)
Mean age squared	0.0001	-0.00022	0.00009
	(0.71)	(2.14)*	(0.75)
Age of household head	-0.00429	-0.00523	-0.00573
	(-0.58)	(-1.05)	(-0.97)
Age household head squared	0	0.00003	0.00003
	(0.01)	(0.68)	(0.52)
Dummy for HH with at least primary education	0.35277	0.48633	0.41196
	(1.94)	(4.20)**	(2.42)*
Dummy for wife with at least primary education	-0.11538	0.05994	-0.06615
	(-0.85)	(0.6)	(0.51)
HH private business employer (Casual Labour is reference group)	0.01399	0.44242	0.01704
	(0.09)	(3.95)**	-(.11)
HH own account worker	-0.08628	0.15083	-0.09639
	(-1.21)	(3.35)**	(-1.42)
HH civil servant	0.1186	0.15228	0.1496
	(-1.5)	(3.08)**	(2.00)*
HH public enterprise worker	0.03707	0.05604	0.04019
	(0.42)	(0.94)	(0.48)
HH private sector employee	0.01968	0.13835	0.02032
	(0.21)	(2.03)*	(0.23)
HH unemployed	-0.33964	-0.26158	-0.33331
	(4.01)**	(4.02)**	(4.10)**
Unemployment rate	0.0459	-0.09441	0.04278
	(0.62)	(-1.64)	(0.6)
Total value of household asset/100	-0.00019	0.00079	-0.00013
	(-1.21)	(6.61)**	(-0.85)
Amhara ethnic group	0	0.12414	0.10277
	(.)	(2.71)**	(1.51)
Harari ethnic group	0	0.82777	1.1488
	(.)	(2.80)**	(2.56)*
Oromo ethnic group	0	0.05828	-0.0118
	(.)	(1.06)	(-0.15)
Tigrawi ethnic group	0	0.26985	0.52223
	(.)	(4.08)**	(3.75)**
Addis (capital city)	0	-0.0617	0.63057
	(.)	(-1.64)	(2.55)*
Household head completed primary*age	0.03269	0.02162	0.03963
	(-1.83)	(1.62)	(2.36)*
Dummy for 1995	0.06851	0.0768	0.07038
	(2.47)*	(2.72)**	(2.64)**
Dummy for 1997	0.17128	0.18571	0.17229
	(6.11)**	(6.55)**	(6.40)**
Dummy for 2000	0.0718	0.02952	0.0675
	(2.30)*	(0.99)	(2.28)*
Fraction of variance due to u_i	0.52	0.32	.60

Source: Authors' computations, HH-Household Head Terms in bracket are t-values, **significant at 1%, * significant at 5%

Similarly, for households in urban areas, the coefficients associated with household characteristics such as size, age, sex of the head of the household, and education turned out to be statistically significant bearing also the expected sign in affecting household consumption. It is interesting to note that except for the occupational group Civil Service, none of the coefficients of the other occupation turned out to be significant in the Hausman-Taylor specification. One of the striking differences between rural and urban areas is the strong effect that completion of primary education has on consumption. In urban areas, completion of primary education, especially by the head of the household, is a strong predictor of higher consumption, suggesting the significance of human capital, while in rural areas, it is physical assets, such as land that matter. It is also interesting to note that the coefficients for household size and its square are almost identical between rural and urban households.

5.2 Policy simulations

One of our objectives for modelling real consumption expenditure is to simulate the effects of potential policy measures on observable household characteristics and thereby on poverty. Success will depend on the predictive power of the estimated coefficients and the significance of the overall statistical model. Table 11 provides some clue as to how well a model of our choice performed in predicting poverty in comparison with the observed poverty rates[25]. It is clear from these tables that the proportion of poverty explained by observable and unobservable household-specific factors is reasonably high. In every case, actual poverty was higher than predicted poverty. This indicates that 'random' shocks were not random with respect to the poor, but, rather consistently affected them negatively. In addition, Table 11 shows the correlation (ranking) between actual and predicted poverty at the household level, which is about 51% for rural areas and 57% for urban areas. This indicates that almost half of the difference in poverty states across households is explained by random-shocks, particularly in rural areas. Differences either in observed attributes of households or unobserved permanent household characteristics contributed moderately to poverty status. Random shocks, which may include measurement errors, and other time-varying unobserved factors, also contributed significantly to poverty incidence.

[25] It should be noted that the predicted consumption assumes a lognormal distribution, so that predicted poverty is constrained by the parametric assumptions. On the other hand, observed poverty estimates are based on non-parametric methods. In general, the difference is not so significant since for large n, consumption distribution approximates lognormal distribution.

Table 11: Poverty decomposition (per adult equivalent) by household observable factors and non-observables, 1994-2000

	1994	1995	1997	2000
Rural Areas				
Headcount ratio due to observable and unobservable individual effects (%)	45	34	23	29
Headcount ratio due to "random-shocks" (%)	2	6	6	11
Overall poverty (%)	47	40	29	40
Contributions of predicted poverty in actual poverty (%)	96	85	79	73
Correlation between actual and predicted poverty at HH level (%)	51%			
Urban Areas				
Headcount ratio due to observable and unobservable individual effects (%)	31	26	19	34
Headcount ratio due to "random-shocks" (%)	2	6	8	4
Overall poverty (%)	33	32	27	38
Contributions of predicted poverty in actual poverty (%)	97	92	82	96
Correlation between actual and predicted poverty at HH level (%)	57.4			

Source: authors' computations

Poverty diagnostic is useful to quantify the effects of potential policy measures on poverty. We illustrate below a few policy experiments and discuss their impact on poverty using our results in Tables 9 and 10. Simulations of the impact of policy on poverty are considered comprehensive if they address two way causality and dynamics which essentially requires a dynamic General Equilibrium framework. In our case, we limit ourselves to a single step (one- way causation), static link between poverty and policy.

Table 12: Simulations of changes in the headcount ratio (percentage points)

	1994	1995	1997	2000
Rural Areas				
Land Reform (redistribution)	-1	-4	-5	-1
Increase in the size of per capita land by 75%	-2	-4	-4	-3
Doubling of per capita land ownership	-3	-4	-5	-4
Increase in the "returns" to land by 20%	-1	-3	-2	-2
Increase in the "returns" to land by 50%	-3	-7	-5	-5
Improvement in infrastructure by 30%	-6	-7	-8	-6
Improvement in infrastructure by 50%	-9	-10	-11	-9
Urban Areas				
Reduction in unemployment	-1.5	-1	-2	-2
Access to primary education (universal primary education)	-9	-11	-10	-10

Source: authors' computations.

Table 12 shows the predicted changes in headcount rates from a few possible policy changes. In the rural model increasing the amount of land[26] or alternatively improving

[26] To make significant impact on poverty, the size of land that should be available on per capita basis has to be large. One possible reason could be that existing land-holdings are quite small, next to nothing, for significant number of households.

its productivity, and improving infrastructure that would allow better access to markets would reduce headcount ratios substantially.

The current tenure system, which came into force in 1974 through a popular revolution, is largely regulated by the government and beyond the control of individual farmers (Kebede and Shimeles, 2003). All land belongs to the government, and farmers have only user-rights. In principle, land is supposed to be allocated on the basis of need and ability to till. So in some sense, we can consider it as quasi exogenous. In our model, the effect of a unit increase in per capita land ownership is considerable with diminishing returns at higher level of per capita land ownership.[27]

In the panel, the average land-holding per capita was 0.25-0.3 hectare, with considerable variation (see also Kebede, 2004). In fact, the Gini coefficient for land is on the average around 51%, suggesting that the current mechanism of land allocation may not be equitable as desired.

Redistribution from land-rich households (30% from the richest decile, 20% from the second and third decline) to households just under the poverty line, allocated on the basis of their potential to exit poverty (least poor among the poor) would not seem to have much impact. Increasing arable land so that everyone had 75% or 100% more would have a much bigger effect. Alternatively, rise in the productivity of land or its marginal return by 20% or even better by 50% would lead to a substantial decline in poverty. It seems therefore that efficiency-enhancing measures as opposed to equity-oriented interventions might have a better impact on poverty in rural areas with regard to land-related reforms. Improving market access (the population of the nearest market divided by the distance to it) might have even more substantial effect.

In the urban model, ensuring universal primary education would have the largest single effect of any of our simulations. Possible impacts on wage structure were not simulated, however. Though estimates vary, unemployment is considered high in Ethiopia, and our model estimated that the head becoming casual labourer rather than unemployed increased consumption expenditure in adult equivalent by 30%. Thus, eliminating unemployment (at least to the level of casual labour) should reduce poverty somewhat as our simulation shows. The low response is because only 5% of household-heads in the panel were unemployed.

Of course, others in the household might be unemployed so we created a ‘household unemployment-rate’ variable, the ratio of the unemployed to the entire working-age groups in each household. In the consumption model (Table 10), this variable turned out to be insignificant. Nevertheless, as Table 13 shows, unemployment is more widespread among the poor than among the non-poor.

[27] The return starts to decline starting from 2.9 Hectares per person.

Table 13: Unemployment rate by poverty status in urban areas of Ethiopia

	1994	1995	1997	2000
Poor households	24.0	23.4	25.0	24.0
Non-poor households	18.0	18.5	19.2	19.3
All households	20.0	20.0	20.5	21.1

Source: authors' computations

Table 14: Marginal effects of a random-effects probit model of the determinants of urban poverty Ethiopia:

Constant	-0.77411 (-2.22)*
Age of household head	-0.0219 (-1.91)
Household size	0.14132 (8.96)**
Dummy for household with at least primary education	-0.58138 (-6.67)**
Dummy for wife with at least primary education	-0.50556 (-4.85)**
HH private business employer	-1.03619 (-3.32)**
HH own account worker	-0.44835 (-4.06)**
HH civil servant	-0.4132 (-3.31)**
HH public enterprise worker	-0.3886 (-2.52)*
HH private sector employee	-0.52278 (-3.03)**
HH casual worker	0.28612 (2.07)*
”Unemployment rate”	0.29523 (2.14)*
Amhara ethnic group (Other Ethnic Groups are references)	-0.2792 (-1.97)*
Oromo ethnic group	-0.23959 (-1.54)
Tigrawi ethnic group	-0.7088 (-3.13)**
Harari ethnic group	-0.13472 (-0.82)
Gurage ethnic group	-0.2792 (-1.97)*
Addis (Jimma is reference town)	-0.06755 (-0.45)
Awasa	-0.05049 (-0.21)
Bahr Dar	-0.49112 (-2.12)*
Dessie	0.39393 (1.5)
Dire Dawa	-0.28371 (-1.42)
Mekele	-0.14969 (-0.53)

Source: authors' computations
* significant at 5%; ** significant at 1%. Terms in brackets are t-ratios
HH-Household Head

We therefore tried a static probit-specification to capture the effect of rate of unemployment at the household level on the risk of falling into poverty, controlling for the effects of observable household characteristics and unobserved individual characteristics. In this specification (Table 14), unemployment rate at the household level is a statistically significant risk-factor for a household to fall into poverty. On the basis of the marginal effects, the probability of a household to fall into poverty as a result of a unit rise in the unemployment rate within the household would be close to 30%, which is substantial. We also note from Table (14) that employment in any of the occupational groups, except for Casual Labourer, by the head of the household is associated with a high probability of exiting poverty in comparison to being unemployed. In addition, education of the head and wife at a primary level is associated with a more than 50% chance of not falling into poverty.

5.3 Determinants of income distribution

We saw in the preceding section how changes in income distribution affected poverty, so it would be of interest for policy purposes to know the determinants of inequality. Using the long-term relationship between log per capita consumption expenditure and a set of household endowments and characteristics that prevailed at the start of the survey has a number of advantages. First, most of the literature on inequality decomposition (e.g. Shorrocks, 1983) essentially focus on the relative roles of the sources of income on overall inequality (such as wages and salaries, or non-labour incomes), or on whether inequality between or within groups is important for overall inequality. But this does not tell us what other household and community characteristics determine earnings and thus inequality. In addition, when the variables are many, the conventional decomposition methods end up having fewer observations so that the computations of mean and variance become problematic (e.g Heltberg, 2003, Morduch and Sicular, 2002). The method proposed also provides exactly additive decompositions so that the sums of the shares add up to unity. For all these reasons, regression based decompositions have been found to be convenient in the inequality literature at least since Oaxaca (1973) who applied the method to quantify the male-female wage differentials in the US.

The commonly applied decomposition methods follow Shorrock's "natural decomposition" rule, where a given inequality index is written as a weighted sum of individual incomes, such as:

$$I(Y) = \sum_{i=1}^{n} a_i(Y) y_i \qquad \textbf{(9)}$$

where Y is a vector of individual income in ascending order, I(Y) is a measure of an inequality index, y_i is individual income and a_i (Y) is the weight to the income of the i^{th} individual[28]. If the rank order of each individual in the income structure is used as a weight, then, (9) gives rise to the Gini coefficient, a popular measure of income inequality.

The contribution to overall inequality of income source "k" or its share may then be written as:

$$s^k \equiv \frac{\sum_i^k a_i(Y) y_i^k}{I(Y)} \tag{10}$$

For example, with the Gini coefficient, the share of income-source "k" in overall inequality is:

$$s_G^k = \frac{\sum_{i=1}^n (i - \frac{n+1}{2}) y_i^k}{\sum_{i=1}^n (i - \frac{n+1}{2}) y_i} \tag{11}$$

Similarly, for the Coefficient of variation, the share of income-source "k" in overall inequality is[29]:

$$s_{cv}^k = \frac{\mathrm{cov}(Y^k, Y)}{\mathrm{var}(Y)} \tag{12}$$

where Y^k is the vector of individual incomes in ascending order derived from income-source "k", which we can approximate by regressing it on a set of exogenous variables and a residual ($\boldsymbol{\beta} X^k$ + **e**). To minimize effects of transitory shocks and measurement error we used mean consumption expenditure per adult equivalent for each household during 1994-2000 as our dependent variable. To minimize the endogenity, we also used the initial household characteristics as regressors. Tables 15 and 16 report the OLS estimates of the determinants of consumption expenditure for rural and urban households with community level fixed-effects, and robust standard errors.

[28] Sen (1973) and also Hagennaars (1987) discuss the underlying social welfare function implied by a particular weighting rule chosen.
[29] Different variations of (11) and (12) can be derived for purposes of computational ease.

As would be expected, such initial household characteristics as size of land, access to market, initial household assets have a positive impact on rural consumption expenditure. The older the head of the household, the lower it was however. Nevertheless, higher mean age of the household members, virtually the inverse of the dependency-ratio, was associated with higher consumption. Most of the village-level fixed-effects were statistically significant with rather large coefficients.

Table 15: Determinants of "long-term" consumption expenditure in adult equivalent, rural areas

Constant	4.374
	(47.44)**
Household size	-0.05
	(7.38)**
Mean age of the household	0.008
	(3.53)**
Age of household head	-0.003
	(2.46)*
Total current value of household assets	0.001
	(3.10)**
Land size per capita	0.709
	(3.31)**
(Land size per capita)^2	-0.319
	-1.72
Access to markets?	0.0006
	(4.64)**
Haresaw (village 1)	0.283
	(2.81)**
Geblen (village 2)	-0.054
	-0.68
Dinki (village 3)	-0.225
	(2.76)**
Debreber (village 4)	0.217
	(3.18)**
Yetmen (village 5)	0.249
	(2.87)**
Shumsheh (village 6)	0.54
	(7.21)**
Sirbana (village 7)	0.508
	(7.36)**
Adele (village 8)	0.628
	(9.59)**
Korodega (village 9)	-0.224
	(3.10)**
Terufe (village 10)	0
	(.)
Imdibir (village 11)	-0.167
	-1.92
Azedeboa (village 12)	0.242
	(3.08)**
Adado (village 13)	0.085
	-1.07
Garagodo (village 14)	-0.255
	(3.35)**
R-squared	0.49
Robust t statistics in parentheses	

Source: author's computations
* significant at 5%; ** significant at 1%

In urban areas, as reported in Table 16, initial household characteristics, such as size, age of the head, educational status, occupation, residence in Addis, ethnic group, and rate of unemployment were statistically significant determinants of long-term consumption over the period with the expected signs[30].

Table 16: Determinants of mean- consumption expenditure, urban areas

Constant	5.162
	(18.74)**
Household size	-0.047
	(-4.81)**
Age of household head	-0.013
	(2.42)*
Age of household head squared?	-0.0005
	(-2.02)*
Dummy for household with at least primary education	0.374
	(6.67)**
HH private business employer	0.511
	(2.62)**
HH own account worker	0.207
	(3.39)**
HH civil-servant	0.116
	(2.14)*
HH public enterprise worker	0.031
	-0.38
HH private sector employee	-0.208
	(2.34)*
HH casual worker	-0.128
	-1.7
”Unemployment” in the household	-0.311
	(-2.96)**
Assetvalue	.002
	(4.48)**
Amhara	0.099
	-1.31
Oromo	0.069
	-0.86
Tigrawi	0.236
	(2.24)*
Gurage	0.09
	-1.0
Harari	0.953
	7.82*
Addis	-0.262
	(-2.33)*
Awasa	-0.179
	-1.27
Bahrdar	0.108
	-0.73
Dessie	-0.186
	-1.21
Dire Dawa	-0.136
	-1.1
Jimma	-0.099
	-0.72
R-squared	0.37

Source: authors’ computations

Note: robust statistics in parenthesis. * Significant at 1%, significant at 5%.; HH-Household Head

[30] We note that the coefficients for most of the occupational groups would turn out to be insignificant when controlling for unobserved household characteristics and endogenity of regressors in a panel data context. (see Table 10).

Using the coefficients just derived, we then decomposed measured-inequality in rural and urban areas for the period 1994-2000 into its determinants. Tables 17 and 18 show the contribution of each variable or set of variables to Gini coefficient and Coefficient of Variations. These two measures have different estimates of the shares because of the difference in their underlying construction (see Morduch and Sicular, 2002, for details).

Nevertheless, the decompositions for the two measures of inequality are qualitatively similar. In rural areas, besides the unexplained residuals, location (aggregates of the village dummies) played by far the largest role in determining inequality followed by size of land, household asset and access to markets[31]. Variations in household-size implied less inequality as measured by the Gini coefficient, but more inequality as measured the Coefficient of Variation. In addition, the role of land ownership, initial asset holdings seem to play an important role in shaping the structure of income inequality in rural areas. An increase in the holdings of both assets (durables as well as land) tends to exacerbate income distributions.

Table 17: Decomposition of inequality in rural areas, 1994-2000 (%)

	Gini	Coefficient of Variation
Household size	-6.3	4.38
Land per capita	8.5	6.9
land per capita squared	1.2	-1.4
Mean age of the household	2.6	2.4
Age of the head of the household	-0.64	0.2
Access to market	6.02	3.64
Household durables	8.24	4.4
Location	38.38	28.38
Residual	42	51
Total	100	100

Source: authors' computations

The role of residuals in affecting inequality was larger in urban areas, because of the prevalence of unaccounted large unobserved individual effects and thus differences in the fitness of the regression models. Differences in employment type (as measured by the Gini) and in location (as measured by the CoV) then contributed most to inequality, followed by initial asset values, and education (household head being

[31] Aggregation of village-level coefficients for rural areas and town fixed effects for urban areas was done by creating a "location" variable that aggregates the dummies for the villages or towns with mean zero. The constant estimated from the regression is adjusted to take into account the overall –sample wide effects picked by the village dummies (see also Morduch and Sicular, 2002) By construction, the contribution of the constant to overall inequality as measured by the Gini coefficient and CoV is zero and thus is not reported. That is, an addition or subtraction of a constant income for each individual does not affect these measures of inequality.

completed primary school). Ethnic background contributed very little despite the role attributed to it in politics since 1991. As in rural areas, variation in household size here also is inequality reducing when the Gini coefficient is used as a measure of inequality. Despite being a key policy-concern in urban Ethiopia, variations in household unemployment rates contributed little to inequality.

Table 18: Decomposition of inequality in urban areas, 1994-2000 (%)

	Gini	Coefficient of Variation
household size	-8.2	5.7
household head completed primary	9.6	5.8
age hhh	-1.0	0.6
Asset	10.9	7.3
Unemployment	0.31	0.2
Ethnicity	1.3	0.7
Occupation	18.0	2.4
Location	9.1	14.4
Residual	60.0	63.0
Total	100.0	100.0

Source: authors' computations

6. Summary and conclusions

We analyzed the state of poverty in rural and urban Ethiopia during 1994-2000. It declined from 1994 to 1997, and then increased strongly in 2000. This finding is consistent with major events that took place in the country: peace and stability, reform and economic recovery during 1994-1997, then, drought, war with Eritrea and political instability during 1997-2000. Macroeconomic figures do not reflect much of these events, however, so we eventually looked at poverty-profiles in greater detail to try to understand the determinants of poverty and income distribution.

Rural areas that grew *enset*, *chat* and coffee had most poverty in 2000, probably because of the severe drought in these areas at that time, as well as declines in the prices of coffee and *chat*. The skewed distribution of land and oxen ownership also had some role in poverty in rural areas. But it is difficult to show exactly why urban poverty increased when the economy was growing during 1997-2000. Because of population growth, per capita income declined but only slightly. Most of the increase in poverty therefore must have been because of increased income inequality. Our data showed that a rise in unemployment and changes in the structure of households (increase in the number of dependents) might have contributed to the rise in urban poverty. Public and private-sector employees did better during the period, while poverty increased sharply among the unemployed and casual workers.

To examine the robustness of these result, we used stochastic dominance criteria and model based decompositions of poverty and inequality. Poverty trends were unchanged regardless of where one reasonably set the poverty-line. The fall and then rise again of Ethiopian poverty in the late 1990s suggest that sustained growth over a long period will be necessary to eliminate poverty.

By controlling for unobserved household effects, it was possible to understand the determinants of poverty and thus to predict it. We estimated a model of consumption expenditure in adult equivalent regressed on household and community characteristics, using instrumental variables to tackle the endogenity between variables and unobserved household-specific factors. The resulting poverty prediction matched observed data rather closely.

Based on this model, we then simulated a set of policy interventions to examine their possible effects on poverty. For rural areas, we simulated the effects of land reform and increased access to markets. The impact on poverty of any conceivable major land redistribution was not impressive; increasing the amount of arable land or its productivity had better effects. Better access to markets might greatly reduce the incidence of poverty, however.

We also examined two urban policy-simulations, eliminating unemployment and universal access to primary school. While the impact of universal access to primary school was considerable, eliminating unemployment led to only a small decline in poverty. But this does not mean that unemployment and poverty are weakly correlated. Inference on the basis of a probit-model showed that, controlling for other factors, a rise in unemployment significantly increases the risk of being in poverty. The simulations, though simple and static, offered some insights into policy-changes that might have an impact on poverty.

The paper also examined the determinants of inequality, changes in which contributed greatly to poverty in this period. Location had by far the largest effect on rural inequality, followed by size of land owned, household asset and access to markets. The importance of location suggests that it was regional differences in economic development that determined differences in inequality.

In urban areas, differences in employment-type (as measured by the Gini coefficient), and in location (as measured by Coefficient of Variation) contributed most to inequality, followed by initial asset values, and household head having completed primary education. Household size reduced inequality as measured by the Gini coefficient. Ethnic background contributed very little to inequality. Also, variations in household unemployment rates contributed little to inequality.

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Appendix Table 1: Minimum national food-basket (per adult per month)

Cereals (kg)	
teff	1.52
Barley	2.58
Maize	4.41
Sorghum	2.4
Pulses (kg)	
Lentils	0.25
Horse beans	1.26
Cow beans	0.31
Chick beans	0.57
shiro	0.57
Vegetables (kg)	
Gomen (cabbage)	0.31
Onion	0.38
Root crops (kg)	
Potato	0.57
Enset	7.68
Other food items	
Milk (lit)	0.25
Coffee (kg)	0.50
Sugar (kg)	0.13
Salt (kg)	1.07
Cooking oil (lit)	0.19
Berbere (red-pepper)- kg	0.5
Bread (kg)	0.38

Source: Taddesse, Kebede, Shimeles (1999)

Appendix Table 2.1: Hausman specification test between fixed and random effect models for rural households

Variables	Coefficients of Fixed-effects model (b)	Coefficients of Random-effects model (B)	(b-B) Difference	S.E (standard error)
Household size	-.2622862	-.1481665	-.114119	.0271257
Household size squared	.0065289	.0043402	.0021887	.001297
Female headed households	.1697438	.0613437	.1084001	.1908353
Size of land per capita	.234206	.5317647	-.2975587	.1162447
Size of land per capita squared	-.0346153	-.1180074	.0833921	.0361374
Mean age	-.0427335	.0016103	-.0443438	.0984099
Age of household head	.0131286	-.0027366	.0158652	.0833156
Current value of household	.0000266	.0003416	-.000315	.0000502
Number of oxen owned	..0459534	.0749905	-.0290372	.0132391
Household size*wife completed	-.1439189	-.1043722	-.0395467	.067879
Household size* female headship	-.0419417	-.0323283	-.0096134	.0196914
Household size* size of land	.0010215	.0005554	.0004661	.0011554
Household size * number of oxen	-.037757	-.0702759	.0325189	.0194827
Rainfall	.0168179	.010846	.0059719	.0102068
round2	-.2618746	-.1594632	-.1024114	.1542778
chi2(15) = 42.02				
Prob>chi2 = 0.0000				

Source: authors' computations

Appendix Table 2.2: Hausman specification test between fixed and random effect models for urban households

Variables	Coefficients of Fixed-effects model (b)	Coefficients of Random-effects model (B)	(b-B) Difference	S.E (standard error)
Household size squared	-.0063225	-.0050958	-0012267	.0004544
Household head is female	-.1636799	-.0407828	-.1228971	.0576461
Age of the head of the household	-.0088589	-.0102218	.001363	.0054033
Age of the head of the household2	.0000435	.0001131	-.0000696	.0000613
Household head completed primary	.3389241	.551355	.212431	.1387839
Household head completed primary*age	-.0046864	-.0060326	.0013462	.0027011
Wife completed primary	.0971751	.1129952	-.0158201	.0886355
Household head owns private business	.0665706	.5009358	-.4343651	.1130286
Household head is own-account worker	-.1002053	.1406865	-.2408918	.0548858
Household head is civil servant	.1333802	.1411931	-.007813	.0612665
Household head is public sector employee	.0433498	..0405734	.0027764	.0646518
Household head is private sector employee	-.0274643	.0830136	-.1104779	.062113
Household size* wife completed primary	.0012958	.0111978	-.0099019	.0114242
Household head is unemployed	-.3402325	-.2802446	-.0599879	.0541598
“Unemployment rate”	.0412641	-.0671138	.1083779	.0474627
Total value of household assets	-1.90e-06	7.71e-06	-9.61e-06	1.08e-06
chi2(15) = 42.02				
Prob>chi2 = 0.0000				

Appendix Table 2.3: Simple correlation between determinants of consumption and unobserved household specific error under different specifications: rural areas

Variables	Correlation with fixed-effects regression household specific residual	Correlation with random-effects Hausman-Taylor regression household specific residual
Dummy for 1994	-0.0001	0.0003
Dummy for 1995	0.0002	0.0008
Dummy for 1997	-0.0001	0.0003
Household size	0.181	0.0284
Household size squared	0.176	0.006
Household head is female	-0.116	0.0079
Wife with primary	0.1846	0.0138
Land size per capita	.0778	0.0262
Land size per capita squared	.0413	0.03
Mean age	.264	.0248
Age of the head of hh	.0651	-.0386
Asset value (birr)	.3037	.0475
Access to market	.2272	-0.018
Teff producing area	-.0744	-.0000
Coffee producing area	.0624	.0000
Chat producing area	.2383	-.445
Number of oxen owned	0.1787	.0318
Interaction terms		
Household size + Wife completed primary	.1934	.015
Household size+ female headed	-0.05	.0039
Household size + size of land	.1581	.0374
Oxen +size of land	.1205	.0405
Rainfall	.0000	.00068

Appendix Table 2.4: Simple correlation between determinants of consumption and unobserved household specific error under different specifications: urban areas

Variables	Correlation with fixed-effects regression household specific residual	Correlation with random-effects Hausman-Taylor regression household specific residual
Dummy for 1994	-0.009	0.0005
Dummy for 1995	0.000	-0.0002
Dummy for 1997	0.000	0.004
Household size	0.200	.1027
Household size squared	0.213	0.09
Household head is female	-0.050	.0323
Wife with primary	0.143	-.0073
Head with primary	0.138	.0283
Age of the head of hh	0.107	.0778
Private business	0.156	.1472
Own account worker	0.171	.1841
Civil servant	-0.0157	.0059
Public sector employee	-.0500	.0021
Private sector employee	0.1558	.0261
Casual worker	0.065	-.0845
Unemployed	-0.020	.0022
Proportion of “unemployed”	-.0985	0.002
Value of household asset	0.3624	0.09
Head completed primary+age	0.1681	0.02
Amhara ethnic group	0.0303	-.0001
Oromo ethnic group	-0.0531	-.00011
Tigrawi ethnic group	0.1126	.0021
Harari ethnic group	.0796	-.0005
Addis Ababa	-0.0500	-.0045

POVERTY TRANSITION AND PERSISTENCE IN ETHIOPIA[1]

Arne Bigsten[2] and Abebe Shimeles[3]

Abstract

Based on a rural and urban data set from Ethiopia, exiting from or re-entering poverty was found to depend on the time spent in or out of poverty. In comparison to urban areas, it was easier to exit or re-enter rural poverty. However, exiting poverty was more difficult the longer households were in that state, even more in urban than rural areas. In addition, the average time spent in poverty following a poverty spell is quite long for a typical household. Time-varying and other household characteristics were examined in the context of exiting and re-entering into poverty. Features of chronic poverty and vulnerability were also analysed and the policy implications discussed.

1. Introduction

Frequently used aggregate measures of poverty, such as the headcount ratio, do not account for past experiences of poverty. Some might have already spent many years in persistent poverty, others might have just fallen into poverty, and still others might have just escaped poverty but have a high probability of falling back in. The first category represent the chronically poor, the second (hopefully) the transient poor and the third the vulnerable. The distinction of these features of poverty, along with the time-varying and individual-specific determinants is very important for policy purposes.

Recent literature on the dynamics of poverty focuses on the mobility across a given income threshold or poverty line, and attempts to distinguish chronic from transient poverty.[4] A household's consumption level at a specific time depends on its assets,

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

and its ability to smooth consumption. If the household is credit constrained it may find it hard to cope with negative shocks. Chronic poverty can thus depend not only on current income but also on the household's lack of assets or its limited ability to translate assets into incomes. Incomes change over time by asset accumulation, changes in returns driven by savings behaviour or exogenous shocks.[5] Household income depends on the gender, education and other characteristics of its members, the changing size of the household due to fertility and migration decisions, as well as the state of the labour market (Bigsten et al., 2003). Part of the exercise in poverty dynamics is to investigate how these factors influence the persistence of poverty.

The dynamics of poverty has generally been assessed in two ways, the spells approach focusing on transitions in and out of poverty, and the components approach, separating the chronic from transient component of poverty (Hulme and Shepherd, 2003, Rvallion and Jalan, 2000). To identify the chronic component of poverty, one can use average consumption over several periods (Rodgers and Rodgers, 1991. The spells approach is a powerful tool for understanding how the transient poor can emerge again from poverty if the analysis can clearly identify the factors that underlay their falling. But to understand chronic poverty one needs to analyse social structures and mobility, or rather immobility, within them.

The discussion of transient poverty leads quite naturally to the discussion of vulnerability, which is not necessarily captured by current income estimates. What one would like to know is the extent to which households near the poverty line have assets that can serve as buffers against shocks. The shocks can be of several kinds, from droughts affecting agricultural output, to unemployment, illness or death of members of the household. Liquid assets (monetary assets or livestock, although in a general crisis the prices of livestock can collapse) can help protect households against these shocks. Households may also be able to incur debt, sell other assets than livestock, or pull children out of school. They may also draw on their social networks or in the end rely on support from government or other institutions.

There have been few empirical studies on the dynamics of poverty. Bane and Ellwood (1986, p. 2-4) classified approaches to the study of poverty dynamics into tabulations of poverty over some fixed periods, methods using spell-durations and exit-probabilities and statistical methods which model the level of some variable such as income, allowing for complex lag error-structures.

[5] Gunning et al (2000) have investigated the income dynamics in the resettlement areas of Zimbabwe. They had data on asset accumulation over time and combined this with estimates of changes in asset returns in an interesting analysis of a process of income convergence. There is little evidence in the literature on the cumulative income of shocks to households.

McKay and Lawson (2003) reviewed the evidence on chronic and transient poverty noting that many studies had concluded that transient was more important than chronic poverty, though they themselves were sceptical. They believe that sometimes too stringent conditions had been imposed for a household to be classified as chronically poor, and also there were measurement errors that might explain why a household at some point in time seemed to escape from poverty. Yaqub (2003) reports evidence from 23 countries on factors that explain upward mobility, which was correlated with more land and more education, while downward mobility was correlated with increased household size and the number of dependents. Dercon and Krishnan (2000) explored short-term vulnerability of rural households in Ethiopia finding that poverty rates were very similar over the 18 months over three surveys, although consumption variability and transition in and out of poverty were high.

This paper examines poverty persistence, chronic poverty and vulnerability using both the spells and components approach on a rich panel data set that covers approximately six years in four waves. To our knowledge such empirical work, notably one based on the spells approach, is rare for less-developed countries, and non-existence for Africa.

The next section outlines the methods used to capture poverty transitions, chronic poverty and vulnerability, section 3 describes the data and report exit and re-entry probabilities for various household types and separating the transient from the chronic components of poverty. Section 4 reports the determinants of chronic poverty and vulnerability and discusses the policy implications. Section 5 summarizes and draws conclusions.

2. Methodology

2.1 Methods for analysing poverty spells and their determinants

The common approach to analyse poverty spells (e.g. Bane and 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 and parametric methods. The probabilities can be considered as random variables with known distributions (see Antolin et al., 1999).

Non-parametric methods are quite powerful in estimating how the probabilities of exiting or re-entering poverty are affected by spell-durations. Exit rates relate to a cohort of households that have just become poor and are “at risk” of exit thereafter. Similarly, re-entry rates refer to cohort of households newly out of poverty and “at risk” of re-entering poverty[6] (see e.g. Bane and Ellwood, 1986, Stevens, 1999, and Devicienti, 2003 for detail 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 due to the exclusion of left-censored observations.

Similarly, re-entry into poverty refers to a situation where a household is at risk of entering into poverty after a spell of being out of poverty.[7] We used the non-parametric Kaplan-Meier 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, ..t_k, then, the number of distinct failure times observed in the data (or the product limit estimate) is given by:

$$\hat{S}(t) = \prod_{j|t_j \le t} \left(\frac{n_j - d_j}{n_j}\right) \quad \textbf{(1)}$$

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 parametric method on the other hand, models the distribution of spell durations via the probabilities of ending a spell.[8] Suppose we are interested in modelling the duration of poverty for household *i* which entered at t_0.[9] We can define a dummy δ_i=1 to distinguish households which completed the spell (exited out of poverty) from those who continued in the poverty spell, δ_i=0 at the end of the period (months, years or rounds in our case). The percentage that completed is the event-rate (or called "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:

$$h_i(t) = pr(T_i = t / T_i \ge t;\ X_{it}) \quad \textbf{(2)}$$

[6] That is, the relevant cohort to analyze poverty exit are those who were poor in round 1, while for re-entry are those who were non-poor in round 1.
[7] The exit rates refer to a cohort of households just falling into poverty and hence at risk of exit thereafter. Similarly, re-entry rates refer to cohort of households just starting a spell out of poverty and are at risk of re-entering poverty (see e.g. Bane and Ellwood, 1986, Stevens, 1999 and Devicienti, 2003). Given this definition, the observations relevant for estimating the exit and re-entry rates are spells that occur in wave 2 due to the exclusion of left-censored observations.
[8] We draw heavily from Jenkins (1995) and Stevens (1999) to discuss the parametric approach to modeling exit and re-entry rates.
[9] The same analogy applies for re-entry. So we restrict the discussion to the modeling of exiting from poverty.

where T_i is represents the time when poverty spell ended, 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 has not ended up to t, that is, [10]

$$\begin{aligned} prob(T_i = t) &= h_{it}\prod_{k=1}^{t-1} 1 - h_{ik} \\ prob(T_i \succ t) &= \prod_{k=1}^{t}(1 - h_{ik}) \end{aligned} \qquad \textbf{(3)}$$

There are two frequently used ways to specifying the distribution of the hazard rate. One is with the proportional hazard model given by:

$$h(t \mid x_{ij}) = h_0 \exp(x_{ij}\beta_x) \qquad \textbf{(4)}$$

where h_0 is the base line 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[11] by adding a multiplicative random error term[12] into equation (4) so that the instantaneous hazard rate becomes:

$$h(t \mid x_j) = h_0\varepsilon_j \exp(x_j\beta_x) = h_0 \exp\lfloor X_j\beta + \log(\varepsilon_j)\rfloor \qquad \textbf{(5)}$$

The underlying log-likelihood function for equation (5) is a generalized linear model of the binomial family with complementary log-log link (Jenkins, 1995).

The other frequent way to specify the distribution the hazard rate is the logistic structure. For distribution function of duration T, F(t)=prob(t<T), for t> 0 and the density function f(t)=dF/dt, the corresponding hazard or conditional probability is (see also above):

[10] See Jenkins (1995) for the details on the derivation of equation (2)

[11] 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.

[12] ε is a Gamma distributed random error term with unit mean and variance

$$h_i(t) = pr(T_i = t / T_i \geq t; \,) = \frac{f(t)}{1 - F(t)} \tag{6}$$

If h_i follows a logistic structure, then:

$$h_i(t) = \frac{\exp(t)}{1 + \exp(t)} \tag{7}$$

Spell durations can again be expressed as a function of duration effects, α_{id}, and a set of variables, X which vary across spells and time. It includes individual characteristics and other factors that influence the flow of resources to the household or individual. Thus,

$$t_{idt} = \alpha_{id} + \beta X_{it} \tag{8}$$

where d indexes number of years in poverty. The probability of individual *i* exiting poverty in year t with a current duration in poverty of d years is given by the hazard function:

$$h_{idt} = \frac{\exp(\alpha_{id} + \beta X)}{1 + \exp(\alpha_{id} + \beta X)} \tag{9}$$

This can be estimated by maximising the relevant log-likelihood function for all observations.

2.2 Measuring vulnerability and chronic poverty

Depending on the definitions of vulnerability, various measures have appeared in the recent literature (see e.g. Prichett et al., 2000, Kamanou and Morduch 2002, Chaudri et al, 2002, Ligon and Schechter, 2003 and Calvo and Dercon, 2005).

Pritchett et al. define vulnerability as the probability of being below the poverty line in an given year, that is

$$V_i = P(y_{it} < z) \tag{10}$$

where V_i is vulnerability, y_{it} is per capita consumption of household i in year t, and z is the poverty line. To estimate vulnerability we followed Pritchett et al (2000) and

McCulloch and Callandrino (2003) in estimating these probabilities.[13] We assumed that the distribution of consumption expenditures was normal, while its mean and variance were allowed to vary across households over time. We computed mean consumption expenditure y^*_i and its standard deviation, s_i , for each household over the four survey waves. The probability of consumption being below the poverty line was then:

$$V_i = P\left(\frac{y_{it}-\mu_i}{\sigma_i} < \frac{z-y_i^*}{s_i}\right) \quad \textbf{(11)}$$

That is the probability the standard normal variate y_{it} will fall below the poverty line normalised by subtracting mean consumption and diving by the standard deviation.[14]

Chronic poverty has been measured in at least two ways in recent literature. Some (e.g. McCulloch and Calandrino 2003) take the number of times an individual has been in poverty to indicate the chronic nature of poverty, and others (Ravallion and Jalan, 2000, and Haddad and Ahmed, 2003) use expected income over a certain period as an indicator of chronic poverty.

This indicator decomposes poverty P_i , into transient component, T_i ,and a chronic component C_i, where each are defined over a stream of income, y_{it} for the i^{th} individual within D time periods, as follows:

$$P_i = P(y_{i1,} y_{i2}, ... y_{iD}) \quad \textbf{(12)}$$

$$C_i = P(Ey_{i1}, Ey_{i2}, ... Ey_{iD}) \quad \textbf{(13)}$$

$$T_i = P_i - C_i \quad \textbf{(14)}$$

We report both measures. We also compare measures of vulnerability with chronic poverty to get an idea of poverty-persistence.

[13] Hoddinnott and Quisumbing (2003))Ligon and Schechter (2004) review of the recent literature on measures of vulnerability.

[14] This measure can be considered a first-order approximation to vulnerability with a number of limitations. Among others, the use of standard deviation as a key indicator of vulnerability means that negative and positive shocks of equal magnitude are treated equally, which is variability not vulnerability per se. It also does not distinguish episodes of increasing consumption from an episode of cyclical consumption. Finally, different degrees of persistence are not distinguished (Kamanou and Morduch, 2002).

3. Data and variables

Data from 1500 rural and 1500 urban households was collected in 1994, 1995, 1997 and 2000 by the Department of Economics, Addis Ababa University, in collaboration with University of Oxford (rural) and Goteborg University (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 into account agro-ecological diversities, and to include all the major towns. For poverty estimates, we computed consumption-expenditure per adult-equivalent (see Bigsten and Shimeles, 2005, for details). We used price data collected with the surveys to adjust for price differences over-time and location, converting values to 1994 prices.[15]

Table 1 shows the distribution of rural and urban sample households by the number of times in poverty. Among the four survey-waves, only about 12% of households were poor every time, slightly more in the urban than in the rural sample. On the other hand, only 16% of the rural sample was never poor, compared to 32% of the urban sample. This may be due to more 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.

It is interesting to note that the percentage of households consistently non-poor and poor are higher in urban areas than rural areas, indicating the fact that poverty is more chronic in urban areas than in rural areas.[16]

Table 1: Percentage of households by poverty status: 1994-2000

Poverty Status	Rural	Urban
Never poor	16	32
Once poor	24	21
Twice poor	25	18
Thrice poor	23	15
Four times poor	11	13

[15] Price data was not collected for the 2000 urban survey. We used instead the price data collected by the Ethiopian Central Statistical Authority, which more or less was compatible with price data collected in previous waves.

[16] To reduce the effect of measurement errors in computing per capita consumption expenditure, we dropped all real per capita *changes* that fell within an interval of 20% of the poverty line.

Tables 2a and 2b report descriptive statistics (means) for the rural and urban samples by the number of times in poverty. Rural households (Table 2a) 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 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.

Table 2a: Descriptive statistics for rural households by poverty status 1994-2000

	Never Poor	Once Poor	Twice poor	Three times poor	Always poor
Household size)	4.9	5.8	6.4	6.9	8.3
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)	1.1	0.9	.7	0.7	0.5
No of oxen owned	2.0	1.7	1.4	1.1	0.8
Crop sale (birr per year)	334	247	158	83	90
Asset value(birr)	225	173	152	87	92
Off-farm employment (%)	24	38	39	45	29
No of oxen owned	2.0	1.7	1.4	1.1	0.8

Source: authors' computation

Table 2b: Descriptive Statistics for urban households by poverty status, 1994-2000

	Never Poor	Poor once	Poor twice	Poor 3 times	Poor 4 times
Household size	5.7	6.3	6.6	6.9	7.6
Age of head	47.0	49.0	50.0	48.0	51.0
Female head (%)	40.0	44.0	46.0	39.0	43.0
Head completed primary school (%)	60.0	44.0	30.0	27.0	20.0
Wife completed primary school (%)	33.0	21.0	16.0	12.0	8.0
Private business employer (%)	3.0	2.0	2.0	0.0	0.0
Own account employee (%)	19.0	17.0	15.0	12.0	16.0
Civil servant (%)	21.0	15.0	11.0	9.0	9.0
Public sector employee (%)	9.0	7.0	5.0	6.0	5.0
Private sector employee (%)	6.0	5.0	5.0	3.0	3.0
Casual worker (%)	4.0	6.0	7.0	14.0	32.0
Unemployed (%)	4.0	4.0	7.0	4.0	9.0
Resides in Addis Ababa (%)	68.0	71.0	79.0	78.0	87.0

Source: authors' computation

Similarly, urban households (Table 2b) were consistently poor more often as their size and the age of the household-head increased. It was also consistently less likely that the head and/or the wife had completed primary schools, and generally more likely that they lived in Addis Ababa. Those with any form of regular employment were generally less likely to be poor more often. Among those poor most often, the occupations (besides casual workers) most represented were own-account workers and civil servants.

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 the head (see also Bigsten and 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) in the hope of capturing 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 rain-fall shocks 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

4.1 Transition probabilities and "Survival Functions"

Table 3 shows transition-probabilities by poverty-status for the rural and urban sampled-households. 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 was 47%. Of those that started poor in the initial period, 47.8% remained poor, whereas of those that started non-poor 61.6% remained non-poor. So, there was substantial persistence of poverty and non-poverty. On the other hand, 38.3% of households who were initially non-poor became poor and 52.2% who had been poor became non-poor in subsequent rounds indicating substantial consumption variation and resulting upward and downward mobility.

Table 3: Transition probabilities by poverty status: 1994-2000

Poverty Status	Poor	Non-Poor	Total
Rural			
Poor	47.8	52.2	100
Non-Poor	38.3	61.6	100
Total	47.0	53.0	100
Urban			
Poor	65.0	35.0	100
Non-Poor	23.4	76.6	100
Total	32.4	67.6	100

Source: authors' computations

Of all transition probabilities in the urban sample, fewer (32.4%) had "poor" outcome whereas 67.2% had "non-poor". However, in a higher percentage (65%) of cases where the household had been poor they remained poor, and in 76.6% of the cases where they had been non-poor they remained non-poor. So in the urban sample, there was less upward and downward mobility, and greater persistence of both poverty and non-poverty.

From table 3 we also see that mobility in and out of poverty is much more extensive in the rural than urban areas. Rural households thus experience larger swings in consumption than urban households. Poverty in the urban economy is to a higher degree of a chronic character. The urban poor seem to have small chances of breaking out of poverty. Tables 1.1 and 1.2 in the appendix give a finer breakdown of transition probabilities by decile, but the picture is essentially the same.

Tables 4a and 4b report poverty-exit and re-entry rates for rural and urban households using the Kaplan-Meier estimator (equation 1).

For rural as well as urban areas, 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, duration dependence. Unlike the simple transition matrices reported in Tables 3a and 3b, here the role of initial conditions and path dependence plays a significant role. Exiting poverty was much harder in urban areas than in rural areas, though the chance of slipping into poverty was higher in rural areas, confirming our earlier picture of more consumption variation and mobility both upward and downward in the rural sample, and more chronic poverty (and non-poverty) in the urban sample. Generally low exit rate corresponds with high probability of staying in poverty. For example, in rural areas, the chance that a household would remain in poverty in all rounds since the start of a poverty spell in round one was 33%, while in urban areas it was 39%. Likewise, 68% of rural and 63% of urban households that had escaped poverty since round one would have fallen back in poverty within two rounds.

Table 4a: Rural survival function, poverty exit and re-entry rates using the Kaplan-Meier estimator

Rounds since start of poverty spell	Survivor function	Exit Rates
1	1.000	.28
	(.)	(.05)
2	0.72	.15
	(.0404)	(.02)
3	0.33	-----
	(.033)	
Rounds since start of non-poverty spell		**Re-Entry Rates**
1	1.000	0.38
	(.)	(.047)
2	0.62	0.23
	(.037)	(.03)
3	0.32	-----
	(.03)	

Source: authors' computations

Table 4b: Urban survivor function, poverty exit and re-entry rates using the Kaplan-Meier estimator

Rounds since start of poverty spell	Survivor's function	Exit Rates
1	1.000	.22
	(.)	(.05)
2	.78	.11
	(.06)	(.03)
3	0.39	……
	(.04)	
Rounds since start of non-poverty spell		**Re-Entry Rates**
1	1.000	0.32
	(.)	(0.05)
2	0.68	0.14
	(.05)	(.02)
3	0.37	--------
	(.03)	

Source: authors' computations

Whereas the exit and re-entry-rates reported on Table 4a and 4b summarized information (at least in the first row) for cohorts that could have begun poverty-spells (or out of poverty spells for re-entry) in 1994, Table 5 (below) reports rural and urban "hazard" rates, a measure of poverty persistence, only for the cohort that was first poor in 1995[17]. Of them, 53.4% (rural) and 58.1% (urban) remained in poverty only for one round, and were recorded as non-poor in the 1997 survey. Their exit rates are much higher than those on the first rows of Table 4. It is also shown that the percentage of households with longer spells[18] declined significantly in subsequent rounds. For such households, the "mean round" spent in poverty is approximately 1.6 for rural and 1.5 for urban areas, or taking into account the 6 years spanning the rounds, the "mean years" spent in poverty are approximately 3.5 and 3.25 years for rural and urban households, respectively.

Table 5: Distribution of the 'number of rounds in poverty out of three rounds' for households starting a poverty spell in round 2.

Number of rounds in poverty	Hazard rates	
	Rural	Urban
1	53.45	58.06
2	33.05	29.44
3	13.5	12.5
	100	100
Mean number of rounds in poverty	1.6	1.54
("mean years")	(3.5)	(3.25)

Source: authors' computations

This suggests that transiting out of a spell of poverty on the average takes longer time once a household falls into poverty.

4.2 Correlates of poverty-exit and re-entry

We estimated both the logistic and proportional hazard models to compare these models in controlling for unobserved household heterogeneity. 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 another (see e.g. Devicienti, 2001).

[17] The relevant cohort is a poverty sequence (N, P, x, x), where N is non-poor, P is poor and x=(N,P). The hazard rate provides the probability that a household observed as non-poor in 1994 and became poor in 1995 would remain so in subsequent rounds.
[18] The shortness of the panel does not allow us to look into multiple spells. In our definition of exit and re-entry, a typical household can be observed completing one spell and just starting another one.

The simple hazard functions consider each spell as uncorrelated. In our case, the shortness of the panel does not allow for multiple spells, especially if the observations at the beginning of the survey are not considered (are left-censored). Thus, we use a random-effects version of the logistics model as well as the proportional hazard model with and without unobserved household heterogeneity.

We address the issue of unobserved individual heterogeneity within the proportional hazard model using Jenkin's (2000) specification of a multiplicative error term capturing each individual household's unobserved characteristics and an additive random error term specific to each household in the logistics set up. We report in Tables 6-10 estimates of the random-effects logistic hazard model (Model 1), the proportional hazard model without unobserved household heterogeneity (Model 2), and the same model that incorporates unobserved household heterogeneity (Model 3).[19]

Table (6) reports coefficients (and corresponding p-values) for exiting poverty. In all three specifications, the duration of the spell of poverty itself had a highly significant negative effect, as did household size and rain variability. This negative dependency on the duration of poverty spell is a common feature observed in similar studies (for example, Devicienti, 2003 for UK, and Hansen and Wahlberg, 2004 for Sweden). The larger the size of the household, for a given amount of consumption capability, the lower will be the per capita consumption and the higher the chance of staying in poverty. The literature on population dynamics generally assumes that a household chooses over a life cycle the optimal household size so that household size is a choice variable, where the estimated coefficients could be a result of reverse causation (from household size to consumption) or could be driven by the unobserved element in the model. Anand and Morduch (1996) argue that the negative correlation commonly reported in poverty studies between consumption and household size could imply that a household deliberately exacerbates its own poverty by increasing the size of its members. As reported in Bigsten and Shimeles (2005), the effect of household size could be positive if the scale-effect is taken into account by using say a quadratic term in regression models, as also contended by Anand and Morduch (1996). However, for a household size close to the mean, the result that household size is bad for poverty is robust regardless of the fact that demographic choices may be good for the family in the long term.

[19] The formal specifications of these models are presented in section 2.

Table 6: Covariates of exiting poverty spell in rural areas

	Logit		Proportional hazards		Proportional hazard with heterogeneity	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
Log of duration	-6.08	.000***	-4.91	0.00***	-4.83	.00***
Demographic						
Household size	-.21	.00***	-.13	.00***	-.48	.00***
Female head	-.06	.75	-.05	.64	-.29	.56
Mean age of the hh	-.00	.14	-.01	.23	-.03	.07*
Wife completed primary school	.03	.94	.04	.87	1.4	.20
Farming Systems						
Teff	-.11	.56	-.09	.43	1.05	.04**
Coffee	.46	.13	.39	.07	2.67	.03**
Chat	.76	.00**	.48	.00***	-1.4	.17
Enset	-.56	.06*	-.44	.03**	-.96	.75
Wealth:						
Asset value (birr)	.00	.01***	.00	.12	.00	.05**
Land size (hectare)	.13	.01***	.06	.02**	.141	.38
Noof oxen owned	.11	.15	.09	.04**	.46	.02**
Access to markets						
Population/distance to nearest town	.00006	.02**	.00003	.03**	.00002	.03**
Exogenous shock						
Rain variability (mm)	-.03	.00***	-.02	.00***	-.03	.08*
Change in rain (mm)	.0074	.00***	.0023	.26	-.04	.00***

Source: authors' computations
*** significant at 1%, ** significant at 5% and * significant at 10%.

Producing *enset* also had highly significant negative effects in the first two models, though far from significant when heterogeneity was controlled for in the proportional hazard model. The mean age of the household had conventionally (or close) negative effects. Asset value, land-size and number of oxen owned all had significant (or close) positive effects as did change in rain volume. Producing cash crops (coffee or chat) gave significant and mostly positive effects, with large differences between the two proportional hazard models, however. Producing *teff* also had a significant and positive effect in the last model.

With respect to re-entering into poverty, while most variables tend to show expected signs (see Table 7), they have however less statistical significant as compared to the case of exiting from poverty. Household size, farming systems, land ownership, rainfall availability seem to do well in most cases in determining the hazard of re-entering into poverty. The time spent out of poverty is negatively related with the probability of re-entering into poverty (or the time spent in poverty is positively related with the probability of re-entering into poverty).

Table 7: Covariates of re-entering rural poverty

	Logit		Proportional hazards		Proportional hazard with heterogeneity	
	Coeff	P-value	Coeff	P-value	Coeff	P-value
Log of duration	2.81	.00**	1.83	.00***	1.13	.00***
Demographic						
Household size	.21	.00**	.12	.00***	.21	.01***
Female head	-.16	.46	-.14	.36	-.24	.45
Mean age of the hh	.003	.72	-.000	.99	-.001	.92
Wife completed primary school	-1.37	.14	-.93	.20	-2.35	.14
Farming Systems						
Teff	-.39	.06*	-.20	.16	-.56	.25
Coffee	-.76	.09*	-.45	.09*	1.17	.09*
Chat	-.89	.15	-.61	.10*	-.53	.54
Enset	.76	.01***	.38	.05**	-1.22	.99
Wealth:						
Asset value (birr)	-.00061	.22	-.0004	.33	-.01	.00***
Land size (hectare)	-.23	.00***	-.20	.16	-.14	.14
Noof oxen owned	.11	.27	.050	.46	.20	.17
Access to markets						
Population/distance to nearest town	-.00004	.22	-.00002	.41	.00002	.65
Exogenous shock						
Rain variability (mm)	.00	.61	.03	.00***	.06	.00***
Change in rain (mm)	-.05	.00**	.00	.56	-.05	.32

Source: authors' computations
*** significant at 1%, ** significant at 5% and * significant at 10%.

For households in urban areas, Table 8 reports that again the duration of the spell in poverty had a highly significant negative effect on the chance of getting out it, as did household size, whereas head completed primary school had a highly significant and positive effect in the first two models, though much less significant in the third. Some other occupations also had significantly positive effects in the first two models though not as large effects as private business. In the third model, casual worker had a highly significant and fairly large positive effect. Residence in Addis, Dire Dawa and Mekele also had significant and positive effects in some models with especially large coefficients in the third model.

As might be expected, being unemployed and casual labourer are occupational categories for which exiting out of poverty is difficult and also vulnerable to re-enter poverty. Ethnic background seems to play little if at all role in affecting poverty mobility.

Table 8: Covariates of exiting urban poverty spell

	Logit		Proportional hazards		Proportional hazard with heterogeneity	
	Coeff	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-val**
Log of duration	-2.23	.00***	-1.6	.00***	-1.69	.00***
Demographic						
Household size	-.24	.00***	-.09	.00***	-.2	.00***
Female head	-.19	.41	.050	.37	-.10	.72
Age of head	.005	.50	.008	.15	.010	.18
Mean age of household	.011	.40	.003	.70	.002	.19
Head completed primary school	1.250	.00***	.60	.00***	.560	.02**
Wife completed primary school	.394	.12	.023	.15	-.070	.82
Occupation of head						
Private business employer	2.28	.00***	1.40	.00***	.99	.23
Own account worker	.61	.02**	.31	.07**	.45	.23
Civil servant	.66	.04**	.47	.02**	.23	.58
Public sector employee	.007	.10*	.040	.19	-.290	.63
Private sector employee	.74	.09*	.50	.05**	.61	.22
Casual-worker	-.04	.94	.15	.60	1.20	.01***
Residence						
Addis Ababa	.69	.09*	.58	.02**	9.08	.00***
Awasa	.05	.94	-.01	.98	-4.90	.99
Bahir Dar	.04	.94	.21	.72	8.5	.00***
Dessie	-.19	-.77	-.00	.99	7.60	.00***
Dire Dawa	.79	.12	.85	.01***	9.00	.00***
Mekele	.83	.21	.92	.02**	19.80	.00***
Exogenous shocks						
Unemployment	-.70	.09*	-.4	.21	-.29	-.49
Ethnic Background						
Amhara	.19	.59	.19	.79	.11	.44
Oromo	.17	.68	-.08	.60	.27	.44
Tigrawi	.46	.39	-.14	.60	-9.8	.04**
Gurage	-.00	.99	.20	.29	.28	.48

Source: authors' computations
*** significant at 1%, ** significant at 5% and * significant at 10%.

Table 9 reports 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 all three specifications. None of the other results are nearly so clear and consistent.

Table 9: Covariates for re-entering poverty spell for urban households

	Logit		Proportional hazards		Proportional hazard with heterogeneity	
	Coeff	P-value	Coeff	P-value	Coeff	P-val
Log of duration	.21	.41	-.14	.13	9.9	.00***
demographic						
Household size	.18	.01***	.08	.00***	.01	.23
Female head	-.02	.94	-.01	.12	-.09	.72
Age of head	-.01	.44	.00	.65	.00	.92
Mean age of household	-.01	.44	-.01	.17	-.00	.63
head completed primary school	-.89	.01***	-.46	.00***	-.19	.40
Wife completed primary school	-.29	.53	-.19	.19	-.65	.02**
Occupation of head						
Private business employer	-1.73	.19	-.68	.09*	-.45	.70
Own account worker	-1.01	.05**	-.19	.16*	-.17	.57
Civil servant	.19	.68	-.18	.25**	.16	.70
Public sector employee	.42	.62	.52	.01***	-.22	.64
Private sector employee	-.04	.95	.19	.39	-.113	.81
Casual-worker	1.56	.01***	.31	.03**	-.23	.52
Residence						
Addis Ababa	-1.66	.01***	-.43	.01***	.76	.18
Awasa	-.79	.36	-.11	.64	1.2	.08*
Bahir Dar	-1.9	.08*	-.49	.13	1.06	.21
Dessie	1.29	.24	.38	.18	.67	.39
Dire Dawa	-1.23	.27	-.27	.34	.81	.24
Mekele	-1.5	.15	-.07	.84	-1.08	.13
Exogenous shocks						
Unemployment	.78	.33	.49	.01***	-.01	.98
Ethnic Background						
Amhara	-.75	.17	-.13	.20	-.52	.35
Oromo	-.45	.44	-.05	.64	-.38	.29
Tigrawi	-.76	.35	-.76	.01***	-.52	.35
Gurage	.03	.96	-.25	.36	-.09	.79

Source: authors' computations
*** significant at 1%, ** significant at 5% and * significant at 10%.

4. "Vulnerability", chronic poverty and their determinants

Tables 10 and 11 report rural and urban "vulnerability" (equation (11) by mean (1994-2000) consumption expenditure-decile and by poverty status. At the high end (the upper six deciles, Table 10), rural households were more vulnerable than urban ones, perhaps reflecting rural susceptibility to weather and price-shocks, versus more secure urban occupations. At the low end, however, rural households were less vulnerable than urban ones, perhaps reflecting their greater ability to subsist on land.

Table 10: "Vulnerability" by inter-temporal consumption expenditure decile

Inter-temporal mean consumption decile	Urban households	Rural households
1	0.99	0.98
2	0.89	0.83
3	0.72	0.64
4	0.46	0.43
5	0.26	0.30
6	0.18	0.22
7	0.14	0.18
8	0.12	0.17
9	0.09	0.16
10	0.07	0.15

When viewed by the number of times in poverty (Table 12), the rural-urban differences are not so striking, but the general pattern is clear: very high vulnerability among those most consistently poor, and about 10% probability even among those "never poor".

Table 11: "Vulnerability" by the status of poverty

Poverty status	Rural households	Urban households
Never poor	.10	.09
Once poor	.25	.24
Twice poor	.44	.41
Three times poor	.65	.68
Always poor	.97	.96

Source: authors' computation

In both rural and urban samples, household size had a significant effect of increasing vulnerability, as did age of the household-head and especially the dependency ratio, while head or wife having completed primary school reduced it (more so in the urban sample). Female headed households had small but statistically significant effects indicating higher rural but lower urban vulnerability.

Table 12a: Determinants of vulnerability in rural Ethiopia: 1994-2000

household size	0.02
	(11.65)**
Farming systems	-0.185
	(12.47)**
Head is female	0.036
	(3.02)**
Head completed primary school	-0.059
	(3.25)**
Wife completed primary school?	-0.032
	-0.93
Size of land (hectares)	-0.021
	(7.74)**
Mean age of the household	-0.006
	(2.99)**
Age of household head	0.003
	(2.05)*
Population of nearest town divided by the distance in kms from the site	0
	(10.34)**
Mmeanage2	0
	-0.4
Agehhh2	0
	-0.24
Dependency ratio	0.121
	(3.48)**
Off-farm employment	0.046
	(4.58)**
Dummy for households which harvested teff during last season	0.007
	-0.68
Dummy for households which harvested coffees last season	-0.126
	(7.19)**
Dummy for household which harvested chat last season	-0.199
	(10.98)**
Dummy for enset sites	0
	(.)
Number oxen owned (bulls, oxen and young bulls)	-0.018
	(4.66)**
difference in rainfall level	-0.001
	(3.91)**
Variability in rainfall level	0.005
	(16.33)**
Constant	0.811
	(13.41)**
Observations	2423
R-squared	0.4
Absolute value of t statistics in parentheses	
** significant at 5%; * significant at 1%	

Table 12b: Determinants of vulnerability in urban Ethiopia

Household size	0.02
	(8.17)**
Mean age of household members	-0.004
	-1.48
Head is female	-0.03
	(2.19)*
Age of head	0.007
	(3.86)**
Head completed primary school	-0.151
	(11.00)**
Wife completed primary school	-0.14
	(9.51)**
Head private business employer	-0.259
	(6.16)**
Head own account worker	-0.099
	(6.01)**
Head civil servant	-0.063
	(3.43)**
Head public enterprise worker	-0.027
	-1.24
Head private sector employee	-0.126
	(4.54)**
Head casual worker	0.09
	(3.90)**
Head unemployed	0.086
	(3.33)**
Dependency ratio (<15+>65)/ hhsz	0.294
	(9.29)**
Mean age squared	0
	-0.28
Age of household head squared	0
	(3.78)**
Addis	0.064
	(2.66)**
Awasa	0.019
	-0.59
Bahir Dar	-0.069
	(2.28)*
Dessie	0.107
	(2.90)**
Dire Dawa	-0.003
	-0.09
Mekele	-0.019
	-0.49
Amhara	-0.092
	(4.55)**
Oromo	-0.075
	(3.45)**
Tigrawi	-0.2
	(6.67)**
Gurage	-0.05
	(2.13)*
Harari	-0.18
	-1.93
Constant	0.342
	(3.65)**
Observations	2769
R-squared	0.3

Absolute value of t statistics in parentheses
** significant at 5%; * significant at 1%

In the rural areas, land-size and the number of oxen owned as well as growing coffee or *chat* reduced vulnerability as did change in rainfall, while rainfall-variability increased it. Off-farm employment was also significantly correlated with higher vulnerability.

In the urban areas, all occupations except causal worker and unemployed reduced vulnerability (all but one at conventional significance levels), with private-business employer having by far the largest effect, followed by private-sector employee. Being a causal worker, or unemployed increased vulnerability. Residence in Addis or Dessie increased vulnerability, while residence in Bahir Dar reduced it. Relative to other ethnic groups in Ethiopia, all the major ethnic groups had reduced vulnerability, with Tigrawi the strongest effect.

We also ran logistic regressions of rural and urban chronic poverty against the same covariates (chronic poverty was defined as mean consumption-expenditure over the four survey rounds). Tables 13 and 14 report the marginal effects, which are generally consistent with the results above for vulnerability.

Again household size had a significant effect of increasing the probability of both rural and urban chronic poverty, as did age of the household head (though not conventionally significant) and the dependency ratio. Mean age of the household reduced chronic poverty, as did primary education, most significantly and strongly for the urban head, and last for the rural wife. Again having female-head had the opposite effects (increasing rural but reducing urban chronic poverty) though neither reached conventional significance levels.

In the rural areas, land-size and the number of oxen owned as well as growing cash-crops (coffee or *chat*) again reduced chronic poverty, as did change in rainfall, while rain-variability again increased it. Off-farm employment was again significantly correlated with increased chronic poverty.

In the urban areas, significance was lower for occupations but the pattern was generally the same. Asset-value reduced chronic poverty while the household rate of unemployment increased it. Residence in Addis Ababa increased chronic poverty, while all ethnic groups had reduced chronic poverty, though only Gurage and Amhara reached conventional significance levels.

Table 13: Rural marginal effects of logit estimate for the determinants of chronic poverty: 1994-2000

Household size	0.168
	(8.42)**
Dummy for non-enset growing areas	-1.026
	(6.62)**
Female headed households	0.185
	-1.43
Head completed primary school	-0.277
	-1.34
Wife completed primary school	-0.003
	-0.01
Land size in hectares	-0.198
	(5.91)**
Mean age of the household	-0.061
	(2.36)*
Age of household head	0.034
	-1.8
Population of nearest town divided by the distance in kms from the site	0
	(9.14)**
Meanage2	0
	-0.17
Agehhh2	0
	-0.07
Dependency ratio	0.803
	(2.07)*
Off-farm employment	0.278
	(2.60)**
Dummy for households which harvested teff during last season	-0.105
	-0.91
Dummy for households which harvested coffees last season	-0.943
	(5.02)**
Dummy for household which harvested chat last season	-1.393
	(6.15)**
Number oxen owned (bulls, oxen and young bulls)	-0.171
	(3.68)**
Difference in rainfall level	-0.006
	(2.59)**
Variability of rainfall	0.044
	(11.52)**
Constant	1.056
	-1.61
Observations	2423

Absolute value of z statistics in parentheses
** significant at 5%; * significant at 1%

Table 14: Urban marginal effects of logit estimate for the determinants of chronic poverty: 1994-2000

Household size	0.237
	(5.64)**
Mean age of household members	-0.13
	(2.49)*
Dummy for female headed households	-0.318
	-1.37
Age of household head	0.041
	-1.48
Dummy for household with at least primary education	-0.805
	(3.42)**
Dummy for wife with at least primary education	-0.372
	-1.39
Head private business employer	-2.078
	-1.67
Head own account worker	-0.503
	-1.78
Head civil servant	-0.08
	-0.25
Head public enterprise worker	0.153
	-0.4
Head private sector employee	-0.608
	-1.23
Head casual worker	0.751
	(2.09)*
Head unemployed	0.468
	-1.06
Mean age squared	0.002
	-1.93
Age of household head squared	-.0003985
	-1.38
Addis	1.196
	(2.08)*
Amhara	-0.896
	(2.65)**
Oromo	-0.649
	-1.81
Tigrawi	-0.969
	-1.89
Gurage	-0.798
	(2.10)*
Harari	-33.518
	0
Asset value	-.0004422
	(7.13)**
No of people not working/no of people within the 15-65 age group	0.912
	(2.39)*
Constant	-0.024
	-0.02
Observations	881

Absolute value of z statistics in parentheses
** significant at 5%; * significant at 1%

Figures 1 and 2 plot each rural or urban household's vulnerability (probability of being poverty) against its mean consumption. While those with mean per-capita consumption-expenditure below or near the poverty-line generally also had high vulnerability, even some with higher mean consumption were still quite vulnerable, indicating that the two measures, while different may both be useful for policy purposes.

Figure 1: Vulnerability and chronic poverty in rural Ethiopia[20]

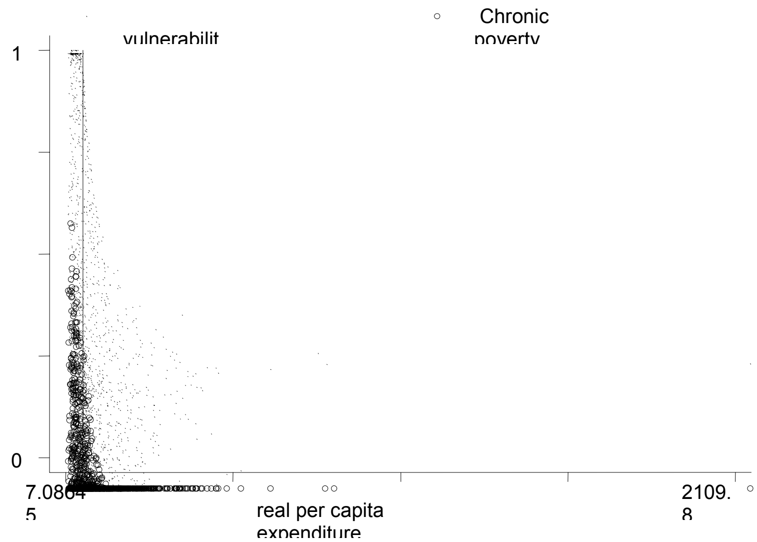
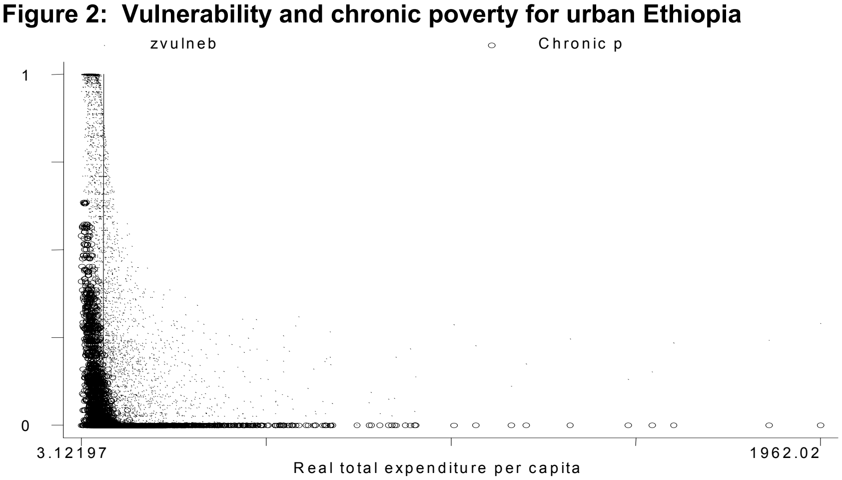


Figure 2: Vulnerability and chronic poverty for urban Ethiopia



[20] Vulnerability stands for a measure of vulnerability, chronic poverty stand for a measure of the poverty gap using long-term consumption expenditure in both figures

5. Summary and conclusions

It is important to make a distinction between chronic and transient poverty for policy purposes.[21] To alleviate chronic poverty requires long-term investment and structural reforms to build up the assets of the poor by enhancing human capital through education, health services and the like, and enhancing financial and physical assets through grants, redistribution of land and natural resources.[22] The policy package might also include direct investments in physical infrastructure, reducing social exclusion via increased employment opportunities and access to markets, and possibly increased long-term social security. The poor tend to live in less accessible areas and to have social positions that make it hard and expensive to help them. But by investing in basic infrastructures, both physical and financial, the government can help reduce their transaction costs.

On the other hand, if poverty is transitory one instead needs temporary interventions to support households during the bad spells. Variability could be reduced and security improved by individually oriented and community-oriented measures, including workfare, micro-finance, micro-enterprise development, and local infrastructure-development, through social funds. If shocks are individual, local networks may able to cope, but if the affect whole villages or regions they cannot. Publicly organised safety nets were virtually non-existent in Ethiopia in earlier times, which meant that the drought in 1983-84 had disastrous effects. Recent droughts in Ethiopia, just as severe, had much less drastic consequences, because the government, together with foreign donors and NGOs, have built up a safety net that can at least provide a minimum level of food to the poor. Other programs, such as limited-term unemployment allowances, social grants, workfare micro-credit or new skill-acquisition programmes may all be called for (Hulme and Shepherd, 2003).

The scope for consumption smoothing is quite limited especially in rural Ethiopia, which means that credit rationing is pervasive. Households may try to sell assets in bad times to survive, but this is hard in a situation when many households are in the same state and they all try to sell assets at the same time. The prices then tend to fall dramatically (Sen, 1981). Security can be improved by individually oriented measures and community oriented measures, including workfare, micro-finance, micro-enterprise development, and local infrastructure development through social funds.

[21] Ravallion and Jalan(2000) test whether transient poverty is determined by the same factors as chronic poverty in rural China. They find that the factors vary considerably between the two types of poverty and that the policies directed at chronic poverty may not be effective tools to deal with chronic poverty.
[22] Redistribution of assets, such as land, may also ease the credit constraints poor people face.

We found that poverty was more persistent in urban than in rural areas. The proportion of urban households that remained poor throughout the sample period was slightly higher than rural areas, as was the proportion of non-poor, suggesting less mobility in and out of poverty. Exit and re-entry probabilities showed that it was easier for rural households to exit poverty as well as to re-enter it. Both exit and re-entry rates declined more four urban households over time in a given state, a result confirmed by our non-parametric hazard-estimates. This suggests the need for different approaches to fighting rural and urban poverty. Reducing variability in rural areas, and expanding opportunities in urban areas could be appropriate strategies.

We compared a logistic specification of exit and re-entry probabilities with two proportional-hazard models, one controlling for unobserved individual heterogeneity. The hazard models performed better in the rural context, and the logistic specification in the urban. The size of the household, primary education of the head or wife, access to markets and rainfall levels and variability were statistically significant in either facilitating exit or preventing re-entry into poverty in rural areas.

The average probability of a household being poor during this period using our measure of vulnerability was 40%, indicating generally high insecurity. In rural areas, the age of the head and the dependency-ratio had significant effects in increasing vulnerability. Whereas land-size, primary education of the head and/or wife, growing coffee or chat, and access to markets had significant effects in reducing vulnerability. In urban areas, household-size, age of the head and town of residence (particularly in Addis Ababa) increased vulnerability, where as the primary education and occupation of the head (excepting for casual work) reduced vulnerability.

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Appendix Table 1.1: Rural transition probabilities by expenditure Decile: 1994-2000

Decile	1	2	3	4	5	6	7	8	9	10
Poorest	**22.41**	15.72	12.04	11.04	8.36	10.70	5.02	6.02	5.02	3.68
2	14.24	**17.55**	11.92	9.93	8.61	9.93	9.60	7.28	5.63	5.3
3	15.63	14.24	**9.03**	12.85	12.85	7.29	7.64	4.51	9.72	6.25
4	9.71	10.43	12.23	**12.95**	10.43	10.43	8.27	6.47	6.47	10.79
5	9.49	10.95	9.49	9.85	**9.49**	10.58	11.31	12.04	9.49	7.3
6	7.25	9.06	10.87	8.7	13.41	**9.42**	10.14	9.42	9.78	11.96
7	4.26	7.45	8.87	8.87	9.93	10.64	**9.93**	14.54	11.35	14.18
8	6.15	5.38	10.0	8.08	6.92	11.54	12.69	**10.38**	12.31	16.54
9	4.42	3.06	8.16	7.14	9.52	8.84	11.56	12.93	**19.05**	15.31
Richest	4.74	6.72	7.51	7.11	9.09	7.91	17.79	10.28	15.42	**13.44**

Appendix Table 1.2: Urban transition probabilities by expenditure Decile: 1994-2000

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**

POVERTY DYNAMICS IN ETHIOPIA: STATE DEPENDENCE AND TRANSITORY SHOCKS[1]

Nizamul Islam[2] and Abebe Shimeles[3]

Abstract

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

Key words: Poverty persistence, state dependence, unobserved heterogeneity

1. Introduction

Existing studies (see Bane and Ellwood, 1986; Stevens, 1994) on the dynamics of poverty commonly use a spell approach to compute the underlying probabilities as functions of the number of durations in a particular spell. This approach, although powerful in capturing the effects of duration in poverty or out of poverty, it does not

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provide explicitly the magnitude of previous states on the risk of being poor in the present state, which provides an opportunity to estimate state dependency of the motion of poverty. That is, if the risk of entering into poverty is dependent on being in poverty in the previous period, after controlling for unobserved individual effects and serially correlated error components, then, it implies that there is much to be gained from policy interventions that reduce poverty in the current period on the evolution of poverty in subsequent periods. This suggests for the need to actually quantify the true state dependence of poverty evolution and its contribution to the risk of being in poverty or not. This paper contributes to the literature on poverty dynamics by estimating an econometric model of poverty dynamics that explicitly takes into account the effect of the lag dependent variable, unobserved heterogeneity and serially correlated error components.

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

2. Data and variables

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

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

Major food expenses among households in Ethiopia are difficult to measure, particularly in rural areas, because of problems related with measurement units, prices, and quality. The consumption period could be a week or a month depending on the nature of the food item, the household budget cycle, and consumption habits.

Own-production is the dominant source of food consumption in rural Ethiopia, particularly with regard to vegetables, fruits, spices and stimulants like coffee and *chat*. Cereal, which makes up the bulk of food consumption, is increasingly obtained from markets as farmers swap high cash-value cereals such as *teff* for lower-value ones, such as maize and sorghum. Even so, food in rural areas is derived from own sources, which makes valuation difficult. The situation is better in the urban setting, where the bulk of consumption items are obtained from markets and measurement problems are less.

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

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

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

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

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

3. A model of poverty dynamics

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

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

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

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

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

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

where h_{it} (d) is the probability that a household *i* leaves the poverty state at duration *d,* given that it has remained in poverty up to *d-1*. Discrete intervals are commonly used to capture the duration dependence of the hazard rate of exiting or re-entering poverty. This specification combines into one the three sources of poverty persistence if the model is estimated without controlling for unobserved household characteristics. In this case, duration dependence is reported to be much stronger. Most studies do adjust for unobserved household characteristics through a joint maximum likelihood estimation of exit and re-entry rates where the hazard rates depend on spell-specific unobserved heterogeneity (e.g. Meghir and Whitehouse, 1997; Stevens, 1999; Devicienti, 2003; and Hansen and Wahlberg, 2004). Under this condition, a number of studies found that the effect of duration in or out of poverty has little role in determining poverty persistence[4]. There are few studies (Biewen 2004, Cappelari and Jenkins, 2004) that attempt to link current state of poverty with its lag, and to our knowledge none that control for serial correlation in the error components. With this limitation in mind, the empirical model used here is a dynamic probit model which controls for state dependence, unobserved heterogeneity and serial correlation -

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

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

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

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

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

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

However, in dynamic model, the individual's poverty status in the initial period may be correlated with the factors captured by unobserved determinants of poverty (α_i).For example low intelligence or a lack of abilities will contribute to the risk of being poor at time t=0. To address this issue, we follow Heckman (1981) suggestion and approximate the initial conditions using static probit model (for equation 3). In order to empirically implement the model, we need to specify the stochastic nature of unobserved heterogeneity. For this, we choose a latent class specification which allows for unobserved heterogeneity (α_i), first order state dependence (γ) and serial correlation (ρ) overtime. We follow the Heckman and Singer (1984) approach in

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

which only the constant term varies across the classes. It is assumed that there exists M different set of unobserved determinants of poverty (α_i) each observed with probability π_m (where π_m>0 and $\sum \pi_m$ =1, m=1,2,…M). This specification allows the arbitrary correlation between initial and other periods. It is straightforward to estimate the model with maximum likelihood techniques. However for correlated disturbances the likelihood function of the above dynamic probit model requires the evolution of T-dimensional integrals of normal density functions. Under such circumstances, simulation based estimation (MSL) as proposed by Lerman and Manski (1981), McFadden (1989), and Pakes and Pollard (1989), among others, can be used (Lee, 1997, 1999). In this case we use simulated maximum likelihood method (for more details see Lee 1997, Hyslop 1999, Islam 2005) and a standard approach to simulation draw has been applied.

4. Results

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

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

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

Column 2 contains the estimated results of latent class probit model which allows for household specific unobserved heterogeneity. The estimated distribution of unobserved heterogeneity (shown at the bottom) indicates that there are two types of households each observed with probability. The estimated probability (0.35) of type 1 households indicates that about 35 percent households have relatively **higher risk of being poor** due to permanent unobserved heterogeneity[5]. The majority, 65 percent, of the households belongs to the type 2 where the households have a relatively lower risk of being poor.

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

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

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

correlation AR(1) in the error components. The results show that the estimated serial correlation coefficient AR (1) is negative and statistically significant, with a magnitude of about -0.19[6].The result indicates that even after controlling for unobserved heterogeneity and first order state dependence SD(1), there is a negative transitory shock in poverty persistency which persist longer than one year but deteriorate in effect over time.[7]

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

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

Again, the model (column 4 Table 4) which allows household specific unobserved heterogeneity, first order state dependence SD(1) and first order auto regressive error components AR(1) shows that the addition of transitory component of the error has significant effect on the model. The model found a statistically significant effect of transitory components in poverty persistency and the coefficient AR(1) is -0.45. However, the effect of transitory shocks in poverty persistence in urban households is stronger than that of in rural households. The results show that the estimated effects of the covariates and heterogeneity distribution are very sensitive to AR (1). The estimated proportion of type 1 households is now 4 percent and the estimated value of support point for type 1 household is -1,192 which is relatively higher than the other (type 1) support point (-1,923). This implies that type 1 (4 percent) households has stronger heterogeneity effect than the type 2 household (96 percent). The result also show a substantial increase in the estimated state dependence when first order

[6] This confirms the negative transitory shocks in other studies. For example, Chay and Hyslop (1998) estimate dynamic models of welfare and labor force participation and find that the estimated AR(1) coefficient is always negative and statistically significant except for the exogenous initial condition models.
[7] The issue about transitory shock is discussed in Lillard and Willis (1978).

autoregressive error components AR (1) is allowed. The estimated true state dependence is 1.49 which is almost three times larger (in magnitudes) than the model without AR (1). The model also shows that the degree of true state dependence is 60 percent lower in rural households than the urban households. This implies that the poverty in urban households is more persistent than the rural households.

5. Conclusion

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

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Appendix Table 1: Percentage of households by poverty status: 1994-2000

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

Source: Bigsten and Shimeles (2005)

Appendix Table 2a: Descriptive statistics for selected variables by the number of times in poverty during 1994-2000: rural households

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

Source: Bigsten and Shimeles (2005)

Appendix Table 2b: Descriptive statistics for selected variables by the number of times in poverty during 1994-2000: urban households

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

Source: Bigsten and Shimeles (2005)

Appendix Table 3: Estimated probit effect (rural areas)

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

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

Appendix Table 4: Estimated probit effect (urban areas)

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

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