ECONOMIC STUDIES

DEPARTMENT OF ECONOMICS
SCHOOL OF ECONOMICS AND COMMERCIAL LAW
GÖTEBORG UNIVERSITY
155

ESSAYS ON POVERTY, RISK AND CONSUMPTION DYNAMICS IN ETHIOPIA

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ISBN 91-85169-14-5
ISBN 978-91-85169-14-6
ISSN 1651-4289 print
ISSN 1651-4297 online

Abstract

The essay on "Poverty, Risk and Consumption Dynamics" addressed issues of household welfare in Ethiopia based on a panel data set for the period 1994-2000.

Paper 1

This paper analysed the state of poverty and income distribution in rural and urban Ethiopia during 1994-2000. Poverty declined from 1994 to 1997, and then increased 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. To examine the robustness of these results, we used stochastic dominance criteria and model based decompositions of poverty and inequality. Poverty trends were unchanged regardless of where one sets the poverty line. Decomposition of inequality revealed that in rural areas 65% of overall inequality was due to location differences, access to market, size of land, dependency ratio in the household, and age of the household. In urban areas, 49% of inequality was attributed to differences in education, occupational categories, and household durables. The results therefore imply that inequality is caused mainly by structural factors with the possibility that it may persist over time before significant decline can be observed.

Paper 2

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.

Paper 3

This paper looked at the effect of variability in consumption (or consumption-risk) on rural and urban poverty and identified factors that reduce or induce it. The results indicate that consumption risk played an important role in the measured level and profile of poverty. Overall, the percentage in poverty increased dramatically when long-term consumption was adjusted for variability. Household size, sex of the head of the household, age, farming systems and town-fixed effects, endowments, parental background, all played significant roles in increasing or decreasing consumption risk.

Paper 4

This paper looked at the dynamics of consumption within an inter-temporal utility-maximization framework. Its main objective was to investigate whether or not consumption had exemplified a martingale-process, that is, whether or not the life-cycle/permanent-income hypothesis would be confirmed. In that case, current consumption expenditure would not have been influenced by information available to the consumer with regard to income-earnings or wealth. Thus, transitory changes in income would not affect consumption. Results showed that current consumption responded to one-period lagged values of income and wealth, including consumption itself. This implies that consumption smoothing was constrained by transitory income and consumption shocks that could persist over time. A non-linear model of consumption dynamics was estimated and the solution for steady state consumption indicated no poverty traps.

Keywords: Ethiopia, poverty, income distribution, policy simulations, poverty spells vulnerability, chronic poverty, consumption risk, transitory shocks, liquidity constraints, poverty traps.

Acknowledgement

Foremost, I thank the grace of the Lord for brining this chapter of my life to a closure. In writing this thesis, my supervisor Arne Lennart Bigsten has been a source of constant guidance, support and understanding. I have had the privilege and honour of co-authoring half of the papers in this essay and others that appeared in international journals and books in earlier periods. Most of all, my association with him in the last several years clearly has helped my career a great deal. So, I remain grateful and thankful always. My thanks also go to Eva-Lena Neth for whom this thesis has taken a long time in coming. However, through out my stay in Gothenburg, starting from my pre-PHD times, Eva-Lena and her family have been a wonderful host and great companion.

It is presumptuous for me to even attempt list the great many people who have contributed to this essay one way or another. There are institutions that sponsored and collected the panel data, respondents who generously shared their life story and the diligent enumerators and supervisors who ensured the quality of the data collection, etc. I sincerely express my thanks to all!

I acknowledge with gratitude the contributions of the following that have read the whole or part of the essay at its different stages: Simon Appleton , Gustav Bjorn, Lennart Flood, Douglas Hibbs, Bereket Kebede , Stefan Dercon, Rick Wicks, and Sher Vericks.

My thanks also goes to: Daniel Abebe, Alem Abraha, Frederik Andersson , Bruck Alemu, Rahel Alemu, Elizabeth Foldi, Sentayehu Kebede, Alemayehu Geda, Alemayehu Seyoum, Nigussie Tefera, Mahmud Yesuf , Anthony Wambugu and Daniel Zerfu.

My special thanks goes to the late Mekonnen Taddesse, John Foday and my father Shimeles Abebe, who have given me the chance to get here and did not live to witness it.

Financial assistance by African Economic Research Consortium and SAREC is gratefully acknowledged.

Finally, my wife Tehetena Alemu, has bore with me the many frustrating and trying moments in the process of writing this thesis. Her strong will, dedication, love and support have been there whenever I needed it. I will remain eternally grateful! And my mother-in-Law Pia Caserta, my mother Zenebech Feleke, have given me their unreserved love and prayers. I express my deepest appreciation to

my five sisters, Teshay, Sebele, Bizunesh, Sinidu, and Tirist and two brothers, Anteneh and Esayas who have believed in me and followed up this event in suspense for many years. Thank you and God bless all of you!

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Overview

This thesis deals with the state of household welfare in Ethiopia during 1994-2000 based on a panel data set for rural and urban areas. The essay is motivated by the fact that Ethiopia is one of the poorest and most populous countries in Africa, where the scourge of poverty continues to haunt the lives of millions. Understanding poverty is of high policy relevance to Ethiopia. Particularly it is of interest to know socio-economic factors that drive poverty; its different manifestations and its persistence over time. This thesis attempts to address some of these issues in four separate, but interrelated papers.

Research on poverty has flourished over the last decade with emphasis on the statistical estimation of its prevalence, depth and severity. Generally household consumption expenditure is used as a key indicator of welfare to evaluate poverty outcomes. The required information is obtained through household income and consumption surveys that are expensive to collect, time consuming to analyze and often times subject to different kinds of measurement errors (e.g. Deaton, 1997). The findings from such analyses commonly end up raising more questions than answers. As a result, the last decade has witnessed advances in the empirical as well as methodological literature that provide interesting insights into the definition and concept of poverty and its manifestations. Some of the advances are in the areas of expanding the definition of poverty to encompass other forms of deprivation through the concept of multidimensional poverty (e.g. Borguignon and Chakravarty, 1998; Duclos et al. 2001), the deepening of the definition of poverty by introducing such concepts as vulnerability associated with several forms of income risk (e.g. Pritchett et al., 2000; Kamanou and Morduch 2002; Chaudri et al., 2002; Ligon and Schechter, 2003, 2004; Christianesen and Subbaro, 2004; and Calvo and Dercon, 2005), and distinguishing transitory from chronic poverty to emphasize the persistence of poverty (e.g. Hulme and Shepherd, 2003, Ravallion and Jalan, 2000). These advances have provided poverty analysts a great deal of scope for policy analysis as well as understanding of the dynamics of poverty. This essay makes use of the recent methodological contributions to analyze poverty states, poverty dynamics, and its link with the variability of consumption.

The paper *"Poverty and Income Distribution in Ethiopia: 1994-2000"* updates previous contributions on poverty in Ethiopia (e.g. Bigsten, Kebede, Shimeles and Taddesse, 2003) by focusing on the evolution of poverty and income distribution during a period of rapid economic recovery, followed by wide range of factors that destabilized the Ethiopian economy, such as external war, drought, and political instability. Even though the analysis is based on panel data that are not nationally representative, and thus, can prevent generalizations, our poverty trends are very similar to official poverty figures, which are based on a nation-wide income and expenditure survey. This suggests that the panel that covers major agro-ecological zones and urban centers is still very useful in tracking changes in household welfare over time. The panel also has the additional advantage of providing very detailed household and community characteristics that are not available in larger survey. The paper exploited the panel nature of the data to estimate a model of poverty by controlling for unobserved individual-specific characteristics and other issues of endogeneity that commonly plague cross-sectional data.

Our results show that poverty decreased in Ethiopia during 1994-1997 and increased in the later period of 1997-2000, which is consistent with the major events that took place in the country. This result is robust to semi-parametric and non-parametric tests. In addition, the paper attempted to look at the relative contributions of observed and unobserved household characteristics, and the residual, which includes random shocks and measurement error to observed poverty. This decomposition is useful to get a sense of how much of the observed poverty is due to persistent differences in household characteristics and random transitory shocks that includes simple measurement errors. From our results, we found that the contribution of the residual in observed poverty is in the range of 4%-27% in rural areas and 3%-18% in urban areas, which is reasonably low given the commonly held assumption that transitory factors account for more of observed poverty than persistent household characteristics. Part of the reason is that most of the omitted variables that could affect permanent attributes of a household are captured through the household-specific error term. In addition, an attempt was also made to control for the effects of these error terms on observed regressors by using valid instruments in estimation. This paper thus made an attempt to grapple with often-ignored aspects of poverty measurement. The rest of the paper reported simulation results as well as inequality decompositions using standard methods. The results revealed that in rural areas, poverty responds quite strongly to improvements in infrastructure and increased size of land or its productivity, while in urban areas educational expansion could reduce poverty significantly. The paper also found that inequality is persistent due to differences in locations in rural areas, and occupations in urban areas.

The paper on *"Poverty Transitions and Persistence in Ethiopia"* dealt explicitly with issues of poverty persistence, chronic poverty and vulnerability using existing methodologies. The paper examined poverty exit and re-entry rates in rural and urban areas taking only single spells into account due to the shortness of the panel. The results showed a clear dependence of the exit or re-entry rates on the duration of the spell and other household characteristics. Some of the interesting findings are that poverty is more persistent in urban areas than rural areas. That is, there is a high probability for a household to stay out of poverty or remain in poverty depending on the initially observed state. This is confirmed in a recent study that attempted to separate the true state dependence from the spurious one (Islam and Shimeles, 2006). In addition, the paper examined the degree of vulnerability to poverty under the assumption that there is a positive probability for any household to be poor. This is compared with determinants of chronic poverty and the results showed that while the two components of poverty are different, the household characteristics that determine them are more or less the same.

This finding motivated the third paper *"Consumption-risk and Poverty in Ethiopia"*, where consumption expenditure figures observed over an interval of a period were adjusted for the welfare loss associated with the variability of consumption in measuring chronic poverty. Invoking the analytical construct in the literature of expected utility theory (e.g. Cruces, 2005), the paper adjusted chronic poverty for consumption variability under alternative assumptions on the degree of risk-aversion. The paper estimated chronic poverty with and without adjusting for risk and reported that risk plays a significant role in affecting poverty. For instance, rural poverty increased from 26% without adjustment to risk to 53% after adjustment in rural areas and similarly this figure increased from 25% to 42% in urban areas. This result remained robust even for consumption expenditure predicted from a model that included strictly exogenous variables and controlled for serially correlated effects of time-varying unobserved factors, including measurement errors, such as seasonality. The paper also reported household characteristics that increased or mitigated risk by considering strictly exogenous factors as demographic variables, farming systems, rainfall, ethnicity, and quasi-exogenous variables such as household size, education, size of land cultivated, occupation of the head of the household etc., in rural and urban areas.

The fact that transitory shocks to income could affect consumption expenditure as reported in the third paper led to the fourth paper *"The Dynamics of Consumption in Ethiopia"*, which attempted to characterize the response of consumption to income shocks using a standard inter-temporal utility maximization framework. In this set up, if households are able to borrow and lend freely, then, what matters for current consumption is discounted value of future income. So, anticipated changes in income will not affect consumption. In other words, households smooth consumption over time so that lagged values of income, consumption, assets or any variable that could increase risk will not affect consumption. In a world of uncertainty and imperfect credit markets, consumption may not be smoothed. Thus, households have borrowing constraints, particularly the poor ones, and thus transitory income shocks could affect consumption. The question is whether or not these shocks are persistent (implying poverty traps).

The paper examined the empirical properties of the "Permanent Income Hypothesis" as this set up is known in the consumption literature using alternative specifications of the model. One model follows strictly a martingale property of consumption with no risk (quadratic utility function) and the other allows for risk, but is fully ensured, or there is a room for precautionary savings (iso-elastic utility function). The estimation method is the Generalized Method of Moments of Arlleno-Bond that uses lags as instruments to control for the endogeneity of the lagged dependent variable. Our result showed that current consumption expenditures indeed responded to lag values of income, wealth and consumption itself, contrary to the martingale hypothesis of the life-cycle consumption model.

An attempt was made to further explore the issue of liquidity constraints, precautionary savings, habit persistence, and transitory consumption shocks as possible causes for our result by separately estimating the dynamic model of consumption for wealthy and poor households. The results indicated a somewhat stronger effect of transitory shocks on consumption among poorer households than non-poor ones pointing towards liquidity constraints or precautionary savings as the most likely cause for consumption variability. The paper then examined if consumption follows a non-linear auto-regressive process on the grounds that the recovery from shocks varies across households. A non-linear model of consumption dynamics revealed that households take different time to recover from a certain shock, but attain the steady state consumption level afterwards. This steady state consumption was found to be stable and unique for both rural and urban households. It was found that for rural areas, the steady state consumption per adult equivalent is about Birr 76 per month, while for urban areas it was nearly Birr 146 per month. For rural areas, this figure is very close to the absolute poverty line, which is Birr 61 per month per person. So, consumption for households in rural areas is near subsistence in equilibrium implying that nearly all households could be at risk of remaining poor without major intervention that shifts the consumption trajectory.

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Poverty and Income Distribution in Ethiopia: 1994-2000

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October 2005

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.[1] 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 and Shimeles (2005), Bigsten and Shimeles (2004), and Bigsten, Kebede, Shimeles, Taddesse (2003).

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 enormous 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 household characteristics and non-observables. Policy simulations are then reported on the basis of the model-based decompositions and their implications discussed. Section 6 summarizes and draws conclusions.

[1] The data were collected by the Department of Economics, Addis Ababa University in collaboration with the Centre for the Study of African Economies, Oxford University and Department of Economics, Gothenburg University.

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:

$$\mathrm{H} = {}^{q}\!/_{n} \tag{1}$$

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:

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

Sen (1976) argued that H and IG lack desirable properties stated in his monotonicity and transfer axioms[2]. 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:

$$P(z,Y) = \mathrm{Max}\ S(z,y), \tag{4}$$

[2] In the context of poverty measurement, monotoncity 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.

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:

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

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.[3]

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.[4] The index is defined as:

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

where $\alpha \geq 0$

where α shows the weight the researcher is giving to the poorest of the poor. If $\alpha = 0$, then p(z,y) reduces to H, whereas if $\alpha = 1$ 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 $\alpha = 2$ its severity.

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

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[3] 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 functiona 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.

[4] For further discussion see chapter 3 in Bigsten et al (2005).

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 calorie content of these items is evaluated and their quantities scaled so as to give 2,200 calorie per day, minimum level nutritionists require an adult person must consume to subsist in Ethiopia. The cost of purchasing such a bundle would be computed using market prices and constitutes the food poverty line. 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 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[5]

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 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.

[5] 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.

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 ton.

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 a mainly cash crop producing areas. 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).

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 (see 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 became aligned with the 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.[6]The values obtained clearly track the major events in Ethiopia in 1990 decade.

[6] 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.

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 Bigste, 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.

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.[7] 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

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

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 consequence of both decline in per capita income and a rise in income-inequality.[8]

[8] 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.

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.

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) and semi-parametric Kernel density estimates (Figures 1 and 2) which construct density functions of the entire per capita distribution. 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.[9]

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.

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.

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

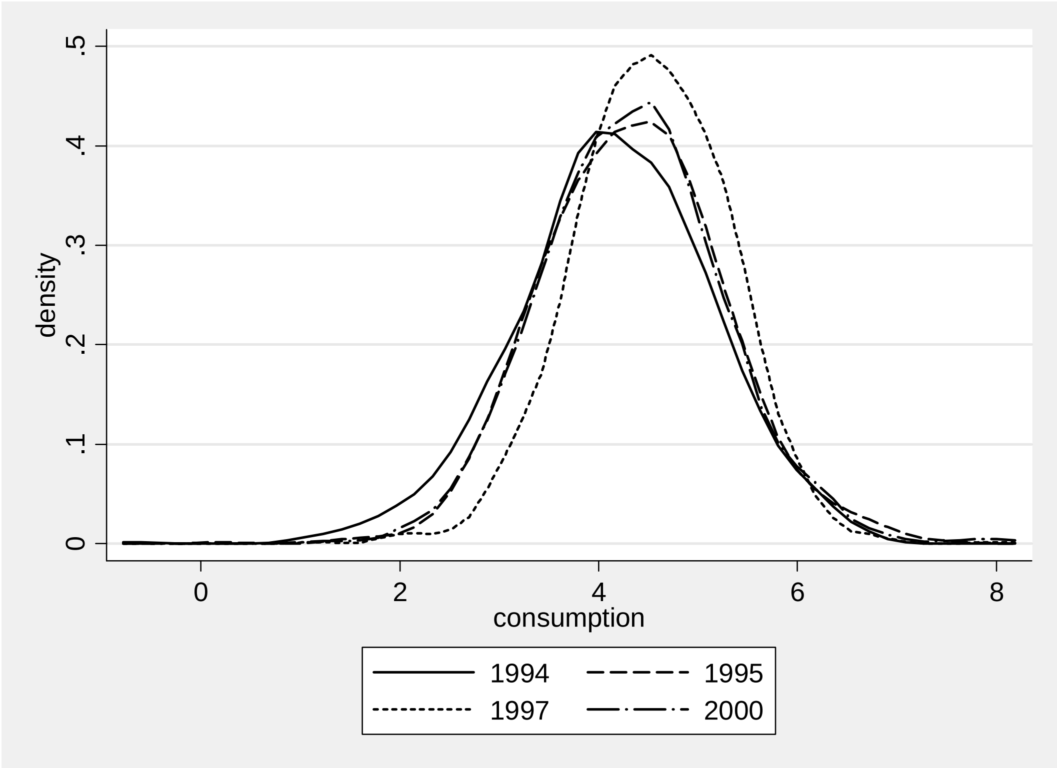
Source: authors' computations

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.[10] 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.

[9] 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).

[10] 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.

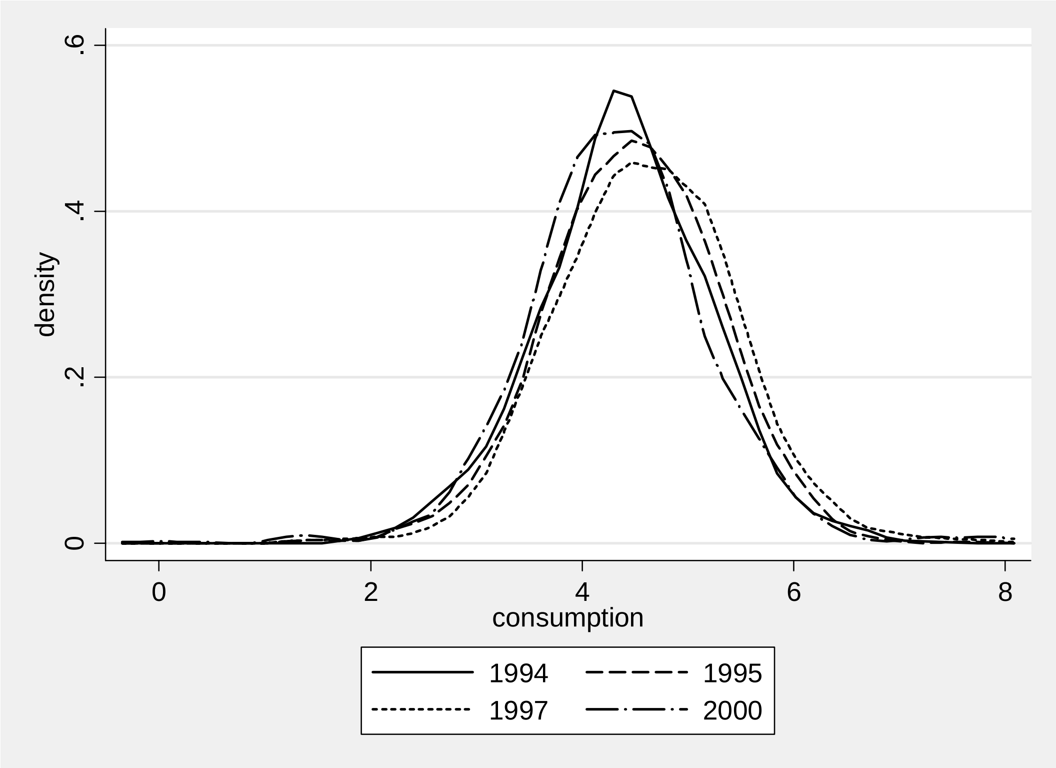
Figure 1: Kernel density Estimates for Rural Households: 1994-2000



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.

Thus, as we have seen, 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.

3.3. Profile of Poverty

As we have already inferred from Figures 1 and 2, 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	11.1
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

	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								
"Land-poor"	58	49	65	59	46	34	71	64
"Land-rich "	40	29	36	26	27	17	31	22
Remoteness								
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 euivalent

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 Diredawa.

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:[11]

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[12]. 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 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

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

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 (y)=∫fy dy* 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)≥p}, pε[0,1],* yields individuals' incomes in increasing order, where *p* is income percentiles. Following Sapspnik (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) iff w(X) > w(Y) $\forall w \varepsilon W_p$.

That is, distribution X rank-dominates distribution Y iff x(p)≥ y(p) ∀ pε[0,1]. If ∀ pε [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 $P_\alpha=\int\{z\text{-}f(y)/z\}^\alpha\, dy$, 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≤p≤.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.

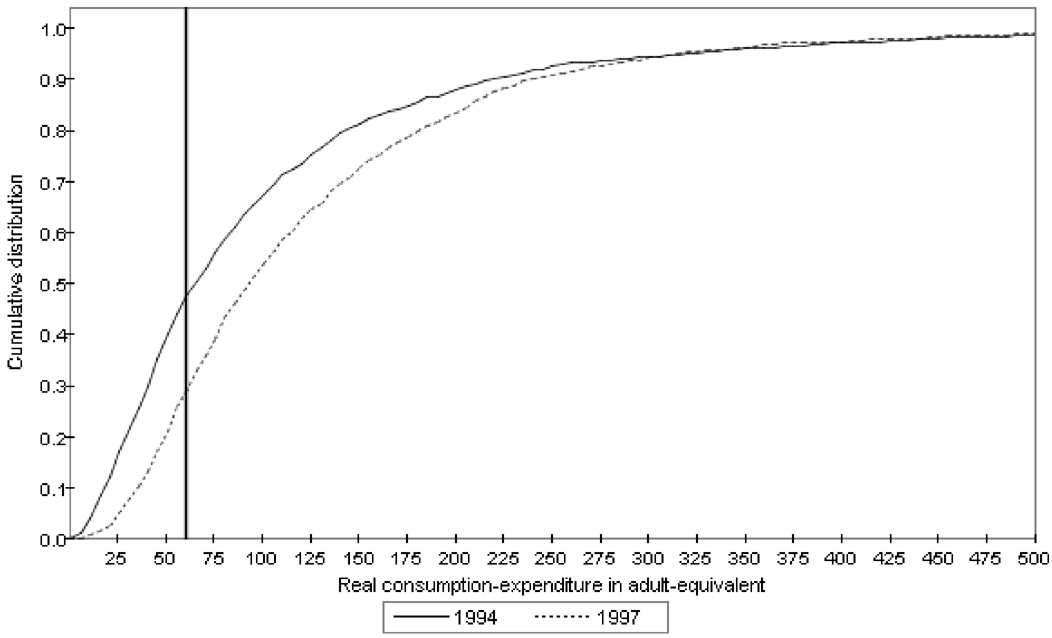
Until Beach and Davidson (1983), inference based on the ordinates of the Lorenz curve had to rely on parameterised Lorenz functions, which are not adequate to undertake the joint (mean income and distribution) dominance test. But Beach and Davidson (1983) proved that the above ordinates of the Lorenz curve are asymptotically normal with mean zero and a variance-covariance matrix $\Omega=(w_{ij})$, where:$w_{ij} = p_i\, [\lambda_i^2 +(1\text{-}p_j)(\xi_{pi}\text{-}Y_i) (\xi_{pj}\text{-} Y_j) + (\xi_{pi}\text{-}Y_i) (Y_j\text{-}Y_i)$ 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: $T_i = (\mu_{i1}-\mu_{i2})/\{\sqrt{(}var(\mu_{i1})/N1+var(\mu_{i2})/N2\}$, 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 dominance-criterion.

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).

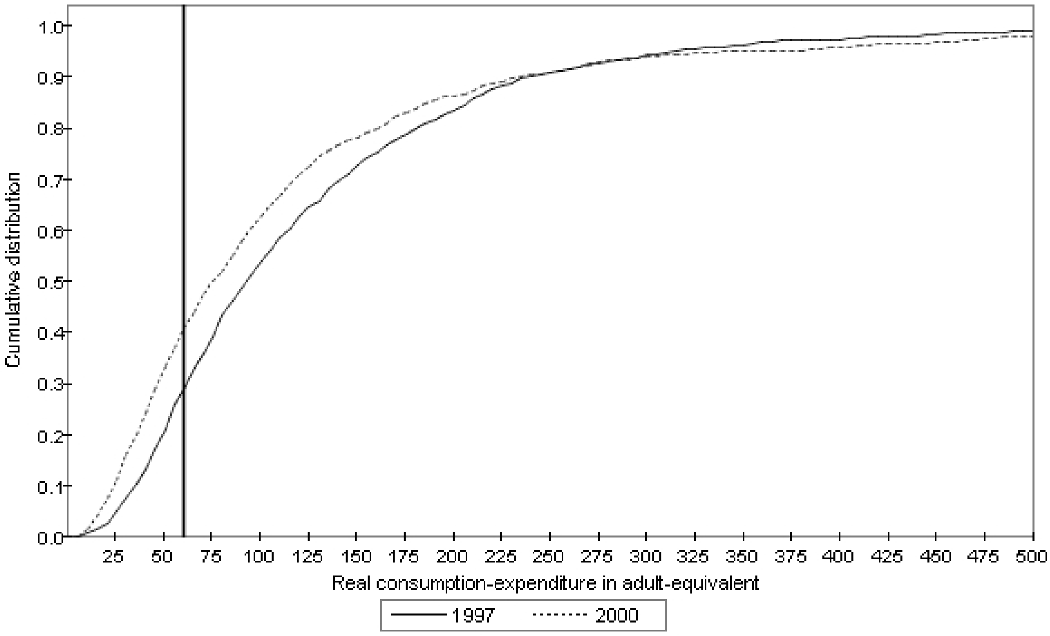
The headcount ratio for 1997 was lower than that for 1997 (Figure 3) up to Birr 208, which is more than three times the poverty-line used, and double the mean income (consumption) that prevailed in 1994. Crossings at higher levels (Birr 221, 227 and 223) are thus irrelevant for our purposes and changing 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

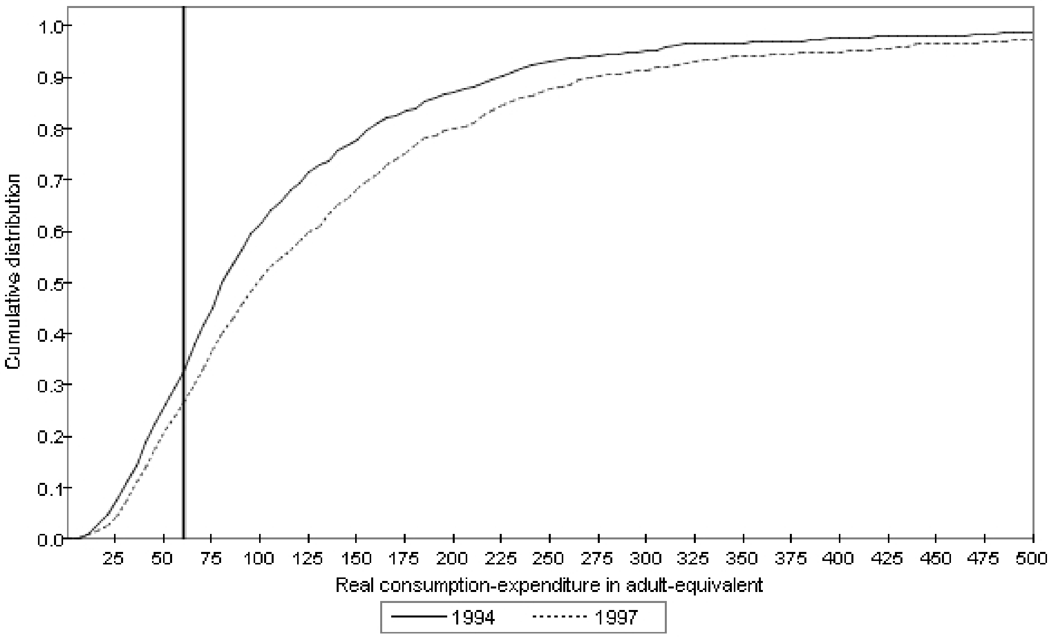
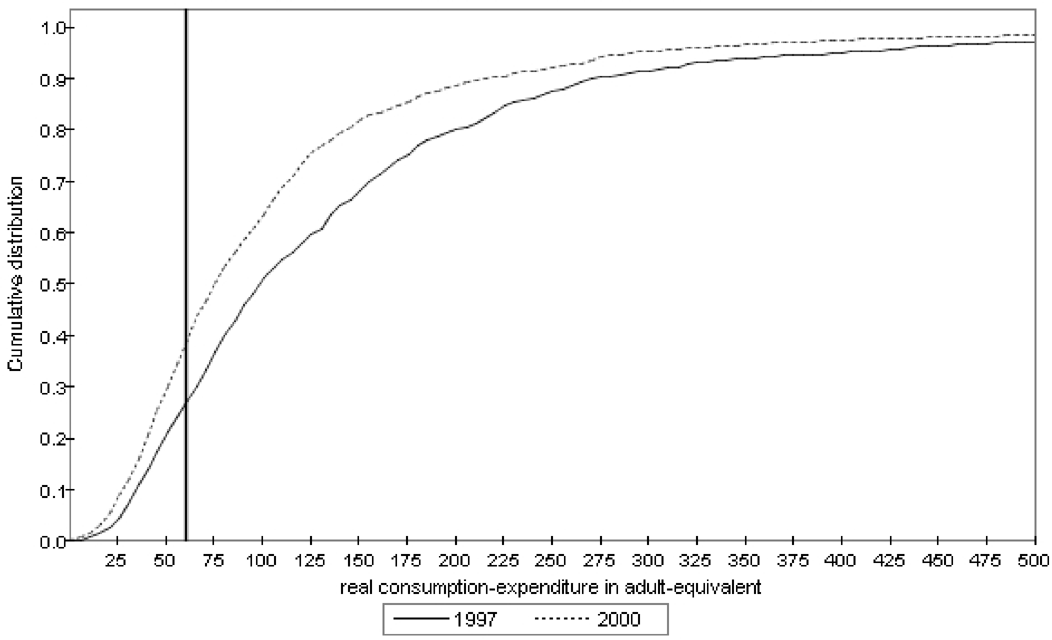
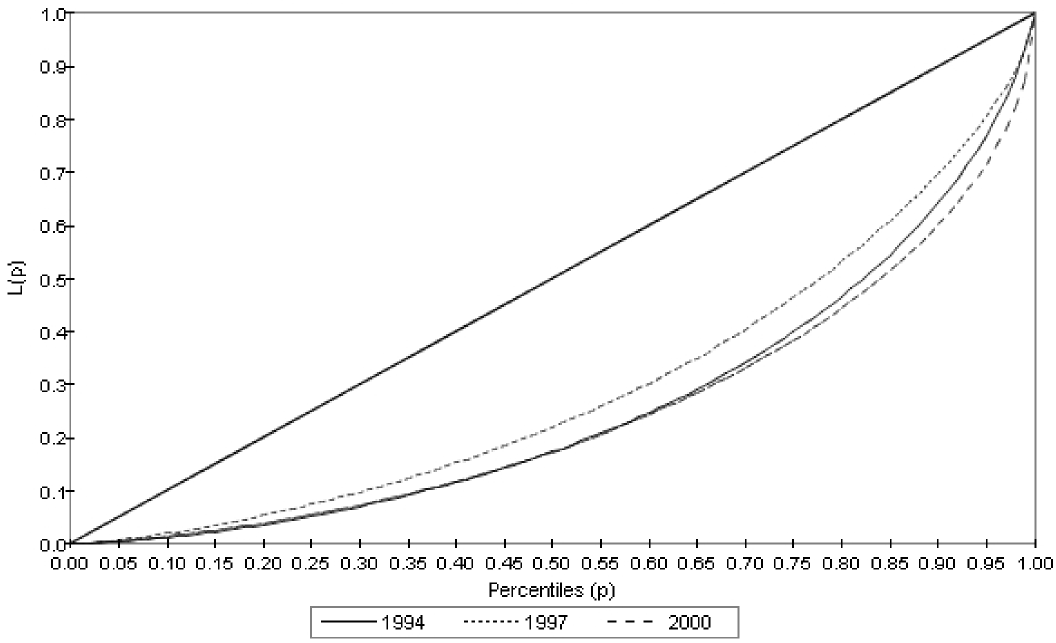


Figure 6: Poverty dominance in urban areas, 1997-2000



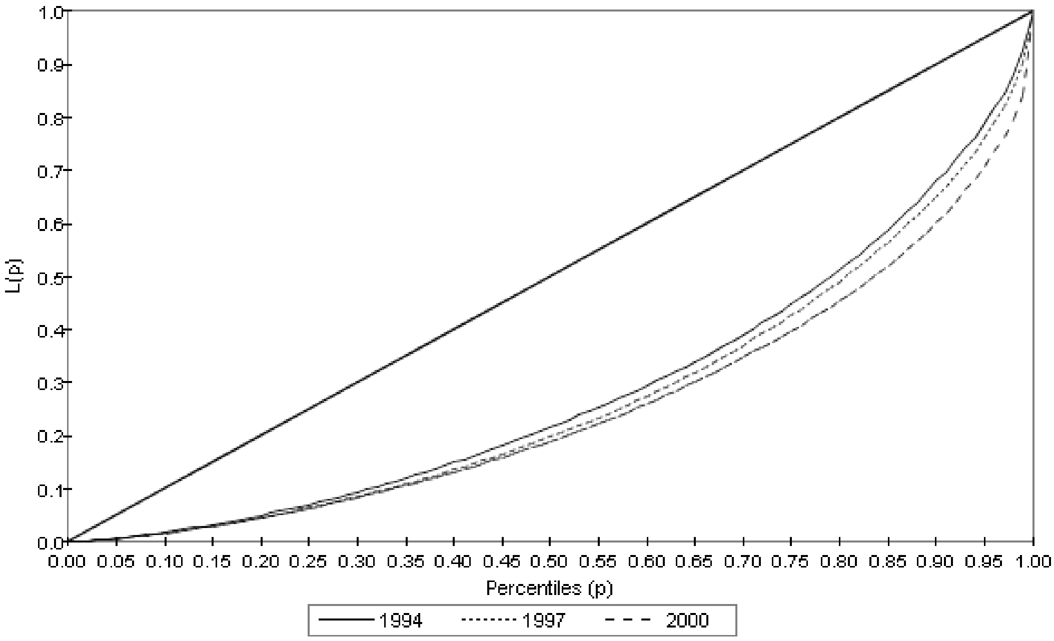
Since income inequality has become an important issue in our discussion of poverty in Ethiopia, Figures 7 and 8 illustrate for rural and urban households its evolution over time by using Lorenz curves. It can be seen that income inequality in rural areas was lowest in 1997 as compared to both 1994 and 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 (2002, 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.[13] 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.

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:

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

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

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

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

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 capita consumption[14]. 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"[15] 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.

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)[16] and the second term is the random term.

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

[14] 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).
[15] 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.
[16] See for example, Decron and Krishinan (2000)

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.

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:

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

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[17].

In order to establish which explanatory variables could possibly be correlated with the unobserved random effects, we first estimated fixed-effects regression of equation (7) from which were able to obtain estimates of u_i for each household in the sample[18]. Next, we compared u_i with each time-varying and time-invariant explanatory variables used in the fixed-effects regression to identify those correlated with the fixed-effects error terms. Appendix Table 2.3 and 2.4 provide results for rural as well as urban areas from this procedure.

[17] 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.

[18] We follow 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.

For rural areas, household size and its square, female household head, wife with primary education, mean household age, value of household assets, access to markets, being in a chat-producing area, the number of oxen owned and several interaction terms all showed correlation with household-specific error-terms of over 0.10. These results give an idea how the explanatory variables would behave with respect to the unobserved fixed-effects in a first-stage regression, but choosing endogenous variables also depends on the underlying economic intuition and other considerations, such as the availability of enough instruments in the model. We chose to treat household-size, age of the head of the household, asset values, access to market and off-farm employment as endogenous. The resulting correlation with unobserved fixed-effects as shown in column 2 of Appendix Table 2.3 is quite satisfactory.

Using the correlation-coefficient in Appendix Table 2.4 as a guide, we treated household size, education of the head of the household, residence in Addis Ababa and being in private business as endogenous variables in the urban model. This yielded some improvement in the correlation between the unobserved fixed effects, visible in the second column of Appendix Table 5.4. The instruments seem weak compared to the rural areas, however.

Tables 9 and 10 show, respectively, the estimated coefficients of determinants of real consumption expenditure per adult equivalent for rural and urban households. Most of the rural coefficients have expected signs and some of them quite significant such as household size, head being female, land-size, number of oxen, asset-value, market-access, dummy for chat producing villages, and several related squared-terms and interaction terms.

Similarly, for households in urban areas, the coefficients associated with household characteristics such as size, age, sex of the head of the household, education, and occupation turned out to be statistically significant bearing also the expected sign in affecting household consumption. 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.

Table 9: Hausman-Taylor Estimate of Rural Consumption Expenditure per adult equivalent

Constant	5.608
	(39.36)**
Household size	-0.109
	(11.07)**
Household size squared	0.005
	(3.87)**
female headed households	-0.123
	(5.03)**
Mean age of the household	0.001
	-0.2
Age of household head	-0.002
	-1.75
Dummy for wife with at least primary education	-1.64
	(0.515)
Per capita size of land in hectares	0.515
	(2.01)*
(Per capita size of land in hectares)^2	-0.101
	(3.01)*
Number oxen owned (bulls, oxen and young bulls)	0.055
	(3.33)**
Total current value of household assets	0.001
	(3.73)**
Population of nearest town divided by the distance in kms from the site (access to market)	0.0001507
	(2.93)**
Farming systems (dummy for enset growing area)	.029
	(-.08)
Dummy for households which harvested teff during last season	0.069
	-1.42
Dummy for households which harvested coffees last season	0.088
	-0.4
Dummy for household which harvested chat last season	0.47
	(6.00)**
Rainfall in mm for stations near survey site	0.004
	(9.77)**
Interaction between HH-size and head being female	-0.025
	(1.99)*
Interaction between HH-size and education of wife	-0.065
	-1.73
Interaction between HH-size and land	0.005
	(1.99)*
Interaction between oxen ownership and size of land	-0.096
Dummy for 1995	.032
	(0.323)
Dummy for 1997	-1.14
	(0.323)
sigma_u	.5150
sigma_e	.74610
rho (fraction of variance due to u_i)	0.322
Wald chi(23)	1030

Source: authors' computations
HH-Household Head

Table 10: Hausman-Taylor Random-Effects Model of Urban Consumption Expenditure: 1994-2000

Constant	4.969
	(25.61)**
Household size	-0.193
	(8.46)**
Household size squared	0.006
	(4.16)**
Female headed households	-0.123
	(5.03)**
Age of household head	-0.004
	-1.29
Age household head squared	0
	-0.52
Dummy for household with at least primary education	0.443
	(2.65)**
Dummy for wife with at least primary education	0.156
	(3.28)**
HH private business employer	0.365
	(2.93)**
HH own account worker	0.089
	-1.68
HH civil servant	0.148
	(2.46)*
HH public enterprise worker	0.043
	-0.62
HH unemployed	-0.319
	(4.61)**
Unemployment rate	-0.035
	-0.56
Total value of household asset	0
	(3.02)**
Amhara ethnic group	0.174
	(2.75)**
Harari ethnic group	1.119
	(2.68)**
Oromo ethnic group	0.063
	-0.83
Tigrawi ethnic group	0.552
	(4.21)**
Addis (capital city)	0.57
	(2.38)*
Household head completed primary*age	-0.005
	-1.53
Dummy for 1994	-0.07
	(2.38)*
Dummy for 1995	0.004
	-0.12
Dummy for 1997	0.107
	(3.55)**
sigma_u	0.522
sigma_e	0.574
rho (fraction of variance due to u_i)	.453
Wald chi(23)	530

Source: authors' computations
HH-Household Head

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. It is clear from these tables that the proportion of poverty explained by observable and unobservable household-specific factors is quite high. In every case, actual poverty was higher than (or in one case the same as) 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, about 51% for rural areas and 57% for urban areas, which are reasonable.

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 factors (%)	47	36	22	34
Headcount ratio due to "random-shocks" (%)	0	4	7	6
Overall poverty (%)	47	40	29	40
Contributions of observables in actual poverty (%)	100	98	76	85
Correlation between actual and predicted poverty at HH level (%)	51%			
Urban Areas				
Headcount ratio due to observable factors (%)	32	26	19	34
Headcount ratio due to "random-shocks" (%)	1	6	8	4
Overall poverty (%)	33	32	27	38
Contributions of observables 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
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[19] 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.[20]

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. 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.

[19] 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.
[20] 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

We therefore tried a probit-specification to capture the effect of household-unemployment on the probability of being in poverty, controlling for the effects of other household characteristics as before. In this specification (Table 14), unemployment is a statistically significant risk-factor for a typical household to fall into poverty.

Table 14. Probit estimates of determinants of poverty in urban Ethiopia:

Constant	-0.811
	(2.51)*
Age of household head	-0.005
	-1.8
Household size	0.17
	(11.83)**
Dummy for household with at least primary education	-0.578
	(6.74)**
Dummy for wife with at least primary education	-0.568
	(5.44)**
HH private business employer	-1.41
	(4.46)**
HH own account worker	-0.463
	(4.32)**
HH civil servant	-0.397
	(3.23)**
HH public enterprise worker	-0.35
	(2.29)*
HH private sector employee	-0.486
	(2.83)**
HH casual worker	0.314
	(2.29)*
”Unemployment rate”	0.284
	(2.03)*
Amhara ethnic group	-0.306
	(2.07)*
Oromo ethnic group	-0.219
	-1.35
Tigrawi ethnic group	-0.717
	(3.08)**
Harari ethnic group	-1.2
	-1.36
Gurage ethnic group	-0.081
	-0.47
Addis	0.077
	-0.3
Awasa	-0.028
	-0.09
Bahrdar	-0.329
	-1.07
Dessie	0.532
	-1.59
Diredawa	-0.234
	-0.81
Jimma	0.063
	-0.22

Source: authors' computations
* significant at 5%; ** significant at 1%
HH-Household Head

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:

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

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[21]. 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:

$$s^k \equiv \frac{\sum_{i}^{k} a_i(Y) y_i^k}{I(Y)} \qquad (10)$$

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

[21] Sen (1973) and also Hagennaars (1987) discuss the underlying social welfare function implied by a particular weighting rule chosen.

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

Similarly, for the Coefficient of variation, the share of income-source "k" in overall inequality is[22]:

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

where Y^k is the vector of individual incomes in ascending oder derived from income-source "k", which we can approximate by regressing it on a set of exogenous variables and a residual ($\boldsymbol{\beta} X^k + \mathbf{e}$). 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 varaible. 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.

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.

[22] Different variations of (11) and (12) can be derived for purposes of computational ease.

Table 15. Determinants of mean consumption expenditure , 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)**
(Landsize per capita $)^2$	-0.319
	-1.72
Acess to markets	0
	(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 compuations
 * 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.

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 (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
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
Diredawa	-0.136 -1.1
Jimma	-0.099 -0.72
R-squared	0.37

Source: authors’ computations

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

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[23]. 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 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.

[23] 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.

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, 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 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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Annex 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 assets	.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	-	.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	-	.062113
Household size* wife completed primary	.0012958	.0111978	-	.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

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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.[1] A household's consumption level at a specific time depends on its assets, 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.[2] 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.

[1] See surveys in Baulch and Hoddinott (2000), Hulme and Shepherd (2003), McKay and Lawson (2003), and Yaqub (2003).
[2] 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.

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.

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[3] (see e.g. Bane and Ellwood, 1986, Stevens, 1999, and Devicienti, 2003 for detail discussion of exit and re-entry rates). Given this definition,

[3] 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.

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.[4] 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:

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

where n_j is the number of individuals at risk at time j, and d_j is the number of failures at time t_j. The product is overall observed failure times less than or equal to t.

The parametric method on the other hand, models the distribution of spell durations via the probabilities of ending a spell.[5] Suppose we are interested in modelling the duration of poverty for household *i* which entered at t_0.[6] We can define a dummy $\delta_i=1$ to distinguish households which completed the spell (exited out of poverty) from those who continued in the poverty spell, $\delta_i=0$ at the end of the period (months, years or rounds in our case). The percentage that completed 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:

$$h_i(t) = pr(T_i = t / T_i \geq t;\ X_{it}) \tag{2}$$

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, [7]

[4] 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.

[5] We draw heavily from Jenkins (1995) and Stevens (1999) to discuss the parametric approach to modeling exit and re-entry rates.

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

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

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

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

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

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[8] by adding a multiplicative random error term[9] into equation (4) so that the instantaneous hazard rate becomes:

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

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):

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

If h_i follows a logistic structure, then:

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

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,

$$t_{idt} = \alpha_{id} + \beta X_{it} \qquad (8)$$

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8 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.

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

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, Christianesen and Subbaro, 2004and 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.[10] 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:

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

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.[11]

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

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

[11] 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).

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:

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

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

$$T_i = P_i - T_i \tag{14}$$

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

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.[12]

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.[13]

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[12] 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.

[13] 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.

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

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 A1.1 and A1.2 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).

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

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 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-etnry-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[14]. 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[15] 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.

[14] 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.

[15] 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.

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 ("mean years")	1.6 (3.5)	1.54 (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). 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).[16]

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

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

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.

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.

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%.

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.

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***
Demographc						
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%.

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 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.

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.

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)**
Diredawa	-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%	

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[17]

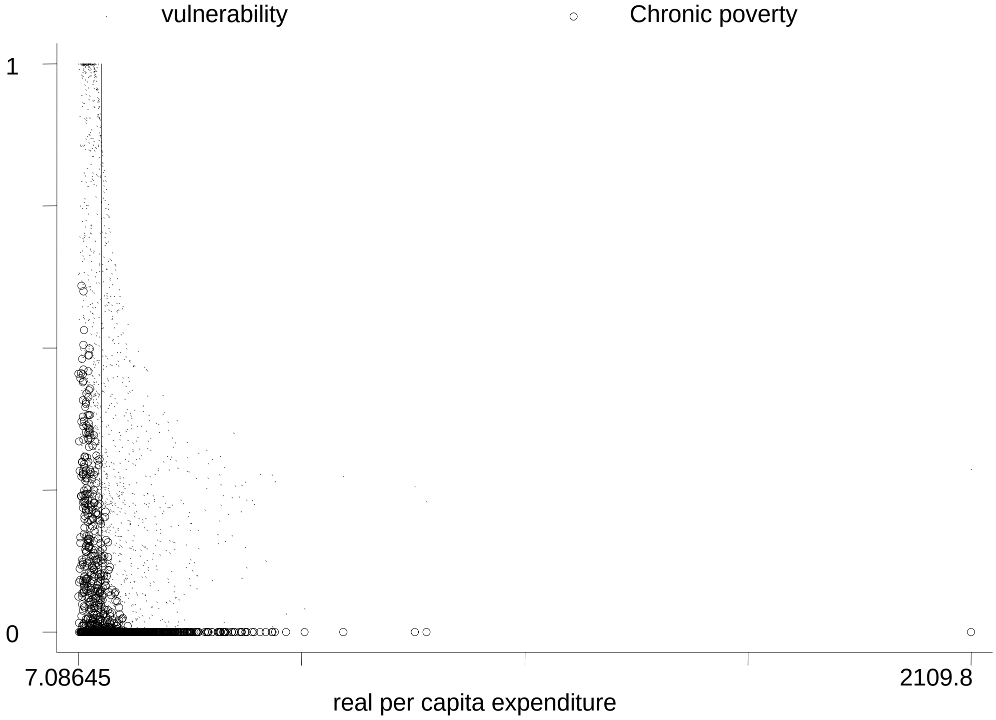
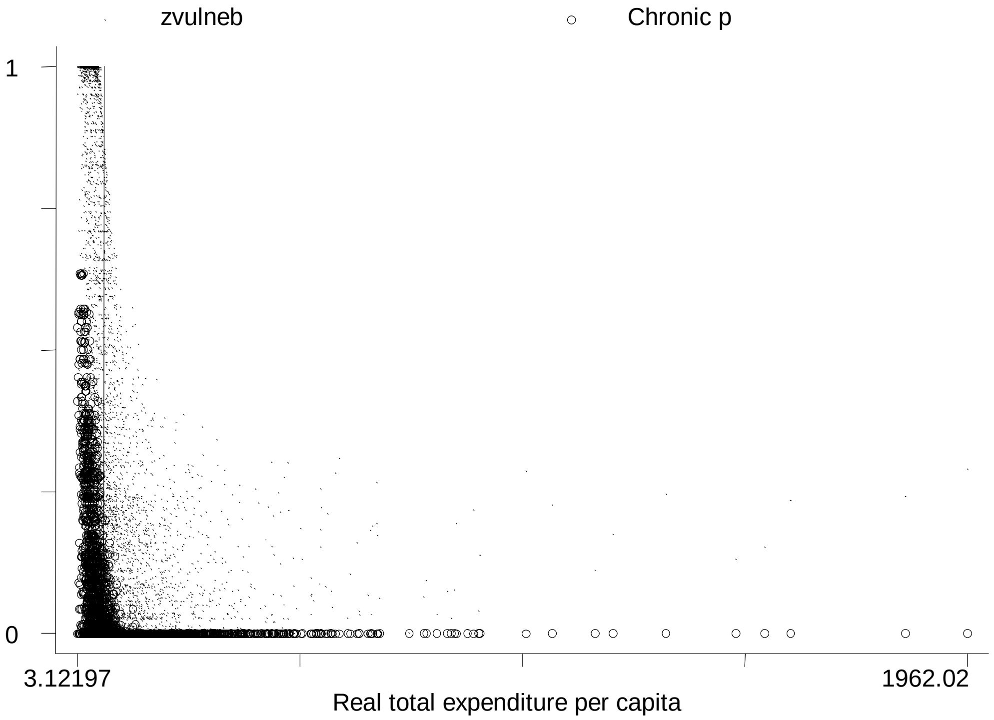


Figure 2: Vulnerability and Chronic Poverty for Urban Ethiopia



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[17] 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.[18] 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.[19] 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.

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

[18] 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.

[19] Redistribution of assets, such as land, may also ease the credit constraints poor people face.

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 A1.1 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 A1.2. 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**

Consumption-Risk and Poverty in Ethiopia[1]

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December 2005

Abstract

Using rural and urban panel data, this paper addresses consumption-risk in the measurement of poverty in Ethiopia, and its determinants. Following recent contributions in the literature on risk and vulnerability, chronic poverty was adjusted for the magnitude of uncertainty in consumption and, household and community characteristics determining both mean household consumption and risk were examined. Taking consumption variability into account substantially changed the poverty profile. Household characteristics that tended to mitigate or increase risk were identified which might be helpful for policymaking.

Keywords: Consumption-risk, poverty, certainty-equivalent income.

[1] An earlier version of this paper was presented in November 2003 at the World Institute for Development Economics Research (WIDER) workshop on Risk, Poverty and Vulnerability in Addis Ababa, Ethiopia. Valuable comments have been received from Stefan Dercon, John Hoddinott, Alemayehu Seyoum, Gunnar Köhilin , and other participants. In addition, I benefited from the insightful comments of seminar participants at the Department of Economics, Göteborg University in September 2004. Special thanks are due to Professors Arne Bigsten and Douglas Hibbs.

1. Introduction

Policy-documents in less-developed countries usually report the state of poverty and the attributes of the poor on the basis of one period observation, thus, presenting only snapshots of the complex picture. But, how persistent is poverty? What individual attributes predispose households to poverty (who are the vulnerable)? How do households respond to different types of shocks to protect themselves from falling into poverty? What drives variability in the main welfare-indicator? How should one take the welfare loss into account in the analysis of poverty? All these are important questions for policy purposes, but answering them requires detailed information on household living standards over time.

Recent literature on consumption risk and vulnerability has provided analytical tools that can help us better understand the conditions and underlying processes of chronic poverty (see for example Ligon and Schechter, 2004; Hoddinott and Quisumbing, 2003 for useful survey). These tools were applied to a panel data set from Ethiopia to analyze the welfare effects of consumption-variability. The idea is that unexpected changes in consumption generally result in welfare-loss, which most studies on (long-term) poverty do not account for.

For instance, it is a well-known empirical fact that chronic poverty, defined over the mean of individual incomes over several periods tends to be lower than poverty rates reported in each period. The reason is that the former smoothes out the consumption variability over time, and as a result leads to lower poverty rates.[2] But, from an inter-temporal point of view, ignoring consumption variability has enormous welfare implications. For instance, it is difficult to compare welfare levels among individuals based only on current consumption expenditure. From an inter-temporal perspective, it is possible for some individuals to prefer lower current consumption levels to avoid future uncertainties, while the reverse may be true for others. Households in general adjust current consumption depending on their perceived risk about the future, which essentially is influenced by the nature of the income earning process, as well as the degree of consumption smoothing possibilities available to them.[3] There is a large

[2] We define current poverty rate as P_t, as the sum of the chronic component, C_t, and the transitory component, R_t, or $P_t = C_t + R_t$

[3] Or alternatively degree of credit market imperfection.

literature devoted to the dynamics of consumption decision by households to understand the roles of initial wealth, permanent income, credit-market imperfections, etc.

In this literature variability in consumption is assumed to be welfare-reducing if individual utility or welfare function is assumed to be concave with respect to consumption, implying some degree of risk-aversion. Thus, it is important to account for the welfare loss in order to make inter-personal comparisons, and thus measure the degree of poverty. Ignoring consumption variability would assume that all households are risk-neutral with respect to uncertain incomes, which is a strong assumption that would need to be justified, particularly in the context of less-developed countries where liquidity constraint, job uncertainties, and other shocks are major reasons for consumption variability.

The main objective was thus to adjust poverty measures for consumption variability arising from either negative or positive shocks. In addition, the paper explores how determinants of individual welfare, such as household demographics, location, parental education and exogenous shocks interact with consumption-variability.

The next section outlines the methodology used for the analysis, while Section 3 describes the data, Section 4 discusses the results and section 5 summarizes and draws conclusions.

2. Methodology

2.1. Theoretical Background

Consumption-based measures of poverty in less-developed countries generally rely on current consumption expenditure when analyzing poverty and the attributes of the poor. As such therefore, they only provide a snapshot of the poverty condition with little to say about the degree of uncertainty that households face about living standards. Though consumption expenditure as a measure of poverty is based on theory (see Haggenars, 1987, Sen and Foster, 1997, Ravallion, 1998), the problem that it has with regard to interpersonal comparison of welfare is further complicated by the uncertainty element. For example, it would be difficult to rate on the same scale an individual with a low consumption level today, but with a relatively secure future, with an individual of high level of consumption today, but uncertain future. It would be desirable to adjust the magnitude of welfare loss associated with consumption variability.

Recent years have seen an upsurge in the literature on the connection between poverty and risk, aiming to introduce a new dimension of poverty, which is vulnerability.[4] Most of these studies focused on the degree of vulnerability to poverty that transpire from income or consumption fluctuations, and do not measure directly the impact on poverty *per se*, excepting for Ligon and Schechter (2003) and Calvo and Dercon (2003). In this regard, this paper followed that of Makdissi and Wodon (2003) and Cruces and Wodon (2003) to adjust poverty measures for consumption variability using the concept of certainty equivalent income.

Consider repeated observations of a welfare indicator, such as per capita income or consumption, for N individuals over T periods denoted by the vector $y_{it}=(y_{i1}, y_{i2}, \ldots y_{iT})$. The task is to aggregate individual welfare over time and construct a scalar summary measure. This is analogous to the tradition in the distributional analysis literature (e.g. Atkinson, 1970 for income-distribution and Hagenaars, 1987 for poverty orderings), where a comparison of welfare between two income-distributions is made on the basis of ethically flexible social welfare criterion. Such measures of inequality as the Gini coefficient, and the Foster et al. (1984) measures of poverty can then be shown to be consistent with a social welfare function, which is quasi-concave in individual utility.[5] The key difference is that incomes were there assumed received with certainty, so that neither individual nor social welfare is affected by variability of income. In fact, since all individuals were assumed identical in all respects except for their incomes, following the axiom of anonymity, social welfare was invariant to changes in the rank of individuals in the income distribution over time.[6]

The link between income distributions and welfare orderings was established through a mapping of social welfare functions into the real line by defining a reference social welfare function that would have prevailed if there were no income inequality, or analogously, by defining an "equally distributed income" for each individual consistent with maximum welfare that can be attained. Thus, inequality was defined as the deviations of actual social welfare from the "socially optimum".

[4] For example, Ravallion, 1988; Dercon and Krishnan, 2000; Pritchett, Suryahadi and Sumarto, 2000; Christiaensen and Subbarao, 2001; Dercon (2002a, 2002b); Duclos, 2002; Ligon and Schechter, 2002; Mansuri and Healy, 2002 ; Skoufias and Quisumbing, 2002; and McCulloch and Callandrino, 2003.

[5] Bigsten and Shimeles (2005) discuss this issue in more detail in the context of the stochastic dominance criterion of poverty orderings.

[6] That is, social-welfare comparisons are insensitive to the relative position each individual takes in the income-structure over time.

Similarly, an aggregate measure of welfare, $\mathcal{W}$ can be defined as a mapping from the space of the distribution of incomes, F, into real line, R, using the concept of "certainty equivalent income". That is, $\mathcal{W}$: F→R establishes a welfare ordering as a function into the real line (see Cruces, 2005 for details).

Two issues require elaboration. The first, and perhaps more important, relates to the conceptual distinction and relation between ex-ante and ex-post utility-functions implied by expected-utility theory. The second relates to the translation of welfare measures from the utility space to money-metric or income space.

A well-known result in the theory of expected utility is that individual utility, *U,* under uncertainty is a function of state-contingent income, that can be represented by:

$$U = \sum_{iw\varepsilon\Omega} \tau_w u(y_w) \equiv E\left[U(\hat{y})\right] \tag{1}$$

where Ω represents the set of all possible states of the world, and y_w is state contingent income and τ_w is the probability attached to each *w* the element of Ω, and $\hat{y}$ is the uncertain income. It is assumed that ex-ante, at time t=0, a household evaluates income prospects that materialize in some future time, say t=1. If *U*(.) is quasi-concave, then, not only does expected utility depend on realized mean income , $\bar{y}$, but also on its variability over time. Since only realized (ex-post) incomes are observed, it is necessary to impose a structure on the measure of poverty or any other measure of welfare (such as vulnerability as in Ligon and Schechter, 2003, 2004) to establish a parallel with ex-ante utility.[7] Cruces (2005) argues that by replacing the probability weights in equation (1) by a discount rate for time preference, it is possible to construct an evaluation function of ex-post or realized streams of income.

The second issue of interest in the connection between poverty and risk is the translation of expected utility into its money-metric equivalent so that poverty measurement proceeds

[7] For example, the stream of future income or at least the *change* in the stream of income is assumed to be stationary to evaluate ex-post income for a forward-looking measure of welfare.

without the assumption of cardinality of utility functions[8]. The concept of "certainty equivalent income" plays a key role, as does the "equally-distributed income" in the social-welfare consistent measures of income inequality or poverty. That is, we can incorporate the elements of risk to the standard measures of poverty if we have repeated observations over time of the welfare indicator for a household or an individual.

2.2. Adjusting poverty for consumption risk

With this background, we can now define a measure of poverty adjusted for risk or variability in consumption. For a stream of income y_{it} over T periods that provides the same utility, let the certainty equivalent income of an individual be y_{ce}. More formally, the utility associated with incomes in T periods can be linked with utility of the certainty equivalent income using the additive structure:

$$u(y_{ce}) = \frac{1}{T}\sum_{t=1}^{T} \delta(t)u(y_{it}) \qquad (2)$$

Or in other words,

$$u(y_{ce}) = Eu(y_{it}) \qquad (3)$$

The function *u(.)* is assumed to be concave to capture non-satiation and risk- aversion, respectively, through the first and second derivatives. The term δ(t) represents the discount rate for time preference which for simplicity is assumed identical across individuals.[9]

The Constant Relative Risk Aversion (CRRA) function is one of the most frequently used structures in the literature to capture the impact of income uncertainty on welfare.

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[8] Legion and Schechter (2003) define their measure of vulnerability as $V^i = U^i(Z) - EU^i(y_i) = \left[U^i(Z) - U^i(E(y_i))\right] + \left[U^i(E(y_i)) - E(U^i(y_i))\right]$ where the first term in the last equality represents a measure of poverty while the second term measures risk. Both elements of welfare (poverty and risk) are evaluated directly from the underlying utility-functions which are defined over the observed stream of income of households or an individual $y_i=(y_{i1}, y_{i2}, \ldots y_{iT})$. While the measure of poverty based on individual utility satisfies a number of the desirable properties of a poverty index suggested by Foster et al (1984), still it retains the cardinality of the utility function which has its own problem of comparability.

[9] The discount rate may be regarded as a weight assigned to individual utility over T periods with the property that 0 <= δ(t) <= 1, and $\sum_{t=0}^{T}\delta(t) = 1$. For ease of exposition, δ(t)=1/T will be assumed throughout.

$$u(y)=\begin{cases}\left[\dfrac{y^{1-\rho}}{1-\rho}\right] & if \quad \rho\neq 1\\ \log y & if \quad \rho=1\end{cases} \tag{4}$$

Or equivalently,

$$y_{ce}=\begin{cases}\left[\dfrac{1}{T}\sum_{i=1} y_{it}{}^{1-\rho}\right]^{\frac{1}{1-\rho}} if \quad \rho\neq 1\\ \prod y_{it}{}^{\frac{1}{T}} \quad if \quad \rho=1\end{cases} \tag{5}$$

Equation (5) essentially provides limiting case for 'permanent' income, which depends on the measure of risk-aversion. If ρ is equal to zero, or if there is no variability in the welfare indicator, then, y_i equals to its mean, as is frequently used in the literature on chronic poverty. An alternative way of adjusting consumption for risk is to use a Taylor's expansion of the certainty equivalent income given in equation (3) around y such that:

$$y_i(\rho)=\bar{y}_i-\frac{1}{2}\frac{\rho}{\bar{y}_i}\sigma_{y_i}{}^2 \tag{6}$$

The expression $\frac{\rho}{\bar{y}_i}$ is the well-known Arrow-Pratt measure of absolute risk aversion.[10] Equation (6)[11] has the advantage over the certainty equivalent measure of risk because it explicitly takes into account the variance in income by controlling for consumption growth (as captured by the mean). The paper reports poverty rates adjusted for both methods of calculating risk: the Certainty Equivalent and the Taylor Approximation methods.

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[10] The Arrow-Pratt measure of relative risk aversion is given by $\rho=-y\dfrac{U''(y)}{U'(y)}$. Thus, dividing by y provides the absolute measure of risk-aversion.

[11] Equation (4) can be obtained easily by noting that the second-order Taylor's expansion for a utility function defined over y is given by

$u(y)=u(y)+u'(y)(y-\bar{y})-\dfrac{u''(y)(y-\bar{y})^2}{2}$. If we take expectations, we get an expression for the certainty equivalent income as a function of mean and variance.

The next step is to measure aggregate risk-adjusted poverty in the usual manner. For the most popular poverty index introduced by Foster et al (1984), risk-adjusted poverty would be[12]:

$$P_\alpha(y_{ce}) = \int_0^z \left[\frac{z - y_{ce}}{z}\right]^\alpha dy_{ce} \qquad (7)$$

In estimating risk-adjusted poverty, which relies heavily on the degree of variation in consumption-expenditure, measurement error that arises from sampling and non-sampling errors is an important issue. Disentangling the measurement error component from other sources of variation is not so easy and available tools are not that precise in dealing with the problem (see Deaton 1997, 1992 for detailed discussion). To minimize the effects of measurement errors in the variation of consumption expenditure the common approach is to fit a regression model using strictly exogenous variables, which takes into account unobserved individual household effects. We adopt Ligon and Schechter's (2004) specification given by equation (8) to deal with the issue of measurement error in estimating risk-adjusted poverty and report how important it is.

$$\ln(y_{it}) = \beta' X + \alpha_i + \eta_t + u_{it} \qquad (8)$$

where, X is a vector of exogenous variables that affect household consumption expenditure, α_i and η_t capture respectively unobserved individual effects and time effects. The use of log consumption expenditure, instead of levels implies that the underlying measurement error term is multiplicative in consumption expenditure, that is, error components that vary systematically across households are controlled for. We used a variation of equation (8)[13] to

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[12] It is important to note that the risk preference implicit in the P_α measure of poverty is given by the absolute measure of risk-aversion which is equivalent to $\rho_\alpha^A(y_{ce}) = -\left[\frac{P''(y)}{P'(y)}\right] = \frac{\alpha(\alpha-1)zP_{\alpha-2}}{\alpha P_{\alpha-1} z} = \frac{(\alpha-1)z}{(z-y_{ce})}$. This implies that for $\alpha > 0$, households are risk averse. Yet, risk-aversion rises with income, and approaches infinity for income approaching the poverty line, which is counter-intuitive (see also Ligon and Schechter, 2004). That is why the use of expected poverty, as in Ravallion (1988), might be less useful in characterizing risk aversion in the context of measuring poverty. Thus, the use of certainty-equivalent income obtained from a well-behaved expected-utility function helps avoid this problem. This measure of risk-adjusted poverty obeys the Focus axiom, which entails that observations above the poverty line not be arguments in the measurement. Quite aptly, most measures of vulnerability (except Calvo and Dercon, 2003), consider the entire distribution.

[13] This is very close to the approach used by Jalan and Ravallion (2001) to approximate the household-specific uncertainty using the error structure given in (13). Their approach was also used to compute the element of unexpected risk or shock experienced by each household, in order to calculate mean consumption over the period.

predict consumption expenditure to minimize the effects of measurement error. We used household demographics (mean age in the household, age of the head of the household and their squares and sex of the head of the household), farming systems fixed effects, rainfall[14] and access to markets as strictly exogenous variables determining consumption outcomes in rural areas. For urban areas, likewise, we used household demographics, ethnic background, town fixed-effects, education and occupation of parents of the head of the household and unemployment rate[15] in the household as determinants of consumption expenditure.

2.3. Household characteristics and consumption risk

To explore the relation of household characteristics to consumption-variation and thus to risk-adjusted poverty, a multivariate analysis of the determinants of mean consumption expenditure and risk-adjusted consumption expenditure over T periods was used. We set up a simultaneous equation structure with the same exogenous variables using Seemingly Unrelated Regression method (SUR) and test for the equivalence of the coefficients of the variables in the regression.[16] Formally:

$$\ln \bar{y}_i = \alpha + X_i \beta + \varepsilon_i \qquad (9)$$

$$\ln y_{ce} = \alpha^{RA} + X_i \beta^{RA} + \varepsilon_e^{RA}$$

where $\bar{y}_i$ is mean of consumption expenditure and, y_{ce} is risk-adjusted consumption for each household over T-periods. The α coefficients are the constant intercepts of the linear equations, and β and β^{RA} are vectors of coefficients related with the explanatory variables. The last expressions on the right hand side of equation (9) are the error terms, which are assumed to be uncorrelated with each other and the vectors of explanatory variables.

The X_i variables included exogenous demographic characteristics such as age of the household (and squared), sex of the head of the household, mean age of the household-members (and

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The results remained unchanged so only that based on predicted consumption expenditure and its variance are reported.

[14] Rainfall data had been collected from observation posts close to the villages. For each village, the average of rain volume in rainy season for the years before and after the survey year was used.

[15] The uunemployment-rate was loosely defined as a ratio of unemployed to working-age (14-65) members of the household.

[16] Cruces and Wodon (2003) discuss the SUR model in disentangling the effect of risk on household consumption expenditure.

squared), plus dummies for the 1994, 1995 and 1997 survey-waves. In addition, quasi-endogenous demographic variables included in some models were household size (and squared), the value of household assets (and squared, and change, and change-squared), plus for the head and the wife having completed primary school. For the rural areas, additional exogenous variables were market-access (defined as the population of the nearest town divided by the distance to it), the volume of rainfall (and squared), and dummies for *teff*-, *chat*-, and coffee-growing areas. For the urban areas, additional exogenous variables were degree of unemployment within the household, dummies for the education and occupational history of the father of the head, and dummies for town of residence and ethnic group. Additional, quasi-endogenous variables were dummies for the occupational status of the head.

Some of these variables seem to be closely linked with the dependent variable, consumption expenditure possibly giving rise to simultaneity bias (see Bigsten and Shimeles, 2005 for details of the computation of consumption expenditure). To minimize such a bias, household and community characteristics that prevailed at the start of the survey were used as proxies for initial conditions.

The interpretations of the coefficients of (9) in the context of risk-adjusted poverty could be made as follows. Let Z be the poverty line, then, the probability of an individual household to fall into poverty is given by the cumulative density function,

$$\begin{aligned} \Pr(\log \bar{y}_i < Z | X_i) &= \Phi\left[-(\alpha + X_i\beta)/\sigma\right] \\ \Pr(\log y_i^{ce} < Z | X_i) &= \Phi\left[-(\alpha^{RA} + X_i\beta^{RA})/\sigma^{RA}\right] \end{aligned} \qquad (10)$$

If the coefficients in the corresponding regressions in equation (10) are the same, then, the variables in question affect consumption expenditure with and without variability equally. But if particular variable coefficients are statistically significant, then, that variable affects variability of consumption and its mean differently.[17] The sign of the difference indicates whether the variable is risk-mitigating or precipitating. If the difference is negative, it means that the variable in question reduces consumption variability and vice versa. One of the limitations of the framework set out in (9) and (10) is that the dependent variable is constant

[17] If one uses the Taylor approximation to adjust individual consumption streams for risk, it may not be necessary to specify simultaneous equations to see how each variable is correlated with risk. It is sufficient to use the second term of equation (4) as the dependent variable.

by construction over the panel. This in effect reduces to a cross-sectional framework in estimating the coefficients of (9) so that it is not possible to control for unobserved individual-effects. To overcome some of these problems, a parallel to our set up given in (9) and (10) can be found in Glewwe and Hall (1998) and Dercon and Krishnan (2000), where the response to aggregate and idiosyncratic shocks are captured by a model of consumption given as[18]:

$$y_{it} = \theta_t (X_i, A_{it}; \delta_i, \rho_i, u_{it}) \tag{11}$$

where, θ_t is a consumption function reduced from an inter-temporal utility maximization framework, A_{it} is household age at time t, ρ is the degree of risk-aversion, δ is rate of time preference. To make (11) operational, Glewwe and Hall (1998) propose the following estimating equation:

$$\ln(y_{it}) = C_t + \beta_t^{'} X_i + \alpha_t A_{it} + \delta_i + \rho_i + u_{it} \tag{12}$$

where $\beta_t^{'}$, α_t are vectors of coefficients at time t , and u_{it} represents the residuals. To analyze the effects of aggregate macroeconomic or even idiosyncratic shocks between two periods, say t and t+1, we difference equation (12) to get:

$$\ln(\frac{y_{it+1}}{y_{it}}) = \Delta C + \Delta \beta X_i + \Delta \alpha A_{it} + \Delta u_i \tag{13}$$

where household specific rates of risk-aversion and time-preference have dropped out. Glewwee and Hall (1998) compare the coefficients of equation (12) and (13) to analyze the effects of aggregate macroeconomic shocks. Dercon and Krishina (2000) extend this framework to look at idiosyncratic shocks as well. We use variants of equation (12) and (13) to examine how aggregate risk and welfare (or poverty) are related in Ethiopia during the study period.

[18] To simplify notation, y_{it} will be used to denote either per capita income or per capita consumption-expenditure depending on the context.

3. The Data

This study was based on a unique panel data set of four waves covering both rural and urban households in the period 1994-2000, one of the few longitudinal data sets available in Africa. This data set originally consisted of approximately 3000 households, equally divided between rural and urban areas. The nature of the data, the sampling methods used in collecting the data, and other features are discussed in greater detail in Bigsten et al. (2005) and covers almost every aspect of household livelihood, including health, education, asset accumulation, labor market participation and other measures of wellbeing and household level economic activities. The data was collected by the Department of Economics, Addis Ababa University, in collaboration with for the rural data the Center for the Study of African Economies, Oxford University, and for the urban data with the Department of Economics, University of Gothenburg. The rural data set covers fifteen villages that represent the country's dominant farming systems: cereal producing areas, export crop producing areas (such as c*hat* and coffee) and *enset* growing areas[19]. Nomadic areas were not included in the survey. The urban data covers six major towns, besides the capital, Addis Ababa. These towns represent about 80%-90% of the urban population in Ethiopia.

Variables, such as household consumption expenditure, size of land owned, value of household durables used in the analysis are constructed from the original data. Since the analysis of consumption-risk requires a balanced data set, we have used for rural 1300 and for urban 1000 households, with a total of about 9,000 observations with implied attrition rates of 11% and 25%, respectively for rural and urban areas. The attrition rate for urban areas jumped significantly from about 8% during 1994-1997 to 25% in 2000 for a number of reasons including non-compliance, change of address, emigration and family dissolution. The effect of attrition on poverty measurement has been minimal (see Bigsten and Shimeles, 2005) as they do not appear to be systematic following some household characteristics.[20]

[19] *Enset* is a root-crop mainly produced in the Southern part of Ethiopia. It is a highly localized food crop that is not widely consumed in the country.
[20] Families that dropped out of the panel were from all towns, and of diverse backgrounds. But, there is a covariate risk that may be at play here. The incidence of HIV-AIDs and displacements that occurred during the Ethio-Ertitrea conflict may have affected certain types of individuals.

4. Empirical Results on the Risk-Adjusted Poverty

4.1. Profile of poverty adjusted for consumption-risk

Since livelihood in Ethiopia is precarious and most households are on the verge of subsistence, the welfare loss associated with consumption variability can be substantial. But, how risk-averse Ethiopian households are and how do we measure risk-aversion across households? Three rates of risk aversion that have some empirical support in the literature were used here. One is a value of $\rho=1$, which in a recent work on Zimbabwe (Elbers et al, 2002) is considered to be the degree of risk-aversion that may prevail for rural households. In addition, $\rho=2$ and $\rho=3$ are also used based on a recent work that has shown to be a reasonable approximation for households in rural Ethiopia (e.g. Yesuf, 2004) and in general in a less-developed country context (Ligon and Schechter, 2004). The effects of these rates of risk aversion on poverty are compared with a risk-neutral situation, where consumption variability implies no welfare loss.

The percentage of chronically poor households (that is those who remained poor four times in the four waves) is substantially higher in urban areas than in rural areas, suggesting poverty was more persistent there.

<Table 1 about here>

In rural areas, household size was clearly associated with being in poverty more often, as was the age of the household (Table 2a). Surprisingly, households with female heads were likely to be "never poor" and less likely to be poor four times. If the head or the wife had completed primary school, household had more land, more household assets, or more oxen they were likely to be poor less often. Off-farm employment did not seem to help.

<Tables (2a) about here>

In urban areas, household-size was again clearly associated with being in poverty more often, as was the age of the household-head (Table 2b). Female-headed households were slightly more likely to be in poverty more often, however. Primary schooling of the head or wife were also clearly related with being in poverty less often as were all occupational categories, except for casual worker and unemployed. Households with private business-employer heads were least likely to be in poverty. Own-account workers had peaks at ends, "never poor" and poor four times, perhaps reflecting a more heterogeneous category than others.

<Tables (2b) about here>

Tables 3a and 3b show estimates of rural and urban poverty based on per capita current consumption (CC) at the time of each of the four survey-waves, plus an estimate based on "permanent income", which, here is mean consumption over the four survey-waves (PC). Instances where poverty based on current consumption was evenly spaced was fairly low, yet was very high for some individual years.[21] This suggests that the scope for consumption smoothing is highly restricted, particularly in the rural areas. There is hardly any functioning formal credit market nor do households typically have much accumulated asset with which to smooth consumption. The risk factor is self-evident. However, poverty was generally higher in the individual years than when based on mean consumption because it was not always the same households who were poor in each of the survey years.

<Tables 3a and 3b here>

Tables 4a and 4b (below) show three measures of risk-adjusted rural and urban poverty (respectively) - headcount, poverty gap, and squared poverty gap-both observed and predicted calculated by certainty-equivalent and Taylor-expansion methods, at four risk-aversion levels (ρ=0, 1, 2, 3). Both rural and urban observed headcount ratios rise substantially with the degree of risk-aversion, even more with Taylor's expansion than with certainty-equivalent. But, whereas rural and urban rates were roughly equal at ρ=0, rural rates were much higher at ρ=3.

Our effort to deal with measurement error did not change much the effect of risk on measured poverty. The risk-adjusted measure based on predicted consumption expenditure was very close to the observed one in both rural and urban areas when ρ=1 for the certainty equivalent approach. In both approaches, poverty increased from 26% to 38% in rural areas, and from 25% to 31% in urban areas. For ρ>1, risk-adjusted measures based on predicted consumption expenditure gravitated towards the non-risk adjusted measure, as they must, since the predicted consumptions in each period approximate to the overall mean. In this situation, it is easy to see that certainty equivalent consumption expenditure and ordinary mean consumption

[21] These are per capita estimates.

expenditure tend to coincide. The same applies to the case with the Taylor's expansion method. In short, measurement error in the way addressed here did not seem to be a major concern, since both observed and predicted measures of risk-adjusted poverty came up with very similar average levels.[22]

<Tables 4a and 4b here>

4.2 Determinants of Consumption Risk

Tables 5a and 5b report rural and urban results for the SUR model given by the equations (9) and (10) for two sets of models. The first three columns use strictly exogenous variables, whereas the next three include quasi-endogenous variables. The first column of each set has log of consumption as dependent variable, whereas the second has log of risk-adjusted (certainty-equivalent consumption). Columns (3) and (6) report the differences between these coefficients and their statistical significance.

Among the strictly exogenous rural variables (Tables 5a), age of the household head was statistically significant for both consumption and risk-adjusted consumption, with similar negative values in both cases, indicating that consumption declined with the age of the household-head, perhaps due to the rapid rise in household size with age. Though not statistically significant in themselves the coefficient for female-headed was negative for risk-adjusted consumption (column 2) compared to a positive result in column (1), and the difference (column 3) was statistically significant. This result were confirmed when quasi-endogenous variables were included as well (columns 3-6) and indicates greater consumption variability for those households.

The variable agro-ecological zone represents a dummy if the village is *enset* growing area or not. Other crops include *teff,* a staple cereal or grain widely consumed in Ethiopia, coffee and *chat*, a strong stimulant with lucrative market opportunities overseas. Accordingly, non-enset areas have a very high level of consumption expenditure than enset areas. Compared with risk-adjusted consumption however, these areas face high degree of consumption variability. Thus, low level of utility as shown by the positive and significant value of the difference in the coefficients of the non-risk adjusted and risk-adjusted consumption expenditure. In short, non-

[22] This does not mean that measurement-error is not important while using consumption data. Glewwe (2004) illustrates how measurement-error in either consumption or income can contaminate analysis in income-dynamics or poverty-dynamics. The solutions he suggests are along the lines posited above.

enset growing areas may have higher consumption expenditure, but also bear high level of risk. When we reclassify the farming systems into teff, coffee, chat and enset growing areas, however, we get the result that chat growing areas are at less risk than teff , coffee or enset growing areas. A rainfall variable was dropped because of colinearity with other variables (such as crops grown), but a squared term was retained in the belief that too much rain (flooding) can be as disastrous as too little (drought). The coefficients were extremely small but the difference between them was significant and positive indicating that too much rain was risk-precipitating. Market-access provided statistically significant higher risk-adjusted than non-adjusted consumption a result that was confirmed when quasi-endogenous variables were included.

Among the quasi-endogenous variables (columns 4-6) there were also some statistically significant differences between the risk-adjusted and non-adjusted coefficients. One of the important factors that may influence consumption risk is the size of the household. Even if bigger households may enjoy some amount of economies of scale in consumption, it is reasonable to expect that consumption risk increases with household size in rural areas, particularly so, when the dependents are large. As shown in Table 5b, both risk-adjusted and non-adjusted consumption expenditure declined with household size, but, started to increase afterwards as captured by the quadratic term. Consumption risk was higher among bigger households, but started to decline due to the scale effect. So, household size is associated with high risk, but its square is associated with low risk. Though it does not reach conventional levels of significance, wife completed primary school seemed to have a larger (and positive) effect on risk-adjusted consumption, compared to head completed primary school-apparently indicating reduced variability for households with educated wives.

Although the difference in the land-size per-capita coefficients was not significant, the difference in the coefficients for the squared term was statistically significant. Apparently, although land-size per capita probably increases both risk-adjusted and non-risk adjusted consumption (though the coefficients were not statistically significant), the rate of increase falls off faster for risk-adjusted consumption, suggesting greater variability as land-size rises. The number of oxen owned increased risk-adjusted more than non-adjusted consumption, indicating reduced variability (that is, more reliable consumption with more oxen).

Off-farm employment seemed to indicate reduced consumption risk-adjusted even more than non-adjusted, and the difference was highly significant. Thus, other things equal, those with off-farm employment seemed to have less consumption and greater variability. This is quite a surprising result given the commonly held view that off-farm employment is a coping-strategy meant to reduce shocks and variability. Perhaps heads engaged in off-farm employment were already disadvantaged with little land and few oxen.

<Table 5a about here>

In urban areas, we found some parallel with the rural areas as far as female-headed households are concerned. Consumption expenditure declined if the head of the household was a female, much more so in the case of risk-adjusted consumption. As a result, in urban areas female headship was associated with high consumption risk. On the other hand, the age of the head of the household seemed to play little role. Consumption expenditure was positively and strongly associated with mean-age in the household (a proxy for the dependency-ratio[23]) as was also the case in rural areas, and fell as the mean age in the household rose beyond some limit unlike the case in rural areas. Town-fixed effects were not significant in determining consumption expenditure, in either adjusted or unadjusted case for risk. Rather, household specific characteristics, such as family background and ethnicity seemed to play an important role in determining welfare. Particularly robust is our result for the occupation and education of the father of the head of the household. Accordingly, household heads whose father had completed primary education, was employed in the civil service, or was self-employed had higher consumption expenditure in terms of risk-adjusted as well as non-adjusted consumption expenditure. As a result, consumption risk was low in these households. It is interesting also to see that household heads with rural background tend to suffer from low consumption expenditure and high risk. These variables certainly served as good instruments for differences in initial opportunities and their effect on current welfare.

As might be expected, high rate of unemployment in the family was negatively and significantly correlated with consumption expenditure as well as high variability. Therefore unemployment is one of the causes of low living standard and vulnerability to shock in urban areas. The other factors we found to have strong impact on consumption expenditure are the ethnic background of the head of the household. We have identified five major ethnic groups that more or less represent the ethnic-mix in urban areas. These are the Amharas, perhaps the largest group in major urban settlements, the Oromo, the largest ethnic group in Ethiopia, the Tigrawi, again a major group in urban areas, the Harari, a prosperous minority group that

[23] Lower average-age indicates the presence of dependents.

reside mainly in Addis Ababa and Harar, close to Dire Dawa, one of our survey towns, and the Gurage, a predominantly self-employed and representative of the business community in Ethiopia with a major presence in all urban centres. We set the Gurage as our reference group and the result as shown in Table 5(b) is interesting. First, coefficients associated with the ethnic group were significant and positive for all groups, with the impact on consumption expenditure being much more stronger in the case of Harari ethnic group, followed by the Tigrawi, Amhara and Oromo groups. However, all, except the Harari, had low consumption risk, probably because the Harari, though prosperous by the standards of other groups, earn their living mainly from trading activities.

Among the quasi-endogenous variables, household size was correlated negatively and significantly with consumption expenditure. However, the extent to which it affected risk-adjusted consumption was lower than for non-adjusted consumption expenditure, implying that household size reduced consumption risk in urban areas. However, the coefficient associated with the squared term implied that consumption risk increased with household size. Even the coefficient associated with change in household size suggested negative consumption risk in urban areas. The coefficient associated with the value of household asset was positively and significantly correlated with long-term consumption and low consumption risk.

<Table 5b about here>

Tables 6a and 6b report results for a consumption model based on equation (13), again with strictly exogenous variables first, then, including quasi-exogenous variables as well. The main focus here is to see if the coefficients of the determinants of consumption expenditure showed any change over time and if that change is significant and in what direction. To do that, regressions on levels and changes in the underlying welfare indicator (log of consumption expenditure in adult-equivalent) were run, addressing in the process auto-regressive disturbance terms.

Among the rural exogenous variables (Table 6a first two columns), the coefficient for female head was significant and positive for both log-consumption regressions (with and without quasi-endogenous variables), while significant and negative for both change in log-consumption regressions (again with and without quasi-endogenous variables), indicating higher degree of consumption risk.

The coefficient for farming systems was significant and positive for all four regressions, indicating that households who were not growing enset had higher consumption as well as variability, indicating more consumption risk. However, when disaggregated by types of crops cultivated, there was strong evidence that suggested much of the shocks were absorbed in chat growing and coffee growing areas. This is consistent with the large deterioration in the terms of trade for coffee and *chat* observed during this period, as well as the drought that took place specifically in these areas (see Bigsten and Shimeles, 2005 for detailed discussion of this issue). It is also clear that the role of rainfall came out quite strongly in this specification with consumption expenditure rising with rainfall and falling in the quadratic term. In addition, better rainfall was associated with positive shock, as one would expect. Considering that other explanatory variables remained insignificant with respect to the regression on changes in consumption, we can say that the seasonality variables captured by the time dummies absorbed most of the shocks in consumption. Among the quasi-endogenous variables, household-size had significant negative coefficients for both regressions, while land-size had significant positive coefficients, all results consistent with the previous findings.

<Table 6a about here>

Among the urban exogenous variables (Table 6b), female headed households had three significant negative coefficients indicating reduced consumption as well as higher risk in consumption, while household mean age had significant positive coefficient for consumption, but a significant negative coefficient for one of the change regressions, indicating that older households faced negative shocks during the period.

The household rate of unemployment had significant negative effects on both consumption equations as we also saw earlier. Among the towns of residence over half had significant negative coefficients on the change regressions (relative to Mekele, the reference town), but, there was only one significant (positive) coefficient on the levels regressions. On the other hand, among the ethnic groups there were no significant coefficients on the change regressions, whereas almost all the coefficients on the consumption regressions were significant and positive (relative to Gurage, the reference group).

Among the father-of-the-head variables, both government employee and self-employed had significant positive coefficients on the consumption regressions, but, none were significant on the change (growth) regressions. More than half of the coefficients of the dummies that control for survey-waves were significant, again suggesting that both consumption and changes were to some extent related to economy-wide influences or independent of the particular determinants studied here.

Among the quasi-endogenous variables, education and many of the occupational categories had significant coefficients on the levels regressions, but not on change (growth)-regressions, indicating that aggregate consumption shocks were not sector-specific. Household size had significant negative coefficients for both regressions while the squared terms were significant and positive, all consistent with earlier results.

<Table 6b about here>

4. Summary and Conclusions

This study looked at the effect of variability in consumption (or consumption-risk) on rural and urban poverty and identified factors that reduce or induce it. The results indicate that consumption risk played an important role in the measured level and profile of poverty. Overall, the percentage in poverty increased dramatically when long-term consumption was adjusted for variability: The rural headcount ratio more than doubled from 26% without adjusting for risk to 53% with risk accounted for, while the urban headcount increased, respectively, from 25% to 42%. The reasons for this disproportionate changes is the higher variability reported in the rural consumption. This has serious policy implications, such as reducing consumption-variability in rural areas though a range of consumption-smoothing possibilities, and raising urban income-earning potential through employment-creation

Household size, sex of the head of the household, age, farming systems and town-fixed effects, endowments, parental background, all played strong roles in increasing or decreasing consumption risk. Access to markets reduced rural consumption-risk, whereas off-farm employment was associated with high-consumption risk. The role of primary education was crucial in urban areas. Households with heads and/or wives who had completed primary education did better at reducing consumption-risk. Households where the head was unemployed or most of its members were unemployed suffered from low level of consumption and high variability.

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Table 1: Poverty status of rural and urban households, 1994-2000(%)

	Rural	Urban
Once poor	28.9	20.4
Twice Poor	23.0	18.3
Thrice Poor	20.0	16.0
Always poor	11.0	13.0
Never Poor	20.8	29.9

Source: Bigsten and Shimeles (2005)

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

Variable	Never Poor	Poor once	Poor twice	Poor 3 times	Poor 4 times
Household size (numbers)	4.9	5.8	6.4	6.9	8.3
Age of head of household (years)	44.0	46.0	47.0	47.0	48.0
Female headed households (%)	23.0	22.0	18.0	22.0	16.0
Household head with primary education. (%)	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
Asset value(birr)	225.0	173.0	152.0	87.0	92.0
Off-farm employment (%)	24.0	38.0	39.0	45.0	29.0
No of oxen owned	2.0	1.7	1.4	1.1	0.78

Source: Bigsten and Shimeles (2005)

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

Variable	Never Poor	Poor once	Poor twice	Poor 3 times	Poor 4 times
Household size (no)	5.7	6.3	6.6	6.9	7.6
Age of head of households(years)	47.0	49.0	50.0	48.0	51.0
Female headed households (%)	40.0	44.0	46.0	39.0	43.0
Head of household with primary educ. (%)	60.0	44.0	30.0	27.0	20.0
Wife with primary education (%)	33.0	21.0	16.0	12.0	8.0
Private business (%)	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 the capital (%)	68.0	71.0	79.0	78.0	87.0

Source: Bigsten and Shimeles (2005)

Table 3a. Rural headcount poverty based on current consumption (CC) and intertemporal consumption (PC) by Region

Region	Headcount (CI-1994)	Headcount (CI-1995)	Headcount (CI-1997)	Headcount (CI-2000)	Headcount (PC-1994-2000)
Haresaw	70	32	36	29	30
Geblen	92	44	40	59	51
Dinki	64	60	52	58	57
Debre Berhan	17	30	12	22	4
Yetmen	20	32	18	68	20
Shumsheha	19	5	30	20	5
Sirbana Godeti	10	16	25	17	7
Adele Keke	8	8	14	56	6
Korodegaga	87	38	74	33	45
Turufe Kechma	25	37	39	29	21
Imdibir	68	79	37	90	76
Aze Deboba	25	45	20	92	33
Adado	47	72	36	72	45
Gara Godo	76	62	64	90	76
Dommaa	50	30	42	80	34
Total	42	37	35	50	31

Source: author's computation.
Note: PC is average per capita consumption expenditure for each household during 1994-2000.
CC is current per capita consumption expenditure.

Table 3b. Urban headcount poverty based on current consumption (CC) and intertemporal consumption (PC) by Region

Region	Headcount (CI-1994)	Headcount (CI-1995)	Headcount (CI-1997)	Headcount (2000)	Headcount (PC-1994-2000)
Addis Ababa	48	44	36	48	38
Awasa	39	36	28	64	36
Bahri Dar	15	26	26	49	18
Dessie	38	35	41	55	35
Dire Dawa	17	28	34	58	27
Jimma	42	25	35	67	38
Mekele	38	31	22	28	25
Total	42	40	34	49	35

Source: author's computations
Note: PC is average per capita consumption expenditure for each household during 1994-2000.
CC is current per capita consumption expenditure.

Table 4a: Risk-adjusted poverty in Ethiopia 1994-2000: Rural areas

Certainty equivalent	ρ=0	ρ=1	ρ=2	ρ=3
Observed (%)				
P0- Headcount ratio	26.0	38.8	46.1	53.4
P1-poverty gap ratio	7.0	21.6	17.5	22.3
P2-squared poverty gap	2.5	14.5	8.6	12.1
Predicted (%)				
P0- Headcount ratio	27.8	38.8	30	31
P1-poverty gap ratio	5.4	12.4	6	6
P2-squared poverty gap	1.5	6	2	2
Taylor's approximation				
Observed (%)				
P0- Headcount ratio	25.5	42.2	59.6	88.3
P1-poverty gap ratio	7.0	16.1	32.7	72.5
P2-squared poverty gap	2.5	8.6	23.4	66.4
Predicted				
P0- Headcount ratio	27.8	29.0	30.0	36.0
P1-poverty gap ratio	5.4	6.0	6.0	8.0
P2-squared poverty gap	1.5	2.0	2.0	2.3

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

Table 4b: Risk-adjusted poverty in Ethiopia 1994-2000: Urban areas

Certainty equivalent	ρ=0	ρ=1	ρ=2	ρ=3
Observed				
P0- Headcount ratio	25.0	31.2	37.8	42.3
P1-poverty gap ratio	6.7	15.5	12.4	15.3
P2-squared poverty gap	2.6	9.9	5.8	7.6
Predicted				
P0- Headcount ratio	24.7	31.2	25.6	26.2
P1-poverty gap ratio	5.6	10.2	6.0	6.1
P2-squared poverty gap	1.9	5.5	2.0	2.1
Taylor's approximation				
Observed				
P0- Headcount ratio	25.0	35.1	47.5	73.1
P1-poverty gap ratio	6.7	11.5	20.1	51.3
P2-squared poverty gap	2.6	5.6	12.4	43.4
Predicted				
P0- Headcount ratio	24.7	25.2	26.0	29
P1-poverty gap ratio	5.6	5.8	6.1	7.0
P2-squared poverty gap	1.9	2.0	2.1	2.5

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

Table (5a). Determinants of risk-adjusted rural consumption expenditure: 1994-2000

	Regression model with strictly exogenous variables			**Regression model inclusive of quasi-endogenous variables**		
	Log Household income [1]	Risk-adjusted consumption [2]	Coefficient difference (1-2) And P-value	Log Household income [1]	Risk-adjusted consumption [2	Coefficient difference (1-2) And P-value
Head is female	.050	-.07	0.12	-.005	-.126	.121
	(1.19)	(-1.47)	(.0007)	(-.12)	(-2.83)	(0.0009)*
Mean age	.011	.003	.008	-.005	-.012	.007
	(1.67)***	(0.36)	(.131)	(-.79)	(-1.68)	(0.1663)*
(Mean age)^2	.0001	0.0002	-.0001	.001	.0001	.0009
	(1.05)	(1.36)	(.968)	(1.38)	(1.43)	(0.871)
Age of head	-.015	-.015	0.000	.001	.008	-.007
	(-2.73)**	(-2.46)**	(.892)	(1.44)	(1.35)	(0.91)
(Age of head)^2	0.00005	.00005	0.0000	-.00007	-.00009	-.00002
	(1.05)	(1.36)	(.564)	(-1.44)	(1.43)	(0.62)
Market access	0.00005	0.00007	-.00002	.00004	.00006	-.027
	(10.87)*	(12.91)*	(.0000)	(7.01)	(9.53)	(.0000)*
Teff growing area	-.024	0.012	-.036	-.054	-.027	-.1067
	(-0.66)	(0.29)	(0.24)	(-1.58)	(-.68)	(0.389)
Coffee growing area	-.213	-.111	-.102	-.107	-.0003	-.074
	(-4.22)*	(-1.97)**	(.017)	(-2.26)	(.00)	(0.016)*
Chat growing area	.317	.40	-.083	.386	.46	.017
	(5.03)*	(5.63)*	(0.12)	(6.81)	(7.1)	(0.16)*
(Rainfall)^2	3.48e-06	3.17e-06	-.000			
	(32.25)*	(26.13)*	(.0006)			
Household size				-.150	-.167	.009
				(-8.04)	(-7.82)	0.33**
(HH size)^2				.004	(.005)	.04
				(4.21)	(4.57)	0.27**
Head completed primary				-.05	-.09	-.04
				(-.92)	(1.41)	0.459
Wife completed primary				.013	.166	-.153
				(.12)	(1.34)	0.13*
Value of asset				.004	.004	0.000
				(7.6)	(6.3)	0.69
(Value of asset)^2				-4.07e-06	-3.6e-06	-4.07e-07
				(-3.86)	(-2.98)	0.62
Number of oxen				.023	.05	-.036
				(2.02)	(3.55)	0.02*

Land size per capita			.968	1.004	-.134
			(4.35)	(3.66)	0.87
(Land size per capita)^2			-.756	-1.23	.001
			(-3.1)	(-4.41)	0.036**
Off-farm employment			-.041	-.15	
			(1.33)	(-4.28)	0.0001*
Change in hh size			-.150	-.016	-.006
			(-2.17)	(-.02)	0.01
(Change in hhsize)^2			(.007)	-.001	.001
			(1.97)	(-.31)	
Change in asset			.009	.008	.001
			(1.97)	(4.75)	0.67
(Change in asset)^2			-.00001	-9.54e-06	-4.67e-07
			(-3.45)	(-2.62)	0.633
Change in land size			-.04	-.432	.392
			(-.14)	(-1.32)	0.14*
(Change in land size)^2			-.08	-.018	-.062
			(-1.01)	(-.18)	0.39
Adjusted-R^2	0.185	0.187	0.36	0.33	

Table (5a). Determinants of risk-adjusted urban consumption expenditure: 1994-2000

	Regression model with strictly exogenous variables			**Regression model inclusive of quasi-endogenous variables**		
	Log Household income [1]	Risk-adjusted consumption [2]	Coefficient difference (1-2) And P-value	Log Household income [1]	Risk-adjusted consumption [2	Coefficient difference (1-2) And P-value
Mean age	0.045	0.045	0	0.032	0.031	0.001
	(3.81)**	(3.52)**	(.968)	(3.05)**	(2.81)**	0.962
Female headed households	-0.05	-0.11	0.064	0.056	0.033	0.023
	(-1.16)	(2.46)*	(.023)	-1.15	-0.64	0.530
Age of household head	-0.006	-0	-0.003	-0.006	-0.005	-0.001
	(-0.99)	(-0.49)	(0.476)	-1.01	-0.74	0.772
(Mean age)^2	-.00347	-.003452	-1.8E-05	0	0	0
	(-1.94)	(-1.79)	(.995)	(2.04)*	-1.86	.954
(Age of household head)^2	-.000046	-.0000757		0	0	0
	(-.69)	(-1.05)		-0.58	-0.48	.465
Addis City	-0.102	0.022	-0.124	-0.148	-0.032	-0.116
	(-0.83)	(-0.17)	(0.120)	-1.35	-0.27	.153
Awasa town	0.03	0.165	-0.135	-0.039	0.102	-0.141
	(-0.19)	(-0.99)	(.002)	-0.28	-0.69	.002
Bahrdar town	0.24	0.26	-0.02	0.176	0.243	-0.067
	(-1.64)	(-1.65)	(0.84)	-1.25	-1.6	.522
Dessie town	-0.059	-0.09	0.028	-0.145	-0.162	0.017
	(-0.36)	(-0.49)	(0.792=	-0.99	-1.03	874
Diredawa town	-0.003	0.162	-0.165	-0.047	0.145	-0.192
	(-0.02)	(-1.09)	(0.068)	-0.38	-1.09	.03
Jimma town	0.028	-0.01	0.038	-0.003	-0.065	0.062
	-0.2	-0.06	(0.681)	-0.03	-0.48	.51
Amhara ethnic group	0.178	0.278	-0.1	0.072	0.148	-0.076
	(3.18)**	(4.61)**	(0.006)	-1.42	(2.73)**	.04
Oromo ethnic group	0.123	0.239	-0.116	0.031	0.132	-0.101
	(-1.9)***	(3.42)**	(0.006)	-0.53	(2.09)*	.02
Tigrawi ethnic group	0.349	0.385	-0.036	0.239	0.293	-0.054
	(3.40)**	(3.49)**	(.586)	(2.57)*	(2.92)**	.45
Harari ethnic group	1.17	0.997	0.173	0.905	0.729	0.176

	(3.28)**	(2.60)**	(0.459)	(2.93)**	(2.20)*	.86
Father of head completed primary	0.188	0.212	-0.024	0.068	0.073	-0.005
	(1.83)***	(1.92)***	(0.72)	-0.74	-0.75	.9344
Father of head is farmer	-0.036	-0.09	0.055	0.032	-0.019	0.051
	-1.58	(-1.86)***	(0.08)	-0.59	-0.32	.21
Father of head is government employee	0.287	0.175	0.112	0.274	0.155	0.119
	(2.91)**	(1.78)***	(0.081)	(3.13)**	-1.65	.067
Father of head is self-employed	0.22	0.157	0.063	0.214	0.159	0.055
	(2.59)**	(-1.71)***	(0.256)	(2.80)**	-1.94	.331
Rate of unemployment	-0.339	-0.47	0.13	-0.219	-0.331	0.112
	(3.97)**	(5.10)**	(0.02)	(2.84)**	(4.00)**	.05
Head completed primary education				0.233	0.227	0.006
				(4.77)**	(4.33)**	.863
Wife completed primary education				0.168	0.25	-0.082
				(3.28)**	(4.55)**	0.031
Household head private business employer				0.37	0.173	0.197
				(2.51)*	-1.09	.071
Household head own account worker				0.17	0.172	-0.002
				(3.00)**	(2.84)**	.953
Household head civil servant				0.091	0.147	-0.056
				-1.48	(2.24)*	.212
Household head public enterprise worker				0	0.057	-0.057
				-0.01	-0.7	.308
Household head private sector employee				0.143	0.193	-0.05
				-1.5	-1.88	.486
Household head casual worker				-0.171	-0.211	0.04
				(2.25)*	(2.58)**	.48
Household size				-0.174	-0.131	-0.043
				(5.92)**	(4.17)**	.05
(Household size)^2				0.008	0.005	0.003
				(4.07)**	(2.40)*	.044
Asset value				0	0	0
				(8.91)**	(9.20)**	o.19
Mean change in household size				-0.242	-0.133	-0.109
				(2.87)**	-1.48	.082

(Mean change in household size)^2				0.011	0.004	0.007
				(2.33)*	-0.72	.036
Mean change in asset-value				0	0	0
				(1.97)*	-1.87	.952
Constant	4.053	3.558	0.495	4.673	0	
	(16.03)**	(13.08)**		(18.55)**	(.)	
Adjusted R^2	17	16		37	36	

Table 6a: Determinants of rural consumption expenditure: 1994-2000

	Log of consumption	Log of consumption	Change in log of consumption	Change in log of consumption
Female headed households	-0.107	-0.1	0.084	0.083
	(3.08)**	(2.86)**	(-1.82)***	(-1.68)***
Mean age of the household	0.01	-0.012	0.001	-0.007
	(-1.68)***	(2.13)*	-0.07	-0.85
Age of household head	-0.021	-0.003	0.005	0.01
	(4.47)**	-0.67	-0.76	-1.38
(Age of household)^2	0	0	0	0
	(2.35)*	-0.24	-0.74	-1.02
(Meanage)^2	0	0	0	0
	-0.73	(2.70)**	-0.06	-0.35
Access to market	0	0	0	0
	(7.65)**	(7.28)**	-1.57	-1.29
Farming systems	0.474	0.241	0.25	0.192
	(10.73)**	(5.56)**	(4.39)**	(3.19)**
Off-farm employment	-0.156	-0.091	0.011	0.044
	(4.98)**	(3.09)**	-0.28	-1.07
Teff growing area	-0.026	-0.019	0.046	0.061
	-0.79	-0.62	-1.1	-1.4
Coffee growing area	0.112	0.113	-0.122	-0.074
	(2.09)*	(2.25)*	(-1.76)***	-1.06
Chat growing area	0.322	0.405	-0.311	-0.247
	(5.65)**	(7.58)**	(4.23)**	(3.33)**
Rain	0.004	.	0.004	0
	(9.18)**		(5.89)**	(2.59)**
(Rain)^2	0	0	0	
	(3.08)**	(10.02)**	(7.59)**	
Dummy for 1995	0.137	0.003	0	0.292
	(4.96)**	-0.12	(.)	(5.71)**
Dummy for 1997	0.29	0.272	0.087	0.356
	(10.48)**	(9.02)**	(2.31)*	(6.96)**
Household size		-0.141		-0.041
		(9.90)**		(2.05)*
(Household size)^2		0.004		0.001
		(5.64)**		-1.26
Household head completed primary		-0.039		-0.032
		-0.76		-0.45
Wife completed primary		0.091		-0.075
		-1.04		-0.6
Current value of household assets		0.001		0
		(8.69)**		-1.36
(Current value of household assets)^2		0		0
		(6.21)**		-0.8
Number oxen		0.033		-0.015
		(3.08)**		-0.87
Land size per capita		0.458		0.297
		(6.05)**		(2.87)**
(Land size per capita)^2		-0.108		-0.044
		(3.50)**		-1.06
Constant		2.072		0
		(8.13)**		(.)

Source: author's computation
Note: *significant at 5%, ** significant at 1%, *** significant at 10%

Table 6b: Determinants of urban consumption expenditure:1994-2000

	Regression model with strictly exogenous variables		**Regression model inclusive of quasi-endogenous variables**	
	Log of consumption	Log of consumption	Change in log of consumption	Change in log of consumption
Mean age of household members	0.03	0.022	-0.006	-0.016
	(3.91)**	(2.96)**	-0.69	(-1.81)***
Dummy for female headed households	-0.138	-0.083	-0.014	-0.105
	(3.85)**	(2.15)*	-0.4	(2.45)*
Age of household head	-0.008	-0.006	0	0.006
	-1.56	-1.17	0	-1.05
$(\text{Age of household head})^2$	0	0	0	0
	-0.52	-0.72	-0.11	-0.66
$(\text{Household mean age})^2$	0	0	0	0
	-1.55	(2.03)*	-0.99	-1.13
Addis Ababa	-0.03	0.026	-0.126	-0.086
	-0.26	-0.25	-1.25	-0.85
Awasa	0.121	0.084	-0.254	-0.208
	-0.82	-0.64	(1.99)*	-1.61
Bahirdar	0.263	0.262	-0.266	-0.26
	-1.89	(2.12)*	(2.20)*	(2.13)*
Dessie	-0.084	-0.149	-0.279	-0.289
	-0.54	-1.07	(2.05)*	(2.11)*
Diredawa	0.077	0.072	-0.296	-0.301
	-0.59	-0.62	(2.58)**	(2.60)**
Jimma	0.024	0.028	-0.315	-0.304
	-0.18	-0.23	(2.72)**	(2.60)**
Father of head completed primary	0.155	0.045	-0.027	-0.036
	-1.6	-0.52	-0.32	-0.42
Father of head is farmer	-0.066	-0.024	-0.016	-0.019
	-1.15	-0.46	-0.31	-0.38
Father of head is government employee	0.244	0.173	-0.059	-0.063
	(2.60)**	(2.08)*	-0.73	-0.76
Father of head is self-employed	0.198	0.175	-0.083	-0.065
	(2.45)*	(2.42)*	-1.19	-0.91
Rate of unemployment	-0.194	-0.164	-0.004	0.007
	(3.28)**	(2.92)**	-0.06	-0.09
Amhara ethnic group	0.233	0.134	0.059	0.047
	(4.44)**	(2.83)**	-1.29	-1.01
Oromo ethnic group	0.168	0.089	0.047	0.041
	(2.73)**	-1.6	-0.88	-0.74
Tigrawi ethnic group	0.389	0.323	0.019	0.013
	(4.01)**	(3.74)**	-0.23	-0.16
Harari ethnic group	1.061	0.836	0.507	0.426
	(3.14)**	(2.79)**	-1.74	-1.45
Household size		-0.19		-0.118
		(10.39)**		(5.44)**
$(\text{Household size})^2$		0.008		0.005
		(6.58)**		(3.89)**
Dummy for household with at least primary education		0.256		-0.052
		(7.00)**		-1.25
Dummy for wife with at least primary education		0.217		-0.01
		(5.31)**		-0.22
Household head private business employer		0.534		-0.045
		(4.79)**		-0.34
Household head own account worker		0.167		0.005
		(3.65)**		-0.09
Household head civil servant		0.147		0.029

		(2.98)**		-0.52
Household head public enterprise worker		0.035		-0.043
		-0.59		-0.61
Household head private sector employee		0.133		-0.089
		-1.95		-1.11
Household head casual worker		-0.175		0.052
		(2.88)**		-0.73
Dummy for 1994	0.053	-0.019	0	0
	-1.8	-0.63	(.)	(.)
Dummy for 1995	0.132	0.048	0.352	0.301
	(4.50)**	-1.59	(9.04)**	(7.51)**
Dummy for 1997	0.259	0.161	0.401	0.342
	(9.23)**	(5.48)**	(10.60)**	(8.74)**
Constant	4.05	4.724	-0.043	0.563
	(19.58)**	(22.94)**	-0.21	(2.46)*

Source: author's computation
Note: *significant at 5%, ** significant at 1%, *** significant at 10%

The Dynamics of Consumption in Ethiopia

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December 2005

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Abstract

The dynamics of household consumption expenditure was examined using a panel-data set from Ethiopia during 1994-2000. In both rural and urban areas, current consumption was found to be correlated with household assets and past consumption. Contrary to the life-cycle/permanent-income hypothesis, this implies that transitory income shocks can affect consumption. For some households negative consumption shocks could have long-term effect suggesting non-linearity in the consumption dynamics, though, no evidence of poverty traps was found as a result of such shocks.

1. Introduction

Consumption expenditure is a key welfare indicator in less-developed countries particularly in the analysis of poverty and income distribution. Analyzing changes in consumption can provide insight into the roles of initial wealth-distributions, imperfections in credit-markets, and uncertainty in the earning process (Deaton, 1992a). The paucity of data has prevented such analysis in less-developed countries until recently. As panel-data became available, however, new results began emerging from these countries shading light on the welfare-implications of uninsured risk and shocks. Some researchers used the neo-classical growth framework (e.g., Dercon, 2004, Gunning et al, 2002, Jalal and Ravallion, 2002), while others looked into the implications of the life-cycle/permanent-income hypothesis to consumption growth (e.g. Morduch, 1990, Deaton, 1992b, Bhargava and Ravallion, 1993, Ravallion and Chaudri, 1997, Ogaki and Atkeson, 1997, Jacoby and Skoufia, 1998, Kurosaki, 2004, Kazianga and Udry, 2004) and recently Dercon and Krishnan (2001), Skoufias and Quisumbing (2003) and Asfaw and Braun (2004) employed this framework to relate a household's consumption variability with its vulnerability to poverty in Ethiopia.[1]

Such studies address a number of important issues useful for policy makers: whether households in poor and subsistence economies smooth consumption (Deaton, 1992b, Bhargava and Ravallion, 1993, Fafchamps et al. 1996, Kazianga and Udry, 2005); the possibility of poverty traps (Jalan and Ravallion, 2002 and Lokshin and Ravallion, 2004); whether imperfections in the credit market cause consumption instability (Morduch, 1990); whether consumption of wealthy and poor households grow differently, and if so why (Ogaki and Atkeson, 1997); how transitory shocks affect welfare (Dercon and Krishnan, 2001, Dercon, 2004, Asfaw and Braun, 2004) and under what conditions initial distributions of wealth and income affect future income distributions (Jappelli and Pistaferri, 2000). Most of these studies used variations of the life-cycle hypotheses. Panel data covering a period long enough to observe fluctuations in consumption expenditure are required to investigate such issues.

[1] The permanent income hypothesis is due to Friedman (1957), while the life-cycle hypothesis originated in Modgliani and Brumberg (1954)

Ethiopia is one of the few countries in Africa where longitudinal data on consumption has been generated since 1994. Five waves for rural, and four waves for urban have been carried out during 1994-2000.[2] Even during this period, there were large variations in consumption as the country passed from chronic conflict and controlled economy to relative peace and market-oriented economic reform, and then into drought and renewed warfare. Shifts in income distribution hindered to a certain degree the pace of poverty reduction (e.g. Bigsten et al., 2003, Bigsten and Shimeles, 2005). It is therefore important to investigate the nature of consumption growth within a theoretical framework that can provide useful characterisation.

In this paper, consumption changes in Ethiopia were examined using the Permanent Income/Life-Cycle hypothesis to determine whether they had evolved as a martingale-process and assess the implications to poverty and income distribution. Previous studies of consumption growth in Ethiopia focused on specific types of shocks, such as rainfall (Dercon 2004), crop failures, seasonality and policy shocks (Dercon and Krishnan, 2000) or illness (Asfaw and Braun, 2004). This study focused first on multiple shocks as they worked their way through the earning-processes and accumulation of assets, second on a cross-section of wealth groups, to assess their inability to smooth consumption via precautionary savings, or liquidity constraints. The paper then addressed the persistence of transitory income shocks and discussed their implications for poverty.

The next section briefly reviews the theoretical basis of the life-cycle hypothesis, and some evidence in its favour. Section 3 describes the setting and the data. Section 4 outlines the econometric model and discusses some estimation-issues. Section 5, then reports the results and Section 6 discusses their implications. Section 7 draws conclusions.

[2] However, the rural panel data actually started in 1989 though with fewer villages than the surveys 1994 onwards.

2. Consumption Growth: theory and evidence

The lifecycle hypothesis is based on the assumption that households evaluate future income prospects to determine their current level of consumption in order to smooth consumption over the life-cycle. If this is true, then, what matters for current consumption is anticipated future income and not current or lagged income.

The most commonly used theoretical models of household consumption growth are based on a general framework where households are assumed to maximize life time utility U, defined over consumption:

$$U(c_t) = E_t \sum_{\tau=0}^{T-\tau} (1+\delta)^{-\tau} u(c_{t+\tau}) \tag{1}$$

subject to lifetime budget constraint:

$$\sum_{\tau=0}^{T-\tau} (1+r)^{-\tau} (c_{t+\tau} - w_{t+\tau}) = A_t$$

where E_t is mathematical expectation conditional on all information available to the individual at time period t, δ is rate of subjective time preference, r is real rate of interest, c_t is consumption, w_t is earnings and A_t is physical assets. Using the sequential maximization rule, at any period t, optimal consumption will be given by[3] Euler's equation for constant rate of time preference and interest rate with the additional assumption that the only uncertainty the household faces originates only from the income earning process:

$$E_t u'(c_{t+1}) = [(1+\delta)/(1+r)]u'(c_t) \tag{2}$$

Equation (2) states that a household sets the marginal utility of expected consumption equal to the marginal utility of current consumption weighted by the rate of time preference and asset prices. This general formulation of the optimal consumption rule has sparked a large empirical and theoretical literature on consumption growth and its determinants. A testable implication of equation (2) is that future consumption is affected only by information provided by current consumption, that is, once a household has decided on current consumption, which is assumed to embed all information on income and asset, then no additional information is needed to

[3] For a straightforward derivation of the Euler's equation see for instance Hall (1978)

determine its future consumption. If we take the expectation-operator out, then future marginal utility will be:

$$u'(c_{t+1}) = \frac{1+\delta}{1+r} u'(c_t) + \varepsilon_{t+1} \qquad (3)$$

where ε_{t+1} is a random disturbance term and $E_t \varepsilon_{t+1}=0$. Equation (3) provided the basis for much of the empirical literature that followed Hall's (1978) seminal paper. Depending on the form of the utility function, a number of variants of equation (3) have been suggested and estimated empirically.[4] The first to spark immense attraction is Hall's assumption of a quadratic utility function with a 'bliss-point' and constant rate of discount rate and interest rate, which led to a consumption function of the following form:[5]

$$c_{t+1} = \beta_0 + \gamma c_t + \varepsilon_{t+1} \qquad (4)$$

If we assume away the 'bliss' point and add the assumption that the rate of time preference and interest rate are equal (which also could be interpreted as equality between the marginal rate of substitution between future and current consumption with marginal rate of transformation), we get a parsimonious model of consumption growth. That is, $\gamma=1$, or current consumption has a unit root with respect to lagged consumption,[6] implying that consumption growth is a random-walk, except for its trend.[7]

Equation (4) and its variants also imply that utility is time-separable and additive. In addition, over their life time, households are assumed to be fully insured from income

[4] A useful survey of this literature is found in for example Deaton (1992), Browning and Lusardi (1996), Hayashi(1997), Carroll(2001) and Browning and Closey (2001) .

[5] The specific utility function used by Hall(1978) is $u(c_t) = -\frac{1}{2}(\bar{c} - c_t)^2$, where the constant c is considered as a 'bliss' point and the intercept term is composed of the constant terms of the Euler equation. This utility function assumes that households are risk-neutral in the Arrow-Pratt sense of measuring risk-aversion. .

[6] The use of a more flexible utility function, such as the Constant Relative Risk-Aversion variety then after approximation to the second-order, the Euler equation becomes a statement about the expected consumption growth rather than the expected consumption change (see e.g. Hayashi, 1997).

[7] If consumers are relatively impatient ($\beta<1/(1+r)$), consumption declines gradually and if they are patient it rises.

risk so that consumption is not affected by transitory changes in income. Thus, consumption is independent of past, current, or predictable changes in income.[8]

The life-cycle hypothesis can be tested if one augments equation (4) with current disposable income and other wealth-variables (X_{it}s) so that:

$$c_{it+1} = \beta_0 + \gamma c_{it} + \sum_{k=1}^{K} \beta_k X_{kit} + \varepsilon_{it} \tag{5}$$

where β_k are coefficients of the asset variables and the subscripts refer respectively to individual household i, time t, and k asset-holdings. The implications of equation (5) and its variants in a less-developing country context have been investigated empirically (e.g. Morduch, 1990, Deaton, 1992b, Ravallion and Chaudri, 1997, Jacoby and Skoufia, 1998) and recently for Ethiopia Skoufias and Quisumbing (2003) employed this framework to relate a household's consumption variability with its vulnerability to poverty, where per capita consumption growth is regressed on per capita income growth. Two important issues arise regarding equation (5). With a quadratic utility function, and equality between rate of time preference and return to asset holdings, consumption over time will be a random walk, except for its trend. Secondly, information on pervious earnings, asset holdings and other features of household fortune should not affect future consumption. Thus, a test of the life-cycle hypothesis involves examining the coefficients of c_{it} and X_{kit}.

If the life-cycle hypothesis is valid, then, consumption equals permanent income; the annuity value of assets plus the present value of expected future income (see e.g. Hyiashi, 1997). Thus, transitory income shocks do not affect consumption growth. In terms of the evolution of the distribution of income (consumption) and also the persistence of poverty, changes in past income, wealth and other important indicators of welbeing do not matter (see for example Ogaki et al., 2004).

While this clearly represents a limiting case particularly for less-developed countries, the reasons why and how it may fail can have significant policy implications. Hall (1978) argued that if consumption was correlated with past income and wealth, including consumption, this could be either because the consumer was liquidity

[8] See Coleman (1998) for further details of the implications of the quadratic expected utility functional form.

constrained, or because those variables were proxies for permanent income, the distinction of which is important for policy purposes. Subsequent works also identified precautionary savings and habit persistence as further reasons for the failure of the life-cycle hypothesis.[9] By construction, quadratic utility function rules out precautionary savings in response to uncertainty in future consumption. This follows from the linearity of the marginal utility function (equation 3) where uncertainty leaves unchanged both current and future consumption. On the other hand, if marginal utility were non-linear, a mean-preserving change in the spread of the distribution of future consumption would affect current and future utility differently. For example, if marginal utility were convex, then, an increase in consumption risk (mean-preserving) would lead to higher future marginal utility so that current consumption will have to decrease to bring back current and future marginal utilities to equality[10]. Thus, lagged transitory income shocks can affect current consumption due to precautionary savings when the marginal utility function is non-linear.

4. The setting and data

The setting in which we test the life-cycle hypothesis was a very poor economy with frequent covariate and idiosyncratic shocks, and borrowing constraints for people close to subsistence, thus preventing insurance against the effects of income shocks. Pervious studies have shown the importance of shocks (Dercon, 2004 and also Skoufias and Quisumbing, 2003) such as drought, illness, and crop failures on consumption expenditure in general (Dercon and Krishnan, 2000, Dercon, 2004, Asfaw and Braun, 2004) and also the importance of lagged income on current consumption (Skoufias and Quisumbing, 2003).[11] The period studied included intense economic reform, rapid recovery (1994-1997) followed by political instability, external war and severe drought (2000). As a result, we expect notable changes in consumption at least at the household level which are suitable to test the martingale hypothesis. In fact, Table (1) shows that real per capita consumption expenditure thus exhibited large fluctuations between 1994 and 2000 in both rural and urban areas.

[9] See Carroll(2001), Lawrence(1991) Osborn (1988)

[10] This can be seen by considering second-order Taylor's expansion of equation (2). We may also note that non-linearity in marginal utility characterizes the attitudes of households towards risk. Prudent households increase current savings if they perceive uncertainty in future consumption. This implies consumption growth could be affected by shocks in labor income.

[11] The results in Skoufias and Quisumbing (2003) for the effect of lag income on current consumption is not robust.

<Table 1 around here>

The panel data (described more fully in Bigsten et al., 2003, 2005) used in this study was collected in five waves for rural areas and four waves for urban areas during 1994 and 2000 for a sample of approximately 1,500 households in each area by the department of economics, Addis Ababa University in collaboration with the Centre for the Study of African Economies (rural data), University of Oxford and Department of Economics, University of Gothenburg (urban data). The data covers several aspects of household livelihood, demography, education, health, income, assets and consumption. Attrition was low for rural households (11%), while for urban households there was a significant drop in the 2000 round (25%), which could affect the sampling properties. A balanced panel of around 1,300 households for rural areas and 950 households for urban areas was used.

The consumption variables used were real total household consumption expenditure, food consumption expenditure and non-food consumption expenditure, all in adult equivalent terms. The components of consumption exclude expenditure on household durables, rent in urban areas, and other expenditure on fixed assets. For rural areas, current value of crops sold by the household adjusted for price changes were used as proxies for lagged income. We also used variability in rainfall as instrument for income shocks for rural households. Wealth variables were total land owned, total value of household assets owned and number of oxen owned. For urban areas, lagged total household income and value of household assets were used to proxy past information on earnings and wealth holdings. We also included a dummy if the head of the household was unemployed to capture transitory income shocks. As an important component of household income, we used monthly cash savings in *iqub*, a widely practiced non-formal saving association in Ethiopia, to capture possibilities for consumption smoothing. The education of the wife was also used as instrument for multiple sources of income in the expectation that in urban areas if the wife is engaged in either formal employment or self-employment, she has probably at least completed primary school. This variable was found to be a good predictor of household income, even better than the education of the head of the household.(e.g Bigsten and Shimeles, 2005).

5. Methods of Estimation

Some serious econometric issues arise in attempting to estimate the parameters of equation (5), which Bhargava and Ravallion (1993) discuss in detail. First, in using a panel, the error term ε_{it} has to be specified to take into account unobserved time-invariant individual effects and individual-invariant time effects:

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

Secondly, using a dynamic linear model where the lag of the dependent variable enters as an explanatory variable raises the issue of the collinearity between lagged consumption and the random error term, that is, $\text{cov}(c_{cit-1}, \quad u_{it}) \neq 0$). A third problem arises out of the possibility of simultaneity between consumption and income determination. Finally, measurement error that could be amplified when lags are taken could have systematic effects across households. To deal with the first three issues, equation (5) is rewritten as:

$$c_{it+1} = \beta_0 + \gamma c_{it} + \sum_{k=1}^{K} \beta_k X_{kit} + \alpha_i + \lambda_t + u_{it} \qquad (6)$$

The concern here is whether or not to treat the unobserved time-specific and individual-specific effects as fixed or random. The choice depends on the degree of inconsistency in the coefficients to be estimated. Generally, treating the unobserved individual effects as fixed generates inconsistent estimates due to what is known as the problem of "incidental" parameters (Hsiao, 2004).[12] On the other hand, treating them as random risks endogeneity of the explanatory variables with the random effects, that can be handled with simultaneous equations.

Estimating with random-effects framework involves differencing of equation (6) and eliminating the individual-effects parameter and use instruments to consistently estimate the others. Even if good instruments are available, the presence of the lagged dependent variable raises the issue of initial conditions if one wishes to use maximum likelihood estimates.[13] But it is possible to use the Instrumental Variable Method (IVM) or the Generalized Method of Moments (GMM) to consistently estimate

[12] Lancaster (2000) discusses in great detail the concept of incidental parameter problem in econometrics. He explains incidental parameters as "nuisance parameters whose number increase with the sample size", pp-394.
[13] See also Bond (2000) for a lucid discussion of these issues.

equation (6). Using GMM involves the loss of at least two period observations during differencing to find instruments, whereas the IVM loses t-1 observations (only one) with mainly lagged values of the explanatory variables as well as the dependent variable as instruments.

To see that, equation (7) rewrites equation (6) by taking the first difference, without the unobserved time-varying effects as follows:

$$c_{it+1} - c_{it} = \gamma(c_{it} - c_{it-1}) + \sum_{k=1}^{K} \beta_k (X_{ikt} - X_{ikt-1}) + u_{it} - u_{it-1} \qquad (7)$$

Applying OLS to this equation therefore leads to inconsistent estimates of γ and the βs since Δu_{it} and u_{it-1} are correlated. But it is possible to use two-stage Least Square with instrumental variables that are correlated with lagged consumption and uncorrelated with the disturbance terms, which will yield consistent estimates for panels with large N and small T (see Hsiao, 2004). For example, if the panel had only three periods, c_{i1} would be the only instrument available to estimate equation (7), but we have four so c_{i1} and c_{i2} are valid instruments. But 2SLS becomes asymptotically inefficient with $T \geq 4$ since the model is over identified as the number of orthogonality conditions and instruments increase with T (see Bond, 2000). This paper reports mainly GMM estimates of equation (6) unless mentioned otherwise.

Finally, there are many possible sources of error in the measurement of consumption as well as the income and wealth variables, some systematic, and others idiosyncratic. Systematic errors in the measurement of consumption-expenditure could be serious (due to un-captured seasonality, price changes, etc.). One remedy is to use multiplicative error structure for consumption expenditure, which hopefully minimizes the systematic components of the error (e.g Ogaki et al. 2004, Parker and Preston, 2005) and assume that the idiosyncratic measurement errors are absorbed in the random error components of the regression equation. Ogaki et al. (2004) also argue that the problems expressed in equations (3) and (4) can be formulated within the context of full-insurance model, where income uncertainties are non-existent.

Hence, we can write: $u'(c_{it})/u'(c_{it-1}) = \mu$.[14] That is consumption growth for all individuals would be the same (see also Deaton, 1992a), where consumers are assumed to be risk sharing so that aggregate shocks are fully absorbed. If utility functions are iso-elastic such that: $u(c_t) = \frac{c_t^{1-\rho} - 1}{1-\rho}$, where ρ is a measure of risk-aversion, consumption growth would be $\ln(\frac{c_t}{c_{t-1}}) = \varphi_t = -\frac{u'(c_t)}{u''(c_t)}$, which is the same for all individuals. Let $c_t^{mh} = c_t^h e_t^h$, where, c_t^{mh} is observed consumption expenditure for each household which is measured with error, c_t^h is the true level of consumption expenditure and e_t^h is the measurement error. Thus, consumption growth can be written as: $\ln(c_{ct}^{mh}) - \ln(c_{t-1}^{mh}) = \varphi_t + e_t^h$ so that one might consider a regression equation:

$$\ln(c_{ct}^{mh}) - \ln(c_{t-1}^{mh}) = \alpha + \lambda_t + \beta' X_t + e_t^h \quad (8)$$

which is a variation of equation (5) above with γ=1. If we wish to test the unitary assumption for lagged consumption, then we can move it to the right hand side of equation (8) and proceed with estimation. In fact, we can think of the specification in equation (5) as implying an additive measurement error if utility function is exponential[15].

This study tested the life-cycle hypothesis by examining the coefficient of the lagged consumption (γ) and the βs in equation (5) and (8). The coefficient of the lagged consumption was tested for significant differences from unity as well as significant difference from zero, an implication of the hypothesis. This is important as most researchers assume that γ=1 and move the lagged consumption to the right-hand side of equation (6) to estimate the determinants of consumption growth (e.g . Skoufias and Quisumbing, 2003 for Ethiopia).[16] The implication is that consumption has a unit root an assumption that may have to be established empirically.

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[14] Each period marginal utility in consumption has to be equal the marginal utility of income, or to the Lagrange multiplier in the solution for the optimization problem in equation (1) if incomes are received with certainty.

[15] $u(c_t) = e^{\rho c_t}$

[16] The commonest approach including the studies cited use growth rate in consumption (log differences) as independent variables, a model usually obtained from a log-linearized Euler's equation where the underlying utility functions are the Constant Relative Risk Aversion types or their variants.

The role played by lagged consumption has stimulated much recent discussion on the dynamics of consumption (Jalan and Ravallion, 2001, and Ravallion and Lokshin, 2001, 2004), where, with non-linearity imposed, estimates of γ provides a useful characterisation of the effects of shocks on consumption (see also section 6 below). Our other concern is the coefficients of the lagged income or wealth variables of equation (6). The life-cycle/permanent-income hypothesis also implies that these coefficients should not be significantly different from zero. The marginal propensity to consume from an unanticipated change in income or wealth should depend only on whether or not the change or shock is transitory or permanent. If it is perceived as transitory, for example short spells of drought or illness or any other shocks, then consumption will change little. On the other hand, if the shocks are seen as permanent, then consumption will adjust to the shock. So, transitory changes in income or wealth do not influence the path of consumption.

Testing this hypothesis as laid out in equation (6) and (7) and (8) may be done sequentially or simultaneously. Here the coefficients of the lagged income and wealth variables were first assumed to be zero and it was tested whether the coefficient of lagged consumption was significantly different from zero or from unity. Next the full model was estimated to see whether consumption was influenced by the lagged income and wealth variables. The Arellano-Bond GMM estimator was used assuming the income and wealth variables as predetermined or quasi-endogenous. Sargan's over-identification test of whether the instruments used are valid will be reported.

5. Results

Tables 2-4 show the estimation results for rural areas for total consumption expenditure, food consumption expenditure and non-food consumption expenditure, for land-poor, land-rich and all households. Model 2 on each table reflects a logarithmic specification.

<Tables 2, 3, 4 about here>

The effect of lagged consumption was most significantly different from zero (or from unity) for non-food, less for food, and least for total consumption. Model 2 (log of consumption), the effects were slightly more significant in each case. This suggests that households recover from shocks, so, the consumption-path is somewhat stable, but it takes time for them to do so. Among the lagged wealth variables, the effect of land-size was significant at conventional levels most often, followed by crops sold and household assets; the number of oxen had no statistically significant effects. Thus, while these variables were statistically significant far from always, the results nevertheless suggest that transitory income-shocks were not fully insured and thus affected consumption.

Rural households were classified on the basis of their land-holdings, an important indicator of rural wealth. Households below the 20th percentile in the distribution of land-holdings were considered land-poor. The effects of food and total consumption expenditure were more significant for land-poor households than for land-rich ones, but the reverse is for non-food expenditure. For Model 2 (the logarithmic specification) the effects were always more significant for land-rich households. Sargan's over-identification test suggests that these estimation results from the logarithmic specification may be more valid than those for Model 1.

Lagged rainfall had significant effect on food and total consumption-expenditure among land-poor households in both models, whereas it was usually significant but with reversed sign among land-rich households.

For urban areas, (Tables 5-7), the effect of lagged expenditure was most significantly different from zero (or from unity) for total consumption, least different for non-food, opposite to the rural results. For Model 2 (log of consumption), the effects were slightly less significant in each case, again opposite to the rural results. Nevertheless, the overall urban result for lagged consumption again suggest that household recover from shocks, so the consumption path is somewhat stable, but, it takes time for them to do so. The effects of food and total consumption-expenditure were more significant for non-poor households, in both models, whereas the effects of non-food expenditure were more significant for poor households.

Among the lagged income and wealth variables, the effect of savings was significant at conventional level, most often followed by unemployment status, then education of the wife; household assets had no statistically significant effects. In each case, the effects were more significant for poor household. In fact, for total consumption-expenditure in either model, not a single income or wealth variable was significant for non-poor households. These results again suggest that transitory income-shocks were not fully insured and thus affected consumption.

<Table 5, 6, 7 about here>

The rural and urban samples were divided into poor and non-poor households mainly to explore differences in liquidity-constraints, though there could also be differences in savings, habit persistence and labour-supply decisions[17] (see Carroll, 2001 and Hyiashi for the review of these issues). In a poor and underdeveloped setting like Ethiopia, it is quite reasonable to assume that the borrowing constraint imposes pressure on both poor households and non-poor ones to adjust consumption expenditure in anticipation of a number of uncertainties. The nature of response however can vary between poor and non-poor households. In rural as well as urban areas, there are households with barely any asset that could be affected by income fluctuations to smooth consumption. In fact, for extremely poor people, what matters for current consumption is current income, implying a Keynesian type consumption function. But even for these types of households, past income shocks, such as drought or unemployment could persist so that variability in lagged income might translate into variability in current consumption.

In addition recent study (Shimeles, 2005) also shows that consumption risk is significantly lower among households with some form of asset in rural as well as urban areas. In light of this, the same regressions were run again but with the urban sample partitioned into those with or without a bank saving-account (Tables 8-10). The effects of lagged food and total consumption-expenditure were more significant more often for those with savings accounts. Among the income-and-wealth variables, however, effects were more often significant for those without savings accounts.

[17] The procedure used to identify households into poor and non-poor groups for urban households is given in detail in Bigsten and Shimeles (2005)

Perhaps not surprisingly, however, lagged savings was significant often for those with savings accounts.

<Table 8, 9, 10 about here>

This shows that saving behaviour indeed affects consumption smoothing in a number of ways. For at least total consumption expenditure and food consumption expenditure, lagged consumption affects current consumption mainly among people without saving accounts. Furthermore, while those without saving account have income shocks such as unemployment and education of the wife to affect current consumption, it is lagged cash savings that affected current consumption among households with accounts in the bank. In summary, the response of current consumption to past information tends to be different between the poor and the non-poor in both rural and urban areas suggesting that liquidity constraint, preferences as well as precautionary savings might be the underlying cause of this behaviour.

6. Discussion

The immediate implications of income-shocks affecting future consumption obviously are that they persist and affect future income-distribution. If the life-cycle or permanent-income hypothesis were valid, only the initial income distribution would affect future inequality and the rank of each household in the income structure would remain unchanged. At the other extreme, if any change in income translates into consumption each period (the Keynesian version of consumption determination), then we would observe significant shifts in the income inequality over time. In the intermediate case that we have, which is that for some households transitory income and wealth shocks have stronger impact on current consumption than others, the situation may lead to some amount of income polarization, or different degrees of persistence of transitory shocks.

We have just seen that lagged consumption expenditure had statistically significant effects which varied between poor and richer households. Jalan and Ravallion (2001) and Lokshin and Ravallion (2001, 2004) explored the dynamics of such situations. The premise is that current consumption expenditure is correlated with lagged consumption expenditure, a fact we have more or less established above. This linear auto-regressive specification however implies that all households would eventually recover fully to their initial level of income if they face income shocks, no matter how large it might be. But for a number of reasons, including the wealth status of households, the time required could vary from across households suggesting non-linearity in consumption dynamics.

But before considering non-linearity in consumption dynamics, let us interpret the coefficients of the first-difference linear-dynamics model reported above. A linear difference such as (5) typically has a closed form solution (assuming other factors unchanged) that looks like:

$$c_{it} = \gamma^t (c_0 - \frac{\beta_0}{1-\gamma}) + (\frac{\beta_0}{1-\gamma}), \qquad \gamma \neq 1 \tag{9}$$

where c_0 is consumption expenditure at t=0 (initial value). It can be shown that the solution or equilibrium given by equation (9) is stable only if $-1<\gamma<1$. Figure 1a and Figure 1b illustrate the path of consumption over time using actual estimates of γ from our data, which were within the desired range of stable equilibrium. If $\gamma<0$, however, (Figure 1a) the speed of adjustment could be faster than if $\gamma>0$ (Figure 1b), with the risk of high volatility of consumption.

<Figure 1a here>

<Figure 1b here>

To see this, consider a household that has faced some negative income shock. The speed of recovery (*SR*) can be then expressed by:

$$SR = -\frac{\Delta c_{it} - \Delta c_{it-1}}{\Delta c_{it-1}} = \frac{\Delta c_{it-1} - \Delta c_{it}}{\Delta c_{it-1}} \cong 1 - \frac{\partial c_{it}}{\partial c_{it-1}} \tag{10}$$

Speed of recovery is positive (the household is gaining lost ground) if *SR*>0, which implies that for recovery to occur $\frac{\partial c_{it}}{\partial c_{it-1}} < 1$[18], which implies that γ should be less than

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[18] For a non-linear difference equation $c_{it} = \phi(c_{it\_1})$, the condition for the stability of equilibrium is given by $\frac{\delta c_{it}}{\partial c_{it-1}} < 1$. Equilibrium occurs at a fixed-point say c_{it}^* so that $c_{it}^* = f(c_{it}^*)$. Any deviation from this equilibrium is a shock and can be captured by $c_{it} - c_{it}^* = f(c_{it-1}) - f(c_{it}^*)$. The speed of

unity. If γ<0, then, the speed of recovery will be faster. On the other hand, if γ<0, it indicates high degree of consumption volatility as shown in Figure (1a) above, implying a welfare loss if households are averse to risk.

The linear auto-regressive model of consumption dynamics assumes that all households have the same speed of recovery and converge to a single equilibrium. But as we have seen consumption dynamics may not be linear. For example, 44% of rural households experienced a decline in real per capita consumption-expenditure during 1994-2000. Of these, only half had recovered fully by 1997, whereas 16% of households had not recovered at all even by 2000.[19]

In the urban sample, 43.5% of households experienced a negative income shocks between 1994 and 1995, but almost all had recovered by 1997 or 2000. Recovery was thus much faster in urban areas, though still with considerable variation across households.

To examine such non-linearities, Ravallion and Lookshin (2004) suggest a polynomial specification in lagged consumption:

$$C_{it} = \beta_0 + \beta_1 C_{it-1} + \beta_2 {C_{it-1}}^2 + \beta_3 C^3{}_{it-1} + \alpha_i + u_{it} \qquad (11)$$

Equation (11) was estimated using GMM on the assumption that the lagged values of consumption expenditure are endogenous as well as other control variables. The standard errors reported are thus robust under these assumptions. The non-linearity in consumption dynamics is shown by the statistical significance of the coefficients of the estimates (Tables 11 and 12). This more or less picks the elements of variations in the response of households to some transitory shocks.

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recovery towards equilibrium is given by SR= $\Delta(c_{it} - c_{it}^*) = f'(c_{it-1}) - f'(c_{it}^*) = f'(c_{it-1}) - 1$. Thus, SR<0 if only $f'(c_{it-1}) < 1$. (see also Fuente, 2000 for a discussion of this result).

[19] This does not necessarily mean that these households did not have a chance to recover their consumption expenditure in the intervening years in which no survey was undertaken, or in any other season, for that matter. This result need to be seen with these possibilities in mind.

In addition, we can infer the nature of consumption dynamics by taking deviations from mean ($\frac{\sum_{t=1}^{T}\sum_{i=1}^{n} c_{it}}{TN}$ - a proxy for steady state consumption expenditure) for each individual or some quintile group and see if it rises or falls with income. Equation (9) provides the adjustment process driven by the estimates of equation (8).[20]

$$C_{pt} = \overline{C}_p + \beta_1(C_{pt-1} - \overline{C}_p) + \beta_2(C_{pt-1} - \overline{C}_p)^2 + \beta_3(C_{pt-1} - \overline{C}_p)^3 \quad (12)$$

As shown in Figure 2 and Figure 3 the deviations of consumption from its trend (time mean for each household) exhibited interesting features across households of different income groups.

<Figure 2 here>

<Figure 3 here>

Our result indicates some degree of convexity for rural households implying that the speed of recovery declines with higher consumption. On the other hand, for urban households the recursive process towards the steady state rises with consumption suggesting concave relationship between current consumption and its lag. For the range of consumption values that we have in our data, the recursive diagrams have not changed shape for both rural and urban areas ruling out the possibility of non-convexity in the dynamics of consumption. The significance of non-convexity in consumption[21] is that there may be two possible points of equilibrium, for poorer and relatively richer households which imply that for some households transitory shocks could be persistent over time (see for example Banerjee and Newman, 1994 for theoretical possibilities of non-convexity in consumption).

We can also examine the nature of equilibrium by solving for the roots of the polynomial using the estimated coefficients. Following Lokshin and Ravallion (2004), we may consider a polynomial specification of the general form, $C^3 + \alpha C^2 + \beta C + \lambda = 0$. Let,

[20] See Jalan and Ravallion (2001) and Lokshin and Ravallion(2002,2004) on this set up.

[21] A function is called non-convex if it exhibits both concavity and convexity over different values of x.

$$q = \frac{1}{3}\beta - \frac{1}{9}\alpha^2 ; r = \frac{1}{6}(\alpha\beta - 3\gamma) - \frac{1}{27}\alpha^2 \tag{13}$$

In terms of the notations of equation (11), these expressions give rise to:

$q = \frac{1}{3}\left(\frac{\beta_3}{\beta_1}\right) - \frac{1}{9}\left(\frac{\beta_2}{\beta_1}\right)^2 ;\; r = \frac{1}{6}\left(\frac{\beta_2\beta_3}{\beta_1^2} - 3(\beta_0)\right) - \frac{1}{27}\left(\frac{\beta_2}{\beta_1}\right)^2$ Then, if $q^3 + r^2 > 0$, there will be one real root and two complex conjugate roots. If $q^3 + r^2 = 0$, then all roots are real and at least two will be equal, and if $q^3 + r^2 < 0$, then the equation will have three real roots. Our coefficients for both rural as well as urban areas had one real root and two complex conjugate roots. The real roots were approximately Birr 76 and Birr 148 per month per adult equivalent, respectively for households in rural and urban areas, which are higher than the poverty line (Birr 61) in both cases and the equilibrium implied also is stable and unique, implying no poverty traps.

7. Conclusions

This paper looked at the inter-temporal utility-maximization of consumption-expenditure for households in Ethiopia. Its main interest was to investigate whether or not consumption had exemplified a martingale-process, that is, whether or not the life-cycle/permanent-income hypothesis would be confirmed. In that case, current consumption expenditure would not have been influenced by information available to the consumer with regard to income-earnings or wealth. Thus, transitory changes in income would not affect consumption.

However, current consumption was found to respond to lagged variables such as income and wealth and consumption itself. This could indicate precautionary savings, liquidity-constraints, habit-persistence, or under rational expectations, the perception that lagged information on income and wealth could be a proxy for permanent income.

In an attempt to disentangle these various implications, the estimation was re-run with the sample portioned into poor and richer households. Current consumption among poor households responded to lagged information more clearly, suggesting liquidity constraints. The response of lagged income and wealth variables among the non-poor could also be due to a mix of precautionary savings and habit persistence.

Households also responded differently to transitory shocks in income, leading to non-linearity in the dynamics of consumption. Some preliminary results on the nature of adjustment of deviations from mean show that some households take much longer time than others to recover from transient shocks. However, in both rural and urban areas, we found unique steady-state consumption expenditure which is stable. There was no evidence of multiple equilibria and thus no poverty traps.

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Table 1: Mean consumption expenditure in rural and urban areas of Ethiopia,1994-2000

Items	1994	1995	1997	2000
Rural Areas				
Real Household monthly consumption expenditure	100.0	118	125	121.0
Real Household food monthly consumption expenditure	83.0	102.0	113.0	110
Real household non-food monthly consumption expenditure	17.0	16.0	12.0	11.0
Urban areas				
Real Household monthly consumption expenditure	113.0	121.0	146.0	118.0
Real Household food monthly consumption expenditure	81.0	78.0	92.0	96.0
Real household non-food monthly consumption expenditure	28.6	36.8	46.5	22.0

Source: author's computation

Table 2. GMM estimates of real rural household consumption expenditure on lagged wealth variables by wealth status

	Model 1:levels of household real consumption			Model2: log of household consumption		
	All hhs	Land Poor hhs	Land rich hhs	All hhs	Land poor hhs	Land rich hhs
Consumption expenditure	0.068	-.165	.11	0.135	0.116	.129
	(1.28)	(-1.81)*	(1.63)	(4.47)***	(0.74)	(3.65)**
Size of land	53.61	399.56	65.4	0.067	1.26	.07
	(4.42)***	(0.67)	(4.2)***	(4.82)***	(0.78)	(4.51)***
Value of crops sold	0.060	-.10	.06	0.135	-.0003	0.000
	(1.85)*	(-.87)	(1.6)	(4.47)***	(-0.45)	(0.53)
Number of oxen owned	-18.11	8.05	-22.2	0.011	-.055	-.008
	(-1.17)	(0.18)	(-1.14)	(1.39)	(-0.45)	(-0.42)
Value of asset owned	0.07	0.008	.039	0.000	0.000	0.000
	(1.13)	(.05)	(0.54)	(1.39)	(0.97)	(0.48)
Rain-fall	-0.7	5.92	-1.38)	-.001	.012	-.002
	(-1.10)	(3.02)**	(-1.84)*	(-2.01)**	(2.27)**	(-3.55)**
Dummy for round	85.7	.008	70.67	0.334	0.22	.296
	(3.28)**	(-0.85)	(2.11)	(11.27)***	(1.03)	(8.77)***
Constant	67.2	37.6	70.72	.07	0.145	.059
	(4.3)***	(1.16)	(3.41)**	(3.76)**	(1.61)	(2.28)**
Sargan's over identification test (p-value)	.0104	0.004	0.0543	0.0007	0.7627	.7776

Source: author's computation
Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%,

Table 3. GMM estimates of real household food consumption expenditure on lagged wealth and income variables by wealth group

	Model 1:levels of household real consumption			Model2: log of household consumption		
	All hhs	Land Poor hhs	Land-rich hhs	All hhs	Land-Poor hhs	Land-rich hhs
Consumption expenditure	-.036	-0.260	-.08	0.066	-.099	.06
	(-0.93)	(-2.5)**	(1.67)	(2.35)**	(-0.79)	(1.88)*
Value of size of land	5.47	54.98	5.34	0.07	1.19	.07
	(2.7)**	(0.38)	(1.58)	(4.62)*	(0.77)	(3.8)**
Value of crops sold	.003	-.0198	.003	0.000	-.000	-.000
	(0.36)	(-0.69)	(0.43)	(-0.23)	(-1.83)*	(-0.01)
Number of oxen owned	-3.86	4.2	-4.6	-0.003	-.003	-.02
	(-1.12)	(0.38)	(-1.09)	(-0.13)	(-0.03)	(-0.89)
Value of asset owned	.003	.026	.002	0.000	0.000	-.000
	(0.24)	(0.63)	(0.18)	(0.08)	(1.15)	(-0.21)
Rain-fall	.002	1.7	-.119	-.000	.000	-.002
	(.02)	(3.57)**	(-0.73)	(-0.94)	(1.85)*	(-2.69)**
Dummy for round	4.17	-35.83	0.68	0.27	.018	0.233
	(.02)	(-2.08)**	(.09)	(8.18)*	(2.99)**	(5.98)*
Constant	3.568	9.07	5.2	-0.03	.12	-.04
	(1.1)	(1.14)	(1.24)	(-1.51)	(1.45)	(-1.76)*
Sargan's overidentification test (p-value)	0.0003	.0354	.0001	.0062	.0333	0.1825

Source: author's computation
Terms in brackets are Z-statistics. *** Significant at 1%, ** significant at 5%, * significant at 10%

Table 4 GMM estimates of real household non-consumption expenditure on lagged wealth and income variables by wealth group

Variables	Model 1:levels of household real consumption			Model2: log of household consumption		
	All hhs	Land-Poor hhs	Land-rich hhs	All hhs	Land-Poor hhs	Land-rich hhs
Consumption expenditure	0.125 (4.91)***	-.17 (-1.86)*	0.125 (4.17)***	0.27 (7.95)*	0.38 (2.14)**	0.24 (6.17)***
Value of size of land	0.44 (1.44)	-3.04 (-0.17)	0.408 (1.12)	.006 (0.33)	-.748 (-0.38)	.007 (0.36)
Value of crops sold	-.000 (-0.22)	.001 (0.47)	-0.000 (-0.23)	.000 (2.58)**	.005 (1.35)	.000 (2.74)**
Number of oxen owned	0.33 (0.86)	.363 (0.26)	-.209 (-0.46)	.024 (1.00)	-.053 (-0.36)	-.01 (-0.38)
Value of asset owned	.007 (4.45)***	.013 (2.38)**	.007 (3.91)***	.001 (5.26)***	.000 (0.71)	0.001 (4.87)***
Rain-fall	.036 (2.35)**	.019 (0.32)	.03 (1.76)*	.003 (3.05)**	.009 (1.51)	.008 (1.76)*
Dummy for round	-3.32 (-5.12)***	-1.11 (-0.5)	-3.7 (-4.71)***	-.203 (-5.13)***	-.127 (-0.56)	-.239 (-5.29)***
Constant	-1.39 (-3.87)**	1.53 (1.54)	-2.15 (-4.84)***	-.022 (-1.00)	.095 (0.91)	-.087 (-3.38)**
Sargan's overidentification test (p-value)	0.000	.020	0.000	.0305	.7627	.2356

Source: author's computation

Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 5 GMM estimates of real household consumption expenditure on lagged wealth and income variables by wealth group for urban households

Variables	Model 1:levels of household real consumption			Model2: log of household consumption		
	All hhs	Poor hhs	Non-poor hhs	All hhs	Poor hhs	Non-poor hhs
Consumption expenditure	-.260	-0.37	-.32	0.159	-.027	.099
	(-3.56)**	(-2.44)**	(-4.15)***	(2.81)**	(-0.2)	(1.32)
Value of monthly savings	0.039	.275	.02	0.001	.001	.000
	(2.45)**	(2.78)**	(1.19)	(1.86)**	(2.05)**	(-.59)
Value of asset owned	-.0000	-.011	-.000	1.6E-06	.000	1.82e-06
	(-.01)	(-0.85)	(-.1)	(0.51)	(0.54)	(.68)
Unemployment status	-328.2	-117.5	-146.6	-.315	-.471	-.203
	(-2.23)**	(-1.82)**	(-0.59)	(-2.96)**	(-2.05)**	(-1.44)
Wife completed primary school	96.85	50.0	125.7	0.153	.257	.04
	(0.83)	(0.77)	(0.75)	(1.82)*	(1.12)	(.48)
Dummy for round	-179.5	-54.67	-225.3	-.1711	-.194	-.17
	(-4.62)***	(3.25)**	(-3.98)**	(-6.10)***	(-3.07)**	(-5.48)***
Constant	177.89	46.5	205.8	.152	.157	.15
	(7.26)***	(3.77)**	(5.28)***	(8.63)***	(3.59)**	(6.83)***
Sargan's overidentification test (p-value)	0.000	0.0019	.0000	0.5420	0.512	.0298

Source: author's computation
Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 6 GMM estimates of real household food consumption expenditure on lagged wealth and income variables by wealth group for urban households

Variables	Model 1			Model2		
	All hhs	Poor hhs	Non-poor hhs	All hhs	Poor hhs	Non-poor hhs
Consumption expenditure	-.277	-0.07	-.37	.085	.06	.14
	(-3.45)**	(-0.71)	(-4.7)***	(1.62)	(.44)	(1.83)*
Value of monthly savings	.01	.183	-.013	0.000	.001	-.000
	(0.72)	(2.9)**	(-0.82)	(0.44)	(2.31)**	(-1.98)**
Value of asset owned	-.003	.0014	-.003	0.000	.0000	.000
	(-0.71)	(0.18)	(-0.75)	(0.06)	(1.05)	(.2)
Unemployment status	-302.5	-93.9	-125.85	-.37	-.51	-.27
	(-2.4)**	(-2.29)**	(-0.67)	(-3.36)**	(1.78)*	(-1.8)*
Wife completed primary school	89.94	34.64	43.3	.104	.113	-.022
	(0.90)	(0.85)	(.34)	(1.18)	(0.37)	(-.23)
Dummy for round	-118.52	-42.57	-2.5	-.168	-.15	-.183
	(-3.55)**	(-3.75)**	(-0.51)	(-5.67)***	(-1.8)*	(-5.46)***
Constant	105.8	29.08	103.57	-.168	.118	.17
	(5.06)***	(3.69)**	(3.48)**	(8.51)*	(2.14)**	(7.16)
Sargan's overidentification test (p-value)	0.000	.0302	.000	0.1427	0.762	.139

Source: author's computation
Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 7 GMM estimates of real household non-consumption expenditure on lagged wealth and income variables by wealth group for urban households

Variables	Model 1			Model2		
	All hhs	Poor hhs	Non-poor hhs	All hhs	Poor hhs	Non-poor hhs
Consumption expenditure	-.097	-.599	-.08	0.03	-.589	-.008
	(-1.86)*	(-3.2)**	(-1.21)	(0.78)	(-3.2)**	(-0.15)
Value of monthly savings	.043	.117	.04	.000	.117	.000
	(4.62)***	(1.85)*	(3.43)**	(1.21)	(1.85)*	(1.15)
Value of asset owned	.003	-.007	.002	0.000	-.007	.000
	(1.33)	(-0.98)	(.83)	(1.25)	(-.98)	(1.14)
Unemployment status	-23.814	-42.9	-30.76	-.21	-42.9	-.26
	(-0.34)	(-1.01)	(-.21)	(-1.66)	(-1.01)	(-1.3)
Wife completed primary school	13.76	13.2	104	0.079	13.23	.1
	(0.25)	(0.3)	(1.03)	(0.78)	(0.3)	(.8)
Dummy for round	5.3	-6.36	-93.52	-.134	-6.4	-.11
	(0.55)	(-0.53)	(-2.75)**	(-3.89)**	(-0.53)	(-2.36)**
Constant	29.08	21.08	93.59	.119	11	.09
	(3.69)**	(2.53)**	(3.97)***	(2.14)**	(1.54)	(2.75)**
Sargan's overidentification test (p-value)	0.013		.0698	0.771	.256	.2395

Source: author's computation

Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 8 GMM estimates of real household consumption expenditure on lagged wealth and income variables by wealth group

Variables	Model 1		Model2	
	HHs with bank account	HHs with no bank account	HHs with bank account	HHs with no bank account
Consumption expenditure	--45	-.12	.17	.12
	(-3.74)**	(-1.45)	(1.17)	(1.93)*
Value of monthly savings	05	-.04	.001	-.000
	(2.13)	(-1.21)	(2.87)**	(-1.52)
Value of asset owned	-.002	.005	.000	.000
	(-.25)	(.07)	(.16)	(.2)
Unemployment status	313.6	-445.11	.04	-.38
	(0.62)	(-3.69)**	(.16)	(-3.13)**
Wife completed primary school	17.8	154.27	.05	.19
	(.05)	(1.57)	(.77)	(1.95)*
Dummy for round	-420.2	-127.5	-.2	-.174
	(-3.36)	(-3.98)**	(-2.69)**	(-5.44)***
Constant	295.0	139.1	.18	.15
	(3.63)**	(6.86)***	(3.63)**	(7.16)***
Sargan's overidentification test (p-value)	0.000	.0384	.5103	.7409

Source: author's computation

Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 9 GMM estimates of real household food consumption expenditure on lagged wealth and income variables by wealth group.

Variables	Model 1		Model2	
	HHs with bank account	HHs with no bank account	HHs with bank account	HHs with no bank account
Consumption expenditure	-.46 (-3.95)**	-.06 (-0.67)	.16 (1.11)	.06 (.98)
Value of monthly savings	.018 (.94)	-.04 (-1.61)	.000 (1.86)*	-.000 (-1.85)*
Value of asset owned	-.004 (-.67)	-.000 (-.01)	.000 (-.29)	.000 (.32)
Unemployment status	12.9 (.03)	-357.14 (-3.92)**	-.15 (-.48)	-.39 (-3.09)**
Wife completed primary school	12.2 (.04)	133.19 (1.85)**	.1 (.49)	.16 (1.49)
Dummy for round	-278.9 (-2.62)**	-83.96 (-3.45)**	-.174 (-2.14)*	-.002 (-.75)
Constant	141.22 (2.02)**	81.8 5.33***	.187 (3.54)**	58.4 (4.7)***
Sargan's overidentification test (p-value)	.0000	.1391	.6636	.3902

Source: author's computation
Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 10 GMM estimates of real household non-food consumption expenditure on lagged wealth and income variables by wealth group

Variables	Model 1		Model2	
	HHs with bank account	HHs with no bank account	HHs with bank account	HHs with no bank account
Consumption expenditure	-.08 (-0.55)	-.075 (-1.21)	-.05 (-.56)	.04 (1.01)
Value of monthly savings	.06 (3.95)**	-.005 (-.22)	.000 (1.88)*	-.000 (-.62)
Value of asset owned	.002 (.57)	.001 (.24)	000 (1.2)	.000 (.04)
Unemployment status	298.6 (1.18)	-88.5 (-1.21)	.22 (.67)	-.22 (-1.53)
Wife completed primary school	13.33 (.08)	28.13 (.46)	.22 (1.13)	.03 (.25)
Dummy for round	-132.8 (-2.1)**	-42.19 (-2.16)**	-.12 (-1.47)	-.12 (-3.1)**
Constant	123.7 (2.93)**	58.4 (4.7)***	.15 (2.6)**	.115 (4.22)***
Sargan's over identification test (p-value)	.0029		.6936	.7933

Source: author's computation
Terms in brackets are Z-statistics. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 11: Non-Linear Consumption Dynamics for rural households

	Model (1)	Model(2)
Lagged consumption expenditure	-.13	-.126
	(-4.5)***	(-4.9)***
Lagged consumption expenditure2	-.000039	.00038
	(-15.6)***	(17.12)
Lagged consumption expenditure3	-2.05e-08	-2.08E-08
	(-5.84)***	(-4.89)***
Lagged trend (wave)	79.011	-2.1
	(3.97)***	(-1.43)
Age of head		-2.98
		(-.052)
Mean age		-2.98
		(-.52)
Household size		-7.5
		(-3.02)**
Land size (hectares)		15.4
		(3.38)**
Number of oxen owned		.89
		(.18)
Value of asset owned		.03
		(1.68)*
Trend		76.7
		(3.97)*

Source: author's computation
Terms in brackets are Z-statistics based on robust standard errors. *** significant at 1%, ** significant at 5%, * significant at 10%

Table 11: Non-Linear Consumption Dynamics for rural households

	Model (1)	Model(2)
Lagged consumption expenditure	-0.35	-0.369
	(-3.05)**	(-3.08)**
Lagged consumption expenditure2	.00016	.0001644
	(5.73)***	(5.75)***
Lagged consumption expenditure3	-7.88e-09	-7.983e-09
	(-5.35)***	(-5.38)***
Lagged trend (wave)	236.4	104.6
	(6.32)***	(2.24)**
Age of head		4.9
		(1.03)
Mean age		1.73
		(1.03)
Household size		-19.6
		(-7.05)*
Household head completed primary		5.5
		(1.16)

Source: author's computation
Terms in brackets are Z-statistics based on robust standard errors. *** significant at 1%, ** significant at 5%, * significant at 10%

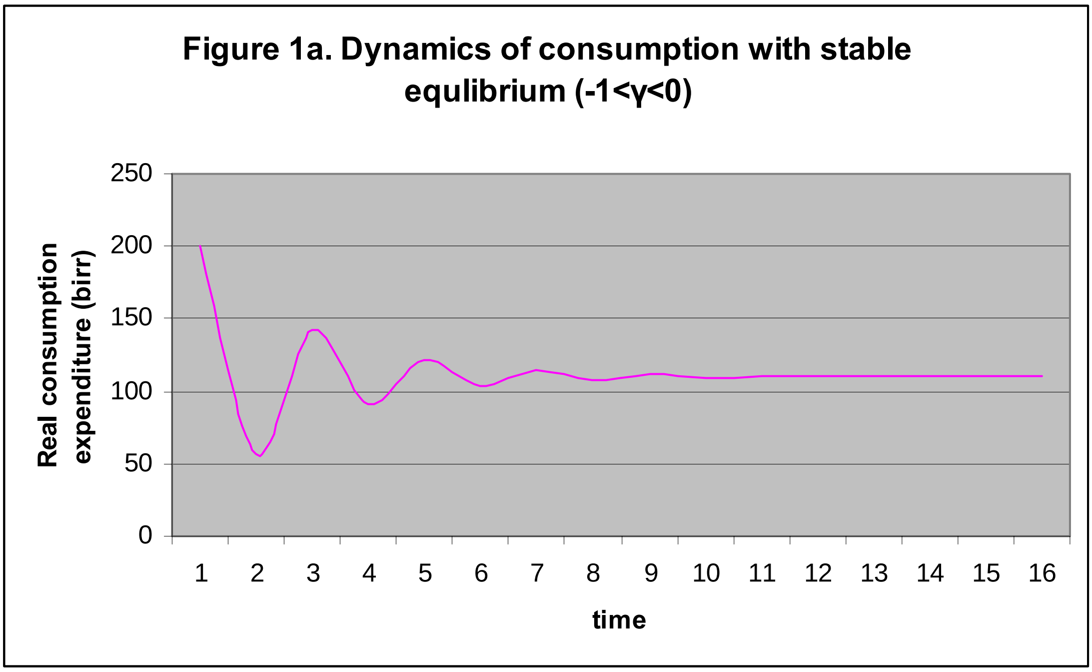
Figure 1a. Dynamics of consumption with stable equlibrium (-1<γ<0)
Real consumption expenditure (birr)
250
200
150
100
50
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
time

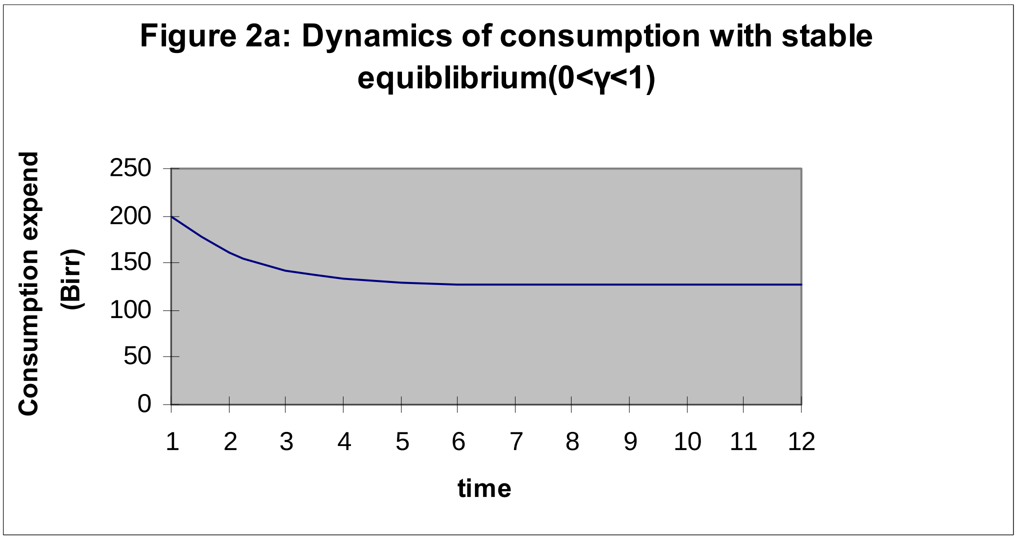
Figure 2a: Dynamics of consumption with stable equiblibrium(0<γ<1)
Consumption expend (Birr)
250
200
150
100
50
0
1
2
3
4
5
6
7
8
9
10
11
12
time

Figure 2: Recursive Model for Consumption Dynamics: rural households

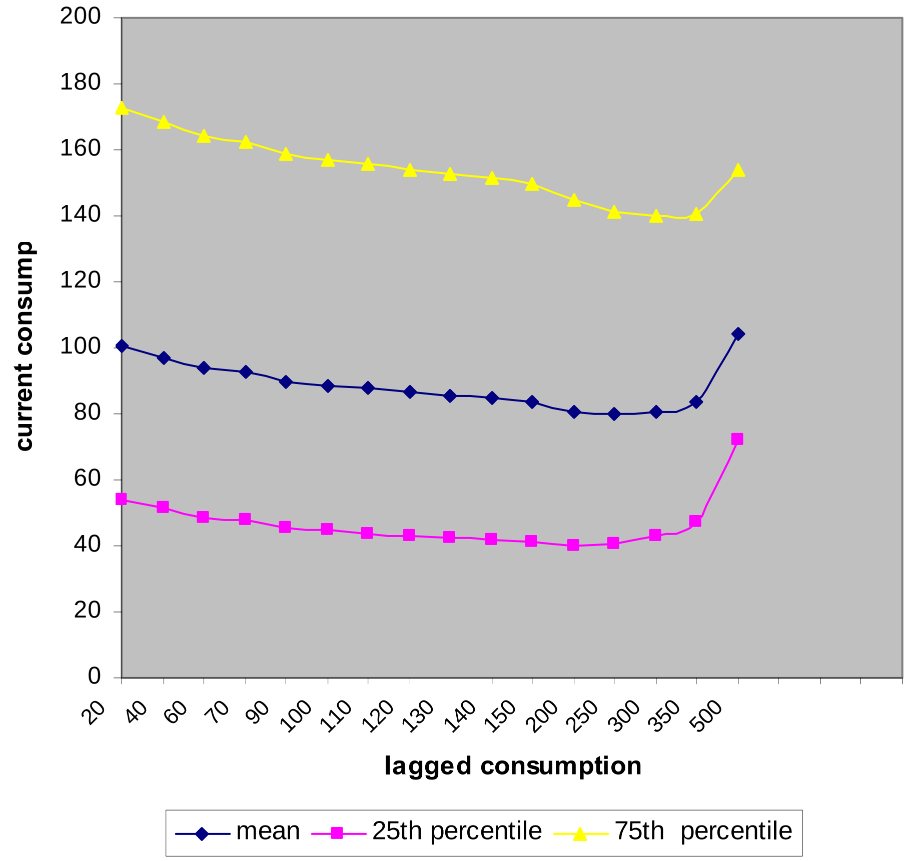

Figure 3: Recursive Model for Consumption Dynamics: urban households