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Shocks, Informal Risk Sharing Strategies and Poverty Dynamics in Rural Ethiopia: Longitudinal Analysis

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Abstract

Based on ERHS data, the study used two-step dynamic nonlinear panel data model to analyze poverty dynamics, the implication of shocks and informal risk sharing strategies on poverty dynamics. The model better explains the dynamic process of rural poverty in Ethiopia, which reveals the existence of true state dependence. Size of land owned, number of oxen, male headship and higher educational attainments reduces the risk of poverty. Only drought shock and death experienced between1977-1983 E.C. have long-term impact on poverty dynamics, whereas the impact of idiosyncratic shocks is wiped-out shortly. Many of informal risk sharing strategies significantly reduce current poverty. But in the long-tem receiving remittance and food gift prolongs poverty. While lending to others and membership in Eqqub have poverty reducing impact both currently and in the long-tem.

Chapter One

1.1 Introduction and Motivation

Understanding poverty and its dynamics by focusing on welfare levels and distribution in a certain socio-economic context is not sufficient and doesn't give us a real picture of the underlying process that contributed to the observed levels of deprivation. It is understood that besides many other factors that explain the welfare and poverty dynamics, risk and shocks are important causes of persistent poverty. People in developing countries face numerous uninsured risks such as human illness, sickness, or death of livestock, crop pests and diseases, and erratic rains or droughts, political strife , etc. (Dercon 2002 and 2005, Hoogeveen et al.2005).

Risk affects whether people can maintain assets and endowments, how these assets are transformed into incomes and earnings are translated into broader development outcomes, such as health and nutrition. Risky events are treated as 'exogenous', not directly under the control of people. However, an essential part of analyzing risk and its consequences for poverty are that households use sophisticated strategies to manage or reduce risk ex-ante, and ex-post strategies to cope with the consequences of risk once shocks occur (Dercon 2005b).

Poor people use different risk-coping strategies that involve risk mitigation through production and employment decisions. There are different markets or technologies available to manage risk such as storage of grain; land fragmentation; implicit insurance provided by networks of family, friends, neighbors, village communities (Townsend 1995 and1993, Deaton 1990 and Rosenzweig 1988). Coping with risk can occur at two stages. First, households can smooth income; this is most often achieved by making conservative production or employment choices and diversifying economic activities. In this way,

households take steps to protect themselves from adverse income shocks before they occur. Second, households can smooth consumption by borrowing and saving, depleting and accumulating nonfinancial assets, adjusting labor supply, sell assets, or send their children to work instead of school to supplement income, and employing formal and informal insurance arrangements such as informal credit and gifts among friends, relatives and neighbors, borrowing from local money lenders, rotating savings and credit associations (ROSCAs), interlinkages in agricultural contracts, and so forth (Daniel 2003, Dercon 2000, Jacoby and Skoufias 1997, Morduch 1995, Udry 1994, Deaton 1992 and Paxon 1992).

In developing countries self-insurance is inadequate to protect households from the risk of fluctuating income. In the absence of formal and other inter-temporal markets an alternative ex-post mechanism, households resort to informal risk-sharing schemes in order to stabilize consumption particularly in the face of idiosyncratic shocks (Daniel 2003). As discussed in Carter 1997, it is rational for households to voluntarily share with their less fortunate neighbors in the hope that their neighbors will help them out sometime in the future. This kind of sharing is denoted as "endogenously enforced" because it does not depend on any external norms or authority to function. Reciprocity schemes, be they endogenously enforced or buttressed by social norms, can be described as vertical or horizontal. Horizontal reciprocity refers to sharing rules between households that have approximately equal wealth endowments, which permit a group to enjoy benefits across individuals in the group. However, there are costs associated with horizontal reciprocity. In addition, to the extent that reciprocity works like a marginal tax on output, it would depress work incentives and potentially result in reduced mean output.

More precisely, there are risks and shocks that adversely affect households. Households employ different coping mechanisms (self-insurance and informal risk sharing arrangements).

Although, anthropologists considered informal risk sharing, especially gift giving, to play a role in securing social status and signaling commitment to the community, Economists tend to view it as they do other transfers like public aid. These coping strategies, although effective in reducing vulnerability and current poverty, can reduce economic growth, long-term welfare, or social mobility (Morduch 1999).

Using Ethiopian Rural Household Survey (ERHS) data, it is found that 95% of households reported being adversely affected by idiosyncratic and covariate shocks between 1999 and 2004. (Dercon, Hoddinott and Woldehanna 2005). To protect themselves ex-ante and ex-post households in rural Ethiopia employ a variety of coping strategies. Skoufias and Quisumbing 2003 (using the ERHS longitudinal data of 1994, 1995 and 1997) and Niggusse 2005 (using panel data of year long intensive monitoring 5th round rural household survey in selected villages of rural Ethiopia) identified the presence of consumption smoothing where households use all means of risk management to insulate themselves from risk and identified the different coping strategies. Applying limited commitment model to empirically test the role of credit transactions and the effect of informal networks on risk-sharing between rural households in Ethiopia, Daniel 2003 found evidence of risk-sharing arrangement through credit transactions, where enforcement problem limits the direct credit transactions in risk sharing arrangements between rural households. Although, there are voluminous works in the area of the impact of risk and shocks vis a vis growth, welfare and poverty in rural Ethiopia, there are still gaps concerning the impact of coping strategies on welfare, growth, or poverty dynamics in rural Ethiopia.

1.2. Objective of the study

The concern of poverty has been earning growing attention among researchers around the world. Many methodological approaches were introduced and applied to measure and understand behavioral aspect of poverty. Recently, there are emerging views and shift

concerning the implication of risk upon poverty dynamics. Although, there are a number of studies explicitly dealt with risk, shocks, informal insurance schemes and their implication on poverty and its persistence, this study takes part in revealing the role of shocks and informal risk-sharing strategies on the dynamics of poverty and growth. Even if, informal risk sharing has its own advantage of reducing risk, under imperfect enforceability this may create adverse incentive problem. Therefore, researchers have to consider these two impacts of informal risk sharing strategies in rural Ethiopia; welfare increasing through smoothing the impact of shock across time and space; and welfare decreasing effect through adverse incentive effect under imperfect information or commitment settings. Based on this motivation, the study has the following objectives: -

- Analyze the dynamics of rural poverty in Ethiopia using the Ethiopian Rural Household Survey (ERHS) panel data from 1994 to 2004.
- Analyze the long-term implication of shocks and informal risk sharing strategies on poverty dynamics.

1.3. Research Questions

The main objective of this paper is to come up with objective answers and implication to the following research questions:-

- What are the main determinants of poverty dynamics over the past 10 years: 1994-2004? Is there true state dependence?
- Do idiosyncratic and covariate shocks have long-term impact on poverty dynamics in rural Ethiopia?
- How can we test the presence of informal risk sharing in rural Ethiopia? What are the short-term and long-term implications of these informal risk sharing arrangements on rural poverty dynamics?

1.4. Limitations of the study

The study uses longitudinal household data of the Ethiopian Rural Household Survey (ERHS) collected by the Department of Economics, Addis Ababa University covering 1477 rural households. However, results should not be taken as being nationally representative. For instance, the sample doesn't include pastoral households or urban areas. Since some of the questions are retrospective and self-reported, there may be memory tumble and observation bias that may lead to under or over-reporting of shock, asset levels, etc.

1.5. Significance of the study

Living with rampant poverty is common for households in rural people in Ethiopia. Understanding the evolution and dynamics of poverty is a key facet of poverty alleviating policies and strategies. In addition to other household specific and covariate determinants, natural and artificial shocks and risks are very common in the day to day lives imposing adverse effect on the livelihoods of the rural dwellers. Given the sever poverty and recurrent shocks, households use different coping strategies. In the absence of formal insurance institutions they resort to informal risk sharing arrangements. By identifying the nature of rural poverty dynamics, the impact of shocks and informal risk sharing strategies on the rural poverty dynamics, the study contributes to the literature and can be used by policy makers and donors and other stakeholders.

1.6. Organization of the paper

We begin with brief review of the literature regarding the concept, measurement, and econometric models of poverty dynamics, in chapter two. Then we go through the concept of risk and shocks and associated coping strategies, especially informal risk sharing in rural village economy settings to relate with poverty and its dynamics. In chapter three, we derived

econometric models of testing consumption insurance starting from the theoretical model which will briefly reveals the theory behind. Next we specified our poverty dynamics model that is appropriate for our panel data. The model is a dynamic random effects model based on two-step procedure. Chapter four and five discusses the data, descriptive findings and empirical findings, respectively. We conclude our study with some implications in chapter six.

Chapter Two

Literature Review

2.1. Theoretical Review: Defining and measuring poverty

For the analysis of poverty one requires to establish a clear definition of poverty. In the literature there are a range of approaches that address the conceptual underpinnings of poverty. Poverty can be defined as a 'pronounced deprivation in well-being' as put by The World Bank 2000. Based on the concept of 'well-being' as a basis to definition of poverty, however, there are a range of approaches; 'welfarist', the cost of basic needs, and 'non-welfarist'. The welfarist approach assesses well-being solely on utility information, derived from the preference of individuals. For walefarist, poverty is associated with economic wel-being and poverty can be said to exist in a given society when one or more persons do not attain a level of economic wel-being deemed to constitute a reasonable minimum by the standards of that society. The concept of wel-being has to be reduced or taken as the total consumption level determining utility. While such an approach has the benefit of empirical tractability, it ignores the multi-dimensional nature of poverty (see Alemayehu 2006, Ravallion and Huppi 1989 and 1991 and Ravallion 1994).

The non-welfarist approach, on the other hand, bases the assessment of well-being on the attainment of certain basic achievements, such as food, clothing and shelter. Sen (1979, 1983 and 1985) argues that the neglect of non-utility information makes welfarism too restrictive, which considers material goods and services as an end to the attainment of well-being, while in fact they are also a means towards achieving well-being allowing the individual to function well. Well-being is seen from the perspective of 'functioning' and 'capabilities', which depends on what kind of life a person is living, and what he/she is succeeding in 'doing' or 'being'. 'Functioning' is an achievement and 'capability' is the ability to achieve. The

relevant functioning can vary from elementary and physical ones as being well nourished, being adequately clothed and sheltered, avoiding preventable morbidity, etc to a more complex social achievements such as taking part in the life of the community, being able to appear in public without shame, and so on. The specific form that their fulfillments may take would tend to vary from society to society.

According to the basic needs approach the basic goods and services are adequate nutrition, shelter, clothing and others like basic education and so on. But the set of basic goods and services is different for different individuals depending on age, sex, type of activity, etc of the specific individual under consideration. One of the major problems that this school faces is how to determine the set of basic needs. A better measure of welfare can be obtained by converting aggregate household consumption into 'consumption per adult equivalent' using appropriate equivalence scale, which vary across sex and age taking into the different consumption requirements of household members (Mekonnen 1999b and Ravallion and Bidani 1994).

2.2. Poverty Measurement

2.2.1. Construction of poverty line

The important part in most of poverty analysis is identification of the poor, which necessitate the poverty line to be determined given the appropriate measure of welfare. Poverty line is understood as a level of standard of living below which a household is considered as being in poverty. To this, there are a number of approaches to determine the poverty line. The welfare approach sets a reference utility level which can be thought of as a poverty line in the utility space. Poverty line is the point on the consumer's cost function corresponding to that reference utility in the consumption space. However, the welfare framework does not provide a well-defined poverty line. Because method of setting poverty line in practice is not based on

welfare term only since welfare approach does not solve the problem of mapping from a consumption space to utility space[1].

Under the non-welfare approach the most commonly applied methods are the direct caloric intake, food-energy intake approach and cost of basic need methods, based on the basic needs or minimum caloric requirement. The direct calorie intake approach defines poverty line as the minimum calorie requirement for survival, equating poverty with malnutrition[2]. The food-energy intake method specifies the cost of attaining a predetermined level of food energy intake and attempt to identify the total consumption expenditure at which a person is expected to attain the minimum food energy requirement (2300 Kcal per day per adult as set by WHO 1985). By regressing the calorie intake on consumption or income, that level of total expenditure which exactly meet the minimum energy requirement becomes the poverty line. However, this method is problematic if it is applied to different regions and periods within the same country[3] (Ravallion and Bidani 1994).

In the Cost of Basic needs approach, developed by Ravallion and Bidani 1994, a basket of goods for which basic food requirements will be met is defined. The cost of this basket of goods at market price became the food poverty line. Then an allowance for non-food goods is added on the food poverty line to obtain the total poverty line. The sum of the food poverty line and allowance for non-food consumption will make up total poverty line. The total household expenditure is converted into per adult equivalent measure to adjust for household size, age, and gender to capture different consumption needs within the household. But his

[1] For more discussion see Greer and Thorbeke 1986, Ravallion 1994, Ravallion and Bidani, 1994, Bigsten et al. 1999, Woldehanna and Alemu 1999/2000.

[2] The limitation of this method is its indication is not representative and it does not take into account the cost of getting the basic caloric requirement. Further more it has no room for non-food requirement (Woldehanna and Alemu 1999/2000).

[3] Therefore, the method yields differences in poverty line in excess of the cost of living faced by the poor.

method does not provide consistent poverty lines across regions. If certain adjustments, such as using common bundle of food items for the whole country, using national average price, and deflating each region's consumption expenditure by the relative price index, are made however it is possible to get consistent poverty line across regions (Woldehanna and Alemu 1999/2000).

2.2.2. Poverty indices

Once the appropriate poverty line is constructed the next important step is to obtain the aggregate measures of poverty. The common aggregate measures of poverty indices are summary measures defined over mean income or consumption, the relevant poverty line, and the parameters characterizing the underlying income distribution (Bigsten et al. 1999). The first measure of poverty is the head count ratio, which gives the proportion of people who are poor, i.e.;

$$H = \frac{q}{n}$$

Where H is the head count ratio, q is the number of poor individuals and n is the population size[4]. The second common poverty index is the poverty gap measure provides an indication of the aggregate shortfall of the poor from the poverty line. This index can be expressed as

$$PG = \sum_{i=1}^{q} (z - y_i)$$
$$i = 1, 2, ..., n$$

Where PG represents the poverty gap, z represents the poverty line and y_i is the consumption (income) of individual i, $i = 1, 2, ..., n$. (See Bigsten et al. 1999).

[4] This index is insensitive to reduction in incomes of the poor i.e. once the individual is identified as poor, the index does not reflect the situation where the poor becomes poorer. Second, it is completely insensitive to the distribution of income among the poor (see Mekonnen 1999)

The most commonly applied measures are the family of indexes developed by Foster, Greer and Thorbecke 1984. These indices possess desirable properties for poverty comparison and are commonly known as FGT measures given by;

$$p_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left[\frac{(z - x_i)}{z}\right]^\alpha \quad , \quad \alpha = 0, 1, 2$$

Where x_i is income or consumption expenditure of household *i*, *z* is the poverty line, *n* is size of population and *q* is the number of poor. p_0 measures the incidence of poverty and tells us only the proportion of the population that are poor. p_1 on the other hand measures the depth of poverty, how much on the average the poor fall below the poverty line. Finally, p_2 is a measure of poverty by weighting the situation of the poor by the square of the shortfall of their income or expenditure from the poverty line (Mekonnen 1999b)[5].

2.3. Modeling Poverty Dynamics

In the poverty literature there are different ways of analyzing poverty dynamics, each with their desirable properties and shortcomings. Poverty is in effect a binary state, and most of the studies measure and analyze it as such. Others are not satisfied with the analysis of poverty as a dichotomous[6] variable. The approaches to modeling poverty in the literature can broadly categorize into five different methodologies.

[5] The FGT measures satisfy the five desirable axioms of poverty. For more discussion see Alemayehu 2006.

[6] The dichotomous approach is criticized because it introduces measurement errors by using arbitrarily defined poverty lines. Plus reducing a continuous variable (income or consumption expenditure) to a qualitative variable may "throw" information away on the variation in the dependent variable with respect to the variation in explanatory variables. This is a particular problem in developing countries since a large number of households concentrated around the poverty line (Deaton 1997, Justino & Litchfield 2002, Aassve et al. 2005).

Components of variance approach

This model, originally used by Lillard and Willis 1978, allows for an error structure to capture the dynamics of income and predict the fraction of the population that are likely to be poor and for how long. The model has an advantage of decomposing income changes into permanent and transitory components, therefore, provide a more accurate assessment of an individual's long-term position[7] . The main short coming of this model is that they can only explain the poverty dynamics of one homogeneous set of individuals at a time denying the fact that poverty is a feature of households and change in composition over time (see Aassve et. al 2005).

Hazard rate model/spell approach

This approach was used by Bane and Ellwood 1986 to model poverty transition using a hazard rate framework and subsequently used by other authors like Stevens 1994 and1999 in the US and Devicienti 2001 in the UK, Begsten and Shimeles 2005 in Ethiopia. In this approach, spells of poverty are identified and hazard functions for exiting poverty are estimated and used to generate distributions of spell lengths for new spells and also for completed and uncompleted spells at a given point in time. Bane and Ellwood classify the triggers for a poverty spell's beginning or end, as well as looking at the expected duration of spell lengths according to the event that triggered the spell both for those just commencing a poverty spell and those already in poverty because of the associated trigger event. Although, the analysis by Bane and Ellwood was for single spells only, Stevens 1999 employed multiple spells of poverty to account for multiple spells and also initial conditions problem. However, in this model there is a considerable static element, where time-varying covariates are assumed fixed for the duration of the poverty or non-poverty spell in question. Further more,

[7] As discussed in Aassve, et al. 2005, examining income rather than just a binary poverty indicator means that no information is discarded.

there are econometric problem of simultaneity and endogeneity introduced when event variables are used to explain poverty transitions, i.e, the underlying processes are likely to be jointly determined. (For more discussion see Aassve et. al 2005, Jenkins 2000).

Markov transition models

This model is proposed by Cappellari and Jenkins 2004 used to make a wide range of specific predictions of poverty rates, exit rates, re-entry rates, and total time in poverty for individuals with different characteristics. For their analysis they use first-order Markov models that control for initial conditions effects and for attrition. They explicitly allow the problem of state dependence in poverty modeling. Although, the study contributes a useful advance in modeling low income transitions, there are a number of issues. As discussed in Aassve et. al 2005, first, the restriction only to first order dynamics is inappropriate for the data. Second, the assumed lag structure rules out the possibility of instantaneous effects of changes in characteristics of poverty status. Furthermore, the model also cannot tell us about the dynamics of poverty other than from one year to the next[8].

Dynamic discrete choice models

This model is developed as an alternative method for distinguishing the effect of state dependence from those of individual heterogeneity. Chay and Hyslop 1998 using both SIPP and PSID data from USA empirically investigate alternative approaches, Auralampalam et al. 2000 using data from Britain applied this model for the analysis of unemployment persistence. Using a sample of prime-aged men from the German Socio-economic Panel (GSOEP), Beiwen 2004 examines the effects of past poverty experience on future poverty

[8] For further discussion consult Cappellari and Jenkins 2004, Aasvee et al. 2005.

status, future employment status and household composition. Islam and Shimeles 2005 also used this approach to model poverty dynamic in rural Ethiopia[9].

Counterfactual decomposition method

Dickens and Ellwood 2001 using data from US and Great Britain between 1979 and 1999 assess the relative impacts of change in a country's demographic composition, wage structure, labor market attachment and welfare policy and benefit levels over a period of years on the poverty rate of changes. For each year, since 1979, Dickens and Ellwood compute the poverty rate given the circumstances[10] and used the counter-factual poverty rate, estimated using 1979 conditions, for comparison. This comparison reveals the effect of those demographic changes have had on poverty from 1979 up until the year in question. For each year, comparing this poverty rate with the previously constructed counter-factual poverty rate, which estimated the effect of demographic change, reveals the effect on poverty changes in the structure of wages since 1979. The main drawback of this model is that the assumption of exogeneity among changes in the different processes and poverty.

Models used by Aassve et al. 2005 emphasize poverty transitions as the result of underlying transitions in economic and demographic variables such as employment, family union and child bearing decisions, stressing their possible interrelatedness through optimizing behavior. Such an approach is in principle capable of incorporating feedback effects of past poverty status on future poverty, employment behavior and household composition. However, feedback effects of past income on employment, family union and childbearing decisions, and

[9]These models have a limitation of ignoring demographic changes and arbitrarily assigning the poverty line for the dichotomous variable treatment of poverty. i.e. it is more the effect of low income that is the driving force for whether poverty experience affects individuals and this is proxied by an arbitrarily defined poverty status (see Aassvee el al. 2005).

[10] These circumstances are work, wage and benefits, hours and benefits, labor market and benefit regime.

direct effects of past income on future income, which is state dependent, are not allowed (Biewin 2004).

As noted above, in their recent work, using panel data from Ethiopia (ERHS and EUHS[11]), Islam and Shimeles 2005 used dynamic probit model that explicitly account for unobserved heterogeneity, first order state dependence and serially correlated error components to test for state dependence and transitory shocks in explaining poverty dynamics in Ethiopia[12]. The result shows that each components of persistence in poverty, i.e., permanent household specific effects, serial correlation in the error component, and the true state dependence, is statistically significant in explaining the dynamics of poverty in both rural and urban Ethiopia.

2.4. Linking Risk and Poverty

The consensus after the works of Sen 1999 is that poverty encompasses more than just low levels of income or consumption. In most cases poverty analysis emphasizes on the welfare levels and distribution in a certain socio-economic context and provides a profile of the characteristics of the poor rendering less attention to the underlying processes that contributed to the observed levels of poverty and its persistence. Among many factors that combined to explain the dynamics of wealth and poverty, risks such as human illness, sickness, or death of livestock, crop pests and diseases, and erratic rains or droughts are considered as the central part of livelihoods in poor areas (Townsend 1994, Dercon 2000, Hoogeveen et al.2005).

There are two consequences of risk on poverty; there is the impact of shock[13] and the behavioral impact. The impact of shock are the event and the coping strategies of the

[11] Ethiopian Urban Household Survey 1994 – 2000.
[12] The authors used Maximum Simulated Likelihood method.
[13] Shock is the manifestation of risk.

household may destroy or reduce the physical, financial, human or social capital of the household. The behavioral impact on the other hand is that households faced with risk and with access to limited insurance alternatives, such as assets or safety nets, are pushed towards risk management strategies such as low risk activities and asset portfolios, at the expense of lower mean return and incomes. If credit market and insurance markets are poorly developed, which is the common feature in developing countries, exposure to risk may induce household to hold portfolios of asset that are least productive for the purpose of buffering consumption. These processes can force an already income poor households further into poverty, derive a non-poor household below the income poverty line, and result in a possibly permanent or persistent poverty (Dercon 2005b).

The direction of causation can also be reversed so that poverty causes exposure to risk. As discussed in Hoogeveen et al.2005, to avoid extreme income poverty households may choose to cultivate in insecure areas, land infested with land mines, areas where rebels are active, or live in an unhealthy/unsafe environment.

2.4.1. Risk and coping strategies

There are different forms of ex-ante and ex-post coping strategies to manage risk and its consequences. These strategies can be categorized into three main institutional arrangements. First, *market based arrangements*; these have great potential and, where available, households and individuals take advantage of the financial products offered by insurance and banking institutions. In reality these formal institutional arrangements are missing in most risk prone and poor regions of the world. Second, *public arrangements;* there are arrangements made by governments to deal with social risks such as unemployment, old age, work injury, disability, widowhood, and sickness. But the coverage of these public arrangements in least developing countries is close to nil. Third, *informal arrangements;* in a

situation where there is missing market or public institutional arrangements to deal with idiosyncratic and common risks, individual households respond to risk through informal arrangements. They involve a system of mutual assistance between family networks or community members (Hoogeveen et al.2005).

Besides these institutional interventions, there are also preventive strategies employed by the household, which are intended to smooth income. These strategies undertaken by the household are costly[14] that involves their production or employment decisions. For instance, making conservative production decisions by favoring variability-reducing inputs and production techniques (Antle, 1987, in Morduch 1995)[15], adopting low-return low-risk crop and asset/income portfolios in less risky low return off-farm activities (Rosenzweig and Binswanger 1993 and Rosenzwieg and Stark 1989) or employment choices – sending their children to work instead of school to supplement income (Jackoby and Skoufias 1997) and diversify economic activities.

While mitigation strategies help individuals reduce the impact of future risky events (shocks), coping strategies are designed to relieve the impact of the risk once it has occurred. These strategies employed by the household are aimed at smoothing their consumption. Households smooth their consumption by borrowing and saving, relying on public or private transfers, depleting and accumulating non financial assets, adjusting labor supply, and employing formal and informal insurance arrangements (Morduch 1995, Hoogeveen et al.2005).

[14] In the literature, these strategies are deemed to be costly and could be a cause for poverty.

[15] For more results see Bliss and Stern 1982, Binswanger and Rosenzweig 1993,

2.4.2. The theory of Full-risk sharing and the theory of limited commitment

Any two agents may be said to share risk if they employ state-contingent transfers to increase the expected utility of both by reducing the risk of at least one. Risk-sharing can be viewed as the cross-sectional equivalent of consumption smoothing over time. Full risk sharing is a situation in which all idiosyncratic risk is eliminated. These shocks are associated with incidence of crop disease and human illness, births, deaths, migration, division of extended families and other endogenous demographic states. Since these risks are shared the marginal utilities of consumption are perfectly correlated across all agents. That is, movement in average group consumption represents aggregate risk. Full risk sharing is an important feature of any Pareto efficient allocation in an Arrow-Debreu economy; provided that agents have von Neumann-Morgenstern preferences, no one is risk-seeking, and at least one agent is strictly risk averse[16] (Townsend 1994).

There are a number of empirical works that tests whether household consumption allocations replicate the Pareto-efficient full risk-pooling outcomes that would result from a complete set of competitive state-contingent markets, i.e, testing the null hypothesis of full risk-sharing. For instance, Mace 1991 and Cochrane 1991 on US data, Deaton 1992 for Cote d'Ivoire, Ghana, and Thailand, Townsend 1994 using ICRISAT data from semi-arid India, Fafchamps and Lund 1997 using data from networks in Philippines, Skoufias and Quisumbing 2003 based on data from Bangladesh, Ethiopia, Mali, Mexico, and Russia, Daniel 2003 using ERHS data from Ethiopia, Niggussei 2005 using data form year long intensive rural survey in Ethiopia, etc are some of the empirical works in the area of risk sharing. Generally, the finding is that the estimated response of consumption to income shocks is small but significant, suggesting a rejection of the null hypothesis of full risk sharing/perfect insurance.

[16] Note that risk aversion and the attitude towards smooth consumption, 'fluctuation aversion', are typically indistinguishable in the standard theoretical framework (Dercon 2005a).

This confirms that there are partial risk sharing via transfers or state-contingent quasi-credit, rotating savings and credit associations (ROSCAs), interlinkages in agricultural contracts, etc, among communities, families, friends, or neighbors.

As noted in Daniel 2003, most of the empirical tests of the full insurance model overlooked the need for identifying appropriate groups within which the informal scheme operates. Based on this concern some researchers have tried to test the theory of full insurance in the informal groups formed through some bondages. Jalan and Ravallion 1999 using data from rural China among the poor households, Lund and Fafchamps 2000 using Filipino data within networks of friends and relatives in rural areas, and De Weet 2002 (in Daniel 2003) based on data from smaller networks of self-selected households Tanzanian village, provided evidence for the rejection of full insurance even among the appropriate groups[17].

Limited information, limited commitment and risk-sharing

Although, it has been argued that information asymmetry among insiders is not a serious bottleneck in rural village economies, the setting in these rural villages is such that the assumption of full information is not a strong one (Udry 1994 and Kocherlakota 1996 in Daniel 2003). It was Kimball 1988 that pioneer the formal establishment of the possibility of mutual assistance pacts under limited commitment system as a risk-sharing mechanism in medieval England. In the static limited commitment context, Coate and Ravallion 1994 work the theoretical framework of Kimball to characterize the conditions under which first best allocations are subgame perfect in a symmetric two-player game. Their model is restricted to pure and stationary insurance arrangements by which transfer at any date depends only on the realized current income (Daniel 2003).

[17] For more discussion see Daniel 2003

Among the efforts made by different authors to explain the failure of full risk-sharing in the context of developing countries, Ligon 1998 and Ligon et al. 2000b are the most citable one, who suggests to relax the assumption of full information and then replace it by a system of private information which excludes some contracting possibilities due to moral hazard and adverse selection problems. The failure of full risk-pooling may be due to either problems of limited information, limited commitment or both (Ligon et al. 2000b). Based on this consideration recent papers appeal to the theory of limited commitment to explain the observed positive relationship of individual consumption with current and lagged individual income[18].

In their successive work, Ligon et al. 2000a, they examine a dynamic limited commitment model of mutual insurance by introducing intertemporal substitution possibilities, such as intertemporal production, storage, or access to external credit market. They show that under certain conditions savings enhance the use of mutual risk-sharing as a subgame perfect equilibrium, while under another condition it encourages agents to renege by tightening their sustainability constraints as it increases utility derived from autarky.

Informal risk-sharing in Ethiopia

There are long historical existences of different informal institutions both in urban and rural community of Ethiopia. Driven by religious, cultural or based on reciprocity, people in rural area share both their bad fortunes and good times. They have customs of gathering to defend their village from aliens, participate in community development activities like erosion preventions, gather for funerals, wedding ceremonies, religious festivals, in sickness, etc. Institutions and activities of the informal sector in Ethiopia include rotating savings and credit

[18] To explain such phenomena it is instructive to use repeated game theory because informal agreements are used to enforce mutually beneficial arrangements without any written and legally binding contracts (Ibid).

association, for example – *Eqqub*, mutual aid association, such as *Iddir*, and local moneylenders, agricultural interlinkages such as sharecropping and calling work party/labor sharing, *Debo/Wonfel*. Eqqub and Iddir are usually formed among persons united in family and friendship, by place of work, by living in the same localities, etc (Daniel 2003).

In the next chapter we first specify theoretical and econometric models of testing consumption insurance and proceed to poverty dynamics model specification that will be appropriate to our panel information. This discussion is deemed to straightforwardly present the underlying theory behind consumption insurance, especially for novice readers in the area.

Chapter Three

3. Model Specification and Estimation Methods

3.1. Theoretical model of consumption insurance

In this part we discus the theoretical and econometric model of consumption insurance, which will be useful for our test of informal risk sharing in rural Ethiopia. The theoretical underpinning of consumption insurance and full risk sharing is based on the theory of full insurance introduced by Arrow (1964) in uncertain economies and later developed by others (Morduch 1995, Towensend 1994, Besley 1995, Deaton 1992, Paxon 1992, Cochrane 1991, Rosenzweig 1988, etc). Under fully functioning market, households will not be vulnerable to income shocks. That is, all risk should be diversified away so that idiosyncratic or transitory shocks should have no impact on consumption level. The consumption insurance tests are based on the proposition that with full-insurance, consumption growth should be independent of idiosyncratic variables[19]. In other words, under full risk-sharing, discounted marginal utility growth of consumption should be the same for all households.

Based on the theoretical model employed by Cochrane 1991, Townsend 1994 and Skoufias and Quisumbing 2003, let us consider an endowment economy with N households indexed by $i = 1,...,N$ maximizes the sum of life time utility subjected to community resource constraints. Assume that expected utility of households is time separable and inter-temporally additive for period $t = 1,...,T$, defined over instantaneous utility $v(.)$. Households face a finite set of possible states of the world, $s = 1,...,S$, each of which occurs with probability $p(s) \in \{1,...,S\}$. Furthermore, let $v'(.) > 0$ and $v''(.) < 0$, i.e., instantaneous utility is concave[20]. This implies that households will have an incentive to smooth consumption.

[19] For more discussion on consumption insurance models see Skoufias and Quisumbing 2003, Attanasio et al. 2000, Cochraine 1991, Townsend 1994, etc.

[20] The individual is risk averse.

For household i at time t and state s with state-contingent consumption $c_{it}(s_t)$ the problem facing a social planner is to solve

$$\max_{\{c_{it}(s_t)\}} \sum_{i=1}^{N} \lambda_i \sum_{t=1}^{T} \beta_i^t \sum_{s=1}^{S} p(s_t) v_i(c_{it}(s_t), \delta_i(s_t)) \qquad [1]$$

Subject to the resource constraint

$$\sum_{i=1}^{N} c_{it}(s_t) \leq \sum_{j=1}^{N} \omega_{it}(s_t) \qquad \text{For all } s_t$$

Where, λ_i is household i's Pareto weight which are assumed to be constant over time, where $\sum_{i=1}^{N} \lambda_i = 1$, β_i^t is household i's rate of time preference, $p(s_t)$ is the probability that state s_t occurs, $v_i(.)$ is the i^{th} household utility function, $c_{it}(s_t)$ is household i's consumption at date t and state s_t, and $\delta_i(s_t)$ is a preferences shocks. Our Lagrange equation, therefore, will be

$$\ell = \sum_{i=1}^{N} \lambda_i \sum_{t=1}^{T} \beta_i^t \sum_{s=1}^{S} p(s_t) v_i[c_{it}(s_t), \delta_i(s_t)] + \mu[\sum_{i=1}^{N} c_{it}(s_t) - \sum_{j=1}^{N} \omega_{it}(s_t)] \qquad [2]$$

If we let $\mu_t(s_t)$ denote the Lagrangian multiplier associated the resource constraint for period t and state s_t. Then the first order conditions, by taking the first derivative of ℓ with respect to consumption and equating it to zero are

$$\lambda_i \beta_i^t p(s_t) v'[c_{it}(s_t), \delta_i(s_t)] = \mu_t(s_t) \qquad [3]$$

The multiplier $\mu_t(s_t)$ depends on aggregate consumption and it is constant across households, so individual household's endowment do not enter into the determination of individual household's consumption allocation, given aggregate consumption and the Pareto weights. However, household's consumption and endowments may be correlated because endowments may be correlated with Pareto weights λ_i. Therefore, observations at two or more dates can be used to remove this time invariant weight (Cochrane 1991).

Since this condition must be satisfied in all periods and states for every agent, for the social planner, it follows that

$$v'_i(c_{it}(s_t),\delta_i(s_t)) = \frac{\lambda_j}{\lambda_i}\left(\frac{\beta_j}{\beta_i}\right)^t v'_j(c_{jt}(s_t),\delta_j(s_t)) \qquad [4]$$

For any period *t*, any pair of agents (*i,j*) and any state s_t, so that $corr(v'_i(.,.), v'_j(.,.))=1$, i.e, the marginal utility across agents will be the same and we have full risk-sharing among households (Ibid).

Given specific parameterization of the utility function, such as an isoelastic utility function;

$$v_i(c_{it}(s_t),\delta_i(s_t)) = \frac{[c_{it}(s_t)]^{1-\rho}}{1-\rho}\theta_{it} \qquad [5]$$

Where, θ_{it} is a multiplicative shock factor and ρ risk aversion coefficient, which is assumed to be constant over time. Substituting [5] into [2] and taking the first order condition for the maximization problem we obtain

$$\lambda_i \beta_i^t p(s_t)[c_{it}(s_t)]^{-\rho}\theta_{it} = \mu_t(s_t) \qquad [6]$$

To get rid of λ_i, we divide the first order condition of [6] for an individual household at two points in time to obtain

$$\beta_i \frac{p(s_{t+1})[c_{it+1}(s_{t+1})]^{-\rho}\theta_{it+1}}{p(s_t)[c_{it}(s_t)]^{-\rho}\theta_{it}} = \frac{\mu_{t+1}(s_{t+1})}{\mu_t(s_t)} \qquad [7]$$

Equation [7] is the condition that marginal utility growth is equated across households for the hypothesis of full risk-sharing to hold. Taking the log of this equation and adding the error term ε_{it+1} will give the following equation

$$\log\left(\frac{c_{it+1}}{c_{it}}\right) = -\frac{1}{\rho}\left[\log\left(\frac{\mu_{t+1}(s_{t+1})p(s_t)}{\mu_t(s_t)p(s_{t+1})}\right) - \log\left(\frac{\theta_{it+1}}{\theta_{it}}\right) - \log(\beta_i)\right] + \varepsilon_{it+1} \qquad [8]$$

This is a simple consumption function, which we would expect to be consistent with any efficient allocation. Where, $\frac{\mu_t(s_t)}{p(s_t)}$ and $\frac{\mu_{t+1}(s_{t+1})}{p(s_{t+1})}$ are related to the aggregate supply of the consumption good in period t and $t+1$, respectively, which are the only determinants of consumption which depends on the random state[21]. The terms $\log(\frac{\theta_{it+1}}{\theta_{it}})$, ρ and $\log(\beta_t)$ represent household preference shifts and ε_{it+1} is measurement error. With the assumption of homoskedasticity of the measurement error and preference shifts, which are uncorrelated across households, the coefficient of additional regressor that is cross-sectionally independent of the preference shifts and measurement error will be zero[22].

3.2. Econometric strategies of testing consumption insurance in the literature

The most commonly applied version of equation [8] in the empirical literature using panel data (in Ravallion and Chaudhuri 1997, Jacoby and Skoufias 1998, Skoufias and Quisumbing 2003 and Nigussie 2005) is of the form,

$$\Delta \ln c_{it} = \sum_{tv} \varphi_{tv}(D_{tv}) + \beta \Delta \ln y_{it} + \phi X_{it} + \Delta \varepsilon_{it} \qquad [9]$$

where $\Delta \ln c_{it}$ denotes the change in log consumption or the growth rate in total consumption per capita of household i in period t (i.e., between round t and round t-1); $\Delta \ln y_{it}$ is the growth rate of household i income; X_{it} is a vector of household or household head's characteristics; D_{tv} denotes a set of binary variables identifying each community separately by survey round[23]; φ_{tv}, β, and ϕ, are parameters to be estimated; and $\Delta \varepsilon_{it}$ is a household-

[21] This shows that the only risk borne by agents in an efficient allocation will be aggregate risk.

[22] That is these regressors do not explain the change in the growth rate of household consumption under the assumption of full risk-sharing.

[23] This set of survey round/community interaction terms is meant to control for the role of aggregate or covariate risk faced by households in the insurance community.

specific error term capturing changes in the unobserved components of household preferences.

Based on the underlying theory of risk-sharing, the coefficient β provides an estimate of the extent to which idiosyncratic income changes play a role in explaining the household-specific consumption growth rate. As noted in Skoufias and Quisumbing 2003, the set of discrete terms, D_{tv}, identifying communities by survey round, serves two interrelated functions. First, the term controls for the role of aggregate (covariate) shocks common to all households within any given community and survey round. Second, given that consumption and income are in logarithms, they also account for potential difference in the round-to-round inflation rate across communities. They also noted that including community/round interaction dummies is equivalent to deviate all variables for their respective community/round mean.

Alternative approach to the specification above in equation [9] is to use shocks instead of income as applied in Dercon and Krishnan 2000. Their measure of vulnerability to poverty is basically determined by the coefficients of shock variables, or index constructed of various shock variables, estimated from a regression equation such as

$$\Delta \ln c_{it} = \sum_{tv} \varphi_{tv}(D_{tv}) + \sum_{i} \beta_i S(i)_{it} + \gamma X_{it} + \Delta \varepsilon_{it} \qquad [10]$$

Where $S(i)$ denotes different shock variables. All other variables are defined as in equation [9], above.

Another attractive approach that explicitly introduces dynamics in the system is an approach applied by Notten 2004 for the analysis of poverty and consumption insurance in Russia. This approach applied Error Correction Model (ECM) to explain risk sharing through consumption smoothing, where the author run a regression of the change in consumption between two periods as the dependent variable on the change in log household income, household

characteristics, and a set of community dummy variables. With perfect credit markets, households will borrow and save so that consumption changes reflect the interest rate between the two periods and the rate at which future consumption is discounted, as well as an error term that reflects adjustments made in the second period based on new information about long-term earnings – that is, permanent income (Notten 2004). Thus using this model it is possible to identify the permanent and transitory effects of shocks on household poverty.

Notten 2004 uses the following specification by adopting Skoufias 2003,

$$\Delta \ln c_{it} = \alpha_0 + \beta_1 \Delta \ln y_{it} + \sum_{j=1}^{k} \gamma_j x_{jit} + \sum_{j=1}^{w} \varphi\ D_{jv} + \varepsilon_{it} \qquad [11]$$

Where, c_{it} represents the total consumption for household i in period t, y_{it} represents the total household income, x_{jit} is a particular characteristic for household i in period t, such as family size and demographic composition, D_{jt} is a binary variable specifying community in which a particular household lives, and ε_{it} is a random error term. Notten 2003 improved this model by rewriting it as a random effect panel model and allowing for dynamics in the estimation as follows;

$$\Delta \ln c_{it} = \alpha_0 + \alpha_1 \ln c_{it-1} + \beta_1 \Delta \ln y_{it} + \beta_2 \ln y_{it-1} + \sum_{j=1}^{k} \gamma_j x_{jit} + \sum_{j=1}^{w} \varphi_j D_{jt} + v_i + \varepsilon_{it} \qquad [12]$$

Where, v_i is an independent and identically distributed ($i.i.d.$) $(0, \sigma_v^2)$ random individual effect, and ε_{it} is and $i.i.d.$ $(0, \sigma_\varepsilon^2)$ error term. The model in equation [12] can be rewritten alternatively as an error correction model (ECM) that allows the study of long and short-run

dynamics in the relationship between expenditures and household income. Rewriting β_2 as $\frac{\alpha_1}{\alpha_1}\beta_2$ for $\alpha_1 \neq 0$. Then the standard estimable model can be rewritten as

$$\Delta \ln c_{it} = \alpha_0 + \beta_1 \Delta \ln y_{it} + \alpha_1 (\ln c_{it-1} - (\frac{-\beta_2}{\alpha_1}) \ln y_{it-1}) + \sum_{j=1}^{k} \gamma_j x_{jit} + \sum_{j=1}^{w} \varphi_j D_{jt} + v_i + \varepsilon_{it} \qquad [13]$$

In this equation, β_1 is the short-run income elasticity of consumption, which can be interpreted as an insurance indicator. When it is close to zero, households insure themselves against income shocks. α_1 is the error correction coefficient, which compensates for the short-run overshooting of consumption and it is expected to be negative and close to unity showing quick convergence of growth in consumption to its long-run equilibrium. $\frac{-\beta_2}{\alpha_1}$ is the long-run income elasticity of consumption.

3.3. Testing partial informal insurance

As discussed in the literature almost all of the empirical works have rejected the hypothesis of full risk sharing among communities. But evidence shows that there is partial risk sharing among community members. To test this hypothesis we use the following model as applied in Harrower and Hoddinott 2004, Skoufias 2002, and others. That is

$$\Delta \ln c_{it} = \alpha + \beta \Delta \ln y_{it} + \theta \Delta(\overline{\ln y_{vt}}) + \gamma X_{it} + \varepsilon_{it} \qquad [14a]$$

Where $\Delta(\overline{\ln y_{vt}})$ represents the growth rate in average village income and the rest of the variables are as defined before. If there is no pooling of resources and risk-sharing, the growth rate in the average community income should have no impact on the growth rate of consumption of any one household. When $\theta \neq 0$, some risk sharing is taking place within communities.

3.4. Testing partial insurance in rural Ethiopia

Empirical results from Ethiopia, using the model in equation [14] are not in line with the theory of informal insurance (see results in Skoufias and Quisumbing 2003 and Niggusse 2005). As an alternative to this model we used a set of instrumental variables in place of the change in log mean village income. These instrumental variables are such as; whether the household has received credit from informal sources; whether the household has lend to others; whether any member of the household is member in *Eqqub;* whether the household has involved in any work party (eg, Debo, Wonfel, etc.); and whether the household has received food gift form informal sources.

Some of these variables, such as remittance, food gift and credit, are part of household total consumption. This causes the problem of endogeneity due to simultaneity bias, where W_{it} is correlated with ε_{it} making pooled OLS estimation inconsistent. There are different approaches to come up with a solutions to this problem. Unit specific dummy variable formulation is equivalent to 2SLS procedure, which acts as their own instruments (see Wooldridge 2003, pp: 310). Following this line of argument all variables representing informal risk sharing strategies are entered as dummy variable in the successive regression models. If we denote these set of variables by W_{it}, our alternative model can be written as

$$\Delta \ln c_{it} = \alpha + \beta \Delta \ln y_{it} + \sum_j \theta_j W_{jit} + \gamma X_{it} + \varepsilon_{it} \qquad [14b]$$

If there is any informal risk pooling in rural Ethiopia, the coefficients of W_{it} should be positive and significant. That is, we expect a positive correlation between the growth rate of household consumption and informal risk sharing arrangements, if there is any. We can also test the hypothesis of full risk sharing using this specification as $H_0 : \theta_1 + \theta_2 + ... + \theta_j = 1$. On the other hand if the individual coefficients are significant while we reject H_0, there is partial risk sharing.

3.5. Econometric model of poverty dynamics in rural Ethiopia

Once we identify the poor and nonpoor, the next step is to analyze the dynamics of poverty over the past 10 years, 1994 to 2004[24]. There are a number of empirical and theoretical models for the analysis of poverty dynamics. The most commonly applied are binary response models. Although, the econometric literature on nonlinear panel data models is growing, there are computational problems and vagueness to clearly establish the issue of identification and estimation of nonlinear models that allow for both individual-specific effects and state dependence[25]. As discussed in Chay and Hyslop 1998, one of the fundamental issues in estimating dynamic binary response models is the issue of unobserved initial conditions of the dynamic process, i.e., initial conditions bias. Although, the practicability and performance of the models is not still well grounded, there are several methods that account for initial condition bias both in the linear dynamic regression models[26] and nonlinear models that allow for both individual effects and state dependence[27] using different simulation techniques.

For our purpose of modeling poverty dynamics in rural Ethiopia, we apply models that account the initial condition issues and state dependence. This is of interest because results in Islam and Shimeles 2005 reveal the importance of state dependence in explaining poverty dynamics in rural Ethiopia. The underlying dynamic binary response panel data model has the following specification:

$$P_{it}^{*} = X_{it}'\beta + \gamma P_{it-1} + v_{it}, \qquad i = 1,...,N \;;\; t = 1,...,T \qquad [15a]$$

$$P_{it} = 1(P_{it}^{*} > 0) = 1(X_{it}'\beta + \gamma P_{it-1} + v_{it} > 0) \qquad [15b]$$

[24] Six survey rounds.

[25] See Chay and Hyslop 1998 for a very good empirical summary of the dynamic binary response panel data models using data from U.S. (PSID and SIPP).

[26] See Anderson and Hsio 1981, Holtz-Eakin et al. 1988 and Arellano and Bond 1991 for linear panel data models.

[27] See Honoré 1993, Honoré and Kyriazidou 1997 and An and Liu 1997 for non-linear panel data models.

$$prob(P_{it}=1|X_{it},\alpha_i,P_{it-1})=F(X'_{it}\beta+\gamma P_{it-1}+v_{it}) \quad [15c]$$

$$v_{it}=\alpha_i+\xi_{it}$$

Where, P_{it}^{*} is the underlying response variable determining the latent process, P_{it} is the poverty status of household *i* during round *t* as measured by the consumption expenditure of the household and P_{it} takes the value of 1 if the household is poor in the relevant period, $1(\bullet)$ is an indicator function which is equal to one if the enclosed statement is true and zero otherwise, X_{it} is a vector of exogenous determinants of poverty status, $X_{it}=(X_{i1},...,X_{iT})$, α_i represents all household-specific, time invariant observed and unobserved factors, ξ_{it} is the transitory error which is assumed to be i.i.d. over time with a distribution function $F(\bullet)$, and finally, β and γ are the parameters to be estimated. In this case γ represents structural state dependence[28] in poverty and α_i is the source of spurious state dependence attributable to permanent unobserved heterogeneity in the household such as intelligence, ability, motivation, attitude, etc.

3.5.1. Panel Specification Test

In this part we test the data whether the there is systematic difference between fixed effects estimates and random effects estimates using Hausman Specification Test. This basically tests whether the vector $(K\times 1)$ of random effects coefficients (efficient estimates) of the time varying variables, $\hat{\beta}_{RE}$, are systematically different from the corresponding fixed effects coefficients (consistent estimates under Ho), $\hat{\beta}_{FE}$, as follows

$$H=(\hat{\beta}_{FE}-\hat{\beta}_{RE})'[A\,\hat{\text{var}}(\hat{\beta}_{FE})-A\,\hat{\text{var}}(\hat{\beta}_{RE})]^{-1}(\hat{\beta}_{FE}-\hat{\beta}_{RE})$$

Ho : difference in coefficients not systematic

[28] In their application of this model to welfare participation, Chay and Hyslop 1998, γ represents "welfare trap".

Where, H is asymptotically distributed as χ_k^2. The result obtained form this test using linear probability[29] fixed effects and random effects specifications for poverty dynamics model is:

Test: Ho: difference in coefficients not systematic
Chi2(38) = (b-B)'[(V_b-V_B)^(-1)](b-B) =52.29
Prob>chi2 =0.0612

As the chi-square test shows that we reject the null hypothesis at 10% level of significance. Therefore, the two specifications are systematically different indicating that there is endogeneity in some of the regressors, where one of the random effects model assumption ($E(X_{it}\alpha_i)=0$) breaks down. Hence, the random effects model is not consistent and efficient. Since fixed effects approaches do not require parametric assumptions about the conditional distribution of the individual conditions, a lot of information being absorbed in order to "non-parametrically" condition out the unobservable individual heterogeneity. As a result, fixed effects estimators may be sub-optimal since they 'throw away' comparisons between individuals that may be informative about the truth. As noted in Wooldridge 2003, if time-constant variables are of interest like the time-varying variables in a panel data variables, the robustness of fixed effects estimator to correlation between the unobserved effects, α_i, and the X_{it} is useless. For these reasons, we use random effects nonlinear model. But to increase the robustness of our random effects model we applied two-step procedure, as specified below, which can control for the correlation between some of the regressors and the unobserved individual effects.

State dependence

As noted above, empirical works show that there is state dependence in the dynamics of rural poverty in Ethiopia. For this we introduce the poverty status of the household in the pervious

[29] We used the linear Probability Model version for testing purpose due to its convenience and simplicity using standard statistical software packages, specifically STATA ™ (See Table 5 in Annex)

period, P_{it-1} as a regressor. This will allow us to test for the presence of genuine state dependence. According to Islam and Shimeles 2005 and Heckman 1981a and1981b state dependence can be spurious or genuine arising form three sources. First, unobserved household characteristics; second, the effect of time varying shocks that are not specific to the household; third, behavioral and preference shifts associated with poverty spell in the past. Genuine state dependence is due to past poverty status that results behavioral and preference shift. To test for the presence of genuine state dependence, one has to control for the other spurious sources of state dependence, i.e. controlling for observable and unobservable individual characteristics.

Unobserved Heterogeneity

Here, we base our model in line with the work of Arulampalam et al. 1997 in their application to unemployment persistence in Britain. Assume the unobservable household specific heterogeneity, α_i, is time-invariant, from the error term in equation [15], we have;

$$v_{it} = \alpha_i + \xi_{it} \qquad [16]$$

Were α_i denotes the household-specific unobservable effect and $\xi_{it} \sim i.i.n(0,\sigma_\xi^2)$. Assume $E(\xi_{it}X_{it}) = 0$ and α_i is random variable. In most cases, the household specific unobserved heterogeneity are correlated with the time-varying characteristics. In this case the maximum likelihood estimates of β will be inconsistent, which pick up some of the effects of the unobservable, α_i (Arulampalam et al. 2000). To overcome this problem, we relax the assumption that α_i and X_{it} are independent. The relationship between the unobserved household specific heterogeneity and the observed household characteristics can be modeled as

$$\alpha_i = \lambda_0 + \bar{X}_i'\lambda_1 + w_i \qquad [17]$$

Where $\bar{X}_i$ is a vector of means of the time-varying covariates for household i over time, $w_i \sim i.i.n(0,\sigma_w^2)$ is independent of X_{it} and ξ_{it} for all i and t. Substituting equation [17] into equation [15a], we obtain

$$P_{it}^{*} = X_{it}'\beta + \gamma P_{it-1} + \bar{X}_i'\lambda_1 + w_i + \xi_{it}^{30} \qquad [18]$$

Were the intercept λ_0 is absorbed in β. Thus this model is similar with the random effects probit model which accounts for the dependence between unobserved household specific effects and the observable household characteristics with additional regressor, $\bar{X}_i$.

The initial conditions problem

Considering the initial conditions problem is another important parcel of dynamic limited dependent variable panel data model. This problem arises because the start of the survey period (1994 in our case) is not the same as the start of the stochastic process generating individuals' poverty experiences. Households observed in the state of poverty in 1994 may be there because of an early history of poverty (state dependence) or because of some observed and/or unobserved characteristics affecting their probability of being poor. As applied in Islam and Shimeles 2005, Arulampalam et al. 2000, Lawless 2005, and others, we follow Heckman 1981c specification of the reduced form equation for the initial observation as

$$P_{i1}^{*} = Y_i'a + \eta_i \qquad [19a]$$

$$\text{var}(\eta_i) = \sigma_\eta^2 \qquad [19b]$$

---

[30] We can easily show that the correlation between the two successive error terms, v_{it} and v_{it-1}, for the same individual is constant, i.e,

$$corr(v_{it}, v_{it-1}) = \frac{\text{cov}(v_{it}, v_{it-1})}{\sqrt{\text{var}(v_{it})\,\text{var}(v_{it-1})}} = \frac{\sigma_w^2}{\sigma_w^2 + \sigma_\xi^2} \qquad t=2,\ldots T$$

$$corr(w_i, \eta_i) = \rho \qquad [19c]$$

Where Y_i' is a vector of strictly exogenous instrumental variables, which are relevant in period one, pre sample information affecting the probability of being poor in period one, and the vector of means, $\bar{X}_i$. For consideration of a non-zero ρ, we use linear specification in terms of orthogonal error components as

$$\eta_i = \varphi w_i + \xi_{i1} \qquad [20]$$

Given the fact that w_i and ξ_{i1} are orthogonal to one another, $\varphi = \rho \frac{\sigma_\eta}{\sigma_w}$[31] and after simplification and substitution we obtain $\text{var}(\xi_{i1}) = \sigma_\eta^2(1-\rho^2)$. Further more, we assume that $corr(P_{i1}\xi_{it}) = 0$ and $corr(X_{it}\xi_{i1}) = 0$ for all *i* and *t*. Then after substituting equation [20] into equation [19a] the 'initial conditions' equation becomes

$$P_{i1}^* = Y_i' a + \varphi w_i + \xi_{i1} \qquad [21]$$

From equation [18] and equation [21] we obtain a complete model of poverty dynamics, which can be estimated using different techniques. The estimation of this full model requires the use of special software or writing a program. However, we use two-step method of estimation suggested by Orme 1997, which is consistent with Heckman's standard sample selection correction method in case of small values of ρ. This procedure has been applied by Arulampalam et al. 1997 and Arulampalam 2002. In this procedure, to account for the correlation between the initial condition and the unobserved heterogeneity, a correction term is added to the conditional model. Then the complete model can be estimated using standard software packages.

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[31] It can easily be shown that $\varphi = \frac{\text{cov}(\eta_i, w_i)}{\text{var}(w_i)}$ and since $\rho = \frac{\text{cov}(\eta_i, w_i)}{\sigma_\eta \sigma_w}$ we can solve to obtain the result.

Closing the model

In order to obtain estimable equation using standard statistical software packages, equation [18] and [21] we need to follow simple steps. First, we estimate the reduced form model for the initial observation, P_{i1}, using a simple probit model and then using the generalized residuals from this regression as a correction to the random effects dynamic probit model for the rest of the sample. Using equation [18] and [19a] we can capture the correlation $corr(w_i, \eta_i) = \rho$ by re-specifying equation [20] as

$$w_i = \phi \eta_i + \upsilon_i \qquad [22]$$

By construction, η_i and υ_i will be orthogonal to each other and similar to the previous specification, $\delta = \rho \frac{\sigma_w}{\sigma_\eta}$, and $\text{var}(\upsilon_i) = \sigma_w^2(1-\rho^2)$. By substituting equation [22] into our random effects dynamic probit model, equation [18] we obtain the following reduced form estimable equation

$$P_{it}^* = X_{it}'\beta + \gamma P_{it-1} + \bar{X}_i'\lambda_1 + \phi\eta_i + \upsilon_i + \xi_{it} \qquad i = 1,...,n \text{ and } t = 1,...,T \qquad [23]$$

$$prob(P_{it} = 1 | X_{it}', P_{it-1}, \bar{X}_i, \eta_i) = F(X_{it}'\beta + \gamma P_{it-1} + \bar{X}_i'\lambda_1 + \phi\eta_i + \upsilon_i + \xi_{it} > 0) \qquad [24]$$

In this specification there are two individual specific random error components, υ_i and ξ_{it}, because ξ_{it} is assumed to be orthogonal to the regressors, we can treat υ_i as the usual error component in a random effects probit model, provided that we can take care of the unobservable η_i. The other issue to note is that (w_i, η_i) are assumed to be a bivariate normally distributed error components[32]. Finally, a test of the null hypothesis that $\rho = 0$ is given by the standard t-test of the coefficient of this additional regressor, ϕ.

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[32] But, as discussed in Arulampalam et al. 1997, the assumption of a bivariate normal distribution of (w_i, η_i) implies that $E(\upsilon_i | P_{i1}) = 0$ and $E(\eta_i | P_{i1}) = \frac{(2P_{i1}-1)\phi(Y_i'a)}{\Phi(\{2P_{i1}-1\}Y_i'a)} = e_i$ where e_i is a probit generalized error in the probit

3.6. Modeling the long-term implication of shocks and informal risk-coping strategies on Poverty dynamics

There are a number of ways of testing the hypothesis of full-risk pooling in our village economy setting. According to the empirical literature on risk and coping strategies, households employ a portfolio of strategies rather than favoring one single coping strategy. Niggusse 2005 found that rural households in Ethiopia employ a range of risk coping strategies, livestock sales, food/crop received through food for work, credit, remittance, food/crop received from friends or relatives within the communities.

Most these variables although not exhaustive, are readily available form the ERHS data. Such as remittances received (both in kind and in cash), food gift from informal sources (gift, loan, other, excluding sources from wage, NGOs, or government, barter), whether households involved in any labor sharing arrangement (work party, like *Debo*, *Wonfel*, etc.), whether any member of the household is/are member/s in *Eqqu,* whether the household borrowed from informal sources, whether the household lend to others. Using these variables the underlying model for our poverty dynamics can be written as:

$$prob(P_{it}=1 \mid X_{it}, P_{it-1}, W_{it}, W_{it-1}) = F(X_{it}'\beta + \gamma P_{it-1} + \bar{X}_i'\lambda_1 + \sum_j \theta_{j1} W_{jit} + \sum_j \theta_{j2} W_{jit-1} + \varphi D_{wt} + \phi\eta_i + \upsilon_i + \xi_{it}) \quad [25]$$

Where, W_{it} is a vector of variables representing informal risk sharing arrangements identified above. W_{it-1} is the lagged value of these variables. While θ_{j1} captures the short-term impact,

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equation given by equation [19], which will be replaced in place of the unobservable η_i. Unfortunately, this bivariate normality assumption implies that υ_i is heteroskedastic, i.e, its variance is not constant, $\text{var}(\upsilon_i \mid P_{i1}) = \sigma_w^2(1-\rho^2\kappa)$, where $\kappa = \dfrac{\phi(Y_i'a)}{\sqrt{\Phi(Y_i'a)\Phi(-Y_i'a)}}$. But, Orme 1997 in Arulampalam et al. 1997 , using Monte Carlo results, shows that as far as the value of ρ is small this heteroskedasticity will not produce inconsistent parameter estimates.

θ_{j2} captures the long-term implication of informal risk sharing arrangements on the poverty dynamics of household *i*. The null hypothesis implies that in the short-term the sign of θ_{j1} is negative ($H_0 : \theta_{j1} < 0$) and θ_{j2} is positive ($H_0 : \theta_{j2} > 0$). The first hypothesis is that in the short-term informal risk sharing reduces the probability of falling into poverty (welfare increasing impact in the short term) and the second proposes that these risk sharing arrangements increases the probability of falling into poverty in the long-term (welfare reducing impact in the long term).

To see the long term impacts of both covariate and idiosyncratic shocks, we directly introduce shocks into our poverty dynamic model. Households in the third round (1994/95) were asked to tell whether they have experienced drought, flood, crime, illness, death, pest and disease (which affected livestock and crop); policy shocks related to labor, quota and land redistribution since the last 20 years. We use these set of shock dummies experienced between 1977 E.C. and 1987 E.C. in our poverty dynamic model to see the impact on poverty dynamics.

3.7. Modeling the implication of informal risk sharing Strategies using Alternative measures of welfare.

The use of binary model for poverty modeling is criticized because it introduces measurement errors by using arbitrarily defined poverty lines and reducing a continuous variable (income or consumption expenditure) to a qualitative variable that may "throw" information away on the variation in the dependent variable with respect to the variation in explanatory variables. Particularly, this is a problem in developing countries, where a large number of households concentrated around the poverty line (Deaton 1997, Justino & Litchfield 2003 and Aassve et al. 2005). Here, we used log of consumption per adult equivalent per month as a measure of

household welfare to model the implication of informal risk sharing strategies on long-term welfare of the rural households. Following the line of argument in the method we proposed above, a variant of equation [24] can be respecified as;

$$\ln c_{it} = X'_{it}\beta + \sum_j \theta_{j1} W_{it} + \sum_j \theta_{j2} W_{it-1} + \alpha_i + \xi_{it} \quad i = 1,...,n \text{ and } t = 1,...,T \qquad [26]$$

Where, $\ln c_{it}$ is log of consumption per adult equivalent of household i at period (round) t. The interpretation of the coefficients on W_{it} and W_{it-1} will be reversed. The null hypothesis is that θ_{j1} is positive, welfare increasing in the short-term and θ_{j2} is negative, welfare reducing in the long-term.

3.8. Definition and Description of variables

The dependent variable for the binary poverty dynamics model is determined using the total povety line for each rounds and it takes 1 if the particular household in that round is poor, otherwise zero. The lagged value of this variable is also used as a regressor. In our level regression model log of real consumption per capita per month is used as dependent variable. Log of real income per capita per month is used as independent variable in regression model of testing consumption smoothing. We used one of the villages, Harasaw, food poverty line to derive our price deflator for both spatial and overtime deflation of nominal values, like consumption and income. We try to control for asset holding of the household by using land holding (in hectare), number of livestock other than oxen and bulls owned and number of oxen (oxen + bulls) owned. Household characteristics are captured using variables such as sex of the head (dummy=1 if the head is male, zero otherwise), age of the head in years, age squared of the head to see the second order effect of age, mean age in the household to capture the age composition in the household, household size, squared value of household size to capture the idea of scale economies at the household level, head's educational level

(three dummies: primary education, secondary education and tertiary education, dummy=1 if true, zero otherwise).

Variables used in the vector of informal risk sharing arrangements are a set of dummy variables such as, whether the particular household received remittance, whether the household has got credit form informal sources, whether the household has lend to others, whether the household received food gift from informal sources, whether any member in the household is member in Eqqub, whether the household has involved in work party (*Debbo*, *Wonfel*, etc; dummy=1 if true, zero otherwise). Information on membership in Iddir and Mahiber was not readily available in all rounds. To analyze the long-term impact of shocks on poverty dynamics, we introduce shocks experienced before 1977 E.C. up to 1987 E.C., such as flood, drought, pest and diseases affecting livestock and crop, illness, death, quota, land policy, labor policy and crime into our model. We divided this time period into two episodes (shock experienced between 1977 E.c. and 1983 E.c. and between 1984 E.c. and 1987 E.c.). So there are two dummies for each shock variable. We defined the episodes based on major economic and political occurrence in the country. In 1977 E.c. the worst famine in Ethiopia has occurred, in 1983 the longest civil war in country came to an end with an overthrow of the socialist regime by EPRDF[33]. Dividing these long-term variables by these major episodes in the country may provide us a good picture of the long–term impact of shocks on poverty dynamics of rural Ethiopia. Interaction between region and rounds are used to capture village level differences, covariate shocks for each round, and other infrastructural differences, inflation, etc. across villages and rounds.

[33] Ethiopian Peoples' Republic Democratic Front

In the next chapter we describe some of our findings regarding poverty profile, its dynamics and informal risk sharing arrangements vis a vis some important household characteristics and wealth status using simple statistics.

Chapter Four

Data and Discussion of Descriptive results

4.1. The Data

We use the longitudinal household data of Ethiopian Rural Household Survey (ERHS) in this study. The survey was conducted in six rounds in 1994[34] (two times), 1995, 1997, 1999, and 2004 which encompasses 15 peasant associations (PAs) in four national regions, covering a sample of approximately 1480 households (See Annex for map). The shares within the sample are broadly consistent with the population shares in the three main sedentary farming systems – the plough-based cereals farming systems of the Northern and Central Highlands, mixed plough/hoe cereals farming systems and farming systems based around *enset* that is grown in southern parts of the country. For these reasons, it can be argued that the sampling frame to select the villages was strictly stratified in the main agro-ecological zones and sub-zones, with one to three villages selected per strata. Further, sample size in each village was chosen so as to approximate a self-weighting sample, when considered in terms of the farming system (Dercon et al. 2005).

We have a balanced panel data set consisting of 1,236 households who are included in all the six rounds. These households are included because all important information are available or responded in each wave. Missing values for some variables are filled by a regression based imputation both based on cross-sectional and time series information.

4.2. The poverty line

In this study, the cost of basic needs (CBN) approach is adopted. To this, first we construct the food poverty line, which is the cost sufficient to get consumption bundle adequate to meet

[34] Two times in 1994. first form March to July and second wave from October 1994 to January 1995.

the predetermined food energy requirement[35]. The market price information collected during the survey period in that particular *Woreda* was used to obtain the monetary value of the food bundles specific to area. Then allowance for basic non-food consumption is made by dividing the food poverty line by the average food share of households at the poverty line. We sum the food poverty line and allowance for non-food consumption to obtain the total poverty line. We used the monthly consumption expenditure pre capita or per adult equivalent to determine whether the household is poor or not. See Table 4d, Annex for the average total poverty line and food share for each round.

4.3. Poverty profile and description of dynamics: 1994-2004

For comparison, we used poverty indices calculated in Bigstine and Shimeles 2005 for the five rounds while we calculated for the last round, 2004. This comparison is valid because the bundle of commodities and the approach adopted to construct the poverty line are identical with the one we employed (See Annex). We can see from Table 4a that poverty declined from 1994 up to 1997. This is due to the fact that there was policy reformulation and recovery of the economy from the longest civil war and socialist economic system and good natural conditions in the first four survey rounds elapsing from 1994 to 1997. In the fourth round, 1997, there is a very high improvement in poverty status of rural households. This is mainly because the data was collected immediately after harvest, which resulted in an exaggerated level of reported income and consumption compared to other rounds. Poverty conditions worsen in the year 2000 due to multiple social, economic, and political crises. There was a full scale war between Ethiopia and Eritrea, a sharp decline in world coffee price, unfavorable weather and macroeconomic condition and 13 million people starved due to drought (see Begisten and Shimeles 2006). There is some recovery in poverty indicators in 2004 compared

[35] The food poverty line calculation is base on the cost of 2200 kcal per day per adult equivalent. The adult equivalent units are calculated using WHO 1985 conversion codes for each age category and sex of the household members. See Annex 1 Table 1 for the common bundle of commodities that gives 2200 Kcal per day per month.

to 2000. This is due to recovery form the 1999/2000 multidimensional crises in the country and good weather conditions in the consecutive years.

Table4a: Poverty Profile in Rural Ethiopia: 1994 – 2004

Poverty Measures	1994	1995	1997	2000	2004*
P0 Per capita	56.0%	49.0%	39.0%	50.0%	42%
P0 Per Adult Equivalent	48.0%	40.0%	29.0%	41.0%	33%
P1 Per Capita	25.1%	21.3%	16.3%	21.7%	18%
P1 Per Adult Equivalent	21.0%	16.0%	10.0%	14.1%	14%
P2 Per Capita	16.7%	13.3%	8.8%	13.7%	11%
P2 Per Adult Equivalent	13.1%	10.2%	6.0%	10.2%	7.8%

Source: Bigstine and Shimeles 2005. *Author's calculation for 2004 (N=1236)

Poverty Entry and Exit

When we look at the status of poverty by the number of times a given household being poor, Table 7 presents that 21.84% of the rural households have never been poor but only 3.4% of the households under consideration were always poor. We see that the percentage of households declines as the number of spell in poverty increase. This implies that there are a large number of vulnerable households concentrating around the poverty line, who fell into poverty for (a) round/s and exit in the other.

Table 4b: Percentage of Household by duration in by Household characteristics: 1994-2004

Poverty status	The whole sample	By Land holding Between quartiles:				Male Headed	Female Headed	Education level of the head			Age of the head				Household size (Median=6)	
		1st	1st and 2nd	2nd and 3rd	3rd			Primary	Secondary	Tertiary	<=25	<=35 >25	<=65 >35	>65	< 6	>=6
Never Poor	21.84	13.21	15.76	26.12	31.85	22.14	20.84	22.28	24.64	33.33	24.05	25.64	20.35	22.06	28.12	15.89
Once Poor	21.44	15.11	18.67	27.09	24.66	21.74	20.43	21.56	31.16	26.67	25.38	26.07	19.11	23.17	24.27	18.75
Twice Poor	16.5	17.85	17.82	17.36	13.12	16	18.21	17.07	16.67	26.67	15.53	15.25	17.31	15.29	17.79	15.29
Thrice Poor	14.4	18.35	15.28	10.77	13.33	14.93	12.65	17.07	15.22	10	16.1	11.55	15.03	14.64	13.49	15.26
Fourth times poor	13.11	18.86	14.69	9.79	9.34	12.37	15.57	11.14	7.97	3.33	9.85	11.62	14.03	12.79	8.73	17.26
Five times poor	9.3	12.31	11.56	6.91	6.56	9.41	8.96	6.11	3.62	0	6.44	6.46	10.49	9.45	5.68	12.74
Always Poor	3.4	4.31	6.21	1.96	1.15	3.42	3.34	4.76	0.72	0	2.65	3.41	3.68	2.59	1.91	4.81

Source: Author's calculation from ERHS data.

Disaggregating the number of times households in poverty by wealth status[36], the percentage of those households who have never been poor increases as their land holding increases. On the other hand, the percentage of households who have always been poor decreases as their land holding increases. This implies that land is important asset for rural households in their course of struggle against poverty. Land poor households are more vulnerable to relentless poverty (repeated/multiple spell in poverty) compared to the land rich. Compared to female, there are higher percentages of male headed households who have never been poor. Clearer pattern can be seen in households categorized by heads' level of education. 33.33% of those attained tertiary education have never been poor, while 22.28% and 24.64% of those attained primary and secondary education have never been poor, respectively. On the other hand, as the level of educational attainment increases, the percentage of households experiencing multiple spell declines. For instance, there are no households who have always been poor among those attained tertiary education. This could be due to the reason that more educated household heads managed to obtain off-farm wage employment, engaged in trade, employment in community service centers like clinic, school, etc. besides their farm activity. The percentage of households who have never been poor is higher for those whose head age is below 35 years compared to the other category. Besides, their percentage declines as duration in poverty spell increases. This implies that younger productive age household heads experience shorter duration in poverty. Due to higher dependency ratio, higher percentage of households whose size is above the median experiences persistent poverty compared to others.

State dependence

Table 6a in Annex shows movement into and out of poverty depending on past poverty status of households. For instance, 57.8% of those households who were poor in round two had

[36] We used land holdings as measure of wealth classified into four classes of wealth, those in the first quartile, between the first and the second quartile, between the second and third quartile, and in the third quartile.

been poor in round one. Similarly, 80.47% of the non poor households in round two were non poor in round one. Except the case of round four, where most of the households were nonpoor, above 50% of those currently poor were poor in the pervious round while above 66% of currently nonpoor households were nonpoor in the previous round.

Table 6b: Transition Matrix: Average

		Status during t	
		poor	nonpoor
status during t-1	poor	**54.31**	45.69
	nonpoor	24.57	**75.43**

Source: Author's calculation from ERHS data.

The average transition matrix as presented in Table 6b summarizes state dependence on average across the rounds further strengthen the presence of substantial state dependence. There is relatively smaller percentage of state dependence in the poor category compared to the nonpoor revealing the concentration of poor households near to the poverty line from below who manage to exit in one round but reenter in the other. Generally, the average transition matrix reveals that there is genuine state dependence in the poverty dynamics of rural Ethiopia. By implication, there is behavioral impact of current poverty where an individual deteriorates both physically, psychologically and socially, losing motivation and downward shift in preference. We can deduce that policies with an appropriate mode of intervention that address current poverty will also reduce future poverty.

4.4. Informal risk sharing

Table 9a and 9b presents the percentage of households who have some form of informal risk sharing arrangements and the intensity of their involvement. As discussed in the literature households use a variety of self-insurance and informal insurance strategies to smooth consumption form idiosyncratic and covariate shocks. In Table 10a, the most widely employed informal schemes are calling work party, credit from informal sources and

membership in Eqqu, respectively. Households who are Land poor, female headed and age of the head above 65 tend to receive more remittance and food gift than the land nonpoor, male headed, and head age below 65, respectively. This clearly shows that there is endogenous self-selection regarding remittance and to some extent food gift, where the recipients are more or less vulnerable group. More interestingly, land non-poor and male headed households tend to participate in work party than those who are land poor and female, respectively. This reveals the advantage of male headed and land rich households in agricultural labor sharing arrangements and other productive engagements in the community.

Table 9a: percentage of households participated in informal arrangements by asset holding and demographic profile

Informal schemes	Overall	Land poor	land nonpoor	Male headed	Female headed	Age Category			
						<=25	<=35>25	<=65>35	>65
Received remittance	8.33	10.40	6.30	7.10	12.47	7.58	5.52	8.55	11.40
Received food gift	4.64	5.61	3.69	4.12	6.38	6.25	5.23	4.17	5.00
Credit	42.81	44.91	40.76	43.52	40.46	39.39	43.72	45.06	34.11
lend to others	6.69	3.73	9.59	7.60	3.63	6.25	9.44	6.23	5.28
Eqqub	16.36	15.63	17.07	17.10	13.88	15.53	16.19	17.26	13.25
Work party	43.26	34.72	51.63	45.78	34.84	42.99	45.75	45.44	31.23

Source: Author's calculation from ERHS data.

The intensity of participation in informal risk sharing schemes is presented in Table 9b. Overall, around 73% of households participate in any one or more of the schemes. About 37.6% participate in any one while 26% in any two of the informal schemes. The percentage of households' participation declines as the number of schemes increase. This shows that there could be an optimal number of network participation for rural households. Further analysis in this regard could be a good research problem in the future.

Higher percentages of land non poor, male headed and head's age ranging between 25 and 65 years households participate in multiple arrangements compared to the land poor, female

headed and heads age above 65 years. This implies that membership in informal risk sharing is not an easily accessible arrangement to every member in the community. Those who are capable and well-to-do actively and intensively participate in informal arrangements compared to others. Hence, vulnerable group in rural community like old aged, land poor and female headed households tend to be relatively neglected compared to other.

Table 9b: Percentage of households members in multiple informal risk sharing arrangements: 1994-2004

Member (Involved) in	Overall	land poor	land Nonpoor	Male Headed	Female Headed	Age Category			
						<=25	<=35> 25	<=65> 35	>65
None	26.13	31.64	20.73	24.28	32.32	27.65	24.18	24.07	36.33
Any 1 Scheme	37.63	34.83	40.38	38.07	36.18	38.26	36.6	38.2	36.33
Any 2 Schemes	26.15	22.63	29.59	27.59	21.31	24.81	29.77	26.74	19.74
Any 3 Schemes	8.37	8.82	7.93	8.41	8.26	7.39	8.21	9.09	6.12
Any 4 Schemes	1.52	1.91	1.15	1.51	1.58	1.52	1.09	1.71	1.3
Any 5 Schemes	0.19	0.16	0.21	0.14	0.35	0.38	0.15	0.18	0.19

Source: Author's calculation from ERHS data.

Chapter Five

Empirical Results and Discussions

5.1. Determinants of poverty dynamics in rural Ethiopia

Using our specification in equation [24], we estimated dynamic poverty model which accounts for state dependence and initial conditions problem. For comparison we also estimated static version of the model, which is given by column (a) in Table 10. From the Wald chi-square we can read that overall both the models are significant at 1%. But it can be observed form the loglikelihood, our dynamic nonlinear model (column (b)) is more robust (smaller value of loglikelihood) than the static version. On the other hand the fraction of variance due to idiosyncratic error term (Rho) has significantly decreased in our dynamic specification. That is the variation in household specific effects is better controlled in the dynamic model.

The coefficient on the lagged dependent variable is positive and significant at 1%. This result dictates that there is genuine state dependence in rural poverty dynamics, where past poverty status inflicts an adverse behavioral and physical impact on the individual that leads to downward preference shift and loss of motivation. This in turn increases risk of poverty and its persistence in the future. In other words, in the course of reducing future poverty, current poverty matters. The correction term, generalized probit error, is also positive and significant at 1% validating our model specification. This indicates that there is serial correlation and ρ is different form zero.

Table 10: Random Effects regression of Poverty dynamics: 1994-2004. Binary dependent variable.

		Random Effects Regression (a)		Dynamic Random Effects Regression (b)	
	Dependent variables	Coefficients	Absolute Z-value	Coefficients	Absolute Z-value
	Const	-1.50318*	6.45	-1.2039*	6.53
	LD(1)	-	-	0.3268*	5.61
	Generalized Probit Error	-	-	0.2878*	7.95
Asset					
	Land size owned	-0.0846703*	4.79	-0.0519**	2.2
	No. of livestock	-0.0201328*	6.76	-0.0069	1.48
	No. of Oxen +Bulls	-0.075565*	4.00	-0.0110	0.49
	Interaction term Land X Oxen	0.0073225	1.50	0.0025	0.53
Household characteristics					
	sex of the head	-0.2926615*	4.73	-0.2436*	4.39
	Household size	0.347603*	11.15	0.3551*	10.06
	(Household size)^2	-0.0106152*	6.00	-0.0099*	5.92
	age of the head	-0.0011719	0.14	0.0023	0.46
	(age of the head)^2	-0.00000556	0.07	-0.00003	0.51
	Mean age in the household	0.0054901	1.39	0.0133**	2.17
	Primary education - head	-0.1345829**	1.97	-0.1599**	2.5
	Secondary education - head	-0.6077186*	3.65	-0.3309**	2.07
	Tertiary education - head	-1.203716*	2.94	-0.6248	1.48
Change in household characteristics and asset					
	Change in household size	0.0023693	0.17	-0.0052	0.27
	Change in mean age in the household	-0.0080153***	1.90	-0.0095***	1.78
	change in age of the head	0.0025523	1.21	-0.0005	0.24
	Change in size of land owned	0.0392977*	3.10	0.0324**	2.07
	Change in no. of livestock ownership	0.0078659**	2.28	-0.0017	0.39
	Change in no. of oxen (oxen + bulls)	0.0153167	1.42	-0.0049	0.38
Mean variables over time					
	Mean of mean age in the household	-	-	-0.0129**	1.99
	Mean household size	-	-	-0.069*	2.98
	Mean size of land owned	-	-	0.0352	1.14
	Mean No. of livestock owned	-	-	-0.0055	0.92
	Mean No. of Oxen (oxen +bulls) owned	-	-	-0.1246*	3.7
Other variables					
	Chat growing village	-0.7085159*	-6.68	-0.2763*	2.72
	Coffee growing village	0.2009743**	2.35	-0.942*	4.75
	Interaction term chat X coffee	0.8573128*	5.00	0.2558	1.48
Rho		0.2692029		0.1378043	
Loglikelihood		-3278.6387		-3059.5507	
Number of observations		6085		6085	
Wald Chi-square		589.92*		1102.09*	

Note:
* Significant at 1%, **significant at 5%, ***significant at 10%. A set of interaction terms between rounds and Villages are included but not reported. Most of these set of dummies are statistically significant.

Most of the correlates of poverty has become less significant, insignificant, the magnitude declines in the dynamic model (b) compared to the static specification (a). For instance, size of land owned, secondary education attained by the head and change in size of land owned have become less significant. While number of livestock owned, number of oxen+bulls owned, tertiary education attained by the head and change in the number of livestock owned have become insignificant.

For brevity, we only interpret correlates of poverty dynamics in column (b). From the set of household asset and wealth regressors like land, livestock and oxen, only the coefficient of size of land owned is negative and significant at 5%, This implies that as the size of land owned increases the probability of being poor declines, which shows the importance of land to reduce the incidence of poverty in the rural Ethiopia. But the coefficient on change in size of land owned is found to be positive and significant at 10% may be indicating the nonmarket and institutional evolution in size of land owned by the household in rural Ethiopia, where land is state owned. Although, current number of oxen + bulls owned are found to be statistically insignificant, the mean number of oxen owned over time is significant at 1%. As mean oxen ownership over time increases the risk of poverty declines.

Compared to female headed, male headed households have lower probability of being poor, cetirus paribus. There are a number of reasons behind this gender differential. One could be female headed households, in most cases, are those whose husband are deceased or widowed making them more vulnerable to poverty than the male headed one. Two due to traditional and religious believes, females in rural Ethiopia are usually denied access to and participation in productive opportunities. Household size increases risk of poverty while its second order effect is to reduce it reflecting the presence of scale economy in the household. But the magnitude of the coefficient of household size square is economically negligible. Educational

level of the head has important implication on household poverty status. Having attained primary, secondary or tertiary schooling by the head reduces the probability of falling into poverty. Although, the magnitude is not economically meaningful, increase in mean age in the household have statistically significant impact of reducing poverty. This can be interpreted as transition of some members from childhood to working age/adult increases the pool of productive age members in the household that has poverty reducing impact. Compared to cereal cultivating regions, dominantly central and northern Ethiopia, households residing in chat and coffee growing areas have lower probability of being poor.

5.2. The Impact of Shocks

In this part we discuss regression result of the impact of long-term idiosyncratic and covariate shock variables on the poverty dynamics. Table 11a presents results from dynamic random effects probit model and Table 11b from pooled OLS and Autoregressive random effects regression models using log real consumption per capita as dependent variable (which is a good measure of welfare).

From Table 11a the coefficient of the lagged dependent variable and the generalized probit error as well as other correlates of poverty remains stable with the inclusion of covariate and idiosyncratic shocks. From the random effects probit regression, Table 11a, the only statistically significant shock is drought experienced between 1984 to 1987 E.c (1992-1995 G.c.), which has a long-term impact on poverty dynamics of rural household from 1994-2004. Households who experienced this shock tend to be currently poor compared to others. All other shock variables are insignificant, implying that their effect is wiped-out shortly and have no significant persistent impact on poverty dynamics. The only shock that could not be insured is covariate shocks like drought, which affects everyone in the village.

Table 11a: Long-term impact of shocks on poverty dynamics. Binary dependent variable

		Dynamic Random Effects Probit Regression	
		Coefficients	Absolute Z-values
	cons_	-1.512066*	7.76
	LD(1)	0.3253846*	5.58
	Generalized Probit error	0.2591905*	7.72
Shock Variables (idiosyncratic +covariate)			
	flood experienced between 1984 and 1987 E.C.	0.0764384	0.91
	flood experienced between 1977 and 1983 E.C.	0.0541858	0.45
	quota shock experienced between 1984 and 1987 E.C.	0.1694219	0.43
	quota shock experienced between 1977 and 1983 E.C.	-0.914174	1.69
	labor policy shock experienced between 1984 and 1987 E.C.	-0.0575056	0.32
	labor policy shock experienced between 1977 and 1983 E.C.	0.0494059	0.26
	drought experienced between 1984 and 1987 E.C.	0.221877***	1.77
	drought experienced between 1977 and 1983 E.C.	0.1505546	1.28
	land policy shock experienced between 1984 and 1987 E.C.	0.4604264	0.83
	land policy shock experienced between 1977 and 1983 E.C.	-0.4003538	0.68
	crime shock experienced between 1984 and 1987 E.C.	-0.080877	0.68
	crime shock experienced between 1977 and 1983 E.C.	-0.0080621	0.06
	Pest and disease affecting livestock: 1984 - 1987 E.C.	0.126181	0.29
	Pest and disease affecting livestock: 1977- 1983 E.C.	0.226592	0.36
	Pest and disease affecting crop: 1984 - 1987 E.C.	-0.1167855	1.53
	Pest and disease affecting crop: 1977 - 1983 E.C.	-0.1018055	1.12
	illness of a member in the household: 1984-1987 E.C.	-0.2083121	0.59
	illness of a member in the household: 1977-1983 E.C.	0.186463	0.44
	death of a member in the household: 1984-1987 E.C.	-0.081753	0.74
	death of a member in the household: 1977-1983 E.C.	0.1787829	1.48
Rho		0.1181752*	
Log likelihood		-3031.7061	
Pseudo R2			
Number of observations		6085	
Wald chi-squared		1148.97*	

Note: * significant at 1%, **significant at 5%, ***significant at 10%. Variables entered into the regression but not reported; size of land owned, no. of livestock owned, no. of oxen owned, sex of the head, age of the head, (age of the head)^2, household size, (household size)^2, mean age in the household, education level, change in size of land owned, change in no. of livestock owned, change in no. oxen owned, change in age of the head, change in mean age in the household, time-mean variables, interaction term between size of land and no. of oxen owned and a set of interaction terms between regions and rounds.

Drought not only affects households over wide geographic area, but also affect the market price against those who want to sell their asset and buy grain. In the asset market price of livestock and other assets declines for the fact that large number of households try to sell their livestock. In the grain market on the other hand price increases due to shortage and high demand. This further worsens the misfortune of rural households. Among the idiosyncratic shocks, none are found to be significant to explain poverty dynamics in rural Ethiopia. This

demonstrates the existence and capability of insuring idiosyncratic shocks through different strategies. Our result reinforces the finding of other researchers, where covariate shocks are important in welfare variation of the household.

As an alternative and check for sensitivity of our binary dependent regression results under Table 11a, we have regressed log real consumption per capita on the shock variables of interest. Table 13b presents the result form pooled OLS and autoregressive random effects regression[37]. The coefficient on drought experienced between 1984 and 1987 E.C. is negative and significant at 5%. This result validates the result we obtained in Table 11a, where drought is important shock variable, where its impact persists for a long period of time. Although, insignificant in the pooled OLS regression, the coefficient on death of a member between 1977 and 1983 E.C. has become negative and significant at 10% in the autoregressive random effects regression. This period is the time where Ethiopians experienced the worst drought which took many lives and there were intensified civil war and forced national military service in the aftermath of the drought up until 1983 E.C. These two major events led to the lost of many productive age individuals in almost all corners of the country. The coefficient on pest and disease affecting crop between 1984 and 1987 E.C. is positive and significant both in the pooled OLS and autoregressive random effects regressions, which is against what we expected. This could be due to measurement error or due to our attempt to relate subjectively and self-reported shock experiences to objectively measured welfare indicators. As can be read from the F-test and Adjusted R^2, overall model fitness is statistically robust.

[37] Note that, after we test for serial correlation we found significant serial correlation in the idiosyncratic error term, i.e. $E(\varepsilon_{it}\varepsilon_{it-1}) \neq 0$. To correct this problem we used autoregressive random effects model with AR(1) which can be written as $\varepsilon_{it} = \rho\varepsilon_{it-1} + e_{it}$, where $e_{it} \sim iid(0, \sigma_e^2)$. We used Stata™ to estimate this regression model.

Table 11b: The impact of shocks on poverty dynamics. (Dependent variable: Log of consumption per capita)

Independent Variables	Random Effects Regression		Autoregressive Random Effects Regression	
	Coefficients	Absolute t-values	Coefficients	Absolute t-values
cons_	4.662572*	41.66	4.650437*	41.61
AR(1) - Rho			0.13720924	
Shock Variables (idiosyncratic + covariate)				
flood experienced between 1984 and 1987 E.C.	-0.0560948	1.18	-0.061462	1.34
flood experienced between 1977 and 1983 E.C.	0.0288412	0.43	0.0285552	0.44
quota shock experienced between 1984 and 1987 E.C.	0.0933373	0.52	0.0988771	0.47
quota shock experienced between 1977 and 1983 E.C.	0.2075789	0.80	0.2141458	0.76
labor policy shock experienced between 1984 and 1987 E.C.	-0.0884439	0.95	-0.0961737	0.99
labor policy shock experienced between 1977 and 1983 E.C.	0.112176	1.14	0.1180725	1.17
drought experienced between 1984 and 1987 E.C.	-0.1722633*	2.83	-0.1715088*	2.65
drought experienced between 1977 and 1983 E.C.	-0.0553591	0.95	-0.0573674	0.93
land policy shock experienced between 1984 and 1987 E.C.	-0.1601288	0.51	-0.1845661	0.61
land policy shock experienced between 1977 and 1983 E.C.	0.2517782	0.73	0.2727666	0.84
crime shock experienced between 1984 and 1987 E.C.	0.0104423	0.16	0.0119753	0.18
crime shock experienced between 1977 and 1983 E.C.	0.0162901	0.23	0.0171748	0.24
Pest and disease affecting livestock: 1984 - 1987 E.C.	0.0608712	0.28	0.0692978	0.29
Pest and disease affecting livestock: 1977- 1983 E.C.	-0.2759709	0.99	-0.2761982	0.84
Pest and disease affecting crop: 1984 - 1987 E.C.	0.1151795*	2.82	0.1174665	2.87
Pest and disease affecting crop: 1977 - 1983 E.C.	0.0207541	0.43	0.0188828	0.39
illness of a member in the household: 1984-1987 E.C.	0.0222369	0.15	0.0372945	0.21
illness of a member in the household: 1977-1983 E.C.	0.0007981	0.00	-0.017068	0.08
death of a member in the household: 1984-1987 E.C.	0.0648979	1.17	0.0650024	1.11
death of a member in the household: 1977-1983 E.C.	-0.1052774***	1.66	-0.1052454***	1.62
Fraction variance due to u_i	0.21241974		0.15302171	
Wald-chi squared	2356.07*		2249.52*	
Overall- R2	0.3208		0.3208	
Number of observations	5751		5751	

Note: * significant at 1%, **significant at 5%, ***significant at 10%. Variables entered into the regression but not reported; size of land owned, no. of livestock owned, no. of oxen owned, sex of the head, age of the head, (age of the head)2, household size, (household size)2, mean age in the household, education level, change in size of land owned, change in no. of livestock owned, change in no. oxen owned, change in age of the head, change in mean age in the household, interaction term between size of land and no. of oxen owned and a set of interaction terms between regions and rounds.

5.3. The Impact of Informal Risk Sharing

5.3.1. Test Result of Partial Informal Risk Sharing

Some of insurance testes based on consumption insurance theory failed to explain informal risk sharing in Ethiopia, in particular. Here, we use an alternative specification. But first we present our test result using equation [14a] and the result is presented in Table 12a from pooled OLS.

The coefficient of change in log income per capita is positive and significant at 1% irrespective of wealth status of the household. This implies that idiosyncratic income is important determinant of consumption growth in rural Ethiopia reflecting the widespread use of self-insurance. As noted in Ligon 200b, this positive sign of the coefficient on income is an indication of limited information or commitment in our rural Ethiopian informal insurance setting. The magnitude of this coefficient, elasticity of consumption to income, increases form 0.07 for the asset poor households to 0.10 for the asset non poor households, which implies that asset nonpoor households relied more on their income than the asset poor to smooth their consumption. Estimated coefficient on mean log village income, θ, is negative and significant for the whole sample, which is against the theory. When we disaggregate these households by asset holding, the coefficient become positive but not significant for asset poor households while negative and significant for asset non poor households. The direction of the coefficient of mean log village income from the asset poor households is in line with the theory but insignificant while those of asset nonpoor is against the theory.

Table 12a: Impact of change in mean log village income on change in log per capita consumption

	Pooled OLS Regression	
	Coefficients	Absolute t-value
All Households		
change in log real income per capita	0.0829597*	8.44
Change in mean log village income	-0.034598**	2.11
constant	-0.2178152**	1.98
No. of Observations	5301	
Fraction of variance due to u_i (Rho)		
F-test	33.45*	
Adjusted/Overall R-squared	0.2154	
Root MSE	0.80738	
Asset poor Households		
change in log real income per capita	0.070047*	5.15
Change in mean log village income	0.0358487	1.46
constant	0.0687297	0.42
No. of Observations	2517	
Fraction of variance due to u_i (Rho)		
F-test	16.87*	

Adjusted/Overall R-squared	0.2223	
Root MSE		
Asset nonpoor Households		
change in log real income per capita	0.1032315*	7.35
Change in mean log village income	-0.0926458*	4.08
constant	-0.0878	-0.51
No. of Observations	2784	
Fraction of variance due to u_i (Rho)		
F-test	19.78*	
Adjusted/Overall R-squared	0.2372	
Root MSE	0.76744	

Note:
* Significant at 1%, **significant at 5%, ***significant at 10%. Standard errors are heteroskedasticity-robust. Asset nonpoor households are those in the top two quartiles in terms of size of land owned while asset poor are those in the bottom two quartiles. Variables entered into the regression but not reported; size of land owned, no. of livestock owned, no. of oxen owned, sex of the head, age of the head, (age of the head)^2, household size, (household size)^2, mean age in the household, education level, change in size of land owned, change in no. of livestock owned, change in no. oxen owned, change in age of the head, change in mean age in the household, interaction term between size of land and no. of oxen owned and a set of interaction terms between regions and rounds. Age and age squared, change in no. of livestock owned, change in household size and all most all of the set of region by round dummies are statistically significant.

The result we obtained is similar with those obtained in Skoufias and Quisummbing 2003[38]. The rejection of the null hypothesis using this model specification seems to defy the historic presence of informal risk sharing arrangements in rural Ethiopia between villagers, family members, friends, neighbors, etc. This necessitates further and detailed investigation. For our purpose, we used alternative estimable specification as in equation [14b], using a set of dummy variables representing informal risk sharing arrangements as instruments in place of the change in mean log village income.

Results from pooled OLS regression of equation [14b] are presented in Table 12b. To check the robustness of our model regression, we have tested for omitted variables and heteroscedasticity. Using Ramsey regression specification-error test for omitted variables, RESET, the test output form **Stata**™ given below, accepts the null hypothesis of no omitted variables in the model.

[38] the magnitude of the estimated value of θ in Skoufias and Quisummbing 2003 is: -0.05 (t-value=1.66)

. estat ovtest

Ramsey RESET test using powers of the fitted values of dlnrcpc

Ho: model has no omitted variables

F(3, 5712) = 1.23

Prob > F = 0.2977

Our test for heteroscedasticty rejects the null hypothesis of homoscedasticity in the variance of the error term at 1%. Considering this problem, the regression reported in table 12a and 12b are corrected for heteroscedasticity using Eric 1967, Huber 1967, and White 1980 approach[39].

Except for credit and involvement in work party, the estimated coefficients are positive and significant for all other informal risk sharing variables for the whole sample. Remittance, food gift from informal sources and lending to others are significant at 1%, while membership in Eqqub is positive and significant at 5% with a meaningful magnitude. From the disaggregated regression we can work out important implications. For instance, the coefficients of remittance, food gift, lending to others, and membership in Eqqub are larger in magnitude for the asset poor households than the nonpoor. From this we can say that for asset poor households informal risk sharing arrangements are important determinant of consumption growth compared to the nonpoor. Generally, from our alternative specification, informal risk sharing arrangements explain the growth rate in household consumption and hence we can not reject the presence of informal risk sharing in rural Ethiopia.

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[39] Heteroscedastic-robust variance matrix estimator is given by $\text{Avâr}(\hat{\beta}) = (X'X)^{-1}\left(\sum_{i=1}^{N}\hat{u}_i^2 x_i' x_i\right)(X'X)^{-1}$.

This matrix was introduced in econometrics by White (1980b), Eicker (1967) or Huber (1967), (see Wooldrigde 2003).

Table 12b: Impact of informal risk sharing arrangements on change in log per capita consumption

Dependent variables	Pooled OLS Regression	
	Coefficients	Absolute t-value
All Households		
Change in log real income per capita	0.0694903*	8.85
Received Remittance	0.1583769*	3.88
Received food gift	0.1741952*	3.37
Received Credit	-0.041826***	1.73
Lend to others	0.1110551*	2.77
Member in Eqqub	0.0628245**	1.97
Involved in Work party	-0.0285886	1.17
constant	-0.2352678**	2.14
No. of Observations	5301	
F-test	32.26*	
Adjusted/Overall R-squared	0.2208	
Root MSE	0.80496	
Asset Poor		
change in log real income per capita	0.0738895*	6.07
Received Remittance	0.1401528**	2.30
Received food gift	0.2126471*	3.37
Received Credit	-0.0256634	0.69
Lend to others	.15585181***	1.93
Member in Eqqub	.0944383**	1.97
Involved in Work party	-.0605539	1.57
constant	-0.0882177	0.53
No. of Observations	2517	
F-test	16.93*	
Adjusted/Overall R-squared	0.229	
Root MSE	0.83751	
Asset nonpoor		
change in log real income per capita	0.0684445*	6.83
Received Remittance	0.0930989***	1.64
Received food gift	0.1849743**	2.46
Received Credit	-0.0396604	1.27
Lend to others	0.092879**	2.01
Member in Eqqub	0.0270099	0.62
Involved in Work party	-0.0311019	0.95
constant	-0.3019951	1.59
No. of Observations	2784	
F-test	18.33*	
Adjusted/Overall R-squared	0.237	
Root MSE	0.76826	

Note:
* Significant at 1%, **significant at 5%, ***significant at 10%. Standard errors are heteroskedasticity-robust. Asset nonpoor households are those in the top two quartiles in terms of size of land owned while asset poor are those in the bottom two quartiles. Variables entered into the regression but not reported; size of land owned, no. of livestock owned, no. of oxen owned, sex of the head, age of the head, (age of the head)2, household size, (household size)2, mean age in the household, education level, change in size of land owned, change in no. of livestock owned, change in no. oxen owned, change in age of the head, change in mean age in the household, interaction term between size of land and no. of oxen owned and a set of interaction terms between regions and rounds. Age and age squared, change in no. of livestock owned, change in household size and all most all of the set of region by round dummies are statistically significant.

We can jointly test the null hypothesis of no informal risk sharing, that is the sum of these coefficients is different from zero as $H_0 : \theta_1 + \theta_2 + \theta_3 + \theta_4 + \theta_5 + \theta_6 = 0$. The test results form Pooled OLS is;

Test from Pooled OLS regression:
test remt+ gift+ credit+ lend+ equb+ workp=0

(1) remt + gift+ credit + lend + equb + workp=0

F(1, 2731) =7.99

Prob > F = 0.0047

As can be shown form the above joint test result, we reject the null hypothesis of no informal risk sharing in rural Ethiopia at 1%. Both individual coefficient and joint test results confirm the existence of some informal risk sharing in rural Ethiopia. Further more, test can be done regarding the theoretical case of full-risk sharing, where the null hypothesis is that there is perfect/full-risk sharing, i.e.: $H_0 : \theta_1 + \theta_2 + \theta_3 + \theta_4 + \theta_5 + \theta_6 = 1$

Test from Pooled OLS regression
. test remt+ gift+ credit+ lend+ equb+ workp=1
(1) remt + gift + credit + lend + equb + workp=1
F(1, 2731) = 33.80
Prob > F = 0.0000

The test rejects the null hypothesis of full insurance at 1% implying that there is no full insurance in rural Ethiopia. This result is consistent with other empirical results.

5.3.2. The implication of informal risk sharing strategies on poverty dynamics

The impact of informal risk sharing strategies on poverty dynamics using dynamic random effects probit specification of equation [25] is presented by Table 13a. To see both the short-term and long-term impacts of these informal arrangements we have included current and lagged values into the regression. There may be some correlation between the lagged and current values of regressors. But result form pair-wise correlation matrix shows that none of them are significantly correlated (see Table 4 in the Annex). As can be compared with Table 10, the inclusion of these regressors, has both increased the magnitude of state dependence and improved the robustness of the model slightly (decrease in value of log likelihood). After controlling for household specific observed and unobserved effects, state dependence, covariate and time varying transitory shocks and other developments, many of the informal risk sharing arrangements significantly affects poverty dynamics. Among our set of informal risk sharing strategies receiving remittance, receiving food gift, lending to others, and membership in Eqcub reduces the incidence of current poverty with statistical significance of 10%, 5%, 1% and 1%, respectively. With the exception of receiving credit and involvement in work party, the sign of all other current informal arrangements is negative, implying that they reduce the probability of being poor, currently. The coefficient of lagged value of receiving remittance is positive and significant at 5%, while all others are insignificant. This can be interpreted as that the long-term impact of remittance is to increase risk of poverty due to adverse incentive impact on the behavior of the recipient household while the impact of the other informal arrangements is statistically insignificant.

Table 13a: Impact of informal risk sharing strategies on Poverty dynamics: 1994-2004. Binary dependent variable

Dependent variables		Random Effects Regression	
		Coefficients	Absolute Z-value
	Const	-1.2104*	6.60
	LD(1)	0.3306*	5.65
	Generalized probit Error	0.2692*	7.89
Informal risk sharing			
	Received Remittance	-0.1391***	1.79
	Received food gift	-0.2157**	2.06
	Received Credit	0.0469	1.08
	Lend to others	-0.2719*	3.12
	Member in Eqqub	-0.2698*	4.03
	Involved in Work party	0.0131	0.23
lagged values of informal risk sharing			
	Received Remittance	0.1754**	2.20
	Received food gift	0.0508	0.54
	Received Credit	0.0296	0.69
	Lend to others	-0.0996	1.11
	Member in Eqqub	-0.0943	1.43
	Involved in Work party	-0.0237	0.40
Rho		0.1259	
Loglikelihood		-3033.7479	
Number of observations		6085	
Wald Chi-square		1137.51*	

Note:
* Significant at 1%, **significant at 5%, ***significant at 10%. Variables entered into the regression but not reported; size of land owned, no. of livestock owned, no. of oxen owned, sex of the head, age of the head, (age of the head)2, household size, (household size)2, mean age in the household, education level, change in size of land owned, change in no. of livestock owned, change in no. oxen owned, change in age of the head, change in mean age in the household, interaction term between size of land and no. of oxen owned and a set of interaction terms between regions and rounds.

The impact of informal risk sharing strategies on log real consumption per capita

As an alternative specification we used log real consumption per capita for a measure of household welfare. From our pair-wise correlation matrix, the lagged values of informal risk sharing arrangements and lagged dependent variable are not correlated (see Table 4 annex). Table 13b shows the estimation result form random effects regression. The coefficient on current values of receiving remittance, receiving food gift, lend to others, and membership in Eqqub are positive and significant at 1% and calling work party is significant at 5%. The

lagged value of remittance and food gift is negative and significant at 10% and 5%, respectively. The coefficient on both current and lagged values of lending to others and membership in Eqqub remains positive affirming the positive short-term and long-term impacts of lending to others and being a member in Eqqub. This is consistent with the result from the binary non-linear regression model in Table 12.

Table 13b: Impact of informal risk sharing on welfare (Dependent variable: Log real consumption per capita): 1994-2004.

Dependent variables		Random Effects Regression	
		Coefficients	Absolute Z-value
	Const	4.420245*	48.04
	LD(1)	0.2771113*	20.99
Informal risk sharing			
	Received Remittance	0.0930886*	2.69
	Received food gift	0.1488263*	3.32
	Received Credit	0.0009847	0.05
	Lend to others	0.1793115*	5.01
	Member in Eqqub	0.1337192*	4.64
	Involved in Work party	0.0626037**	2.33
lagged values of informal risk sharing			
	Received Remittance	-0.1095821*	2.95
	Received food gift	-0.0684201***	1.65
	Received Credit	0.0046341	0.24
	Lend to others	0.1200696*	3.12
	Member in Eqqub	0.0521295***	1.83
	Involved in Work party	-0.0439497***	1.63
Adjusted R-square		0.3113	
Number of observations		5751	
F-test		44.32*	

Note:
* Significant at 1%, **significant at 5%, ***significant at 10%. Variables entered into the regression but not reported; size of land owned, no. of livestock owned, no. of oxen owned, sex of the head, age of the head, (age of the head)^2, household size, (household size)^2, mean age in the household, education level, change in size of land owned, change in no. of livestock owned, change in no. oxen owned, change in age of the head, change in mean age in the household, interaction term between size of land and no. of oxen owned and a set of interaction terms between regions and rounds.

Further more, simple but indicative inferences and tests can be made regarding the short-term and long-term impacts of these set of informal risk sharing arrangements on household welfare. For instance, we can check whether the short-term welfare increasing impact of receiving remittance

and food gift is fully offset by the long-term welfare reducing impact. Based on the pooled regression, test statistics are reported in Table 16 for statistically significant coefficients. Quite interestingly, welfare increasing impact of remittance and food gift in the short-term is counterbalanced by the long-term welfare reducing adverse incentive effect. These receipts are direct cash or in kind transfers and can be treated like other transfers such as public aid (Cox and Jimenez 1991 in Morduch 1999). Although, they have significant impact to reduce current poverty, in the long-term these direct and free transfers could reduce work incentive (adverse incentive impact) and trigger dependency. This is because the remitter can not easily observe the associated long-term adverse behavioral impact has no calculated mechanisms of checking the adverse behavioral consequences.

Table 14: Statistical Tests

Null Hypothesis	F-test	P-value	Decision
Ho: Remit + Remit_lg=0	0.00	0.9985	Accept Ho
Ho: gift + gift_lg = 0	1.13	0.2871	Accept Ho
Ho: lend + lend_lg = 0	28.05	0.0000	Reject Ho
Ho: Eqqub + Eqqub_lg = 0	22.8	0.0000	Reject Ho

Source: Author's calculation from ERHS[40]

An important and theoretically consistent implication can be derived from the test result of both lending to others and membership in Eqqub. Lending to others and membership in Eqqub are important means of household saving in rural Ethiopia. Lending to others can be considered as both saving and investment by households in rural areas. Through lending to others, households can put away their income from current consumption and earn interest rate, which is usually large, that can be reinvested on productive activities or consumed in the future. The risk of default on the other hand is very small in rural setting, where there are minimal information asymmetry problem among villagers. Compared to formal lending institutions, enforcement mechanisms, social exclusion and other punishment methods, are effective resulting in relatively smaller default rate. Eqqub on the other hand is a rotating saving and credit scheme, where members

[40] By simple test the Ho: lend + lend_lg >0 and Ho: Eqqub + Eqqub_lg >0 are accepted.

contribute constant amount of money each period and collect a sum of pooled money when it is their turn. As Table 17 (Annex:xxx) shows most of this money is spent on the purchase of food items and other household consumables like clothes, while smaller proportion still goes to the purchase of livestock. Generally, what the test result tells is that saving in the form of lending to others and Eqqub have an important positive short-term and long-term impact on the welfare of rural households.

Chapter Six

Conclusion and Implications

The main objective of the paper was to uncover factors that determine the nature of rural poverty dynamics in rural Ethiopia from various dimensions, assess the impact of shocks and informal insurance strategies on poverty dynamics. Using the longitudinal data collected over ten years in six waves, the paper has come up with important findings. Unlike static treatment, our dynamic consideration besides enabling us assessing short-term and long-term impacts of determinants of poverty, the model is more robust and it confirms the existence of genuine state dependence in rural poverty dynamics. That is, once households are poor the probability of becoming poor in the succeeding period/s is higher due to behavioral and physical deterioration.

Household wealth status as measured by land size holding and mean number of oxen owned, sex of the head, level of education attained by the head and mean age in the household are important household characteristics that determine poverty dynamics. Cetirus paribus, land is important asset for rural dwellers which significantly reduce the risk of poverty. But its change reinforces the risk of poverty, which is may be indicating the non-market institutional evolution of land in rural Ethiopia. Our result also shows that female headed households are vulnerable to risk of poverty than male headed. Those households residing in chat and coffee growing villages have lower risk of being poor compared to others.

Rural households are found to smooth most of the idiosyncratic shocks whereas there is difficulty to insure covariate shocks like drought. Except drought experienced between 1983 to 1987 E.c., most of the shocks have no long-term impact on the poverty dynamics of rural Ethiopia. This indicates the importance of drought in the lives of rural Ethiopians, where it

takes long time for households to return back to their long-run level of welfare once they experience drought shock. This shock affects different market outcomes that further restricting the possibility of self-insurance through selling out assets. In our alternative specification, in addition to drought, death experienced between 1977 and 1983 E.c. is also found to be significantly and adversely affecting poverty dynamics in the survey period. Although death is idiosyncratic shock, it was common for most of the households in the period under consideration. The period was characterized by many country wide crises such as the worst 1984 drought, intensified civil war and forced military service, and the downfall of socialist regime, which combined to increase the incidence of death of many productive age Ethiopians.

The most commonly applied model of testing informal insurance in a village economy setting fails to explain the existence of informal risk sharing in rural Ethiopia. Alternatively, we used a set of dummy variables representing informal risk sharing arrangement in our model. Based on our model the regression result confirms the existence of informal insurance arrangements. Except credit, remittance, food gift from informal sources, lending to others and membership in Eqqub positively and significantly explains the growth rate of household real consumption per capita. While household idiosyncratic income still explains the growth rate in consumption indicating the importance of self-insurance and the existence of imperfect information, limited commitment or both, as discussed in Ligon 2000. The test result also rejects the theoretical case of full-risk sharing in rural Ethiopia.

Examining the short-term and long-term impact of informal risk sharing strategies on poverty dynamics is also the main objective of the paper. After we controlled for state dependence, household characteristics, covariate time varying transitory shocks and other developments, receiving remittance, food gift, lending to others and membership in Eqqub significantly

reduce the risk of current poverty. But in the long-term the impact of receiving remittance and food gift is to increase the probability of falling into poverty. The short-term positive impact of these receipts is fully offset by the long-term negative impact. This could be due to adverse incentive impact of gifts on work incentive that create dependency. While the impact of lending to others and membership in Eqqub have poverty reducing impact both in the short-term and the long-term, signifying the importance of saving in the form of contribution to Eqqub and saving and investment in the form of lending to others.

Although results derived form the study are indicative and robust, there are some problem related with the model and variables used. For instance, we applied non-linear dynamic random effects panel data model based on two-step procedure that do not take Autocorrelation into consideration. The model is more robust (Homoskedastic), when ρ is small. But the magnitude of ρ is arbitrary that is difficult to defined whether it is large or small. We also tried to relate objectively measured poverty outcomes with self-reported subjectively assessed shock variables that may introduce measurement error. To keep our panel data balanced we drop out many households that increases attrition rate in the data. In addition, the set of dummy variables representing informal risk sharing arrangements used in our model are not exhaustive, which disregarded membership in Mahiber, Iddir, etc. due to lack of consistent information for each panel wave. Further more we only use one lag to approximate the long-tem impacts. And these lags should not be interpreted as one year lag. The lag length ranges from four months to four year.

Given these shortcomings, important implications still can be derived from the study that will be helpful and indicative both for researchers and policy makers. Poverty in rural Ethiopia is caused by different factors related to the structure of the economy, where the majority of dwellers are agrarian heavily relied on rain-fed and subsistence agriculture. Recurrent drought

and shocks adversely affects rural households that increase variability of income, while there are limited off-farm opportunities that restrict households' ability to generate alternative income and strengthen self-insurance. According to our results, some of existing informal risk sharing strategies available to the household like remittance and food gift increases long-term risk of poverty, and hence they are not effective insurance means in the long-term.

Interventions that reduce risks, especially recurrent drought in rural areas, can help to ameliorate the massive rural poverty. This can be accomplished through irrigation schemes, road and other infrastructure, meteorological information, and other preventive interventions. On the other hand, investment in human capital through education and health, creating rural off-farm income generating opportunities, market integration and information plus price incentive will help to reduce the risk of poverty and vulnerability. Give the possibility of crowding out the existing informal arrangements, institutional interventions that makes saving safe and more convenient through saving-oriented microfinance institutions, formal banks or postal saving arrangements will increase the capacity of self-insurance and reduces poverty. On the other hand the crowding out of some of informal arrangements, for example remittance and food gift, may have valuable social benefits through ameliorating adverse incentive problems. Further works on the impact of informal risk sharing strategies on poverty dynamics using dynamic limited commitment game-theoretic approaches and other appropriate models could be a good research problem.

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Annexes

Table1: Minimum Food Basket (per adult per month)

Food Item	Urban Area	Cereal Area	Enset Area	Ethiopia
Cereals (in Kg)				
Teff	8.51	1.63	0.29	1.52
Barley	0.53	4.24	0.73	2.58
Maize	4.56	3.82	4.95	4.41
Sorghum	0.70	4.53	0.05	2.40
Pulses (in kg)				
Lentils	0.53	0.35	0.05	0.25
Horse Beans	0.26	1.84	0.68	1.26
Cow peas	0.53	0.35	0.34	0.31
Chick peas	0.18	0.71	0.97	0.57
Shiro	0.79	0.92	0.05	0.57
Vegitables (in kg)				
Gomen	0.35	0.21	0.44	0.31
Onion	0.79	0.35	0.19	0.38
Root Crops (in Kg)				
Potato	0.97	0.14	0.97	0.57
Enset	-	-	18.05	7.68
Other food items				
Milk (lt)	0.35	0.49	0.73	0.25
Coffee (kg)	0.26	0.57	0.39	0.50
Sugar (kg)	0.26	0.14	0.05	0.13
Salt (kg)	0.61	1.20	0.87	1.07
Cooking Oil(lt)	0.61	0.28	0.10	0.19
Berbere (kg)	0.61	0.85	0.24	0.50
Bread (kg)	0.97	0.14	0.63	0.38

Source: Dercon and Mekonnen 1999.

Table2: Nutritional (Calorie) based equivalence scales

Age in Years	Men	Female
0 - 1	0.33	0.33
1 - 2	0.46	0.46
2 - 3	0.54	0.54
3 - 5	0.62	0.62
5 - 7	0.74	0.70
7 - 10	0.84	0.72
10 - 12	0.88	0.78
12 - 14	0.96	0.84
14 - 16	1.06	0.86
16 - 18	1.14	0.86
18 - 30	1.04	0.80
30 - 60	1.00	0.82
60 Plus	0.84	0.74

Source: Calculated from the World Health Organization

Table 3: Households Walfare Dynamics in real terms: 1994-2004

Variables	1994a	1994b	1995	1997	2000	2004
Total consumption at the hh level	367.43	384.07	291.42	461.41	405.76	380.87
Total consumption per capita	66.44	70.85	54.71	104.80	76.93	69.94
Total consumption per adult equivalent	73.76	83.23	63.43	105.77	87.26	79.28
Food consumption per capita	48.24	59.81	41.98	93.29	62.98	52.06
Food consumption per adult equivalent	58.26	73.16	52.44	98.30	75.27	65.54
Non-food per capita	17.16	10.64	10.98	10.15	11.17	11.52
Non-food per adult equivalent	20.87	13.15	14.38	10.52	13.40	14.30
Share of food expenditure per adult equivalent	0.82	0.87	0.85	0.87	0.85	0.83

Source: Author's Calculation from ERHS.

Table 4d: Average Total Poverty line and Food share by round

	Round 1	Round 2	Round 3	Round 4	Round 5	Round 6
Total Poverty	42.77	44.54	52.79	40.35	50.71	55.55
Food Share	0.82	0.87	0.85	0.87	0.85	0.83

Source: Abebe Shimeles and Author's Calculation.

Table 4c: Pair -Wise correlation between lagged real consumption per capita and current and lagged values of informal risk sharing arrangements

stata™ output:

. pwcorr lnrconspc_lg dumremt dumgift credit lend equb workp dumremt_lg dumgift_lg credit_lg lend_lg equb_lg w
> orkp_lg, star(0.1)

	lnrconspc_lg	remt	gift	credit	lend	equb	workp	remt_lg	gift_lg	credit_lg	lend_lg	equb_lg	workp_lg
lnrconspc_lg	1												
remt	-0.0677*	1											
gift	-0.0183	0.0634*	1										
credit	-0.0614*	0.0665*	0.0385*	1									
lend	0.0712*	0.0111	-0.0026	-0.0146	1								
equb	0.0300*	0.0513*	-0.0057	-0.0002	0.0523*	1							
workp	0.0753*	0.0558*	0.0378*	0.1417*	0.0855*	0.0054	1						
remt_lg	0.0022	0.1051*	0.0814*	0.0845*	-0.0049	0.0164	0.0828*	1					
gift_lg	0.0375*	0.0152	0.0593*	0.0390*	0.0047	-0.0038	0.0650*	0.0691*	1				
credit_lg	-0.0296*	0.0522*	0.0252*	0.2581*	-0.0263*	-0.0121	0.1265*	0.0722*	0.0426*	1			
lend_lg	0.1167*	-0.0227*	0.0158	-0.0159	0.1741*	0.0223*	0.0883*	0.0073	0.0098	-0.0142	1		
equb_lg	0.0485*	0.0521*	-0.0099	0.0044	0.0377*	0.4703*	-0.0017	0.0216*	0.0001	-0.0124	0.0428*	1	
workp_lg	0.0397*	0.0548*	0.0309*	0.1114*	0.0780*	-0.0115	0.7012*	0.0507*	0.0606*	0.1533*	0.0853*	-0.0073	1

Note: *significant at 10% or better

Table 5: Hausman Specification test between random effects and fixed effects: Using linear probability model

	--------Coefficients------			
	(b) fe	(B) re	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Land size owned	-0.0147429	-0.0132695	-0.001473	0.0040567
No. of livestock	-0.0068631	-0.0190995	0.0122364	0.0038037
No. of Oxen +Bulls	-0.0019636	-0.0031956	0.001232	0.000895
Interaction term Land X Oxen	0.0006584	0.0010609	-0.000403	0.0007076
sex of the head	-0.089412	-0.0712854	-0.018127	0.0217964
Household size	0.1010962	0.082227	0.0188692	0.0080157
$(\text{Household size})^2$	-0.0025727	-0.0024055	-0.000167	0.0003872
age of the head	0.0021932	0.0018902	0.0003029	0.0010568
$(\text{age of the head})^2$	-0.0000281	-0.0000188	-9.28E-06	0.0000109
Mean age in the household	0.0028452	-0.0003268	0.0031721	0.0024653
Primary education - head	-0.0050859	-0.0431151	0.0380291	0.0169095
Secondary education - head	0.0164841	-0.0896667	0.1061508	0.0301924
Tertiary education - head	0.0596164	-0.0906771	0.1502935	0.0472543
Change in no. of livestock ownership	-0.000634	0.0005469	-0.001181	0.000623
Change in no. of oxen (oxen + bulls)	0.0018877	0.0075668	-0.005679	0.0017044
Change in household size	-0.0076757	0.0025887	-0.010264	0.0033486
change in age of the head	-0.0001119	-0.0004328	0.0003209	0.0003578
Change in mean age in the household	-0.0023622	-0.0005197	-0.001842	0.000988
Change in size of land owned	0.0104011	0.0089059	0.0014952	0.0020536

b = consistent under Ho and Ha;obtained from xtreg

B =inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:Ho: difference in coefficients not systematic

chi2(38) = (b-B)'[(V_b-V_B)^(-1)](b-B)=52.29

Prob>chi2 =0.0612

Note: A set of regional dummies by round are included but not reported

Table 6a: Transition Matrix: 1994-2004

Status in		Round 2		Round 3		Round 4		Round 5		Round 6	
		Poor	Nonpoor	Poor	Nonpoor	Poor	Nonpoor	Poor	Nonpoor	Poor	Nonpoor
Round 1	Poor	**57.8**	42.2	67.8	32.18	33.9	66.09	39.9	60.12	52.6	47.4
	Nonpoor	19.5	**80.47**	32.5	67.5	9.07	90.93	24.4	75.59	33.8	66.25
Round 2	Poor	-		**76.1**	23.86	34.3	65.68	45.7	54.32	55.7	44.32
	Nonpoor			31.4	**68.59**	11.3	88.69	22.7	77.26	33.9	66.08
Round 3	Poor			-		**33.2**	66.84	43.6	56.41	53.5	46.5
	Nonpoor					7.22	**92.78**	19.5	80.49	31	68.97
Round 4	Poor					-		**50.6**	49.38	58.1	41.91
	Nonpoor							26.1	**73.87**	37.7	62.31
Round 5	Poor							-		**59.2**	40.84
	Nonpoor									33.8	**66.16**

Source: Author's calculation

Table 7: Percentage of households duration in poverty by shock experience

Shock Experience	Poverty Status by duration: 1994-2004 G.C.						
	Never Poor	Once Poor	Twice Poor	Thrice Poor	Fourth times poor	Five times poor	Always Poor
flood experienced between 1984 and 1987 E.C.	12.99	22.60	12.43	10.73	20.34	12.99	7.91
flood experienced between 1977 and 1983 E.C.	14.29	19.48	15.58	9.09	16.88	12.99	11.69
quota shock experienced between 1984 and 1987 E.C.	11.11	22.22	22.22	11.11	22.22	0.00	11.11
quota shock experienced between 1977 and 1983 E.C.	20.00	40.00	40.00	0.00	0.00	0.00	0.00
labor policy shock experienced between 1984 and 1987 E.C.	19.90	17.80	14.66	16.23	17.28	10.99	3.14
labor policy shock experienced between 1977 and 1983 E.C.	19.77	18.02	13.95	17.44	16.86	11.05	2.91
drought experienced between 1984 and 1987 E.C.	16.65	17.36	17.95	15.70	16.17	11.53	4.64
drought experienced between 1977 and 1983 E.C.	15.74	16.37	18.27	16.24	16.50	12.06	4.82
land policy shock experienced between 1984 and 1987 E.C.	12.50	18.75	25.00	25.00	18.75	0.00	0.00
land policy shock experienced between 1977 and 1983 E.C.	14.29	21.43	21.43	21.43	21.43	0.00	0.00
crime shock experienced between 1984 and 1987 E.C.	17.68	16.67	18.69	13.13	18.69	11.62	3.54
crime shock experienced between 1977 and 1983 E.C.	16.00	15.33	18.67	14.00	18.00	13.33	4.67
Pest and disease affecting livestock: 1984 - 1987 E.C.	14.29	28.57	28.57	0.00	14.29	14.29	0.00
Pest and disease affecting livestock: 1977- 1983 E.C.	25.00	0.00	50.00	0.00	25.00	0.00	0.00
Pest and disease affecting crop: 1984 - 1987 E.C.	17.95	18.59	16.03	16.35	13.46	11.22	6.41
Pest and disease affecting crop: 1977 - 1983 E.C.	18.02	16.86	15.12	16.86	13.37	13.37	6.40
illness of a member in the household: 1984-1987 E.C.	23.53	23.53	17.65	11.76	11.76	5.88	5.88
illness of a member in the household: 1977-1983 E.C.	27.27	18.18	9.09	18.18	9.09	9.09	9.09
death of a member in the household: 1984-1987 E.C.	17.94	16.03	14.89	16.03	17.56	13.74	3.82
death of a member in the household: 1977-1983 E.C.	15.35	15.35	12.87	17.82	19.31	15.35	3.96

Source: Author's calculation from ERHS data.

Table 8: Proportion of Households in informal risk-sharing arrangements by No. of times being poor

Variables	No. of times in poverty						
	Never poor	Once Poor	Twice Poor	Thrice Poor	Fourth times poor	Five times poor	Always poor
obtain credit	0.37	0.40	0.45	0.46	0.47	0.44	0.57
lend to others	0.11	0.09	0.05	0.05	0.04	0.03	0.04
member in eqqub	0.17	0.19	0.17	0.18	0.13	0.10	0.18
calls work party	0.49	0.43	0.40	0.41	0.39	0.47	0.38
receives remittance	0.06	0.07	0.08	0.10	0.09	0.12	0.13
receives food gift	0.05	0.05	0.04	0.05	0.04	0.05	0.06

Source: Author's calculation

Table 9c: Percentage of households in informal risk sharing arrangements by woreda

Woreda	Received Remitance	Received Food gift	Obtained Credit	Lend to others	Member in Eqqub	Involved in Work party
Atsbi	3.78	2.67	25.11	0.89	0.89	9.56
Sebhassahsie	2.05	3.22	22.81	0.88	0.00	4.68
Ankober	3.85	2.99	42.31	2.56	4.27	48.08
Basso na Worana	7.10	2.27	23.77	10.26	41.81	23.77
Enemayi	0.94	5.03	28.93	7.55	9.75	44.34
Bugena	6.19	2.65	44.10	4.72	10.32	60.03
Adaa	4.28	4.28	34.68	5.63	12.39	36.04
Kersa	7.77	8.33	61.74	10.42	4.36	72.92
Dodota	10.33	5.43	38.95	8.51	1.45	76.63
Shashemene	12.69	9.85	54.92	20.83	9.28	53.79
Cheha	31.77	7.81	58.85	4.43	62.50	72.66
Kedida Gamela	6.55	5.65	67.56	5.36	16.07	50.30
Bule	3.05	1.22	28.86	2.64	17.28	16.26
Boloso	19.41	6.78	68.13	2.38	11.90	46.89
Daramalo	2.98	3.87	60.12	5.65	25.30	29.46
Average	**8.18**	**4.80**	**44.06**	**6.18**	**15.17**	**43.03**

Source: Author's Calculation from ERHS.

Table 15: Percentage of households spending from receipts for different purposes.

Reason	Eqqub
food for household	56.98
clothes for household	16.31
other household goods	3.38
goods for equb members only	1.41
sheep/goats	1.31
cattle/horse/camel	3.01
other assets/tools	1.43
health expenditure	1.00
repay low	3.91
building materials	1.99
down payment for input purchase	1.15
tax payment	0.57
expansion of business	1.72
others	5.84

	Credit
to buy farm or other tools/implements	7.04
to buy inputs	13.42
to buy livestock	3.76
to pay for hired labour	1.38
to pay rent/taxes	1.95
to start an off-farm business	3.31
to buy food/goods for the household	40.20
for transportation	1.83
to pay for building materials	4.45
to pay for health expenses	10.20
to pay for education expenses	0.95
for weeding	2.96
funeral expenses	3.48
other	5.09

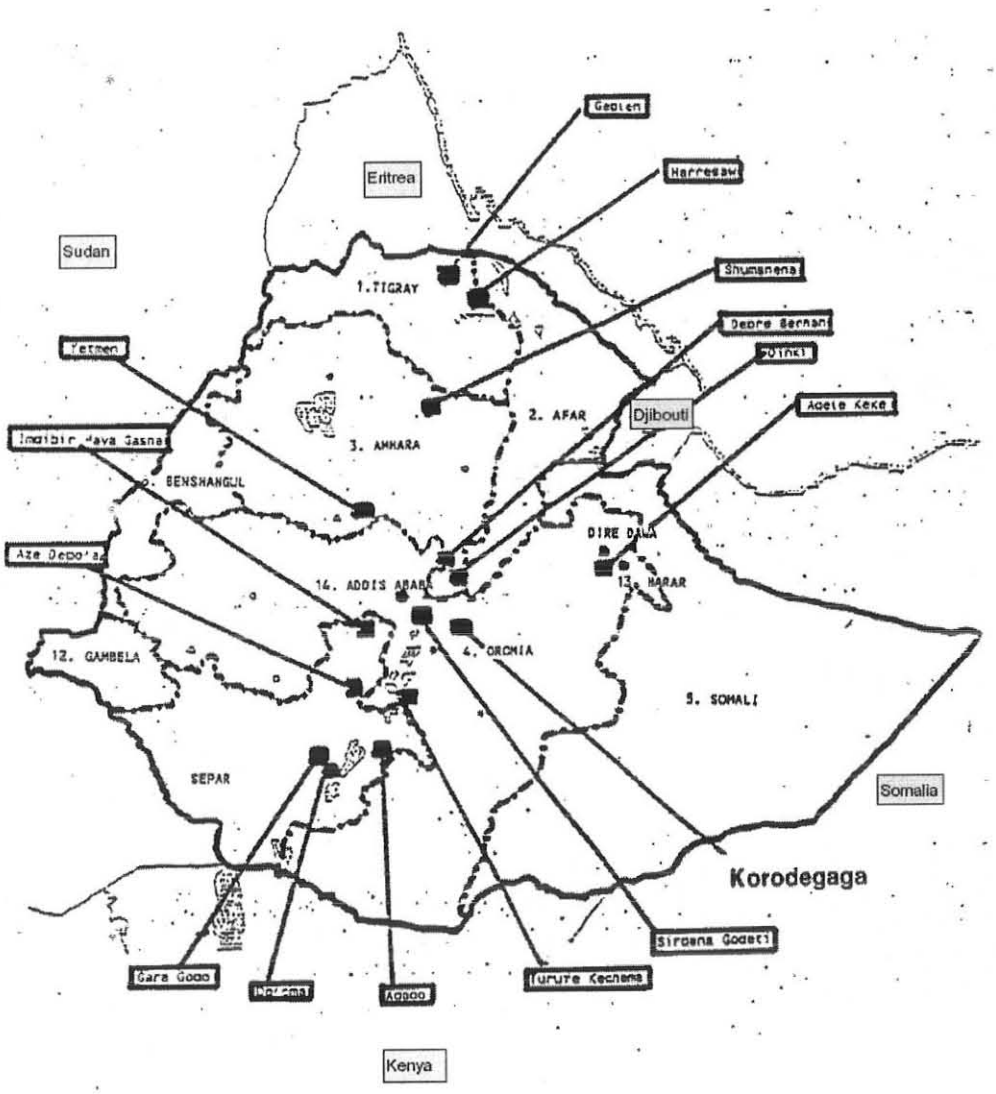
Sourc: Author's Calculation from ERHS

Table 16: Definition and Description of variables

Variable	Description
P_{it}	Dummy =1 if the household i is poor in period t, otherwise zero.
Lnrcpc	log of real consumption per adult equivalent per month
Lnry	Log of real consumption per adult equivalent per month
P_{it-1}	Previous poverty status.
Asset holdings	
land	Sized of land owned per household in hectare
livstk	No. of livestock other than oxen and bulls
Oxen	No. of oxen + bulls
dlivstk	Change in no. of livestock owned
doxen	Change in no. of oxen and bulls owned
dland	Change in size of land owned.
Household demographic characteristics	
sex	Sex of the head =1 if male, otherwise zero.
age	age of the head in years
agesqr	age square, to see the second order effect of age
hhsize	household size
hhsizesqr	square of household size to see household economies of scale
mage	mean age in the household
predu	Dummy=1, if head of the household has primary education
seduc	dummy=1, if head of the household has secondary education
teduc	dummy=1, if head of the household has tertiary education
dhhsize	Change in household size
dmage	Change in mean age in the household
dage	change in age of the head
Over time mean variables	
mmage	Mean of mean age in the household
mhhsize	Mean household size
mland	Mean size of land owned
mlivstk	Mean No. of livestock owned
moxen	Mean No. of Oxen (oxen +bulls) owned
Regional and Community characteristics dummies	
Chat	Chat growing village
Coffee	Coffee growing village
DVit	Region X Round interaction term. (5X5=25 variables)

Figure 1: Map of

Ethiopia.



Declaration

I, the undersigned, declare that this thesis is my original work and has not been presented for a degree in any other university, and that all source of materials used for the thesis have been duly acknowledged.

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Signature:

Date: 7/8/06

Place and date of submission: _____.