COPING WITH RURAL RISK: ASSETS, LABOUR ALLOCATION, MIGRATION, AND COMMUNITY NETWORKS

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Contents

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List of Tables

List of Figures

Abstract

Coping with Rural Risk: Assets, Labour Allocation, Migration, and Community Networks

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Given the importance of agricultural income for rural households, erratic weather conditions pose an austere threat to these households' livelihoods. This thesis explores ways through which households in agrarian economies smooth their consumption, engage in community networks, and readjust their labour allocation in response to shocks. In a setting of inherent risk, absence of institutional insurance, and labour market inefficiencies, poor households are often left to their own devices to cope with risk. The aim of this study is to examine the different risk-coping strategies adopted by households in rural India, assess their effectiveness, and derive implications for public policy. The results suggest that, in an environment characterised by agro-climatic risk, households are able to self-insure and smooth their consumption in the face of income shocks. Their coping mechanisms, however, may reduce their resilience to future shocks. In fact, small landholders tend to rely more heavily on their productive asset stock, while medium landholders find it optimal to preserve and accumulate their productive assets when exposed to exogenous income shocks. Households also change their labour allocation and reduce their self-employment in agriculture. Furthermore, households in rural areas can migrate to urban areas or engage in societal risk-sharing arrangements to mitigate the risk. The results of this thesis suggest that being part of a community network discourages individuals' migration and increases the likelihood of undertaking riskier activities. The findings also confirm the importance of portfolio adjustments and the diversification of household assets in buffering consumption. These conclusions form the basis of several policy implications, the most important of which is providing formal insurance schemes to encourage the accumulation of assets, technology, and skills.

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To my late and much lamented grandfather,
who valued scholarship above all else.

Thesis Introduction

Rural risk is ubiquitous in the developing world. Households in developing countries are often forced to adopt risk-management and risk coping mechanisms to buffer the income shocks (Dercon, 2002). In this thesis, I investigate the ways through which households cope with income shocks in an environment characterised by agro-climatic risk, failure of institutions, lack of formal insurance mechanisms, and labour market imperfections. The thesis begins with a chapter that assesses the extent to which households in rural India smooth their consumption and productive assets in the face of income shocks. I then turn my attention to the changes in labour market participation in response to shocks, and discern the role played by social networks as an informal insurance mechanism that holds households back from migrating and increases the tendency to participate in risky activities. The final chapter highlights the importance of portfolio adjustments in smoothing consumption while treating portfolio and production decisions as endogenous in a system of equations.

In India, households experience a multitude of risk factors: climatic risk, economic downturns, and several forms of household-specific shocks. The results of experiencing these shocks include failure of harvest, loss of livestock, and malnutrition of household members. The concepts of risk-management and risk-coping mechanisms are, therefore, central to understanding the livelihoods of poor people. The research on risk coping mechanisms has been the subject of many studies in economics (e.g. Munshi and Rosenzweig (2016); Dercon (2002); Fafchamps et al. (1998); Jacoby and Skoufias (1998); Townsend (1994); Rosenzweig and Binswanger (1993); Paxson (1992)). Dercon (2002) identifies two main strategies for dealing with risk. Before the shock occurs, *ex-ante* risk-management measures could be adopted. These include income smoothing, income skewing, diversification of income sources, and adjustment in household labour supply. After the shock occurs, households cope (*ex-post*) with risk through asset liquidation which they would have accumulated in good times, and risk sharing among community members which requires communal arrangements. In addition, labour market participation, income diversification, and migration are crucial for coping with income shocks (Munshi and Rosenzweig, 2016; Ito and Kurosaki, 2009; Rose, 2001).

The focus of this thesis is on climatic risk through fluctuations in rainfall levels and the ex-post risk coping mechanisms. By documenting the ways through which poor households cope with income shocks and smooth their consumption, one can draw powerful policy conclusions that help shield these households from destitution and vulnerability to further shocks. Firstly, I explore the role of autarkic consumption smoothing by asset liquidation as a self-insurance mechanism, in order to understand whether household risk-coping decisions affect their resilience to future contingencies. Secondly, I explore the role of labour allocation in hedging against fluctuations in rainfall - arguably the most important input in rural agriculture - and incorporate the role of social networks in shaping these decisions. Social connections in developing countries, especially in India, are crucial to many aspects of the economic and social well-being of households (Munshi, 2014). The importance of these networks in finding jobs, obtaining loans, and other forms of support is paramount. They are also a necessary institution in enhancing economic efficiency in the absence of formal/governmental institutions (Munshi, 2014). Such networks are very strong not only in insuring households within them but also in sanctioning households who do not commit to the "rules of social cooperation". When households are faced with a weather shock, it is natural for them to adjust their labour supply in order to insure against expected risk or cope with realized shocks. The rationale behind this is that households who switch between sectors (agricultural and non-agricultural) may not necessarily be seeking higher profits, but simply acting on their aversion to risk. Lastly, I look at the simultaneous decisions in production and portfolio adjustment as a risk coping strategy. These findings together form the basis of several policy implications, perhaps the most important of which is providing formal insurance schemes not only to allow households to insure against exogenous shocks, but also to accumulate productive assets, technology, and skills. As such, this thesis contributes to the literature by highlighting important issues in risk coping mechanisms and development economics. I also contribute to the empirical literature by using a very recent dataset collected by the Institute of Crop Research in the Semi-Arid Tropics (ICRISAT) from 2009 to 2015. To the best of my knowledge, this data has not been used in empirical studies in development economics to date. I also use the previous version of the ICRISAT dataset from 1976 to 1983 to revisit some of the findings in the previous literature and compare the results to the recent data. The ICRISAT carries out high-frequency data collection and uses survey instruments that provide valuable information on households' socio-economic status, transactions carried out by the household in a given month, ownership and utilization of assets, and an employment module that documents each member's activity on a monthly basis. These datasets are extremely rich and unrivalled in the quality and quantity of information they provide for the purpose of studying household risk and informal insurance strategies.

The Structure of the Thesis

It has been agreed that the alternative format of thesis submission, through a collation of papers as opposed to a traditional thesis format, is more suitable for this research for several reasons. The primary reason for using this format is that the third chapter of this thesis is co-authored with my supervisor Dr. Katsushi Imai and is published in *Agricultural Economics*[2]. As such, this paper has been included in its published format as the third, and final, chapter of the thesis. A second reason is that, although the different chapters fall under the same theme of risk-coping mechanisms, they differ in the questions I address. Therefore, the different parts of the thesis complement each other to provide a coherent and continuous thesis. In this section, I provide a brief synopsis of the different parts of my thesis.

In the first chapter, I use the monthly ICRISAT panel data from 2009 to 2012 and test whether households smooth their consumption in response to weather-driven income shocks in rural India. I find that the net balance of aggregate savings is almost perfectly responsive to income shocks. Consistent with a standard poverty trap model, my findings suggest that small and medium landholders hold on to their livestock and machinery and dis-save less productive consumer durables, whereas richer households draw from a variety of assets in face of shocks. The poor households' reliance on less productive assets as buffer stock means that their ability to generate future income is not structurally jeopardized. The results imply that households are able to self-insure even when institutions fail to provide formal insurance mechanisms and when markets operate inefficiently. According to a poverty trap model, households' self-insurance mechanism, through excessively drawing on their asset stock, may reduce their resilience to future shocks.

In the second chapter, I test the hypothesis that rural networks may shape households' decisions to adjust the share of their time allocation across a range

[2]The bibliography is inserted after each section of the thesis because Chapter 3 has been published with its own references.

of labour activities. Households who are part of a risk sharing network have been shown to be averse to migration as it may result in social sanctioning from the peer and information asymmetry due to the unobservable nature of migrants' income. Furthermore, the knowledge of having a safety net alters their attitudes towards risk in the labour market. I use a monthly panel data in rural India covering the period from 2010 to 2015, and applied a seemingly unrelated regression estimation to take into account the simultaneity in labour supply decisions. The results confirm that households who are part of the risk sharing network tend to decrease their labour share of migration and increase their labour supply in agricultural activities if they face a weather shock. I have also explored gender differences in households' labour market responses, and have found that male migration is responsive to income shocks and network participation, while female migration is not.

In the third chapter, we construct the cash and asset balances using detailed transaction data of households in rural India and generate monthly and seasonal ICRISAT panel data for the period 1976–1983. The empirical literature on household savings tends to treat savings simply as the residual of income minus consumption. We have found that households, irrespective of their landholding status, cope with temporary shocks adequately by using crop inventory, currency, and capital assets, rather than livestock, as buffer assets. The importance of portfolio adjustments in smoothing consumption is also confirmed by the use of a system of equations in which both portfolio and production decisions are made endogenous. We conclude that not only the level but also the diversification of household assets are important for buffering consumption. As an extension, we have explored the monthly ICRISAT panel data for the period 2009–2012 in the same villages and have found a similar pattern in household portfolio responses to income shocks.

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CHAPTER 1

Consumption Smoothing and Risk Coping Mechanisms: Evidence from Rural India

1.1 Introduction

Given the importance of agricultural income for rural households, erratic weather conditions pose an austere threat to these households' livelihoods. Households can easily manage risk in a situation where labour and credit markets work perfectly or an institutional structure exists to insure people rather than leaving them to rely on their own savings devices. In such a setting, households are able to diversify risk and have a generally wider access to formal insurance (Townsend, 1995; World Bank, 2013). Institutional failure is ubiquitous in developing countries, particularly in rural areas where credit and labour markets do not function perfectly. Thus, households need to find ways to insure themselves. When faced with income shocks, households who draw on their own savings or assets face a more serious problem: they undermine their ability to generate income in the future.

As a consequence of liquidating their productive asset stock, households are less resilient to future income shocks. This phenomenon is referred to as asset poverty. Carter and Barrett (2006) provide a theoretical explanation for the existence of an asset threshold, above which households can escape the poverty trap, and below which they are held in chronic poverty. This asset level was termed in the literature as the 'Micawber threshold' (Carter and Barrett, 2006; Lipton, 1993). Furthermore, the authors argue that asset poverty gives an insight into the mechanism whereby a household is stochastically (temporarily) poor or structurally (chronically) poor. In other words, drawing on the household's asset stock extensively may lead to severe destitution over time.

Carter and Lybbert (2012) show that, based on a certain threshold of productive assets, household behaviour bifurcates between the asset-poor households who smooth (or preserve) their assets and forgo current consumption, and richer households who liquidate their assets to smooth their consumption. Carter and Lybbert's findings are based on a period of severe drought (one of the worst in recent history) which is likely to have generated a total paralysis of commodity, labour, and credit markets. At times of such severe weather conditions, households with fewer livestock are likely to have lost much of their assets, making it even more difficult for them to cope with a shock. In addition, returns to assets could be low or sometimes negative during such common shocks (Dercon, 2002).

In this paper, we analyse rural households' exposure to rainfall shocks. As these shocks have a less devastating effect than severe natural disasters, households could still smooth their consumption but not necessarily at the expense of their productive asset stock. In the first instance, households would try to liquidate their less productive assets. As such, this paper provides an alternative explanation for the poverty trap framework of Barrett et al. (2011) where households smooth their productive assets and liquidate less productive ones to buffer income shocks.

This paper aims to identify the transmission channels through which households smooth their consumption, and by doing so we investigate whether these households smooth their productive assets. We use a monthly panel dataset from the semi-arid tropics of India between July 2009 and June 2012 to assess the extent of consumption smoothing and analyse the role played by a portfolio of productive and less-productive assets as buffer stocks in the face of income shocks. Following the footsteps of Paxson (1992), Townsend (1995) and Carter and Lybbert (2012), our study contributes to this strand of the literature in several ways. Perhaps the strongest contribution of this paper is the use of a new and rich household dataset from a rural region in India characterised by agro-climatic risk. This data allows us to revisit empirical questions in the literature and build on newly developed theoretical models. Methodologically, we adopt the Fixed Effects Vector Decomposition technique in order to analyse variables that are time-invariant, particularly because of our use of monthly data. We also provide evidence in support of the poverty trap model proposed by Carter and Barrett (2006). In particular, households do not liquidate their productive assets, such as livestock or machinery, when faced by an exogenous shock, but they rely on the liquidation of less productive assets, such as consumer durables. The households' behavioural responses are found to vary across different landholding classes. While we observe the co-existence of consumption smoothing and asset smoothing for the sample households, our results provide an alternative explanation for household risk-coping behaviour.

The structure of this paper is as follows. Section 1.2 reviews the literature in this research area. Section 1.3 discusses the ICRISAT dataset in detail. The methodology adopted in our analysis is discussed in Section 1.5. Section 1.6 analyses whether household consumption is smoothed, and investigates autarkic consumption smoothing through the response of a portfolio of assets to income shocks. The final section concludes.

1.2 Literature Review

1.2.1 Risk Coping

Poor households typically live in an environment characterised by inherent risks, institutional failures, and credit and labour market imperfections. Upon the occurrence of an exogenous shock that leads to a reduction of income, households need to self-insure via intertemporal transfers (building up asset stocks in good times, and liquidating them during rough periods), formal insurance (actuarial, credit, etc.), or informal insurance (within their communities). By drawing on their asset stock, households face the risk of falling into 'structural poverty' (Carter and Barrett, 2006; Radeny et al., 2012). Households generally have an incentive to avoid using their asset stock to ensure an adequate income stream in the future. However, when a shock occurs in the presence of liquidity and credit constraints, they may not have other options. Dercon (2002) offers a detailed analysis of the ways through which households manage risk at times of income volatility. He differentiates between two types of risk: idiosyncratic (household specific) and common (community wide). In practice, it is rarely feasible to distinguish between the two types of shocks because an idiosyncratic shock can turn into a common shock (e.g. by contagion, drop in demand, or other mechanisms), or vice versa (Dercon, 2002). However, the shocks that result from these risk factors affect households differently depending on their asset holding, type of work that they carry out, and their access to risk sharing and risk coping arrangements. In our empirical model, we attempt to capture the idiosyncrasy of common shocks by including various household specific characteristics (e.g. land areas by slope and soil types).

Dercon (2002) identifies two main strategies for how households can deal with risk. Before the shock occurs, risk management measures could be adopted. These include income smoothing, diversification of income sources, and adjustments in household labour supply. After the shock occurs, however, households cope with risk by liquidating the assets which have been accumulated in good times, or share the risk within the community. Strategies adopted before the occurrence of the shock, like income diversification, have several disadvantages. Theoretically, if income sources are not correlated (i.e. the return from one activity is not correlated with the return from the other), diversifying income sources would be ideal as that would decrease the variance of the income portfolio without altering the mean income (Dercon, 2002). However, this is rarely the case, rendering income diversification a very costly activity because the average income could decrease. Furthermore, income diversification is not very effective when certain activities have seasonal cycles (e.g. particular crops may only be planted and harvested in one season). When returns of different activities are correlated, the income diversification may make the households eventually more susceptible to exogenous shocks. This implies that the attempts to diversify income may not be sufficient measures to cope with shocks. Although the use of assets for risk-coping could be an option in times of distress, during an episode of common shocks, asset returns could be very low or even negative. Thus, selling assets may not be possible when everybody tries to sell the assets at the same time, driving the asset prices down (Dercon, 2002).

1.2.2 Consumption Smoothing and Self-insurance

Paxson (1992), in her seminal work, investigates the saving and dissaving behaviour among Thai farmers to understand their risk-coping behaviour. She decomposes income into the three components: Permanent, Transitory, and Unexplained. Permanent income is defined as the "expected income [...] conditional on the resources (and information) of the households at the beginning of the period" (Paxson, 1992, p.16), while transitory income is the difference between realised and expected income. Paxson uses a short-term horizon to estimate permanent income as opposed to a life-cycle model that defines permanent income as a function of the stock of life-time wealth. Empirically, Paxson estimates permanent income as a function of households' characteristics, such as age, sex, education, and the amount of land owned. She identifies the transitory income component by using rainfall as an exogenous instrument. Based on this method of decomposition, the study finds that households shield their consumption from shocks using savings: they save during positive shocks and dissave in response to negative ones. Kurosaki (2006) uses data from the North-West Pakistan and finds that households do not smooth their income sufficiently and notes the importance of land ownership and remittances in coping with shocks. Disaggregating the same dataset into rich and poor households, Lee and Sawada (2010) find that households constrained by credit and liquidity have a higher incentive for precautionary savings, while richer households that are less credit-constrained have a lower tendency to be engaged in this type of savings. This highlights the essential role that precautionary savings play in the context of developing countries.

According to Paxson (1992), savings are defined as 'Income minus Consumption', a form of 'net balance'. In other words, a negative balance of savings implies that households "used" other sources to offset a negative income shock. Although the investigation of aggregate savings behaviour provides some insight into household responses to shocks, little can be explained by this approach on *how* households manage to smooth consumption using various household assets.

Using the data from Burkina Faso collected during severe droughts in the early 1980s, Fafchamps et al. (1998) analyse the mechanisms through which households smooth their consumption and examine the role of assets, such as livestock, as a form of buffer stock. They argue that livestock serves not only as a physical asset and a form of insurance, but also as a prestige asset. Consequently, households would not easily let go of their livestock even during periods of hardship. The authors find compelling evidence that households do not use livestock as a buffer even during severe drought periods, but other household assets, such as grain-stocks, cash holdings, consumer durables, and other valuables, serve as more prominent means for self-insurance. Kazianga and Udry (2006) use the same dataset to explain what could be an alternative mechanism whereby households cope with risk. They find the results of Fafchamps et al. (1998) intriguing because the size of livestock holdings at the end of the survey period was large enough to insure against these shocks, should households have sold them. Their findings suggest that households' consumption fluctuates with income, indicating that consumption smoothing is not achieved. Kazianga and Udry (2006) argue that, when households are liquidity-constrained, households prefer to forgo consumption to save more according to the permanent income hypothesis (Carroll, 1997). This could explain the findings of Fafchamps et al. (1998). Furthermore, they convey that households deliberately interrupt their consumption to preserve their assets.

Carter and Lybbert (2012, p. 263) revisit this puzzling finding and ask: "If households are not smoothing their consumption, then what are they doing?". They find that above an estimated threshold of livestock holding, households smooth their consumption; while below that threshold households smooth their assets and consequently forgo consumption. They find that there exists a bifurcation in behavioural regimes (consumption versus assets smoothing) based on a livestock-holding threshold. The authors adopt a poverty trap framework positing the existence of two steady state equilibria (Barrett et al. (2011); Carter and Barrett (2006)). Households with an initial asset holding below the estimated threshold converge to the low level equilibrium and stick to a small-scale and low return activity, and those above that threshold eventually switch to a higher level of technology and move to the high level equilibrium.

The research on the role of assets in smoothing consumption of households in rural India has been inconclusive. Using the ICRISAT data from India from 1975 to 1984, Rosenzweig and Wolpin (1993) show that livestock sales and purchases are proportionate to household income. Using the same data, Lim and Townsend (1998) find that livestock does not serve as a buffer stock while grain stocks do, which is consistent with Fafchamps et al. (1998). They show that livestock and capital assets are not used as buffer stocks, whereas currency and crop inventory play a major role in offsetting income shocks, and that credit and insurance markets are not completely absent.

1.2.3 Theoretical Foundations of Asset Smoothing

The intertemporal choice model of Deaton (1991) is the theoretical foundation of credit-constrained household behaviour facing a risky stochastic income. Deaton's impatient agent only has an incentive to save for precautionary motives. The implication of Deaton's result is that households will smooth consumptions intertemporally using the assets they accumulate in a way that marginal utility of current consumption is equal to the discounted expected utility of future consumption.

Barrett et al. (2011) adopt a similar model to Deaton's but they do not treat assets as mere buffer stocks. They rather (implicitly) recognize the productive potential of assets. Their poverty trap model is given as such:

$$max_{c,L} E_0\{\sum_{t=0}^{\infty}(\frac{1}{1+\delta})^t u(c_t)\}$$

$$subjectto$$

$$x_t(L,\theta) \equiv F(L_t) + (1-\tau)\theta_t L_t$$

$$F(L_t) = max[F^h(L_t), F^l(L_t)]$$

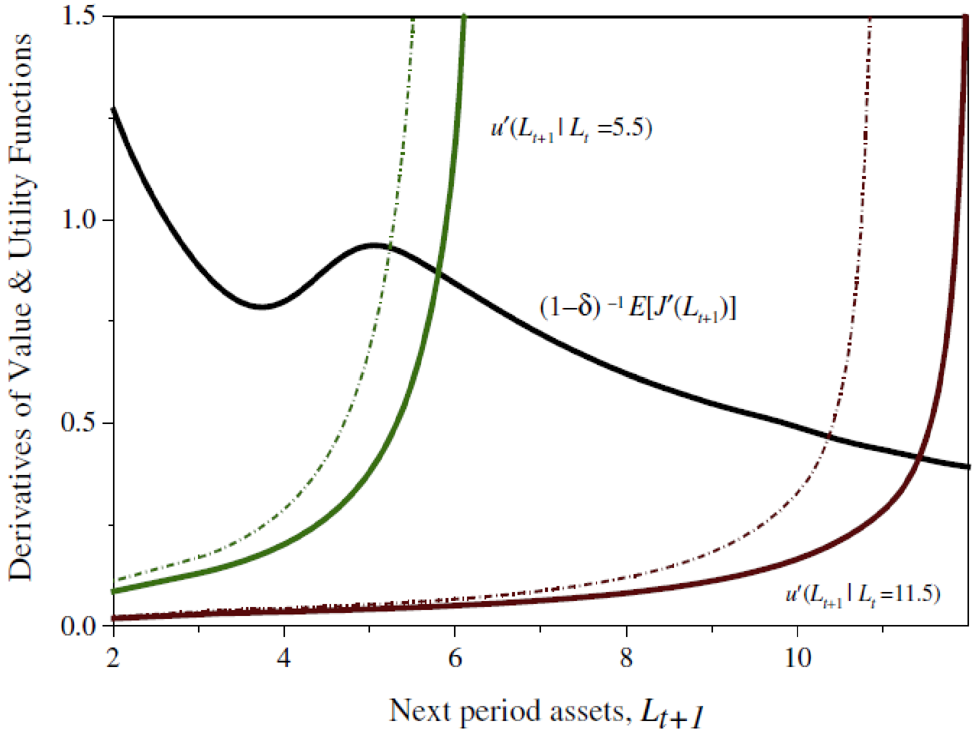
$$c_t \leq x_t$$

$$L_{t+1} = x_t - c_t$$

$$L_t \geq 0 \forall t$$

where c is consumption, x is the cash-on-hand (or income), L is a productive asset stock with diminishing returns (as opposed to being buffer stocks in Deaton

(1991)) and the superscripts h and l denote high and low technologies, and τ is the rate of return. The model maximizes discounted utility subject to a budget constraint determined by L and the random factor θ (the first constraint). The second constraint takes into account different productivity levels of assets - high and low technologies- where the high technology is less preferred until a minimum level of capital (L*) because of the sunk costs associated with it. The third constraint limits the consumption level to less than or equal to cash-on-hand (no borrowing), and the fourth constraint illustrates that the household carries over the difference between cash-on-hand and consumption to the next period. The reason L_t cannot be negative is because the household cannot be in debt under the credit constraint assumption. The two equilibria of this poverty trap model imply that the marginal return of asset does not follow a continuous monotone path, but rather has a break-point where the choice of technology (and thus the returns) change as shown in Figure 1.1.



Note: The red line shows this period's marginal utility of consumption for an individual who begins with 11.5 units of assets. The green line shows that of an individual who begins with 5.5 units of assets. The solid black line represents the marginal value function. The dashed lines represent the marginal utility after a shock reduced income (or cash on hand) by 8%.

Figure 1.1: Consumption versus Asset Smoothing Regimes.
Source: Carter and Lybbert (2012)

The dynamic programming output of Carter and Lybbert's Bellman function based on the theoretical model above suggests that households with lower asset level (reflected with a lower conditional L_t in Figure 1.1) would liquidate proportionately less assets. For instance, in Figure 1.1, the households with lower initial asset holding would respond to an 8% income shock with less sale of assets (around 5%) as opposed to those with higher initial holding who respond with around 10 % reduction in assets. This phenomenon is referred to in the literature as asset smoothing. Contrary the prior empirical literature on buffer assets and consumption smoothing, the model does not explore whether poorer households are necessarily forgoing consumption. Although households in their empirical analysis did not smooth their consumption (Carter and Lybbert, 2012; Kazianga and Udry, 2006, and others), the period studied involved a severe drought and sour living conditions whereby households could not have marketed their assets adequately (Verpoorten, 2009). In this paper, we explore a period of moderate income shocks and investigate how households manage to achieve both consumption smoothing and (productive) asset smoothing. In other words, households have the option to market their assets as different households are affected by shocks to different extents but preserve their productive assets nevertheless. Therefore, we test the implication of Barrett et al.'s model that at times of shock, the household resort to liquidating the less productive assets if they have the option to. We also look at portfolio responses across different landholding classes to see whether a bifurcation in behavioural responses occur for households with different wealth levels.

Table 1.1: States, districts, villages, and households in ICRISAT dataset 2009-2012.

State	District	Village	No. of Households
Andhra Pradesh	Mahbubnagar	Aurepalle	70
		Dokur	50
	Prakasam	J.C. Agraharam	40
		Pamidipadu	40
Maharashtra	Akola	Kanzara	62
		Kinkhed	52
	Solapur	Kalman	61
		Shirapur	89
Karnataka	Bijapur	Kapanimbargi	40
		Markabbinahalli	40
	Tumkur	Belladamadugu	40
		Tharati	40
Gujarat	Junagadh	Karamdichingariya	40
		Makhiyala	40
	Panch Mahal	Babrol	40
		Chatha	40
Madhya Pradesh	Raisen	Papda	40
		Rampura Kalan	40
		Total	864

1.3 Data

1.3.1 Data Description

We contribute to the empirical literature on consumption smoothing and risk-coping by constructing a monthly panel dataset using household survey data from July 2009 to June 2012 collected by ICRISAT in India. The dataset covers 18 villages in 9 districts, spanning across 5 Indian states as shown in Table 1.1. Figure 1.2 represents the geographical distribution of sample districts in India. In each village there are between 40-90 respondent households chosen at random from a village census listing. The households in each village are stratified based on their landholding classes: landless, small, medium, and large landholding. After dropping a few households with missing observations, we have obtained a balanced panel dataset for 755 households over 34 waves. In this study, the data in August and September 2009 have been dropped for data comparability issues.[1]

[1]The data for these two months includes a lot of missing values and seemingly incorrect observations.

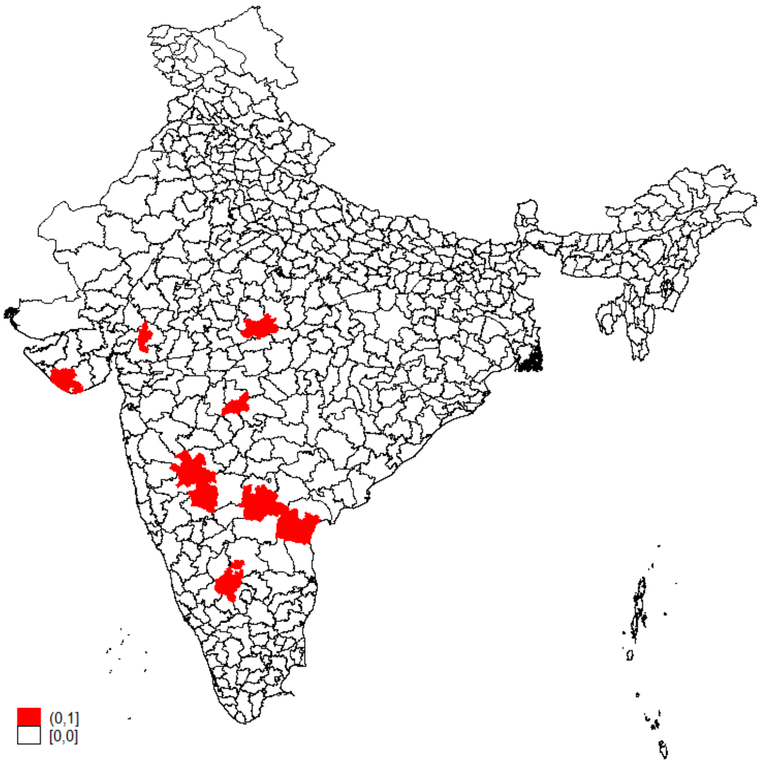


Figure 1.2: Geographical representation of the districts in Table 1.1.

Monthly rainfall data are obtained from the Indian Meteorological Department and are matched to the household data at the district level.

1.3.2 Main Variables Construction and Definition

Income

The employment module of the ICRISAT survey has information on most income-generating activities of the individuals who have completed 6 years of age. It includes the data on types of labour participation (farm vs. non-farm activities), place and location of work, days of work and working-hours per day. It records cash and kind income, as well as unemployment days. Another module that is crucial for the computation of income is the transaction module. This module includes detailed information of all the transactions made within the previous month. From the transaction module, we obtain the data on benefits from government programs, rents on capital, pensions, interest, and remittances. Based on this information, household income is calculated as the sum of farm income, non-farm income, benefits, pensions and interest, and remittances.

Consumption

Table 1.2 describes how we construct the household aggregate consumption by closely following the Indian National Sample Survey's guidelines (NSS Documentation, 2011, Schedule 10, Part 9)[2]. Consumption includes food and non-food expenditure. As some of the non-food expenditure items are infrequent expenses, we take their monthly average (that is, the annual total divided by 12). These infrequent items include: clothing, education, medical expenses and short-life household durables. Although the NSS documentation makes a distinction between institutional (e.g. hospital admission) and non-institutional (e.g. a doctor's visit) medical expenses, such information is not available in the ICRISAT survey. Therefore, we classify all the medical expenditure under the same category; we sum all the medical expenses over the year and divide them by 12. We separate the non-food expenditures into two categories: the expenditure recorded on a monthly basis and the monthly expenditure equivalent based on the annual aggregate of several lump-sum expenditures divided by 12. We treat long-life consumer durables - such as jewellery, bicycles, and refrigerators - as savings and we exclude them from our consumption measure.

[2]The NSS documentation explains which survey questions should be used to derive the monthly variables or the annual variables.

Table 1.2: Construction of Consumption Variable

Food Expenditure	Cereals, pulses, oils, vegetables, milk and dairy products, spices, meat, fish, eggs, bread and others
Non-Food Expenditure	**Monthly total of:** Toddy and Alcohol, Entertainment Marriage and ceremonies expenses (excluding dowry) Cell and land line phone bills, Rent on house Cigarettes, pan, ganja, Cosmetics Electricity and water charges Charcoal, LPG, firewood, kerosene and dung cakes Taxes on house, land, and vehicle Travel, petrol, diesel, vehicle maintenance and repairs
	Monthly average of the annual total of: Clothes, shoes, and socks etc. Medical Expenses: Institutional and Non-Institutional Education (fees, books, stationary, transport, uniform) Household articles and small durables ($<$ 2 years of life)

Saving or Net Balance

In this study, we refer to the aggregate savings measure of Paxson (1992) as a 'net balance' of 'income *minus* consumption'. Consumption does not include expenditure on long-life consumer durables, hence allowing the net balance to capture these assets as savings. If consumption is greater than income, the 'net balance' measure will be negative and *vice versa* (Paxson, 1992).

Livestock

Central to our analysis is the livestock module of the ICRISAT survey which collects data on 1) maintenance of livestock including total expenditure on fodder, labour costs, grazing shares and values, 2) the change in livestock, including sale and purchase of livestock, and 3) production and output from livestock. We are interested in the net sales of livestock as this could be an indication as to whether households are using livestock as a buffer stock when shocks occur. We construct a "net livestock sales" measure, which is the value in Indian Rupees of the difference between the sale and purchase of livestock for every survey month. In our empirical analysis, we group households into different landholding classes in order to account for the fact that initially richer households are able to sell more livestock or other assets.

Other Capital Assets

The transaction module also collects data on the sale and purchase of capital assets. Items included in this category are: land, house, machinery and farm implements, consumer durables, and others. The two main categories reported in this section of the survey are machinery, farm implements and consumer durables, with very few households reporting transactions of other asset categories. We calculate the net sale of machinery, farm implements and consumer durables as the sale revenue minus the purchase cost for every survey month. The variable "capital assets" is calculated as the sum of net sales of consumer durables and net sales of machinery and farm implements together.

Although the literature has paid ample attention to the use of grainstocks as buffer-stocks, the ICRISAT dataset does not include a monthly crop production schedule (which is a flow measure), and only has a seasonal module for cultivation. The general endowment module of the survey includes a crop inventory which is recorded on an annual basis, making it a stock measure. Therefore, it is not possible to use the monthly change in grainstocks in our analysis.

Demographic Variables

In our analysis, we use two sets of household demographic variables. One comprises "sex/age/education" categories and another is the "life-cycle variables". The "sex/age/ education" categories include a set of count variables of an exhaustive combination of sex, age and education. Examples of the "sex/age/education categories" are: the number of female household members aged between 0 and 5, or the number of female household members aged between 18 and 64 who have only finished primary education; the number of male household members aged between 18 and 64 who have completed their intermediate education; etc. We construct these categories for both men and women across five different age groupings: 0 to 5, 6 to 11, 12 to 17, 18 to 64, and above 65. Individuals aged between 18 and 64 are further divided into 5 educational categories: primary school, middle school, high school, intermediate education, and higher education. The "life-cycle variables" categories include only age characteristics of the household composition; that is, the number of household members aged less than 5, between 6 and 11, 12 and 17, 18 and 64, and above 65.

Rainfall

We match rainfall information from the Indian Meteorological Department to the household survey at the district level. We use two different measures of rainfall in our analysis. First, we define a variable that we call 'rainfall deviation' (r_t), which is the difference between the current month's rainfall and the normal long-run average of rainfall, or its historical average, for that particular month. Second, we construct a variable of three months lagged rainfall deviation (R_{dL}), or the sum of the rainfall deviations of the past three months. For example, with current rainfall deviation (denoted r_t), the three months lagged deviation (R_{dL}) would be $r_{t-1}+r_{t-2}+r_{t-3}$. We interact R_{dL} with a vector of land areas categorised by slope and soil characteristics. This vector includes areas of lands with levelled, slight, medium and steep slopes, and areas of lands with loam, clay, clay-loam, and problematic soil types[3]. Including the interaction of the land characteristics with R_{dL} allows us to capture the household specific response to the rainfall deviation in the previous three month period.

[3]These are categories defined by the ICRISAT survey.

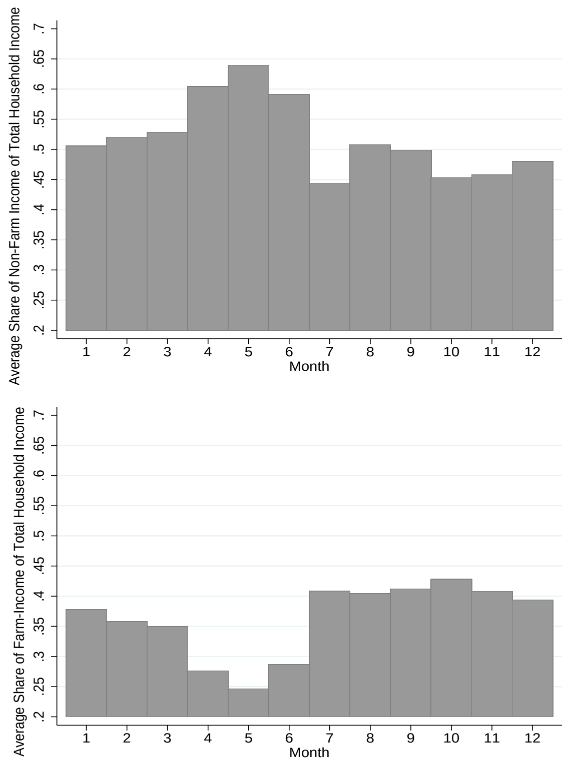


Figure 1.3: Histograms of the shares of income (farm and non-farm) across calendar months

1.3.3 Descriptive Statistics

Figure 1.3 illustrates the distribution of income sources across months. The figure shows that household income sources follow a seasonal path. Between the months of July and December, the share of household income from farming activities increases but decreases over the the rest of the calendar months. The opposite trend is observed for non-farm income which is the dominant income source. However, household total income also fluctuates across different months, as shown in Figure 1.4, and the returns to agricultural activities may be significantly lower relative to the amount of labour spent in agriculture. Therefore, this distribution shows that seasonality in income is important and that deviations in rainfall and weather conditions are crucial for explaining variation in household incomes.

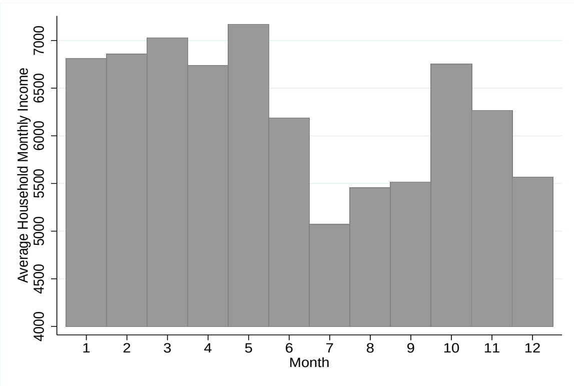


Figure 1.4: Monthly income distribution

The rainfall conditions are very volatile with a very large variance (see Table 1.3). In addition, income and consumption have a large standard deviation relative to their means suggesting a large monthly variation in both measures. It is worth noting that the low standard deviation of food consumption is consistent with consumption smoothing behaviour. In fact, in order to compare the variation of food consumption and income, the coefficient of variation (CV)[4] is calculated. While the CV of income is around 155%[5], the CV of food consumption is only around 52%. This is indicative evidence of consumption smoothing, but further analysis is needed to investigate how households achieve it. Other household characteristics include demographic information, income, consumption, net balance, and assets (summary statistics are reported in Table 1.3).

[4] Defined as $(Std.Dev./Mean) * 100$.

[5] CVs greater than 100% were reported in the 1975-1985 ICRISAT data for India (Rosenzweig and Binswanger, 1993).

Table 1.3: Summary Statistics

Variable	Mean	Std. Dev.	Std. Dev. (Within HH)	Min	Max	Obs. No.	No. of HH
Number of Household Members Aged:							
Less than 5	0.42	0.77	0.29	0	7	29272	883
Between 6 and 11	0.54	0.85	0.32	0	6	29272	883
Between 12 and 17	0.59	0.86	0.30	0	5	29272	883
Between 18 and 64	3.12	1.53	0.43	0	11	29272	883
More than 65	0.49	0.85	0.48	0	13	29272	883
Other Demographic Characteristics							
Age of Household Head	48.55	12.49	2.19	16	87	29260	883
Household Size	5.17	2.34	0.53	1	24	29272	883
Income Characteristics:							
Income	6307.16	9632.85	7018.89	0	463041	28995	883
Farm Income	1472.14	2460.90	1764.06	0	45280	28995	883
Non-Farm Income	3926.58	7315.74	4572.30	0	330000	28995	883
Share of Farm Income	0.36	0.41	0.25	0	1	24695	859
Share of Non-Farm Income	0.52	0.42	0.26	0	1	24695	859
Consumption Characteristics:							
Total Consumption	6222.17	14775.02	13968.36	0	1227882	29273	883
Food Consumption	3034.89	1591.60	892.24	0	19235.4	29266	883
Non-Food Consumption	2293.37	13971.83	13565.77	0	1219790	29224	883
Share of Food Consumption	0.60	0.15	0.11	0.003	1	29219	883
Share of Non-Food Consumption	0.29	0.13	0.10	0	0.99	29223	883
Consumption Characteristics:							
Net Balance (or Saving)	113.09	15448.96	6349.37	-1218382	439032.5	29336	884
Net Sale of:							
a) Livestock	824.18	7041.20	6758.92	-110000	335000	18435	649
b) Consumer Durables	-1449.16	11330.35	10576.67	-420000	140000	4153	691
c) Machinery and Farm Implements	-3218.40	37785.14	34061.15	-750000	630000	4153	691
Capital Assets (b)+(c)	-4667.55	39327.96	35562.61	-750000	630000	4153	691
Rainfall:							
Rainfall Deviation	2.13	68.02		-172.8	701.6	29272	
Three Month Lagged Rainfall Deviation	10.82	145.22		-360.1	899.9	29272	

Data Limitations

This dataset has several limitations that limit the scope of the analysis. As previously mentioned, one of the most important buffer stock saving that households could use to smooth their consumption - grain stocks - lacks the data at the monthly level. This makes it impossible to analyse the sale, purchase, and own consumption of this asset at times of shocks. Furthermore, while information on self-reported shocks is available these are only available at the annual level. Therefore, any analysis of the idiosyncratic shocks facing the household (e.g. health shocks, death of an earning member, theft, etc.) cannot be explicitly modeled. We use the residual of the transitory shock as a proxy for these shocks, which will be further elaborated in the next sections. The lack of information on monthly grain stocks is particularly a drawback in the analysis of shocks of landless households who are less affected by weather shocks as it makes it impossible to evaluate the effect of such shocks on a vulnerable group in the sample. While the conclusions drawn in this paper are informative of the risk coping mechanisms of landholders (small, medium, and large), the inferences made cannot be generalized to those who are landless. More explicitly, the coping mechanisms adopted by landless households may be considerably different to those who possess land.

1.4 Empirical Strategy

This section draws upon the empirical footsteps of Paxson (1992); Fafchamps et al. (1998); Kazianga and Udry (2006), and Carter and Lybbert (2012) and adapt them to our data and methodology. We take a more general approach to income decomposition by using total household income, while most previous studies have focused on crop income solely (except a few e.g. Paxson (1992)).

While most other studies have used annual datasets and used seasonal rainfall variations, we use current monthly rainfall deviation and sum of lagged rainfall deviations of the previous three months (as discussed in Section 1.5.2), both of which are moving variables as opposed to seasonal deviations matched to monthly data. The model that we estimate is:

$$Y_{hdt} = \lambda_0 + \boldsymbol{X^P_{hdt}}\boldsymbol{\lambda_1} + R_{dL}\boldsymbol{L_{hdt}}\boldsymbol{\lambda_2} + \lambda_3 r_{dt} + \boldsymbol{\mu_{dt}} + \varepsilon_{hdt} \tag{1.1}$$

where Y_{hdt} is the total income of household h in district d at time t, $\boldsymbol{L_{hdt}}$ is a vector of land areas by soil and slope types, $\boldsymbol{X^P_{hdt}}$ is a vector of household characteristics that predict the household's permanent income component, namely the "sex/age/education" variables. For rainfall, we take two measures, both of which are moving measures: r_{dt} represents the deviation of rainfall from its long-run average for month t, and R_{dL} is the sum of deviations of months $t-1$, $t-2$, and $t-3$ for district d. We interact the latter with the vector $\boldsymbol{L_{hdt}}$ to obtain the household specific effects of the lagged rainfall deviation (Carter and Lybbert, 2012). The model is estimated using pooled OLS, but district-time fixed effects $\boldsymbol{\mu_{dt}}$ are included. Based on the estimates of Equation (1.1), we decompose income as follows:

$$\begin{aligned}
&\text{Permanent:} && \hat{Y}^P = \hat{\lambda}_0 + \boldsymbol{X^P_{hdt}}\boldsymbol{\hat{\lambda}_1} \\
&\text{Transitory:} && \hat{Y}^T = R_{dL}\boldsymbol{L_{hdt}}\boldsymbol{\hat{\lambda}_2} + \hat{\lambda}_3 r_{dt} + \boldsymbol{\hat{\mu}_{dt}} \\
&\text{Unexplained:} && \hat{Y}^U = \hat{\varepsilon}_{hdt}
\end{aligned}$$

The permanent income includes the variables that capture the permanent income-generating characteristics; such as the demographic composition of the household, information on gender, education and age. To estimate transitory income, we use the rainfall variables and their interactions with land areas, as well as the district-time dummies, which would capture regional and weather related circumstances affecting transitory income. The residual of these two components ($\hat{Y}^P$ and $\hat{Y}^T$) out of actual income (Y_{hdt}) forms the unexplained income ($\hat{Y}^U$).

After decomposing income into its components, we assess the response of net balance to shocks to observe whether consumption is being smoothed or not. As described in Section 1.3.2, this net balance is what is referred to in the literature as savings. We treat long-life consumer durables as savings by excluding them from the consumption measure (Paxson, 1992). We use the predictions of income components, $\hat{Y}^P$, $\hat{Y}^T$, and $\hat{Y}^U$ for estimating the savings (or net balance) model. Because transitory income involves an interaction term between lagged rainfall and land areas, landless households are excluded from any further analysis. This is due to the fact that, transitory income component for landless households does not have much variation, given that our district-level rainfall variable takes the same value within a district. This is an obvious limitation of our analysis as we may be excluding the most vulnerable group of the distribution. The net balance model is specified as:

$$NetBalance_{hdt} = \beta_1 \hat{Y}^P_{hdt} + \beta_2 \hat{Y}^T_{hdt} + \beta_3 \hat{Y}^U_{hdt} + \boldsymbol{\beta_4 Z_{hdt}} + \beta_5 V_d + \epsilon_{hdt} \tag{1.2}$$

where $\boldsymbol{Z_{hdt}}$ is a vector of life-cycle variables and V_d proxies the variability in income as measured by the standard deviation of district level rainfall. β_2 is the propensity to save out of transitory income; if β_2 is equal to 1 then households are saving (dissaving) all positive (negative) transitory shocks. This result would suggest that households smooth their consumption. This is because we allow the net balance to be negative in order to understand whether consumption is being smoothed when income shocks occur (*i.e.* consumption is greater than income).

Carter and Lybbert (2012) suggest that unexplained income includes some unobserved transitory effects, such as health shocks or labour market conditions. To analyse whether this is the case in our context, we have summed transitory and unexplained income components to create a variable called "shocks", and we have repeated the same regressions.

After investigating the degree to which households smooth their consumption, we turn to the responses in asset sales to income shocks. In this analysis, the aim is to observe whether households liquidate their assets in response to income shocks, and if so which kinds of assets do they mainly rely on. The empirical model to test this is as follows:

$$NetAssetSales_{hdt} = \beta_1 \hat{Y}^P_{hdt} + \beta_2 \hat{Y}^T_{hdt} + \beta_3 \hat{Y}^U_{hdt} + \boldsymbol{\beta_4 Z_{hdt}} + \epsilon_{hdt} \tag{1.3}$$

where $\hat{Y}^P_{hdt}$,$\hat{Y}^T_{hdt}$, and $\hat{Y}^U_{hdt}$ are the estimated permanent, transitory and unexplained components respectively, and $\boldsymbol{Z_{hdt}}$ is a vector of life-cycle variables, as specified in Equation (1.2). We focus on a portfolio of assets which includes both productive and non-productive assets. Productive assets consist of livestocks and machinery, the latter includes farm implements. Although non-productive assets must ideally include consumer durables as well as grain stocks (Lim and Townsend, 1998), we restrict our analysis to consumer durables to represent non-productive assets due to the data limitations on grain stocks as we discussed in Section 3. We also combine $\hat{Y}^T_{hdt}$ and $\hat{Y}^U_{hdt}$ into "Shocks" as we have previously discussed.

The coefficients of Equation (1.3) must be interpreted carefully. Intuitively, the coefficients β_2 and β_3 must be negative (unlike the saving behaviour) because Net Sales must be negatively related to shocks. This means that positive income shocks lead to negative net asset sales (a purchase) and negative shocks lead to net positive asset sales (liquidation). Economic theory does not provide a clear-cut explanation of the magnitude of β_2, but a coefficient close to -1 is reasonable because a shock of, say, -100 Rupees could be offset by the sale of 100 Rupees worth of assets.

1.5 Methodology

In our estimations of the response of savings and assets to income shocks, several methodological issues have to be addressed. The key issues of concern are: the choice of estimation technique and the use of rainfall as an instrument for transitory income.

1.5.1 Estimation Technique

Panel Data Methods

To account for household-specific, time-invariant unobservable characteristics affecting the income and asset responses, we apply panel data methods in our estimations. We first employ pooled ordinary least squares (OLS) estimation in our savings and asset response equations. However, pooled OLS is likely to produce biased estimates because it does not control for the unobserved time-invariant households characteristics and the correlation of the error term over time. For this reason, we use a fixed effects (FE) model and a random effects (RE) model. After performing the Hausman specification test, we reject the hypothesis that the household-level effects are uncorrelated with the covariates we control for. We therefore choose the FE model. However, because the household composition may affect the decision to save, dissave, purchase assets or sell them, we have also included them in our estimation regression. The FE model is known to address the endogeneity of unit effects (or household fixed effects in this case) by swiping them away through differencing these variables from their household means.

But the FE model is inefficient for estimating parameters of variables with little longitudinal variation (Plümper and Troeger, 2007). Since our dataset is at the monthly level, and the household demographic variables are rarely changing, we use a more efficient estimator - the Fixed Effects Vector Decomposition.

Fixed Effects Vector Decomposition

The fixed effects model does not allow for the estimation of time-invariant variables which are swiped away. Due to its inefficiency in estimating the effect of variables that are rarely changing, Plümper and Troeger (2007) propose a method that allows us to efficiently estimate the parameters of these variables. This method is particularly useful in our study as we rely on household demographics such as the “sex/age/education” categories which rarely change in a monthly panel dataset. In cases where variables have little longitudinal variance, a three-step procedure called “fixed effect vector decomposition” (FE-VD), proposed by Plümper and Troeger (2007), provides a better and more efficient estimator than the fixed effects method. To briefly illustrate the application, suppose we have a panel dataset and an empirical model of the following form:

$$Y_{it} = \beta \boldsymbol{X_{it}} + u_i + \epsilon_{it} \tag{1.4}$$

where Y is the outcome variable, and $\mathbf{X}$ is a vector containing some time-variant variables and others that are time-invariant (or rarely changing), u_i is the unit effect and ϵ_{it} is the i.i.d. error term. The way this method would be applied is:

1. Baseline Model: Fixed Effects (FE) of Y on the covariates ($\mathbf{X}$).

2. Predict the fixed effect $\hat{u}_i$ of the FE model and regress it on the time-invariant covariates. This estimation is done at the i level.

3. Predict the residual ($\hat{r}$) of the OLS regression in step 2 and run the full model using OLS of Y on $\mathbf{X}$ and $\hat{r}$.[6]

In essence, this technique decomposes the fixed effect into an explained component and an unexplained one ($\hat{r}$). Including the unexplained component in an OLS regression of the baseline model allows for the computation of correct standard errors and produces more reliable estimates in a panel data with unit effects than any other estimator. The invariance condition proposed by the Plümper and Troeger (2007) implies that the *between* variation in the rarely-changing variables must be greater than the *within* variation. In a symposium on this methodology, Greene (2011) argues that the efficiency gains from using this methodology are illusory and that the estimator is similar to the least square dummy variable estimation. Breusch et al. (2011) also express concerns that the FE-VD method reproduces the fixed effects estimates with time varying variables, but the standard errors are underestimated. In response to these criticisms, Plümper and Troeger (2011) defend the properties and reliability of the FE-VD method and show that the claims presented by Greene (2011) and Breusch et al. (2011) "are either wrong or obsolete" (Plümper and Troeger, 2011, p.147). Breusch et al. (2011) have shed light on some inefficiencies based on an assumption of perfect instrumental validity in their data-generating process where instruments should be uncorrelated with the unit effects. However, Plümper and Troeger claim that the correlation between chosen instruments and unit effects are unobserved for the researchers. Plümper and Troeger have convincingly argued that FE-VD performs much better than any other estimator for applied empirical work under the conditions of time-invariance hereby specified. For this reason, we have used FE-VD as our preferred estimation technique in our analysis.

[6] In order to deal with heteroscedasticity or serial correlation, robust standard errors must be used in the first and third stages of this method.

1.5.2 Rainfall as an instrument for transitory income

The choice of an appropriate instrument to predict changes in income has been subject to much debate in empirical studies. Studies by Carter and Lybbert (2012), Munshi (2003), Newhouse (2005) and Paxson (1992) have reinforced the validity of the use of rainfall as an exogenous determinant of transitory income (or sometimes referred to as transient income). Based on this strand of the literature, rainfall appears to be the most appropriate instrument for the prediction of income in rural settings. This is because rainfall 1) is externally and exogenously determined by nature (Tanboon, 2005), 2) is correlated with income of farming households (Paxson, 1992), and 3) affects saving and asset behaviour only indirectly through income. These provide necessary conditions for valid instruments.

Although some precautionary responses might be observed depending on households' expectations of weather conditions, two things are worth noting. First, rainfall shocks are often unpredictable and any behavioural responses to rainfall shocks are usually channelled via income shocks (Fafchamps, 1993). Second, in the African context, studies such as Scoones (1994) have shown that livestock numbers (primary productive assets) do follow the regional drought cycle. However, several studies have shown that this is not the case in India. In fact, Rosenzweig and Wolpin (1993, p.226) have indicated that "[distress] sales of livestock in India would not be observed, even when consumption credit is constrained"[7]. Furthermore, while one may argue that if rainfall is truly a common shock, then informal insurance mechanisms such as risk sharing among households cannot occur, Townsend (1994, p.586) points out that "there is mounting evidence that

[7] Rosenzweig and Wolpin (1993, p.227) also mention that the "high incidence of bullock turnover, despite the critical role of bullocks for farmers' capabilities to produce income (to be tested below), reflects not only farmers' evident inability to accumulate financial assets but the extensive nature of the bullock market".

rainfall is not uniform even within the confines of the lands of an eight-square-mile village". Some researchers have argued that rainfall may be a weak instrument (see Tanboon (2005)). However, in a rural setting with main risk resulting from natural disasters and weather conditions (World Bank, 2013), rainfall seems to be the most suitable instrument for the decomposition of income into its various components in the Indian context.

1.6 Main Findings

A central aim of this paper is to evaluate the impact of a certain exogeneous shock on income. Following our previous discussions and assuming that one of the major risk factors in the region where the survey was conducted is the erratic rainfall (World Bank, 2013), the deviation of rainfall from its historical average is used as an indicator representing the shock. To evaluate the impact of such risk, we begin by decomposing income into its different components: permanent income determined by the households' permanent endowment (e.g. household composition), transitory income which is the deviation of income from its permanent level, and an unexplained component which is unobserved by the researchers.

1.6.1 Decomposing Income Components

We first begin by decomposing income based on the specification given in Equation 1.1. One issue faced with this estimation strategy is the differences in levels of aggregation. Rainfall is measured at the district level, while other covariates are at the household level. The difference in aggregation levels may lead to underestimation of the standard errors and would then misreport the significance of the results because the explanatory variables share a common-variance component allowing them to correlate with the error term (Moulton 1986, 1990). To circumvent this problem, we use bootstrapped and district-clustered standard errors.

The results of Equation 1.1 are shown in Table 1.4. Rainfall has a significant effect on household total income. However, a substantial proportion of household income cannot be explained in a high risk environment (Carter and Lybbert, 2012), such as the semi-arid tropics. This is reflected by the relatively low R^2 of this model. Rainfall deviation has a positive and significant effect on household income. This is an expected result as a negative rainfall deviation (drought) tends to decrease income, while a positive one increases it. The coefficient of rainfall deviation suggests that a -1 mm^3 deviation in rainfall from its long run average decreases monthly income by 3.98 Indian Rupees. This also means that a severe drought can have a large impact on household income. The age/sex/education categories are mostly significant with expected signs. For instance, as the number of male members increases, total household income tends to increase. A household with more members having achieved higher levels of education tends to have a higher permanent income. Based on these estimates, we have decomposed household income into different components and have reported their kernel densities in Figure 1.5. The multi-modal distribution of transitory income reflects the significant regional differences in risky shocks, *i.e.* each of the nine modes is likely to represent the impact of the nine district-level rainfall deviations. Most of the transitory income is distributed on the negative side of the distribution, further highlighting the inherent risk of these regions.

Table 1.4: Income Regression used to extract household income components.†

Transitory Income Components[a]	Coefficient	Std error	Permanent Income Components[b]	Coefficient	Std error
Rainfall deviation	3.98	[0.79]***	HH members aged 0 to 5	737.97	[156.81]***
Lagged Rainfall	-0.72	[0.72]	Male HH members aged 6 to 11	119.34	[72.67]
Lagged Rainfall Interactions			Female HH members aged 6 to 11	-588.65	[76.09]***
Levelled Slope	-0.10	[0.06]	Male HH members aged 12 to 17	400.51	[90.91]***
Slight Slope	-0.20	[0.08]***	Female HH members aged 12 to 17	231.16	[99.52]**
Medium Slope	-0.30	[0.28]	Male with primary educ. or less, aged 18 to 64	1,104.12	[167.28]***
Steep Slope	-2.84	[2.38]	Female with primary educ. or less, aged 18 to 64	-597.05	[145.71]***
Loam Soil	0.15	[0.28]	Male with Middle School educ., aged 18 to 64	2,109.425	[198.45]***
Clay Soil	-12.13	[12.96]	Female with Middle School educ., aged 18 to 64	-492.83	[176.90]***
Clay Loam Soil	0.52	[0.37]	Male with High School educ., aged 18 to 64	1,412.05	[123.08]***
Problematic Soil	-0.27	[0.42]	Female with High School educ., aged 18 to 64	1,197.20	[175.39]***
District-Time fixed effects included			Male with Intermediate educ., aged 18 to 64	1,683.77	[126.75]***
			Female with Intermediate educ., aged 18 to 64	1,126.57	[239.62]***
			Male with Higher educ., aged 18 to 64	4,089.10	[248.31]***
			Female with Higher educ., aged 18 to 64	1,410.4	[312.72]***
			Male aged 65 or more	-21.51	[172.58]
			Female aged 65 or more	352.47	[184.33]*
			Constant	4,555.08	[490.36]***
			R-Squared	0.14	
			Observations	23,015	

† Bootstrapped standard errors are reported.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
All the above covariates are estimated simultaneously, the division into two columns is for expository purposes only.
[a] As defined in Equation (1.1): $Y^T = R_{dL}\boldsymbol{L_{hdt}\lambda}_2 + \lambda_3 r_{dt} + \boldsymbol{\mu_{dt}}$.
[b] As defined in Equation (1.1): $Y^p = \lambda_0 + \boldsymbol{X^P_{hdt}\lambda_1}$.

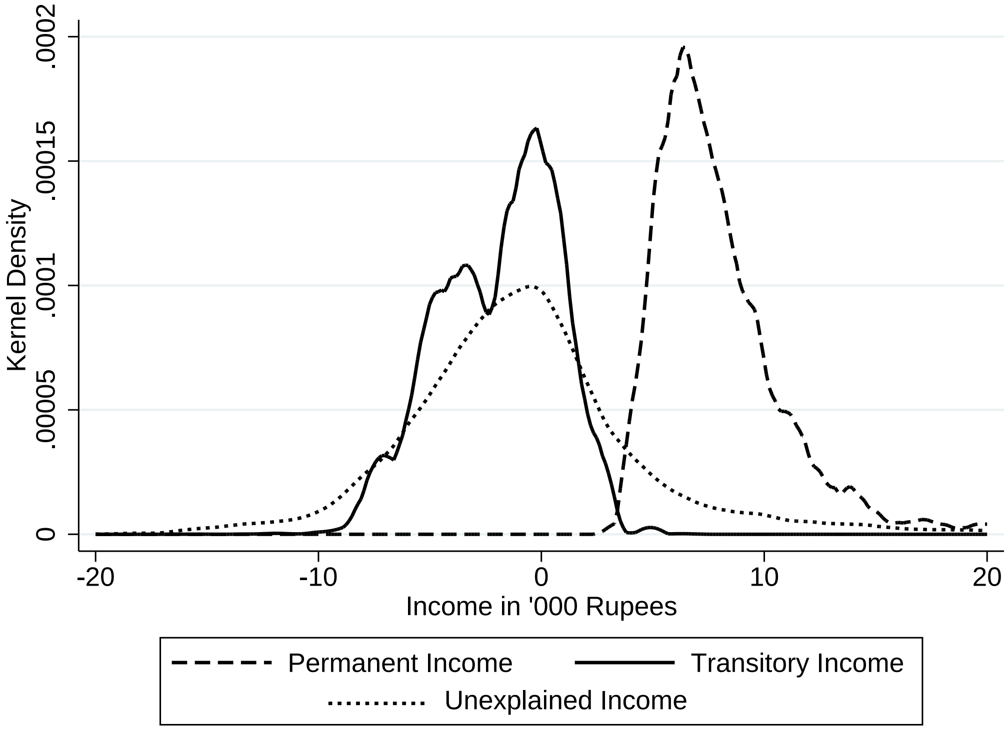


Figure 1.5: Kernel densities of household income components.

1.6.2 Response of Savings to Shocks

The results of response of net balance (savings) to all three income components and the response to "shocks" are presented in Table 1.5. The table shows OLS, FE[8], and FE-VD estimations. The results are consistent across the different specifications - the net balance is very highly responsive to transitory shocks. The results vary as we move from the OLS specification to the FE and FE-VD. As discussed, OLS is likely to produce biased results. The results of FE and FE-VD are very similar for transitory and unexplained shocks, but as expected differ considerably in the coefficient of permanent income. The permanent income includes rarely changing variables, which the FE-VD method is selected to address. If we consider the unexplained income to include "unobserved" shocks, then the coefficient of "Shock (Y^T+Y^U)" is pertinent to the discussion and suggests that consumption is very highly smoothed with a significant coefficient of 0.94 (FE), and 0.98 (FE-VD). This means that consumption is being smoothed and that the propensity to save out of transitory income is equal to one. In other words, when a household faces an income shock of -100 Rupees, the net balance is above -94 Rupees (consumption is 94 Rupees more than income). This implies that consumption is highly smoothed despite the reduction in income. If we consider the transitory shocks resulting from rainfall deviations (Y^T), then the coefficient is 0.69 (FE) and 0.72 (FE-VD), which nevertheless suggests a very high level of consumption smoothing, but not a complete one.

[8]The hypothesis that household-level effects are uncorrelated with the covariates we control for is rejected by Hausman's specification test and therefore we use fixed effects model.

Table 1.5: Response of Saving to Shocks.†

	OLS		FE		FE-VD	
	(1)	(2)	(3)	(4)	(5)	(6)
Y^P	0.31**	0.32**	0.25**	0.27**	0.73***	0.70***
	[0.11]	[0.11]	[0.10]	[0.11]	[0.07]	[0.07]
Y^T	0.54***		0.69***		0.72***	
	[0.11]		[0.05]		[0.04]	
Y^U	0.93***		0.96***		0.99***	
	[0.02]		[0.02]		[0.02]	
Shock (Y^T + Y^U)		0.91***		0.94***		0.98***
		[0.02]		[0.02]		[0.02]
V_d	-7.15	7.08			-0.28	9.55***
	[6.91]	[4.68]			[1.77]	[1.41]
Constant	1376.88	579.05	-1117.97*	-776.21	-585.79**	-1012.05***
	[1600.69]	[1503.46]	[653.49]	[644.09]	[290.37]	[303.02]
Life-cycle Variables Included	Y	Y	N	N	Y	Y
Observations	23015	23015	23015	23015	23015	23015
R^2	0.29	0.28	0.23[a]	0.23[a]	0.35	0.35
No. of Households	755	755	755	755	755	755

† Bootstrapped standard errors are reported in brackets.
* p <0.10, ** p <0.05, *** p <0.01.
Full regression estimates are available upon request.
[a] R^2 of within variation is reported for the fixed effects method.

1.6.3 Response of Assets to Shocks

In this sub-section we investigate the response of assets to shocks in order to assess the extent to which households preserve their assets ('asset smoothing' according to Carter and Lybbert (2012)) or liquidate them to smooth consumption. Our empirical model is specified as in Equation 1.3.

Table 1.6: FE-VD results of asset responses to income shocks. †

	Net Sales of:							
	Livestock		Consumer Durables		Machinery		Capital Assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y^P	-0.12***	-0.11***	-0.27**	-0.27***	-3.15***	-3.17***	-3.42***	-3.44***
	[0.03]	[0.03]	[0.11]	[0.10]	[0.90]	[0.90]	[0.92]	[0.93]
Y^T	0.12***		-0.41***		-0.40*		-0.81***	
	[0.02]		[0.07]		[0.20]		[0.24]	
Y^U	-0.00		-0.40*		-0.13		-0.55***	
	[0.00]		[0.20]		[0.11]		[0.16]	
Shock($Y^T + Y^U$)		0.00		-0.40**		-0.14		-0.54***
		[0.00]		[0.20]		[0.10]		[0.15]
Constant	1444.19***	1288.78***	-267.53	-264.54	10846.55***	11288.45***	10579.02***	11023.91***
	[198.82]	[186.15]	[813.01]	[637.49]	[3677.89]	[3811.68]	[3774.25]	[3914.03]
Observations	16792	16792	3627	3627	3627	3627	3627	3627
R^2	0.10	0.10	0.24	0.24	0.19	0.19	0.20	0.20
F-test	7.88	7.17	7.78	5.62	2.74	2.99	4.09	3.94

† Robust standard errors are reported in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Full Regressions are available upon request.

The results of Equation 1.3 reported in Table 1.6 suggest that net livestock sales do not respond to income shocks, as the transitory income variable in column (1) has a positive coefficient (near zero) and the "shock" variable in column (2) is not statistically significant. This suggests that households preserve livestock, which is one of the most productive assets in rural settings. We find strong evidence to reject the hypothesis that β_2=-1 for livestock, which means that they are not used as buffer stocks and is consistent with the empirical literature (e.g. Fafchamps et al. (1998); Lim and Townsend (1998)). On the other hand, both the transitory income and the unexplained components are negatively and significantly associated with the sale of consumer durables (column (3)) and so is the shock variable (column (4)). Consumer durables which include items, such as bicycles and refrigerators, are generally responsive to Y^T as well as Y^U. From columns (5) and (6), machinery seems to be responsive to transitory income whose coefficient is negative and significant, but less responsive to 'shocks' whose coefficient is low in magnitude and statistically insignificant. This category is considered to be productive as it includes assets used in income-generating activities, such as tractors. The coefficients in these specifications are larger in magnitude than those of livestock yet statistically insignificant. When we combine machinery and consumer durables under capital assets (in columns (7) and (8)), the results are negative and significant, which is largely driven by the results of consumer durables. We conclude that households resort to liquidating less productive assets at times of need and preserve their productive assets. The results confirm the testable implication derived from Barrett et al. (2011) and Carter and Barrett (2006).

To further understand the behaviour of households across different landholding classes, we repeat the analysis of net asset sales for small, medium, and large landholders separately. Because the data collection has been random within each

Table 1.7: Summary Results of FE-VD Estimates of Asset Responses in Different Landholding Classes.[†]

Landholding Class[a]	(a) Livestock		(b) Consumer Durables		(c) Machinery		(b)+(c) Capital Assets	
	Y^T	Shock	Y^T	Shock	Y^T	Shock	Y^T	Shock
Small Landholding	0.09 [0.02]**	-0.01 [0.01]	-0.46 [0.10]**	0.09 [0.10]	-1.02 [0.75]	-0.25 [0.10]**	-1.47 [0.66]**	0.16 [0.01]
Medium Landholding	0.13 [0.04]***	0.00 [0.01]	-0.83 [0.31]***	-0.60 [0.30]**	-0.56 [0.33]*	-0.20 [0.18]	-1.38 [0.49]***	-0.80 [0.18]***
Large Landholding	0.15 [0.04]***	0.00 [0.00]	-0.02 [0.05]	-0.04 [0.10]	0.26 [0.35]	0.28 [0.16]**	0.24 [0.37]	0.24 [0.22]

[†] Robust standard errors are reported in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Full regressions are available upon request.
[a] Landholding classes are defined by the ICRISAT survey and used to stratify households.

strata of landholding class, focusing on each class separately does not cause sample selection bias. The results are summarised in Table 1.7. As mentioned, the sign of the coefficients of these variables has no theoretical underpinning, but we expect it to be negative. The landless households are dropped from this analysis for the reasons previously discussed. We find strong evidence to reject the hypothesis that households use livestock as a buffer stock, i.e. coefficient of Y^T or *Shock* is equal to -1. Despite the fact that all landholders have similar average livestock holding as revealed in our data, the coefficient of net livestock sales is close to zero for all three landholding classes. We find evidence that small landholders liquidate machinery and consumer durables in the wake of income shocks, but the coefficient of machinery is larger than that of consumer durables. It is crucial to note that households in the small landholding class seem to be more affected by Y^U as captured by the *Shock* variable. For medium landholders, the coefficient of consumer durables is larger than that of machinery, which suggests that these landholders rely more heavily on less productive assets (i.e. consumer durables) than productive ones (machinery).

Consistent with the theoretical discussion of Carter and Barrett (2006), households with a low initial asset holding (proxied by land) do liquidate machinery or productive assets to smooth consumption. These households would not find it optimal to forgo consumption and accumulate assets to achieve the non-poor equilibrium. The large landholders tend to be better insured against shocks. This is because households in this landholding class tend to have (i) a large spatial dispersion of land and can draw from a large pool of assets in coping with risks, and (ii) better access to credit and weather information and can adopt ex-ante risk management strategies more easily. Households in small and medium landholding classes, on the other hand, have an incentive to smooth their productive assets and forgo less productive assets, such as consumer durables, in order to accumulate assets up to a certain asset threshold to converge to a high-level equilibrium (Carter and Barrett, 2006). The results disaggregated by small, medium, and large landholding households provide strong support for the poverty trap model and are consistent with the claim that households close enough to the asset poverty line (e.g. medium landholders) use less productive assets in times of economic distress and preserve their most productive assets.

1.7 Conclusion

This paper analyses the ability of households to cope with transitory income shocks using monthly panel data from the International Crops Research Institute for the Semi-Arid Tropics between 2009 and 2012. Research on Sub-Saharan Africa, Thailand, and other parts of the world has shown mounting evidence of households' engagement in consumption and asset smoothing in the face of shocks. While we have also found evidence in support of consumption and asset smoothing behaviours in the recent Indian context, we have provided an alternative explanation to these behaviours along the lines of an asset-based poverty trap model. Our findings suggest that households in rural India achieve consumption smoothing despite frequent occurrence of weather-related income shocks. The net balance of aggregate household savings - defined as 'income minus consumption' - is almost perfectly responsive to such shocks. That is, consumption fluctuations are reduced despite income volatility. We also find that households smooth their main productive asset - livestock - and resort to liquidating less productive assets at times of need.

The poverty trap model by Carter and Barrett (2006) identifies a dynamic asset threshold above which a household has an incentive to smooth productive assets in order to converge to a non-poor steady state in the future. This indicates that households would prefer to forgo current consumption and preserve productive assets in order to insure against future contingencies. The land-poor households do not find it optimal to forgo consumption to accumulate assets to converge to a high level equilibrium. By disaggregating our analysis into different landholding classes, our findings suggest that medium landholders hold on to their livestock and machinery, and rely on less productive consumer durables. Richer households or large landholders do not have to use their assets to smooth consumption (except a less extensive use of consumer durables for transitory income shocks) given that they are rich in a variety of assets and can draw from a larger pool of assets. The results of this paper provide evidence in support of the testable implications of the asset-based approach to chronic poverty and poverty traps (Carter and Barrett, 2006).

The results imply that households are able to self-insure even when institutions fail to provide formal insurance schemes and markets operate inefficiently. The existence of an asset-based poverty trap suggests that enabling them to access credit, insurance, and savings makes poor households less dependent on their asset stock and capable to cope with shocks more efficiently. In addition, the jeopardy posed by forgoing consumption in favour of asset accumulation is austere, as younger household members would be seriously disadvantaged as a result (Hoddinott, 2006). Among many policy implications, our results suggests that governmental social protection schemes should be geared towards promoting asset accumulation. While households are able to self-insure using their asset stock, the jeopardy caused by such risk coping mechanism is that households may eventually fall into an asset poverty trap. One way to achieve this would be to facilitate poor households' access to credit and insurance, for instance through subsidies for microcredit or microinsurance schemes where appropriate. Access to such schemes allows households to shield themselves against income shocks and promotes asset accumulation. In India, the National Rural Employment Guarantee Scheme may provide a good (income-based) buffer that allows households to smooth their income and consumption without having to liquidate their assets. This constitutes an avenue for further research to be undertaken to assess this scheme's role in asset smoothing. Moreover, equipping rural households and farmers with advanced knowledge on farming choices and technologies may enhance yield despite weather adversities and therefore reduce the magnitude of the shock. Access to agricultural extension schemes, weather-indexed insurance, and to reliable (long-range) weather forecast are essential to preventing the poor from making ill-informed decisions (Rosenzweig and Udry, 2014; Mobarak and Rosenzweig, 2013; Barnett and Mahul, 2007; Chantarat et al., 2007). While the current analysis focuses on ex-post responses of households to income shocks, households may adopt ex-ante risk management strategies should they have probabilistic expectations about these shocks (Dercon, 2002). Such strategies typically involve income diversification and income skewing. Recent studies have posed significant importance on the allocation of labour, and the differences in gender roles in anticipation of an income shock. Future research, therefore, should be geared towards understanding the risk taking (or aversion) of rural households and how this may affect the strategy they choose to manage or cope with risk.

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CHAPTER 2

Risk, Labour Allocation, and Migration: Do Networks Matter?

2.1 Introduction

Although there has been a fair amount of research on the role of community networks in understanding household behaviour and self-insurance mechanisms (e.g Townsend, 1994; Mazzocco and Saini, 2012), there is little that we know about the substitutability of risk-sharing networks and the adjustment in labour supply as household risk-coping strategies. The premise of this paper is that households members who rely on their peers within a risk-sharing arrangement are less likely to migrate in the face of shocks as they may lose the benefits of this network. Their attitudes towards risk may also be altered should they know they have a network to rely on. More precisely, households may be more willing to take risk. These community networks may explain, at least in part, the low rural to urban migration in India. Households' labour supply decisions are also altered by the resultant behavioural changes and risk preferences of being part of a network. As a result, these labour market decisions can have serious implications on households' welfare, vulnerability, and poverty status. This paper assesses changes in households' supply of self-employment in agriculture, agricultural labour, non-agricultural labour, and migration work in response to weather-driven shocks, with particular focus on the role of community networks.

The recent literature has posed a lot of emphasis on the role of social networks as a vital informal institution for the livelihoods of vulnerable groups (Beaman, 2012; Munshi, 2003). In addition, there is empirical evidence to suggest that rural to urban migration in India - as well as in most Asian countries - has decreased (Overseas Development Institute, 2014). One hypothesis is that rural networks are so strong that they could explain the large rural-urban wage disparity and low internal male migration in India (Munshi and Rosenzweig, 2016). More explicitly, households whose members migrate to urban locations may lose the benefits of their risk-sharing arrangement at the village of origin. This happens because peers within the network would find it difficult to sanction migrant households if they do not commit to the risk-sharing arrangement. This characterises the asymmetry in information resulting from migration (Munshi and Rosenzweig, 2016). The threat of losing this network arrangement could, therefore, inhibit internal migration and influence labour market participation decisions by changing risk preferences. While this is one deterrent factor for migration, in this paper we focus on the role of networks as a risk coping mechanism and do not test the social sanctioning mechanism explicitly. When households are faced with a weather shock, it is natural for them to adjust their labour supply in order to insure against expected risk or cope with realized shocks. The rationale is that households who switch between sectors (agricultural and non-agricultural) may not necessarily be seeking higher profits, but simply acting on their aversion to risk. Households who are part of a risk-sharing arrangement may find it more appealing to engage in risky activities - e.g. in agriculture - given the safety net offered by this network.

The contribution of this study to the literature of risk coping mechanisms is threefold: (1) we assess the role played by community networks in shaping households decision-making, and find that these networks can have a deterrent effect on migration by serving as a risk coping mechanism through inter-household transfers, but can serve as an incentive to participate in risky agricultural activities, (2) we examine a comprehensive portfolio of households' labour activities and dis-aggregate the responses by gender within the households, and (3) we use a very recent dataset from rural India to test our hypothesis. Understanding the role played by networks in shaping households decisions and preferences is extremely important in the developing world. The implications that we derive from the labour market adjustment, spatial mobility through migration, and the safety net of risk-sharing networks are valuable in understanding the role of social networks as an informal institution. We also examine the importance of non-agricultural (work at the home village) and migration as a strategy to diversify agricultural production risk and mitigate climate uncertainty. Based on our results, we find that facing a negative weather shock, households allocate less time in agricultural activities (self-employment and wage work), and more time in non-agricultural labour, domestic work, and migration. However, households who are part of a community-based risk sharing network increase their supply to riskier activities and reduce their migration. Through these channels, this paper bridges together the literature on risk coping, migration, and networks.

To test our hypothesis, we use a monthly household panel dataset collected by the ICRISAT in the semi-arid tropics of India from 2010 to 2015. We make use of a detailed employment survey that lists each household's work activities within a given month, and monthly village-level rainfall collected by the same organization. This dataset is extremely rich and unrivalled in the quality and quantity of information it provides for the purpose of studying household risk and informal insurance strategies.

The aim of this paper is to identify the role played by community networks in shaping inter-activity decisions in areas characterised by agro-climatic risk. Given the severity of climate change in the current age and the growing uncertainty in agricultural production, the labour market decisions are crucial in understanding household behaviour and identifying ways to reach out to the poorest of the poor. Much of the previous literature of migration has focused on the role of networks at the destination rather than the village of origin (Munshi, 2003; Munshi and Rosenzweig, 2006; Munshi, 2011). However, Munshi and Rosenzweig (2016) provide an intriguing theory and empirical assessment of the significance of the *general* riskiness of the village of origin and the caste-based networks that reduce *permanent* rural-urban migration. They argue that households who benefit more from their network's insurance mechanism are less likely to migrate. Part of the problem of mis-allocation of resources and the growing rural-urban wage gap in India is attributed by the authors to low internal migration driven by the strength of community networks at the origin. Munshi and Rosenzweig (2016) indicate that households with migrant members are less likely to access network-based insurance. In order to avoid the information and commitment problems, households of this network can either move to the urban area as a group, or members can migrate temporarily. Our paper extends the findings of Munshi and Rosenzweig (2016) to assess the effect of the network's insurance mechanism on the decision to migrate and changing the household's labour portfolio within the village itself based on concurrent weather shocks. This approach marries the theory of Munshi and Rosenzweig (2016) with the literature on labour adjustments as an insurance mechanism (e.g. Kochar (1999); Rose (2001); Ito and Kurosaki (2009) and others).

The rest of the paper is structured as follows: the next section is a survey of the literature on migration, labour allocation, and risk-sharing. The subsequent section describes the data sources and variables and provides some descriptive evidence. We then establish our empirical model and its econometric considerations. Finally, we discuss our results and conclude[1].

2.2 Literature Review

The literature on risk coping and management can be classified into several strands: asset portfolio adjustment, labour allocation and income diversification, risk sharing arrangements within a network, and formal insurance. The formal insurance mechanisms are near absent in rural India, so households need to smooth

[1]Further robustness tests are also given in the appendix.

their consumption via buffer stock savings (e.g. Imai and Malaeb, 2015), income smoothing (e.g. Kochar, 1999), risk sharing arrangements (e.g. Townsend, 1994), or migration (e.g. Stark and Levhari, 1982). The purpose of this paper is to bridge the gap in the literature on income smoothing and risk sharing arrangements to further improve our understanding of risk coping strategies.

2.2.1 Migration

Munshi and Rosenzweig (2016) suggest that much of the rural urban wage gap could be explained by the low mobility of Indian males between the two areas. They provide theoretical and empirical evidence to suggest that households who are part of a risk-sharing arrangement at the caste level in rural India do not find it optimal to migrate for several reasons. Members of the network cannot observe the migrant household's full income which could create information problems and lack of commitment to the social contract. Furthermore, this network cannot socially sanction these households efficiently as one or more of their members is away from the village and as a result, cannot enforce this informal contract easily post-realization of income shock. The authors suggest that two strategies can be adopted to circumvent this issue. One way is to move to the city as a group (moving the network) which is costly and often unrealistic. Another way is to migrate temporarily to take up short-term employment. Munshi and Rosenzweig (2016), however, only explore the permanent migration in their paper and not the temporary aspect. The authors point out that temporary migration will not fill the large number of jobs in urban areas and will not promote learning and task-specific skills by workers. Therefore, it may not contribute to narrowing the rural-urban wage gap. It does, however, constitute a viable strategy to hedge against weather risk.

De Weerdt and Hirvonen (2013) study the domestic migration in Tanzania, and find that those who moved out of their area of origin between year 1991 and 1994 have grown twice as rich as those who remained in the same place. They find that migrants help insuring their non-migrant household members through transfers. However, households do not only adopt migration for its financial rewards, but also to escape community and familial obligations; that is evading the commitment to the risk-sharing arrangements (Platteau, 2000). Nevertheless, rural Indian households are known to form and rely on their community networks to smooth their consumption and share the risk (Munshi and Rosenzweig, 2016; Townsend, 1994).

Under the expected-income hypothesis, migration has been traditionally seen as a response to differences in intersectoral returns: individual move from sector/area A to B, if expected returns in B are greater than those in A. However, this framework does not factor in the role of risk (coping and management) in households' decision making process (Stark and Levhari, 1982). Much of the literature, in fact, has cast serious doubt on migration's role in capturing these expected gains. The externalities of migration have included an increase in urban unemployment (Todaro, 1969), creation of urban slums, and an increase in both poverty and inequality of urban areas. The risk-aversion hypothesis and the relative deprivation approach, therefore, have gained much more praise in this literature (Stark and Levhari, 1982; Stark, 1984). This motivates our belief that migration from rural to urban areas insures (risk averse) households against income shocks. Without accounting for rural risk, it is easy to mistakenly deem rural-urban migration an income maximization strategy, while in fact it may be strongly driven by households' aversion to risk (Stark and Levhari, 1982; Katz and Stark, 1986).

Rosenzweig and Stark (1989) analyze the inter-linkage between the marriage market and the labour market in India. The authors suggest the marriage of daughters to distant households serves as an implicit inter-household risk-sharing arrangement. They observe a significant enhancement in food consumption smoothing amongst households who have married one or more female members to distant locations, and that farmers facing larger income risk tend to adopt such coping strategies.

2.2.2 Adjusting Labour Allocation

In the face of weather shock, households tend to adjust their labour supply in order to insure against risk or cope with realized shocks. Rose (2001) tests rural Indian households' responses to weather risk based on their ex-ante and ex-post labour supply. Rose (2001) assumes a two-period model: in the first period households decide whether or not to participate in the labour market - this participation requires a time-input that is taken away from farm work and thereby affecting output; in the second period, the weather shock is observed and households reap the benefits or incur losses. The findings of the study imply that households are more likely to participate in the labour market ex-ante in areas with high weather uncertainty, and ex-post after an unexpectedly bad weather shock. The author shows through simulations that as the coefficient of variation in rainfall varies from the lowest to the highest value, the likelihood of participation in the labour market increases by around 20%. However, neither does Rose (2001) observe the changes in composition of the labour hours, nor does she assess the heterogeneous components of the labour market (agricultural wage work, non-agricultural work within the village or abroad). The households' participation in the different labour markets is likely to differ and have significant welfare implications on these households.

Ito and Kurosaki (2009) revisit the role of portfolio diversification in income sources and labour allocation. They find that households increase their participation in the off-farm labour market with the increase in weather risk. Furthermore, they posit that when agricultural work is compensated with in-kind wages (as opposed to cash), households' food security is improved. When food security is of paramount interest to farmers, they find it more attractive to opt for agricultural in-kind work rather than non-agricultural work. Households who avoid risk by moving between sectors and labour markets may lose the dexterity and specialization in a particular skill. This hinders households' ability to reach their full output potential and may exacerbate problems of poverty, vulnerability, and inequality.

Dimova et al. (2015) describes the rural economies of the developing world to be largely dominated by farming activities - often at subsistence level. Farmers, therefore, tend to either specialize in production techniques that hedge against environmental shocks (e.g. adopting technologies resistant to pests, or production processes adaptable to droughts), or diversify their income sources by allocating some of their labour hours to off-farm activities (Dimova et al., 2015). The literature on this insurance mechanism indicates that households increase their off-farm labour subject to the occurrence of a shock (pests and diseases, idiosyncratic shocks, weather shocks etc.). Contrary to popular belief, Dimova et al. (2015) conjectures that *ganyu* - an off-farm form of cheap and exploitative labour in Malawi - is a viable shock buffering strategy for poor and rich farmers facing genuine destitution. The authors note, however, that the off-farm labour market does not necessarily constitute a consumption smoothing strategy in the case of Malawi, even when entry into the off-farm market is not restricted. Furthermore, in the African context, Mathenge and Tschirley (2015) argue that participation in off-farm labour represents a long-term strategy to deal with *anticipated* income shocks, but does not provide evidence to short-term adjustments in labour market as a result of unexpected shocks.

Kochar (1999) investigates the ability of households to smooth consumption by smoothing income. Using the ICRISAT data from India from 1979 to 1984, the author finds that household male members increase their labour market participation and decrease their on-farm labour in response to adverse shocks. Conditional on labour hours, consumption is negatively affected by contingencies in crop income, suggesting that the consumption smoothing is largely promoted by the adjustment in labour allocation.

2.2.3 Risk Sharing and Community Networks

Mazzocco and Saini (2012) emphasize the role of caste groups in buffering income shocks and serving as a safety net. Mazzocco and Saini (2012) propose a method to test risk sharing in rural Indian villages for households with heterogenous risk preferences. They reject the hypothesis of risk sharing efficiency at the village level (Townsend, 1994), but they provide evidence of its efficiency at the caste level. This suggests that the caste constitutes a strong risk-sharing unit in rural India. The risk-coping options available to households, according to Mazzocco and Saini (2012), are gifts and transfers, borrowing from village lenders, saving technologies, and crop diversification. The existence of this societal institution is likely to influence the households' welfare in buffering income shocks, and shape their preferences and decisions.

Social connections in developing countries, especially in India, are crucial to many aspects of the economic and social well-being of households (Munshi, 2014). The importance of these networks in finding jobs, obtaining loans, and other forms of support is paramount. Although it may seem as though networks distort the functioning of the economy (credit and labour markets), they are in fact a necessary institution in enhancing economic efficiency in the absence of formal/governmental institutions (Munshi, 2014). These networks are very strong not only in insuring households within them but also in sanctioning households who do not commit to the "rules of social cooperation".

This social sanctioning and punishment mechanism has a crucial implication in our context: households who are part of a network are less likely to migrate to avoid being sanctioned. One can also conceive of the idea that the existence of such an "insurance" mechanism may alter household risk preferences: they may be more willing to undertake risky activities - e.g. agriculture. The network formation may also allow households to overcome credit constraints that may reduce inequality and enhance inter-generational mobility (Munshi, 2014). Rosenzweig (1988) confirms the critical role of families in rural India as an institution that mimics the role of formal organizations (e.g. governments). Kinship ties and community networks are, at least in part, understood in terms of consumption smoothing and risk buffering. However, these same networks that provide a safety net constitute an insurance mechanism that binds their members to a single location (Rosenzweig, 1988). Furthermore, Rosenzweig (1988) reports that households in rural India indeed prefer familial and social transfers to the use of credit markets. This evidence is in sharp contrast with risk-sharing networks in Africa, where cultural norms inhibit such transfers (Mebratie et al., 2015).

Fafchamps and Lund (2003) examine the risk-sharing arrangements in rural Phillipines using detailed information on gifts, loans, and asset sales. They find that shocks have a strong effect on transfers and informal loans within the network but little to no effect on the sale of livestock. The risk-sharing network appears stronger between friends and family than it is at the village-wide level.

Chiappori et al. (2014) measure the heterogeneity in risk preferences among Thai rural households and find evidence that risk preferences are unrelated to wealth and other household characteristics. Despite the fact that (hypothetically) eliminating rural risk would benefit the average households, they argue that the less risk averse households actually benefit from the existence of rural risk as they seek insurance premium from the risk-sharing arrangement. In other words, risk loving households are paid for the insurance they provide within the network. This provides further evidence that risk preferences are influenced by the network's safety net. Morten (2013) links the issues of risk-sharing and migration by implementing a model of risk sharing with limited commitment and endogenous temporary migration. She argues that migration decreases risk-sharing, and risk sharing itself reduces migration. Furthermore, Morten (2013) finds that the gains in consumption that result from migration for households in rural India are around 7% lower than those who benefit from network-based insurance. To the best of our knowledge, our paper is the first to assess the different labour market decisions (including migration) while accounting for the simultaneity in these decisions using detailed household data on networks.

2.3 Analytical Framework

Several theoretical models have explored the response of households' labour supply adjustment to shocks. Two of the most notable models in the literature are Rose (2001) and Ito and Kurosaki (2009). Rose (2001) explores the ex-ante and ex-post response to rainfall shocks and suggests that given these shocks households reduce their self-employment in agriculture and increase their market labour supply. Ito and Kurosaki (2009) suggests that off-farm labour options are not homogenous; they differ by labour activity and renumeration method (in-kind versus cash). In this paper, we explore ex-post decision to change labour supply given a rainfall shock across several activities: self-employment in agriculture (a), agricultural wage labour (b), non-agricultural wage labour in the village (c), labour supply in migration (d), and domestic work (e). The model assumes a unitary model of the household where all members decide jointly on the redistribution of labour hours across the different activities.

Similar to Rose's construction, the model we propose is as follows:

$$s^i = F(\sigma, N, C)$$

where s^i is the share of labour hours allocated to activity $i \in (a, b, c, d, e)$, σ is the rainfall shock (or deviation from long-run average), N is the network participation, and C is a vector of other household characteristics that affect the choice of labour activity.

Based on Ito and Kurosaki (2009), the household shall respond to a negative rainfall shock by decreasing self-employment in agriculture, and increase the supply in agricultural and non-agricultural wage labour. Migration also becomes an attractive (but possibly expensive) option when households are faced with a shock (Munshi and Rosenzweig, 2016). The adjustment in domestic work, which is mainly carried out by women, has no theoretical underpinning. The reason is that in a unitary household model women may choose to reduce their domestic work and supply more hours in income-generating activities thereby buffering the impact of the shock on income. However, they may in some instances increase their domestic work if their main shore was on the household's own land.

Being part of a network makes households more likely to engage in risky activities (e.g. self-employment in agriculture) as it constitutes a form of insurance against low or failed yield. However, it is likely to reduce migration in general for households as they may risk loosing the benefit of the network (Munshi and Rosenzweig, 2016). Furthermore, being part of a network may reduce the differential effect of a negative income shock on migration (i.e. $s^d_\sigma > 0$, $s^d_{\sigma N} < 0$). The effect of having the insurance of a social network on agricultural and non-agricultural wage work has no clear theoretical foundation and will be treated as an empirical question in this paper. Finally, being part of a network may decrease domestic work as a signal to other members in the network of the effort the household is exercising. However, given the role of networks as a insurance mechanism it could also cause households to make less effort, and therefore increase the share of hours in domestic work.

2.4 Econometric Specification

In this section, we provide a detailed description of our empirical model of the adjustment in time allocation across the different labour activities. Given the simultaneity in household decisions across different activities, we take a simultaneous equation modelling approach. The intuition is similar to that of a demand system where the demand of one good/input is jointly determined with the demand for another. In this example, we build on the premise that the decision to supply a certain amount of time (share) into one activity is naturally a simultaneous decision. In particular, we use the seemingly unrelated regression (SUR) model developed by Zellner (1962) to account for the correlation in the error terms between the different equations. This correlation is a direct implication of the simultaneity in decisions, i.e. increasing the time allocated to one activity necessarily reduces the maximum amount of time available that can be allocated to another activity. In other words, our specification allows the decision to supply a certain share of the household's time to one activity versus another to be jointly estimated in a system of equations.

Consider a sample of low income households indexed h=1,...,N, in the villages v=1,...,V. We have information on the working days and average working hours of each individual within the household in each activity: a) self-employment in agriculture, agricultural wage labour, non-agricultural labour, migration work, and domestic work. We construct from this data the shares of the total working time in each of these activities (five categories). For each household, we have share variables y^i_{hvt} where i=1,...,5 is the index of each share category. We assume a linear specification of the shares as a function of a K-dimensional vector X: the first element in X is 1 - the intercept - and the last element is a variable specific to each equation in order to identify each category. The reason we use an identification variable is that the system of equations with identical K-dimensional vector of explanatory variables will reduce to a single-equation ordinary least square method (Greene, 2012). This necessitates the use of an identifier for each of the equations in the system. The estimation approach is based on generalized least squares (GLS) in a seemingly unrelated regression model (SUR) (Zellner, 1962; Baltagi, 2013; Greene, 2012). The GLS estimation is applied to the following stacked system:

$$\begin{bmatrix} y^1 \\ y^2 \\ y^3 \\ y^4 \\ y^5 \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 & 0 \\ 0 & 0 & X_3 & 0 & 0 \\ 0 & 0 & 0 & X_4 & 0 \\ 0 & 0 & 0 & 0 & X_5 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \end{bmatrix} \tag{2.1}$$

Each equation in the SUR model is of the following form:

$$y^i_{hvt} = X^i_{hvt}{}'\beta^i_{hvt} + \epsilon^i_{hvt} \tag{2.2}$$

where i=*1,...,5*, is the subscript for each activity (self-employment in agriculture, agricultural wage labour, non-agricultural labour, migration, and domestic work), and h,v, and t are household, village, and time indexes, respectively. β^i_{hvt} is a K-dimensional vector of the coefficient estimates (for K variables within X^i_{hvt}). The main explanatory variables used to answer the research question are the lagged rainfall deviation ($DEVIATION$), a binary variable on whether a household is part of a social network (NET), and the interaction term of the lagged rainfall deviation with the network variable ($DEVIATION \times NET$). Other control variables include: a binary variable for large landholders, a binary variable for medium landholders (and small landholders are therefore the reference group), caste dummies, and household life-cyle variables[2]. To control for price fluctuations and seasonality, we include farm and non-farm wages at the village level as well as village and month fixed effects. ϵ^i_{hvt} is each equation's error term. By construction, the SUR GLS model allows the disturbances to be contemporaneously correlated while accounting for the simultaneity in decisions across the different i categories. The dependent and explanatory variables that make up y^i_{hvt} and the K-dimensional vector X^i_{hvt} are given in Table 2.1 along with their corresponding summary statistics. The variable used to identify each equation is the lagged level of hours of labour supply by *other villagers* of each activity. For instance, to identify the equation of self-employment in agriculture, we use lagged total hours of own-farming hours less the household's own supply of own-farming hours (i.e.

[2]The life-cycle variables are the "sex/age/ education" categories that include a set of count variables of an exhaustive combination of sex, age and education. Examples of the "sex/age/education categories" are: the number of female household members aged between 0 and 5, or the number of female household members aged between 18 and 64 who completed primary education, or the number of male household members with intermediate education aged between 18 and 64. We construct these categories for both men and women across five different age groupings: 0 to 5, 6 to 11, 12 to 17, 18 to 64, and above 65. Individuals aged between 18 and 64 are further divided into 5 educational categories: primary school, middle school, high school, intermediate education, and higher education. We also include the age and education of the household head.

other lagged total hours of other villagers in activity i). The use of this identifier is motivated by the fact that activity-specific labour supply at time *t-1* of other villagers is correlated with the household's supply of this same activity at time t, but does not directly affect the household's supply of other activities at time t.

2.5 Data and Descriptive Evidence

We use a monthly household panel data survey from the Institute of Crop Research in Semi Arid Tropics (ICRISAT) for the years July 2010 to June 2015[3]. The data includes 887 households from 18 villages. The data is based on a stratified sample of randomly selected households within four landholding classes: landless, small, medium, and large landholdings. In this analysis, we exclude the landless households as they do not have the choice to enter into self-employment in agriculture and they may bias the estimates in other labour activities (e.g. domestic work which will inherently be larger for those households). The stratification in the data collection allows us to exclude these households without causing a sample selection problem because households are randomly selected within each strata. While this does not pose a problem in the statistical sense, it is a clear disadvantage of the study at hand in that we exclude the most vulnerable group of the distribution - the landless. This reduces the generalizability of the result and therefore any claim on the response of landless households to shocks in terms of labour supply warrants a thorough separate analysis. As a result, we reduce our sample to 713 households. In this section, we provide an overview of the relevant variables and provide some descriptive evidence of labour allocation and migration in rural India.

[3]The data originally included the months of the year 2009 as well, but these waves have been dropped due to differences in the definition of relevant employment variables

2.5.1 Main Variables

We consider five types of labour market activities carried out by the household: self-employment in agriculture, agricultural wage labour, non-agricultural labour[4], migration, and domestic work. To calculate the share of labour allocated in each activity, we sum up all the hours of work in a particular month for all household members. We then calculate the share of time allocated to each activity as a proportion of the total hours supplied at the household level. Consider, for example, a household of 3 members. One member supplies 100 hours in agricultural labour, the second member works 50 hours abroad in short-term migration work and a further 100 hours in non-agricultural labour in the home village, and the third reports 100 hours of domestic work. The total hours reported will be 350 hours, of which 28.6% is in agricultural labour, 14.2% in migration work, 28.6% in non-agricultural labour, and the remaining 28.6% in domestic work (which includes home-production). The shares used in this analysis are between 0 and 1, and always sum up to 1 within the household.

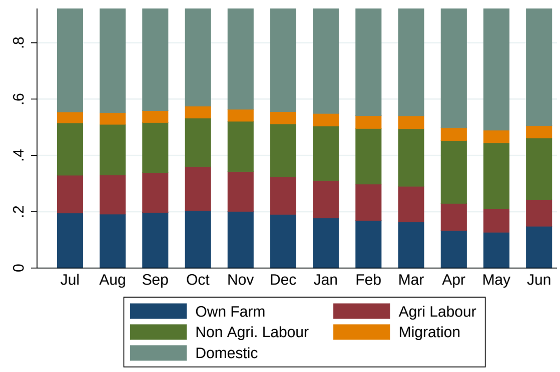
Given the importance of rainfall in the agro-climatic environment of rural India, we use it as a proxy for income and weather shocks. In our analysis, we use the *t-1* lagged deviation of village-level rainfall from its long-run average.

The main difficulty in carrying out this analysis, is to find a suitable variable to identify households' network and risk sharing arrangements. One of the features of the ICRISAT survey is that it administers an annualized survey about households' general endowment characteristics in July of every year, as well as the monthly questionnaires about transaction, employment, and other details for every other month. In the annual survey in July, households are asked whether

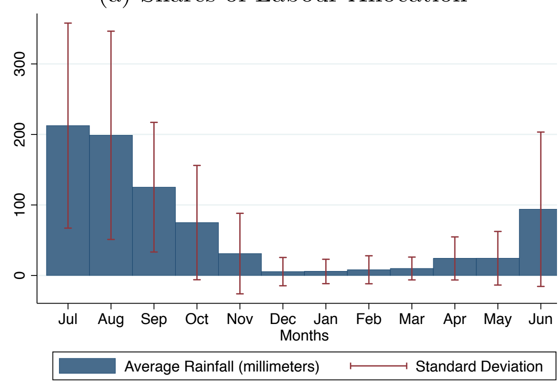
[4]This category includes both self-employment and dependent employment as they cannot be distiguished in the data.

or not they have been affected by a certain type of risk during the previous crop year. Due to the intrinsic risk that prevails in the unstable agro-climatic environment of the survey villages, 76% of the households in our sample report having been affected by a shock during the previous 12 months. The households were then asked about their adopted mechanisms for coping with these shocks. The different coping mechanisms reported include - selling assets, getting a mortgage/loan, depleting own savings, or seeking help from family and friends. These variables are fundamentally valuable for answering the main research question in this paper. The use of these variables can be justified on the grounds that the bias due to reporting errors or manipulations of answers may be smaller than, for instance, household income which is based on aggregation of different items and/or sensitive to the respondents' subjective judgement (Deaton, 1997). This variable is therefore an objective response to a question on coping mechanisms, and not a subjective perception of how good or bad it is. As a proxy for community risk-sharing networks, we construct a binary variable (NET) that takes the value 1 if at least one of the household members has sought help from family and friends and 0 otherwise. We find that around 45% of households who were affected by a shock have relied on family and friends for support in the previous year. As a robustness check, we construct another binary variable (NET-G) that takes the value 1 if the household has received gifts and transfers in a previous month, and 0 otherwise. The descriptive statistics of the dependent and explanatory variables and their definitions are presented in Table 2.1.

2.5.2 Descriptive Evidence



(a) Shares of Labour Allocation



(b) Rainfall

Figure 2.1: Monthly Distribution of Shares of Labour Allocation and Rainfall

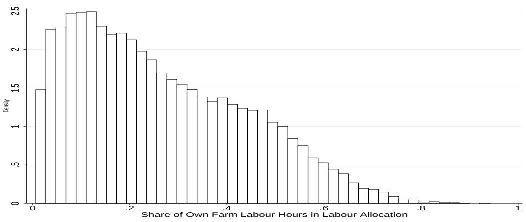
We begin our analysis by providing some descriptive evidence to the labour allocation across the different months and the distribution of rainfall in the villages. We observe a seasonal trend in the time allocated to each activity as shown in Figure 2.1 over the cropping year[5]. The lean and slack seasons (between January and June) decrease the labour supply to farm work inherently (Basu, 2013). We also observe an increase in the share of own farm labour hours increases in the monsoon season (July to October), and gradual increases after the monsoon rains (March to July). The agricultural wage labour seems to follow a similar trend as it is dictated by the amount of farming work that takes place within the village (or district). The non-agricultural labour supply (at the home village and in migration) follows an inverse trend which suggests that it constitutes a viable risk-coping strategy. Comparing panels 2.1a and 2.1b of Figure 2.1, the negative co-movement of farming and agricultural labour supply with the trend of rainfall is readily observed. One important message that can be drawn from the descriptive evidence is that households rely on migration and

[5]Cropping year is considered to be from July to June of each year.

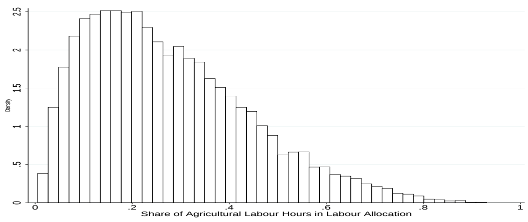
non-agricultural labour supply when weather risk is high. Another implication hereof is that the substitution effect between the different activities is likely to be an important risk-coping mechanism.

Figure 2.2 shows in the first panel (2.2a) the distribution of the shares of own-farm labour allocation[6]. It is evident that most households in the sample have at least some of their labour allocation in farming activities on their own land. The reason the distribution is skewed to the right is due to the presence of small land-holders, who will inherently supply less of their time share to farming activities. Most of the labour time share goes to domestic work (2.2c) which is mainly carried out by female household members. As expected, most households allocate a significant amount of their time to agricultural (2.2b) and non-agricultural (2.2d) wage labour. Although the mean share of hours allocated to migration (2.2e) within the household is low (around 4%), the distribution of the migration share of labour allocation is very large for households whose members do participate in migration (around 10% of the sample households). Further descriptive statistics and variable definitions are given in Table 2.1.

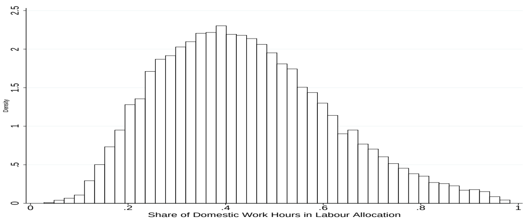
[6]Shares are displayed on the x-axis and the density on the y-axis. The sample mean of each category includes zeros in each of the shares and are reported in Table 2.1, but the households with an allocation of zero hours in a given category are excluded from the histogram. The densities are based on 40780 observations of 713 households.



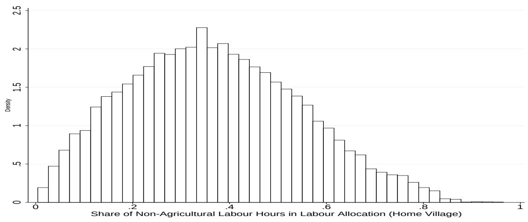
(a) Share of Own Farm Labour Allocation



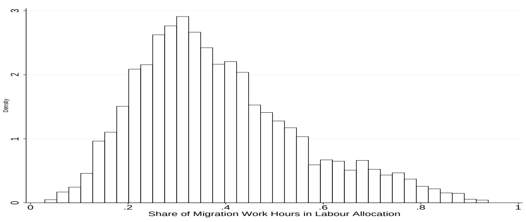
(b) Share of Agricultural Wage Labour Allocation



(c) Share of Domestic Work Allocation



(d) Share of Non-Agricutural Labour Allocation



(e) Share of Migration

Figure 2.2: Distribution and Mean of the Shares of Different Labour Activities out of total Labour Allocation

Table 2.1: Summary Statistics and Variable Definitions

Dependent Variables	Definition	Mean	S.D.	Obs.
Self-Employment in Agri.	Labour share allocated to self-Employment in Agriculture	.211	.193	40795
Agri. Labour	Labour share allocated to Agricultural Labour	.107	.163	40795
Non-Agri. Labour	Labour share allocated to Non-Agricultural Labour (Home Village)	.179	.220	40795
Migration	Labour share allocated to Migration Work	.040	.128	40795
Domestic	Labour share allocated to Domestic Work	.462	.198	40795
Explanatory Variables				
$DEVIATION$	Lagged Rainfall Deviation at the Village Level	1.69	106.08	40515
NET	Network Variable	0.14	0.35	40780
$DEVIATION \times NET$	$DEVIATION$ interacted with NET	0.51	46.74	40515
LARGELAND	Dummy Variable for Large Landholder	0.283	0.451	40780
MEDLAND	Dummy Variable for Medium Landholders	0.303	0.459	40780
MALE6TO11	No. Male HH members aged 6 to 11	0.105	0.377	40792
FEMALE6TO11	No. Female HH members aged 6 to 11	0.378	0.732	40792
MALE12TO17	No. Male HH members aged 12 to 17	0.110	0.369	40792
FEMALE12TO17	No. Female HH members aged 12 to 17	0.440	0.773	40792
MALEPRIMEDUC	No. Male with primary educ or less aged 18to64	0.182	0.440	40792
FEMALEPRIMEDUC	No. Female with primary educ or less aged 18to64	1.084	0.970	40792
MALEMIDDLEDUC	No. Male with middleschooling aged 18to64	0.099	0.327	40792
FEMALEMIDDLEDUC	No. Female with middleschooling aged 18to64	0.401	0.621	40792
MALEHIGHSCHOOL	No. Male with highschool aged 18 to 64	0.181	0.459	40792
FEMALEHIGHSCHOOL	No. Female with highschool aged 18 to 64	0.542	0.770	40792
MALEINTERMEDIATE	No. Male with intermediate educ aged 18 to 64	0.100	0.327	40792
FEMALEINTERMEDIATE	No. Female with intermediate educ aged 18 to 64	0.260	0.550	40792
MALEHIGHERED	No. Male with higher ed aged 18 to 64	0.121	0.405	40792
FEMALEHIGHERED	No. Female with higher ed aged 18 to 64	0.275	0.650	40792
MALE65ORMORE	No. Male aged 65 or more	0.087	0.287	40792
FEMALE65ORMORE	No. Female aged 65 or more	0.303	0.560	40792
$AGEHHH$	Age of HH head	50.452	12.325	40792
$EDUHHH$	Education of HH head	1.744	1.735	40792
$AGRIWAGE$	Average Monthly Agricultural Wages at Village level	11228.56	6880.83	40956
$NAGRIWAGE$	Average Monthly Non-Agricultural Wages at Village level	2108.25	3665.95	40956

2.6 Econometric Considerations

Rainfall

The primary difficulty in identifying the relationship between income shocks and differential time allocation in labour activities is that both may be influenced by unobserved household characteristics. By failing to control for these characteristics, the estimates may suffer from omitted variable bias because of the joint determination of households' labour activities and their incomes. In order to circumvent the problems of income measurement and endogeneity, we use rainfall deviation as a plausibly exogenous proxy for such shocks (Björkman-Nyqvist, 2013). Rainfall in itself is an important determinant of decision making in agriculture. Given the simultaneity in these labour decisions, rainfall also affects the time allocation into other labour activities. In the risky agro-climatic environment of rural India, rainfall deviations constitute a serious threat to farmers' livelihoods and welfare. Therefore, it appears appropriate to use the rainfall variable as one of our main covariates to explain the changes in households' labour supply allocation in the villages. The use of the rainfall variables is also motivated by the literature on risk coping and management in and outside India (Dercon, 1998; Rose, 2001; Lichand and Mani, 2016; Dercon and Krishnan, 2003; Ito and Kurosaki, 2009; Dimova et al., 2015). In our specification, we use the *t-1* lagged deviation of village-level rainfall from its long-run average. In order to make the interpretation of these deviation clearer, we split our deviation measure into its negative ($NEGDEV$) and positive ($POSDEV$) components (Björkman-Nyqvist, 2013). The reason behind this lies in the difficulty in interpreting a variable that takes on both negative and positive values. For instance, a negative coefficient on such a variable may not be intuitive to interpret. Thus, splitting it into its two components facilitates the interpretation of these coefficients[7].

Networks

Households have a choice of whether or not to participate in a risk-sharing arrangement. One may argue, therefore, that there is a problem of endogeneity due to households' self-selection into the network: the same household characteristics that affect their decision to participate in one activity versus another may affect their decision to participate in a risk-sharing network. One of these unobserved characteristics is households' attitude to risk. Households who are more risk averse may engage in a risk-sharing arrangement and at the same time avoid risky activities (such as agriculture or migration). Another characteristic could be unobserved household abilities that may lead others to collaborate with them in mitigating shocks, thus forming a network, and may in turn affect their ability to engage in certain non-agricultural activities or migrate. Due to the difficulty in finding a suitable instrumental variable[8] to address this issue, we employ several econometric strategies to check the robustness of our results.

One of these strategies is to use a variable for networks that is inherently

[7]We also explore whether there is any non-linear relationship between the household response through labour allocations and rainfall shocks in two ways: 1) including a quadratic term of the rainfall deviation, and 2) changing the definition of rainfall deviation to 2 standard deviations away from the mean. The coefficients of these variables are not statistically significant, which suggests that the response is considered to be broadly linear. This is also supported by the observation that the period under consideration does not include any episode of severe drought or flood.

[8]We have contemplated the use of several IVs: general riskiness of the village, distance to local markets, intensity of the transfers and gifts among other villagers, household wealth etc. However, all of these variables may themselves be correlated with the error terms and the unobserved heterogeneity in households' characteristics. On the one hand, implementing an equation by equation two-stage least square approach, may account for the self-selection problem but will not account for the simultaneity in decisions across labour activities. On the other hand, using a three-stage least squares approach, which would account for the correlation of the disturbances across equations, will be problematic because no suitable IV could be identified that satisfies the exclusion restrictions. We, thus, resort to other econometric methods to address this issue.

exogenous in measurement to the contemporary residuals. The variable defined as NET in the previous section can be thought of as "whether or not this household has the option to seek help from family and friends". The definition of this variable is of extreme importance in this context. If households have the option to seek help from their network given that they have done so in the past, this may not necessarily have a direct effect on their current decisions in way that would violate the exogeneity assumption of this variable. The endogeneity bias can result from the fact that households seek from others who *can* help at a certain period (i.e. not affected by current shocks). By using data on networks at the beginning of each survey period, without information on gifts and transfers, we minimize the potential simultaneity bias (Fafchamps and Lund, 2003).

Based on the findings in the literature, one can assume that risk preferences and abilities are increasing or decreasing with wealth (Fukunaga and Huffman, 2009; Bellemare and Brown, 2010). Therefore, restricting our sample to a homogeneous wealth group (e.g. small landholders) should account for the self-selection problem. We find that our results are robust to restricting our sample to small landholders and to dropping large landholders from the analysis. Furthermore, if one can assume that unobserved abilities and risk preferences are fixed over time (Rosenzweig, 1988; Wooldridge, 2015), then a fixed effects approach could be employed to assess the impact of networks on household labour allocation (Fafchamps and Lund, 2003). The main drawback of this approach is that the cross-equation correlation of the error terms is not accounted for. As a robustness check, we carry out the same estimation of Equation 2.2 for each labour category separately using the fixed effects method where the time-invariant characteristics of the households are swiped away by the time-demeaning apparatus of this method. Our results remain robust to this change in estimation methodology. The robustness tests aforementioned are presented in the Appendix.

Clustering

Our households are clustered within 18 villages. In a single equation modelling approach, clustering the data at the village level would yield correct standard errors. In a seemingly unrelated regression analysis, clustering the data is computationally unfeasible. Therefore, we use a bootstrapping iteration strategy to compute standard errors in order to make correct inferences (Boldea and Magnus, 2009). Although there is no general prescription on the number of bootstrap repetitions, we use 500 repetitions given the large sample size. The bootstrap procedure is based on random re-sampling from the estimation sample with replacement of the observation in its repetitions. This method promises to provide estimates with less bias and more robust standard errors.

2.7 Results and discussion

The generalized least square estimates[9] of the SUR model are presented in Table 2.3. Greene (2012) provides two propositions that justify the use of SUR. The greater the correlation between the regression residuals (or disturbances) across the equations, the higher the gains in efficiency from using generalized least squares in a SUR model. Furthermore, the lower the correlation between the explanatory variables, the more suitable is the generalized least squares model. We confirm that the correlation between covariates is very low. The correlation matrix of the residuals of the 5 regressions within the system are presented in Table 2.4. Non-negligible correlations appear in the correlation matrix of the equations' residuals.

The coefficient estimates of $DEVIATION$ and $DEVIATION \times NET$ must

[9] A subset of the results is given for presentation purposes

be interpreted with caution. When rainfall deviation is negative, the movement in the shares is opposite to the sign of the coefficient. For example, a positive sign on the coefficient of $DEVIATION$ on the share of self-employment in agriculture, suggests that a negative deviation decreases the time share allocated in this category. If, for instance, $DEVIATION$ decreases, i.e. becomes more negative, households will reduce their share of self-employment in agriculture. The coefficient of NET represents the average effect of being part of a network, and a positive coefficient suggests that being part of a network increases the share of labour allocation in the outcome variable. The interaction term $DEVIATION \times NET$ represents the differential effect of being part of a network subject to experiencing a rainfall deviation. Along with the regression estimates, we provide a summary table of the movement in shares of the different labour allocation categories in Table 2.2 to facilitate the interpretation of the results.

Table 2.2: Movement of Shares based on GLS Estimates of the SUR Model

	Shares of				
	Self-Emp in Agri.	Agri. Labour	Non-Agri. Labour	Migration	Domestic Work
Negative deviation of rainfall	↓	↓	↑	↑	↓
Experiencing a negative deviation while part of a network	↑			↓	
NET	↑	↓	↓		↑

Note: Only statistically significant results are reported

To test the specification, the Breusch-Pagan test rejects the null-hypothesis of the independence of the residual series at 1% significance level and 10 degrees of freedom. This suggests that the error terms of the different categories are significantly correlated. The Wald test also rejects the hypothesis that the coefficients of the main variables are jointly equal to zero across equations. Having established the empirical specification of the model, we now discuss the estimates presented in Table 2.3 and summarized in Table 2.2. We begin by discussing the results of our estimation for each labour category separately.

We find that households significantly decrease self-employment in agriculture subject to a negative rainfall deviation. A deviation of $-1mm^3 \times (10^{-3})$ in rainfall decreases the share of self-employment in agriculture by 4.69%. However, households that are part of a network do in fact increase self-employment in agriculture subject to a negative rainfall shock. These households are found to increase their share of self-employment in agriculture by 9.37% in response to a $-1mm^3 \times (10^{-3})$ deviation in rainfall. This represents the differential effect of being part of a network on experiencing a shock, i.e. those who have the benefit of a network-based insurance mechanism are more likely to engage in risky agricultural work despite the negative rainfall shock. Furthermore, on average there is a positive and significant effect of being part of a network on working in self-employment in agriculture. This could be explained by the change in risk preferences of households that are part of a risk-sharing network (Chiappori et al., 2014). Households who know they have the safety net of the network have a lower aversion to risk, which could be the driver to undertake riskier activities (such as own-farm work) during times of negative rainfall shocks. We find that as the education level of the household head and other household members increases, the share of agricultural self-employment decreases. The results also suggest a negative and significant effect of the agricultural and non-agricultural wages at the village level on households' supply of labour in agriculture. This a sensible result as it indicates that households may find wage work more attractive as the wages increase.

As for agricultural wage labour (column 2 of Table 2.3), both a rainfall shock increases the households' share of household's labour supply in this category, consistent with the findings of Ito and Kurosaki (2009). A $-1mm^3 \times (10^{-3})$ deviation in rainfall is expected to increase supply of wage labour in agriculture by 3.05%.

We find that the differential effect of being part of a network and experiencing a shock is not significant but the average effect is negative and significant. This suggests that being part of a network has no bearing on their shift from self-employment in agriculture to agricultural wage labour during times of shock, but on average those who are part of a network are less likely to be in agricultural wage employment. Furthermore, we observe a positive and significant effect of agricultural and non-agricultural wages at the village level on share of agricultural wage work. This result is consistent with the literature on rural labour supply: as village-level wages increase, wage labour becomes more attractive.

Similar to the case of agricultural wage labour, the results indicate that households significantly increase their non-agricultural labour subject to a negative rainfall shock. A $-1mm^3 \times (10^{-3})$ deviation in rainfall is expected to increase supply of wage labour in agriculture by 4.45%. We find that the differential effect of being part of a network is not statistically significant. However, households who have the network's insurance are less likely to engage in non-agricultural work. Agricultural wages have a positive and significant effect on households' share of this activity. Non-agricultural wages, however, have a positive and insignificant effect on it, which suggests that non-agricultural wage labour is generally more attractive to households even as prices increase in the agricultural wage market.

A $-1mm^3 \times (10^{-3})$ rainfall deviation increases the share of migration work by 2.31%, and the coefficient is statistically significant. Munshi and Rosenzweig (2016) has noted one important mechanism that the migration of female members decision to migrate is more responsive to the marriage market than it is to purely economic considerations . Although we do not test the hypothesis on marriage considerations, this observation is supported in a separate finding in this study that confirms that female migration is not responsive to rainfall shocks.

Being part of a network does not appear to have a significant effect on migration - on average - but does reduce the likelihood and the share of migration work given a negative rainfall deviation. This depicts the role of insurance that the network provides during times of distress as an informal risk-sharing mechanisms (Platteau, 2000; De Weerdt and Hirvonen, 2013). As expected, an increase in rural agricultural wages has no statistically significant effect on migration. Non-agricultural wages, however, have a positive and significant coefficient on migration which could reflect the increase in rural commodity prices as a result of an increase in non-agricultural wages (Ito and Kurosaki, 2009).

The share of domestic work also decreases in response to a negative rainfall shock, which indicates that households place less importance on domestic work and chores during bad times, given the incentive to supply more labour that generates income. It is important to note that in rural India, the search for jobs is less of a problem (than, say, the urban labour market) given the informality of the rural market and the abundance of daily labour activities[10]. Being part of a network has a positive and significant effect on domestic work. This could also reflect the lower risk aversion and moral hazard of households who have the insurance of their network's safety net.

One limitation of the analysis thus far is that we do not explore the dynamics at the individual level. This would have been a very interesting exercise as the aggregate shares at the household level may mask some variations at the individual level. These dynamics could be influenced by female fertility choices, the marriage market, and gender equality among other factors. While important, these intra-household considerations are beyond the scope of this study. We do, however, investigate the possibility that the coefficient of the share of migration

[10] Anecdotal evidence suggests that daily labourers gather at the town squares to be picked up for a certain task on daily basis. No claim can be made, however, on the welfare outcomes in terms of income, health, and skills out of these activities.

Table 2.3: GLS Estimates of the Seemingly Unrelated Regression Model

	Shares of				
	Self-Emp in Agri.	Agri. Labour	Non-Agri. Labour	Migration	Domestic Work
$DEVIATION(10^{-3})$	4.69***	-3.05***	-4.45***	-2.31***	5.84***
	[1.20]	[1.04]	[1.45]	[0.82]	[1.25]
$DEVIATION(10^{-3}) \times NET$	-9.37***	1.10	0.81	4.21***	2.66
	[2.07]	[1.79]	[2.50]	[1.41]	[2.15]
NET	0.49*	-2.16***	-2.54***	-0.11	5.38***
	[0.26]	[0.23]	[0.31]	[0.18]	[0.27]
$AGEHHH$	-0.13***	-0.05***	0.07***	-0.01	0.15***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
$EDUHHH$	0.10*	-2.24***	1.35***	-0.19***	1.08***
	[0.05]	[0.05]	[0.07]	[0.04]	[0.06]
$AGRIWAGE \times 10^{-3}$	-0.25***	0.14***	0.19***	-0.00	-0.10***
	[0.01]	[0.01]	[0.02]	[0.01]	[0.02]
$NAGRIWAGE \times 10^{-3}$	-0.43***	0.18***	0.05	0.07***	0.13***
	[0.03]	[0.03]	[0.04]	[0.02]	[0.03]
Observations	39627	39627	39627	39627	39627
R^2	0.16	0.15	0.05	0.14	0.15
χ^2	6317.48	6572.03	2984.02	6000.77	7157.00
$df(\chi^2)$	28.00	28.00	28.00	28.00	28.00

Other controls included: life-cycle variables, dummy variables for large-landholders and medium landholders, caste dummies, village and time fixed effects. The identification variables, as expected, are all significant at 1% level

Bootstrapped Standard errors in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: Correlation of the Disturbances of the Equations in Table 2.3

		Shares of				
		(a)	(b)	(c)	(d)	(e)
Self-Employment in Agriculture	(a)	1				
Agri. Wage Labour	(b)	-0.20	1			
Non-Agri. Wage Labour	(c)	-0.42	-0.23	1		
Migration	(d)	-0.16	-0.07	-0.18	1	
Domestic Work	(e)	-0.09	-0.24	-0.38	-0.22	1

Breusch-Pagan test of independence: $\chi^2(10) = 23460.71$, Pr = 0.00

in Table 2.3 may differ considerably between male and female household members. Much of the literature on migration in India (e.g. Munshi and Rosenzweig, 2016) suggests that male migration is predominantly more responsive to labour market considerations than female migration. Therefore, in an attempt to understand the differences in responses in the case of migration between males and females, we dis-aggregate our shares by gender. The seemingly unrelated regression model of Equation 2.2 is repeated, but now with 10 equations (5 categories for each gender). The results are presented in Table 2.5. We find that the share of male migration does indeed increase in response to a negative rainfall shock and the result is statistically significant; while the response of females' migration to shocks is negligible and statistically insignificant. We also find that the coefficient of DEVIATION interacted with the NET variable is statistically significant for male migration, but not for females. This indicates that males are less likely to leave the village during times of distress if they have the network's insurance to rely on. This is consitent with the findings of Munshi and Rosenzweig (2016) and could explain to a certain degree the decline of male rural-urban migration. We do not assess the reasons why female migration is not responsive to income shocks and to participation in a network, but the literature suggests that the migration of females in India is mainly driven by considerations related to marriage (Munshi and Rosenzweig, 2016; Rosenzweig and Stark, 1989). One further interesting finding, however, is that while the average effect of being part of a network is insignificant for males' migration, the females' migration is reduced when the household is part of a network. This could provide some evidence that females are more likely to stay in the village - even for marriage purposes - depending on the strength of the risk-sharing network; we do not however test this hypothesis. Finally, while the disaggregated results across the other labour activities confirm the findings in the aggregated household case, we do not find any structural difference between male and female behaviour in the labour market participation.

Table 2.5: GLS Estimates of the Seemingly Unrelated Regression Model: Shares by Gender

	Shares of									
	Self-Emp. in Agri.		Agri.		Non-Agri.		Migration		Domestic Work	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
$DEVIATION(10^{-3})$	4.63***	-0.19	-1.10*	-2.06***	-4.26***	-0.22	-2.29***	0.01	0.90	4.81***
	[0.85]	[0.59]	[0.63]	[0.75]	[1.24]	[0.67]	[0.74]	[0.26]	[0.66]	[1.12]
$DEVIATION(10^{-3}) \times NET$	-8.89***	-0.42	1.59	-0.48	-0.34	1.03	3.95***	0.24	1.83	0.90
	[1.47]	[1.02]	[1.09]	[1.29]	[2.13]	[1.15]	[1.28]	[0.45]	[1.14]	[1.93]
NET	0.49***	0.08	-0.33**	-1.76***	-1.19***	-1.34***	0.16	-0.29***	2.60***	3.10***
	[0.19]	[0.13]	[0.14]	[0.16]	[0.27]	[0.14]	[0.16]	[0.06]	[0.14]	[0.24]
$AGEHHH$	-0.04***	-0.09***	-0.04***	-0.02***	0.03***	0.04***	-0.00	-0.01***	0.07***	0.06***
	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
$EDUHHH$	0.39***	-0.25***	-1.15***	-1.08***	1.01***	0.36***	-0.21***	0.03**	0.29***	0.78***
	[0.04]	[0.03]	[0.03]	[0.03]	[0.06]	[0.03]	[0.03]	[0.01]	[0.03]	[0.05]
$AGRIWAGE \times 10^{-3}$	-0.23***	-0.02***	0.06***	0.07***	0.19***	-0.01	0.01	-0.01***	-0.02**	-0.08***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]
$NAGRIWAGE \times 10^{-3}$	-0.47***	0.05***	-0.09***	0.26***	-0.03	0.09***	0.02	0.05***	-0.29***	0.41***
Observations	39627	39627	39627	39627	39627	39627	39627	39627	39627	39627
R^2	0.14	0.13	0.08	0.14	0.04	0.07	0.14	0.03	0.14	0.17
χ^2	5651.42	4374.18	3214.88	6039.85	1962.55	3329.48	5755.90	827.96	5809.11	5757.48
df(χ^2)	28.00	28.00	28.00	28.00	28.00	28.00	28.00	28.00	27.00	27.00

Other controls included: caste dummies, village and time fixed effects. The identification variables, as expected, are all significant at 1% level
Bootstrapped Standard errors in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.8 Conclusion

The role of community networks in rural areas of the developing world constitutes a vital institution that households rely on not only for social purposes, but also for economic and risk-coping strategies. We base our premise on the fact that households in rural India form networks and engage in risk-sharing arrangements in order to buffer income shocks. In order to analyze the households' time allocations across a range of activities, we hypothesize that the role of networks is crucial in informing their decisions and shaping their attitudes towards risk. Therefore, this paper studies the role of networks in changing the households' allocation of their time resources into self-employment in agriculture, agricultural wage labour, non-agricultural labour, migration, and domestic work subject to weather-driven shocks. The proposed mechanisms are based on the heterogeneity in risk preferences between households who are part of a network and those who are not, the asymmetry of information in migration due to unobserved income, and social sanctioning of households who send their members to urban locations.

Using a seemingly unrelated regression model, we find that households reduce own-farm work and domestic work in response to negative rainfall deviations, but increase agricultural wage work, non-agricultural work, and migration work. Furthermore, we find evidence that households who are part of a risk-bearing network increase their participation in risky activities (e.g. self-employment in agriculture that is generally riskier than wage employment), but decrease the share of their time supplied outside the confines of the village given a rainfall shock (e.g. migration). Furthermore, we find that male migration is more responsive to rainfall shocks than that of female members (see Table 2.5). A reason why this may be the case is that female migration choices are more responsive to the marriage market than to purely economic considerations[11] (Rosenzweig and Stark, 1989). Lastly, by challenging some the assumptions made in our model on the choice of methodology, definition of outcome variables, and the response of domestic work in a unitary model, we perform a series of robustness checks. Our results remain robust to these changes in the variable definitions and the choice of methodology.

There are certain limitations to the conclusiveness of this study. Firstly, the exclusion of the landless households from the analysis means that the results are not representative of a group - arguably the most vulnerable - of households that may respond to shocks differently given that they do not have the option to engage in self-employment in agriculture. Secondly, the households' structure and intra-household decisions are likely to have an impact on their labour supply decisions. In other words, men and women within the household may be allocated different tasks depending on their abilities, preferences, and their bargaining power. Therefore, we do not attempt to make any claims on intra-household allocation of resources, fertility choices, or gender equality. In this context, an analysis of individuals clustered within households can have significant conclusions and policy implications. We also avoid making any inferences on welfare of the household subject to the changes in the labour allocation. In chapter 1 of this thesis, we find that households in rural India have a smooth consumption and liquidate their non-productive assets to self-insure against income shocks. Therefore, any claim on the welfare implications of the change in labour portfolio needs to be complemented with an income smoothing analysis conditional on these changes. Another important dimension of the rural labour

[11] We say "purely" economic considerations as one may argue that the marriage market itself may be a coping mechanism that allows spatial cooperation between households across districts or regions.

market in India that is not addressed in this paper is the National Rural Employment Guarantee Scheme because the data is not available in the ICRISAT's monthly surveys. Therefore, in this analysis we cannot disentangle the difference between labour hours supplied as part of this scheme and others that are not. Our discussion on the role of rural community networks and their deterrent effect to migration are likely to be very useful in understanding the role played by the employment guarantee schemes in rural communities. While these questions are all very important, they are beyond the scope of this study and will constitute important avenues for future research.

There are numerous policy implications that can be drawn from the results of this paper. A main message is that when rural-urban mobility is low - such as the case of India - and resources are inefficiently allocated (Munshi and Rosenzweig, 2016), introducing affordable and accessible credit schemes for rural households can prove to be of extreme value. The purpose of credit access may not necessarily substitute community networks as households may be averse to borrowing from rural institutions. Nevertheless, institutional access to credit may increase the likelihood of households' migration to urban areas without the fear of losing the safety net. The spillover effects of rural-urban migration can have a positive impact on rural households through remittances, education, enhancing skills and entrepreneurship, and promoting rural development. This also calls for the need to implement formal and efficient insurance schemes that shield households from rural shocks in risky agro-climatic environments. The increased dexterity and efficiency of adopting one activity and mastering it are crucial to rural development. Therefore, reducing the resultant magnitude and frequency of rural shocks can lead to significant welfare improvements for the households and their social networks.

Appendix

Robustness Checks

Following our discussion on rural networks and the possibility of endogeneity in the networks measure, we carry out in this Appendix several robustness checks to support our claims. In terms of self-selection into the network, the past rainfall deviations must be correlated with network participation/formation (risk aversion). To be more certain in correcting for the possibility that self-selection bias remains, we adopt several other robustness tests.

If one can assume that unobserved abilities and risk preferences are fixed over time (Rosenzweig, 1988; Wooldridge, 2015), then a fixed effects approach could be employed to assess the impact of networks on household labour allocation (Fafchamps and Lund, 2003). The main drawback of this approach is that the cross-equation correlation of the error terms are not taken care of (Rosenzweig, 1988). As a robustness check, we carry out the same estimation of Equation 2.2 for each labour category *separately* using the fixed effects method where the time-invariant characteristics of the households are swiped away by the time-demeaning apparatus of this method. The results (Table 2.6) remain robust for this change in methodology.

On the one hand, the literature has established that risk preferences and abilities are increasing or decreasing with wealth (Fukunaga and Huffman, 2009; Bellemare and Brown, 2010). Therefore, homogenizing the wealth groups in the sample should take care of the self-selection problem. We therefore restrict our sample to small and medium landholders to get a homogeneous sub-sample in preferences and wealth. We avoid the use of actual wealth measures (land, livestock, etc.) to overcome problems of measurement error. If self-selection is a problem because of unobserved heterogeneity across landholding classes, then restricting our sample in this way may distort the results. We find that the opposite happens, and our results are robust to this restriction. Results of this procedure are given in Table 2.7.

Furthermore, we present results with changes in the outcome variables. In Table 2.8, we exclude the domestic work from the computation of the shares of hours work. In other words, the sum of self-employment in agriculture, agricultural wage labour, non-agricultural work, and migration shares add up to 100% for each household. The reason we do carry out this robustness analysis is that one may argue that in a unitary model of the household, an activity such as domestic work, that is usually only carried out by women, does not enter into the collective decision of the household. This, however, is debatable. Consider, for instance, a household whose male members predominantly work in self-employment in agriculture, while women mainly do the domestic work. During periods of drought or rainfall shocks, the household may collectively decide to send women to work on the farm while men engage in other forms of labour activities. Nevertheless, after exploring the possibility that the unitary model should exclude domestic work, we find that our results are robust to this change in the construction of shares as shown in Table 2.8.

In Table 2.9, we change the definition of the outcome variable from shares of hours allocated in a given month to the hours of work per capita (of adults in the household) in each activity. We find that the results support the findings of the previous analysis using hours per capita.

Table 2.6: Fixed Effects Model - Robustness of results

	Shares of				
	Self-Emp in Agri.	Agri. Labour	Non-Agri. Labour	Migration	Domestic Work
$DEVIATION(10^{-3})$	0.18	-1.78**	-1.55*	-1.06*	4.22***
	[0.77]	[0.73]	[0.84]	[0.55]	[0.86]
$DEVIATION(10^{-3}) \times NET$	-8.14***	0.39	-0.37	3.72***	4.41***
	[1.33]	[1.27]	[1.46]	[0.94]	[1.48]
NET	2.65***	-0.64***	-1.03***	0.06	-1.04***
	[0.20]	[0.19]	[0.22]	[0.14]	[0.22]
$AGEHHH$	0.01	0.10***	-0.14***	0.02	0.01
	[0.02]	[0.02]	[0.03]	[0.02]	[0.03]
$EDUHHH$	0.82***	-0.20	-1.91***	-0.93***	2.22***
	[0.32]	[0.30]	[0.35]	[0.23]	[0.35]
$AGRIWAGE \times 10^{-3}$	0.13***	0.09***	-0.02	0.07***	-0.26***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
$NAGRIWAGE \times 10^{-3}$	0.02	0.05**	-0.01	0.15***	-0.21***
	[0.02]	[0.02]	[0.03]	[0.02]	[0.03]
Observations	39627	39627	39627	39627	39627
R^2	0.32	0.34	0.40	0.55	0.17

Other controls included: number of working males, number of working females, and number of non-working people within the household, caste dummies, village and time fixed effects.
Standard errors in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: GLS Estimates: Analysis of the Response Excluding Large Landholders

	Shares of				
	Self-Emp in Agri.	Agri. Labour	Non-Agri. Labour	Migration	Domestic Work
$DEVIATION(10^{-3})$	4.79***	-3.09**	-7.39***	-1.54	8.34***
	[1.33]	[1.29]	[1.74]	[0.96]	[1.43]
$DEVIATION(10^{-3}) \times NET$	-8.62***	0.42	1.77	4.50***	0.81
	[2.31]	[2.24]	[3.04]	[1.68]	[2.48]
NET	0.77***	-3.02***	-1.99***	0.51**	5.07***
	[0.29]	[0.28]	[0.38]	[0.21]	[0.31]
$AGEHHH$	-0.14***	-0.06***	0.08***	-0.03***	0.18***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
$EDUHHH$	-0.29***	-2.52***	2.07***	-0.36***	1.18***
	[0.06]	[0.06]	[0.08]	[0.05]	[0.07]
$AGRIWAGE \times 10^{-3}$	-0.28***	0.09***	0.16***	-0.00	0.01
	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]
$NAGRIWAGE \times 10^{-3}$	-0.35***	0.14***	0.07*	-0.01	0.17***
	[0.03]	[0.03]	[0.04]	[0.02]	[0.03]
Observations	28360	28360	28360	28360	28360
R^2	0.20	0.17	0.06	0.20	0.17
χ^2	5982.54	5408.83	3194.77	6858.50	6233.20
$df(\chi^2)$	27.00	27.00	27.00	27.00	27.00

Other controls included: life-cycle variables, dummy variables for large-landholders and medium landholders, caste dummies, village and time fixed effects. The identification variables, as expected, are all significant at 1% level

Bootstrapped Standard errors in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: GLS Estimates: Analysis of the Response Excluding Domestic Work from Share of Household Labour Allocation

	Shares of			
	Self-Emp in Agri.	Agri. Labour	Non-Agri. Labour	Migration
$DEVIATION(10^{-3})$	13.45***	-2.83	-5.50**	-3.96***
	[2.47]	[1.83]	[2.41]	[1.20]
$DEVIATION(10^{-3}) \times NET$	-15.22***	6.41**	-0.13	8.24***
	[4.27]	[3.16]	[4.16]	[2.07]
NET	4.35***	-2.71***	-1.28**	0.55**
	[0.54]	[0.40]	[0.52]	[0.26]
$AGEHHH$	-0.15***	-0.03***	0.20***	-0.00
	[0.02]	[0.01]	[0.02]	[0.01]
$EDUHHH$	1.24***	-4.04***	3.13***	-0.22***
	[0.11]	[0.08]	[0.11]	[0.06]
$AGRIWAGE \times 10^{-3}$	-0.67***	0.34***	0.35***	-0.04***
	[0.03]	[0.02]	[0.03]	[0.01]
$NAGRIWAGE \times 10^{-3}$	-0.63***	0.47***	0.09	0.05*
	[0.06]	[0.05]	[0.06]	[0.03]
Observations	38399	38399	38399	38399
R^2	0.12	0.14	0.05	0.12
χ^2	5224.76	6204.66	2534.87	4794.36
$df(\chi^2)$	28.00	28.00	28.00	28.00

Other controls included: life-cycle variables, dummy variables for large-landholders and medium landholders, caste dummies, village and time fixed effects. The identification variables, as expected, are all significant at 1% level
Bootstrapped Standard errors in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: GLS Estimates: Analysis of the Response using hours of work per capita

	Hours (per capita) of				
	Self-Emp in Agri.	Agri. Labour	Non-Agri. Labour	Migration	Domestic Work
$DEVIATION(10^{-3})$	10.44***	-2.42	-6.76**	-2.15	14.94***
	[2.12]	[2.17]	[2.86]	[1.73]	[2.00]
$DEVIATION(10^{-3}) \times NET$	-18.57***	-2.23	-3.20	5.66*	-11.08***
	[3.65]	[3.75]	[4.95]	[2.98]	[3.45]
NET	3.73***	-2.54***	-4.63***	-0.42	6.37***
	[0.46]	[0.47]	[0.62]	[0.37]	[0.43]
$AGEHHH$	-0.29***	-0.22***	-0.09***	-0.05***	-0.43***
	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]
$EDUHHH$	-0.18*	-4.50***	2.48***	-0.47***	0.07
	[0.10]	[0.10]	[0.13]	[0.08]	[0.09]
$AGRIWAGE \times 10^{-3}$	-0.38***	0.07***	0.11***	0.10***	-0.30***
	[0.03]	[0.03]	[0.04]	[0.02]	[0.03]
$NAGRIWAGE \times 10^{-3}$	-0.77***	0.10*	-0.15**	0.09**	-0.82***
	[0.05]	[0.05]	[0.07]	[0.04]	[0.05]
Observations	39633	39633	39633	39633	39633
R^2	0.22	0.16	0.07	0.14	0.29
χ^2	10983.90	7238.02	2482.39	6435.64	16972.05
$df(\chi^2)$	28.00	28.00	28.00	28.00	28.00

Other controls included: life-cycle variables, dummy variables for large-landholders and medium landholders, caste dummies, village and time fixed effects. The identification variables, as expected, are all significant at 1% level

Bootstrapped Standard errors in brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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CHAPTER 3

Buffer stock savings by portfolio adjustment: Evidence from Rural India

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Buffer stock savings by portfolio adjustment: evidence from rural India

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Abstract

The empirical literature on household savings tends to treat savings simply as the residual of income minus consumption. This article takes a unique approach to reconstruct the cash and asset balances using detailed household transaction data on farm households in rural India and generates monthly and seasonal ICRISAT panel data for the period 1976–1983. We have found that households—irrespective of their landholding status—cope with temporary shocks quite well by using crop inventory, currency, and capital assets, rather than livestock, as buffer assets. The importance of portfolio adjustments in smoothing consumption is also confirmed by the use of a system of equations in which both portfolio and production decisions are made endogenous. It is concluded that not only the level but also the diversification of household assets are important for buffering consumption. As an extension, we have explored the monthly ICRISAT panel data for the period 2009–2012 in the same villages and have found a similar pattern in household portfolio responses to income shocks.

JEL classifications: C33, D12, O16

Keywords: Buffer Stock; Savings; Consumption; Credit; Portfolio Adjustment; India

1. Introduction

The traditional literature on savings and consumption smoothing has focused on the aspect of "buffer-stock" savings in contrast to the traditional literature of life cycle saving by modeling either the liquidity constraints of households (Deaton, 1990, 1991, 1992, 1997; Zeldes, 1989) or the precautionary nature of savings (e.g., Carroll, 1997; Kimball, 1990). Buffer-stock savings are particularly important in investigating rural poverty in developing countries because of the salient features of rural economy associated with its uncertainty or risk, e.g., due to the dependence on the agricultural sector, poor health services, low level of sanitation, and lack of access to formal credit. All of these factors combined lead to welfare deterioration among the poor and their economic development (Carter and Lybbert, 2012). However, most of the previous studies, except a few (e.g., Carter and Lybbert, 2012), treat savings simply as the residual of income minus consumption. The main aim of the current study is to shed a light on the "black box" by disaggregating the savings into various subcomponents and examine the extent to which households in rural India buffer their consumption by adjusting their assets.

Much of the empirical literature has focused on the role of precautionary or buffer-stock savings for household risk-coping in the context of developing countries, in and outside India. For instance, using the annual ICRISAT data, Rosenzweig and Wolpin (1993) emphasize the role of bullocks for credit-constrained households in rural India as a buffer stock for consumption. One of their main findings is that sales of bullocks increase when income streams decrease, and vice versa. However, Lim and Townsend (1998), through a close investigation of how rural farming households financed their deficit based on the monthly ICRISAT data, conclude that livestock—including bullocks and major capital assets—play little part in smoothing intertemporal shocks. They insist that buffer stock of crop inventory and currency, together with credit or insurance, are much more important. Chaudhuri and Paxson (1994), also using the monthly ICRISAT data in India, investigate the impact of seasonality in income on seasonality in consumption. They conclude that seasonal patterns in consumption are common across households within villages but are not related to income seasonality. Based on the seasonal data of rainfall, Jacoby and Skoufias (1998) reach a similar conclusion by estimating the household response to anticipated and unanticipated income shocks.

Outside India, Carter and Lybbert (2012) device a technique to understand the coexistence of consumption and asset

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smoothing regimes based on the poverty trap model of Barrett et al. (2011), assuming that assets are not merely buffer stocks, but contemporarily act as productive assets with positively-diminishing returns. They employ a Hansen threshold estimation method for data from rural Burkina Faso between 1981 and 1985, which is a period where households are faced with severe drought. Carter and Lybbert find that while those who are richer in assets—proxied by tropical livestock units—managed to smooth their consumption well, the asset poor households tend to preserve their assets and smooth their consumption limitedly. There exists a critical herd size threshold that separates households with high- versus low-consumption smoothing, and those with such high smoothing levels who rely primarily on livestock to achieve it (Carter and Lybbert, 2012). Lee and Sawada (2010) assess the precautionary savings motive, or "prudence," in Pakistan, based on 14 rounds of survey from 1986 to 1991. Their results confirm the theory of precautionary savings behavior among Pakistani households, particularly among those facing liquidity constraints. Using the same sample as Carter and Lybbert (2012), Kazianga and Udry (2006) find little evidence of consumption smoothing behavior. They confirm that households with subsistence income in Burkina Faso do not liquidate their assets in favor of current consumption, and households who face land-income volatility to a greater extent save more given their income shocks. With the same dataset, Fafchamps et al. (1998) show that livestock sales did not adequately serve as precautionary savings, particularly against negative income shocks, such as drought. Drawing upon a dataset from Thailand, Paxson (1992) concludes that most of the transitory income attributed to rainfall shock is saved, that is, the saving behavior of farmers accords with the theoretical predictions of buffer-stock savings. The literature suggests that household savings matter in risk-coping, but the role of livestock savings/dissavings is generally limited. In other words, household assets other than livestock are likely to be important.

The contribution of this article to the above empirical literature is twofold. First, we look at not just the change in stock of a single asset, such as bullocks, but also the *total* portfolio adjustment of households that face various risks: The possibility exists that the sale of bullocks and the purchase of other items, like consumer durables, for instance, may take place simultaneously. In this article, we focus on dynamic changes in the portfolio of households, such as those pertaining to livestock, production capital, or consumer durables, which has largely been neglected in the empirical literature. Here, we empirically examine how households mitigate income risk by portfolio adjustment. Second, we explicitly take account of household portfolio adjustment by the system of equations in which 1) transitory income, changes in a variety of household assets, and expenditure are simultaneously estimated and 2) some forms of savings, namely, changes in financial assets, agricultural inputs, and production capital, are allowed to affect transitory income shocks. Most of the past literature on household savings assumes that savings in themselves do not affect income. However, in rural economies, this is not a realistic assumption, because 1) physical assets have roles of production assets as well as savings or accumulation and 2) transitory changes in financial assets or credit availability are key factors to transitory income changes. The idea is similar to Behrman et al.'s (1997) study that incorporates the sequential decision-making process in agricultural production in estimating saving function.[1]

2. Data

In this study, we construct monthly data on income, consumption, savings, and credit using the ICRISAT data—both monthly and seasonal data—between 1975/76 and 1984/85.[2] This dataset is well known for its high quality and influence in the emergence of several of development economics' core findings (Dercon et al., 2013; Walker and Ryan, 1990). The survey is structured in such a way that households are stratified according to their landholding classes. Forty households in each village consist of four classes: the landless, small farmers, middle farmers, and large farmers. Our analysis is based on the household transaction module, the production modules, the household member schedule, and the general endowment schedule in the ICRISAT dataset. One of the distinguished features of the ICRISAT dataset is the unusually detailed information that the household transaction module records.[3] As the contribution of the analysis in this article is closely associated with the use and adjustment of data in the transaction module, we first briefly describe its features.

The main purposes of the transaction module are to assess the income position of households, to compute consumption quantities and expenditures, and to record production expenditures and changes in the debt or credit positions of the household (Singh et al., 1985). In principle, the transaction module records all market transactions of households, including purchases, sales, gifts, credit, and other market transactions with recall of about four-week intervals (Lim and Townsend, 1998).[4] The interview on this schedule was continued every month in the first week during the period 1975/76 (crop year from July 1975 to June 1976) to 1984/85 in three Indian villages, namely Aurepalle, Shirapur, and Kanzara.[5] All the cash and kind trans-

[1] The main difference between our study and Behrman et al.' s (1997) is that while the former deals with the portfolio of the entire household savings, the latter uses only a component of the savings, namely 1) net changes in financial assets, 2) net borrowing, and 3) transfers to friends and relatives.

[2] The first year (1975/76) and the final two years (1983/84–1984/85) have been dropped from the final estimations taking account of the consistency between the data recorded in the transaction modules and the income or consumption data.

[3] Although the ICRISAT data set itself has widely been used in the literature, few studies have used the original information found in the transaction module.

[4] Lim and Townsend (1998) describe in detail the structure of the transaction module and the way of constructing the monthly data on income, consumption, and asset change. We closely follow their methods and aggregate them to the seasonal data.

[5] In the other seven villages where the survey was carried out, transaction data were collected for only three or four years for the selected time frame.

Table 1
The comparison of CV (coefficient of variation) of monthly income and CV of monthly consumption in rural India, 1976–84

CV for each year, 1976–84								
	Average CV of income (a)	Average CV of consumption (b)	Average reduction	No. of observations	t-test (a)−(b)		Smoothing ratios 1− (b)/(a)	Confidence interval (95%)
Landless	100.8	43.8	57	205	2.4	**	0.57	1.027
Small farmer	103.1	49.3	53.9	243	8.16	**	0.52	0.648
Medium-sized	169.8	49.4	120.3	240	5.32	**	0.71	0.969
Large farmer	167.4	58.6	108.8	243	15.22	**	0.65	0.734
Total	136.6	50.5	86	931	10.4	**	0.63	0.748

**= significant at 1% level. * = significant at 5% level. + = significant at 10% level.

actions after the previous interview were recorded in cash value either as cash inflow or as cash outflow, which make it possible to calculate monthly income, consumption, and changes in different components of the household asset.[6] Appendix 1 provides detailed information on how variables on monthly asset changes have been created using the transaction module.

As an extension, we have also explored the ICRISAT Village Dynamics in South Asia data from July 2009 to June 2012 with focus on the same three villages for comparative purposes. The survey design of the new waves is very similar to the older one. We also match monthly rainfall data obtained from the Indian Meteorological Department to the survey data at the district level. The new dataset includes 90 households from Aurepalle, 89 households from Shirapur, and 62 households from Kanzara. The dataset is fairly balanced across different months.[7]

Due to minor differences in survey questionnaires and the difficulty in tracking households between old and new datasets, we opt not to pool all the data. The apparent drawback of using this dataset is that the crop inventory is recorded on an annual basis only and cultivation output data are collected on a seasonal basis. So, it is not feasible to accurately recover monthly information on grain stocks.

3. The specification and the empirical results

First, we compare the coefficient of variation (CV) of monthly consumption with the CV of monthly income in each year. Table 1 shows the results in four different landholding classes: the landless, small farmers, medium-sized farmers, and large farmers. For all the landholding classes, the CV of monthly consumption is significantly lower than that of monthly income at a 1% level, which implies that households smooth consumption during a single crop year. However, Table 1 also suggests that the extent to which households stabilize their consumption varies across different landholding classes. Although the average CVs of income of large and medium farmers are relatively higher (about 170%) and those of small farmers and the landless are lower (about 100%), the average CVs of consumption are almost the same across different landholding classes (about 50%). We also construct the smoothing ratios (SRs) defined as SR = 1 – $CV_{\text{Consumption}}$ / CV_{Income} where SR of 1 (or 0) corresponds to complete consumption smoothing (or no consumption smoothing) (Carter and Lybbert, 2012). The results that are shown in the last column indicate that SR varies across different landholding classes—with SR the highest for medium-sized farmers (0.71) and the lowest for small farmers (0.52), although due to the wide confidence intervals, these ratios are not statistically different from each other. Overall, our result is consistent with that of Townsend (1994) who shows that variation in consumption is surprisingly lower than variation in income based on the annual data of the Indian ICRISAT survey.

Then, an empirical question arises: how well did households smooth consumption across months within a single crop year? Following Paxson (1992) and Fafchamps et al. (1998), we try to capture savings as a function of both permanent and transitory component of income:

$$S_{it} = \alpha_0 + Y_{it}^P\ \alpha_1 + Y_{it}^T\ \alpha_2 +\ VAR_{it}\alpha_3 + W_{it}\alpha_4 + \varepsilon_{it}, \qquad (1)$$

where S_{it} is the saving in various forms, Y_{it}^P is the permanent income, i.e., the portion of income that is constant over time, and Y_{it}^T is the transitory income. i and t denote household and time (or year-month, $t = 1$ for July 1976, $t = 2$ for August 1976, ..., $t = 84$ for June 1983), respectively.[8] VAR_{it} (variance of income) and W_{it} (household characteristics) are assumed to be factors that affect the level of savings. If household savings behavior can be described appropriately by the life cycle/permanent income hypothesis, then α_1 would be 0; that is, permanent income does not affect the level of savings.

A crucial empirical question would be to identify the permanent and transitory components of household income. The studies on Indian households, such as those of Bhalla (1979,

[6] There have been some discussions as to whether the data on consumption (own consumption of home production in particular) and grain stock are correctly recorded. Ravallion and Chaudhuri (1997)—based on the technical details given by Gautam (1991)—note a systematic underreporting problem in the ICRISAT data on own consumption of crop outputs produced at home. They argue that Townsend (1994) overestimates the degree of risk sharing in the village mainly due to the measurement-error problem. We have corrected the transaction data following Gautam in retrieving the cash and asset balances using the transaction data.

[7] For this analysis based on the new data, we focus only on monthly changes.

[8] A subscript denoting village, v, is omitted for simplicity (except for the rainfall variables).

Table 2
Estimations of the reduced-form income equations based on the ICRISAT data from 1976 to 1983 (summary results)

	Case A (Monthly income)	Case B (Crop income in peak season)
Variable	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio
Transitory factors		
Rainfall variables:[1]		
(R_1- mean of R_1) :$R_1 = r_0 + r_{-1} + r_{-2} + r_{-3}$ where r_{-t} is the *t*th *lagged monthly rainfall*	−2.22 (−2.35)*	–
(R_1 − mean of R_1)*(Owned Land)	0.66 (5.56)**	–
(R_2 − mean of R_2): $R_2 = r_{-4} + r_{-5} + r_{-6} + r_{-7}$	−3.37 (−3.60)**	–
(R_2 − mean of R_2)*(Owned Land)	0.81 (6.87)**	–
(R_3 − mean of R_3): $R_3 = r_{-8} + r_{-9} + r_{-10} + r_{-11}$	2.35 (2.53)*	–
(R_3 − mean of R_3)*(Owned Land)	−0.94 (−8.16)**	–
(R_4 − mean of R_4): R_4 = Rainfall in June–September	–	−10.76 (−2.11)[2]
(R_4 − mean of R_4)*	–	0.04 (1.77)†
(R_4 − mean of R_4)*(Owned Land)	–	0.002 (2.15)*
(R_5 − mean of R_5): R_5 = Rainfall in October–Dec	–	23.80 (1.80)†
(R_5 − mean of R_5)[2]	–	−0. 21 (−1.32)
(R_5 − mean of R_5)*(Owned Land)	–	0.003 (0.40)
Seasonal dummies:[3]		
Whether July or not	85.86 (0.99)	–
Whether August or not	208.00 (2.38)*	–
Whether September or not	340.37 (3.84)**	–
Whether October or not	889.42 (10.06)**	–
Whether November or not	831.07 (8.98)**	–
Whether December or not	764.12 (8.30)**	–
Whether January or not	398.63 (4.38)**	–
Whether February or not	558.59 (6.37)**	–
Whether March or not	724.17 (8.23)**	–
Whether April or not	556.82 (6.42)**	–
Whether May or not	204.59 (2.38)*	–
Permanent factors		
Village dummies:[3]		
Whether Shirapur or not	−144.57 (−1.79)†	−30.2.09 (−3.17)**

Continued

Table 2
Continued

	Case A (Monthly income)	Case B (Crop income in peak season)
Whether Aurepalle or not	−194.36 (−2.42)*	−4,010.96 (−4.55)**
Sex/age/education variables:		
Number of people aged 0–5	−7.30 (−0.32)	−122.26 (0.48)
Number of males aged 6–11	53.90 (1.65)†	9.26 (0.03)
Number of females aged 6–11	25.48 (0.70)	42.75 (0.11)
Number of males aged 12–17	−59.23 (−1.63)	749.12 (1.94)*
Number of females aged 12–17	47.56 (1.33)	−352.16 (−0.90)
Number of males aged 18–64		
Illiterate	41.08 (1.00)	395.84 (0.84)
Primary school or less	114.36 (2.19)*	72.55 (0.13)
Secondary school	116.68 (2.02)*	84.82 (0.13)
Post-secondary school	102.79 (2.00)*	458.13 (0.89)
Number of females aged 18–64		
Illiterate	84.63 (2.08)*	−1,010.68 (−2.15)*
Primary school or less	23.61 (0.35)	777.29 (1.04)
Secondary school	116.68 (2.02)*	−303.69 (−0.44)
Post-secondary school	102.79 (2.00)*	−1,299.04 (−1.21)
Number of males aged 65 or more	−158.81 (−1.97)*	82.12 (0.10)
Number of females aged 65 or more	−61.47 (−0.60)	465.16 (0.61)
Variable on the caste:1979		
whether high caste or not	−59.85 (−0.63)	460.50 (0.42)
whether mid-high caste or not	158.34 (1.80)†	1,354.87 (1.51)
whether mid-low caste or not	4.17 (0.04)	1,514.69 (1.47)
Owned land (ha)	23.93 (2.78)**	362.53 (4.69)**
Share of owned land which is irrigated	773.79 (7.52)**	5,465.59 (4.41)**
Stock of livestock (Rs)	0.08 (7.07)**	0.65 (5.73)**
Stock of production capital (Rs)	0.02 (6.44)**	0.04 (1.05)
Input spending in slack season (Rs)	–	1.98 (1.99)**
Constant	−322.61 (−2.54)**	1,679.3 (1.49)
Number of observations	7,703	504

Note: [1] Square takes negative value when the deviation is negative. [2]Number in parentheses is t-ratio. ** = significant at 1% level. * = significant at 5% level. † = significant at 10% level. [3]Dummy variable.

1980) and Wolpin (1982), identify permanent income by the instrumental variables that are correlated only with the permanent component and compute transitory income as the rest of household income. One problem with this approach is that it is difficult to distinguish transitory component from measurement error. Paxson's (1992) study of rice farmers in Thailand isolates the transitory components of income which are exogenous by directly estimating the effects of transitory rainfall variation on crop income. We closely follow Paxson's estimation strategy by using the rainfall data to identify the transitory component.

The permanent component is determined by household characteristics and regional dummies, both of which affect long-term income-earning abilities of households. Permanent income is characterized as

$$Y_{it}^P = \beta_t^P + \beta_v + X_{it}^P \beta_1 + \varepsilon_{it}^P, \tag{2}$$

where β_v is a village fixed effect and X_{it}^P is a set of household characteristics. ε_{it}^P is the error component.

Transitory income is

$$Y_{it}^T = \beta_t^T + R_t^T \beta_2 + L_{it} \otimes R_t^T \beta_3 + \varepsilon^T{}_{it}, \tag{3}$$

where β_t^T is a seasonal dummy variable, R_{vt}^T is a vector of village-specific shocks, namely, rainfall shocks, and L_{it} is the household landholding, which is interacted with a set of rainfall variables to take account of the fact that the rainfall shock affects households differently according to the size of their land. Combining the Eqs. (2') and (3'), we can describe the income equation as

$$Y_{it} = \beta_t + R_{vt}^T \beta_2 + L_{it} \otimes R_t^T \beta_3 + \beta_v + X_{it}^P \beta_1 + \gamma_i + \varepsilon_{it}. \tag{4}$$

Through the estimation of income equation (4) as in Paxson, we can decompose total household income into permanent and transitory components. γ_i is household fixed effect, that is, the unobserved characteristics that may be added to the permanent component. The predicted permanent and transitory incomes are then denoted by

$$\hat{Y}_{it}^P = \hat{\beta}_v + X_{it}^P \hat{\beta}_1 + \hat{\gamma}_{iv} \tag{2'}$$

$$= \hat{Y}_{it} - \hat{Y}_{it}^T$$

$$\hat{Y}_{it}^T = \hat{\beta}_t^T + R_t^T \hat{\beta}_2 + L_{it} \otimes R_t^T \hat{\beta}_3. \tag{3'}$$

Empirically, we first draw upon the two-step procedure in which income equation is estimated in the first step and savings equation for the change of each asset in the second.

In the present study, we use lagged deviations from the mean of village-level monthly rainfall in the ICRISAT data following the specification of Paxson (1992) and Fafchamps et al. (1998) based on the rainfall data to identify the transitory component. More specifically, we have defined rainfall variables in such a way that the seasonal pattern of rainfalls and their temporary shocks are captured at the same time. We have grouped lags of rainfall variables into three groups: the sum of the current rainfall and the first, the second, and the third lags (R_1), that of the fourth to the seventh lags (R_2), and that of the 8th to the 11th lags (R_3).[9] Monthly dummy variables, which express the deterministic seasonal patterns within a single crop year, are also included in the transitory factors.

The factors that determine permanent income include village dummies, sex/age/education variables, and the dummy variables on caste. To capture the combined effects of sex, age, and education on the permanent component of income, we generate count variables for the whole sample to capture the effects of the 15 groups by sex, age group, and educational status (e.g., number of people aged 0–5, or number of males with primary education aged between 18 and 64). Owned land as well as a share of the irrigated area in owned land is added as permanent factors.

One of the problems with the above estimation based on the monthly data is that it does not take explicit account of the seasonal nature of agriculture in formulating an income equation. Therefore, we apply a slightly different specification to estimate the crop-income equation, drawing upon Jacoby and Skoufias (1998) and Carter and Lybbert (2012).

In the estimation of seasonal income, we model crop income in the peak season as a function of 1) the household characteristics (sex/age/education variables, castes) in the agricultural slack season, 2) the variables on production capitals and inputs in the slack season, 3) village dummies, 4) the rainfall in the slack season and its cross term with owned land in the slack season, and 5) the rainfall in the peak season (October to December) and its cross term with owned land in the slack season (June to September). In the first stage, the profit in the peak season is estimated.

$$\pi_{it} = \beta_1 + X'_{it-1}\beta_2 + \beta_3 R_{vt-1}^s + \left(L_{it-1} \otimes R_{vt-1}^s\right)' \beta_4 + \beta_5 R_{vt}^P + \left(L_{it-1} \otimes R_{vt}^p\right)' \beta_6 + \vartheta_i + e_{it}, \tag{5}$$

where X'_{ist} is farm/household characteristic and information set available at the slack season; R_{vt-1}^s is the rainfall before planting (June–September) (capturing transitory shocks in the slack season); and R_{vt}^p is the rainfall after planting prior to harvesting (October–December) (capturing shocks in the corresponding period).[10] t stands for crop year ($t = 2$ for 1977/78; $t = 3$ for 1978/79, $\ldots$, $t = 7$ for 1982/83). L_{it} stands for the household land holding. Rainfall variables are interacted with the current owned land to take into account the fact that rainfall affects the

[9] Here, the issues are whether our rainfall variables are justifiable and whether they are robust to other definitions. First, no single definition of rainfall variables can be considered ideal as it is difficult to match the past rainfall trends with the income on monthly basis given the seasonality of agricultural production. Our definition is admittedly arbitrary in terms of grouping of lags, but it would capture a part of the lagged effects of rainfalls on household income. We have tried a few other definitions (e.g., different groupings or number of lags) as robustness checks and have obtained broadly similar results. The final choice of lags or grouping has been guided by statistical significance of rainfall variables.

[10] In the case where we estimate seasonal income, rainfall variables are defined to capture the season-specific transitory rainfall shocks. The results are robust to other definitions of rainfall variables.

Table 3
Two-step random-effects GLS estimates of savings equations

Panel A: Based on monthly data

Dependent variable:	Case (a) △Capital assets (−Σ△ K_{ijt} P_{ijtt})	Case (b) △Crop inventory (−Σ△ $S_{ijt}P_{ijt}$)	Case (c) △Input inventory (−Σ△ $I_{ijt}P_{ijt}$)	Case (d) △Financial assets (−Σ△ $B_{ijt}P_{ijt}$) (including credit)	Case (e) △Cash holdings[2] (−△M_{jt})
Explanatory variable:	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio
Transitory income	0.13 (4.09)**	0.54 (11.42)**	−0.02 (−4.70)**	0.10 (2.52)**	0.23 (5.78)**
Permanent income	0.11 (2.73)*	0.56 (9.64)**	−0.002 (−0.42)	0.09 (1.92)†	−0.02 (−0.37)
Number of observations	7,703	7,703	7,703	7,703	7,703

Dependent variable:	Case (f) Savings total (sum of cases a–e)	Case (g) △Physical savings (sum of a and b)	Case (h) △Livestock[4]	Case (i) △Production capital[4]	Case (j) △Consumer durables[5]
Explanatory variable:	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio
Transitory income	0.99 (19.26)**	0.67 (11.64)**	0.01 (1.38)	−0.06 (−1.60)	0.19 (7.20)
Permanent income	0.82 (10.94)**	0.65 (8.45)**	−0.06 (−4.95)**	0.09 (1.95)	0.04 (1.03)
Number of observations	7,668	7,703	7,703	7,703	7,703

Panel B: Based on seasonal data

Dependent variable:	Case (a) △Capital assets (−Σ△ K_{ijt} P_{ijtt})	Case (b) △Crop Inventory (−Σ△ $S_{ijt}P_{ijt}$)	Case (c) △Input inventory (−Σ△ $I_{ijt}P_{ijt}$)	Case (d) △Financial assets (−Σ△ $B_{ijt}P_{ijt}$) (including credit)	Case (e) △Cash holdings[2] (−△M_{jt})
Explanatory variable:	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio
Transitory income	−0.06 (-0.46)	0.42 (1.37)	0.03 (2.01)*	−0.33 (−1.48)	0.88 (2.62)**
Permanent income	0.04 (1.02)	0.55 (7.66)**	0.02 (4.27)**	−0.03 (−0.60)	0.28 (3.12)**
Number of observations	504	504	504	504	504

Dependent variable:	Case (f) Savings total (sum of cases a–e)	Case (g) △Physical savings (sum of a and b)	Case (h) △Livestock1980	Case (i) △Production capital[4]	Case (j) △Consumer durables[5]
Explanatory variable:	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio	Parameter Estimate *t*-ratio
Transitory income	1.02 (2.94)**	0.35 (1.01)	0.0 2 (0.37)	−0.17 (−1.13)	0.11 (1.30)
Permanent income	0.79 (7.60)**	0.57 (6.65)**	−0.04 (−2.74)**	0.02 (0.50)	0.02 (0.98)
Number of observations	504	504	504	504	504

Note: [a]Number in parentheses is t-ratio. ** = significant at 1% level. * = significant at 5% level. † = significant at 10% level. [2]Both production capital (case (h)) and consumer durables (case (i)) are a part of capital assets (case (a)).[3]Livestock (case (j)) is a part of production capital of financial assets (case (d)).

households differently according to the size of land. Transitory and permanent crop income can be written as

$$\hat{\pi}_{it}^{T} = \hat{\beta}_3 R^{s}_{vt-1} + \left(L_{it} \otimes R^{s}_{vt-1}\right)' \hat{\beta}_4 + \hat{\beta}_5 R^{P}_{vt} + \left(L_{it} \otimes R^{P}_{vt}\right)'$$

$$\hat{\beta}_6, \hat{\pi}_{it}^{P} = \hat{\beta}_1 + X'_{it-1}\hat{\beta}_2 + \vartheta_i$$

$$= \hat{\pi}_{it} - \hat{\pi}_{it}^{T}.$$

In the second stage, the household savings response to transitory crop-income shocks and permanent incomes is estimated.

$$Savings_{\,it} = \sigma + \gamma^{T}\hat{\pi}_{it}^{T} + \gamma^{P}\hat{\pi}_{it}^{P} + \mu_i + e_{it}. \tag{6}$$

Savings in this case are defined as the net increase in a variety of assets during the peak period. In order to capture the seasonality in agriculture, we use the household crop income in the peak season, rather than the total household income. If γ^T is positive and significant, we can conclude that households save when the transitory crop income (both expected and unexpected transitory income) in the peak season is high, and dissave when transitory income is low.

Table 2 shows the GLS estimates of the reduced forms of monthly and seasonal income estimations specified by the above equations. The estimation results associated with rainfall show that 1) rainfall during the period from the 11th lagged month to the 8th lagged month has a positive impact on monthly income

Table 4
System of equations (based on 3SLS for monthly data and seasonal data): income equation

Variable	Case A (monthly income) Parameter Estimate *t*-ratio	Case B (seasonal crop income) Parameter Estimate *t*-ratio
Rainfall variables:[1]		
(R_1 − mean of R_1): $R_1 = r_0 + r_{-1} + r_{-2} + r_{-3}$ where r_{-t} is the *t*th *lagged monthly rainfall*	2.53 (2.21)*	–
(R_1 − mean of R_1)*(Owned Land)	0.23 (1.77)†	–
(R_2 − mean of R_2): $R_2 = r_{-4} + r_{-5} + r_{-6} + r_{-7}$	−1.45 (−1.23)	–
(R_2 − mean of R_2)*(Owned Land)	0.38 (3.98)**	–
(R_3 − mean of R_3): $R_3 = r_{-8} + r_{-9} + r_{-10} + r_{-11}$	−1.75 (−1.49)	–
(R_3 − mean of R_3)*(Owned Land)	−0.49 (−5.08)**	–
(R_4 − mean of R_4): R_4 = Rainfall in June–September	–	9.49 (1.55)
$(R_4 - \text{mean of } R_4)^2$	–	−0.016 (−0.73)
(R_4 − mean of R_4)*(Owned Land)	–	−0.001 (−1.56)
(R_5 − mean of R_5): R_5 = Rainfall in October–December	–	9.01 (0.63)
$(R_5 - \text{mean of } R_5)^2$	–	−0.03 (−0.19)
(R_5 − mean of R_5)*(Owned Land)	–	0.006 (1.18)
Seasonal dummies:[3]		
Whether July or not	242.75 (2.27)*	–
Whether August or not	214.87 (2.36)*	–
Whether September or not	260.10 (3.07)**	–
Whether October or not	384.10 (4.23)**	–
Whether November or not	320.72 (3.54)**	–
Whether December or not	254.76 (2.94)**	–
Whether January or not	246.22 (2.54)**	–
Whether February or not	314.29 (3.67)**	–
Whether March or not	507.11 (5.28)**	–
Whether April or not	364.00 (3.76)**	–
Whether May or not	251.96 (3.27)**	–
△ Production capital	1.64 (8.41)**	1.80 (3.27)**
△ Input inventory	6.82 (7.14)**	54.22 (6.71)**
△Financial assets	3.08 (20.36)**	−0.52 (−1.49)
(including credit)		3,389.43 (6.30)
Constant	250.40 (2.72)**	
Number of observations	7,703	504

Note: [1]Square takes negative value when the deviation is negative.
[2]Number in parentheses is t-ratio. ** = significant at 1% level. * = significant at 5% level. † = significant at 10% level.
[3]Dummy variable.

and 2) the cross terms of owned land and rainfall during the period from the seventh lagged month to the fourth lagged month (or from the third lagged month to the current month) have positive and significant effects on monthly income. The latter implies that the income of households with larger areas of land is more strongly affected by rainfalls. In case B where crop income in the peak season is applied, we find that 1) the interaction term of owned land and rainfall during the slack season (June to September) has a positive and significant effect on crop income in the peak season and 2) rainfall during the peak season (October to December) has a positive impact on crop income.

Panel A of Table 3 includes the summary results of two-step GLS estimates of monthly and seasonal savings in various forms. Each form of savings is estimated separately. Cases (a)–(e), corresponding to the identity (Eq. (1)), show the net increase in capital assets (production capital assets *plus* consumer durables), crop inventory, input inventory, financial assets (including credit), and cash holdings, respectively. Saving or dissaving as a form of crop inventory is the most important device for households to buffer consumption. The second important device of consumption smoothing is currency, as case (d) shows. As expected, currency is not saved from the increase in permanent income. In the case of capital assets (case (a)) and financial assets (case (d)), both transitory and permanent incomes have positive and significant coefficients. They are important not only as a device of consumption smoothing but also as a measure to save permanent income. Financial assets in case (d) include financial savings, credit (in terms of lending *minus* borrowing), and gifts from others, although they consist mainly of credit. Consumption smoothing through village-level risk-sharing mechanism roughly corresponds to "credit" in case (d), considering the dominant role of informal borrowing and lending in the rural credit market. The fact that the coefficient of transitory income in case (d) is not so large (0.10) implies that households smooth consumption through intertemporal savings, rather than through risk sharing among different households within the village.

Cases (f) and (g) show that consumption is considerably smoothed out by savings, physical savings in particular. These results correspond to those in Table 1. Case (h) suggests that livestock is not used as a buffer stock, contrary to the results shown by Rosenzweig and Wolpin (1993). We decompose the net change of capital assets (case (a)) into the net change in production capital (case (i)) and the net change of consumer durables (case (j)). In monthly analysis, consumer durables seem more important than production capital as buffer stocks.

Panel B of Table 3 shows the case of GLS estimates of a savings equation in which the seasonal data are used. Cash holdings (case (e)) are the most important factor to buffer consumption because transitory income affects positively and significantly the net change in cash holdings. Crop inventory

Table 5
System of equations (based on 3SLS for monthly data and seasonal data): asset equations

Panel A: Based on monthly data

	△Production Capital	△Consumer Durables	△Crop inventory	△Input inventory	△Financial assets	△Cash holdings[2]
Explanatory variable:	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)
Monthly income	0.02	0.12	0.44	0.003	0.23	0.11
(Transitory income)	(0.92)	(5.79)**	(18.84)**	(0.83)	(8.42)**	(3.62)**
Net worth: Real assets – liabilities	–	–	–	–	–	0.0003
						(3.84)**
Stock of production capital	0.04	–	–	–	–	–
Stock of consumer durables	(4.01)**	−0.002	–	–	–	–
Stock of grain stock	–	(−4.75)**	−0.07	–	–	–
Owned land	–	–	(−8.58)**	0.63	–	–
Stock of net borrowings	–	–	–	(2.22)*	−0.0002	–
	–	–	–	–	(−0.47)	−65.67
	−51.93	−5.44	77.26	2.07	−116.75	(−1.19)
	(−1.00)	(−0.14)	(1.78)	(0.31)	(−2.33)	
Number of observations	7,703	7,703	7,703	7,703	7,703	7,703

Panel B: Based on seasonal data

	△Production Capital	△Consumer durables	△Crop inventory	△Input inventory	△Financial assets	△Cash holdings
Explanatory variable:	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)	Parameter Estimate (*t*-ratio)
Crop Income in peak season (Transitory income)	0.06	0.03	0.36	0.02	0.06	0.41
	(2.37)*	(1.58)	(7.05)**	(8.03)**	(1.59)	(5.14)**
Net worth: Real assets – liabilities	–	–	–	–	–	−0.025
						(−2.23)*
Stock of production capital	0.04	–	–	–	–	–
Stock of consumer durables	(4.08)**	−0.005	–	–	–	–
Stock of grain stock	–	(−0.37)	0.15	–	–	–
Owned land	–	–	(0.63)	−1.48	–	–
Stock of net borrowings	–	–	–	(−1.23)	−0.02	–
Constant	–	–	–	–	(1.01)	−287.40
	−271.22	−10.16	−0.43	−61.21	−514.98	(−0.33)
	(−0.78)	(−0.05)	(−0.001)	(−2.61)	(−0.96)	
Number of observations	504	504	504	504	504	504

Note: Number in parentheses is t-ratio. ** = significant at 1% level. * = significant at 5% level. † = significant at 10% level.

seems to be used as a buffer stock, though the coefficient associated with transitory income is not significant. Financial assets and capital assets do not serve as buffer stock at all. Rather do they increase consumption fluctuations, because transitory income has negative coefficients. Case (f) implies that consumption is significantly smoothed out across different seasons but the physical savings (case (g)) are less important. The buffer-stock role of consumer durables is not clearly observed.

If the results based on the monthly data are decomposed by the landholding classes, it is found that all the landholding classes smooth consumption well, relying upon physical assets.[11] For all the landholding classes, crop inventory plays an important part for consumption smoothing, while capital assets are used only for large farmers and the landless. Only for large farmers do cash holdings and savings/dissavings of livestock serve as buffer stock. For the landless, on the other hand, production capital is one of the main devises to smooth consumption.

4. Extensions

The methodology in the last section has the following two limitations. First, as the savings equation in the second step is estimated for each form of household asset separately, the coefficient of transitory income does not reflect the relative importance of different household assets. To see the household

[11] Details will be provided on request.

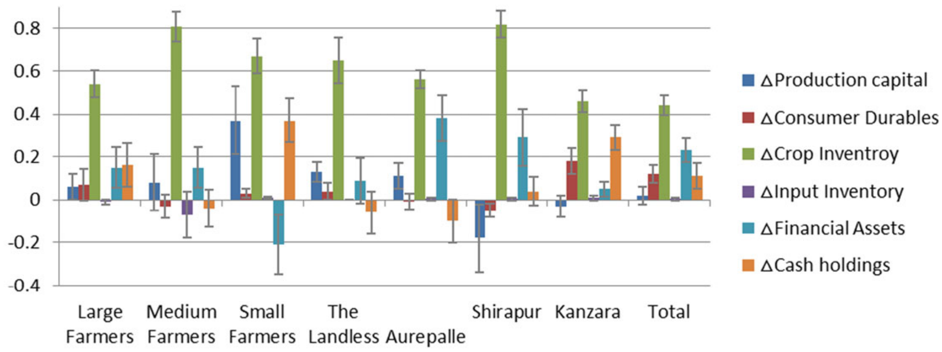

Fig. 1. Household reaction to transitory crop income shocks: Decomposition by landholding class and village (based on 3SLS shown in Table 5): Monthly data.

response of portfolio adjustment to income shocks more clearly, it is necessary to estimate savings equations simultaneously. Second, some categories of the savings in the second step are likely to affect the income equation in the first step. In particular, the changes in production capital, input inventory, and financial assets (credit in particular) might affect the transitory income. In this section, we therefore estimate the system of equations as an extension of the methodology put forward by Paxson (1992).

The following system of equations is estimated by three-stage least-squares estimation:

$$Y_{it} = \beta_t^T + R_{vt}^T\beta_1 + L_{it} \otimes R_{vt}^T\beta_2 + \Delta P_{it}\beta_3 + \Delta I_{it}\beta_4 + \Delta F_{it}\beta_5 + \beta_6 V_v + \gamma_i + \varepsilon_{it}, \quad (7)$$

where Y_{it} is monthly income, β_t^T is a set of dummies to capture the seasonal fluctuations, and R_{vt}^T is a vector of lagged rainfall shocks. L_{it} is the stock of household landholding at the beginning of the crop year to be interacted with landholding. ΔP_{it}, ΔI_{it}, and ΔF_{it} are the net monthly changes in production capital, input inventory, and financial assets, respectively. V_v is a village-level dummy variable. γ_i is the household fixed effects. Because we focus on the temporary shocks in Y_{it}, we subsume permanent factors under γ_i :

$$\Delta K_{it} = \alpha_{k0} + Y_{it}\alpha_{k1} + R_{vt}^T\alpha_{k2} + W_{it}\alpha_{k3} + \alpha_{k4}V_v + \alpha_{k5}k_{it-1} + e_{it}^k, \quad (8)$$

where ΔK_{it} is the net monthly change in capital asset.

W_{it} are the household characteristics that are assumed to affect savings. Asset changes are assumed to be influenced by an endogenous temporary income shock, Y_{it}, and rainfall shocks. k_{it-1} is the annual stock of production capital at the last crop year that identifies the equation.[12]

The other savings equations are specified similarly.

$$\Delta D_{it} = \alpha_{d0} + Y_{it}\alpha_{d1} + R_{vt}^T\alpha_{d2} + W_{it}\alpha_{d3} + \alpha_{d4}V_v + \alpha_{d5}d_{it-1} + e_{it}^d, \quad (9)$$

$$\Delta S_{it} = \alpha_{s0} + Y_{it}\alpha_{s1} + R_{vt}^T\alpha_{s2} + W_{it}\alpha_{s3} + \alpha_{s4}V_v + \alpha_{s5}s_{it-1} + e_{it}^s, \quad (10)$$

$$\Delta I_{it} = \alpha_{I0} + Y_{it}\alpha_{I1} + R_{vt}^T\alpha_{I2} + W_{it}\alpha_{I3} + \alpha_{I4}V_v + \alpha_{I5}L_{it-1} + e_{it}^I, \quad (11)$$

$$\Delta F_{it} = \alpha_{f0} + Y_{it}\alpha_{f1} + R_{vt}^T\alpha_{f2} + W_{it}\alpha_{f3} + \alpha_{f4}V_v + \alpha_{f5}f_{it-1} + e_{it}^f, \quad (12)$$

$$\Delta M_{it} = \alpha_{m0} + Y_{it}\alpha_{m1} + R_{vt}^T\alpha_{m2} + W_{it}\alpha_{m3} + \alpha_{m4}V_v + \alpha_{m5}n_{it-1} + e_{it}^{fn}, \quad (13)$$

where ΔD_{it}, ΔS_{it}, ΔI_{it}, ΔF_{it}, and ΔM_{it} are the net increases in consumer durables, crop inventory, input inventory, financial assets, and cash holdings, respectively. d_{it-1}, s_{it-1}, L_{it-1}, f_{it-1}, and n_{it-1} are the annual stock of consumer durables, grain stock, owned land, net borrowings, and net worth (i.e., real assets *minus* liabilities), respectively. The system of equations of (7)–(13) is first estimated for monthly data. The same specification is then applied to seasonal data.

Here, the important question is the extent to which the system of simultaneous equations captures the simultaneity in household decision making of portfolio adjustment where households take into account their holding of a particular asset, when making adjustment in another asset. Ideally, the interactions between different household assets should be explicitly modeled, but the data limitations do not allow us to disentangle the complex causal relationships among different assets in terms of

[12] In the asset equations, household fixed effects are not included (while a number of household characteristics are included) to make the conversion of estimations achievable.

the households' portfolio adjustment and their underlying decision making. First, while our system of simultaneous equations could capture interactions between the income equation and the asset equations, the cross-interactions across asset-change equations are not *explicitly* modeled as each asset change is only identified by its lags, while they are *indirectly* linked through income changes, as contemporaneous interactions among error terms are allowed.[13] Second, our approach is inherently limited—as in most of other econometric approaches—in a sense that the *ex ante* portfolio adjustment decision is captured only by the past data. While households decide in advance whether they want to save or dissave a certain asset component, the actual savings reflected in the data may be different because of a lot of constraints for savings (e.g., the market of livestock, price changes). Given these limitations, our regression result is at best a summary of the household portfolio adjustment behavior based on the *ex post* data. To supplement our approach of using the system of simultaneous equations, we carry out a cluster analysis to understand, albeit descriptively, the different risk coping responses and observe the households' characteristics based on their asset dissaving patterns in the wake of income shocks.

Table 4 shows the results of the income equation for monthly data (case A) and seasonal data (case B). The net increase in production capital and input inventory has positive and significant impacts on both the monthly and the seasonal income. Monthly income is positively affected by the net change in financial assets, including credit. The coefficient estimate of financial assets is not significant for seasonal crop income (case B).

Table 5 shows the results of asset change estimations for monthly data (panel A) and seasonal data (panel B). The overall results are not so different from those in Table 3. In panel A, crop inventory is the most important device in smoothing consumption. The coefficients associated with financial assets have become larger than those shown in Table 3, while the relative importance of cash holdings has decreased. Consumer durables are still important as buffer stock, while production capital and input inventory are not.

It is evident from panel B of Table 4 that crop inventory and cash holdings are used as buffer stock for seasonal fluctuation in crop income. In addition, production capital, consumer durables, and financial assets play a minor role in buffering consumption. Transitory income has a positive and significant impact on the input inventory, which suggests that farmers adjust the timing of purchasing and selling so that consumption smoothing can be achieved.

Comparisons of panel A and panel B are insightful in inferring some features of household portfolio-adjustment behavior. While financial assets (including credit) are one of the important

[13] We could use, for example, lagged values of asset changes as instruments, but this would make the system too complex to be estimated. We do not have valid external instruments to identify each asset-change equations due to the data limitations.

Table 6
Estimations of the reduced-form income equations based on the ICRISAT data from 2009 to 2012

Variable	Monthly income: Parameter Estimate	*t*-ratio
Transitory factors		
(R_1 − mean of R_1): $R_1 = r_0 + r_{-1} + r_{-2} + r_{-3}$ where r_{-t} is the *t*th lagged monthly rainfall	9.19	(2.88)*
(R_1 − mean of R_1)*(Owned Land)	−0.86	(−3.05)*
(R_2 − mean of R_2): $R_2 = r_{-4} + r_{-5} + r_{-6} + r_{-7}$	12.87	(3.48)**
(R_2 − mean of R_2)*(Owned Land)	−1.14	(−3.41)**
(R_3 − mean of R_3): $R_3 = r_{-8} + r_{-9} + r_{-10} + r_{-11}$	8.41	(1.83)
(R_3 − mean of R_3)*(Owned Land)	−0.78	(−2.03) †
Seasonal dummies:		
Whether July or not	−684.78	(−1.08)
Whether August or not	1,304.32	(1.65)
Whether September or not	1,039.87	(1.31)
Whether October or not	2,199.24	(3.30)**
Whether November or not	1,140.77	(1.52)
Whether December or not	−673.11	(−1.06)
Whether January or not	1,167.83	(1.55)
Whether February or not	957.93	(1.75)
Whether March or not	1,249.56	(1.90)
Whether April or not	1,594.66	(2.32)†
Whether May or not	3,112.72	(3.97)**
Permanent factors		
Village dummies:[1]		
Whether Shirapur or not	3,352.02	(4.89)**
Whether Aurepalle or not	3,564.00	(4.84)**
Sex/ age/ education variables:		
Number of people aged 0–5	660.73	(2.37) †
Number of males aged 6–11	315.03	(1.26)
Number of females aged 6–11	−910.40	(−5.35)**
Number of males aged 12–17	561.56	(3.56)**
Number of females aged 12–17	−446.66	(−2.29) †
Number of males aged 18–64		
with primary education or less	2,690.79	(9.44)**
with middle school education	2,411.26	(7.74)**
with high school education	2,881.85	(16.99)**
with intermediate education	1,587.41	(5.42)**
with higher education	1,856.04	(3.96)**
Number of females aged 18–64		
With primary education or less	−329.74	(−1.03)
With middle school education	1,347.64	(2.70)*
With high school education	961.89	(2.19) †
With intermediate education	2,321.40	(3.74)**
With higher education	1,374.18	(1.99) †
Number of males aged 65 or more	−276.17	(−1.12)
Number of females aged 65 or more	421.49	(1.21)
Variables on the caste[1]		
Backward caste	−880.68	(−1.04)

Continued

Table 6
Continued

Variables on the caste[1]		
Forward caste	−576.36	(−1.14)
Nomadic tribe	1,918.43	(3.33)**
Scheduled caste	1,383.56	(2.02) †
Other caste	−240.98	(−0.34)
Owned land (ac.)	−100.89	(−2.87)*
Share of owned land which is irrigated	−629.40	(−1.05)
Stock of livestock (Rs.)	−52.97	(−8.51)**
Constant	−930.29	(−1.18)
Number of observations	2,902	

Note: Number in parentheses is t-ratio. ** = significant at 1% level. * = significant at 5% level. † = significant at 10% level. [1]Dummy variable.

devices for consumption smoothing in the case where monthly data are used, they are not important in the case of seasonal data. It is rather the case that currency plays a key role in mitigating the seasonal fluctuation. While consumer durables are used as buffer stocks for monthly crop shocks, it is production capital that appears to mitigate seasonal crop shocks. This implies that the relatively productive assets, which are closely associated with crop production, tend to be used as buffer stocks to mitigate the seasonal crop shocks.

As we have discussed, our approach using the system of simultaneous equations does not fully capture the interactions between different household assets. Accordingly, we have carried out a cluster analysis to examine the household portfolio effects by closely following Kusunose and Lybbert (2014) (see Appendix 2 for details). The results of this analysis are broadly consistent with those of econometric analyses in Tables 3 and 5. However, cluster analysis does not provide any clear evidence in support of interactive portfolio effects using more than one type of asset to cope with a monthly income shock. In other words, dissaving of multiple assets does not appear to be more effective than that of a single asset for coping with an income shock that occurs in a particular month. However, as Kusunose and Lybbert note, cluster analysis is descriptive in nature and our results based on this approach should be interpreted with caution.

Furthermore, we have reestimated the results of Table 5 village-wise and based on the different landholding classes. Figure 1 comparatively shows the coefficient estimates and their confidence intervals in error bars for the different landholding classes and villages using monthly data. For all landholding classes, crop inventory is the most important device for buffering consumption, as its coefficient estimate is the largest and statistically significant for all categories. For large farmers, apart from crop inventory, cash holdings and financial assets—both of which are statistically significant—are used as buffer stock. For medium farmers, while the role of the crop inventory is still prominent, financial assets are also important, having a positive and significant estimate. Small farmers seem to have various forms of smoothing consumption, namely, crop inventory, cash, and production capitals, all of which are statistically significant. For the landless, production capital supplements the buffer-stock role of the crop inventory. The role of cash holdings as a buffer stock is not evident in the case of the landless households, suggesting that they may not have enough cash that can be used to cope with income shocks.

We also disaggregate the results by villages. In Kanzara where the average household income is high, the importance of the crop inventory as buffer stock is lower—though it is statistically significant—than in the other two villages. In addition, cash holdings and consumer durables also serve as buffer stocks as both respond positively to income shocks. In Shirapur and Aurepalle, the role of the crop inventory is dominant, but financial assets are also important. Cash holdings play no role in smoothing consumption in Shirapur and Aurepalle in Fig. 1.

It is difficult to find any common pattern across different landholding classes or villages. However, it is noteworthy that consumption smoothing is achieved through savings or dissavings of several kinds of assets and not by a single asset over a long period.[14] Another important implication derived from our results concerns the relative importance of the risk-sharing mechanism among households and the autarky of intertemporal risk-coping mechanism. Among a variety of portfolio choices, it can be reasonably assumed that a majority of "financial assets" (which include informal borrowing and lending and gifts) are classified into the former and the rest (i.e., sum of production capital, consumer durables, crop inventory, input inventory and cash holdings, and a part of financial assets, such as financial savings) is classified into the latter. As the coefficient of transitory income associated with financial assets is positive but not large, it is adequate to conclude that the intertemporal savings (which draw upon crop inventory, capital assets, or cash holdings) are more fundamental to risk coping mechanisms than they are to risk sharing (such as lending or borrowing between households in the village).

5. Results based on more recent ICRISAT data

Using a more recent ICRISAT dataset between 2009 and 2012, we investigate the behavioral responses of households in the same regions of rural India (Aurepalle, Shirapur, and Kanzara). The variables in this section are slightly altered according to data availability and survey design of the new data. We first estimate the income equation given in Eq. (4) and then decompose income into transitory and permanent components in the same fashion as Eqs. (2')' and (3')'. In this section, we focus on the results based on monthly fluctuations. Table 6 shows the results of the reduced-form income equation based on

[14] This may not be evident in the results of the cluster analysis; because of this method's inability to capture sequential dissavings of multiple assets over time. It is likely that households sell on asset at one point in time, but several assets over a longer period.

Table 7
Two-step random-effects GLS estimates of savings equations using 2009–2012 ICRISAT data

	Case (A)		Case (D)		Case (F)	
Dependent variable:	ΔCapital assets[1]		−ΔLoan balance		Total savings[3]	
Explanatory variable:	Parameter Estimate	t-ratio	Parameter Estimate	t-ratio	Parameter Estimate	t-ratio
Transitory income	0.01	(0.30)[2]	0.45*	(2.48) †	0.93***	(31.47)**
Permanent income	0.07	(0.38)	−0.55	(−1.34)	1.41***	(6.72)**
Number of observations	548		2,260		2,902	
	Case (H)		Case (I)		Case (J)	
Dependent variable:	ΔLivestock		ΔProduction capital		ΔConsumer durables	
Explanatory variable:	Parameter Estimate	t-ratio	Parameter Estimate	t-ratio	Parameter Estimate	t-ratio
Transitory income	0.00	(0.22)	0.01	(0.29)	0.00	(0.28)
Permanent income	−0.43	(−1.13)	0.06	(0.27)	−0.01	(−0.25)
Number of observations	2,902		548		548	

Note: The capital letter designation of the cases corresponds to their lower case designation in Table 3 for ease of comparison. [1]Capital assets include consumer durables and production capital. [2]Numbers in parentheses are t-ratio. ** = significant at 1% level. * = significant at 5% level. † = significant at 10% level. [3]Total savings = Income − Consumption.

monthly data. It is found that the coefficient estimate of rainfall is positive and significant, while the interaction of rainfall and area of owned land is negative and significant. The latter suggests that larger landholders tend to be more severely affected by rainfall shocks. This result is consistent with the coefficient estimates of the third lag of rainfall and its interaction with land based on old ICRISAT data (case A of Table 2).

Based on this decomposition of income into permanent and transitory components, we estimate household response of the following assets to transitory shocks: savings (total), net loan balance, livestock, consumer durables, and machinery as reported in Table 7. The selection of these categories was guided by the availability of the comprehensive asset data in the new ICRISAT data. To facilitate comparisons between Tables 3 and 7, the same letters are used in upper case for the asset categories (e.g., case (F) in Table 7 corresponds to case (f) in Table 3).[15] That is, cases (A), (F), (H), (I), and (J) show the net increases of capital assets, saving (total), livestock, production capital, and consumer durables, respectively. Case (D) shows the net decrease in loan balance. As previously noted, the monthly fluctuations of crop inventory could not be retrieved from the new dataset.

Here, we restrict our attention to the coefficient estimates of transitory income for each case, because they are likely to capture the households' asset responses to income shocks. In case (F) of Table 7 in which total savings is a dependent variable, the coefficient estimate of transitory income is 0.93—which is close to 1—and highly significant, which suggests that households smooth their consumption well (Carter and Lybbert, 2012; Paxson, 1992)[16] . This is close to the coefficient estimate of transitory income for total savings (0.99) in case (f) of Table 3 based on the old ICRISAT data. Consistent with our findings from the 1976–1983 dataset in Table 3, livestock (case (H)) does not have a vital role as buffer stock, nor do consumer durables (case (J)), production capital (case (I)), or capital assets (case (A)), have a vital role as buffer stock. Coefficient estimate is close to 0 in both cases. Loan balance (case (D)), however, appears to be the most responsive to transitory income with a positive and significant coefficient. The coefficient estimate is 0.45, the largest among all the cases except total savings. That is, if income increases by 1,000 rupees, net loan balance tends to decrease by 450 rupees. This is similar to case (d) of Table 3 based on the old dataset in which the coefficient of financial assets (including credit) is positive and significant, though much smaller than in case (D) of Table 7. This implies that the relative importance of credit as a means of risk coping increased in more recent years. Production capital or consumer durables is statistically insignificant (cases (I) and (J)) as in cases (i) and (j) of Table 3. It is difficult to carry out further extensions based on the new dataset, e.g., to estimate the system of equations, because the data for only a part of household assets are available. However, the results based on the new ICRISAT panel data are broadly consistent with our main findings based on the old ICRISAT data.

6. Conclusion

One of the most important implications derived from the panel data estimation is that not only the level but also the

[15] It is noted that only part of the asset categories are available in the new ICRISAT data.

[16] Given that Saving = Income – Consumption, a decrease in income by, say, 1,000 rupees is offset by a decrease in saving by as much, keeping consumption smooth.

diversification of household assets is important for smoothing consumption. The results of our analysis yield several crucial conclusions.

First, in the case where monthly data are used, savings as changes of major household assets have a role in buffering consumption. In particular, change in crop inventory, currency capital assets (consumer durables in particular), and financial assets (credit in particular) are important for consumption smoothing. We confirm that when permanent income increases, a household saves crops, production capital, and financial assets, rather than currency or livestock. In general, livestock plays little part in smoothing the fluctuation of household consumption within a single year. These results derived from monthly data are not so different in the case where crop income in the peak season is estimated, except that cash holdings play a more important role as buffer stock in the latter. These results are based on the ICRISAT panel data for the period 1976–1983, but we have examined the robustness of our results using the new ICRISAT monthly panel data for the period 2009–2012. We have found using the new dataset that financial assets, rather than livestock, play a more important role when households respond to transitory income shocks. This is consistent with the main findings based on the old dataset.

Second, the importance of portfolio adjustment and the consumption-smoothing mechanism are also confirmed by the system of equations in which portfolio adjustment and production decisions are simultaneously estimated. This result is important, not just because the majority of the past studies on consumption smoothing or savings treat income as exogenous, but also because the empirical studies on savings do not normally pay explicit attention to the aspect of portfolio adjustment.

Third, decomposition by the landholding class or village suggests that consumption smoothing is achieved through savings or dissavings of several kinds of assets and not by a single asset. The pattern of portfolio adjustment, however, differs among different landholding classes. While large farmers rely on a number of assets, including crop inventory, currency, financial assets, and capital assets in smoothing consumption, small and medium farmers use the crop inventory as a main device for buffering their consumption. The landless households smooth consumption through an adjustment of multiple assets, such as grain stock, financial assets, production capital, and consumer durables. However, our cluster analysis does not provide any clear evidence in support of interactive portfolio effects (i.e., dissaving more than one type of asset *simultaneously*) to cope with a monthly income shock. The household is thus likely to use a single asset at one time, or in a particular month, to cope with a sudden income shock, but more than one type of assets over a long period.

Fourth, it appears that intertemporal savings, which draw upon crop inventory, capital assets, or currency, are more important as a measure of risk coping than risk sharing, through lending or borrowing across different households. On the one hand, these results are in sharp contrast with the analysis of Townsend (1994) which shows that consumption is smoothed out by the risk-sharing arrangement within the villages on the basis of the annual ICRISAT data. On the other hand, our discussion is in line with Ravallion and Chaudhuri (1997), a critique against Townsend's seminal article. Our findings suggest that Townsend's results, which support the "risk-sharing" hypothesis, can be largely affected by the autarkic "intertemporal savings" of each household that can follow a common trend among different households within the villages.

It is often argued that the poor are constrained by lack of access to credit or savings, but the present study suggests that once we track the record of all the household assets, even the landless households cope with income shocks quite well by adjusting a variety of their assets over time. Any policy interventions to address the vulnerability of the poor in rural areas should consider this aspect. Future studies should investigate whether the pattern of the portfolio adjustment is similar, or whether the portfolio adjustment (e.g., dissaving of production capital) has any implications for poverty dynamics.

Appendix

1. Constructions of monthly and seasonal asset variables

Based on household transaction and crop-production modules, we have calculated the following monthly variables. All of these are household variables. Seasonal variables are constructed by aggregating the monthly variables during the agricultural slack season from April to September and the peak season from October to March.

Real Monthly Income is the sum of monthly income from agriculture, labor, trade, handicrafts, and net transfers:

$$Y = Y_{agriculture} + Y_{labour} + Y_{trade} + Y_{handicrafts} + Net\,Transfers. \tag{A.1}$$

Real Monthly Consumption is sum of monthly expenditures on all the food and nonfood expenditures:

$$Consumption = \sum Expenditure_{food/non-food}. \tag{A.2}$$

Financial Savings is the net real monthly increase of financial assets based on the difference between financial assets and the withdrawal:

$$\begin{aligned} Financial\,Savings = {} & Savings + Deposits + LifeInsurance \\ & + Others - Withdrawal. \end{aligned} \tag{A.3}$$

Credit is the net real monthly decrease in liabilities:

$$Credit = Lending - Borrowings + Repayment. \tag{A.4}$$

Change in Financial Assets—denoted as $-\Sigma\triangle B_{ijt}P_{ijt}$ above—is the sum of (A.3), (A.4), and income from gift and others.

The Net Real Monthly Increase of All the Livestock is based on bullocks, cows, young cattle, buffalo, young buffalo, horses, donkeys, goats, sheep, pigs, poultry, and others:[17]

$$\Delta Livestock = Purchase - Sale - LossLivestock. \quad (A.5)$$

The Net Real Monthly Increase of Main Production Capital is based on dry land, wet land, wells, tanks, cattle sheds, cattle yards, storage facilities, oil, or electric pumps:

$$\Delta Main\ Prod\ Capital = Purchase - Sales - Loss\ Prod\ Capital + Expenditure\ On\ Prod\ Cap. \quad (A.6)$$

Net Real Monthly Increase of All Consumer Durables that are *not* included in Consumption, e.g., jewellery, cycles, furniture, etc.:

$$\Delta Main\ Durables = Purchase - Sales - Loss\ Durables + Expenditure\ On\ Durables. \quad (A.7)$$

Change in Capital Assets–referred to as $-\Sigma\Delta K_{ijt}\ P_{ijtt}$ above—is the sum of (A.6) and (A.7).

Savings is computed as the difference between Income and Consumption:

$$Savings = Income - Consumption. \quad (A.8)$$

Monthly Change in Currency—referred to as $-\Delta M_{jt}$ above – is the difference between the acquisition of cash and the use thereof.

Change in Crop Inventory – referred to as $-\Sigma\Delta S_{ijt}P_{ijt}$ above—is the sum of crop production and purchase less crop sales and the consumption of self-produced crops:

$$\Delta Crop\ Inventory = Crop\ Production + Crop\ Purchase - Sale\ Crops - Consumption\ Crops. \quad (A.9)$$

Change in Input Inventory—referred to as $-\Sigma\Delta I_{ijt}P_{ijt}$ above—is the net change in fertilizers, manure, pesticides, and insecticides:

$$\Delta Input\ Inventory = \Delta Fertilisers + \Delta Manure + \Delta Pesticides + \Delta Insecticides. \quad (A.10)$$

All of (A.1)–(A.10) are in monthly terms and deflated by the village-level monthly CPI—referred to as $P_{ct}Y_{it}$ above.

2. Cluster analysis on the effects of different household assets to cope with shocks

Drawing upon Kusunose and Lybbert (2014), we have carried out cluster analysis to further investigate the effects of different household assets to cope with income shocks. We have used *k-means* clustering method through which *k* clusters are created, each containing households of similar characteristics or trends (in our case, dissaving of certain assets). The method initially allocates households randomly into the *k* clusters, then rearranges them such that it minimizes each cluster's within variation to keep similar households in each, and maximizes cross-cluster variation (Kusunose and Lybbert, 2014). This method is discussed in further detail in Brown et al. (2006).

We have clustered all the monthly observations according to whether a household reduced a particular type of asset, namely, livestock, production assets, consumer durables, and crop inventory, or any combination of these assets in case the household reduced more than one type of assets. For cluster analysis, binary variables are defined as whether a household reduced more than 10% of the initial asset balance of each type of asset in a particular month. We do not include cash balance as the initial balance of cash holdings is unavailable. Credit balance—or liability—is not considered either because the meaning of the balance is different from that of other assets with positive values.

Although this is a descriptive analysis and subject to limitations (e.g., ignoring the panel structure of the data), comparisons of means of total or food consumption per capita across different clusters would provide an insight into whether the use of more than one type of asset would facilitate household risk coping. Also, we are able to characterize different types of households by comparing other variables, such as consumption or the initial stock of various household assets.

We have identified eight mutually exclusive clusters in Appendix Table according to whether a household sold, or reduced more than 10% of the stock of, one or more types of assets in a particular month. Cluster 1 is the benchmark case where households did not sell any types of asset. Clusters 2–5 correspond to the cases in which households sold only one type of asset, namely, livestock, production capital, consumer durables, and grain stock in a particular month. Cluster 6 is the case where a household sold livestock and production capital at the same time, while consumer durables and grain were dissaved simultaneously for cluster 7. Those four types of asset reductions appear in cluster 8.

The results will have to be interpreted with caution as the figures are unconditional means of observations for clustered observations. However, it is found that (i) clusters of households selling only livestock (cluster 2) or only consumer durables (cluster 4) have consumption lower than the benchmark case (cluster 1) and these clusters of households are characterized with low levels of initial assets that were sold; (ii) households selling only production capital (cluster 3) had consumption not much different from the benchmark case, which is consistent with our econometric results (case (a) of Table 3); (iii) selling grain stock appears to be the most effective risk-coping strategy (cluster 5) resulting in the highest total or food consumption—which is in line with our econometric result (case (b) of

Table 3), but these households tend to have higher levels of not only grain stock, but also other assets; (iv) in general, there is no clear evidence to show that the use of multiple assets facilitate keeping the consumption levels (e.g., clusters 6 and 7); and (v) households selling all the four assets had consumption (cluster 8) only slightly lower than the benchmark case, but this is probably because such a drastic reduction of assets was possible for households with higher levels of initial assets.

In sum, the results of cluster analysis are broadly consistent with those of econometric analyses in Tables 3 and 5, but they do not imply that the use of multiple assets is more effective than relying on only a single asset for coping with monthly income shocks.

Appendix Table

		Cluster 1 No pattern	Cluster 2 Sold livestock[1]	Cluster 3 Sold production capital[1]	Cluster 4 Sold consumer durables[1]	Cluster 5 Sold grain[1]	Cluster 6 Sold livestock and production capital[1]	Cluster 7 Sold consumer durables and grain[1]	Cluster 8 Sold livestock, production capital, durables, and grain[1]
	No. of observations	6,674	2,176	69	223	1,059	886	484	2,237
Means of variables									
Consumption	Per capita food consumption	21.5**	13.85**	18.59	12.32	23.72*	7.96**	8.11**	16.22
	Total per capita consumption	22.7**	14.89**	20.49	13.08	25.16*	8.58**	8.76**	17.26
Initial stock at the beginning of the year	Initial stock of consumer durables	3,701.97**	1,505.23**	4,535	6.95**	4,508.04**	1,353.76**	0**	3,182.95
	Initial stock of grain stocks	554.78**	207.08**	432.06	1,273.63**	653.94**	217.8**	48.45**	517.66
	Net borrowing at the beginning of the year	2,123.42**	1,312.67**	2,402.98	140.14**	2,208.45*	1,546.32	184.64*	1,805.6
	Initial stock of livestock	2,577.33**	478.57**	2,676.04	1,480.27**	2,912.93**	866.36	2,525.31*	1,977.45*
	Initial stock of production Capital	1,756.38**	588.78**	765.97	750.36	1,686.66	818.09	1,134.43	1,352.96

[1] A clustering variable for "selling asset" is defined as a binary variable, taking 1 if a household reduced more than 10% of the initial stock of household asset, and 0 otherwise. We used four clustering variables for livestock, production capital, consumer durables, and grain stock.
[2] "*" shows that the mean differs from the mean of the rest of the sample at 5% significance, while "**" is used for the cases significant at 1% level.

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Summary and Conclusion

Economists, policy makers, and development practitioners are constantly trying to develop a deeper understanding of the livelihoods of the poor, their resilience to income shocks, and ability to smooth their consumption despite fluctuations in income streams. In welfare states, the provision of insurance schemes through formal institutions and socio-economic benefits shields households from risks to their subsistence needs. In such settings, households do not need to rely on their own saving devices, community networks, and adjustments in labour supply to cope with risk. In this thesis, I have explored ways through which households smooth their consumption, cope with income shocks, and readjust their labour market participation in a setting of inherent risk, lack of formal insurance mechanisms, credit constraints, and labour market imperfections.

Based on the foregoing, the thesis conceptualises and measures households consumption smoothing and risk coping mechanisms in rural India through three different lenses. Specifically, the study:

1. assesses the extent to which households smooth their consumption and cope with income shocks using their asset holding (productive and non-productive) in an area of high agro-climatic risk,

2. examines the role of social networks in shaping risk-coping decisions in income diversification by looking at the allocation of households' labour supply and migration in response to shocks,

3. and explores the role of buffer stock savings as a risk-coping strategy while treating the production and portfolio decisions as endogenous.

In this section of the thesis, I summarize the main findings that emerge from this study, discuss the avenues for future research, and draw the relevant policy implications.

The purpose of the first chapter is to investigate the households' consumption and asset smoothing strategies. I find that households smooth their consumption despite the realization of income shocks. Based on this finding, I explore the ways that households use their asset stock to achieve this consumption smoothing. As a theoretical framework, I rely on a poverty trap model by Carter and Barrett (2006) that identifies an asset threshold above which a household has an incentive to smooth productive assets in order to converge to a non-poor steady state in the future. This suggests that households can engage in consumption and asset smoothing simultaneously. I find that households liquidate their less productive assets (e.g. consumer durables) in the face of income shocks and smooth their productive stock (e.g. livestock). The results disaggregated by small, medium, and large landholding households provide strong support for the poverty trap model. The findings are consistent with the claim that households close enough to asset poverty line (e.g. medium landholders) use less productive assets in times of economic distress and preserve their most productive assets. The large landholders tend to be better insured against shocks because they have a large spatial dispersion of land, can draw from a large pool of assets in coping with risks, have better access to credit, and can adopt ex-ante risk management strategies more easily. Consistent with the theoretical discussion of Carter and Barrett (2006), households with a low initial asset holding (proxied by land) liquidate machinery or productive assets to smooth consumption as they would not find it optimal to forgo consumption and accumulate productive assets to achieve the high level non-poor equilibrium.

In the second chapter, I turn my attention to the role of social networks and adjustments in labour market participation in response to risk. Social connections in developing countries, especially in India, are crucial to many aspects of the economic and social well-being of households (Munshi, 2014). The importance of these networks in finding jobs, obtaining loans, and other forms of support is paramount. They are also a necessary institution in enhancing economic efficiency in the absence of formal/governmental institutions (Munshi, 2014). Such networks are very strong not only in insuring households within them but also in sanctioning households who do not commit to the "rules of social cooperation". When households are faced with a weather shock, it is natural for them to adjust their labour supply in order to insure against expected risk or cope with realized shocks. The rationale behind this is that households who switch between sectors (agricultural and non-agricultural) may not necessarily be seeking higher profits, but simply acting on their aversion to risk. In addition, there is empirical evidence to suggest that rural to urban migration in India - as well as in most Asian countries - has decreased (Overseas Development Institute, 2014). One hypothesis is that rural networks are so strong that they could explain the large rural-urban wage disparity and low internal male migration in India (Munshi and Rosenzweig, 2016). More explicitly, households whose members migrate to urban locations may lose the benefits of their risk-sharing arrangement at the village of origin. This happens because peers within the network would find it difficult to sanction migrant households if they do not commit to the risk-sharing arrangement. This characterises the asymmetry in information resulting from migration (Munshi and Rosenzweig, 2016). The threat of losing this network arrangement could, therefore, inhibit internal migration and influence labour market participation decisions by changing risk preferences. Households who are part of a risk-sharing arrangement may find it more appealing to engage in risky activities - e.g. in agriculture - given the safety net offered by this network. I provide empirical evidence using the ICRISAT data from 2010 to 2015 in support of this hypothesis. On average, households decrease their self-employment in agriculture and increase their labour supply in migration when faced with a negative rainfall shock. However, the results confirm that households who are part of a risk-sharing network tend to decrease their labour share of migration and increase their self-employment in agriculture in the wake of weather shocks. I have also explored gender differences in households' labour market responses, and have found that male migration is responsive to income shocks and network participation, while female migration is not.

The third chapter of this thesis has been published in *Agricultural Economics* as "Buffer stock savings by portfolio adjustment: Evidence from rural India" with Dr. Katsushi Imai. In this paper, we take construct the cash and asset balances using detailed transaction data of households in rural India, and generate monthly and seasonal ICRISAT panel data for the period 1976–1983. While the empirical literature on household savings tends to treat savings simply as the residual of income minus consumption, our approach dis-aggregates savings into several components to assess households' portfolio adjustment as a risk-coping mechanism. We find that households, irrespective of their landholding status, cope with transient shocks by using grainstocks, currency, and capital assets - rather than livestock - as buffer assets. We also find empirical evidence to suggest that portfolio adjustments are crucial in smoothing consumption. We use a system of equations methodology in which both portfolio and production decisions are made endogenous. We conclude that not only the level but also the diversification of household assets are important for buffering consumption. Furthermore, to compare the evidence between the old ICRISAT data to the newer ones, we explore the monthly panel data for the period 2009–2012 in the same villages. We find similar patterns in households' portfolio responses to income shocks.

Policy Implications

Among many policy implications, these results call for actions to be taken by international donors, and national and local governments to facilitate poor households' access to credit and insurance (e.g. through subsidies for microcredit or microinsurance schemes where appropriate). Access to such schemes not only allows households to shield themselves from income shocks, but also to accumulate assets, technology, and skills. Moreover, equipping rural households and farmers with knowledge on farming choices and technologies may enhance yield despite weather adversities. Access to agricultural extension schemes and weather-indexed insurance are also essential to preventing the poor from making ill-informed decisions (Mobarak and Rosenzweig, 2013; Barnett and Mahul, 2007; Chantarat et al., 2007). The Mahatma Gandhi National Rural Employment Guarantee Scheme (MG-NREGS) is also likely to be an important risk-coping device in rural India. Dey and Imai (2014) provide evidence that the participation in this scheme improves economic security and contributes to poverty alleviation. The implication of the improved economic security suggests that the MG-NREGS can significantly contribute to smoothing consumption through income smoothing. Furthermore, Rosenzweig and Udry (2014) show that reliable long-range weather forecast can have a significant effect on rural wages, out-migration, labour allocation, investment decisions, and farm profits. This reflects the importance of improving the accuracy and reliability of the long-range monsoon forecast released by the Indian Meteorological Department. Improvements in this forecast (and its dissemination) allow households to adjust ex-ante to expected shocks, thus reducing the ex-post severity of the shock.

Directions for Future Research

Several avenues for future research emerge from this study. Perhaps one of the most sensible extensions to the current findings is to assess the role of the MGNREGS as a risk-coping strategy. Finding answers to questions on this scheme's role in smoothing income and consumption can have valuable policy implications on the effectiveness of workfare programs in comparison to conditional cash transfers (e.g. PROGRESA in Mexico). It would also be interesting to assess the substitutability of informal risk-sharing, out-migration, and the employment guarantee scheme in rural India as mechanisms to mitigate income shocks. Furthermore, extending the results of the second chapter to capture the intra-household dynamics in the labour market participation (at the individual level) would enhance our understanding of households' responses to risk. It may also provide some answers to the reasons behind the recent decline in female labour force participation in rural India.

The application of the methods and the logic used in assessing these shocks could also be extended to different contexts. Naturally, the change in context would require specific considerations, particularly in relation to econometric issues, but the implications of risk and coping strategies do have many common features vis-a-vis assets, labour allocation, displacement/migration, and social networks. Several situations where risk-coping mechanisms are crucial: wars and violence, natural disasters, climate change, among many other examples. Given the outbreaks of wars and violence around the world (e.g. in Syria, Iraq, Afghanistan, Burundi, and others), the risk-coping mechanisms constitute a daily practice for refugees and displaced individuals. Political shocks are also exogenous (to a certain extent) to household characteristics and decisions, but the question remains: how do households cope with various shocks? Natural disasters - such as Haiti's earthquake in 2010 - is another example where households need to readjust to living conditions and cope with unexpected shocks. This suggests that enhancing our understanding of the risk-coping mechanisms of such vulnerable groups can be powerful in informing policy making. At present, the likelihood of the dooming effects of climate change and violent political upheavals are high. This extends the usefulness of the methods and results presented in this thesis to a much larger perspective. The ubiquity of risk and uncertainty in all aspects of life makes the understanding of people's economic coping mechanisms key to assessing their overall welfare.

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