SHOCKS, RESILIENCE AND FOOD SECURITY, ESSAYS IN DEVELOPMENT ECONOMICS

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SHOCKS, RESILIENCE AND FOOD SECURITY,

ESSAYS IN DEVELOPMENT ECONOMICS

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As development practitioners, we face the challenge of ensuring food security in an increasingly shock-prone world. Poor and vulnerable households are unable to smooth their food consumption in times of drought, flood or when pests destroy their crops. This dissertation draws on the poverty literature and posits resilience as a latent capacity allowing households to recover from the effects of shocks. It presents several definitions and measurements across multiple contexts. In particular, this thesis explores the tension between focusing on a shock-specific response and emphasizing household well-being in a stochastic context. It analyzes both short and long term measurements of food security in Malawi and Ethiopia, investigating the effects of internal interventions as well as household-level characteristics that may allow households to better manage risk. The first chapter motivates the investigation in the context of eliminating hunger and expanding our understanding of socio-ecological systems. The second chapter investigates the causal impact of the Productive Safety Net Program (PSNP) in Ethiopia, finding that it mitigates the effect of drought on long-term food insecurity. The third chapter uses a novel 12 month high frequency dataset in Malawi to track the incidence and persistence of subjective shocks. It finds that households living in the flood plain and those with fields far from home are more resilient to the effects of drought, while female-headed households are less resilient to the effects of illness. It also illustrates the use of machine learning algorithms to identify

predictors of short-term food insecurity. The fourth and final chapter picks up on the insight that households with spatially dispersed parcels may better manage risk. Using a natural experiment from Ethiopia, it shows that land fragmentation reduces both short and long-term food insecurity. Endowed with a diversified set of parcel characteristics, households grow a more varied set of crops, mitigating the effect of drought. Together, these chapters argue that reducing food insecurity and improving resilience is possible. In order to avoid doing more harm than good, external interventions must take into account households' and communities' existing ability to mitigate shocks.

BIOGRAPHICAL SKETCH

Erwin Knippenberg is a PhD Candidate at Cornell University. He is of Franco-Dutch origin, growing up in West Africa and Southeast Asia.

Prior to Cornell Erwin was an Overseas Development Insitute Fellow at the Liberian Ministry of Finance. He helped set up the development coordination unit and worked closely with donors on aligning projects with national priorities. He also has a background in social entrepreneurship.

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To my parents, Agnes Soucat and Rudolf Knippenberg. Thank you for making me want to change the world.

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CHAPTER 1

INTRODUCTION

"Substantive freedoms include elementary capabilities like being able to avoid such deprivations as starvation, undernourishment, escapable morbidity and premature mortality."

Amartya Sen

Development as Freedom

"The belly is an ungrateful wretch, it never remembers past favors, it always wants more tomorrow."

Aleksandr Solzhenitsyn

One day in the Life of Ivan Denisovich

1.1 Motivation

Hunger is the ultimate obstacle to human flourishing. Chronic hunger occupies the mind at the expense of all else, becoming a near obsession. Hunger deprives individuals of their most elementary freedom from deprivation, and its physical effects hasten an early death. Hunger also impedes individuals' instrumental effectiveness, in the words of Sen (2001). These include the freedom to take advantage of opportunities for education, employment, social and civic participation. Specifically, with respect to hunger, Sen continues:

"Protective security is needed to provide a social safety net for preventing the affected population from being reduced to abject misery, and in some cases even starvation and death."

Over the past half-century humanity has engaged in an unprecedented social experiment: the elimination of global poverty and hunger in order to provide this protective security. The United Nations Sustainable Development Goals aims to end both hunger and poverty by 2030 (UN, 2015). These goals are ambitious but attainable. The poverty rate has halved since 1990, assuming a poverty line of $1.25 in 2005 PPP, and is on a downward trend approaching zero (Chandy et al., 2013). In parallel, undernourishment at the global level has decreased from 18.6% to 10.8% of the global population between 1991 and 2015 (FAO, 2017a). Ending both hunger and poverty is possible, fueled by the cumulative wealth of resources, research and effort poured into understanding and addressing these twin scourges. Yet further progress is jeopardized by the threat climate change poses to food security. Droughts in particular threaten to become increasingly frequent and severe over the next century (Dai, 2011). These pose particularly salient risks for the poorest, many of whom depend on rain-fed agriculture or pastoralism to survive. They often lack access to credit, insurance and formal safety nets that would allow them to mitigate the impact of such shocks, making them particularly vulnerable (Dercon, 2006). These incomplete markets hinder households' ability to smooth consumption over time or over states of the world. Dissaving is hard when assets are in illiquid form, such as cattle or land (Dercon et al., 2005). Living with this uncertainty makes households less likely to invest in lucrative but risky technologies, perpetuating their state of poverty and creating a dynamic poverty trap (Carter and Barrett, 2006). Households that do manage to accumulate sufficient assets to emerge from poverty risk sliding back when they experience a shock. Instead they rely on informal mechanisms to manage risk, often relying on social networks which facilitate borrowing in times of need (Fafchamps and Gubert, 2007). Yet the persistence of chronic hunger reveals that, even when these mechanisms do exist they are far from sufficient. Understanding and, whenever possible, strengthening these mechanisms to smooth consumption and provide protective security is key. In addition to its short-term consequences, shocks and the experience of hunger have long-term adverse consequences. Children who experience malnutrition at a young age due to drought or conflict are physically shorter and less educated than their peers (Alderman et al., 2006). Young girls becoming mothers pass these adverse effects on to their children, who have lower outcomes in terms of education and income (Tafere, 2017). This has spurred interest in mechanisms to mitigate the effect of shocks, particularly around the concept of development resilience. The concept of resilience in development seeks to quantify the dynamic well-being of individuals and households subject to shocks. It draws from the ecology literature, where Holling (1973) posited resilience as an ecosystem's ability to remain within the boundaries of a domain of attraction. For example, vegetation will gradually recolonize the ashes after a forest fire. Ostrom (2009) argues that human societies can also self-organize in such a way as to maintain or restore equilibrium. As an illustration, she documents how farmers managing irrigation works in the foothills of Nepal and lobster fishermen in Maine operate within a complex, self-contained socio-economic system without the need for government or market oversight. Deep dives into the dynamics of these systems can help us better understand which interventions strengthen them, and which may prove counterproductive. Elements of this thesis explore the role that socio-ecological systems play in determining a household's response to shocks; in particular it demonstrates how relying on a diversified portfolio of agro-ecological characteristics reduces risk exposure and improves food security outcomes.

1.2 Resilience and Food security

In order to study food security in the context of shocks, resilience and vulnerability are useful short-hands for the concepts I seek to tackle. These both build on existing measure of poverty dynamics by quantifying how welfare trajectories shift in response to external stimuli. Though related, the two concepts are distinct; resilience is not simply the inverse of vulnerability. According to Gallopin (2006):

"Vulnerability does not appear to be the opposite of resilience, because the latter is defined in terms of state shifts between domains of attraction, while vulnerability refers to (or at least also refers to) structural changes in the system, implying changes in its stability landscape."

How to precisely define these terms remains a subject of much debate. Indeed, comparing different definitions and the measurements they imply constitutes a central theme of this dissertation. As a working definition the reader can think of vulnerability as a unit's susceptibility to shocks, and resilience as a unit's ability to recover from these shocks. An emergent literature has sought to differentiate and quantify these concepts empirically. These efforts can be roughly categorized as follows:

1. Classification and compilation of multiple indicators into a comprehensive measure or index (Alinovi et al., 2009; Béné et al., 2012).
2. An emphasis on the capacity to recover to equilibrium after a shock (Constas et al., 2014a; Vollenweider, 2015).

3. A moments based approach defining resilience as a probability (Barrett and Constas, 2014a; Cissé and Barrett, 2016).
4. A property of time-series, focusing on fluctuations and trend lines (Chavas, 2016, Smerlak and Vaitla, 2016).

Alinovi et al. (2009) build on existing insights into the factors that mitigate the impact of shocks on food security. They identify six categories of variables which constitute resilience, and use principal component analysis to compile an index. Though a useful first approximation, the methods suffers from two significant drawbacks: the researcher must choose which measures to incorporate ex-ante, and the resultant index has little intuitive interpretation. Béné et al. (2012) though skeptical of resilience as an alternative to traditional poverty measures, propose to evaluate interventions along two dimensions: the intensity of change (coping, adapting or transforming), and the time horizon (reducing impact vs. addressing structural causes). Though they do not quantify these measures, they offer a framework defining the purpose of a given intervention.

Constas et al. (2014a) present an attempt to consolidate efforts at quantifying resilience in the context of food insecurity. They emphasize the importance of focusing on dynamic well-being Y_{it} in the context of shocks Z_{it} conditional on characteristics X_{it}. Y_{it} can be a measure of assets or consumption, though in the context of this thesis it relates directly to food security. This approach explicitly acknowledges that the effect of mitigating factors may depend on the shock in question. For example, characteristics affecting a household's recovery from drought differ from those affecting a households recovery from illness. The Constas et al. approach allows explicit modeling of these effects, holding all else constant, by conditioning the effect of shocks Z_{it} on household characteristics X_{it}.

As one of the first to operationalize this approach, Vollenweider (2015) uses a distributed lag non-linear model to estimate the impact of past shocks on present consumption. The estimated parameters allow him to project consumption trajectories into the future. However because the paper relies on cross-sectional data it assumes household un-observables are orthogonal to the recovery trajectory. This is of particular concern regarding weather shocks, as households living in different climactic zones will certainly have adapted to the expected occurrence of shocks.

Recent work has expanded the number of empirical investigations into resilience. The FAO uses principal component analysis to capture the variation in various elements of a households capacity to cope with shocks, and compiles it into a latent resilience index for Mali and Uganda (d'Errico and Pietrelli, 2017; d'Errico and Di Giuseppe, 2018). It finds this to be highly correlated with fluctuations in a household's food security outcomes. Smith and Frankenberger (2018) interact specific shocks with measures of households resilience capacities. Drawing from the literature, they classify these capacities into absorptive, adaptive, and transformative. Absorptive capacities seek to mitigate the impact of shocks and include the availability of assets and savings. Adaptive capacities spread risk by diversifying livelihoods and relying on social safety nets. Finally transformative capacities seek to change the underlying dynamics, for example by improving governance, improving access to markets or empowering women.

In an attempt to recover the complexity of households' response to shocks, Barrett and Constas (2014a) focus on the distribution of well-being outcomes conditional on observable characteristics. The emphasis on stochastic dynamics presents resilience as a latent parameter of the probability distribution of well-being. In a follow-up paper, Cissé and Barrett (2016) propose estimating resilience as the conditional mean and conditional variance of a household well-being indicator (e.g. assets) and, by positing a known distribution, constructing the conditional probability p(X,Z) that this indicator will be above a given threshold. A particularly elegant feature of this measure is that it can be disaggregated to the household level or aggregated up to reflect the resilience of particularly communities, regions or countries. Unlike Constas et al. (2014a) this approach does not condition the effect of shocks on household characteristics. In that sense, the measure confounds the effect of a shock on well-being and the response capacity, which we may want to distinguish.

Finally, some authors have rejected the emphasis on equilibrium and focused instead on time-trend trajectories. Smerlak and Vaitla (2016) look at long term trends in country-level caloric availability. Instead of positing a threshold or equilibrium level of food adequacy, they consider a country resilient if its long-term food insecurity trend is non-negative and any shocks experienced do not persist over time. In parallel Chavas (2016) uses a threshold quantile auto-regressive model and defines a resilient system as one where the first unit roots $|\lambda| > 1$ given a particularly negative sequence of shocks (in the bottom quantile of yields) but returns to a more stable $|\lambda| < 1$ when yields are at or above average. Here the well-being trajectory is the focus and shocks are implicit.

Each of the approaches above entails certain trade-offs, some of them determined by data availability and others by the nature of the hypothesis to be tested. In my thesis, I draw principally from Constas et al. (2014) and Barrett and Constas (2014), though with elements of Smerlak and Vaitla (2016) informing my work on high frequency data. This tension between focusing on a shock-specific response and emphasizing household well-being in a stochastic context is a leitmotiv of my thesis. I also explore how different data sets can inform our analysis, including year-on-year panel data, high frequency data and data augmented with geophysical characteristics. From a methodological perspective, I seek to infer causality in a non-experimental context using a variety of econometric tools, and demonstrate how new machine learning techniques can be used for predictive purposes.

1.2.1 Temporal Dimension of Resilience

A particularly important component of resilience analysis is the temporal factor (Constas et al., 2014a). Given the consensus that resilience is a latent capacity to withstand and recover from shocks, it is important to consider over what timespan that recovery is allowed to occur, or not occur. For example, does a household recover from drought as soon as the next rain comes? Or do the detrimental effects on human capital imply that it may take years for it to fully recover? As discussed earlier, if experienced at a critical developmental age, these effects may even prove permanent over an individual's life cycle (Alinovi et al., 2009). A more prosaic example is the illness or death of one's family member. Though the immediate effects on household livelihood may be brief and measure in months, such an event can traumatize an individual for life.

This thesis considers the temporal factor by attempting to measure the impact of shocks and resilience over different timespans. Chapter 2 looks at household's experience of hunger over a decade and finds the effects of drought to persist across the years. Chapter 3 takes a single year and observes the shifts in households subjective shock persistence, as well as short term persistence. Chapter 4 seeks to capture a mechanism for mitigating shocks endowed to a household decades ago. As the different approaches reveal, different measures may be appropriate. Some of these are fast moving, like the perception of shocks or the Coping Strategy Index, which measures food stress over the past week and can shift quickly. Others are more slow moving by design: Months Hungry measures the experience of hunger over an entire year. A comparative approach such as the one undertaken in chapter 4 can therefore prove illustrative of the differing sensitivities.

Furthermore, consider seasonality. The existence of a recurrent hungry season is an unfortunate empirical reality for many households living at or near subsistence, as they wait for their crop to mature while their stores dwindle. Datasets like the World Bank's Living Standards and Measurements Survey acknowledge seasonality with separate planting and harvest modules. Chapter 3 is particularly illustrative in this respect. One of the most important insights from monthly measures of subjective shocks is how they vary intra-annually. Crop disease may seem insignificant to a household when seeds are sown, but become a vitally urgent matter as its effects on the ripening harvest are revealed. Any analysis of shocks based on inter rather than intra-annual data must implicitly assume that the incidence of a shock varies linearly year on year. As the chapter explores, this may significantly under-estimate the importance of that shock to a household's well-being.

1.3 Outline

In my dissertation, I apply econometrics and machine learning tools to the analysis of food security and resilience using longitudinal household data collected in Ethiopia and Malawi. A complementary logic links the three papers:

- Chapter 2 uses instrumental variable analysis to evaluates a country-level cash transfer program over an eight-year window. In addition to demonstrating the program's effect in mitigating hunger due to drought, it provides a proof of concept for evaluating the impact of an intervention on long-term food insecurity.

- Chapter 3 takes a deep dive into a single district in rural Malawi over a 12-month window, measuring subjective shocks and short-term food insecurity. It explores multiple analytical approaches to trace these dynamics, estimating an auto-regressive model, using a Blundell Bond estimator and harnessing machine learning algorithms. Among other results, it finds that having distant fields is an important determinant of household's ability to recover from drought.
- Chapter 4 expands on this spatial diversification narrative in greater depth in the context of Ethiopia. It harnesses land redistribution as an exogenous source of land fragmentation, and explores the impact of fragmentation on both short and long-term food insecurity.

In my second chapter I assess the impact of a social protection program, Ethiopia's Productive Safety Net Program (PSNP), on the longer-term impacts of drought on household food security. The chapter finds that reported drought shocks reduce the number of months a household considers itself food secure and that these impacts persist for up to four years after the drought has ended. Using an instrumental variable approach, the results suggest that receipt of payments reduced the initial impact of drought shocks by 62 percent and eliminates their adverse impact on food security within two years. This impact is largest for program beneficiaries with little or no land. Results are robust to using an objective measure of drought derived from satellite data.

My third chapter harnesses monthly household data collected in Malawi to understand vulnerable households' food insecurity dynamics and their ability to cope with shocks. I worked with an NGO, Catholic Relief Services (CRS), in implementing a 12-round household survey using smartphones. I estimate an auto-regressive model to track households' experience of subjective shocks over time. I find that households with spatially dispersed fields are less likely to experience the adverse effects of drought, while female-headed households are more likely to experience the adverse effects of a family member falling ill. Using a Blundell-Bond estimator, I find that differences in land farmed, gender of household head, and having spatially dispersed fields lead to shifts in the distribution of expected well-being outcomes. Finally, I harness machine learning techniques to predict future well-being. I find that zones of crisis are concentrated in specific geographic areas, making targeting all the more important.

My fourth chapter assesses the relationship between land fragmentation and food insecurity. Households are not passive in the face of shocks. There is an older literature on the role of land fragmentation as a risk-coping mechanism, but much of this literature failed to advance largely because of endogeneity and related data issues. This chapter uses a natural experiment in Ethiopia, where land redistribution under the communist regime split land into fragmented parcels, and a ban on land sales restricted any subsequent endogenous reallocation. Using a wide set of land fragmentation indicators, it shows that these consistently cause a decrease in household food insecurity. The chapter expands upon this mechanism by showing that land fragmentation allows households to buffer the effects of drought, and that households with diverse parcel characteristics and crop types experience less food insecurity.

The sum of these chapters provides an exploratory investigation into methods to measure and mitigate food insecurity in a shock prone world. It compares and seeks to reconcile different conceptual approaches around risk, vulnerability and resilience. It demonstrates how questions raised by these conceptual clashes can be addressed through a toolkit combining novel data and rigorous analytical techniques. Though it demonstrates the potential benefits of external intervention, these papers also highlight the rich set of mechanisms households and communities employ to manage risk, and cautions against taking these mechanisms for granted. In seeking to tailor these questions to pressing matters of policy, it is my sincere hope that this thesis informs researchers, practitioners and policymakers working to eliminate world hunger.

CHAPTER 2

SHOCKS, SOCIAL PROTECTION AND RESILIENCE: EVIDENCE FROM ETHIOPIA

2.1 Introduction

The malign effect of shocks has long been a concern within economics. One long running strand of work, the consumption smoothing literature, has focused on whether these events result in transitory welfare losses (Carter et al., 2007; Dercon et al., 2005; Zimmerman and Carter, 2003). A second such strand, the vulnerability literature, examines what type of households are unable to smooth consumption (Dercon, 2006). The third and more recent strand of work examines whether these shocks have long term adverse consequences (Alderman et al., 2006; Barrett and Santos, 2014; Hoddinott and Kinsey, 2001; Mancini and Yang, 2009). Increasingly, this third strand centers around the concept of resilience. While resilience as a concept has its earliest roots in engineering, it is used most extensively in ecology and psychology. In ecology, Holling (1973) introduced the term, describing it as the amount of disturbance a system can absorb before shifting into an alternative state (Walker et al., 2006). Other writers have focused on the speed of return to a pre-existing equilibrium following a perturbation or shock (Perrings, 2006). Around the same time, psychologists also began exploring the notion of resilience (Garmezy, 1974). In development, interest in resilience has arisen out of concern over the cumulative effect of humanitarian crises caused by climatic events and political instability. Viewed as a strategic approach to deal with the range of unpredictable risks that undermine efforts to reduce poverty and improve food security, resilience has emerged as a key concept for policy and program development (Béné et al., 2012; Constas et al., 2014b; Walsh-Dilley et al., 2016). Hoddinott (2014) writes, "resilience focuses attention on the idea that short-term shocks are malign not just because of their immediate effects but also because of their adverse long-term consequences".

Academic work on resilience has focused heavily on definition and measurement. There are a plethora of definitions (Barrett and Constas, 2014a; Béné et al., 2012; Constas et al., 2014a). Early efforts to measure resilience, which include constructing a multi-dimensional index, are based on ex ante assessment of characteristics associated with resilience (Alinovi et al., 2009). Rather than assume that the determinants of resilience are known, subsequent approaches seek to estimate these determinants empirically. Barrett and Constas, 2014a propose estimating a stochastic distribution in wellbeing outcomes such as consumption and food security (Barrett and Constas, 2014a). Using a moments based approach, Cisse and Barrett (2016) measure resilience ex-ante as the distribution of expected welfare over time . While this approach has desirable properties, it does not map recovery trajectories in response to specific shocks, which may be important in the context of impact evaluation (Constas et al., 2014a). An alternative approach uses cross-sectional household data to estimate vulnerability and resilience separately (Vollenweider, 2015). Specifically, it uses a distributed lag non-linear model to estimate the lagged impact of past shocks on present consumption, and assuming the past is a good predictor of the future, then uses these to project consumption trajectories into the future.

Building on the insight of Barrett and Constas (2014) that resilience is a capacity, the contribution of our article is an assessment of how a social protection intervention shifts the relationship between shocks and outcomes. The setting is

Ethiopia, and the intervention is the Productive Safety Net Program (PSNP), one of the largest social protection programs in sub-Saharan Africa. Using longitudinal household data, we find that it takes households four years to recover from a drought shock. However, PSNP payments reduce vulnerability and increase resilience. At average payment levels, the PSNP reduces the post-drought drop in food security by 62 percent and eliminates the adverse impact of drought on food security within two years.

To address concerns regarding the subjectivity of our shock variable, we run robustness check using the Standard Precipitation Evapo-transpiration Index. Computed using remote sensing data, it is widely considered an objective measure of drought. We matched it to our observations and found the results to be consistent with the above in sign, significance and magnitude.

2.2 Ethiopias Productive Safety Net Program

The catalyst for Ethiopias Productive Safety Net Program was a major drought in 2002-03 that resulted in more than 13 million people being left reliant on emergency food aid. While this assistance was successful in preventing outright starvation, it left untouched the underlying vulnerability of many Ethiopians to rainfall shocks. In response, the Government of Ethiopia, in consultation with major international donors including the UKs Department for International Development, USAID and the World Bank, developed a new intervention, the Productive Safety Net Program (PSNP). Implementation of the PSNP began in January 2005. Operating in eight regions, the PSNP continues to provide benefits to approximately eight million people with a budget of approximately 500 million dollars per year. During preparatory work associated with the inception phase of the PSNP, discussions were held about the desirability of randomizing access to the program in order to evaluate its impact. The Government of Ethiopia rejected this idea.

The goals of the PSNP are twofold: eliminate the food gap, the number of months the household cannot satisfy its food needs; and prevent distress sales, that is to stabilize household asset holdings (GFDRE, 2009). The PSNP is a targeted intervention. It does not operate everywhere in Ethiopia; rather, it is focused on woredas which historically have been drought-prone recipients of food aid. [1] Within woredas, households are selected using a process that combines both administrative and community mechanisms. Administrative mechanisms include the provision of a specified number of clients that can be included within a specific administrative area (woreda, kebele), guidance found in the PSNPs Program Implementation Manual (PIM) on targeting criteria to be used at the community level, and oversight to ensure transparency and accuracy. Household selection is carried out via community (kebele) targeting, particularly the identification of clients by community Food Security Task Forces (FSTFs). The PIM specifies that households who are targeted should fall into the following categories: be community members; have faced continuous food shortages in the last three years; be acutely food-insecure due to a shock resulting in the severe loss of assets; lack adequate family support and other means of social protection and support; level of household assets (land, livestock, land quality); income from agricultural and nonagricultural activities; and households perceived to be vulnerable, such as female-headed households and elderly households or households with chronically-ill members (GFDRE, 2010).

Payments are provided in the form of food and cash. Particularly in the early

[1] A woreda is equivalent to a county or district. A kebele is equivalent to a sub-district.

years of PSNP implementation, there were difficulties in ensuring these payments were regular and complete. This was a particular problem for food payments; see Berhane et al (2011, 2013, 2015) and Gilligan et al (2007, 2009). Most beneficiaries receive these payments for undertaking labor intensive public works. These works are intended to improve economic productivity; they include road construction and maintenance, land rehabilitation, small scale water harvesting and irrigation works and well construction. This work is undertaken between January and June each year, the dry season in much of Ethiopia. There are variations in the amount of work done across woredas, reflecting woreda and regional decisions made about the type of public works to be undertaken, the labor intensity of that work and random factors such as delays in obtaining materials and obtaining access to complementary capital equipment; again see see Berhane et al (2014, 2015) and Gilligan et al (2007, 2009) . A smaller number, approximately 15 percent of the caseload, receives payments without having to work. This component, called Direct Support, is targeted largely to households unable to supply labor such as those consisting of elderly persons or those with disabilities (Coll-Black et al., 2012).

2.3 Empirical Specification

Figure 2.1 provides a visual means of conceptualizing resilience as a recovery trajectory. The horizontal axis is time. The vertical axis is a welfare outcome of interest to a policymaker. Given the objectives of the PSNP, we put household food security on the vertical axis. We represent the pre-shock path of food security for household Q by the chord HH-Q. A shock occurs which causes food security to fall. The magnitude of this initial drop can be thought of as capturing the households vulnerability to shocks. Gradually, food security recovers, reaching pre-shock levels at time period T. The length of time it takes to recover from the shock can be thought of as a measure of resilience. Now consider a second household, R. It shares a similar pre-shock food security trajectory with household Q. However, when the shock occurs, household R is a beneficiary of a social protection intervention. This reduces the magnitude of the initial shock and shortens the recovery period. The goal of our empirical work is to estimate these trajectories.

In this figure we focus on a consumption measure rather than assets. One reason for doing so is that consumption is a welfare measure; assets matter to the extent that they affect consumption but they do not intrinsically contribute to welfare. Second, as Zimmerman and Carter (2003) and Hoddinott (2006) note, selling assets in response to shocks today risks permanently lowering future consumption and in fact a much older literature that focused on household behavior under famine conditions made this point explicitly: to sell off the meagre assets a household possessed under dire circumstances is to invite future destitution Corbett, 1988. Consequently, a focus on assets might obscure the true impact of the shock on household welfare. A third reason is more practical. Some PSNP beneficiaries are destitute. If these households are unable to borrow, a reasonable assumption in rural Ethiopia, a shock has no effect on asset holdings because these holdings are already at zero Bernard and Spielman, 2009. An asset based outcome would require us to either drop such households or assume that they were unaffected by a shock because we observed no change in their outcome metric. An empirical representation of Figure 2.1 for household Q is given by equation (1):

$$Y_{it} = \alpha + \sum_{l=t}^{t-L} \beta_l Shock_{il} + \gamma X_{it} + \epsilon_{it} \tag{2.1}$$

Y_{it} is the outcome of interest, here a measure of household food security. The shock experienced by the household is denoted as $Shock_{il}$. Representing shocks in this way allows us to map the recovery trajectories within a household up to L periods after they experience a given shock, controlling for subsequent shocks. Absent a shock, food security is a function of X_{it}, a set of household level controls. In Figure 2.1, the pre-shock measure of food security reflects X_{it} and α. The βs capture the impact of the shock. The coefficient on β_l when l = t captures the immediate effect of the shock. The coefficient on l when β_l = t-L indicates whether a household is still experiencing adverse consequences to its welfare from a shock experienced in period t-L. So for example, β_{t-2} is the lagged impact on current welfare of a shock experienced two years previously. Rejecting the null of $\hat{\beta}_t = 0$ for $l \in [t = 1; t = L]$ is strong evidence of the persistence of a shocks impacts. Estimating (1) allows us to plot that households recovery trajectory, and therefore its resilience.

Now consider household R, the beneficiary of the social protection intervention. This household is a participant in the PSNP; further, we assume that the benefits of participation rise monotonically with the amount of payments it receives from the program. With this in mind, we introduce two new terms into equation (1): $Treat_{il}$; and $Treat_{il} * Shock_{il}$. We write this as:

$$Y_{it} = \alpha + \sum_{l=t}^{t-L} [\beta_{1l} Shock_{il} + \beta_{2l} Treat_{il} + \beta_{3l} Treat_{il} * Shock_{il}] + \epsilon_{it} \tag{2.2}$$

We can infer the effect of payments as follows: β_{2l} is the effect of the treatment on the household food security absent any shock. We expect β_{2l} to be positive. β_{3l} is the main coefficient of interest, as it allows us to evaluate the programs effect on household vulnerability and resilience. In the short term, when l=t, it measures whether payments mitigate household vulnerability. A positive and significant coefficient would suggest that treatment decreased vulnerability. In the long term, when l = t-L we can plot the recovery trajectory of treated beneficiaries.

A positive coefficient here reflects a more rapid recovery trajectory, indicating increased household resilience. However, we face an endogeneity problem. In section 2, we explained that the PSNP is a targeted intervention. This targeting, on both food security outcomes as well as characteristics correlated with food security, implies that the payment levels received by beneficiary households might well be correlated with the disturbance term in (2), yielding biased parameter estimates. Some of this correlation can be accounted for by estimating a household fixed effects model that also includes time-varying household characteristics:

$$Y_{it} = \sum_{l=t}^{t-L} [\beta_{1l} S_{il} + \beta_{2l} T_{il} + \beta_{3l} T_{il} * S_{il}] + \gamma X_{it} + \mu_i + \epsilon_{it} \tag{2.3}$$

Here, for brevity, we have substituted S for Shocks and T for Treatment. Under the assumption that after controlling for μ_i and X_{it} , $E(T, \epsilon_{it}) = 0$ and $E(T * Shocks, \epsilon_{it}) = 0$, equation (3) yields unbiased estimates of β_{1l},β_{2l}, and β_{3l}. Our initial estimates are based on this specification.

2.4 Data

The data requirements for equation (3) are significant. We need a dataset with the following characteristics:

1. Longitudinal household data to allow for household fixed effects estimation.
2. A consistently measured outcome variable.
3. Shocks occurring within the data collection time-frame with both cross-sectional and temporal variation.
4. Data on payment levels with sufficient exogenous variation to identify program impacts.

2.4.1 Data Collection

A feature of the PSNP is the bi-annual collection of longitudinal data on beneficiaries and non-beneficiaries, five survey rounds over a nine year period. The first survey, in 2006, used a two stage clustered sampling approach. Across the four regions where the PSNP operated (Amhara, Oromiya, SNNP and Tigray), 68 woredas (districts) were randomly selected using probability proportional to size (PPS) sampling based on estimated numbers of beneficiaries. Within each selected woreda, a random sample of two or three kebeles (depending on the region) was selected. Beneficiary lists were used to select randomly 17 PSNP households and lists of non-beneficiaries were used to select an additional eight yielding a sample of 25 households per kebele. Additional rounds were collected in 2008, 2010, 2012 and 2014.

These surveys have a number of strengths. Data are collected at approximately the same time (June and July) in each round and so our results are not confounded by differences in survey timing across years. Questions pertaining to household food security, program participation and shocks are identical across all rounds as are a rich set of control variables. Both PSNP participants and non-participants are selected within the same geographic localities meaning, inter alia, they are exposed to the same shocks and share the same time invariant and time varying locality characteristics. Attrition is low, approximately two percent per year. Much of this attrition is due to kebeles being dropped where the PSNP ceased operating. Work investigating whether potential differences in attrition rates can be attributed to differences in baseline characteristics shows that being a program beneficiary was not correlated with the probability of attrition. Older and smaller households were slightly more likely to attrite than other household types, but the impact of these characteristics on attrition was small (Berhane et al., 2013; Berhane et al., 2011).

2.4.2 Welfare Variable: Months Food Secure

The primary goal of the PSNP was to reduce the food gap. This was measured by asking survey participants to report the number of months, out of the preceding 12 months, that they had problems satisfying the food needs of the household with a month where the household had problems satisfying food needs being defined as one where the household experienced hunger for five or more days. We convert this to *Months Food Secure* by starting with 12 months and subtracting the number of months when households reported having problems satisfying their food needs. This somewhat non-standard measure has two advantages. First, the Government of Ethiopia uses this to assess the impact of the PSNP.[2]. Second, it allows us to measure food-security over a 12 month period. This contrasts with measures such as caloric acquisition or food expenditures that are typically reported over a shorter period such as seven or 14 days. Such measures are more sensitive to seasonality and other factors leading to short term fluctuations, which might mask our attempts to measure long run impacts.

Figure 2.2 shows how *Months Food Secure*e has evolved over the nine years covered by the PSNP surveys. In general, food security improves with the distribution shifting rightwards over time. The proportion of households experiencing no reported hunger (*Months Food Secure*=12) increases from 34.9% to 48.4%.

However, notice that this trend is not linear; reported *Months Food Secure* deteriorate in the 2010 round, when the proportion of fully food secure household

[2]The super goal of the PSNP is the elimination of the food gap where the food gap is defined as 12 months food secure

dropped to 29.7%. We know from rainfall data that Ethiopia experienced a severe drought in 2009. This deterioration is an example of drop shown in Figure 2.1; the question which arises is whether access to the PSNP mitigated the effect of such a shock and whether it sped recovery from it.

2.4.3 Shock data

The survey instrument collects information on self-reported shocks. Specifically, households were asked: We would like to learn about shocks in the last two years. Has this household been affected by a serious shockan event that led to a serious reduction in your asset holdings, caused your household income to fall substantially or resulted in a significant reduction in consumption? We would like to learn more about the worst shocks in the last 2 years. This was followed by 17 questions on different types of shocks that households might have experienced divided into three broad categories: Covariate climatic shocks, including drought, floods, frost and pest incidence; Covariate economic shocks, including lack of access to inputs and price shocks affecting either inputs or outputs; and Idiosyncratic shocks, such as death, disease or divorce affecting a family member.

Figure 2.3 shows the five most frequently reported shocks by survey round. Drought is by far the most frequently reported shock. In every survey round, at least 20 percent of respondents reported being affected by drought in the two years preceding the survey with this figure rising to nearly 80 percent in the 2010 round. Given their frequency we focus on drought. In our estimates below, *Drought* is defined as equaling one if a household reports experiencing a drought shock in the two years prior to the survey.

2.4.4 Treatment: PSNP Payments

All survey rounds collected self-reported information on payments received by PSNP beneficiaries from participation in Public Works and from Direct Support. Specifically, for each survey round we know the total amount of payments that the household received in the nine months preceding the survey. These nine months overlap with the 12 months recall period for the food gap. We use these data to construct our measure of treatment, *PSNP Payment*, the value of the payment received.

Payments are received either as cash or in-kind (usually wheat or maize). In-kind payments are valued using data on local market prices. To account for inflation, which at times was substantial over the period covered by these surveys, we follow the methods outlined in Berhane, Hirvonen, and Hoddinott (2015). We construct a cereal price index, a weighted average of prices of the 6 main cereals (maize, teff, barley, wheat, sorghum and millet) in a given community in a given year. We weigh them by the consumption shares of each cereal type, collected at the household level and aggregated up to the community. Our price index thus captures both temporal and cross-sectional differences in price levels. We then deflate nominal payments using 2014 as a benchmark. *PSNP Payment* is expressed in 100 birr increments with each increment equivalent to about 5 USD in 2014.[3] Table 2.1 reports these payments by region and year.

[3] Because this is expressed in real terms, these figures may differ from previous articles such as Berhane et al (2014) .

2.4.5 Additional controls

In addition to household fixed effects, we control for household land ownership, education as a proxy for human capital, and the age, size and gender composition of household. Some of these variables, such as household size, are correlated with household food security. Their inclusion improves the precision of our parameter estimates. Others, such as land ownership, are correlated with both household food security and the likelihood of receiving PSNP payments. Descriptive statistics for these control variables in two round, 2006 and 2014, are shown in Table 2.2.

2.5 Results

We begin by estimating equation (1) . While this does not include the impact of the PSNP, it allows us a first look at how reported drought shocks affects household food security. Results are shown in Table 2.3. Column (1) reports the contemporaneous effect of drought with columns (2), (3) incorporating additional lags in the drought variable to reflect long term effects.[4] Table 2.3 shows that drought reduces food security and that it has persistent effects. Given our definition of shocks, each lag is equivalent to two years. Column (3), for example, indicates that *Drought* reduces *Months Food Secure* by 1.56 months initially. Two years after the drought occurs, *Months Food Secure* is still reduced by 0.55 months and four years after the drought, *Months Food Secure* is reduced by 0.35 months. We illustrate this in Figure 2.4.

We can construct a version of Figure 2.1 by taking the results from column (3),

[4]We test and reject unit roots for our lagged variables. For robustness we ran the above specification with a Prais-Winsten feasible generalized least squares estimator and got qualitatively equivalent coefficients, of the same sign and significant.

and plotting them along with their 95% confidence intervals. We take the constant as representing a baseline level of 10.25 months food secure for a representative household. Assuming the household suffers from drought, its level of food security can be computed as $\hat{\beta}_0 + \hat{\beta}_{drought} \approx 10.25 - 1.56 = 8.69$ months food secure. To infer the effects of the drought two years after it ends we compute $\hat{\beta}_0 + \hat{\beta}_{L.drought} \approx 10.25 - 0.55 = 9.7$ months food secure. Up to four years after the drought ends the household is still less food secure than it would have been otherwise.

2.5.1 Ordinary least squares estimates

Next, we estimate equation (3), using an Ordinary Least Squares (OLS) estimator with fixed effects. The results are reported in Table 2.4. Looking at the coefficients on the interaction terms in column (3), we again see that *Drought* reduces *Months Food Secure*. The interaction terms between *Drought* and *PSNP Payment* is positive, indicating that the PSNP offsets some of the impact of drought. However, the magnitude of this effect is small; at mean payment levels, payments reduce the effect of the drought by 0.1 months.

2.5.2 Instrumental variables estimates

Results in Table 2.4 control for household fixed effects and the time varying household characteristics. This removes much of the potential correlation between the disturbance term and PSNP treatment but possibly not all. To address this, we need instrumental variables that are correlated with payments but not correlated with household food security.

Furthermore, to address concerns that kebele level program implementation is correlated with beneficiary household un-observables, we use these exogenous variables to construct a Hausman Instrument Hausman, 1994. We aggregate the characteristics at the woreda level and take the average, excluding own-kebele characteristics:

$$OtherZ_{kt} = \frac{\sum_{i=1}^{|W|} Z_{iwk} - \sum_{i=1}^{|K|} Z_{iwk}}{|W| - |K|} \tag{2.4}$$

Where W is the set of observations in a given woreda, and K the set of observations in a kebele. This reflects underlying trends in program implementation at the woreda level that would affect the kebele, but excludes potential correlation with kebele level un-observables, which may be correlated with individual outcomes.

Our description of the PSNP in section 2 suggests the following candidates for exogenous instrumental variables:

1. *Public Work Months*: The total number of months in which public works were undertaken. An increase in the number of months when the PSNP employed beneficiaries in the woreda as a whole could be positively correlated with payments at the household level if it reflects greater resource availability overall. However, because our Hausman instrument explicitly excludes own kebeles, it is possible that an increased allocation elsewhere in the woreda would imply decreased resource availability in the households kebele, leading to a negative correlation. The mean number of months of public works is 5.4.
2. *Cash Payments*: An indicator variable equaling one if a payment was made in cash. Analysis of PSNP payment processes showed that cash payments were made in a more complete and timely fashion than payments made in-kind; see Berhane et al (2011, 2013). However, in years of high inflation,

food payments were more likely to retain their purchasing power, suggesting that the cash payment reduces the real value of payments Berhane et al., 2015. This indicator has a mean of 0.84.

3. *Cash Payments * Distance to Town*: An indicator variable constructed as the interaction between the cash payment dummy described above and distance to the nearest town. As Berhane et al (2011, 2013, 2015) show, distances beneficiaries must travel to payment sites can be large, particularly for food payments. Cash payments may overcome, to some extent, the difficulties that more remotely located households might have in receiving the payments. In other words, we expect that the cash payments increase in the likelihood of household receiving payments and that this correlation gets stronger the more remotely located the household is. We proxy remoteness with distance from the center of the kebele to the nearest town. The mean of this interaction term is 12.9.

Table 2.5 shows the correlations between these instruments and payments received by PSNP households. (Note that the sample size is larger than that reported in other tables because we include lagged treatment variables.) Note that we create instruments for our endogenous interaction term by interacting the instrument with the exogenous variable drought.

Table 2.5 shows a negative correlation between village level payment and own payments. Though seemingly counter-intuitive, recall that this is a Hausman instrument at the woreda level, explicitly excluding payments from the households own kebele. Hence the negative correlation suggests that given a fixed budget, an increase in public works provided to other kebeles reduces the amount of work (and therefore payments) to the own kebele. Receiving payments in cash is positively correlated with level of payments, possibly due to the reasons described above. Our interaction between cash payment and distance is also positively correlated, suggesting that cash helps overcome remoteness to a certain extent.

Table 2.6 reports the results of estimating equation (3) using the Hausman IV approach with a system GMM estimator. Standard errors are clustered at the kebele level. We present three estimates: column (1) reports findings with no lags; column (2) reports a two year lag structure while column (3) gives the results with a four year lag structure. Noting that the coefficients on the initial drought shocks and the interaction term between the initial drought shock and PSNP payments are similar across all three columns, we focus on column (3).

As we saw earlier, *Drought* reduces *Months Food Secure* and the magnitude of their effect is large. Using column (3), a household reporting a drought shock in the previous 12 months saw its months food secure fall by 4.55 months. *PSNP Payment* offsets much but not all of this initial shock. Recall that mean payments are approximately 500 birr per year and that in Table 2.6, payments are reported in 100 birr increments. This means that for the average beneficiary, PSNP payments offset 2.8 months of the drought shock a 62 percent reduction in vulnerability.[5] There is a lagged effect of drought; in column (3), this is a reduction of 2.1 months in food security two years after the drought ended. However, at the mean level of payments, this is nearly completely offset by PSNP payments (5 multiplied by 0.36 = 1.8). By contrast, households not receiving any PSNP payments do not benefit from this mitigation and suffer the full effect of the drought. They do not return to their pre-drought level of food security until four years after the drought ended (column (3)). Figure 2.5 graphs these trajectories for PNSP households receiving mean levels of payments and non-PSNP households. Table 2.6 and figure

[5] $(500birr/100) = 5,\ 5 * 0.56 = 2.8)$

2.5 convey the core findings of the article.

The magnitude of the coefficients on *PSNP Payment* and the interaction term increases substantially relative to our OLS fixed effects specification. This suggests that while our OLS specification controlled for both household fixed effects and some time varying household characteristics that were correlated with program targeting criteria, they did not control for other unobservable factors that were correlated with both payments and the extent of food insecurity. Using both the OLS and IV estimates, we constructed a Hausman test. This rejected the null hypothesis that the OLS estimates were unbiased. We constructed a Hansen J test. P values are reported at the bottom of Table 2.6; these show that we do not reject the null hypothesis of the validity of our instruments.

Results in Table 2.6 assume that the impact of shocks, and of the PSNP, is the same across all households. This may not be true. For example, relatively wealthier PSNP households may be better able to consumption smooth in the face of shocks, something our estimates do not take into account. We consider heterogeneous effects across four household characteristics: land holdings; baseline (2006) food security; baseline (2006) livestock holdings; and household heads grade attainment.[6]

We disaggregate our sample into two groups: households with land holdings less than or equal to one hectare, and households with more than one hectare of land.[7] Results are shown in Table 2.7. Column (1) is the aggregate result, column (2) restricts results to households with 1 ha of land or less and column (3) restricts

[6]We use baseline values for these because subsequent values may be affected by both drought and payments received from the PSNP.

[7]An alternative approach would be to split the sample into two groups of equal size. However, because a large fraction of the sample reported operating exactly one hectare of land, this was not feasible.

results to households with more than 1 ha of land. *Drought* has a larger effect on households with smaller land holdings. But for these poorer households, *PSNP Payment* has a relatively larger offsetting effect, implying that these payments have a particularly powerful effect on enhancing the resilience of poor households. This is seen clearly when we use the results from Table 8 to graph the food security trajectories of PSNP and non-PSNP households, disaggregating by land holdings. Households with more than one hectare of land suffer a smaller reduction in food security and recover more quickly compared to households with one hectare or less. Among households with less than one hectare of land, the PSNP cushions the initial effects of drought shocks and permits a faster recovery from them. The dis-aggregated results are illustrated in figure 2.6.

Next we disaggregate by initial (2006) household food security; specifically we disaggregate the sample based on whether the household had food security above or below the mean level for the region it resided in. Results are shown in Table 8. Column (1) is the aggregate result, column (2) restricts results to household below the mean level of *Months Food Secure* in 2006, and column (3) restricts them to households above the mean. Results are similar to those found for the land disaggregation. Households that initially are more food insecure experience a greater reduction in food security following a drought shock compared to more food secure households. However, among these initially food insecure households, recovery from drought is faster when they receive PSNP payments.

We disaggregate by initial (2006) livestock holdings; specifically we disaggregate the sample based on whether the household had livestock holdings above or below the mean level for the region it resided in. We also disaggregated by whether the household head had any formal schooling. In both instances, we find no differences in treatment effects across these disaggregations. Results are available on request.

2.6 Robustness Checks

We consider five potential concerns regarding our results: measuring drought through the use of self-reported shocks, sample composition, the presence of other interventions, alternative estimators, and accounting for time effects.

2.6.1 Self-reported versus measured shocks

Our results are based on household self-reports of drought shocks. To the extent that these capture a households perception of what has occurred rather than what actually occurred, they may contain measurement error. Reverse causality is another possibility. Beneficiaries may mistakenly believe that receiving payments is conditional on experiencing a shock and so report that these have occurred even when they did not. All these possibilities will result in biased parameter estimates.

We can address these by replacing our self-reported shocks with measured shocks. To do so, we obtained geo-spatial climate data, specifically the Standardized Precipitation-Evapotranspiration Index (SPEI). SPEI was developed as a multi-dimensional measure of drought incorporating the effects of variations in precipitation and temperature. It combines two widely accepted measures, the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI). It is available from 1901 to 2013 with a 0.5 degrees spatial resolution and monthly frequency.

SPEI, based on the water balance equation, measures wetness as positive values and dryness as negative values, incorporating prior precipitation, moisture supply, runoff and evapo-transpiration. It is a relative probability index sensitive to timescale. Intuitively, what constitutes an episode of drought or flooding depends on the pre-existing agro-ecological context. This determines what is 'enough water, and the lag between the arrival of water inputs as rain, runoff or snow-melt, to its availability for watering crops or livestock. This comparison between actual and historical can be made over different timescales allowing the user to distinguish between hydrological, environmental, and other droughts. We used a 12 month timescale, capturing variations in drought conditions over the past year, reasoning that this was the scale that most affected households in our sample as well as being most comparable to our self-reported drought measure. Since the available SPEI datasets are at the global level, we extracted observations for Ethiopia using its geo-coordinates. SPEI data were matched to individual woredas GIS coordinates using inverse distance weighting.

Figure 2.7 illustrates SPEI in Ethiopia by region. Values less than zero indicate drought conditions, a cursory comparison with Figure 2.3 suggests that these measured drought shocks correspond with the frequency of self-reported shocks; most notably in 2009.

Using these SPEI data, we run the same IV specification as in table 2.6, using the same set of lags for previous droughts but replacing our binary variable for self-reported drought with a new independent binary variable *SPEI*, that equals one if the average of 12 months prior SPEI was less than zero. When we do so, the results in table A.1 are similar to those reported in Table 2.6.

2.6.2 Sample Composition

Our sample includes households in the Amhara region of Ethiopia. Some of these households received PSNP payments through funding provided by the US government. These payments were all in the form of in-kind payments. Given our IV strategy, we wondered if their inclusion affected our results. As a robustness check, we excluded these households and re-ran the IV model used to estimate equation (3). Doing so gave similar results (see Table A.2).

As noted in section 2, some PSNP beneficiaries, those with no able bodied members, such as widows, orphans and disabled individuals unable to perform public works, unconditional payments called Direct Support. Their payments might be unaffected by one of our instruments, the number of months when public works employment was provided. As a robustness check, we also excluded these households and re-ran the IV model used to estimate equation (3). Doing so gave similar results (see Table A.3).

2.6.3 Other Interventions

Suppose that in addition to the PSNP, there was another intervention operating in the woredas in our sample and that it had a similar beneficiary profile. If this were the case, we might incorrectly ascribe the impact of such a program to the PSNP.

There is only one such program that fits this description. Initially, the PSNP was complemented by a series of food security activities called the Other Food Security Program (OFSP) (Berhane et al, 2014). The OFSP aimed to increase incomes through the provision of credit for activities that would improve crop and livestock production. Problems with its implementation led to a re-design; the replacement program, the Household Asset Building Program (HABP), had a greater emphasis on technical assistance. Both the OFSP and HABP were intended to assist a subset of PSNP beneficiaries. As a robustness check, we re-estimated equation (3) including as an additional control, participation in the OFSP/HABP. Doing so had no substantive effect on our estimates (see Table A.4).

2.6.4 Alternative estimators

Our dependent variable is a discrete count variable, taking on integer values from 0 to 12. As a robustness check we estimated equation (3) using a household fixed effects instrumental variable Poisson maximum likelihood estimator. Poisson household fixed effect results are presented in table A.5 and instrumental variable poisson household fixed effect results in table A.6. Because we use a non-linear estimator, in order to recover the average marginal effect we must multiply the coefficients by the sample average of the outcome variable. The results are consistent with the results reported in Table 2.6 in sign, magnitude and significance. For example, using the model specification with two lags, the marginal effect of the interaction term PSNP payment by drought in past year is 0.39 which is statistically indistinguishable from the equivalent coefficient reported in Table 2.6, column (3).

2.6.5 Accounting for time effects

Results such as those shown in Figure 2.2 suggest that we should be concerned about controlling for time (secular) trends. Doing so, however, is not without its own problems; in particular there is a high correlation between reported drought shocks and some of our survey years, most notably 2010, making it infeasible to include survey round dummies. We note that we control for some of the effects of secular change; for example our price deflator ensures that the effect of inflation on payments is taken into account. At the household level, our inclusion of the age of the household head will also capture some of these secular trends.

Yet, despite all this, one might be concerned about time trend effects. A further way of addressing this is to detrend our dependent variable. As a robustness check, we did so, subtracting the predicted outcome from the time trend alone.[8] The results are available in table A.7 and are consistent with our principle results in sign, significance and magnitude.

2.7 Conclusion

The malign effect of shocks has long been a concern within economics, partly because they result in transitory welfare losses and partly because they may have persistent effects. In development discourse, this latter concern has spurred interest in the concept of resilience and how public interventions such as social safety nets can enhance resilience. However, operationalizing these ideas has been constrained by their daunting data requirements which include: (1) Longitudinal household

[8]Specifically, we regressed $Y_{it} = \gamma_0 + \theta_t + \epsilon_{it}$ and generated the predicted variable $\hat{Y}_t^{Trend}$. $Y_{it}^{detrend} = Y_{it} - \hat{Y}_t^{Trend}$

data to allow for household fixed effects estimation; (2) A consistently measured outcome variable; (3) Measured shocks that occur within the data collection timeframe with both cross-sectional and temporal variation; and (4) Data on payment levels with sufficient exogenous variation to identify program impacts.

Within this context, we assess the impact of a social protection program, Ethiopias Productive Safety Net Program, on the longer term impacts of drought on household food security. Surveys conduced over multiple years satisfy these data requirements. We find that drought shocks reduce the number of months a household considers itself food secure and that these impacts persist for up to four years after the drought has ended. Using a Hausman instrumental variable estimator, we find that receipt of PSNP payments reduced the initial impact of drought shocks by 62 percent and eliminates their adverse impact on food security within two years. In this way, the PSNP strengthens the resilience of its beneficiaries against adverse shocks. This impact is largest for PSNP beneficiaries with little or no land. Our results are robust to how shocks are measured, changes in sample composition, the presence of other interventions and the estimator used. If this findings can be replicated with other programs in other settings, they suggest that social protection interventions are a mechanism for mitigating the adverse effects of climatic shocks.

Tables

Table 2.1: **Mean *PSNP Payment* Received, by year and region**

				Round		
Region	2006	2008	2010	2012	2014	Total
Tigray	6.16	3.84	4.66	8.06	5.70	5.63
	(10.30)	(7.42)	(8.63)	(12.69)	(11.44)	(10.30)
Amhara	2.34	0.79	1.36	5.06	3.36	2.62
	(4.65)	(2.33)	(6.04)	(10.06)	(8.15)	(7.20)
Oromiya	5.84	2.88	2.06	10.59	7.29	5.61
	(9.89)	(5.41)	(5.26)	(19.93)	(16.48)	(12.87)
SNNP	4.72	3.78	6.18	7.47	5.24	5.44
	(7.55)	(6.35)	(11.21)	(12.23)	(11.20)	(9.97)
Total	4.81	2.33	3.04	7.03	4.88	4.38
	(8.56)	(5.27)	(7.94)	(13.34)	(11.37)	(9.83)

Note: Real price index adjusted values, reported in 100 birr increments.
Standard deviation in parentheses

Table 2.2: **Selected HH Characteristics, by Round and PSNP Status**

(a) **First Round (2006)**

	PSNP Beneficiary	Non-PSNP Beneficiary	p value
Land (ha)	1.28	1.17	0.00
Age of Household Head (years)	44.39	45.98	0.00
Education of Household Head (years)	0.54	0.47	0.04
Household Head is Male	0.78	0.74	0.01
Number of Males 0-6	0.59	0.61	0.42
Number of Females 0-6	0.58	0.61	0.27
Number of Males 7-15	0.67	0.70	0.37
Number of Females 7-15	0.63	0.67	0.22
Number of Males 16-60	1.08	1.02	0.02
Number of Females 16-60	1.14	1.15	0.73
Number of Males ¿60	0.12	0.13	0.40
Number of Females ¿60	0.09	0.12	0.02

(b) **Last Round (2014)**

	PSNP Beneficiary	Non-PSNP Beneficiary	p value
Land (ha)	1.18	0.96	0.00
Age of Household Head (years)	49.70	51.82	0.00
Education of Household Head (years)	0.57	0.41	0.00
Household Head is Male	0.79	0.61	0.00
Number of Males 0-6	0.51	0.42	0.00
Number of Females 0-6	0.50	0.42	0.00
Number of Males 7-15	0.92	0.76	0.00
Number of Females 7-15	0.83	0.77	0.09
Number of Males 16-60	1.23	1.05	0.00
Number of Females 16-60	1.27	1.22	0.07
Number of Males ¿60	0.17	0.16	0.29
Number of Females ¿60	0.11	0.19	0.00

Table 2.3: **Impact of *Drought* on *Months Food Secure* by Lagged *Drought***

	(1)	(2)	(3)
Drought in past year	-1.314***	-1.409***	-1.563***
	(0.092)	(0.094)	(0.10)
Drought 2 years ago		-0.372***	-0.550***
		(0.079)	(0.092)
Drought 4 years ago			-0.349***
			(0.094)
constant	10.01***	10.13***	10.28***
	(0.030)	(0.039)	(0.057)
N	8005	8005	8005

Note: Coefficients correspond to $Drought_t$, $Drought_{t-1}$ and $Drought_{t-2}$ in eqn (1), respectively. N restricted to 2010, 2012 and 2014 due to double lag structure.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: **Impact of *Drought* and *PSNP Payment* on *Months Food Secure*, Household Fixed Effects**

	(1)	(2)	(3)
PSNP Payment	0.008	0.011*	0.012**
	(0.005)	(0.005)	(0.005)
Drought in past year	-1.300***	-1.352***	-1.507***
	(0.240)	(0.260)	(0.252)
PSNP Payment * Drought in past year	0.017**	0.022***	0.020**
	(0.007)	(0.008)	(0.009)
PSNP Payment 2 years ago		0.017***	0.018***
		(0.006)	(0.007)
Drought 2 years ago		-0.282	-0.464*
		(0.230)	(0.251)
PSNP Payment * Drought 2 years ago		0.011	0.007
		(0.009)	(0.013)
PSNP Payment 4 years ago			0.005
			(0.008)
Drought 4 years ago			-0.315
			(0.221)
PSNP Payment * Drought 4 years ago			-0.017
			(0.016)
N	8005	8005	8005

Note: Coefficients correspond to eqn (3), where S_{it} is the incidence of drought and T_{it} is the PSNP payment received. N restricted to 2010, 2012 and 2014 due to double lag structure. Standard errors in parentheses.

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

Table 2.5: **Instrument Relevance: First Stage Regressions for Endogenous Variables**

	(1) PSNP Payments	(2) PSNP Payments * Drought
Public Work Months	-0.013***	
	(0.004)	
Cash Payments	0.210***	
	(0.066)	
Cash Payments * Distance to Town	0.002***	
	(0.000)	
Public Work Months * Drought		0.507***
		(0.160)
Cash Payments * Drought		2.260**
		(1.116)
Cash Payments * Distance to Town		-0.040***
* Drought		(0.010)
N	15604	15604
F-Statistic	34.255	6.470

Note: Use entire sample to instrument the set of endogenous variables. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: **Impact of *Drought* and *PSNP Payment* on *Months Food Secure*, Instrumental Variables and Fixed Effects**

	(1)	(2)	(3)
PSNP Payment	0.019	0.048**	0.077***
	(0.034)	(0.023)	(0.022)
Drought in past year	-4.097***	-3.693***	-4.548***
	(1.359)	(0.376)	(0.617)
PSNP Payment * Drought in past year	0.489**	0.542***	0.560***
	(0.222)	(0.112)	(0.135)
PSNP Payment 2 years ago		0.102	0.024
		(0.088)	(0.058)
Drought 2 years ago		-1.500*	-2.064***
		(0.802)	(0.495)
PSNP Payment * Drought 2 years ago		0.359*	0.358***
		(0.194)	(0.120)
PSNP Payment 4 years ago			0.111
			(0.077)
Drought 4 years ago			-0.741
			(0.632)
PSNP Payment * Drought 4 years ago			-0.060
			(0.159)
N	8005	8005	8005
Hansen J-Test	0.906	0.529	0.500

Note: Eqn(3) Instrumented. N restricted to 2010, 2012 and 2014 due to double lagged structure.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: **Impact of *Drought* and *PSNP Payment* on *Months Food Secure*, Instrumental Variables and Fixed Effects, Disaggregated by Land Area Operated**

	(1) All	(2) Greater than 1 HA	(3) 1 HA or less
PSNP Payment	0.077***	0.160***	0.033
	(0.022)	(0.037)	(0.027)
Drought in past year	-4.548***	-2.026***	-6.490***
	(0.617)	(0.592)	(1.176)
PSNP Payment * Drought in past year	0.560***	0.198	0.939***
	(0.135)	(0.124)	(0.188)
PSNP Payment 2 years ago	0.024	0.201**	-0.055
	(0.058)	(0.085)	(0.067)
Drought 2 years ago	-2.064***	-0.229	-2.817***
	(0.495)	(0.735)	(0.685)
PSNP Payment * Drought 2 years ago	0.358***	0.109	0.514***
	(0.120)	(0.160)	(0.149)
PSNP Payment 4 years ago	0.111	0.111	0.025
	(0.077)	(0.070)	(0.063)
Drought 4 years ago	-0.741	-0.394	-2.783**
	(0.632)	(0.383)	(1.177)
PSNP Payment * Drought 4 years ago	-0.060	-0.110	0.546*
	(0.159)	(0.124)	(0.285)
N	8005	2077	5928

Note: N restricted to 2010, 2012 and 2014 due to double lagged structure. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: **Impact of *Drought* and *PSNP Payment* on *Months Food Secure*, IV, Disaggregated by 2006 *Months Food Secure***

	(1) All	(2) Above Mean	(3) Below Mean
PSNP Payment	0.077***	0.001	0.152***
	(0.022)	(0.028)	(0.045)
Drought in past year	-4.548***	-5.375***	-3.542***
	(0.617)	(0.653)	(1.126)
PSNP Payment * Drought in past year	0.560***	0.739***	0.369**
	(0.135)	(0.160)	(0.153)
PSNP Payment 2 years ago	0.024	-0.186***	0.126*
	(0.058)	(0.065)	(0.073)
Drought 2 years ago	-2.064***	-3.768***	-1.051*
	(0.495)	(0.674)	(0.565)
PSNP Payment * Drought 2 years ago	0.358***	0.746***	0.178*
	(0.120)	(0.150)	(0.104)
PSNP Payment 4 years ago	0.111	0.016	0.303**
	(0.077)	(0.076)	(0.145)
Drought 4 years ago	-0.741	-2.199***	1.494
	(0.632)	(0.655)	(1.032)
PSNP Payment * Drought 4 years ago	-0.060	0.271	-0.455**
	(0.159)	(0.172)	(0.202)
N	8005	4296	3709

Note: N restricted to 2010, 2012 and 2014 due to double lagged structure. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

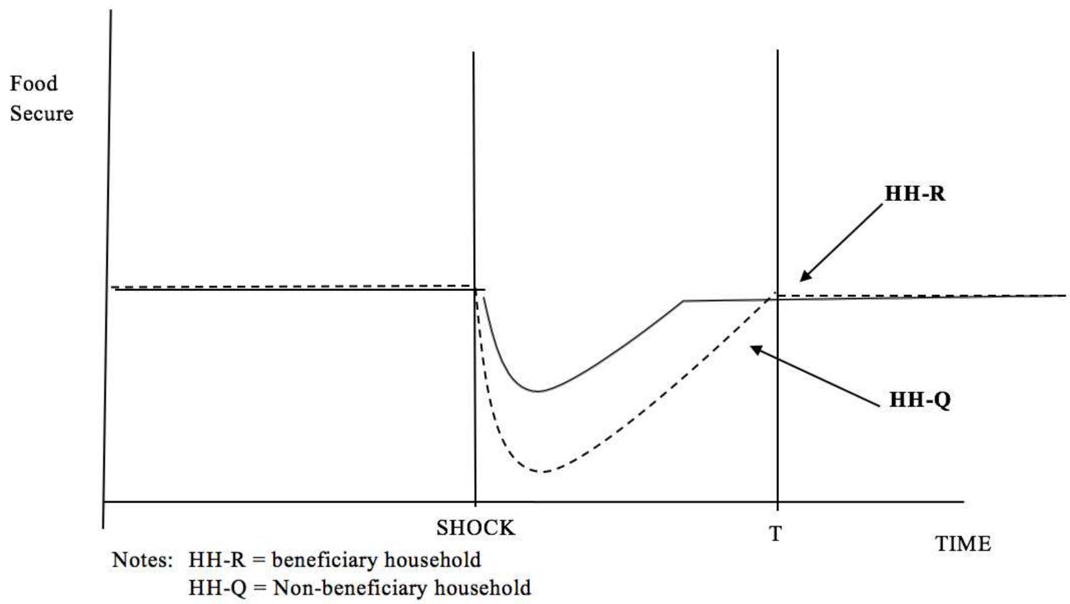


Figure 2.1: Food security and resilience over time

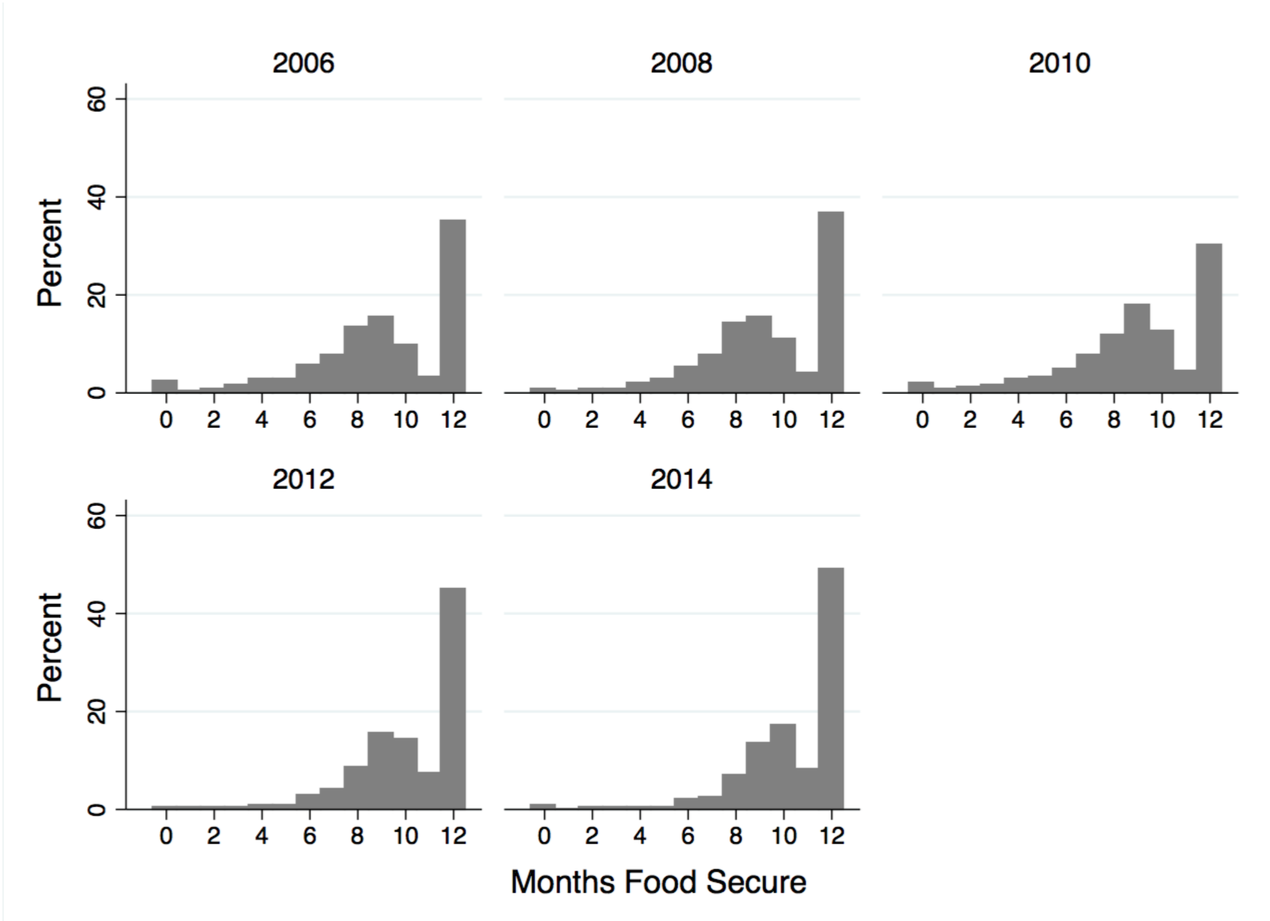


Figure 2.2: Distribution of months food secure, by round

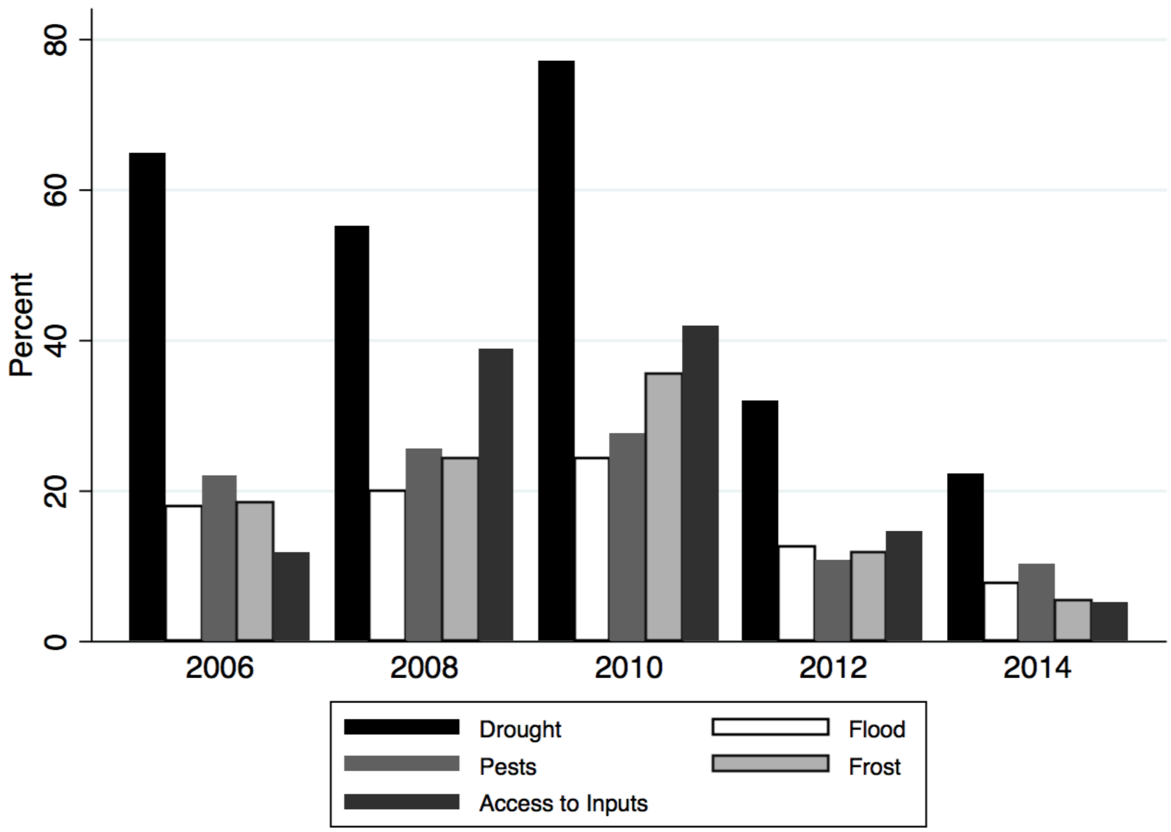


Figure 2.3: Percent households reporting selected shocks in two years prior to survey round, by round

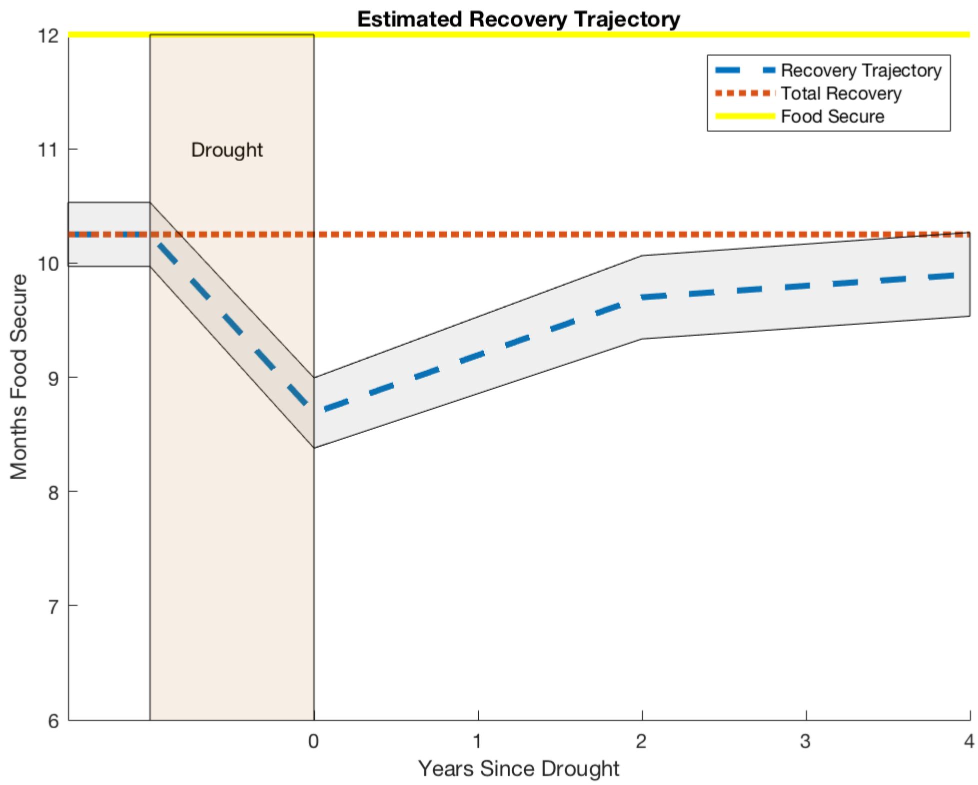


Figure 2.4: Recovery trajectory from drought

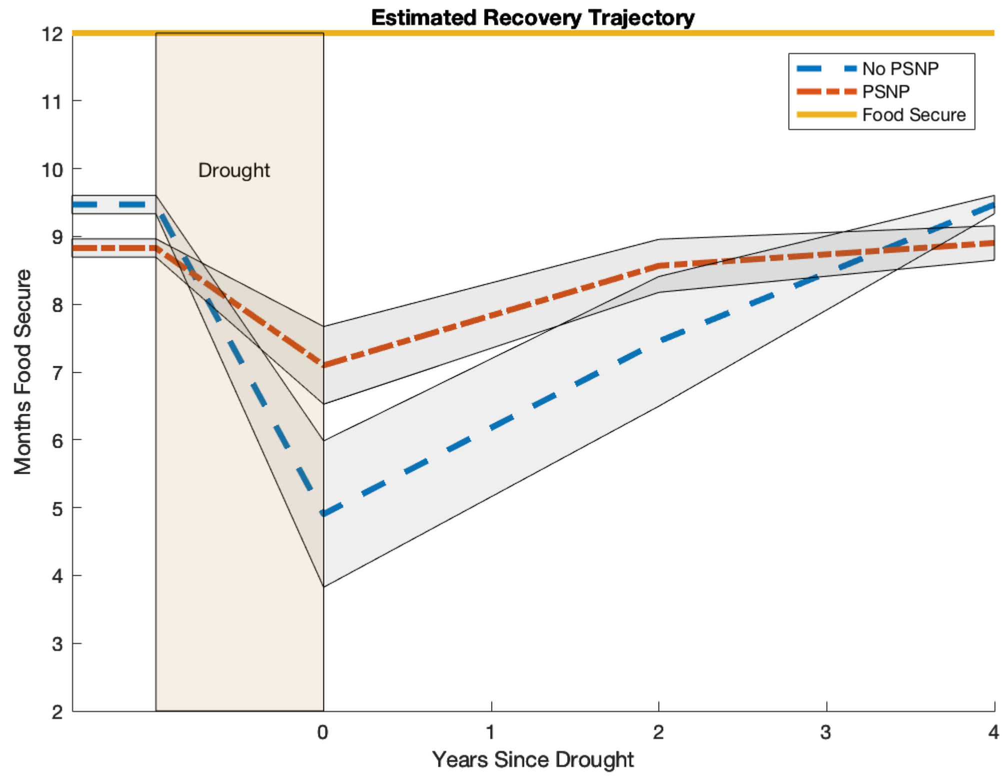


Figure 2.5: PSNP and non-PSNP recovery trajectories

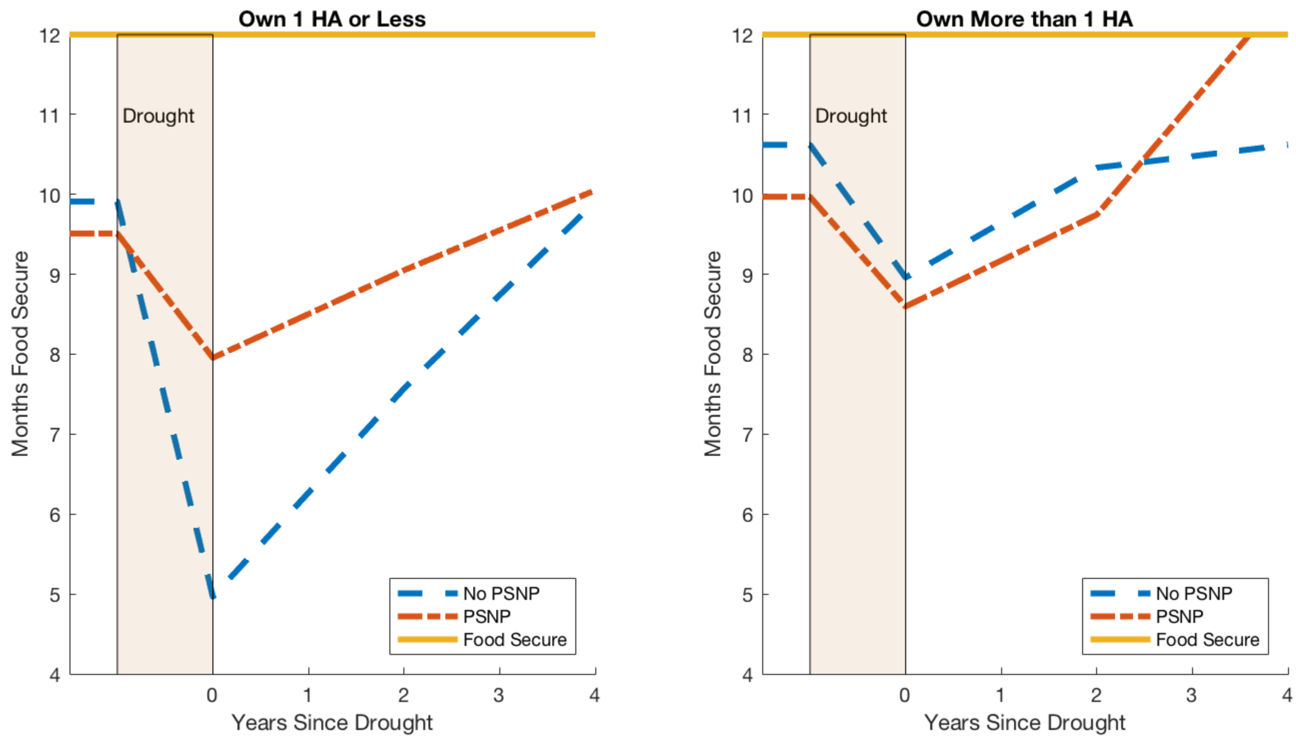


Figure 2.6: Recovery trajectories, disaggregated by land ownership

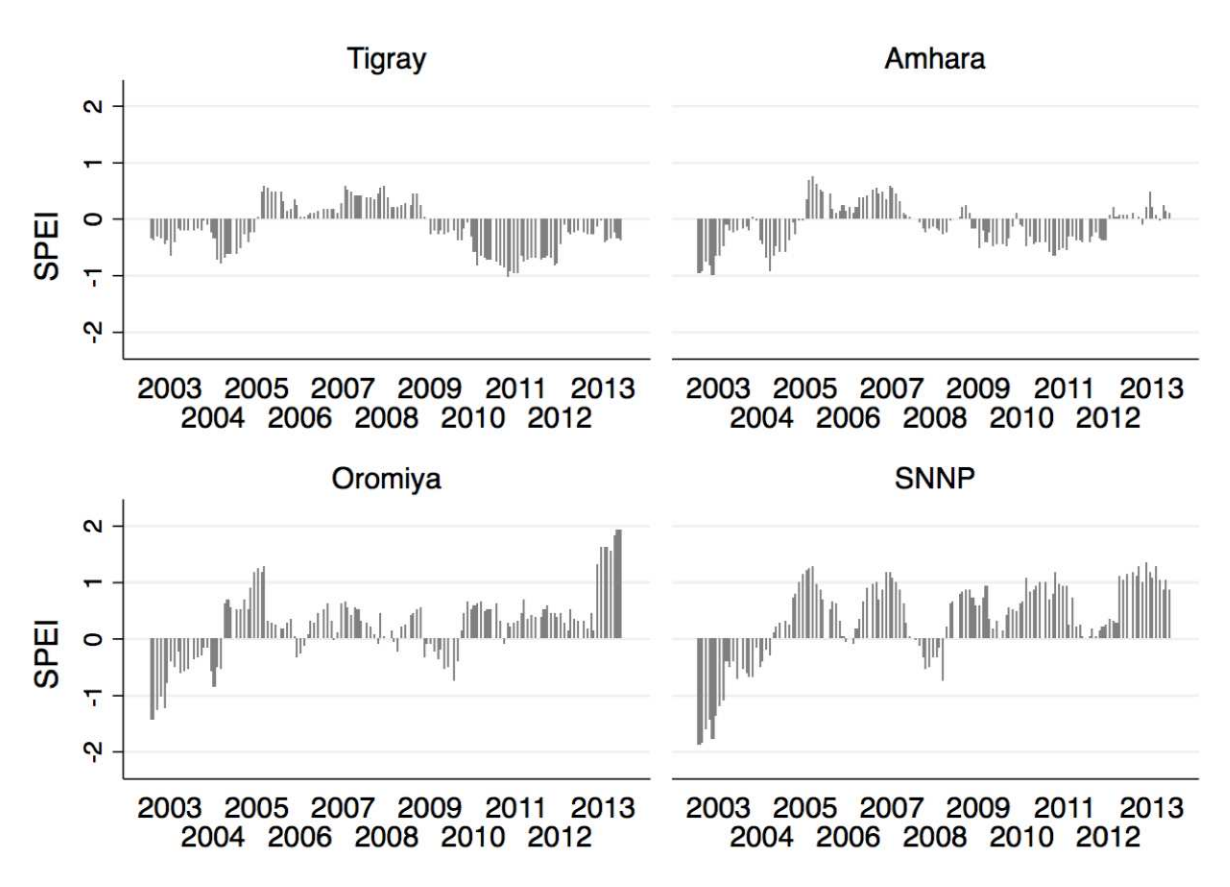


Figure 2.7: Standardized Precipitation Evapotranspiration Index (SPEI), by region and year

CHAPTER 3

RESILIENCE AND THE DYNAMICS OF FOOD INSECURITY, EVIDENCE FROM MALAWI

3.1 Introduction

In the last 20 years, the literature has shifted from viewing poverty as static to seeking to understand its dynamic nature (Carter and Barrett, 2006). This includes acknowledging the high level of stochastic risk poor households face as their income and assets fluctuate. Their livelihoods are particularly vulnerable to weather shocks, since they often rely on subsistence agriculture or pastoralism (Dercon, 2006). Faced with limited access to credit, insurance, and liquid assets, these vulnerable households struggle to smooth consumption (Carter et al., 2007; Zimmerman and Carter, 2003). This leads to both transitory and long-term welfare losses, as they are forced to forgo investments and sometimes cut down on critical food intake (Barrett and Santos, 2014; Hoddinott and Kinsey, 2001). In order to help understand such adverse consequences in an uncertain environment, (Barrett and Constas, 2014b) argue that the concept of resilience seeks to quantify how stochastic well-being trajectories shift over time.

The literature on resilience spans many fields, including ecology, engineering and psychology. Holling (1973) characterized it as an ecological system's ability to remain or return to a dynamic equilibrium in the face of recurring shocks. Engineers view it as a physical system's ability to "mitigate hazards" (Tierney and Bruneau, 2007). Psychologists view it as 'adaptation to adversity' (Lee et al., 2013). In development, interest in resilience has arisen out of concern over the cumulative effect of humanitarian emergencies. It has emerged as a key concept in dealing with the range of risks undermining efforts to reduce poverty and food insecurity, (Béné et al., 2012; Walsh-Dilley et al., 2016).

One methodological approach looks at resilience as the perceived persistence of specific shocks. Constas et al. (2014b) present an attempt to consolidate efforts at quantifying resilience in the context of food insecurity. They emphasize the importance of focusing on dynamic well-being Y_{it} in the context of shocks Z_{it} conditional on characteristics X_{it}. Y_{it} can be a measure of assets, consumption, or food security. This approach explicitly acknowledges that the effect of mitigating factors may depend on the shock in question. Trying to operationalize this approach, Vollenweider (2015) uses a distributed lag non-linear model to estimate the lagged impact of past shocks on present consumption, and projects consumption trajectories into the future. The paper assumes household unobservables are orthogonal to the recovery trajectory. This is of particular concern regarding weather shocks, as households living in different climactic zones will certainly have adapted to the expected occurrence of shocks.

Barrett and Constas (2014b) frame the concept of development resilience as changes in the distribution of well-being. Heuristically, households make consumption and investment decisions according to their expected well-being trajectories, subject to stochastic shocks. At certain points along this trajectory it may prove optimal not to forfeit current consumption by investing in asset accumulation, choosing instead to remain at a permanently lower level of well-being, a 'poverty trap' (Carter and Barrett, 2006). Barrett and Constas therefore define resilience as "the capacity over time of a person, household or other aggregate unit to avoid poverty in the face of various stressors and in the wake of myriad shocks." Resilience is presented conceptually as the set of possible realizations of future well-being.

The emphasis on stochastic dynamics allows us to think of resilience as a function of the probability distribution of well-being.

In a followup paper, Cissé and Barrett (2016) propose estimating resilience as the conditional mean and conditional variance of a household well-being indicator (e.g. assets) and, by positing a known distribution, constructing the conditional probability $\hat{p}(X, Z)$ that this indicator will be above a given threshold. The third stage regression $\hat{p}(x, z) = \beta X + \gamma Z$ estimates the effect of household covariates X_{it} and shocks Y_{it} on this probability, labeled 'resilience'. An elegant feature of this measure is that it can be disaggregated to the household level or aggregated up to reflect the resilience of particularly communities, regions or countries. However its approach does not distinguish between shocks and household characteristics, confounding the direct effect of a shock on well-being and the latent response capacity, which we may want to distinguish. It also does not allow for households to be resilient to certain shocks but not others.

One can also think of resilience as a predictor of future food insecurity. This approach draws inspiration from an emerging interdisciplinary literature, which seeks to improve the accuracy of targeted social programs when lacking comprehensive data on income and consumption. This *Proxy Means Testing* (PMT) uses easily identifiable indicators, such as asset ownership, as proxies for poverty. However such PMT-based formulas, while good at excluding the non-poor, tend to miss many qualifying households. Brown et al. (2016) show that a typical PMT-based formula applied to data from nine African countries can predict less than half of the extreme poor. Attempts to improve targeting accuracy have sought to harness geo-spatial data and advances in machine learning. McBride and Nichols (2015) present evidence that applying machine learning algorithms to PMT development can substantially improve the out-of-sample performance of these targeting tools. Rather than predicting poverty, we will draw from this methodological approach to predict food insecurity.

Resilience can be characterized using longitudinal data. Smerlak and Vaitla (2016) look at long term time trends in country level caloric availability. Taking a purely non-parametric approach, they consider a country resilient if its long-term food insecurity trend is non-negative and any shocks experienced do not persist over time. In parallel Chavas (2016) uses a threshold quantile auto-regressive model and defines a resilient system as one where the first unit roots $|\lambda_1| > 1$ given a particularly negative sequence of shocks (in the bottom quantile of yields) but returns to a more stable $|\lambda_1| < 1$ when yields are at or above average. Though these methods are appealing in their non-parametric emphasis on time trends, they are limited by the need for a very long time series and lack of plausible counter-factuals. A minimum of 45-50 rounds required to identify path dynamics is implausible given the time span of most development projects and inevitable attrition.

This paper uses a novel 12-month dataset to map out the dynamics of shocks and well-being in terms of food insecurity. The data was collected from a series of sentinel sites in southern Malawi during a humanitarian emergency. Our team, in collaboration with Catholic Relief Services (CRS), piloted the 'Measuring Indicators for Resilience Analysis' (MIRA) project: a low-burden, monthly survey measuring food insecurity. Drawing inspiration from the literature, our paper uses this data to explore and expand on three methodological approaches to measuring resilience and food security:

1. An analysis of resilience as the perceived persistence of shocks

2. An analysis of shifts in the stochastic distribution of food security over time.
3. An exercise in selecting the best predictors of future food insecurity.

Using an auto-regressive estimation model, we focus on the adverse effects of subjective shocks and food insecurity as measured using the Coping Strategy Index. These measures are fast moving and sensitive to aggravating or mitigating factors, making them well suited for monthly panel data. In order to illustrate what can be done with our data using this framework, we perform three types of analysis.

We start with an analysis estimating the persistence of subjective shocks. In being subjective, the incidence and persistence of these shocks reflects their effects on household well-being. For example, if two households experience the same meteorological drought but one reports itself recovered earlier than the other, than we can consider that household more resilient. We further test whether observed household characteristics are correlated with the estimated persistence of specific shocks. We find that having fields far from home and living in the flood plain is correlated with a lower persistence of drought's adverse effects, while female headed households and households with a chronically ill member experience more persistent effects of illness.

We then perform an analysis plotting the stochastic distribution of food insecurity outcomes. We use a Blundell-Bond estimator to trace households' food insecurity trajectories as a stochastic distribution, explicitly allowing for explanatory co-variates that may shift this trajectory. We find that living in the flood plain, having fields far from home and the gender of the household head shift the distribution of CSI. We also find that though livestock seems to have little effect, the amount of land households farm improves the distribution of expected outcomes.

Finally, we seek to identify the best predictors of food insecurity in the immediate future. We use the Least Absolute Shrinkage and Selection Operator (LASSO), which introduces a penalty term for additional coefficients and explicitly identifies the best performing ones. We compare its performance to that of a random forest algorithm, which runs a series of regression trees, splitting the dataset into subsets defined by each variable. We find that the best predictors across both algorithms are previous levels of food insecurity, living in a flood plain and distance to drinking water. Mapping out our predictions and comparing them to actual outcomes, we find with high accuracy that high levels of food insecurity are concentrated in small pockets, reflecting the local nature of most shocks. This can inform geographic targeting decisions.

This paper makes the following contributions: We outline an approach for collecting monthly rapid response data tailored to measuring such resilience outcomes. We then demonstrate three different approaches for measuring resilience and the key characteristics that drive it: the first based on subjective shock persistence, the second on the stochastic distribution of food insecurity, and the third on predicting future food insecurity.

The rest of the paper is organized as follows: Section II outlines our data collection strategy and summary statistics. Section III outlines how we can use transition probabilities to describe the persistence of subjective shocks' adverse effects. Section IV uses a Blundell-Bond estimator to infer the projected distribution of food insecurity as measured using the Coping Strategy Index. Section V demonstrates our use of LASSO to infer the best predictors of future food insecurity. Section VI concludes.

3.2 Data

3.2.1 The MIRA project

Malawi is a landlocked country in southeastern Africa. With fertile land and an influx of immigrants from its less stable neighbors, it has one of the highest population densities in the region. Eighty-four percent of its population lives in rural areas, most of them reliant on subsistence agriculture (Bank, 2010). These factors make it particularly vulnerable to weather related shocks. As a case in point, the Shire river basin in southern Malawi was hit by devastating floods in January 2015, displacing hundreds of thousands of people. With resettlement underway, a consortium of development partners worked with the government to launch the United in Building and Advancing Life Expectations (UBALE) program, a program that serves three of the poorest and disaster-prone districts in MalawiChikwawa, Nsanje, and Rural Blantyre. Over the course of our survey (2016-2017), southern Malawi was severely affected by a cyclical El-Niño, which led to severe drought and widespread crop failure.

Catholic Relief Services approached Cornell with a proposal to pilot a low-burden, high frequency data collection protocol that would enable researchers and policymakers to track household food insecurity on a monthly basis. This differed from most 'early warning' systems in its panel structure, which permitted more sophisticated analysis than repeated cross-sectional data. In particular, this data set was to permit the development of measures specific to shocks and coping capacities which CRS would use in its impact evaluation. This agreement became the Measuring Indicators for Resilience Analysis (MIRA) project.

The survey was piloted in April 2016. Once finalized, a 45 minute baseline survey containing demographic, livelihood, economic, and shock history data was administered between May 18th and June 30th 2016. These household characteristics were considered either time invariant or sufficiently slow moving as to remain fixed over a year's time. In addition to standard indicators of assets, such as land and livestock, our pilot uncovered locally important indicators of prosperity. A substantial minority of households who lived far from some of their fields had a secondary 'house,' often a shack where they could store tools and sleep overnight if necessary. It therefore proved a useful proxy for spatial dispersion of the household's fields. We also wanted to control for basic demographic indicators, including the incidence of chronic illness and disability.

The same households received monthly follow-up visits from June 2106 onwards, every month for a year up to and including May 2017. During these visits, enumerators equipped with smart-phones administered a 'rapid-response' 5-15 minute survey tracking the persistence of shocks and related food insecurity outcomes. Importantly, the surveys retain respondents prior information, allowing for follow-up questions that focused on the continued effects of previously reported shocks. This case management feature allowed us to more explicitly track the persistence of experienced shocks over time.[1] In order to address issues of attrition, the researchers in partnership with CRS worked closely with community leaders to convey the importance of the data collection exercise.[2]

[1]The open source CommCare survey application was selected for the high frequency survey because of its case-management functionality, which allows for a dynamic survey based on previous response. Surveys saved on enumerator's smart-phones were uploaded to the cloud every month, making anonymous household data available in near real time to researchers for prompt analysis.

[2]Tracking households month-on-month was facilitated by relying on local enumerators who knew the community. These enumerators were incentivized by a compensation scheme which paid them per successful survey uploaded, reducing attrition. To prevent fraud, the field supervisor in collaboration with the researchers monitored their meta-data, including location and time of survey.

In June 2017 the initial data collection exercise in Chikwawa was capped with an end-line. This 45 min survey collected the same set of questions as the baseline in order to construct a panel dataset (see supplementary materials). Because of the noted importance of social networks, it also included a module on family and community ties the household had with other members of the community. It also included a final round of high frequency data. A second round was initiated in August 2017 encompassing the districts of Chikwawa, Nsanje and Blantyre in southern Malawi and intended to run until July 2018.

3.2.2 Sampling

Sampling was performed using a combination of purposive and random sampling. The purposive sampling was used to ensure variation in flooding history and risk. The Shire river flood plain, though more prone to flooding, is also more fertile than the higher lands surrounding it, and less prone to drought. In order to identify this flood plain objectively, we used flood-risk data from the Dartmouth Flood Observatory.

Within the district of Chikwawa in southern Malawi, we selected 3 traditional authorities (TAs): Mikhwira, Ngabu, and Lundu.[3] Within each TA we randomly sampled community level administrative units, called Group Village Heads (GVH). We stratified our sample to ensure it contained both GVHs in the flood plain and GVHs above the floodplain. This allowed for within TA, between GVH heterogeneity in how households experience drought and floods. Figure 3.1 illustrates the 2015 flood-zones and sampled households.

[3]During the roll-out an initially selected village was dropped and replace with a village in another TA, M'bande.

After stratifying the GVHs in each TA into high and low flood risk categories, two to three GHVs were randomly selected from each TA-strata for a total of 17. One to two villages were then randomly selected from each GVH and 15-25 households were randomly selected from each village. As we can see from table 3.1, the final sample was 580 households, from 31 villages, divided between high risk flood-zones and low risk non flood-zones.

With random selection carried out at the community and household level, the household is used as the unit of analysis.

3.2.3 Key Variables

We can classify our data into three types: household characteristics X_i, shocks $Z_{i,t}$ and food insecurity $Y_{i,t}$.

Our baseline includes a series of household characteristics X_i which were not included in the high frequency survey. We included existing measures from previous surveys for consistency, and added a few which our preliminary field work flagged as particularly relevant. These include measures of assets, such as the amount of land farmed, measured in hectares, and livestock owned, measured using Tropical Livestock Units (TLU).[4]

Based on their geo-location, we determined whether households lived in the flood plain as defined by the extent of the 2015 flood. As discussed earlier, we use owning a second house as a proxy for having fields far from home, as members of the households would need to overnight there. Followup interviews on the ground

[4]Tropical Livestock Units are a standardized measure used to aggregate the value of a household's livestock, with weight equivalents for every species (Le Houérou and Hoste, 1977). We used the following weights: cattle: 1, donkeys: 1, goats: .15, pigs: .2, chickens: .01

revealed that these secondary houses are usually little more than shacks, with negligible value as a standalone asset. We also collected characteristics about the head of the household, including their age, gender and education level. Finally, we asked if any members of the household were chronically ill or disabled.[5] Table 3.2 summarizes these statistics. We use these to create sub-groups studying their effect on shock persistence and welfare trajectories.

We also collected on reported shocks $Z_{i,t}$, where we define shocks as an unexpected event adversely affecting food insecurity.[6] Households were asked about a series of 14 subjective shocks they may have experienced, as well as their perceived severity. The dynamic questionnaire then prompted any household about previously reported shocks, asking their perceived state of recovery. As long as the household had not recovered, the questionnaire would prompt again in subsequent rounds. They were also asked about any new shocks experienced. A household could therefore experience the adverse effects of several shocks at once, and experience the same type of shock again after having previously recovered.

We chose to use a subjective measure of shocks based on the premise that households are better able to internalize the impact of the shock on their own food insecurity. There is evidence to support that subjective measures track well with objective measures of well-being (Oswald and Wu, 2010; Stevenson and Wolfers, 2013). While communities are exposed to similar level of objective risk, their responses and perceptions are highly heterogeneous (Barrett et al., 2001; Doss et al., 2008). Realized shocks are also heterogeneously perceived by the community, subject to individual reference points (Hunter et al., 2013). As it reflects a household's

[5]For confidentiality reasons we did not explicitly ask about HIV status. However conversations with enumerators and local health officials suggest that 'chronically ill' was often understood as implicitly referring to HIV.

[6]We chose to exclude potentially positive shocks as the effects on food insecurity are asymmetrical (Taylor, 1991).

perception of a shock rather than its objective incidence, the measure is inherently endogenous to a household's capacity to cope. For example, a household may experience the effects of drought long after the objectively measured drought is over. In this context, observing the trends in the incidence and persistence of a shock's adverse effects can inform us about trends in households' wellbeing and coping capacity.

Figure 3.2 shows the reported household incidence of frequently reported subjective shocks across the 12 months monitored. These include drought, flooding, illness and crop-disease. The dotted line represents the trend lines based solely on the first and last round.

Finally we track food insecurity $Y_{i,t}$, measured using the Coping Strategy Index (CSI). The CSI is a composite weighted score of various strategies households engage in when faced with short term food shortages (Maxwell, 1996). Coping strategies reflect activities households may be compelled into, often due to food insecurity, and compose the set $c \in C$. These include borrowing food, taking on piece work for additional income, consuming less preferred foods, reducing either the number or the size of meals and in extreme cases sending children to beg. The survey asks the number of days in the past week a household engaged in each of these activities, then multiplies those days by a weight w_c.[7]

CSI is therefore the weighted sum of days engaged in each coping strategy c:

$$CSI = \sum_{c}^{C} w_c * days_c \tag{3.1}$$

Where $days_c$ is the number of days a household had engaged in a given coping

[7] We use the following weighting: Borrow food=2, Piece Work=1, consuming less preferred foods=1, reducing meals=1, reduce size of meals=1, children begging=4. These recommended weights are the result of extensive consultation and calibration. See Maxwell et al., 2003 for further details.

strategy c over the past week, and w_c is the assigned severity weight.

CSI is useful for rapidly measuring food insecurity in a humanitarian context, strongly correlated with more complex and time intensive measures of food insecurity (Maxwell et al., 2008). A higher CSI score indicates higher food insecurity and therefore lower well-being. A household with a CSI of 10 may do some piece work on the side, eat less preferred foods or limit portion size a few days a week. A household with a CSI of 30 may do this every day, while also skipping meals and occasionally borrowing food. A household with a CSI of 60 is engaging in all these coping mechanisms daily, but must also send its children out to beg on occasion. A household engaged in all coping strategies all the time has a maximum CSI score of 70. In the context of chronic food insecurity, as in the Shire river basin, we consider CSI a valid measure of negative wellbeing.

For illustrative purposes, we disaggregate the observed trajectory of CSI using household characteristics. For binary variables we disaggregate the population by type, and for continuous variables we disaggregate by whether a household is above or below the median.

Figures 3.3 and 3.4 illustrate the non-parametric CSI trajectories disaggregated by these observable characteristics. We immediately notice that the data collection exercise began in the midst of a food emergency, with high levels of CSI throughout the population. The severity of the emergency as measured using CSI abated by the end of the year, but not equally for all groups. From Figure 3.3, there is no significant difference in the CSI trajectory when dis-aggregated by the household head's age, years of education, or whether a member of the household is chronically ill. Households headed by men are worse off at first, but the trend quickly converges with households headed by women.

From Figure 3.4a, households with above median Tropical Livestock Units (TLU) experience lower levels of CSI overall, but their trends mimic those of their neighbors who have below median TLU. We see a marginal difference for households with above median access to land, but not economically significant. From Figure 3.4b, households living in the flood plain recover much faster and see their CSI drop. Having a secondary house, and therefore spatially dispersed fields, makes one marginally less food insecure, but the trends match those of households without a secondary house.

3.2.4 Attrition

Attrition is a recurring concern when collecting panel data. If too many observations drop out of the sample, it erodes the statistical power of our estimates. We therefore over-sampled initially, allowing for up to 5% monthly attrition. Non-random attrition can also be a concern. This is problematic when it leads to correlation between our error term and our observables, leading to bias.

Table 3.3 illustrates attrition across time. Monthly attrition was 1.25 % on average, though much higher in certain months. Between June and July logistical friction due to a change in enumerators and data collection platform meant a village was missed. In December, seasonal flooding washed out the roads, and an enumerator passed away. To mitigate attrition due to these events, households missed in a given round were still sought out for interviews in subsequent rounds, allowing them to re-enter the sample rather than drop out entirely.

To control for potentially non-random attrition, we use a Heckman style two step estimator (Heckman, 1979). We label an observation $Missing_{i,t} = 1$ if we have no observation for household i in period t, and $Missing_{i,t} = 0$ otherwise. We use probit maximum likelihood to estimate whether this attrition is driven by observable characteristics. Since this is a panel we control for time effects and community fixed effects.[8] Finally, to address concerns that we are selecting on unobservables we use the enumerators' unique code as an additional explanatory variable. The exclusion restriction is valid under the assumption that the identity of the enumerator will affect the likelihood of response but not the well-being of the households interviewed. From Table 3.4 living in a flood plain is positively correlated with the probability of a missing observation. We had anticipated this discrepancy when we stratified our sample. Other coefficients become insignificant once we control for community and enumerator fixed effects. The predicted probability of selection is used to generate a Heckman inverse Mills ratio $\hat{\lambda}$, which we use as control in our subsequent specifications.

Similarly to Lillard and Panis, 1998, we run the probit and use the predicted outcome to generate the household level inverse Mills ratio $\hat{\lambda}$. Because attrition was driven both We include $\hat{\lambda}$ as a control in our subsequent regressions. We must still assume that, conditional on

3.3 Resilience as Perceived Shock Persistence

The perceived persistence of a shock's effects is a good indicator of resilience. Take two households experiencing the same shock in a given month; in the next month, if one household is still experiencing the effects of the shock while the other has fully recovered, then the latter household is more resilient. The perceived persistence of

[8] Since we are estimate a probit we cannot use a household fixed effect, see Wooldridge, 2010

a shock's effects is therefore a good indicator. The greater the shock's persistence, the lower the household's resilience to that particular shock.

With 12 rounds we can look at how persistent shocks' effects are over time. We estimate a linear probability model with discrete states of the world. This allows us to generate Markov Transition Matrices mapping the probability of experiencing a shock's adverse effects and the probability of those effects persisting, for each month and every shock experienced. We then regress these predicted persistence probabilities against observed characteristics.

We posit two states $Z^s_{i,t} \in \{0, 1\}$, reflecting whether household i is experiencing the adverse effects of a subjective shock $s \in S$ in period t. Using the questionnaire's dynamic nature, respondents were prompted on the persistent effects of previously reported shocks if $Z^s_{i,t-1} = 1$. If households reported a full recovery, then $Z^s_{i,t} = 0$. If a household reported not yet recovering from the given shock, then the shock's effects persisted and $Z^s_{i,t} = 1$. In the next round households were prompted about the effects of ongoing shocks, as well as whether they experienced new ones. In both cases, positive responses meant $Z^s_{i,t+1} = 1$. As an illustration Table 3.5 shows the correlation between prevalent shocks and food security. As an inherently subjective measure, tracking household's perception of shocks allows us to approximate how that shock affects a household's well-being. Households could therefore experience multiple shocks at once and fluctuate in and out of experiencing a given shock over time.

3.3.1 Specification

Given these two states, experiencing and not experiencing shock s, the probability of passing from state k to state j is a Markov process:

$$Pr(Z_t^s = j | Z_{t-1}^s = k) = p_{kj} \tag{3.2}$$

Where $k, j \in \{0, 1\}$.

To estimate shock persistence, we use an auto-regressive (AR) linear probability model with one lag.[9]

$$Z_{i,t}^s = \gamma_0 + \gamma_1^s Z_{i,t-1}^s + \gamma_t'^s (Z_{i,t-1}^s * \delta_t) + \delta_t + \mu_i^s + \epsilon_{i,t} \tag{3.3}$$

where γ_1^s conditions the perceived shock s on previously experiencing shock s, $\gamma_t'^s$ allows this persistence to vary by round, δ_t is a monthly time fixed effect and μ_i^s is a household fixed effect. With a linear probability model, the coefficients have an intuitive interpretation: $p_{0,1}^s = \gamma_0^s + \delta_t$ is the probability of experiencing the adverse effects of a given shock, conditional on not experiencing them previously. $p_{1,1} = \gamma_0^s + \gamma_1^s + \gamma_t'^s + \delta_t$ is the probability a shock's adverse effects will persist into the next period. γ_t^s and δ_t allow for a non-stationary process since the transition probability can change over time.[10]

We can present our estimated coefficients as a Markov Transition matrix:

[9] Our results are robust to additional lags.

[10] To avoid collinearity we must set one of the time fixed effects to equal 0. This is arbitrary but then becomes the month of reference for the other δ_t terms.

	$Z^s_{i,t} = 0$	$Z^s_{i,t} = 1$
$Z^s_{i,t-1} = 0$	$p^s_{0,0} = 1 - (\gamma^s_0 + \delta_t)$ (Probability of not experiencing new shock s, given shock s was not experienced previously)	$p^s_{0,1} = \gamma^s_0 + \delta_t$ (Probability of experiencing new shock s, given shock s was not experienced previously)
$Z^s_{i,t-1} = 1$	$p^s_{1,0} = 1 - (\gamma^s_0 + \gamma^s_1 + \gamma'^s_t + \delta_t)$ (Probability of shock s not persisting, given shock s was experienced previously)	$p^s_{1,1} = \gamma^s_0 + \gamma^s_1 + \gamma'^s_t + \delta_t$ (Probability of shock s persisting, given shock s was experienced previously)

Our key parameters of interest are $p^s_{1,1}$, the probability of shock s persisting, and $p^s_{1,0}$ the probability of recovering from shock s. We can think of $p^s_{1,0}$ as resilience to shock s. $p^s_{0,1}$ is the probability of shock s occurring when it hasn't occurred before. Since it is a subjective measure, we can also think of $p^s_{0,1}$ as vulnerability to shock s.

3.3.2 Estimating Shock Persistence

We estimate equation (3), the persistence of shocks over time. We take the four most frequent shocks: $S = \{\text{drought, flooding, crop disease illness}\}$ and regress them against their own values, lagged by one month. Table 3.6 uses a least squares regression controlling for household and time fixed effects, with errors clustered at the Group Village Head (GVH) level. For succinctness we only report $\hat{\gamma}_0^s$ and $\hat{\gamma}_1^s$ for a given shock s. As discussed earlier, since we allow the coefficients to vary over time these reported estimates offer only a snapshot, determined by which time dummy we set as point of reference. Here we set it as May 2017, our last round.[11]

Our data also allows us to explore whether multiple shocks interact and whether those effects exacerbate or mitigate one another. Table 3.7 estimates (3) but includes lags of the other most prevalent shocks. The only significant cross correlation is that experiencing flooding makes it more likely to experience crop disease in the subsequent round.

With four shocks and 11 rounds[12], we can construct a total of 44 transition matrices. For illustrative purposes we choose three periods of reference aligned with the agricultural calendar: November (round 6), when planting begins; February (round 9), the height of the hungry season; and May (round 12), when the harvest comes in (Malcomb et al., 2014). Tables 3.8, 3.9, 3.10 and 3.11 present these transition matrices across months for our four shocks of interest.

Recall that $\hat{p}_{1,1}^s = \hat{\gamma}_0^s + \hat{\gamma}_1^s + \hat{\gamma}_t^s + \delta_t$ is the persistence of shock s, the probability that a household continues experiencing its adverse effects one month later. As an illustration, from Table 3.8a, the probability of the effects of drought persisting in November is 88.5%. Households only had a 11.5% chance of recovering from the effects of drought in the next month, which we consider an indicator of low resilience. This does not change much over the subsequent six months, as the probability of a drought's effects persisting are 85.3% in February (Table 3.8b) and 86.1% in May (Table 3.8c).

[11]This is done by setting the relevant time dummy, i.e. $\delta_{May2017} = 0$ and $\gamma^s_{May2017} = 0$.
[12]We lose one round by construct due to the lag

These tables allow us to track how the perceived incidence and persistence of the adverse effects of subjective shocks vary of over time. For example, while the effects of flooding are highly persistent in November (Table 3.9a), by May (Table 3.9c) the persistence of their effects has subsided significantly. Conversely the persistence of illness is quite stable throughout the three rounds, as we can see in Table 3.10. Figure 3.5a illustrates this change in the persistence of shocks $\hat{p}^s_{1,1}$ visually across all rounds. We see that while the persistence of a drought's effects remains stable across time, the persistence of crop-disease's effects increase. Unsurprisingly this increase coincides with the planting season.

In addition to estimating persistence, a useful feature of the specification is that we can separately estimate the probability of a household experiencing the effects of a new shock, its incidence $\hat{p}^s_{0,1} = \hat{\gamma}^s_0 + \delta_t$. For example, crop-disease starts at a lower level of incidence in Table 3.11a with $\hat{p}^s_{0,1} = 15.1\%$ but this rapidly climbs to 44.8% in Table 3.11b and 41.9% in Table 3.11c. It makes sense that the adverse effects of crop disease are most acute when the planted harvest is nearing maturation. Figure 3.5b illustrates how $\hat{p}^s_{0,1}$ changes over time for each shock s. We notice that incidence and persistence do not necessarily move in tandem. For example, the effects of drought are very persistent, at $\hat{p}^s_{1,1} > 80\%$ throughout the year, where $s = drought$. By contrast $\hat{p}^s_{0,1}$ fluctuates over time, reflecting the seasonality of a drought's incidence.

3.3.3 Shock Persistence and Household Characteristics

The results of having mapped out the persistence of shocks begs the question: what are the household characteristics correlated with the persistence of a given shock s? From the above specification we can predict the probability of persistence of shock s for a given household i at time t, $\hat{\rho}^s_{i,t} = \hat{p}^s_{0,1} + \hat{\mu}^s_i$. We can then regress this predicted value against time invariant characteristics X_i:

$$\hat{\rho}^s_{i,t} = \alpha_0 + \alpha_1 X_i + \zeta_{i,t} \tag{3.4}$$

allowing us to infer the correlation between these fixed effects and household characteristics $\frac{\delta \hat{\rho}^s_{i,t}}{\delta X_i} = \hat{\alpha}_1$.[13] A negative correlation indicates that households with these characteristics are less likely to experience the persistent effects of a given shock. As discussed earlier, we consider such non-persistence of a shock's effects as a sign of resilience. We estimate equation (4) using the observed characteristics from the baseline. Figure 3.6 presents estimated correlations with their bootstrapped standard errors. These descriptives are inherently endogenous, but can help inform which type of households are more vulnerable to shocks.

Living in a flood plain is negatively correlated with the persistence of a drought's adverse effects, but positively correlated with the persistence of illness's adverse effects. Both of these make sense, as soil in the flood-plain is likely to retain more moisture, but the abundance of stagnant water offers breeding pools for malaria and cholera. As discussed earlier, having a secondary house indicates the household has fields far from its primary home, where they sometimes have to spend the night. This suggests that households with spatially dispersed fields are more resilience to drought. Female headed headed households are more likely to experience the persistent effects of illness and are therefore less resilient. Finally, we unsurprisingly find a significant correlation between the persistence of an illness's effects and whether the household has a chronically ill member.

[13]Since these are point estimates, we bootstrap the above two-step process.

3.3.4 Resilience as a Conditional Moments-Based Approach

An alternative to looking at the persistence of specific shocks is to think of resilience as the stochastic distribution in food insecurity outcomes $y_{n,t}$. For comparative purposes we also estimate the above data using the Cissé and Barrett, 2016 approach. This is a three step process:

The first step estimates

$$CSI_{it} = \sum_{\gamma=1}^{3} (\beta_{M,\gamma} CSI_{i,t-1}^{\gamma}) + \delta_{M,1} X_{i,t} + \delta_{M,2} Z_{i,t-1} + u_{i,t} \tag{3.5}$$

where $Y_{i,t}$ is CSI, $X_{i,t}$ the set of covariates and $Z_{i,t}$ the set of shocks experienced.

The second step regresses the same specification on estimated variance, $\sigma^2_{CSI} = hatu^2_{i,t}$:

$$\sigma^2_{CSI} = \sum_{\gamma=1}^{3} (\beta_{V,\gamma} CSI_{i,t-1}^{\gamma}) + \delta_V X_{i,t} + \epsilon_{i,t} \tag{3.6}$$

We posit $C\hat{S}I_{it}$ and $hatsigma^2_{i,t}$ as the first and second moments of a conditional distribution, respectively. Under the assumption that $CSI_{i,t}$ has either a normal or gamma distribution, we construct the cumulative density function and calculate $\hat{p}_{i,t}(X, Z) = P(CSI_{i,t} \leq C\bar{S}I)$, where $C\bar{S}I$ is a threshold level of food insecurity. We posit $C\bar{S}I = 10$ The estimated parameters are reported in Table 3.12a. We can then estimate

$$\hat{p}_{i,t} = \sum_{\gamma=1}^{3}(\beta_{R,\gamma} CSI^{\gamma}_{i,t-1}) + \delta_R X_{i,t} + \eta_{i,t} \tag{3.7}$$

Where $\hat{p}_{i,t}$ can be thought of as 'resilience'. Estimates of equations (5), (6) and (7) for both a normal and gamma distribution are reported in Table 3.12b. Of the household covariates, flood plain has a large and significant positive correlation with household resilience. The correlation with having a secondary house is large in magnitude and positive but not statistically significant. The other characteristics we identified as important relative to specific shocks, such as gender and being chronically ill, are not significantly different from 0. Of the shocks, experiencing flooding is correlated with a significant decrease in resilience, as does drought, though the effect is only significant for $\hat{P}_{Gamma}$. The effect of Illness is marginally significant and negative.

These results highlight the similarities and differences between an approach focusing on subjective shock persistence and one based on conditional moments. The insights are broadly similar: they emphasize the persistent adverse effects of flooding and drought on household food security. Both also highlight that living in the flood plain and having a secondary house mitigates these adverse effects. Some of the details differ: Gender and being chronically ill have no significant effect on $\hat{p}_{i,t}$ in Table 3.12. There are two possible explanations: those characteristics only affect the persistence of illness for the 20-25% of households experiencing illness at any given time, so the effect might be lost in the statistical noise. Alternatively, since persistent illness has little to no effect on food security (see Table 3.5), characteristics shifting the persistence of illness may not affect the stochastic distribution of food security. This comparative analysis showcases how the two approaches complement each other and offer a fuller picture of household resilience.

3.4 Distribution of Food Insecurity

We can also harness this data to infer seasonal trends in food insecurity over time. We use the Coping Strategy Index (CSI) as our measure of food insecurity. In general, the more coping strategies a household employs, the worse off it is, and households which are resilient should experience decreasing levels of CSI over time. We draw our model from the literature on poverty dynamics and posit CSI as an observed outcome from a stochastic distribution of potential outcomes. This allows us to verify whether the characteristics we identified as determinants of resilience also affect the trajectory of food insecurity.

We estimate an AR(1) model using a Blundell-Bond estimator (Blundell and Bond, 1998). From the predicted values, we plot the distribution of outcomes as ΔCSI conditional on observable characteristics.

3.4.1 Specification

To motivate our investigation, we build on existing theory concerning household poverty dynamics: Specifically, we postulate a conditional trajectory for dynamic food insecurity Y_t:

$$Y_t = F(Y_{t-1}, Z_t|X) \tag{3.8}$$

Food insecurity is a function of previous food insecurity Y_{t-1} and any shock Z_t experienced. F(.) can be a higher order polynomial.[14] X represents conditioning

[14]There is a larger literature on the production function of households living at or near subsistence level, well summarized in Barrett et al., 2016. This production function is often non-linear. Multiple technologies may lead to a convex hull with one or multiple kinks. Lumpy assets, such as livestock, may make it difficult to incrementally acquire wealth over time. A linear function would therefore misspecify how current food insecurity relates to future food insecurity.

variables, which may lead to different trajectories. Our observed food insecurity outcome $y_t \sim Y_t$ is a random variable drawn from an unknown conditional distribution.

We model the conditional distribution of food insecurity trajectories, CSI, as a continuous state Markov chain (Sargent and Stachurski, 2016). We can infer the distribution of $y_t \sim \psi_t$ given the prior distribution $\psi_{t-1}(y_{t-1})$:

$$\psi_t(y_t) = \int p(y_t, y_{t-1})\psi_{t-1}(y_{t-1})dy_t \tag{3.9}$$

where $p(y_t, y_{t-1})$ is the joint distribution of $y_{t-1} \in S_{t-1}$ and $y_t \in S_t$. This result can be generalized to a Cumulative Distribution Function:

$$F_t(y_t) = \int G(y_t, y_{t-1})F_{t-1}dy_t \tag{3.10}$$

one can compute the family of distributions $G(y_t, .)$ by setting:

$$G(y_t, y_{t-1}) := \mathbb{P}\{\beta_0 + \sum_{k=1}^{K} \beta_k y_{t-1}^k + \xi_t \leq y_t\} \tag{3.11}$$

an AR process with a polynomial of degree K. As discussed earlier, we want to allow for non-linearity in the dynamics of CSI over time by estimating a higher order polynomial. We can construct the above by estimating:

$$y_{i,t} = \beta_0 + \sum_{k=1}^{K} \beta_k y_{i,t-1}^k + Z_{i,t} + \delta_t + \epsilon_{i,t} \tag{3.12}$$

and plotting the predicted distribution. For robustness, we control for observable shocks with $Z_{n,t}$.[15] δ_t controls for time fixed effects.

In order to condition this distribution on various characteristics X_i, we run the above specification on observable subsets of the sample. These criteria include

[15]These include the four principle shocks reported: drought, flood, crop-disease and illness.

age, education, gender, whether the household have a chronically ill member at home, as well as land farmed, tropical livestock units, whether the household lived in the flood plain and whether the households has a secondary home. As before, for binary variables we disaggregate the sample by type, and for continuous variables we disaggregate by whether a household is above or below the median value.

3.4.2 Estimator: Blundell Bond System GMM

An AR process allows us to exploit the Arellano Bond (AB) estimator (Arellano and Bond, 1991), which addresses potential endogeneity by differencing the regression and instrumenting the lagged dependent variable with previous lags.

A followup paper (Blundell and Bond, 1998) addresses the issue of weak instruments. Instead of differencing the dependent variable, it differences the instruments, making them exogenous to the fixed effect and demonstrating that this achieves greater efficiency. It also performs better closer to the unit root. Because this combines the original AB estimator with a transformed equation by stacking the observations, it is often referred to as the System General Method of Moments (GMM) estimator.

To illustrate, take an AR(1) model:

$$y_{nt} = \alpha y_{n,t-1} + \eta_i + \upsilon_{nt} \tag{3.13}$$

where η_n represents time invariant unobservables, υ_{nt} is a time varying stochastic error term and $\mu_{nt} \equiv \eta_n + \upsilon_{nt}$. We assume the following moment conditions in order for our estimates to be consistent:

A1) $E(\upsilon_{nt}, \upsilon_{ns}) = 0 \; \forall t \neq s$ (No serial correlation)

A2) $E(y_{n1}, \upsilon_{nt}) = 0$ for $t = 2, ...T$ (Initial Conditions)

A3) $E(\mu_{n3}, \Delta y_{n2}) = 0$ for $t = 2, ...T$ (Initial deviations uncorrelated with aggregate error)

Which imply

$E(\mu_{nt}\Delta y_{n,t-1}) = 0$ for $t = 3, ...T$

Note that stationarity is a sufficient but not necessary condition to satisfy A3. Any first period randomly distributed deviation from the long term mean will preserve this assumption. This gives us a set of instruments $\Delta y_{n,t-1}$ to exploit.

The model explicitly assumes an AR(1) process. In general, an observed AR(T) process requires us to restrict our set of instruments to the set $t \geq T - 1$. Fortunately we can take advantage of our relatively long panel. We also report Sargan's J-test of over-identified restrictions.

3.4.3 Estimation

Using CSI as a measure of food insecurity we estimate equation (9) using a Blundell-Bond estimator for $K = 2$. We include a square term in order to allow for non-linearity in the persistence of CSI across the spectrum of potential outcomes.[16] As we observed in Figures 3.3 and 3.4, there was an acute food crisis

[16]We test for high order polynomials and find that they introduce too much noise, rendering all coefficients insignificant.

at the beginning of the data collection period, leading to high inital levels of CSI which only gradually abated. In order to capture these shifting dynamics, we divided our sample into two halves, June-November and December-May. The results are presented in Table 3.13. Column (1) presents the specification for the entire year sampled, June through May. Column (2) estimates the specification for the first half of the year, and column (3) estimates it for the 2nd half of the year.[17]

We ran a series of tests on the specification to verify our assumptions. Under our first identifying assumption there is no serial correlation of order 3 or above. By construct, the residuals of the differenced errors in the Blundell Bond model are serially correlated AR(1). We also find evidence of AR(2) correlation in some of our specifications, so in order to avoid serial correlation we restrict our lagged instruments to period t-3 and higher. We test and fail to reject the null of no AR(3) serial correlation.

We investigate the exclusion restriction on our constructed instrumental variables with the Sargan-Hansen test, which tests the validity of over-identified restrictions.[18] The null hypothesis is that the over-identified restrictions are valid, and rejection of the null would therefore cast doubt on the consistency of our estimates. The Sargan-Hansen test fails to reject the null in all our specifications, except for columns (1) and (3) of Table 3.17a. Given the number of regressions we run, it is statistically plausible that this is a false positive, but we nevertheless refrain from interpreting these results.[19]

[17]Unlike the estimation in section 3, we cannot divide our sample down further as the Blundell Bond estimator requires a minimum of 4 rounds, 5 if we want to run a Sargan-Hansen over-identification test.

[18]An issue with system GMM is that the large number or instruments generates weakens the Sargan-Hansen statistic, increasing the likelihood of type I error. We use the Windmeijer, 2005 small sample correction and the collapsed instruments matrix suggested by Roodman, 2009, restricting the set of lags for increased precision.

[19]For robustness we run the same specification while varying the number of lagged instruments, consistently failing to reject Sargan-Hansen with similar coefficient estimates.

We estimate equation (9) for sub-samples of the population to determine which household characteristics affect the expected distribution of CSI. This conditions the distribution of our expected outcomes on characteristics X_n. Tables 3.14, 3.15 3.16 and 3.17 give us the results from estimating a second order lagged polynomial, dissaggregated by observable characteristics as discussed above. Columns (1)-(3) run the specification for observations above the median, or where the binary variable equals 1. Columns (4)-(6) run the specification for observations below the median, or where the binary variable equals 0. Columns (1) and (4) run this specification for the full time span of the sample, June through May. Columns (2) and (5) run the specification for the time period June-November, and columns (3) and (6) run the specification for the time period December-May. For robustness we estimate the same set of results with the inverse mills ration γ, with similar results in order and magnitude. These are reported in the supplementary tables.

In order to interpret these results intuitively we predict the change in CSI conditional on these characteristics and project the resultant distribution. We predict the outcome variable $C\hat{S}I_{n,t}$ and by extension $\Delta C\hat{S}I_{n,t} = C\hat{S}I_{n,t} - CSI_{n,t-1}$, then project the resultant distributions. This is the expected change in CSI next month, averaged over the sample or relevant sub-sample. Because the recovery happens largely in the second half of the year, we focus on columns (3) and (6) in each of the above tables, giving us Figures 3.7 and 3.8. From Figure 3.7a, younger households are practically indistinguishable from older households in the projected change in CSI. Households with above median education are slightly more likely to experience increased CSI, though the difference is not economically meaningful. From Figure 3.7b, male headed households are more likely to experience increasing levels of food insecurity on average, but have a long left tail. Female headed households are more stable, with their expected change in CSI centered around 0.

Households with and without a chronically ill member have similar distributions.

From Figure 3.8a, households with access to more than 2 hectares of farming land can expect little change on average in CSI, while households with less than median levels have a greater risk of experiencing increased CSI. Unsurprisingly, having more land is a good hedge against hunger. There is no distinguishable difference in the distribution for households with or without livestock. We do not interpret the results for flood plains because we reject Hansen's J test (see above). Interestingly, households with a secondary home have a left skewed distribution, implying that they can expect lower CSI and therefore a quicker recovery. This coincides nicely with the insights from Figure 3.6, where having a secondary house makes it less likely for the effects of drought to persist.

To summarize, the characteristics that most influence a household's food insecurity by shifting the predicted distribution of ΔCSI are gender, access to land and owning a secondary house.

3.5 Predicting Food Insecurity

A third approach to measuring resilience is as the predictor of food insecurity in the immediate future. In the reduced form specification above we based our choice of observable characteristics on informed priors, which is not necessarily desirable when we seek to maximize predictive accuracy. Instead we propose to search through the full scope of available data to find the best predictors of future CSI. We do this using supervised machine learning algorithms. We compare two algorithms, the Least Absolute Shrinkage and Selection Operator (LASSO) and Random Forest. Both allow us to identify the best predictors by selecting a subset of promising variables within a larger set. We also show how the predicted outcomes from these algorithms can be used for geographic targeting.

The use of these algorithms has recently gained popularity in terms of both predicting poverty and shortlisting variables for the purpose of targeting. In terms of targeting, Jean et al., 2016 show how running an image recognition algorithm through publicly available satellite imagery significantly improves geographic poverty targeting. Blumenstock et al., 2015 use Call Detail Records (CDR) from respondents' cell-phones to predict poverty in Rwanda. A complimentary body of work is concerned with improving accuracy of targeted social programs when lacking comprehensive data on income and consumption. McBride and Nichols, 2015 present evidence that applying machine learning algorithms to PMT development can substantially improve the out-of-sample performance of these targeting tools. Kshirsagar et al., 2017 use a bootstrapped LASSO to select a subset of indicators which accurately predict poverty rates, and show that they outperform a random distribution benchmark. Building on this literature, we innovate here by applying this approach to dynamic food security data.

Though a wide array of popular supervised machine learning tools exist, the general premise is straightforward.[20] Divide the dataset in two subsets. Using the first subset of the data, the 'training' set, the model is calibrated. These calibrated parameters are then used to predict outcomes in the second, 'testing' subset of the data. The performance of an algorithm is judged by its predictive accuracy, as measured using the R^2. The process is then iterated in an attempt to improve performance. In addition, as an intermediary step some algorithms explicitly identify a subset of variables that are considered the best predictors.

[20]'Supervised' machine learning use inputs x to predict outputs y. 'Unsupervised' tools seek to identify patterns in x without corresponding outputs.

These are the predictors we are interested in.

We use the Least Absolute Shrinkage and Selection Operator (LASSO) and Random Forests to identify the best predictors of CSI. LASSO was selected because it retains much of the structure of linear regression analysis, allowing for intuitive interpretation of the coefficients. These can be compared in sign and magnitude to results elsewhere in the paper. Random Forest offers a salient contrast, as by design it is non-linear and every variable is implicitly allowed to interact with every other variable. Though more flexible, this 'black box' approach makes it difficult to interpret the sign of any one coefficient, as it depends on all the others. Comparing the performance of both is therefore useful. More sophisticated deep learning algorithms using neural networks were too demanding of the data given our limited sample size.

We trained our data on the 10 rounds from June to March (the 'training' set) and sought to predict the likely outcomes for April and May (the 'test' set), comparing it with actual CSI levels in those two months.[21] A feature of using this machine learning technique is that it harnesses all the variables collected, rather than just the data described in section 2. These included asset indicators from the baseline, such as quality of the home, distance to drinking water and diet. They also included time varying indicators, such as the type and source of assistance a household received and any change in assets. We kept all variables with less than 2% of observations missing.[22] After this cleaning process, we were left with an $\mathbb{R}^d$ space of predictors, where d=79 variables.

[21] A rule of thumb is splitting the data into roughly 80 % training and 20 % testing. We erred on the side of a slightly larger training dataset because the algorithms further subdivide this dataset for cross-validation.

[22] In order to avoid dropping too many observations, we substituted values for those missing variables using nearest matches from observed data, randomly sampling from the set of nearest observations.

3.5.1 LASSO

In a traditional regression, additional parameters always increase predictive performance but risk overfitting the data. LASSO, short for Least Absolute Shrinkage and Selection Operator, is a linear regression which penalizes additional parameters β by including the term $\lambda'\|\beta\|$.[23] The modified least squares operator is therefore

$$\min_{\beta \in \mathbb{R}^d} \left\{ \frac{1}{N} \sum_{i=1}^{N} (Y_{i,t} - \beta X_{i,t})^2 + \lambda\|\beta\| \right\} \tag{3.14}$$

Each $\beta \in \mathbb{R}^d$ must therefore add sufficient explanatory power to overcome the penalty term $\lambda\|\beta\|$, otherwise it is minimized to 0. Since we have no good a priori for the penalty term λ' the algorithm we use, glmnet, uses coordinate descent and a soft threshold operator to iterate through a plausible range (Friedman et al., 2010). For each candidate λ', the algorithm randomly subsets the training data further and computes the mean cross-validated mean squared error (MSE). It settles on two candidates values of λ': $\hat{\lambda'}^{min}$ minimizes the mean cross-validated error. $\hat{\lambda}^{1se}$ is the most parsimonious model in terms of number of parameters β while within a standard error of the minimum. Since we seek to identify the subset of best predictors, we report the results from $\hat{\lambda}^{1se}$, the parsimonious model.

In order to identify the best predictors of CSI, we bootstrap the training data and run the LASSO algorithm through a thousand iterations, similar to Kshirsagar et al., 2017. We then compute the mean coefficient and its standard deviation and keep the 10 most significant variables.[24] We report these predictors in Table 3.18. Lagged CSI is unsurprisingly a strong predictor of future CSI. Location, as indicated by community id (GVH), is also a strong predictor. Receiving assistance from

[23]We use λ' to differentiate from the inverse mills ratio λ, defined earlier.

[24]We kept non-statistically significant variables for their potential predictive power.

the government and receiving it as food are both predictors of future decreases in CSI, and therefore decreased food insecurity. The algorithm selects four types of asset indicators: distance to drinking water, whether any assets were bought, whether assets were sold, and the quality of the floor. Every additional minute of walking distance to drinking water increases predicted CSI. Interestingly both buying and selling assets are predictors of decreased CSI, suggesting that what matters is liquidity. Living in a flood plain decreases predicted CSI, and experiencing drought last month increases it.

With the exception of living in a flood plain, these predictors do not directly correspond to the characteristics we used in our earlier specification. Unlike those characteristics, five of these predictors vary over time and are therefore good proxies for a household's fluctuating state of food insecurity in the immediate. This points to a difference in time frame. Whilst our earlier approaches sought to estimate characteristics contributing to resilience over a year or half year time frame, this exercise emphasizes predictive accuracy over a one to two month time frame. Time frame therefore affects the characteristics of interest to our resilience analysis.

We then use the estimated parameters to predict CSI in our test data and compare its performance to the actual CSI outcomes. When compared, our LASSO algorithm gives us an $R^2 = 56.4\%$.

3.5.2 Random Forest

While it does allow us to narrow down the set of predictors, a LASSO algorithm remains a linear regression. An alternative approach, regression trees, offers a more flexible functional form (Hastie et al., 2009). A regression tree chooses variables in the set $x_j \in X$ and the value of that variable s, that split the set into two 'branches' which form half planes R_1 and R_2. x_j and s are chosen through an optimization process which jointly minimizes the mean squared error for the dependent variable y_i in each of the half planes defined by the branches.

$$\min_{js}[\min_{c_1} \sum_{x_i \in R_1(j,s)} (y_i - C_1)^2 + \min_{c_2} \sum_{x_i \in R_2(j,s)} (y_i - C_2)^2] \tag{3.15}$$

where

$$c_1 = \frac{1}{n}\sum_i (y_i | x_i \in R_1(j,s)) \text{ and } c_2 = \frac{1}{n}\sum_i (y_i | x_i \in R_2(j,s)) \tag{3.16}$$

Each half plane is in turn split into two branches and the process is iterated to create a 'tree' which fits the data. Single regression trees tend to suffer from over-fitting, mistakenly attributing random variations in the outcome to an explanatory variable. In order to correct for this, random forest randomly select a subset of $x_j \in X$ as candidate variables for the regression tree, which it fits to the data (Breiman, 2001). By repeating the process, it can compare the cross-mean performance across these 'trees', hence creating random forest. Because the performance of any given variable is conditional on its parent branches, regression trees do not allow for explicit coefficient estimates. Instead variable x_j's performance is measured as ΔMSE_j, ie the increase in Mean Squared Error if the variable is omitted.

We bootstrap the training data and run the random forest algorithm through a thousand iterations. This gives us a thousand values for each variable: ΔMSE^b_j. We calculate the mean across bootstrapped values and divide by the standard deviation to normalize it. This allows us to rank the 10 best predictors of CSI, listed in Table 3.19. Note that because these are not coefficients, we cannot say whether individual variables predict increased or decreased CSI. Like LASSO, it finds that

CSI last month, location and the distance to drinking water are good predictors. Indeed five of the top ten variables overlap between the two approaches. Unlike LASSO, the regression tree algorithm favors household characteristics from the baseline. Many of these correspond to the characteristics we used in our other specifications, including age, education, land farmed and whether the household lived in a flood plain. A household's dietary diversity score is also a good predictor.[25] The quality of a households roof and whether anyone in the household is pregnant or nursing round of the top ten variables selected.

By running the subset of selected variables through one more iteration of a random forest, we generated out of sample predictions for April and May, giving us an $R^2 = 55.6\%$.

Figure 3.9 compares the predictors across both algorithms. Five of the top ten variables overlap or are very similar. Previous months CSI is the best predictor in both cases, followed closely by geographic location as indicated by group village head. Other good predictors include the households distance to drinking water, the quality of their home and whether they live in a floodplain. The differences between what each algorithm picks up are illustrative as well, and speaks to the differences in the objective function optimized. LASSO, by weighing each variable as a stand-alone in a linear regression, favors time varying variables that immediately affect CSI. By optimizing iteratively, regression trees implicitly condition variables on each other, thereby favoring underlying variables which affect CSI via their effect on other variables. Hence it favors time invariant characteristics. Though LASSO performs marginally better in terms of out of sample R^2 (56.4% vs. 55.6%), this must be traded off against the additional difficulty and expense

[25] Dietary diversity score, or DDS, is the sum of food types a household reports having consumed in the past 24 hours.

of collecting monthly data from these sentinel sites.

3.5.3 Mapping predicted outcomes

Since this data collection exercise occurred during a humanitarian emergency, we worked with our partners on the ground to feed data into their decision making process. Given the uneven pace of households recovery from drought, we sought to determine if there were lingering 'pockets' of food insecurity. We used the predictions from the above algorithms to map out the predicted CSI levels $C\hat{S}I$ in Figure 3.10. The first column maps the actual CSI outcomes in April and May. The subsequent columns show the outcomes as they were predicted using the LASSO and Random Forest algorithms, respectively. This allowed us to demonstrate the usefulness of a high resolution system of sentinel sites.

Equipped with such a map, decision makers could target necessary interventions with improved accuracy. Though not always precise in magnitude, the predictions provide an accurate forecast of where we could expect high levels of CSI. These tended to be in tightly circumscribed geographical areas. Such concentrated levels of high CSI were due to localized co-variate shocks: some communities were still struggling to recover from the effects of drought. Communities in the flood plain experienced the adverse effects of localized flooding, while other communities experienced outbreaks of crop disease.

3.6 Conclusion

Efforts to measure resilience are increasingly prevalent in development economics. Rather than adapt our method to the available data, we collected a novel 12 month data-set from sentinel sites in southern Malawi. We use this data to present three approaches to modeling resilience. This allows us to offer insights into the characteristics driving households' resilience.

We describe the persistence of subjective shocks, modelled as a non-stationary Markov Matrix. We find that some shocks, like drought, are very persistent in their effects, while the persistence of shocks like flood and crop disease vary over time. We also contrast shock persistence with experiencing the adverse effects of new shocks, and show that the two do not necessarily move in tandem. By estimating household level shock persistence and regressing it against household characteristics, we find that households with fields far from home and those living in the flood plain are more resilient to the effects of drought, and households headed by a woman or with are chronically ill member are less resilient to the effects of illness.

Next we estimate the persistence of food insecurity, measured using the Coping Strategy Index (CSI), and test whether household characteristics shift this persistence. We split our sample in two to allow for an initial humanitarian emergency with high levels of CSI, followed by a gradual and heterogeneous recovery. As an illustration we plot the expected change in the distribution of food insecurity. We find that access to land, and having fields far from home shift the distribution of food insecurity.

Finally we use a predictive algorithm to select the best predictors of future CSI from our dataset. Using a LASSO algorithm, we narrow down the set of best predictors to a subset with the most predictive power. When we compare this to a Random Forest Algorithm, we find that previous levels of food insecurity, location and distance to drinking water are the best predictors. We also note that LASSO favors time varying variables, while the regression trees algorithm favors time invariant characteristics because it implicitly conditions variables on each other. The out of sample predictive accuracy is similar, with an R^2 of 56.4% for LASSO and 55.6% for Random Forest. Mapping the predicted CSI against actual CSI gives a relatively accurate indication of which zones experience high levels of CSI. We find that these zones are geographically concentrated, and would therefore benefit from targeted interventions.

As a next step in our research, we are expanding our sample to three districts and collecting monthly data for a second year in Southern Malawi. This will allow us to make year on year comparisons, comparing seasonal trends in a 'normal' year to those in a year of extreme drought or flooding. We are also seeking to replicate our methodology in other shock prone countries such as Madagascar and Nigeria, allowing for cross-country comparisons of resilience characteristics. We hope to start setting in place a system of sentinel sites, providing both early warning of a humanitarian emergency and valuable data for analysis.

A particularly promising vein of research is in contributing to improved Proxy Means Targeting in the context of natural disasters, or Post-Disaster PMT. By combining sentinel site data like ours to geo-spatial and phone record data, researchers can calibrate the latter and use it to predict post-disaster food insecurity when on-the-ground data is unavailable. It would be a valuable exercise to compare various proposed algorithms, including LASSO, Regression Trees and Neural Networks, in terms of their predictive performance and feasibility in a humanitarian emergency.

Tables

Table 3.1: **MIRA Study Sample**

Traditional Authority	GVH Strata (Flood Risk)	General Village Head (N=17)	Villages (N=31)	Households (N=580)
Mikhwira	High N=106	Mpama	2	40
		Kanyimbiri	2	32
		Salvala	2	34
	Low N=102	Nyambalo	2	39
		Chagambatuka	2	38
		Champhanda	2	25
Ngabu	High N=86	Jombo	2	50
		Nkhwazi	2	36
	Low N=114	Malikopo	2	39
		Kalulu	2	39
		Chapomoko	2	36
Lundu	High N=92	Mafale	2	38
		Biliati	2	39
		Sekeni	1	15
	Low N=59	Bestala	2	38
		Biyasi	1	21
Maseya	Low N=21	M'bande	1	21
Totals by Risk	High risk	8	15	284
	Low risk	9	16	296

Table 3.2: **Household Covariates**

Characteristic	N	Mean	Std. Dev.	Min	Max
Land (Ha)	580	2.59	1.91	.2	20
Tropical Livestock Units	580	.63	2.66	0	38
Lives in Flood Plain (1=Yes)	580	.50	.50	0	1
Secondary House* (1=Yes)	580	.19	.39	0	1
Head of Household:					
Age (Years)	580	42.71	16.2	0	97
Gender (1=male)	580	0.76	0.43	0	1
Education (Years)	580	6.26	4.21	0	15
Chronically ill or disabled	580	0.16	0.37	0	1

*An indicator of owning fields far from home.

Table 3.3: **Sample Attrition Over Time**

Missing	June	July	August	September	October	November
No	580	557	572	567	566	543
Yes	0	23	8	13	14	37

Missing	December	January	February	March	April	May
No	421	428	463	490	465	443
Yes	159	152	117	90	115	137

Table 3.4: **Determinants of Missing Observations, Probit**

	Missing		
	(1)	(2)	(3)
Land Farmed (HA)	-0.0397	-0.0386	-0.00717
	(0.0379)	(0.0376)	(0.0279)
Tropical Livestock Units	0.0218	0.0312*	0.0302
	(0.0260)	(0.0187)	(0.0184)
Flood Plain	0.755***	2.932***	3.139***
	(0.139)	(0.553)	(0.601)
Secondary House	0.508***	0.172	0.120
	(0.171)	(0.138)	(0.144)
Age of HH Head	-0.00176	-0.00478	-0.00145
	(0.00468)	(0.00479)	(0.00336)
Education	-0.00267	0.00113	0.00932
	(0.0186)	(0.0184)	(0.0130)
Gender	0.148	0.0835	0.133
	(0.175)	(0.177)	(0.125)
Chronically ill	-0.129	-0.0180	0.106
	(0.186)	(0.192)	(0.135)
Year Fixed Effects	YES	YES	YES
Community Fixed Effects	NO	YES	YES
Enumerator Fixed Effects	NO	NO	YES
N	6215	6215	6215

The above were used to generate a Heckman style inverse Mills ratio λ
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: **Shocks and Food Security**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Drought	2.361**			
	(1.068)			
Flood Water		3.688**		
		(1.591)		
Illness			0.818	
			(1.067)	
Crop Disease				2.747*
				(1.312)
Constant	12.07	13.77	12.09	14.42
	(26.84)	(26.82)	(27.50)	(26.89)
N	5795	5795	5795	5795

Not reported: time fixed effects δ_t, household fixed effects μ_t^s and inverse mills ratio $\hat{\lambda}$. Village clustered standard errors in parentheses

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

Table 3.6: **Lagged Effect of Most Frequent Shocks, OLS**

	Drought	Flooding	Illness	Crop Disease
Drought	0.521***			
(1 month lag)	(0.0602)			
Flood Water		0.133		
(1 month lag)		(0.132)		
Illness			0.403***	
(1 month lag)			(0.0667)	
Crop Disease				0.400***
(1 month lag)				(0.0843)
Constant	0.340***	0.104***	0.132***	0.419***
	(0.0516)	(0.0287)	(0.0173)	(0.0578)
N	5165	5165	5165	5165

Not reported: time fixed effects δ_t, interaction of time fixed effects and lagged coefficient γ_t^s, household fixed effects μ_t^s. For reference, we set $\delta_{May2017} = 0$, inverse mills ratio $\hat{\lambda}$. Clustered standard errors in parentheses

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

Table 3.7: **Persistence Across Shocks, OLS**

	Drought	Flooding	Illness	Crop Disease
Drought	**0.380*****	0.024	0.0053	-0.004
(1 month lag)	(0.041)	(0.024)	(0.023)	(0.031)
Flood Water	0.017	**0.406*****	0.031	0.104**
(1 month lag)	(0.028)	(0.047)	(0.028)	(0.044)
Illness	-0.004	-0.013	**0.419*****	0.0113
(1 month lag)	(0.015)	(0.022)	(0.045)	(0.027)
Crop Disease	-0.004	-0.010	0.031	**0.456*****
(1 month lag)	(0.021)	(0.018)	(0.019)	(0.044)
N	4956	4956	4956	4956

Not reported: time fixed effects δ_t, household fixed effects μ_t^s, inverse mills ratio $\hat{\lambda}$. Village clustered standard errors in parentheses

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

Table 3.8: **Transition Matrices for Drought**

(a) **November (Planting Season)**

	$Drought_t = 0$	$Drought_t = 1$
$Drought_{t-1} = 0$	$\hat{p}^s_{0,0} = 54.2\%$	$\hat{p}^s_{0,1} = 45.8\%$
$Drought_{t-1} = 1$	$\hat{p}^s_{1,0} = 11.5\%$	$\hat{p}^s_{1,1} = 88.5\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Nov2016}$ and $\hat{\hat{\delta}}_{Nov2016}$, where s=drought, in table 3.6, column (1)

(b) **February (Hungry Season)**

	$Drought_t = 0$	$Drought_t = 1$
$Drought_{t-1} = 0$	$\hat{p}^s_{0,0} = 58.3\%$	$\hat{p}^s_{0,1} = 41.7\%$
$Drought_{t-1} = 1$	$\hat{p}^s_{1,0} = 14.7\%$	$\hat{p}^s_{1,1} = 85.3\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Feb2017}$ and $\hat{\hat{\delta}}_{Feb2017}$, where s=drought, in table 3.6, column (1)

(c) **May (Harvest Season)**

	$Drought_t = 0$	$Drought_t = 1$
$Drought_{t-1} = 0$	$\hat{p}^s_{0,0} = 56\%$	$\hat{p}^s_{0,1} = 34\%$
$Drought_{t-1} = 1$	$\hat{p}^s_{1,0} = 13.9\%$	$\hat{p}^s_{1,1} = 86.1\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{May2017}$ and $\hat{\hat{\delta}}_{May2017}$, where s=drought, in table 3.6, column (1)

Table 3.9: **Transition Matrices for Flood**

(a) **November (Planting Season)**

	$Flood_t = 0$	$Flood_t = 1$
$Flood_{t-1} = 0$	$\hat{p}^s_{0,0} = 88.3\%$	$\hat{p}^s_{0,1} = 11.7\%$
$Flood_{t-1} = 1$	$\hat{p}^s_{1,0} = 45\%$	$\hat{p}^s_{1,1} = 55\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Nov2016}$ and $\hat{\delta}_{Nov2016}$, where s=flood, in table 3.6, column (2)

(b) **February (Hungry Season)**

	$Flood_t = 0$	$Flood_t = 1$
$Flood_{t-1} = 0$	$\hat{p}^s_{0,0} = 87.9\%$	$\hat{p}^s_{0,1} = 12.1\%$
$Flood_{t-1} = 1$	$\hat{p}^s_{1,0} = 50.6\%$	$\hat{p}^s_{1,1} = 49.4\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Feb2017}$ and $\hat{\delta}_{Feb2017}$, where s=flood, in table 3.6, column (2)

(c) **May (Harvest Season)**

	$Flood_t = 0$	$Flood_t = 1$
$Flood_{t-1} = 0$	$\hat{p}^s_{0,0} = 89.6\%$	$\hat{p}^s_{0,1} = 10.4\%$
$Flood_{t-1} = 1$	$\hat{p}^s_{1,0} = 76.4\%$	$\hat{p}^s_{1,1} = 23.6\%^*$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{May2017}$ and $\hat{\delta}_{May2017}$, where s=flood, in table 3.6, column (2)
*though $\hat{\gamma}^{Flood}_1$ is insignificant, the sum of the two coefficients is significant

Table 3.10: **Transition Matrices for Illness**

(a) **November (Planting Season)**

	$Illness_t = 0$	$Illness_t = 1$
$Illness_{t-1} = 0$	$\hat{p}^s_{0,0} = 86.2\%$	$\hat{p}^s_{0,1} = 13.8\%$
$Illness_{t-1} = 1$	$\hat{p}^s_{1,0} = 44.7\%$	$\hat{p}^s_{1,1} = 55.3\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Nov2016}$ and $\hat{\delta}_{Nov2016}$, where s=illness, in table 3.6, column (3)

(b) **February (Hungry Season)**

	$Illness_t = 0$	$Illness_t = 1$
$Illness_{t-1} = 0$	$\hat{p}^s_{0,0} = 86.7\%$	$\hat{p}^s_{0,1} = 13.3\%$
$Illness_{t-1} = 1$	$\hat{p}^s_{1,0} = 44\%$	$\hat{p}^s_{1,1} = 56\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Feb2017}$ and $\hat{\delta}_{Feb2017}$, where s=illness, in table 3.6, column (3)

(c) **May (Hunger Season)**

	$Illness_t = 0$	$Illness_t = 1$
$Illness_{t-1} = 0$	$\hat{p}^s_{0,0} = 86.8\%$	$\hat{p}^s_{0,1} = 13.2\%$
$Illness_{t-1} = 1$	$\hat{p}^s_{1,0} = 46.5\%$	$\hat{p}^s_{1,1} = 53.5\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{May2017}$ and $\hat{\delta}_{May2017}$, where s=illness, in table 3.6, column (3)

Table 3.11: **Transition Matrices for Crop Disease**

(a) **November (Planting Season)**

	$CropDisease_t = 0$	$CropDisease_t = 1$
$CropDisease_{t-1} = 0$	$\hat{p}^s_{0,0} = 84.9\%$	$\hat{p}^s_{0,1} = 15.1\%$
$CropDisease_{t-1} = 1$	$\hat{p}^s_{1,0} = 29.8\%$	$\hat{p}^s_{1,1} = 70.2\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Nov2016}$ and $\hat{\delta}_{Nov2016}$, where s=crop disease, in table 3.6, column (4)

(b) **February (Hungry Season)**

	$CropDisease_t = 0$	$CropDisease_t = 1$
$CropDisease_{t-1} = 0$	$\hat{p}^s_{0,0} = 55.2\%$	$\hat{p}^s_{0,1} = 44.8\%$
$CropDisease_{t-1} = 1$	$\hat{p}^s_{1,0} = 27\%$	$\hat{p}^s_{1,1} = 73\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{Feb2017}$ and $\hat{\delta}_{Feb2017}$, where s=crop disease, in table 3.6, column (4)

(c) **May (Harvest Season)**

	$CropDisease_t = 0$	$CropDisease_t = 1$
$CropDisease_{t-1} = 0$	$\hat{p}^s_{0,0} = 58.1\%$	$\hat{p}^s_{0,1} = 41.9\%$
$CropDisease_{t-1} = 1$	$\hat{p}^s_{1,0} = 18.1\%$	$\hat{p}^s_{1,1} = 81.9\%$

Calculated from $\hat{\gamma}^s_0$,$\hat{\gamma}^s_1$,$\hat{\gamma}^s_{May2017}$ and $\hat{\delta}_{May2017}$, where s=crop disease, in table 3.6, column (4)

Table 3.12: **Estimating Resilience, Conditional Moments Approach**

(a) **Estimated Resilience Parameters**

variable	**mean**	**standard deviation**	**min**	**max**
$\hat{CSI}$	25	8.4	5.9	75
$\hat{\sigma}^2_{CSI}$	121	30	48	252
$\hat{P}_{Normal}$	.14	.16	5.9e-06	.71
$\hat{P}_{Gamma}$	.13	.2	1.7e-14	.81

We posit $\hat{CSI} = 10$ to calculate $\hat{P}_{Normal}$ and $\hat{P}_{Gamma}$

(b) **Resilience, Household Covariates and Reported Shocks**

	$\hat{CSI}$	$\hat{\sigma}^2_{CSI}$	$\hat{P}_{Normal}$	$\hat{P}_{Gamma}$
CSI	0.094***	0.026***	-0.162***	-0.167***
	(0.002)	(0.001)	(0.024)	(0.030)
Land Farmed (HA)	-0.001	-0.017***	-0.008	-0.009
	(0.002)	(0.001)	(0.026)	(0.029)
Tropical Livestock Units	-0.004***	-0.008***	0.009	0.013
	(0.001)	(0.001)	(0.019)	(0.021)
Flood Plain	-0.063***	0.012***	0.244**	0.337***
	(0.006)	(0.003)	(0.109)	(0.126)
Secondary House	-0.010	0.152***	0.143	0.187
	(0.008)	(0.003)	(0.121)	(0.135)
Age of HH Head	0.005**	0.024***	0.006	0.008
(decades)	(0.002)	(0.001)	(0.033)	(0.036)
Education of HH Head	0.000	-0.001**	-0.002	-0.002
	(0.001)	(0.000)	(0.013)	(0.015)
Gender of HH Head	0.032***	0.044***	-0.070	-0.100
	(0.008)	(0.003)	(0.118)	(0.132)
Chronically Ill	-0.005	-0.080***	-0.062	-0.078
	(0.008)	(0.004)	(0.132)	(0.148)
Drought	0.131***	0.349***	-0.178	-0.244**
	(0.008)	(0.004)	(0.109)	(0.120)
Flood	0.065***	-0.172***	-0.465***	-0.603***
	(0.007)	(0.003)	(0.141)	(0.168)
Illness	0.059***	0.046***	-0.156	-0.227*
	(0.007)	(0.003)	(0.113)	(0.128)
Crop Disease	-0.026***	-0.055***	0.045	0.059
	(0.006)	(0.003)	(0.101)	(0.116)
N	4931	4931	4931	4931

Not reported: CSI^2, CSI^3, inverse mills ratio $\hat{\lambda}$

Standard errors in parentheses

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

Table 3.13: **Coping Strategy Index with Lagged Polynomial, GMM**

	June-May (1)	June-Nov (2)	Dec-May (3)
CSI	1.723**	4.258	1.807*
	(0.720)	(2.983)	(0.953)
CSI^2	-0.0126	-0.0725	-0.0127
	(0.0123)	(0.0717)	(0.0145)
N	5139	2633	2395
ar2p	0.0000277	0.795	0.118
ar3p	0.140	0.144	0.463
hansenp	0.578	0.121	0.848

(1) full sample, (2) first six month, (3) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.

Two-step robust standard errors in parentheses

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

Table 3.14: **Coping Strategy Index with Lagged Polynomial, GMM, disaggregated**

(a) **Disaggregated by Age of Household Head**

	Median=40 years					
	Above Median			Below Median		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	1.219	8.034	1.309	1.760**	2.212*	1.928
	(0.999)	(4.992)	(1.141)	(0.688)	(1.246)	(1.381)
CSI^2	-0.00373	-0.148	-0.00874	-0.0139	-0.0241	-0.0117
	(0.0178)	(0.104)	(0.0187)	(0.0111)	(0.0267)	(0.0199)
N	2444	1312	1132	2695	1432	1263
ar2p	0.00200	0.539	0.401	0.00493	0.122	0.106
ar3p	0.441	0.444	0.768	0.195	0.500	0.520
hansenp	0.923	0.481	0.763	0.324	0.271	0.415

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t

Two-step robust standard errors in parentheses

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

(b) **Disaggregated by Education of Household Head**

	Median=7 years					
	Above Median			Below Median		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	1.061*	2.915***	1.558	0.431	2.477	0.918
	(0.565)	(0.959)	(1.635)	(0.937)	(1.551)	(0.903)
CSI^2	-0.00297	-0.0364**	-0.0104	0.0131	-0.0345	0.00158
	(0.00937)	(0.0176)	(0.0236)	(0.0177)	(0.0300)	(0.0143)
N	2263	1195	1068	2876	1549	1327
ar2p	0.000715	0.0878	0.210	0.0240	0.777	0.198
ar3p	0.974	0.208	0.853	0.0796	0.667	0.413
hansenp	0.110	0.847	0.0885	0.374	0.00824	0.231

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.

Two-step robust standard errors in parentheses

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

Table 3.15: **Coping Strategy Index with Lagged Polynomial, GMM, disaggregated**

(a) **Disaggregated by Gender of Household Head**

	Female			Male		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	-0.528	1.869	0.640	2.084***	2.518*	2.421
	(1.862)	(2.622)	(0.976)	(0.803)	(1.332)	(1.793)
CSI^2	0.0225	-0.0270	0.00441	-0.0184	-0.0288	-0.0213
	(0.0305)	(0.0416)	(0.0156)	(0.0138)	(0.0280)	(0.0269)
N	1285	669	616	3854	2075	1779
ar2p	0.285	0.826	0.291	0.000884	0.160	0.355
ar3p	0.744	0.735	0.545	0.162	0.153	0.657
hansenp	0.234	0.160	0.711	0.779	0.129	0.562

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months
Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.
Two-step robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Disaggregated by Whether Household Member is Chronically Ill**

	Chronically Ill			No One Chronically Ill		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	2.432	3.756	1.919*	1.900**	-0.989	1.733
	(1.792)	(2.337)	(1.053)	(0.943)	(3.561)	(1.068)
CSI^2	-0.0222	-0.0619	-0.0225	-0.0171	0.0472	-0.0130
	(0.0296)	(0.0381)	(0.0159)	(0.0157)	(0.0829)	(0.0162)
N	876	470	406	4263	2274	1989
ar2p	0.763	0.709	0.273	0.0000108	0.462	0.0454
ar3p	0.236	0.829	0.222	0.318	0.727	0.865
hansenp	0.198	0.0513	0.466	0.402	0.0386	0.834

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months
Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.
Two-step robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.16: **Coping Strategy Index with Lagged Polynomial, GMM, disaggregated**

(a) **Disaggregated by Land Farmed**

	Median=2 HA					
	Above Median			Below Median		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	1.113	-5.665	0.916	2.110*	2.316*	2.556
	(0.876)	(14.54)	(0.869)	(1.086)	(1.380)	(1.828)
CSI^2	-0.00346	0.131	-0.00183	-0.0180	-0.0233	-0.0242
	(0.0161)	(0.299)	(0.0137)	(0.0177)	(0.0278)	(0.0282)
N	2084	1128	956	3055	1616	1439
ar2p	0.00140	0.639	0.264	0.0160	0.685	0.301
ar3p	0.679	0.836	0.782	0.152	0.166	0.486
hansenp	0.789	0.531	0.784	0.389	0.348	0.700

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.

Two-step robust standard errors in parentheses

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

(b) **Disaggregated by Tropical Livestock Units**

	Median=.01 TLU					
	Above Median			Below Median		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	1.056	2.063*	1.483	1.727**	1.625*	1.135
	(1.503)	(1.121)	(0.992)	(0.775)	(0.925)	(0.793)
CSI^2	-0.00316	-0.0234	-0.00972	-0.0115	-0.0118	-0.00226
	(0.0266)	(0.0248)	(0.0158)	(0.0129)	(0.0147)	(0.0125)
N	2491	1343	1148	2648	1401	1247
ar2p	0.0147	0.356	0.573	0.000255	0.0535	0.0567
ar3p	0.194	0.675	0.397	0.426	0.571	0.848
hansenp	0.436	0.332	0.863	0.993	0.0837	0.571

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.

Two-step robust standard errors in parentheses

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

Table 3.17: **Coping Strategy Index with Lagged Polynomial, GMM, disaggregated**

(a) **Disaggregated by Whether Household Lives in Flood Plain**

	Lives in Flood Plain			Lives Outside FLood Plain		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	0.813*	2.046**	0.707*	-1.441	0.394	-3.935*
	(0.469)	(1.000)	(0.413)	(1.134)	(2.903)	(2.118)
CSI^2	0.000742	-0.0258	-0.00168	0.0376**	0.00842	0.0735**
	(0.0104)	(0.0240)	(0.00783)	(0.0189)	(0.0571)	(0.0325)
N	2364	1364	1000	2775	1380	1395
ar2p	0.0704	0.255	0.0374	0.00147	0.239	0.880
ar3p	0.200	0.255	0.198	0.565	0.832	0.996
hansenp	0.000737	0.0677	0.0188	0.150	0.100	0.979

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.

Two-step robust standard errors in parentheses

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

(b) **Disaggregated by Whether Household Has A Secondary House**

	Has a Secondary House			Does Not Have a Secondary House		
	June-May	June-Nov	Dec-May	June-May	June-Nov	Dec-May
	(1)	(2)	(3)	(4)	(5)	(6)
CSI	1.966	2.276	-1.009	1.743**	6.294	2.377**
	(2.244)	(1.592)	(1.484)	(0.716)	(4.645)	(1.107)
CSI^2	-0.0205	-0.0250	0.0275	-0.0130	-0.117	-0.0206
	(0.0380)	(0.0331)	(0.0271)	(0.0123)	(0.101)	(0.0169)
N	865	509	356	4263	2230	2033
ar2p	0.0773	0.475	0.516	0.000537	0.633	0.322
ar3p	0.426	0.362	0.419	0.299	0.517	0.644
hansenp	0.267	0.687	0.175	0.0913	0.230	0.990

(1) and (4) full sample, (2) and (5) first six months, (3) and (6) last six months

Not reported: controls for drought, flood, pests and illness $Z_{i,t}$, time fixed effects δ_t.

Two-step robust standard errors in parentheses

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

Table 3.18: **Top Variables Selected by LASSO Algorithm**

Variable	Coefficient
CSI Last Month	0.473***
	(0.015)
Group Village Head	0.012***
	(0.002)
Received Assistance from Government Last Month	-1.535**
	(0.727)
Received Assistance as Food Last Month	-0.662*
	(0.417)
Distance to Drinking Water	0.013*
(minutes walking)	(0.007)
Quality of Floor	-0.518
	(0.368)
Sold Assets Last Month	-0.818
	(0.691)
Purchased Assets Last Month	-0.778
	(0.694)
Lives in Flood Plain	-0.662
	(0.562)
Experienced Drought Last Month	0.434
	(0.371)
N	4308
Out of sample R^2 (April, May)	56.4 %

Sample restricted to training set, (June-March)

Bootstrapped standard errors in parentheses

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

Table 3.19: **Top Variables Selected by Random Forest Algorithm**

Variable	ΔMSE* (standardized)*
CSI Last Month	21.70
Group Village Head	25.58
Age	19.98
Education	17.32
Land Farmed (ha)	17.91
Dietary Diversity Score	17.02
Distance to Drinking Water (minutes walking)	14.27
Quality of Roof	16.76
Pregnant or Nursing Household Member	14.65
Lives in Flood Plain	13.80
N	4308
Out of sample R^2 (April, May)	55.6 %

Sample restricted to training set, (June-March)

*Increase in MSE when variable is omitted, measure of variable importance

Figures

Figure 3.1: MIRA households and incidence of 2015 flooding from the Dartmouth Flood Observatory (Brakenridge and Anderson, 2004)

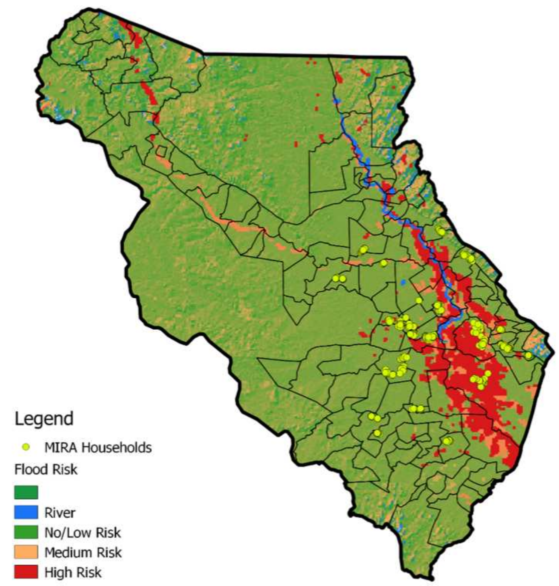


Figure 3.2: Most frequent shocks reported

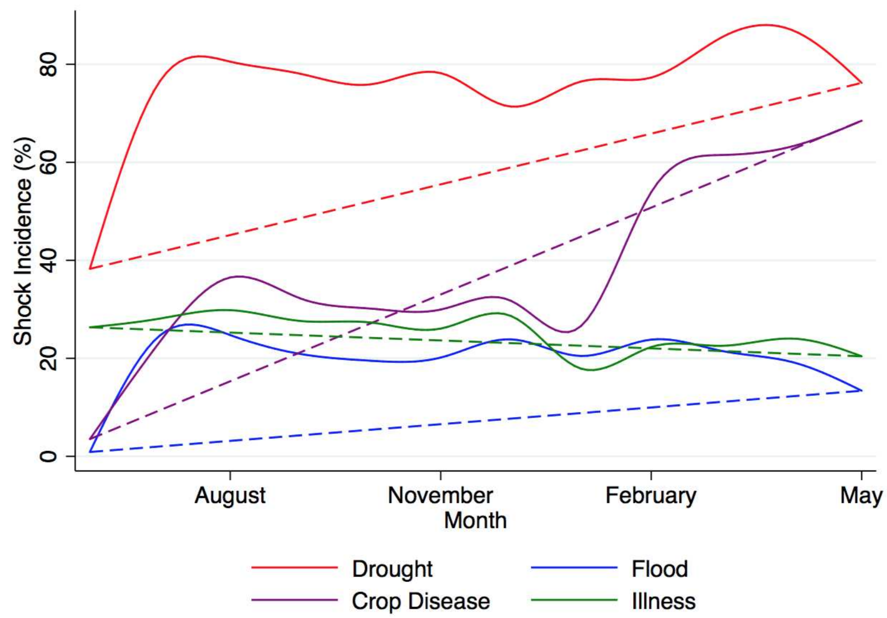
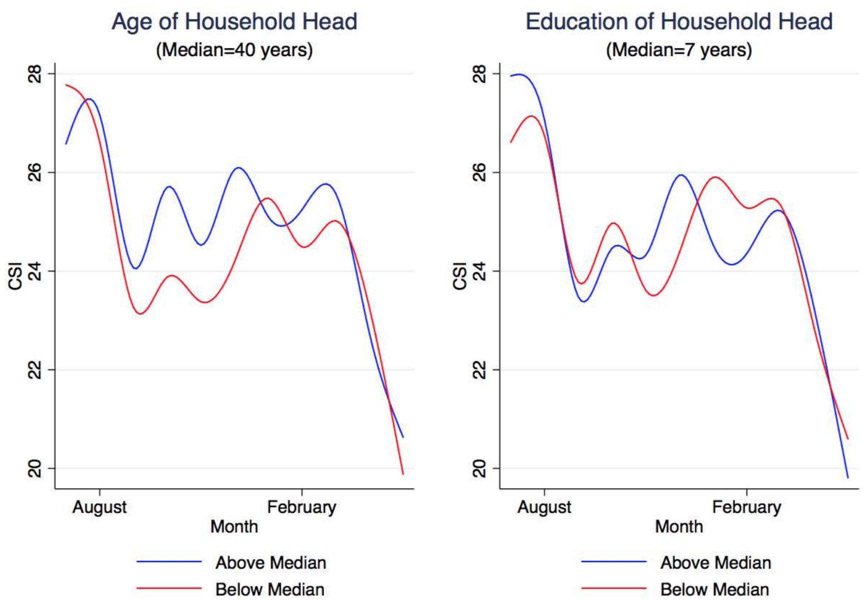


Figure 3.3: Trajectory of Coping Strategy Index disaggregated by demographic characteristics

(a)



(b)

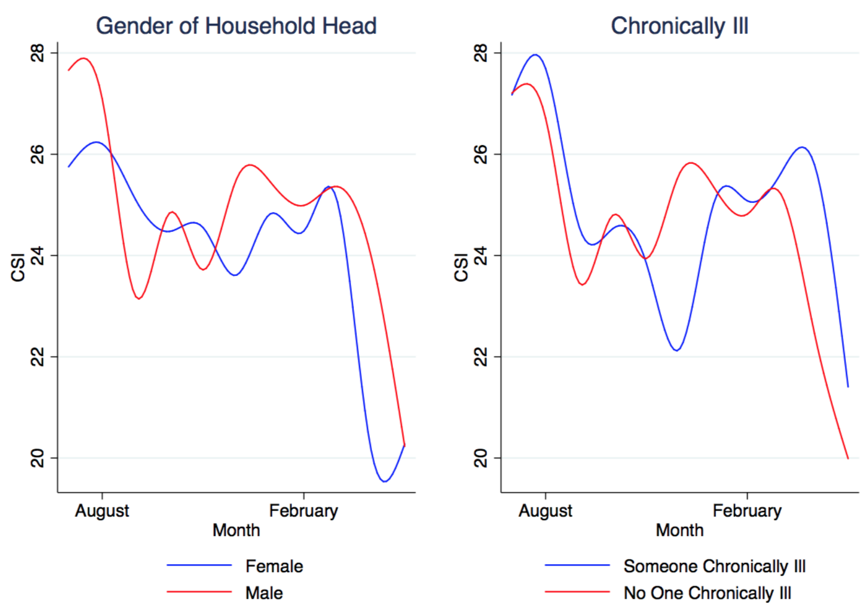
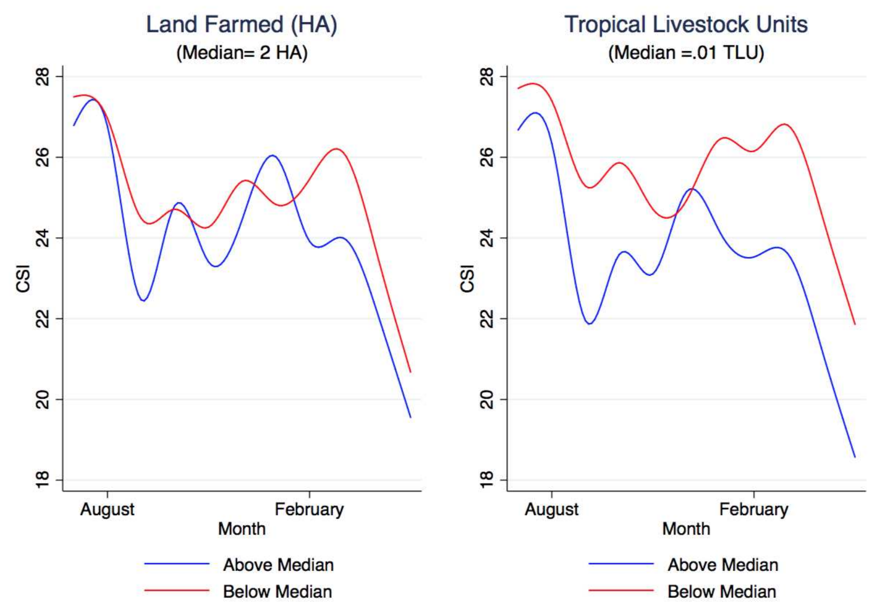


Figure 3.4: Trajectory of Coping Strategy Index disaggregated by assets and geographic characteristics

(a)



(b)

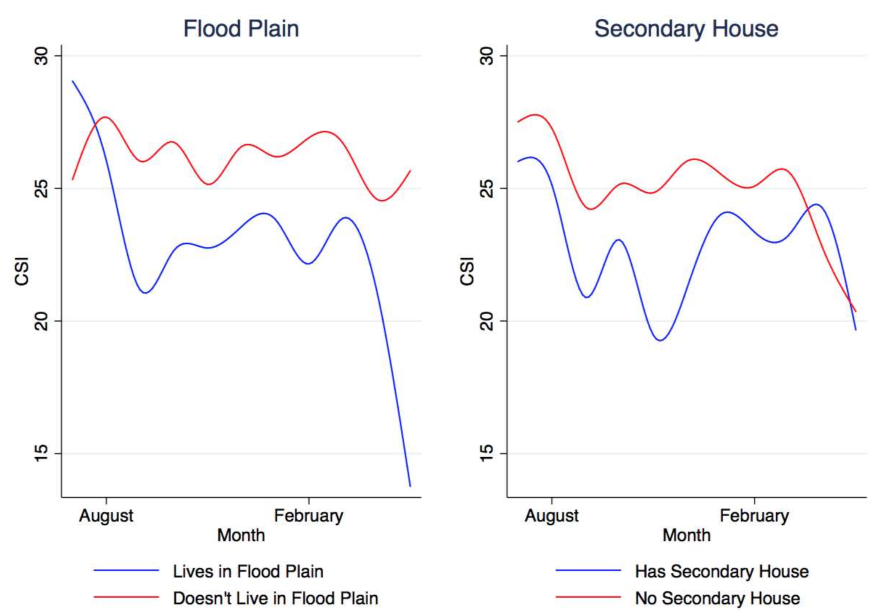
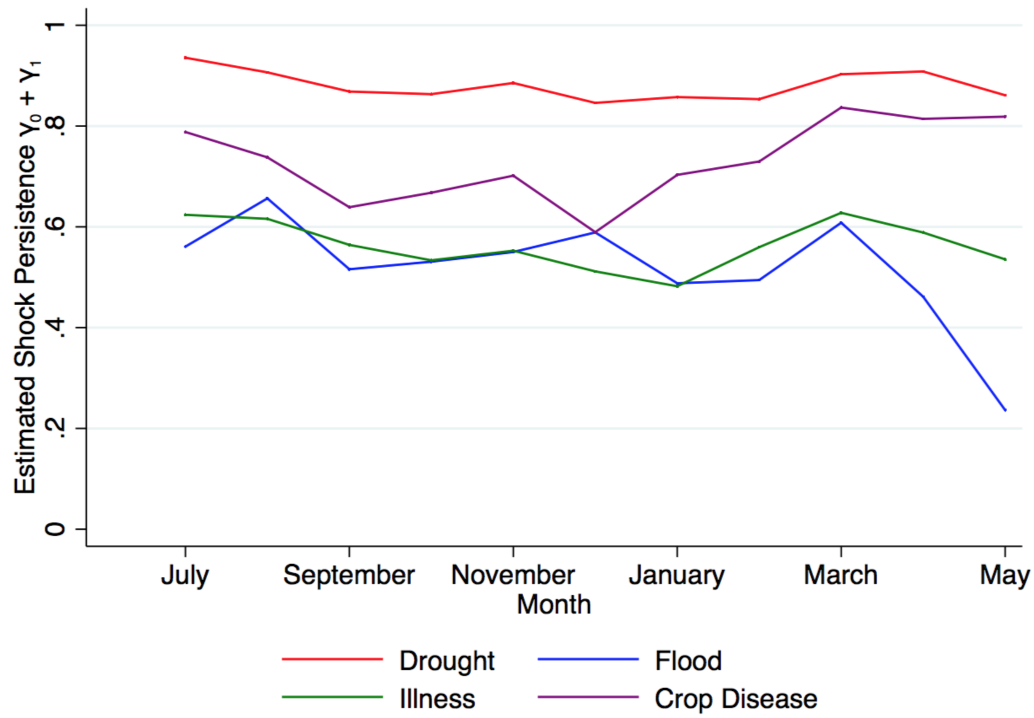


Figure 3.5: Illustration of the parameters calculated from table 3.6 as they vary by round.

(a) Estimated parameter $\hat{p}^s_{1,1} = \hat{\gamma}^s_0 + \hat{\gamma}^s_1$, the perceived persistence of shock's effects



(b) Estimated parameter $\hat{p}^s_{0,1} = \hat{\gamma}^s_0$, the perceived incidence of new shocks

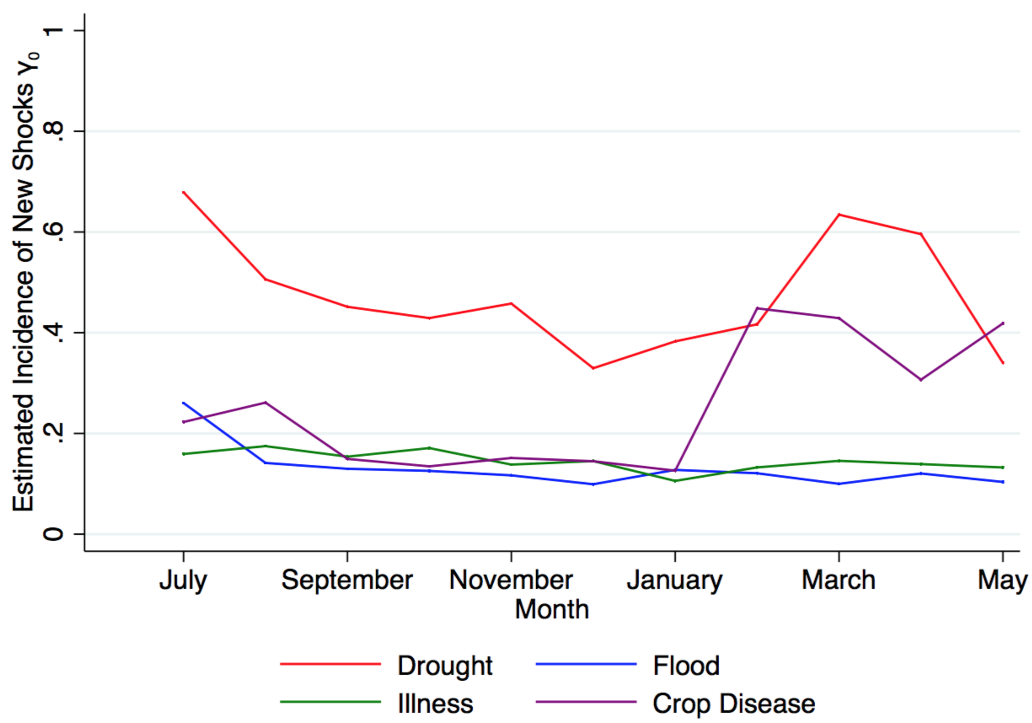


Figure 3.6: Correlation between estimated shock specific probability $\hat{\rho}^{s}_{i,t}$ and household characteristics (bootstrapped s.e)

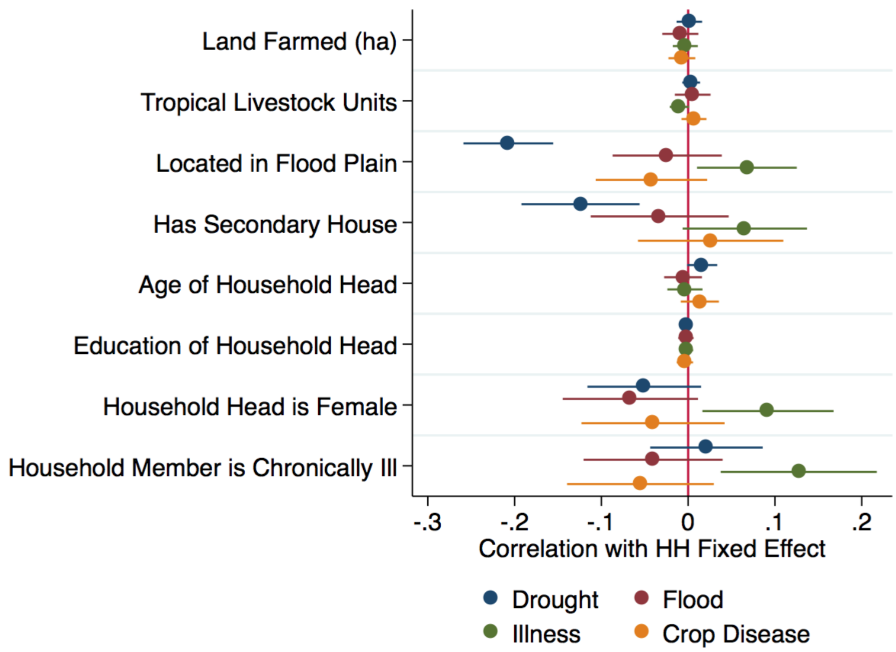
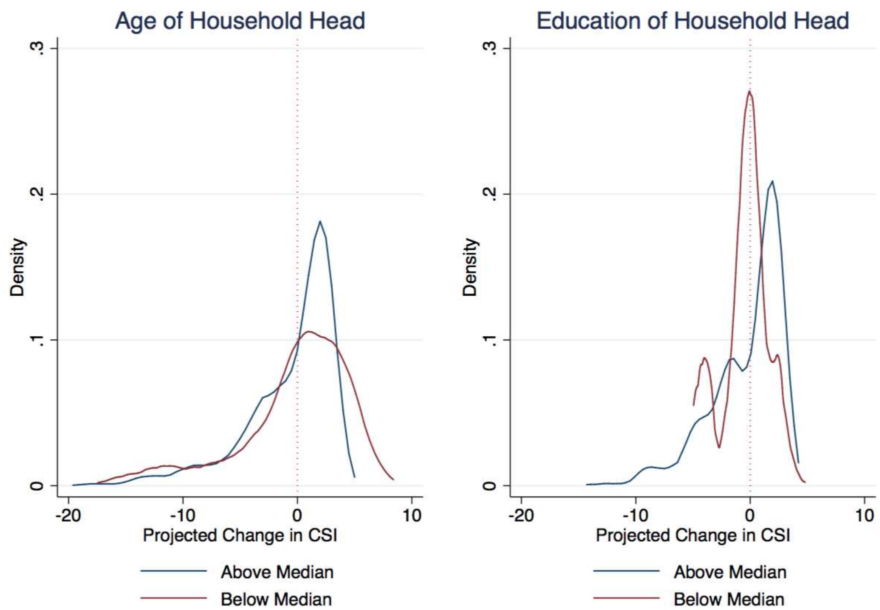


Figure 3.7: Predicted probability distribution functions for Δ CSI for December through May, conditional on demographic characteristics

(a) Predicted from table 3.14, col (3) and (6)



(b) Predicted from table 3.15, col (3) and (6)

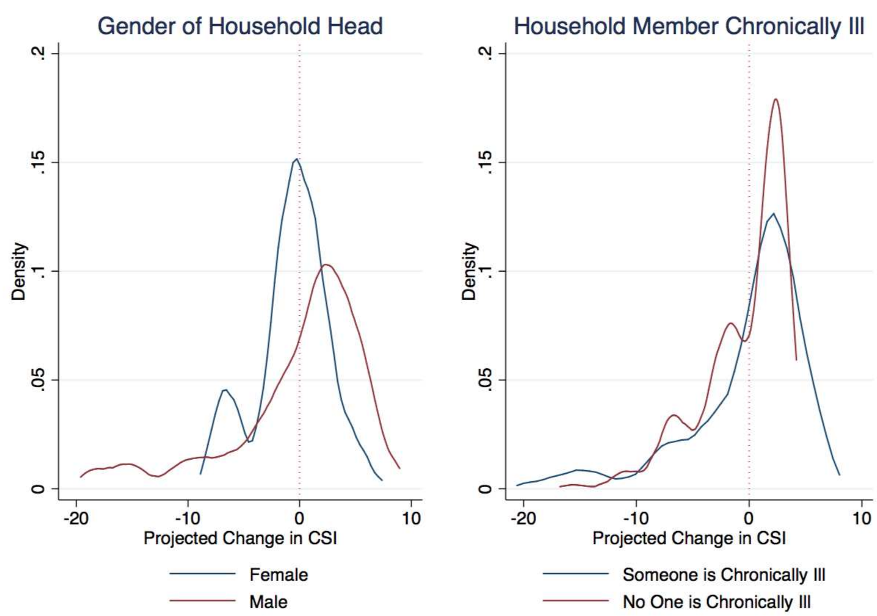
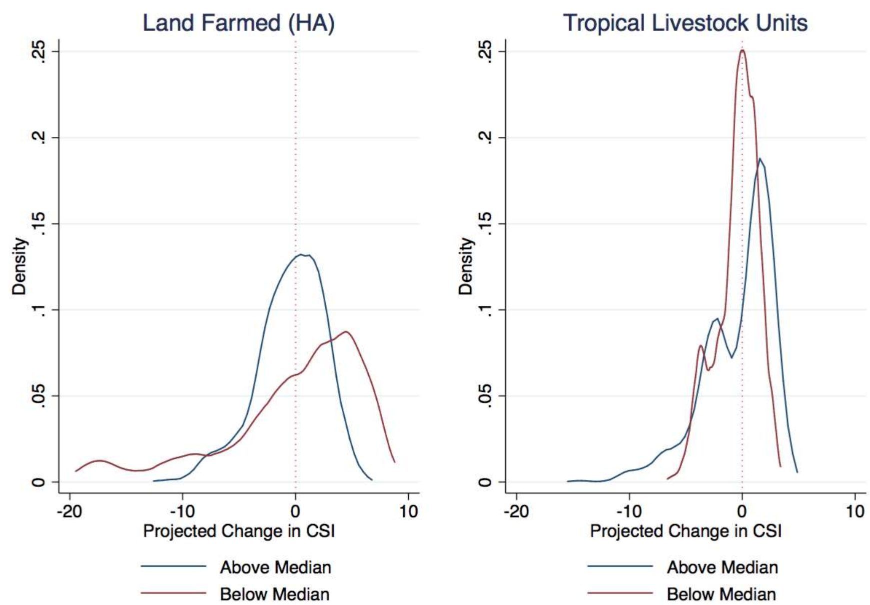


Figure 3.8: Predicted probability distribution functions for Δ CSI for December through May, conditional on assets and location

(a) Predicted from table 3.16, col (3) and (6)



(b) Predicted from table 3.17, col (3) and (6)

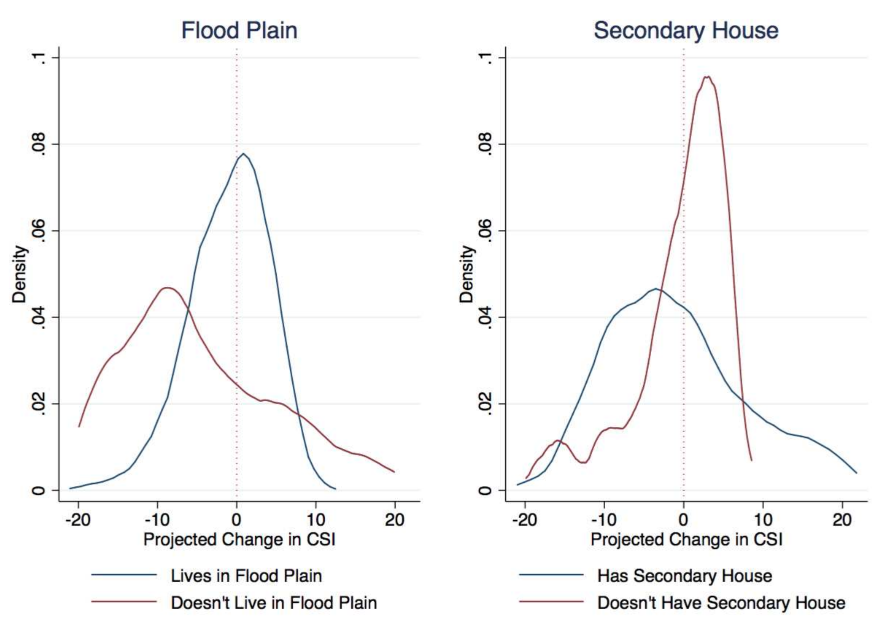
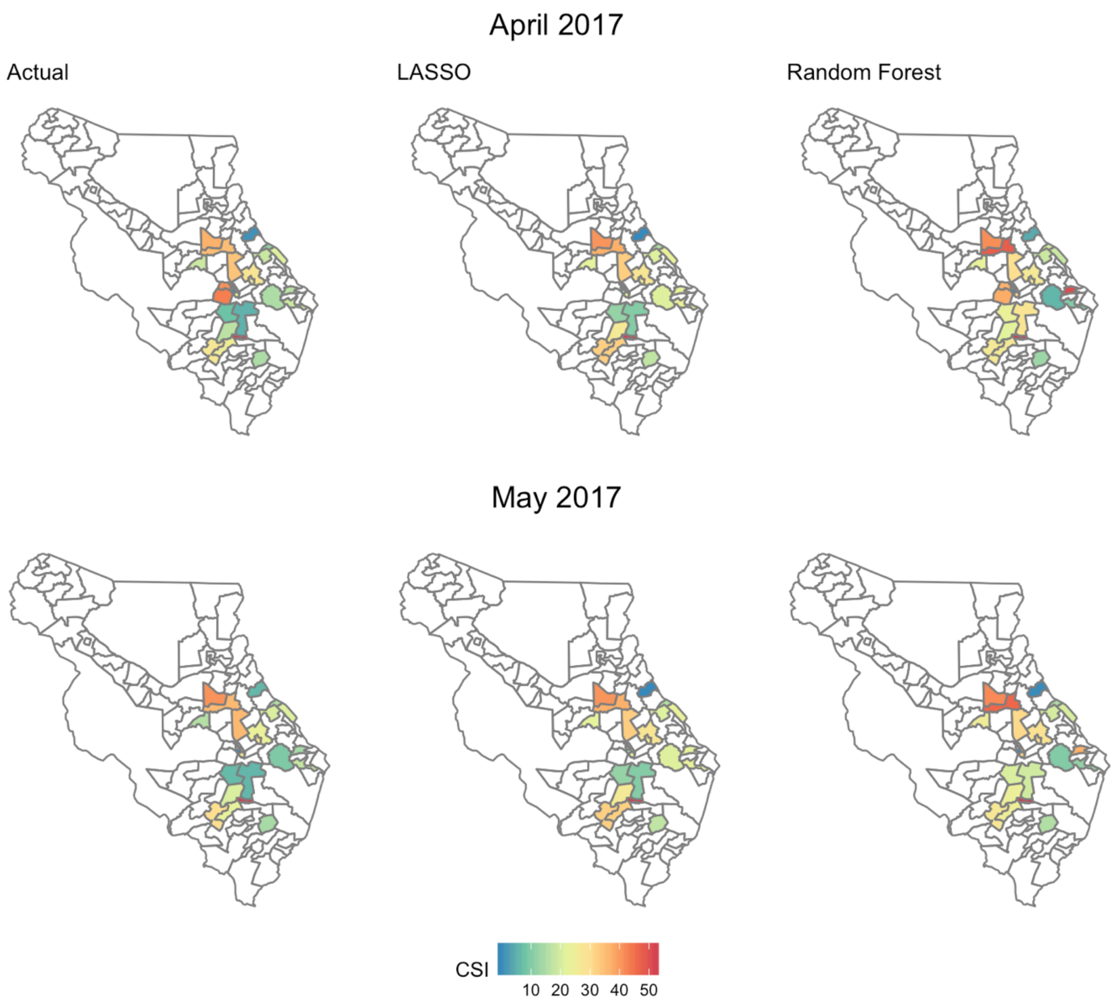


Figure 3.9: Top predictors of CSI

	LASSO	Random Forest
	CSI Last Month	CSI Last Month
	Group Village Head	Group Village Head
	Received Assistance from Government Last Month	Age
	Received Assistance as Food Last Month	Education
	Distance to Drinking Water	Distance to Drinking Water
	Quality of Floor	Quality of Roof
	Sold Assets Last Month	Dietary Diversity Score
	Purchased Assets Last Month	Land Farmed (ha)
	Lives in Flood Plain	Lives in Flood Plain
	Experienced Drought Last Month	Pregnant or Nursing Household Member
N	4308	4308
R^2	56.4 %	55.6 %

Sample restricted to training set, (June-March) and tested on April-May

Figure 3.10: Actual and predicted CSI in April and May



CHAPTER 4

LAND FRAGMENTATION AND FOOD INSECURITY IN ETHIOPIA

4.1 Introduction

Large gains have been made in reducing food insecurity, but an estimated 815 million people still suffered from chronic malnutrition in 2017 (FAO, 2017b). Subsistence farmers in particular struggle to smooth their consumption over time. Households are vulnerable if they cannot rely on credit, savings, social networks or other mechanisms to manage risk and smooth their food consumption in the face of shocks (Dercon et al., 2005; Dercon, 2002; Fafchamps and Gubert, 2007). Such households' inability to deal with risks perpetuates poverty and chronic food insecurity, as they tend to forego risky but potentially lucrative activities with long-term payoffs in order to avoid downside risk (Dercon, 2006; Carter et al., 2007). Deprivations also have long term adverse effects on education and wage outcomes, especially if experienced at a young age (Alderman et al., 2006; Barrett and Santos, 2014). These negative effects can perpetuate across generations (Tafere, 2017). Recent literature has emphasized interventions aimed at making households more 'resilient' to the adverse effects of such shocks, and found that these were effective at reducing food insecurity (Cissé and Barrett, 2016; Knippenberg and Hoddinott, 2017). It is well documented that household characteristics may also influence their ability to mitigate risk and smooth food consumption in the face of heterogeneous shocks (Morduch, 1994).

We explore one such characteristic: a household's level of land fragmentation. Land fragmentation is a state of division of holdings into discrete parcels that are dispersed over a wide area but operated by a single farmer and his or her household. It is often driven by a combination of increased population density, inheritance and government policy (Demetriou et al., 2013). It is pervasive in contexts where incomplete land markets and lack of access to credit constrain attempts at land consolidation for commercial purposes (Binswanger et al., 1995).

A strand of thought within agricultural and development economics has long expressed concern regarding the negative effects of land fragmentation in terms of crop production and yield (Monchuk et al., 2010). Land fragmentation is associated with lower agricultural output and reduced productivity, as farmers with more parcels are further from the production possibility frontier. This has been demonstrated across a wider array of agricultural contexts, including rural China (Tan et al., 2010; Nguyen et al., 1996; Wan and Cheng, 2001), India (Rahman and Rahman, 2009; Jha et al., 2005; Monchuk et al., 2010) and Vietnam (Van Hung et al., 2007), though some studies find no significant effect on yields (Tan et al., 2008). Land fragmentation is also associated with higher production costs, particularly in terms of labor, because of the lost time spent getting to spatially separated parcels (Van Hung et al., 2007; Tan et al., 2008). Finally smaller, more fragmented parcels hinder mechanization, increase fixed costs like fencing and are likelier to lead to land disputes (Foster and Rosenzweig, 2011; Demetriou et al., 2013).

A complimentary but dissenting view points to the benefits of land fragmentation as diversifying risk through the spatial variance in land characteristics. In a seminal study, Blarel et al. (1992) model how land fragmentation reduces aggregate risk to the household . Assuming imperfect correlation in yields across parcels, increased fragmentation decreases the variance of total farm income per hectare over time. They demonstrate this empirically using panel data from Rwanda. In a recent working paper, Veljanoska (2016) uses panel data from Uganda to show that land fragmentation mitigates the adverse impact of deviations in rainfall on yield . This is relevant to contemporary concerns regarding climate change and associated increased variability in rainfall and temperature. Land fragmentation also encourages crop diversification (Van Hung et al., 2007). Though suggestive, these studies tend to focus on yields rather than inquire as to the effects of fragmentation on food security in a shock-prone environment.

With the exception of Veljanoska (2016), the above studies do not attempt to assess whether fragmentation reflects conscious decisions by farms to spatially diversify (for example, through renting in parcels that are not contiguous with each other) or whether it reflects exogenous factors such as rules and customs regarding land access. A rational farmer operating in a functioning land market would seek to optimize her portfolio of land holdings, making fragmentation endogenous to ability. To address this concern we exploit a unique natural experiment: Ethiopia's land reforms under the former communist regime. We propose to harness this historical event as an exogenous source of household-level land fragmentation. Our identification strategy is premised on the assumption of exogenous land redistribution in an incomplete market. We will argue that the main driver of land fragmentation was redistribution efforts, and that land thereby acquired was then bestowed to the next generation. Household-level unobservables, such as ability, are therefore orthogonal to the level of land fragmentation.

The paper explores the question of land fragmentation and food security using Ethiopia's Living Standards and Measurement Study-Integrated Survey on Agriculture (LSMS-ISA), a three round panel dataset jointly collected by the World

Bank and Ethiopian government. This dataset combines household level characteristics and food security indicators with details on the parcels households farm, including the origin of their tenure, size and geo-spatial characteristics. This rich set of indicators allows us to explore the link between land fragmentation and food security.

Bringing together the literature on land fragmentation and food security, this paper uses detailed parcel-level data to construct and compare a series of land fragmentation measures, and shows that land fragmentation reduces food insecurity. It harnesses a policy-driven natural experiment, using robustness checks and an instrumental variable approach to argue that this effect is causal. Finally, it unpacks the risk diversification mechanism, demonstrating that the reduction in food insecurity is due to variation in plot characteristics and crop diversification, allowing farmers to absorb adverse weather shocks.

The remainder of the paper is structured as follows: Part 2 reviews the history of land tenure in Ethiopia, in particular the nationwide land redistribution efforts under the communist government. Part 3 walks the reader through the LSMS dataset and presents summary statistics. Part 4 presents the principal specification. Part 5 includes the principle results, that land fragmentation reduces food insecurity, and presents evidence that this relationship is causal. Part 6 explores how land fragmentation helps farmers mitigate risk. Part 7 concludes.

4.2 Land Tenure in Ethiopia

For historical reasons, households access to land in Ethiopia differs from land tenure systems found elsewhere in Africa.

Until 1974, Ethiopia had a complex land tenure system characterized by its diversity. Broadly speaking, the tenure system differed between the highlands constituting the core of the old Christian Kingdom, the subsequently conquered southern low-lands, and the peripheral area characterized by pastoralism (Ofcansky and Berry, 1991). In the highlands the major form of land tenure was *rist*, a form of communal ownership within family lineages, entitling every male and female descendant to a share of land in the form of usurfruct rights. Since the land belonged to the family rather than the individual, it could not be sold, mortgaged or bequeathed outside the family (Kebede, 2002). Since *rist* rights could be passed on through both male and female descendants, in principle individuals who could trace their ancestry several generations back had access to a large set of *rist* rights. Conflicting claims were resolved through informal channels and litigation in court (Kebede, 2002). These overlapping claims guaranteed access to land for most farmers and impeded inter-generational land consolidation.

By contrast, *gult* was an ownership right bequeathed by the monarch or regional governors, often as reward for military service. *Gult* owners formed an aristocracy entitled to a share of the harvest and to labor services from the peasantry, including mobilization in times of war (Ofcansky and Berry, 1991). *Samon* was land entrusted to the church, which also collected tribute from the peasantry. After conquering the south at the end of the 19th century, emperor Menelik distributed *Gult* rights to northern nobles and loyal southern landlords. This meant that, in contrast to the northern highlands where tenancy was rare, feudal sharecropping predominated in the south, constituting 65-80% of holdings (Kebede, 2002). Somali and Afar were predominantly pastoral, though beginning in the 1950s malaria eradication and irrigation led to attempts at large-scale commercial agriculture. All this changed with the overthrow of Emperor Haile Selassie by the

Marxist Derg regime in 1974.

Under pressure from the peasantry and university students, on March 4 1975 the new government announced its land reform program, which nationalized all land and abolished tenancy (Ofcansky and Berry, 1991). It also prohibited land sales, rentals or the use of hired labor. Large landowners, including the nobility, church and those who operate large commercial estates, had their land seized. The government encouraged peasant cooperatives to form in each kebele (community) and proceed in redistributing the land. Peasants were to receive 'posessing rights' to a plot of land not exceeding 10 hectares, though in practice they often received much less. Families received land in proportion to household size, each adult eligible for one timad of land, or about 1/4 of a hectare (Holden and Yohannes, 2002).[1] In an attempt to ensure equitable quality, land was classified into 4 categories according to soil depth: deep, medium, shallow and very shallow. The cooperatives then sought to ensure each family had access to a parcel of land in each of these four categories (Kosec et al., 2016). Land fragmentation increased as a result. A study found that in Gojjam, a region in northern Ethiopia, the proportion of farmers with three or four parcels of land more than doubled (Ofcansky and Berry, 1991). Land redistribution was particularly prevalent in the highlands, where *rist* was the dominant form of land tenancy. In the more fertile south and particularly modern day SNNP, the reforms focused on abolishing sharecropper payments to their landlords, thereby giving them defacto tenure of their homesteads.

The Derg fell in 1991, but did not seek to reverse the reforms. In 1995, the new government issued a proclamation entrenching the state ownership of land in the constitution. Sales remained prohibited, as the government wanted

[1] Traditionally a 'Timad' is the amount of land two ox can plow in a day. This will tend to vary accordingly to land topology, but is held to be approximately 1/4 of a hectare in the literature.

to mitigate the pressure of landless farmers migrating to the city. State control of land also facilitated control of the population. Rules were loosened to allow for limited renting and sharecropping. Existing allocations were frozen in place, though the government continued to redistribute public land at the margin in order to accommodate new families and dampen urbanization pressures (Kosec et al., 2016). To address concerns of land seizure, the government has sought to entrench existing land tenure rights through a nation-wide land certification scheme, though without the right to sell or mortgage the titled land (Deininger et al., 2011). Local authorities used communal and participatory measures to establish rights to the land, resolve disputes and issue households with a certificate.

Though the current government maintained the exogenous distribution of land, we may be concerned that subsequent re-allocations could introduce endogeneity. As we discussed, both the communist regime and current administration have maintained severe restrictions on the sale of arable land (Deininger et al., 2011). Any potential inter-generational re-allocation through inheritance would face the following constraints:

1. By law, parcels cannot be smaller than a half timad, restricting households' ability to sub-divide land among their children (Kosec et al., 2016).
2. Although any child can in principle inherit land, customary norms and practices tend to favor men, either the eldest or youngest, especially as marriage is predominantly patrilocal and sons are expected to care for their parents (Fafchamps and Quisumbing, 2005).

A final concern is that households may optimize at the margins by renting in and renting out land. We address these concerns in our robustness checks. As we shall see from the data, the historical reforms and constraints on land re-allocation have perpetuated high levels of land fragmentation. We use these reforms as an exogenous sources of variation in land fragmentation, leading to different food security outcomes at the household level.

4.3 Specification

Our principle specification is a reduced form regression, estimating the impact of land fragmentation ($F_{i,t}$) on food security ($Y_{i,t}$):

$$Y_{i,t} = \beta_0 + \beta_1 F_{i,t} + \beta_2 A_{i,t} + X_{i,t} + \delta_t + k_i + \epsilon_{i,t} \tag{4.1}$$

where $\epsilon_{i,t}$ is a time variant error term. δ_t controls for time fixed effects. k_i is a Kebele fixed effectamer, the smallest administrative unit in Ethiopia. $A_{i,t}$ is the total land farmed by the household in hectares.

Since we argue that land fragmentation is historically exogenous, we cannot exploit inter-temporal variation in land tenure across the three rounds. These variations are largely driven by decisions to rent-in or rent-out land. This may allow a household to optimize their land portfolio at the margin, introducing endogeneity. We therefore fix our measure of household land fragmentation to the first round available and run a pooled regression. As a result we cannot control for household fixed effects directly, and instead saturate the model with household level controls $X_{i,t}$. These include gender of household head, their age, the size of household, dependency ratio, and an asset index constructed using principal component analysis.

We use population level weights in all our estimation, and cluster errors at the household level.

4.4 Data

We use data from the Living Standards and Measurement Study-Integrated Survey on Agriculture (LSMS-ISA), an initiative to collect high quality, standardized data in developing countries in order to inform policy making. These surveys collect socio-economic panel data at the household level, with a special focus on agricultural statistics and the link between agriculture and other household income activities. Ethiopia's LSMS-ISA data-set is a panel with three rounds collected in 2011-2012, 2013-2014, and 2015-2016. It initially collected data on 3,776 rural households, before expanding to 5,262 in the 2nd wave to include households living in urban areas.[2] After dropping the major cities and keeping only households for whom we have complete parcel records, we have a sample of 3,730 households in the first round, increasing to 4,607 households in the second round and 4,449 households in the third round. The attrition rate from round 1 to round 2 is 2.1% and from round 2 to round 3 is 3.4%. The survey is representative at the national and regional levels with population weights to adjust for over-sampling. It was implemented by the World Bank's Development Data Group in collaboration with the Central Statistics Agency of Ethiopia, with funding from the Bill and Melinda Gates Foundation.

Ethiopia's LSMS-ISA data is characterized by its combination of detailed agricultural data with household characteristics. It contains both household and

[2] A number of these households living in peri-urban areas has access to land parcels, and we include them in our analysis.

parcel level indicators, including detailed data on the following:

- Parcel-level data detailing the origin of land tenure for each parcel of land.
- Parcel-level measures of area, crop, geophysical characteristics and location, allowing for the calculation of land fragmentation measures. [3]
- Household-level data on welfare outcomes specific to food security.
- Household-level data on demographic characteristics and assets held by the household.
- Household-level data on shocks experienced, such as drought.

This combination of household-level and parcel-level variables allows us to estimate the specification outlined above, explicitly linking agricultural land fragmentation to household-level well-being, conditional on household characteristics.

4.4.1 Origin of Land Tenure

Given the diversity of land tenure in Ethiopia before the redistribution efforts, the natural experiment is not equally valid everywhere. As outlined above, though the scope of the land reforms was nationwide their implementation differed across regions. In the highlands where ownership was traditionally defined by *rist*, the emphasis was on equitable land re-allocation according to family size. This attempt to ensure each family had access to parcels of similar quality created exogenous variation by administrative fiat. In the lowlands where tenure was largely defined

[3] Land data in the LSMS-ISA is collected at three levels of aggregation: parcels; fields; and plots. Plots are the smallest unit of analysis. Multiple plots can make up a field. Multiple fields make up a parcel; parcels are the highest unit of land aggregation. For our main analysis we chose to aggregate all these measures up to parcels, weighed by area. See appendix for details.

by *gult*, tenants simply seized the farms they already cultivated, so there was less redistribution leading to exogenous variation. We see this in the data. On aggregate, 79% of households sampled either received land directly from the government via local leaders, or inherited it from their parents (Table 4.1). Yet this varies signficantly by region. These forms of ownership are dominant in the Ethiopian highlands (Amhara, Tigray and Oromiya). Because the lowlands were dominated by sharecropping, there was less redistribution, as is particularly evident in SNNP. We therefore drop the lowlands as a robustness check. In pastoral areas (Afar and Somalie) many households are squatters, likely making land tenure endogenous. We therefore exclude these areas in our subsequent regressions.

Table 4.2a illustrates how the patterns in land tenure stayed largely unchanged over time. The one interesting trend to note is that many of the parcels in the 'other' category were purchased, despite the ban on land sales. Followup interviews found that these were taking advantage of a loophole allowing land transactions if they include a built structure. The survey therefore added an explicit question regarding land purchases in round 3.

We also see some limited incidence of land leasing. Ethiopia is unusual in that it is characterized by reverse-land tenancy. Households with fewer working age adults, often headed by widows and the elderly, lease out their land to those with the manpower and capital to farm it. We see evidence of this in Table 4.2b, where households renting land are younger on average, have smaller families and a lower dependency ratio. Households renting out land are much likelier to be female headed, older and with a higher dependency ratio.

Since both the purchase and renting-in of land would allow farmers to endogenously restructure their portfolio of land holdings, we conduct two robustness checks: we restrict our specification to households whose land holdings are either inherited or received from local leaders; and we instrument our fragmentation measures with the number of parcels inherited or received.

4.4.2 Measuring Land Fragmentation

The pattern of tenure suggests that land fragmentation is exogenous to the household. A key part of the literature is how to measure it. Land fragmentation is the dispersion of parcels across the landscape, as illustrated in Figure 4.2, where we see examples of consolidated and fragmented parcels. There are multiple approaches to measure land fragmentation, summarized in Table 4.3.

The simplest measure of land fragmentation is the number of parcels K held by a household. All else being equal, more parcels suggests greater fragmentation. However this does not take into account the different size of parcels, which we denote α_k. One measure incorporating both parcel count and size is the Simpson FI measure:

Simpson land fragmentation index (FI):

$$FI = 1 - \frac{\sum_k^K \alpha_k^2}{(\sum_k^K \alpha_k)^2} \tag{4.2}$$

Where K is the number of parcels, and α_k their size in square meters. A score of 0 would indicate no land fragmentation, while as $K \to \infty FI \to 1$.

According to Demetriou et al. (2013) this index has three properties:

1. Fragmentation increases proportional to n
2. Fragmentation increases when the range of parcel sizes α is small

3. Fragmentation decreases as the area of large parcels increases and that of the small parcels decreases.

The Januszewski index is similar to the Simpson index in scale and composition (Januszewski, 1968).[4] For conciseness we do not report it in our principal regressions.

We also consider a measure of fragmentation which captures the variability of fragment size, as proposed by Monchuk et al . They point out that the Simpson index conflates the effect of increased number of parcels $\frac{\delta FI}{\delta n} > 0$ with the effect of increased variability in fragment areas $\frac{\delta FI}{\delta \sigma^2} < 0$. Since both of these can be thought to increase' fragmentation, they propose to isolate the effect of variability in fragment area through the following measure:

$$S_k = \frac{\sqrt{(\alpha_k - \bar{\alpha})^2}}{\bar{\alpha}} \tag{4.3}$$

A shortcoming of the above is that it registers a value of 0 for a single parcel aswell as for a number of parcels with the same size. It should therefore be considered as complementary to other measures, such as the *number of parcels*, rather than a perfect substitute. For a household we take the weighted average of S_k.

The above measures consider the size and number of parcels, but not their physical dispersion. If the correlation between fragmentation and labor costs is driven by travel time, this is an important measure. With the georeferenced coordinates of each parcel, we calculate D_t, the minimum round trip distance to reach all parcels and return home (Igozurike, 1974).

[4] $J = 1 - (\frac{\sqrt{\sum_k^K \alpha_k}}{\sum_K^n \sqrt{\alpha_k}})$, As $K \to 1$ fragmentation increases.

$$D_t = \min_{x_{kj}} \sum_{k}^{K} \sum_{j \neq k}^{K} c_{kj} x_{kj} \tag{4.4}$$

$$\text{where } x_{kj} = \begin{cases} 1 & \text{use path between parcel } k \text{ and } j \\ 0 & \text{otherwise} \end{cases}$$

and c_{kj} is the distance from plot k to plot j. We calculate D_t using a travelling salesman algorithm, finding the shortest route connecting multiple parcel locations as defined by their longitude and latitude.[5]

Parcel Characteristics

Calculating the Simpson Fragmentation Index and deviations in parcel size both require an accurate measures of parcel area α. Most measures in the data were calculated using GPS coordinates. When GPS observations were missing, enumerators measured area using a rope-and-compass method. They also inquired as to the farmer's own estimate of the field size. Across three rounds 10.4% of parcels were missing area measurements taken by GPS, the bulk of them in the first round. Where GPS measures were missing but rope-and-compass measures were available, we used the rope-and-compass measures of α. This allowed us to recover half of the missing observations. In order to validate this substitution, we regressed GPS measured area on rope-and-compass area for those parcels with overlapping measures, and found them to be strongly correlated, with a $\hat{\beta} = 1.04$ and $R^2 = .44$.[6]

[5] The parcel coordinates are first flattened to cartesian space. A distance matrix is calculated for each household's parcels, and fed into a travelling salesman minimization algorithm, specifying the home as the start and end point.

[6] See appendix for details.

We attempted to incorporate the self-reported measures, but many of these were expressed using traditional Ethiopian measures of area, such as the 'timad'.[7] Our attempts to convert these measures to standard hectares found them to be poorly correlated with GPS measures of area.[8] Furthermore, it is well documented that self-reported measures of parcel area suffer from non-random measurement error (Carletto et al., 2015).

The number of parcels K, their average size $\bar{\alpha}$ and the total area farmed by a household $\sum \alpha_k$ are reported in Table 4.4a. We find evidence that the pattern of land tenure due to land redistribution persists. In the highland regions most affected by the reforms, the number of parcels are in the range of $\approx (3.5, 4.5)$, which corresponds neatly with the four categories of land discussed earlier. In other parts of the country, the number of parcels is closer to 2. In these regions land tenancy is characterized by homesteads. The size of parcels varies, but tends towards a quarter or half hectare. Recall that the distribution was done in 'timads', approximately a quarter hectare. Finally, the total number of hectares held by households is between .9 and 1.5 hectare, reflecting strict limits on large land tenure and further evidence of the legacy of land redistribution efforts.

In addition to area α, the data-set contains geovariables matched at the plot level using non-scrambled GPS coordinates. These include:

1. Distance from plot to household (in km)
2. Slope of the plot (in percentages)

[7] A 'Timad' is traditionally the amount of land that can be plowed in a day.

[8] The LSMS Ethiopia documented district specific units of conversion from 'Timad' to hectare. We therefore attempted to convert these self-reported measures but produced a large number of outliers. As an alternative, we tried using a standard conversion for the 'Timad', treating it as 1/4 of an acre in line with the FAO standard. However, comparisons between self-reported area and GPS measurements when the two overlapped showed the former to be inconsistent. See appendix for further details.

3. Plot elevation (in metres)

4. Plot potential wetness index[9]

These plot level characteristics were averaged at the parcel level, weighted by plot area. They are summarized in Table 4.4b.

4.4.3 Food Insecurity

We investigate the impact of land fragmentation on food insecurity $Y_{i,t}$. We use two measures of food insecurity: the number of Months Hungry a household experiences and the Coping Strategy Index (CSI). Months Hungry captures the long-term, extensive experience of hunger while CSI captures the short term, intensive experience of hunger.

Months Hungry measures the temporal extent of hunger. It is the sum of months in the past year a household experienced hunger for five or more days. Households were asked whether, in the last 12 months, they faced a situation when they did not have enough food to feed the household for five of more days. Those who did were prompted to list in which months they lacked sufficient food. The sum of those months constitutes the measure of Months Hungry.

$$\text{Months Hungry} = \sum_{m}^{12} \mathbb{1}(\text{days hungry}_m \geq 5) \tag{4.5}$$

The Coping Strategy Index measures the intensity of hunger. The CSI is a composite weighted score of various strategies households engage in when faced

[9]Local up-slope contributing area and slope are combined to determine the potential wetness index: $WI = ln(A^s/tan(b))$ where A^s is flow accumulation or effective drainage area and b is slope gradient. Data matched from the Africa Soil Information Service by the World Bank.

with short-term food shortages (Maxwell, 1996). It is a measure of the intensity of hunger. Coping strategies c are a set of 8 questions which reflect undesirable activities households are forced to engage in due to food insecurity, a set of strategies $c \in C$.[10] As these strategies are unpleasant, unhealthy and socially stigmatizing, resorting to them is an indicator of short term food stress (Maxwell et al., 2003). The survey asks the number of days in the past week a household engaged in each of these activities, then multiplies those days by a weight w_c indicating its severity. The scores are then compiled into the following index:

$$\text{Coping Strategy Index} = \sum_{c}^{8} days_c * weight_c \tag{4.6}$$

Where $days_c$ is the number of days a household had engaged in a given strategy c over the past week, and w_c is the assigned severity weighting based on existing literature.

CSI is useful for rapidly measuring food insecurity in a humanitarian context, strongly correlated with more complex and time intensive measures of food insecurity (Maxwell et al., 2008). A higher CSI score indicates greater levels of food insecurity and therefore lower well-being. For example, a household with a CSI of 10 may eat less preferred foods or limit portion size a few days a week. A household with a CSI of 30 may do this every day, while also skipping meals and

[10] Coping strategies and corresponding weights:

"In the past 7 days, how many days have you or someone in your household had to...	Number of Days	Weight
Rely on less preferred foods?		1
Limit the variety of foods eaten?		1
Limit portion size at mealtimes?		1
Reduce number of meals eaten in a day?		2
Restrict consumption by adults for small children to eat?		2
Borrow food, or rely on help from a friend or relative?		2
Have no food of any kind in your household?		3
Go a whole day and night without eating anything?"		4

occasionally borrowing food. A household with a CSI of 70 is engaging in all these coping mechanisms daily, but also occasionally spends a day and night without eating.

To understand both the extent and intensity of hunger, Figure 4.1 illustrates the percentage of households in each round and region which experience non-zero CSI and non-zero Months Hungry. In general there is a trend towards improved food security outcomes, with fewer households reporting food insecurity in later rounds. Yet in some regions up to 40% of the population continues to experience chronic food insecurity in the latest round.

Household Controls

As we are not using a household fixed effect, we want to control for household characteristics that would affect food security. These include demographic characteristics such as whether the household head is female, the size of the household, and its composition in terms of the dependency ratio.[11]

We also use a roster of 40 reported assets to create an asset index using Principal Component Analysis (PCA).[12] The index plots all households along the first axis of a PCA vector, maximizing variance. Assuming that none of these are inferior goods, the index therefore offers an ordinal ranking of households' wealth in terms of their asset holding.

The above statistics are summarized in Table 4.5. These include measures of food insecurity, land fragmentation and household level controls.

[11] The dependency ratio is calculated as $\frac{\text{HH Members aged 0-14 \& 65 and older}}{\text{HH Members aged 15-64}}$.

[12] Principal Component Analysis (PCA) aims to reduce the dimensionality of a matrix by transforming each row vector x_i using a unit vector of weights w_k so as to maximize the variance of the resultant vector $t_{k(i)} = x_i \dot{w})k$ (Hotelling, 1933).

Shock Statistics

The LSMS dataset also matches household level GPS coordinates with geospatial characteristics, most notably the level of rainfall. By comparing it to long term trends we can construct the standardized deviation (Z score) $Z_{i,t}$ of total rainfall in the wettest quarter, which farmers rely on most for their crops. These deviations allow us to objectively quantify weather shocks a household has experienced in a given year, and infer whether land fragmentation mitigates or exacerbates the effect of these shocks on food security.

4.5 Results

4.5.1 Land Fragmentation and Food Insecurity

We estimate equation (1) in Table 4.6, separately for Months Hungry and the Coping Strategy Index across our four measures of land fragmentation.

Table 4.6a shows a significant negative correlation between land fragmentation and the temporal extent of hunger measured as Months Hungry. This negative correlation is consistent in sign and magnitude across measures of land fragmentation. At the margin, the coefficients reflect changes in the number of Months Hungry a household experiences. As an illustration, from Table 4.6a column (1) farming an additional parcel of land, holding area constant, reduces the number of months hungry on a scale equivalent to farming an additional 2.2 hectares.[13] From column (2), a household at the 25th percentile of the Simpson Index ($FI \to 0$)

[13] $\frac{\hat{\beta}_{Parcels}}{\hat{\beta}_{Area}} = \frac{-0.060}{-.027} = 2.22$

moving to the 75th percentile of land fragmentation ($FI = .656$), while holding area constant, would decrease the number of Months Hungry by a third of a month.[14] This effect is comparable to effects achieved through external cash grant programs (Knippenberg and Hoddinott, 2017).

Table 4.6b finds a negative correlation between land fragmentation and the intensity of hunger measured using the Coping Strategy Index. At the margin, the coefficients reflect changes in the intensity of coping strategies employed by the household, both in terms of their frequency and severity.[15] To illustrate using results from Table 4.6b column (2), moving from the 25th to 75th percentile of land fragmentation decreases CSI by -2.22, the equivalent of going hungry so one's children can eat for a day. This negative correlation retains its significance across the various measures of fragmentation, suggesting it is a combination of the number of parcels, deviation in parcel size and distance travelled that is driving the narrative. The total area farmed also reduces CSI, but only marginally.

4.5.2 Endogeneity Concerns

A concern when using non-randomized data is the potential endogeneity of the key independent variable $F_{i,t}$, measuring land fragmentation. We address some of the potential sources of endogeneity through the following robustness checks.

Table 4.7 restricts the specification to the highlands where the natural experiment is most relevant. This sub-sample, which includes the highlands of Amhara, Tigray and Oromia, includes about half of the original observations. It finds equi-

[14] $\hat{\beta}_{Simpson} * (.656 - 0) \approx -.354$

[15] i.e. eating less preferred foods is less severe (Weight=1) than going a whole day and night without eating (Weight=4).

valent effect of land fragmentation on food security in both sign and magnitude. The coefficient on deviations in parcel size (Table 4.7a col (3)) loses significance, likely because of the smaller sample size, but is otherwise consistent with the coefficient in Table 4.6a col (3).

If land fragmentation is a risk diversification strategy, then farmers may seek to optimize their portfolios of land holdings in order to minimize risk. These farmers may have more fragmented land holdings because of their unobserved ability, which would also be correlated with reduced food insecurity. Despite legal restrictions we find evidence of land being bought and rented in. This may enable more entrepreneurial farmers to diversify their land holdings. Table 4.8 therefore restricts the sample to farmers for whom all parcels are either inherited or received from the government.[16] It finds similar effects in sign, significance and magnitude for both Months Hungry (Table 4.8a) and CSI (Table 4.8b) across all measures of fragmentation.

The variation in land fragmentation may be driven by farmers adding or subtracting a parcel at the margin. Tables 4.9 and 4.10 use the number of parcels inherited or received from the government as an instrumental variable for land fragmentation, similar to the identification strategy used by Veljanoska, 2016. The first stage regression in Tables 4.9a and 4.10a confirms the instrument's relevance. The second stage regressions in Tables 4.9b and 4.10b finds results similar to Table 4.6 in sign and significance, allaying our concerns of bias. In columns (1) and (2) these coefficients are of similar magnitude, while in columns (3) and (4) they are almost an order of magnitude larger. The instrument only explains 10-16% of the variation for the latter two measures of land fragmentation *Deviation in Parcel*

[16]Though many of these households do live in the highlands, there is only a 48% overlap between this sub-sample and the previous one.

Size and *Distance Travelled*. Since variation in the second stage is driven by the instrument, a weaker instrument may push the coefficient upwards (Angrist and Pischke, 2008).

4.5.3 Non-Linear Estimation

A separate concern lies with mis-specification due to non-linearity of the data generating process. Both the CSI and Months Hungry have a mass point at 0. Furthermore, Months Hungry is a discrete count variable, taking on integer values from 0 to 12. Hence there is a concern that using a linear regression does not properly reflect the underlying data-generating process. As a robustness check we estimate our principle specification across fragmentation measures using two alternative Maximum Likelihood Estimators (MLE). Table 4.11 estimates a Poisson MLE, and Table 4.12 estimates a negative binomial MLE. Because we use a non-linear estimator, to compare the average marginal effects we multiply the coefficients by the sample average of the outcome variable. The results are consistent with the results reported in Table 4.6 in sign, magnitude and significance.

4.5.4 Selection into the Sample

Finally, we may be concerned about non-random selection into the sample. The LSMS data only observes household who retained their allocated land and passed it on to their children. If households who received favorable fragments retained their land and are more likely to be food secure, while those granted unfavorably fragmented areas were more likely to perish, out-migrate or abandon their land, this sample would not be representative. While this does not affect the internal validity of our analysis, it may temper the external validity, as we are not observing the full universe of households allocated land fragments by the government.

4.6 Land Fragmentation as Risk Mitigation

What drives this relationship between land fragmentation and reduced food insecurity? If we allow that land fragmentation decreases yields and profits as the literature suggests, the effect on food security must be through risk mitigation. Building on Blarel et al. (1992) we argue that land fragmentation allows households to better manage the downside risk of shocks such as drought. With incomplete access to credit and markets, households with multiple parcels are endowed with an inherently more diverse portfolio. This diversity is reflected in the difference in parcel level characteristics, which is correlated with decreased food insecurity. Households can take advantage of this diversified portfolio by tailoring the crop grown to the parcel characteristics. Households with more land fragmentation also grow a greater diversity of crops, which is correlated with decreased food insecurity.

4.6.1 Land Fragmentation and Rainfall Deviation

Under the risk mitigation hypothesis, land fragmentation is particularly useful in the context of severe shocks. To illustrate this, we estimate

$$Y_{i,t} = \beta_0 + \beta_1 F_{i,t} + \beta_2 Z_{i,t} + \beta_3 F_{i,t} * Z_{i,t} + A_{i,t} + X_{i,t} + \delta_t + k_i + \eta_{i,t} \qquad (4.7)$$

where $Z_{i,t}$ is the standardized deviation (Z score) of total rainfall in *Meher*, the rainy season (June-September). Trivially we expect $\hat{\beta}_2 < 0$, a good year of rainfall decreases food insecurity and vice versa. Our interest is in testing whether land fragmentation exacerbates this sensitivity to rainfall $\hat{\beta}_3 < 0$ or mitigates it $\hat{\beta}_3 > 0$
.

From Table 4.14 we find that rainfall indeed correlates with decreased food insecurity as measured by CSI. Since $\hat{\beta}_3 > 0$, land fragmentation mitigates the sensitivity of food security to rainfall.

Figure 4.3 illustrates this visually. Figure 4.3a illustrates the difference in distribution of CSI between households with a low level of land fragmentation (FI=0) and households with perfect fragmentation (FI=1), in a normal year, where the Z-score for rainfall is 0. We find that households with diversified plots have lower levels of CSI, ceteris paribus. Figure 4.3b illustrates the difference in distribution of CSI outcomes for the same two households in a year of drought, where the Z-score for rainfall is -2. We find that though both types of households see increases in the CSI levels, the difference between the two increases. The household with no land fragmentation experiences more severe food insecurity in times of drought.

4.6.2 Reduced Risk through Diversification

This drought buffering effect is linked to a diversified portfolio. Land fragmentation means a greater diversity in parcel level characteristics. We therefore expect households with a more diverse portfolio of land to have better food security outcomes. Tables 4.15 and 4.16 regress the household level average characteristics and standard deviation against Months Hungry and CSI, respectively. These characteristics include distance from the home, slope, elevation and wetness. Tables 4.15a and 4.16a show a null result, suggesting that the level is not significantly correlated with food security. There is no optimal slope, elevation or wetness. However, having a diverse set of plots does improve food security. Table 4.15b shows a negative and significant correlation between Months Hungry and the standard deviation in distance, slope and elevation. Table 4.16b suggests that households with a diverse set of plots in terms of slope and wetness experience lower levels of CSI. Together, these results suggest that agro-ecological heterogeneity plays an important role in helping households diversify their portfolio. Though no particular slope, elevation or wetness is ideal, a heterogeneous mix offers a good buffer against shocks, leading to better food security outcomes.

Endowed with this portfolio of land characteristics, farmers can choose the crops grown accordingly in order to minimize risk. Dercon, 1996 models how households with fewer assets mitigate their risk by cultivating low yield, low variance crops, such as sweet potato, while households with more assets are likelier to cultivate high yield, high variance cash crops such as cotton. In the case of Ethiopian farmers, this portfolio of land is an endowment under our assumption of exogeneity, which households can take advantage of by tailoring their crops to the lands characteristics. Table 4.17 regresses these parcel characteristics against the five most prevalent crops grown and find that these characteristics shift the probability of planting given crops. For example, farmers are more likely to plant teff and less likely to plant coffee in soils with a high wetness index. This suggests that one of the advantages of a diverse set of parcel characteristics is the ability to plant several different crops.

Agro-ecological variation may effect food security via crop diversity or by directly reducing production risk within a given crop. Mediation analysis using a controlled direct effects regression can help disentangle these two mechanisms (Baron and Kenny, 1986). Given the variation in geovariables $GV_{i,t}^{sd}$, food security $Y_{i,t}$ and crop diversity as the mediator $CD_{i,t}$, CDE estimates:

$$CD_{i,t} = \gamma_0 + \gamma_1 GV_{i,t}^{sd} + \gamma_2 X_{i,t} + \epsilon_{i,t} \tag{4.8}$$

$$Y_{i,t} = \beta_0 + \beta_1 GV_{i,t}^{sd} + \beta_2 CD_{i,t} + \beta_3 X_{i,t} + \eta_{i,t} \tag{4.9}$$

Where $\hat{\beta_1}$ is the direct effect and $\hat{\gamma_1} * \hat{\beta_2}$ is the indirect effect. Table 4.18 explores the relationship between land fragmentation, crop diversity and food insecurity.'Number of Distinct Crops' counts the number of different crop types a household grows across its parcels. From Table 4.18a, increased diversity in agroecological characteristics increases the diversity of crops grown. Table 4.18b suggests that the increased diversity of crops contributes to improvements in household food security, evidence of the indirect effect of agroecological heterogeneity via crop diversification. In the case of CSI, variation in slope and wetness also directly affect food security, likely by reducing production risk within a given crop. Both mechanisms operate in tandem.

4.7 Conclusion

Land fragmentation is much maligned as an obstacle to agricultural productivity. Drawing from the link between land enclosure and the industrial revolution in the UK, they argue that land consolidation is a precondition for households to emerge out of poverty. Yet this overlooks the benefits land fragmentation may confer to subsistence farmers in terms of food security. By allowing them to diversify their risks, farmers are less vulnerable to a shock wiping out their crop. An empirical investigation of this question is hampered by the potential endogeneity of land allocation decisions.

We exploit a natural experiment in Ethiopia, where the pattern of land redistribution under the communist government was maintained by law and custom, arguing that land fragmentation is therefore orthogonal to farmer's ability. We find that higher levels of of land fragmentation decrease both short terms and long term food insecurity. This result is robust to various subsets of the data and alternative specifications.

Unpacking this mechanism, we demonstrate that land fragmentation mitigates the impact of drought on food security. Higher land fragmentation means households are endowed with a more diverse set of parcels in terms of walking distance, slope, elevation and wetness. The level of these characteristics has no effect on food security, but a higher standard deviation translates to improved food security outcomes. In part, this is because a farmer with multiple parcels can cater the crop she grows to her parcel's characteristics. Farmers who grow more crop types are more food secure.

This paper suggests that efforts at land consolidation should be approached with caution. Though they may improve agricultural productivity, in the absence of credit and insurance markets land fragmentation plays a crucial role in allowing households to mitigate risk by diversifying their crop portfolio. The paper also highlights how households living at or near subsistence levels resort to informal risk mitigation mechanisms. Though incomplete, these mechanisms must be understood before they are intentionally or unintentionally disrupted by external interventions. As in medicine, development practitioners should abide by the rule: "First, do no harm".

Table 4.1: **Land Tenure By Region**

	Highlands			Pastoral*	
Tenure Type	Tigray	Oromia	Amhara	Afar	Somalie
Granted by Local Leaders	64%	33%	48%%	14%	15%
Inherited	13%	44%	33%	31%	52%
Rent	11%	4%	5%	9%	1%
Borrowed for Free	3%	4%	3%	3%	1%
Moved in Without Permission	1%	7%	0%	38%	27%
Shared Crop	0%	0%	0%	0%	0%
Purchased	1%	2%	2%	1%	1%
Rented out	5%	2%	4%	1%	2%
Other	2%	4%	3%	4%	0%
Total	100%	100%	100%	100%	100%

	Lowlands			
Tenure Type	Benshagul Gumuz	SNNP	Gambelia	Total
Granted by Local Leaders	64 %	20%	48%	36%
Inherited	8%	67%	21%	43%
Rent	6%	2%	2%	5%
Borrowed for Free	3%	2%	4%	3%
Moved in Without Permission	8%	0%	4%	5%
Shared Crop	1%	0%	0%	0%
Purchased	4%	2%	7%	2%
Rented out	1%	3%	2%	3%
Other	4%	4%	13%	4%
Total	100%	100%	100 %	100%

Source: LSMS Ethiopia parcel dataset

* Subsequently excluded from analysis

Tables

Table 4.2: **Land Tenure**

(a) **Parcel Tenure Type by Round**

Tenure Type	2011/2012	2013/2014	2015/2016	Total
Granted by Local Leaders	4,000	4,335	4,214	12,549
Inherited	3,599	4,904	4,989	13,492
Rent in	1,284	1,478	754	3,516
Borrowed for Free	372	142	163	677
Moved in Without Permission	446	309	323	1,078
Shared Crop	0	0	794	794
Purchased	0	0	524	524
Rented out	319	763	955	2,037
Other	507	425	34	966
Total	10,527	12,356	12,750	35,633

Source: LSMS Ethiopia parcel dataset

(b) **Household Demographics by Tenure Type**

Tenure Type	**Female**	**Age**	**HH Size**	**Dependency**
Granted by Local	26 %	50.23	5.09	1.27
Inherited	21 %	42.98	5.24	1.47
Rent	34 %	36.91	3.84	1.03
Borrowed for Fre	30 %	39.69	4.21	1.21
Moved in Without	24 %	46.01	5.46	1.56
Shared Crop	5 %	.	5.63	1.34
Purchased	21 %	52.12	5.34	1.47
Rented out	44 %	51.49	4.26	1.48
Other	19 %	41.13	5.32	1.20
Total	24 %	45.59	5.09	1.37

Source: LSMS Ethiopia household dataset & parcel dataset

Table 4.3: **Proposed Fragmentation measures**

Measure	Equation	Interpretation	Data required
Number of Parcels	Np	• n number of parcels	• Parcel count
Simpson	$FI = 1 - \frac{\sum_k^K \alpha_k^2}{(\sum_k^K \alpha_k)^2}$	• n number of parcels • α size in square meters • A total size of the land holdings • $K \to \infty FI \to 1$	• Parcel count • Parcel area
Monchuk et al	$S_k = \frac{\sqrt{(\alpha_k - \bar{\alpha})^2}}{\bar{\alpha}}$	• Captures deviation from the average size • Independent of number of parcels	• Parcel area
Igozurike	D	• Round trip distance to reach all fields • Measured with travelling salesman algorithm	• Parcel Geocodes

Source: Authors

Table 4.4: **LSMS Land Statistics**

(a) **Mean Number and Size of Parcels**

Region	**Number of Parcels**	**Average Parcel Area (HA)**	**Household Area (Ha)**
Highlands			
Tigray	3.17	0.43	1.29
Amhara	4.54	0.27	1.23
Oromia	3.85	0.51	1.69
Lowlands			
Benshagul Gumuz	3.43	0.48	1.46
SNNP	2.48	0.40	0.93
Gambelia	2.06	0.21	0.47
Total	3.24	0.39	1.17

Source: LSMS Ethiopia parcel dataset

(b) **Parcel's Physical Characteristics**

Region	**Distance (km)**	**Slope (%)**	**Elevation (m)**	**Wetness Index**
Highlands				
Tigray	1.20	11.88	1859.73	12.92
Amhara	0.99	14.72	2122.35	12.69
Oromia	0.80	10.33	2007.55	12.71
Lowlands				
Benshagul Gumuz	1.64	6.17	1294.88	12.97
SNNP	1.37	15.42	1894.25	12.61
Gambelia	1.40	3.69	754.68	14.53
Total	1.13	11.98	1828.64	12.92

Area-weighted household mean of parcel level values

Source: LSMS Ethiopia parcel dataset

Table 4.5: **Household Level Statistics**

Variable	**Mean**	**Standard Deviation**	**Min**	**Max**
Food Insecurity				
Coping Strategy Index	4	8.3	0	84
Months Hungry	.9	1.7	0	11
Fragmentation				
Number of Parcels	3.2	2.7	1	26
Simpson Fragmentation Index	.38	.31	0	.95
Deviation in Plot Size	.46	.48	0	7
Round Trip Distance Travelled (Travelling Salesman)	4.2	6.6	0	60
Household Controls				
Household Head is Female	.28	.45	0	1
Household Size	4.7	2.4	1	16
Dependency Ratio $\left(\frac{\text{\# under 15 or over 64}}{\text{\# between 15 and 64}}\right)$	1.2	1.1	0	11
Age of Household Head	44	16	3	100
Asset Index	.29	3	-1.2	42

Table 4.6: **Food Insecurity and Land Fragmentation, Pooled OLS**

(a) **Month Hungry and Land Fragmentation**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.063***			
	(0.010)			
Simpson Fragmentation Index		-0.539***		
		(0.103)		
Deviation in Parcel Size			-0.115**	
			(0.054)	
Distance Travelled				-0.009***
				(0.003)
Total Household Area Farmed	-0.037***	-0.043***	-0.050***	-0.050***
	(0.012)	(0.012)	(0.013)	(0.013)
N	8698	8698	8698	8445

(b) **CSI and Land Fragmentation**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.240***			
	(0.055)			
Simpson Fragmentation Index		-3.390***		
		(0.670)		
Deviation in Parcel Size			-0.825***	
			(0.293)	
Distance Travelled				-0.064***
				(0.019)
Total Household Area Farmed	-0.173***	-0.170***	-0.211***	-0.215***
	(0.048)	(0.046)	(0.052)	(0.051)
N	8698	8698	8698	8445

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar, Somalie)
Not reported: controls for gender of household head, dependency ratio, size of household, asset index, Kebele, round. Household clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.7: **Food Insecurity and Land Fragmentation, Highlands Only**

(a) **Months Hungry and Land Fragmentation**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.060***			
	(0.011)			
Simpson Fragmentation Index		-0.562***		
		(0.119)		
Deviation in Parcel Size			-0.091	
			(0.062)	
Distance Travelled				-0.010**
				(0.004)
Total Household Area Farmed	-0.027**	-0.033***	-0.040***	-0.039***
	(0.012)	(0.012)	(0.013)	(0.013)
N	4768	4768	4768	4779

(b) **CSI and Land Fragmentation**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.163***			
	(0.043)			
Simpson Fragmentation Index		-2.502***		
		(0.548)		
Deviation in Parcel Size			-0.626**	
			(0.255)	
Distance Travelled				-0.076***
				(0.022)
Total Household Area Farmed	-0.152***	-0.150***	-0.174***	-0.168***
	(0.050)	(0.049)	(0.051)	(0.050)
N	4768	4768	4768	4779

Fragmentation measures fixed to first round. Sample limited to Ethiopian Highlands (Amhara, Tigray & Oromia). Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele, round. Household clustered standard errors in parentheses

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

Table 4.8: **Food Insecurity and Land Fragmentation, Inherited or Granted Parcels Only**

(a) **Months Hungry and Land Fragmentation**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.086***			
	(0.016)			
Simpson Fragmentation Index		-0.630***		
		(0.140)		
Deviation in Parcel Size			-0.223***	
			(0.082)	
Distance Travelled				-0.015***
				(0.005)
Total Household Area Farmed	-0.037***	-0.041***	-0.046***	-0.049***
	(0.014)	(0.014)	(0.015)	(0.016)
N	4843	4843	4843	4749

(b) **CSI and Land Fragmentation**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.291***			
	(0.095)			
Simpson Fragmentation Index		-3.628***		
		(0.936)		
Deviation in Parcel Size			-1.186***	
			(0.448)	
Distance Travelled				-0.070**
				(0.030)
Total Household Area Farmed	-0.201***	-0.190***	-0.221***	-0.237***
	(0.066)	(0.064)	(0.070)	(0.072)
N	4843	4843	4843	4749

Sample limited to households with parcels inherited or granted from local leaders.
Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, region and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.9: **Months Hungry and Land Fragmentation, Instrumental Variable**

(a) **First Stage**

	(1) Number of Parcels	(2) Simpson Fragmentation	(3) Deviation in Parcel Size	(4) Distance Travelled
Number of Parcels inherited or received from local authorities	0.730***	0.065***	0.052***	0.476***
	(0.025)	(0.003)	(0.004)	(0.057)
N	8853	8853	8853	8763
R^2	0.630	0.447	0.168	0.108

Standard errors in parentheses

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

(b) **Second Stage, Regressing on Months Hungry**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.064***			
	(0.012)			
Simpson Fragmentation Index		-0.718***		
		(0.131)		
Deviation in Parcel Size			-0.894***	
			(0.170)	
Distance Travelled				-0.102***
				(0.020)
Total Household Area Farmed	-0.055***	-0.052***	-0.033**	-0.026
	(0.012)	(0.012)	(0.013)	(0.016)
N	8602	8602	8602	8513

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects. Household clustered standard errors in parentheses

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

Table 4.10: **CSI and Land Fragmentation, Instrumental Variable**

(a) **First Stage**

	(1) Number of Parcels	(2) Simpson Fragmentation	(3) Deviation in Parcel Size	(4) Distance Travelled
Number of Parcels inherited or received from local authorities	0.730***	0.065***	0.052***	0.476***
	(0.025)	(0.003)	(0.004)	(0.057)
N	8853	8853	8853	8763
R^2	0.630	0.447	0.168	0.108

Standard errors in parentheses

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

(b) **Second Stage, Regressing on CSI**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.361***			
	(0.057)			
Simpson Fragmentation Index		-4.068***		
		(0.593)		
Deviation in Parcel Size			-5.194***	
			(0.793)	
Distance Travelled (km)				-0.555***
				(0.097)
Total Household Area Farmed	-0.166***	-0.151***	-0.038	-0.007
	(0.047)	(0.044)	(0.052)	(0.068)
N	8602	8602	8602	8513

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects. Household clustered standard errors in parentheses

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

Table 4.11: **Food Insecurity and Land Fragmentation, Poisson MLE**

(a) **Months Hungry and Land Fragmentation**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.075***			
	(0.008)			
Simpson Fragmentation Index		-0.389***		
		(0.053)		
Deviation in Parcel Size			-0.122***	
			(0.032)	
Distance Travelled				-0.012***
				(0.003)
Total Household Area Farmed	-0.115***	-0.136***	-0.151***	-0.147***
	(0.014)	(0.014)	(0.014)	(0.014)
N	8698	8698	8698	8445

(b) **CSI and Land Fragmentation**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.106***			
	(0.004)			
Simpson Fragmentation Index		-0.687***		
		(0.027)		
Deviation in Parcel Size			-0.172***	
			(0.016)	
Distance Travelled				-0.017***
				(0.001)
Total Household Area Farmed	-0.054***	-0.064***	-0.086***	-0.085***
	(0.005)	(0.006)	(0.006)	(0.006)
N	8698	8698	8698	8445

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar Somalie).
Not reported: controls for gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects. Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: **Food Insecurity and Land Fragmentation, Negative Binomial MLE**

(a) **Months Hungry and Land Fragmentation**

	Months Hungry			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.089***			
	(0.013)			
Simpson Fragmentation Index		-0.520***		
		(0.098)		
Deviation in Parcel Size			-0.169***	
			(0.057)	
Distance Travelled				-0.016***
				(0.005)
Total Household Area Farmed	-0.098***	-0.110***	-0.120***	-0.119***
	(0.018)	(0.018)	(0.018)	(0.018)
N	8698	8698	8698	8445

(b) **CSI and Land Fragmentation**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Number of Parcels	-0.143***			
	(0.020)			
Simpson Fragmentation index		-1.089***		
		(0.145)		
Deviation in Parcel Size			-0.247***	
			(0.082)	
Distance Travelled				-0.024***
				(0.006)
Total Household Area Farmed	-0.039**	-0.044***	-0.054***	-0.056***
	(0.016)	(0.016)	(0.015)	(0.015)
N	8698	8698	8830	8613

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar, Somalie)
Not reported: controls for gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.13: **Months Hungry and Land Fragmentation interacted with Rainfall, Pooled OLS**

	Months Hungry			
	(1)	(2)	(3)	(4)
Total rainfall in wettest quarter (mm)	-0.128***	-0.184***	-0.032	-0.117***
	(0.045)	(0.055)	(0.044)	(0.039)
Number of Parcels	-0.053***			
	(0.011)			
Number of Parcels* Total rainfall in wettest quarter (mm)	0.011			
	(0.007)			
Simpson Fragmentation Index		-0.434***		
		(0.109)		
Simpson Fragmentation Index * Total rainfall in wettest quarter (mm)		0.219**		
		(0.091)		
Deviation in Plot Size			-0.105*	
			(0.056)	
Deviation in Plot Size Total rainfall in wettest quarter (mm)			-0.094	
			(0.060)	
Distance Travelled				-0.006
				(0.004)
Distance Travelled * Total rainfall in wettest quarter (mm)				0.006*
				(0.004)
N	5861	5861	5861	5817

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar & Somalie).
Not reported: controls for farmed area, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.14: **CSI and Land Fragmentation interacted with Rainfall, Pooled OLS**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
Total rainfall in wettest quarter (mm)	-1.223***	-1.129***	-0.987***	-0.881***
	(0.209)	(0.259)	(0.194)	(0.171)
Number of Parcels	-0.153***			
	(0.056)			
Number of Parcels * Total rainfall in wettest quarter (mm)	0.138***			
	(0.036)			
Simpson Fragmentation Index		-2.446***		
		(0.548)		
Simpson Fragmentation Index * Total rainfall in wettest quarter (mm)		0.949**		
		(0.436)		
Deviation in Plot Size			-0.681**	
			(0.273)	
Deviation in Plot Size * Total rainfall in wettest quarter (mm)			0.517**	
			(0.242)	
Distance Travelled				-0.057**
				(0.023)
Distance Travelled * Total rainfall in wettest quarter (mm)				0.036**
				(0.018)
N	5838	5838	5838	5794

Fragmentation measures fixed to first round. Excludes cities, pastoral areas (Afar & Somalie).
Not reported: controls for farmed area, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.15: **Months Hungry and Geo-Variables**

(a) **Household Mean of Characterisitics**

	Months Hungry			
	(1)	(2)	(3)	(4)
$\overline{Distance}$	-0.007			
	(0.008)			
$\overline{Slope}$		-0.002		
		(0.005)		
$\overline{Elevation}$			0.000	
			(0.000)	
$\overline{Wetness}$				0.007
				(0.016)
N	8551	8573	8573	8573

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Household Standard Deviation of Characteristics**

	Months Hungry			
	(1)	(2)	(3)	(4)
$Distance^{sd}$	-0.080***			
	(0.021)			
$Slope^{sd}$		-0.022***		
		(0.006)		
$Elevation^{sd}$			-0.001***	
			(0.000)	
$Wetness^{sd}$				-0.028
				(0.026)
N	8552	8574	8574	8574

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.16: **CSI and Geo-Variables**

(a) **Household Mean of Characterisitics**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
$\bar{Distance}$	0.033			
	(0.043)			
$\bar{Slope}$		-0.012		
		(0.021)		
$\bar{Elevation}$			-0.000	
			(0.001)	
$\bar{Wetness}$				0.137
				(0.103)
N	8348	8348	8348	8348

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **Household Standard Deviation of Characteristics**

	Coping Strategy Index			
	(1)	(2)	(3)	(4)
$Distance^{sd}$	-0.057			
	(0.112)			
$Slope^{sd}$		-0.113***		
		(0.029)		
$Elevation^{sd}$			-0.003	
			(0.002)	
$Wetness^{sd}$				-0.349***
				(0.093)
N	8327	8349	8349	8349

Not reported: controls for total area farmed, gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.17: **Parcel Characteristics and Crop Grown, Probit**

	Maize (1)	Sorghum (2)	Teff (3)	Wheat (4)	Coffee (5)
Distance	-0.006***	-0.001	-0.001	0.002*	-0.004*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Slope	-0.010***	0.008***	-0.002*	0.001	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Elevation	-0.001***	-0.001***	-0.000***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wetness	-0.009*	-0.010*	0.030***	0.022***	-0.021***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
N	48468	48468	48468	48468	48468

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.18: **Land Fragmentation, Crop Diversity and Food Insecurity**

(a) **Number of Crops and Land Fragmentation**

	Number of Distinct Crops			
	(1)	(2)	(3)	(4)
$Distance^{sd}$	0.090***			
	(0.025)			
$Slope^{sd}$		0.023***		
		(0.008)		
$Elevation^{sd}$			0.003***	
			(0.001)	
$Wetness^{sd}$				0.129***
				(0.024)
N	5904	5918	5918	5918

Not reported: land area, controls for gender of household head, dependency ratio, size of household, asset index, Kebele and time fixed effects.
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) **CSI and Number of Crops**

	Months Hungry	CSI
	(1)	(2)
Number of Distinct Crops	-0.030*	-0.353***
	(0.016)	(0.071)
$Distance^{sd}$	-0.008	-0.154
	(0.023)	(0.106)
$Slope^{sd}$	-0.011	-0.126***
	(0.007)	(0.028)
$Elevation^{sd}$	0.000	0.001
	(0.001)	(0.002)
$Wetness^{sd}$	0.014	-0.352***
	(0.025)	(0.110)
N	5904	5753

Not reported: controls for area, Kebele ect...
Household clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 4.1: Incidence of food insecurity across regions

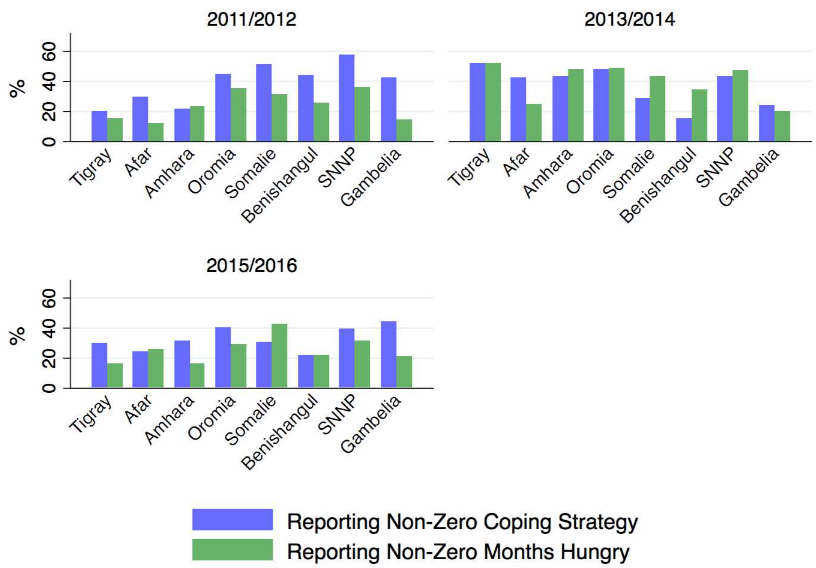


Figure 4.2: Illustration of land fragmentation

(a) Consolidated parcels

(b) Fragmented parcels

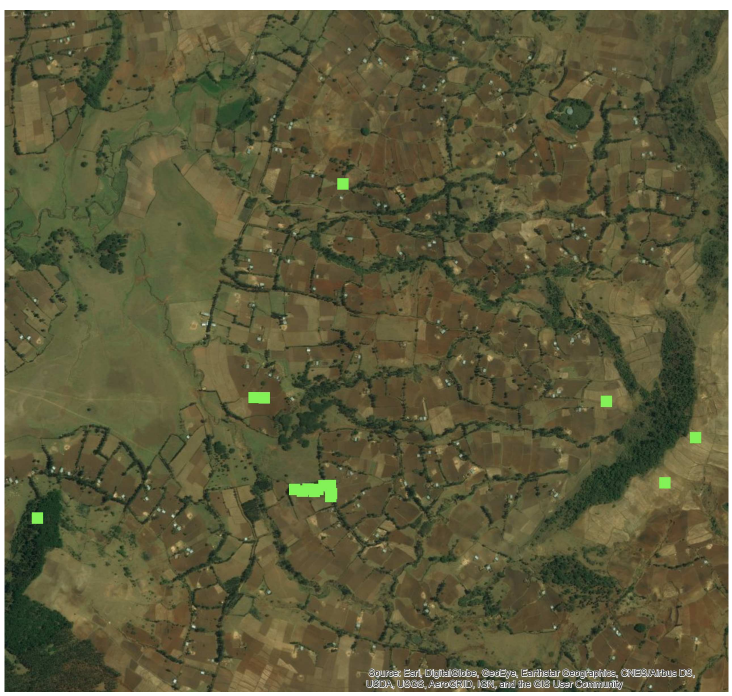
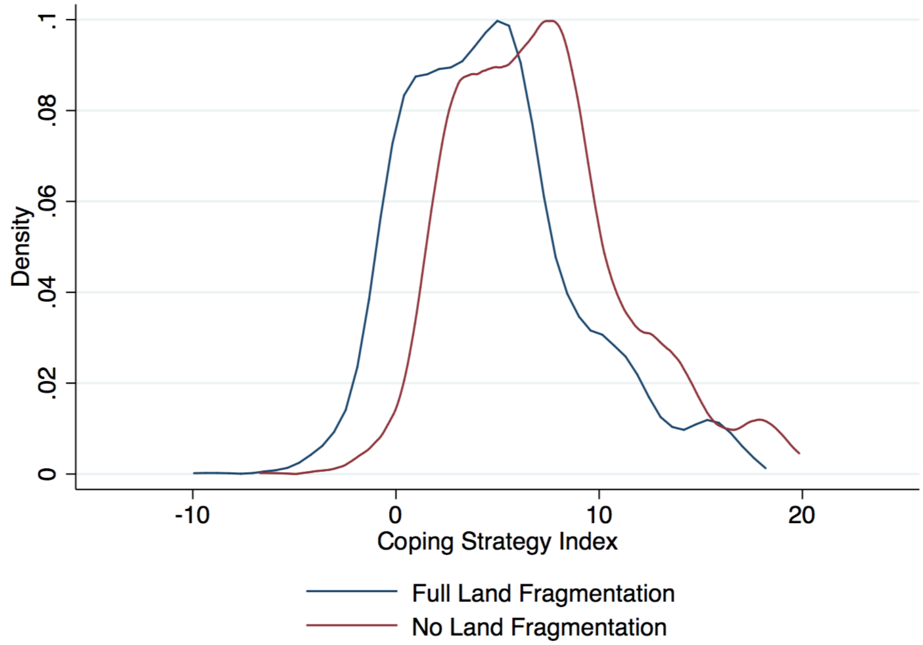
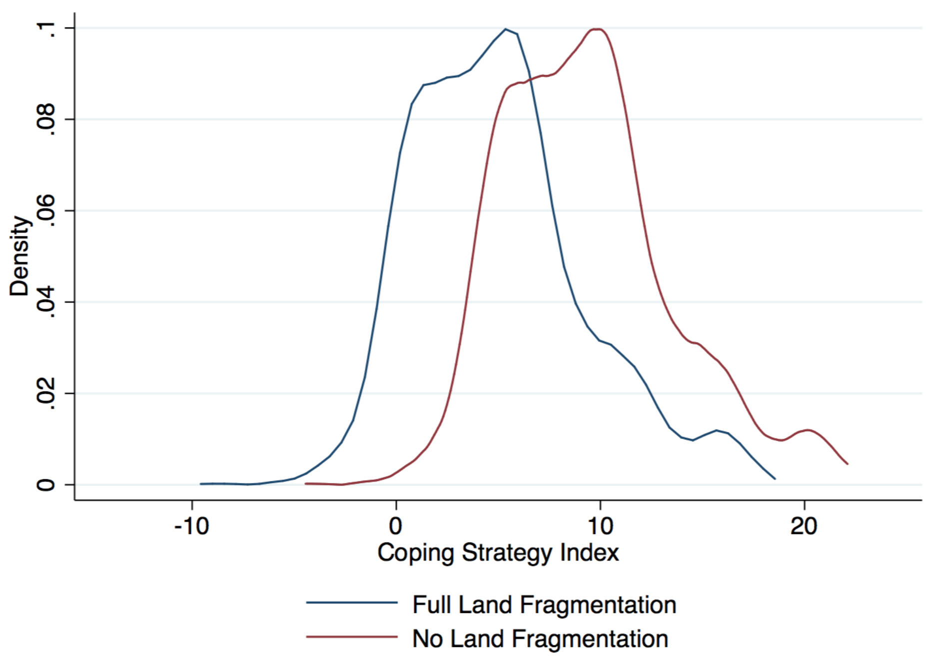


Figure 4.3: Distribution of Food Insecurity

(a) Non-Drought Year (Z-score= 0)



(b) Drought Year (Z-score= -2)



APPENDIX A

SUPPLEMENTARY TABLES TO CH 2

Table A.1: **IV with objective SPEI measure of drought occurence**

	(1)	(2)	(3)
PSNP Payment	0.103	-0.112	0.026
	(0.093)	(0.090)	(0.055)
Negative SPEI in past year	0.856	-1.101	-2.005***
	(0.783)	(0.729)	(0.770)
PSNP Payment * Negative SPEI in past year	-0.134	0.330**	0.403***
	(0.141)	(0.156)	(0.114)
PSNP Payment 2 years ago		0.016	-0.025
		(0.076)	(0.091)
Negative SPEI 2 years ago		-2.346***	-3.150***
		(0.718)	(0.957)
PSNP Payment * Negative SPEI 2 years ago		0.312***	0.381***
		(0.100)	(0.130)
PSNP Payment 4 years ago			0.083
			(0.071)
Negative SPEI 4 years ago			-1.710***
			(0.566)
PSNP Payment * Negative SPEI 4 years ago			0.269**
			(0.123)
N	8005	8005	8005
J-Test p-value	0.2857	0.3932	0.3861

SPEI: Standard Precipitation Evapotranspiration Index, negative values indicate drought conditions

t statistics in parentheses

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

Table A.2: **IV including USAID implemented Woredas**

	(1)	(2)	(3)
PSNP Payment	0.056**	0.076***	0.194***
	(0.027)	(0.023)	(0.023)
Drought in past year	-3.721***	-3.478***	-3.840***
	(0.862)	(0.426)	(0.507)
PSNP Payment * Drought in past year	0.410***	0.511***	0.479***
	(0.141)	(0.114)	(0.108)
PSNP Payment 2 years ago		0.174**	0.083*
		(0.069)	(0.045)
Drought 2 years ago		-0.781	-0.969**
		(0.737)	(0.378)
PSNP Payment * Drought 2 years ago		0.279	0.180*
		(0.199)	(0.105)
PSNP Payment 4 years ago			0.097*
			(0.051)
Drought 4 years ago			-0.318
			(0.465)
PSNP Payment * Drought 4 years ago			-0.086
			(0.142)
N	8623	8623	8623

Standard errors in parentheses

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

Table A.3: **IV excluding Direct Support Beneficiaries**

	(1)	(2)	(3)
PSNP Payment	0.015	0.045*	0.036***
	(0.041)	(0.024)	(0.014)
Drought in past year	-3.852***	-3.552***	-4.922***
	(1.273)	(0.362)	(0.542)
PSNP Payment * Drought in past year	0.415**	0.514***	0.590***
	(0.185)	(0.095)	(0.123)
PSNP Payment 2 years ago		0.138	0.050
		(0.090)	(0.051)
Drought 2 years ago		-1.373*	-2.118***
		(0.793)	(0.614)
PSNP Payment * Drought 2 years ago		0.331*	0.348***
		(0.171)	(0.125)
PSNP Payment 4 years ago			0.023
			(0.058)
Drought 4 years ago			-1.198**
			(0.484)
PSNP Payment * Drought 4 years ago			0.033
			(0.131)
N	6543	6543	6543

Standard errors in parentheses

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

Table A.4: **IV with HABP control**

	(1)	(2)	(3)
PSNP Payment	0.013	0.055**	0.116***
	(0.027)	(0.023)	(0.020)
Drought in past year	-3.798***	-3.775***	-4.142***
	(1.140)	(0.324)	(0.540)
PSNP Payment * Drought in past year	0.414**	0.513***	0.470***
	(0.179)	(0.092)	(0.118)
HABP	-0.340***	-0.245*	-0.403***
	(0.111)	(0.138)	(0.134)
PSNP Payment 2 years ago		0.037	0.031
		(0.088)	(0.047)
Drought 2 years ago		-1.698**	-1.457***
		(0.755)	(0.387)
PSNP Payment * Drought 2 years ago		0.370**	0.242**
		(0.175)	(0.095)
PSNP Payment 4 years ago			0.176***
			(0.068)
Drought 4 years ago			-0.054
			(0.471)
PSNP Payment * Drought 4 years ago			-0.151
			(0.125)
N	7075	7075	7075
Hansen J-Test	0.9224	0.5394	0.5867

Standard errors clustered at the village level in parentheses

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

Transfers are in 100 birr increments

Table A.5: **Poisson ML estimator with Fixed Effects**

	(1)	(2)	(3)
PSNP Payment	0.001*	0.001**	0.001**
	(0.001)	(0.001)	(0.001)
Drought in past year	-0.143***	-0.147***	-0.164***
	(0.015)	(0.015)	(0.017)
PSNP Payment * Drought in past year	0.002*	0.002**	0.002*
	(0.001)	(0.001)	(0.001)
PSNP Payment 2 years ago		0.002***	0.002***
		(0.001)	(0.001)
Drought 2 years ago		-0.030**	-0.049***
		(0.013)	(0.015)
PSNP Payment * Drought 2 years ago		0.001	0.001
		(0.001)	(0.001)
PSNP Payment 4 years ago			0.001
			(0.001)
Drought 4 years ago			-0.034**
			(0.015)
PSNP Payment * Drought 4 years ago			-0.002
			(0.002)
N	8005	8005	8005

Standard errors in parentheses

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

Table A.6: **Poisson ML estimator with Instrumental Variables**

	(1)	(2)	(3)
PSNP Payment	-0.007	-0.005	-0.001
	(0.005)	(0.005)	(0.005)
Drought in past year	-0.387***	-0.337***	-0.292***
	(0.065)	(0.077)	(0.080)
PSNP Payment * Drought in past year	0.030***	0.023***	0.015
	(0.007)	(0.008)	(0.011)
PSNP Payment 2 years ago		-0.007	-0.016
		(0.011)	(0.010)
Drought 2 years ago		-0.190***	-0.239***
		(0.052)	(0.056)
PSNP Payment * Drought 2 years ago		0.030***	0.041***
		(0.011)	(0.011)
PSNP Payment 4 years ago			0.009
			(0.012)
Drought 4 years ago			0.068
			(0.099)
PSNP Payment * Drought 4 years ago			-0.046
			(0.032)
N	8005	8005	8005

Standard errors in parentheses

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

Table A.7: **IV with Detrended Measure of Food Security**

	(1)	(2)	(3)
PSNP Payment	0.032	0.013	0.015
	(0.033)	(0.021)	(0.020)
Drought in past year	-3.185**	-3.340***	-4.426***
	(1.340)	(0.376)	(0.473)
PSNP Payment * Drought in past year	0.365*	0.475***	0.556***
	(0.214)	(0.105)	(0.111)
PSNP Payment 2 years ago		-0.062	-0.094
		(0.081)	(0.062)
Drought 2 years ago		-1.609**	-1.836***
		(0.714)	(0.440)
PSNP Payment * Drought 2 years ago		0.377**	0.337***
		(0.167)	(0.104)
PSNP Payment 4 years ago			0.069
			(0.083)
Drought 4 years ago			-0.934
			(0.587)
PSNP Payment * Drought 4 years ago			0.032
			(0.159)
N	8005	8005	8005

Standard errors in parentheses

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

APPENDIX B

MEASURING LAND IN CH4

B.1 Plot, Field and Parcel

The Ethiopian Living Standards Measurement Survey Integrated Survey on Agriculture (LSMS-ISA) is a household panel data set with three rounds collected in 2011-2012, 2013-2014, and 2015-2016.

Land data is collected at three levels of aggregation: parcels; fields; and plots. Plots are the smallest unit of analysis. Multiple plots can make up a field. Multiple fields make up a parcel; parcels are the highest land unit.

For example, consider a sample household who was interviewed in the 2013/14 survey round. She has two parcels of land, $Parc_1$ and $Parc_2$.

- $Parc_1$ is divided into two fields, $Parc_{1,F1}$ and $Parc_{1,F2}$.
  - $Parc_{1,F1}$ consists of a single plot ($Parc_{1,F1,P1}$).
  - $Parc_{1,F2}$ is divided into two plots ($Parc_{1,F2,P1}$, $Parc_{1,F2,P2}$).
- $Parc_2$ is divided into three fields, $Parc_{2,F1}$, $Parc_{2,F2}$ and $Parc_{2,F3}$.
  - $Parc_{2,F1}$ has two plots ($Parc_{2,F1,P1}$, $Parc_{2,F1,P2}$).
  - $Parc_{2,F2}$ has one plot ($Parc_{2,F2,P1}$).
  - $Parc_{2,F3}$ has one plot ($Parc_{2,F3,P1}$).

It is important to note that different data were collected at the parcel, field and plot level.

At the **parcel** level, the following data were collected on all parcels owned or rented in:

- Number of fields in parcel
- How parcel was acquired (granted by local leaders; inherited; rented in etc)
- Whether household has a land certificate for the parcel
- Details on parcels and/or fields rented in or out

At the **field** level, the following data were collected:

- Use during current season (farmed, fallow, etc)
- Size as reported by farmer
- Size as measured by GPS
- Size as measured by rope and compass
- Input use
- Crop Type
- Crop Yield

At the **plot** level, the following data were collected:

- Land characteristics: slope, elevation, distance from household and potential wetness index
- geo-spatial coordinates. [1]

[1] Due to confidentiality issues, we do not have access to the actual gps coordinates; however characteristics derived from these were made available.

At what level of aggregation (parcel, field, plot) should fragmentation be measured? To determine this, we note a number of additional features of the data collection on parcels, fields and plots:

- Unique parcel and field identifiers are available, which allow for merging data between modules within rounds, but no unique plot ids are available, which eliminates plot level comparisons as feasible.
- In rounds 2013/14 and 2015/16, parcel data from previous rounds was pre-filled; this means that, for existing parcels recorded in 2011/2012 enumerators returned to the same parcels in subsequent rounds. Further, information on parcels was collected in a consistent manner across all rounds with unique identifiers. This means that it is possible to construct a panel of parcels.
- It is difficult to construct a panel of fields. There are two reasons for this: (1) The numbering of fields is not consistent across rounds; and (2) In the 2015/16 round, no data were collected on fields that were not managed by the household (for example, fields that were rented out; fields that had been given as gifts to others etc).

This implies that we can calculate the following on a consistent basis across all three rounds:

1. For each round, the number of fields operated by the household and characteristics of those fields.
2. For each round, the number of parcels operated by the household. Aggregating the field data (with or without adjustments for the size of each field), we can construct aggregate characteristics of each parcel.

3. For each round, we can construct aggregate characteristics of the holdings operated by the household (with or without adjustments for the size of each parcel).
4. We can construct a panel of parcels operated by the household over all rounds.
5. We can construct a panel of land operated by the household over all rounds.

When merging land data across rounds, we noted the following issues driving attrition:

1. There was some data loss after the first survey round, partly because of households moving and partly because of errors in pre-populating the second round survey instrument with parcel level data.
2. There was also a change in methodology between rounds two and three. Previously enumerators continued collecting data on all the parcels surveyed in round one. However since a number of these parcels were subsequently rented our or used for sharecropping, this led to data inconsistencies. As a result, in round three enumerators only collected data on parcels being operated by the household. This means that we can consistently measure the size (and fragmentation) of land holdings operated by the household but not the size (and fragmentation) of holdings to which the household has access because, for round three, we have little information on parcels that were rented out.

B.2 Measuring Area

In order to measure area at the parcel level, we need to sum it from the field level measurements. The original data files contained a small number of duplicate observations; these, comprising approximately one percent of the data on parcels, were dropped.

Constructing a consistent measure for area from the various measures available was done through the following process.

We begin with field measures taken by GPS (measured in m^2). We divide these by 10,000 to convert to hectares. Fields larger than 20 hectares are considered outliers and are dropped. In order to ensure we were not missing a crucial element of variation we looked into the regional distribution of these 'large' reported parcels. Most of them seem to be in Oromiya or Tigray, though the largest one is in Somale. Either these reflect particularly large land-owners sampled, or enumerator error. In either case, we decide to exclude them from our principal analysis.

Table B.1: **Large Parcels Excluded from Dataset**

region	**mean**	**N**
Tigray	21.79	8
Afar	.	0
Amhara	.	0
Oromiya	31.15	14
Somalie	126.41	2
Benishangul Gumu	.	0
SNNP	81.22	2
Gambella	.	0
Harari	.	0
Dire Dawa	.	0
Total	39.45	26

Source: LSMS Ethiopia parcel dataset (round 1)

Across three rounds 10.4% of parcels were missing area measurements taken by GPS, the bulk of them in the first round. Where these data are missing, measurements were made either using rope-and-compass or were based on farmer self reports. Where GPS area data were missing but rope-and-compass were available, the rope and compass measures were used. For consistency these were similarly truncated below 20 hectares, though there were no outliers. This allowed us to recover half of the missing observations, as evidenced from the table below:

Table B.2: **Parcels Missing Measurements of Area**

Round	**Missing GPS AREA**	**Missing GPS+Plot & Compass**
2011/2012	18.6 %	4.37 %
2013/2014	6.4 %	6.39 %
2015/2016	6.4 %	6.39 %
Total	10.4 %	5.73 %

Source: LSMS Ethiopia parcel dataset (panel)

Self-reported holdings suffer from non-random measurement error (Carletto et al., 2015). To complicate matters further, many farmers report these using non-standard measures. The most widespread in Ethiopia is the 'Timad', traditionally the amount of land that can be plowed in a day. The LSMS Ethiopia documented district specific units of conversion. We therefore attempted to convert these self-reported measures to hectares, but this produced a large number of outliers. As an alternative, we tried using a standard conversion for the most common measure, the Timad, treating it as 1/4 of an acre in line with the FAO standard.[2]

As Table 5 shows, there were cases where both GPS and rope-and-compass measures or GPS and self-reported measures were obtained. This allows us to assess the correlation between these alternative ways of measuring land holdings.

[2] We only converted measures expressed in acres, hectares or Timad. Any other measures were converted as missing observations.

Table B.3: **Missing Area observations (Round 1)**

	Rope & Compass Area		
GPS Area	Not Missing	Missing	Total
Not Missing	458	25,658	26,116
Missing	4,570	1,401	5,971
Total	5,028	27,059	32,087

Source: LSMS Ethiopia parcel dataset (panel)

	Self Reported Area		
GPS Area	Not Missing	Missing	Total
Not Missing	25,656	460	26,116
Missing	5,568	403	5,971
Total	31,224	863	32,087

Source: LSMS Ethiopia parcel dataset (panel)

We regress the GPS reported area against four alternative measures: (1) the area measured using rope and compass, (2) self reported area converted into acres using the conversion rates provided in the dataset, (3) self reported area where Timad was converted into acres at the rate of 8 Timads to an acres, and (4) self-reported area in its original units.

The coefficients confirm that for the small overlapping set GPS and Rope & Compass area are strongly correlated and one accounts for almost half the variation in the other ($R^2 = .44$). But irrespective of the conversion we use, the coefficients on self-reported areas are small and the R^2 low, one that barely improves when we attempt to convert the reported areas into standard hectares. We therefore use the rope-and-compass measures when GPS measured area is not available. However, we do not use the farmer self-reported area data.

Table B.4: **Correspondence between Area Measures**

	(1)	(2)	(3)	(4)
	$area_{gps}$	$area_{gps}$	$area_{gps}$	$area_{gps}$
area (rope & compass)	1.004***			
	(0.00980)			
area (self-reported 1)		0.0000479***		
		(0.00000809)		
area (self-reported 2)			0.0000525***	
			(0.00000859)	
area (self-reported original)				0.0000841***
				(0.00000692)
_cons	0.00271***	0.184***	0.188***	0.132***
	(0.000741)	(0.00187)	(0.00225)	(0.00121)
N	458	25,656	25,656	25,656
r2	0.440	0.000702	0.000942	0.00165

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

Standard errors in parentheses. Self Reported 1 uses conversion rates provided by the dataset.
Self Reported 2 uses a standard 1/8 hectare conversion rate from the Timad. Orig uses no conversion.

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