Resilience, Shocks, and the Dynamics of Food Insecurity
Evidence from Malawi *

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Abstract

We seek to understand vulnerable households' food insecurity dynamics and their ability to cope with shocks. We draw on the poverty literature and posit resilience as a latent variable capturing the stochastic dynamics of households' food insecurity, measured using the Coping Strategy Index, a good proxy in a humanitarian emergency. In order to inform our analysis empirically, the 'Measuring Indicators for Resilience Analysis' project collected 12 months of data in Malawi. In order to illustrated the usefulness of this novel data-set, we demonstrate three approaches to measuring resilience. We first postulate resilience as the non-persistence of subjective shocks over time. We find that households living in the flood plain and those with fields far from home are more resilient to drought. Using a Blundell-Bond estimator, we estimate the conditional distribution of food insecurity. We find that differences in the quantity of land farmed and having fields far from home shift the distribution of food insecurity. Finally, we use LASSO and Random Forest algorithms to identify predictors of future food insecurity. We find that previous food insecurity, living in the flood plain and distance to drinking water are consistently good predictors. Food insecurity is concentrated in specific geographic areas, emphasizing the importance of targeting.

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, 2014) 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). Though differing in the details, a broad consensus exists that resilience focuses on the underlying parameters that determine a system or an individual's ability to restore equilibrium following a shock.

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). 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." How then to measure resilience?

One methodological approach look at resilience as the perceived persistence of specific shocks. 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 (2014) 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. However, the third stage regression $\hat{p}(x, z) = \beta X + \gamma Z$ restricts variation to the observables, generating a very high R^2. By reusing the same functional form three times, it risks compounding any bias due to misspecification. It also necessarily posits an arbitrary poverty line in order to construct its probabilistic measure of resilience. We will therefore draw from Barrett and Constas (2014) conceptually but use a methodological approach that differs from Cissé and Barrett (2016).

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. Separately, Jean et al. (2016) show how running an image recognition algorithm through publicly available satellite imagery significantly improves geographic poverty targeting. 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 autoregressive 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:

1. Resilience as the perceived persistence of shocks.
2. Resilience as changes in the distribution of food insecurity.
3. Resilience as predictor 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. Each draws from the literature to tackle the concept of resilience in a slightly different way, finding the key characteristics that make a household more or less resilient.

We start with an analysis estimating the persistence of subjective shocks, reasoning that households which recover faster are 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 measure food insecurity using the Coping Strategy Index. We use a Blundell-Bond estimator to trace households' food insecurity trajectories as a stochastic distribution, explicitly allowing for explanatory covariates that may shift this trajectory. We again find that having fields far from home and the gender of the household head shift the distribution of CSI. We also find that the amount of land farmed 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.

2 Data

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 Malawi—Chikwawa, 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 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.

A final endline survey was rolled out in June 2017, with questions mirroring those of the baseline survey to provide a classic baseline-endline panel.

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 obviously 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.[1] 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 1 illustrates the 2015 flood-zones and sampled households.

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 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 household level, the household is used as the unit of analysis.

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

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).[2]

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 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.[3] Table 2 summarizes these statistics. We use these to create subgroups 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.[4] 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 perception of a shock rather than its objective inci-

[2]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

[3]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.

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

dence, 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 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.[5]

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

$$CSI = \sum_{c}^{C} w_c * days_c \tag{1}$$

Where $days_c$ is the number of days a household had engaged in a given coping 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 and 4 illustrate the non-parametric CSI trajectories disaggregated

[5] 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.

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, 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 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 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.

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 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.

In order to investigate whether this attrition is non-random we first ran a probit regression of baseline characteristics on the incidence of missing observations across the entire sample. $Missing_{i,t} = 1$ if we have no observation for household i in period t, and $Missing_{i,t} = 0$ otherwise. As we see from table 4, both living in a flood plain and having a secondary house were positively correlated with the probability of the observation being missing. This is unsurprising, as the frequent washout of roads made access difficult for enumerators. Households with a secondary house were more likely to be away cultivating their distant fields. We also notice significant time effects independent of household characteristics. We therefore control for this in our specification, allowing for non-stationarity.

Furthermore, to control for this non-random attrition, we use a Heckman style two step estimator (Heckman, 1979). Similarly to Lillard and Panis (1998), we run the probit and use the predicted outcome to generate the household level inverse Mills ratio $\hat{\lambda}$. In our supplementary tables, we rerun our specifications using $\hat{\lambda}$ as a control. It registers as barely significant and does not significantly change the size or magnitude of our results.

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 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 $Z^s_{i,t+1} = 1$. Households could therefore experience multiple shocks at once and fluctuate in and out of experiencing a given shock over time.

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:

$$Pr(Z^s_t = j | Z^s_{t-1} = k) = p_{kj} \tag{2}$$

Where $k, j \in \{0, 1\}$.
To estimate shock persistence, we use an auto-regressive (AR) linear probability model with one lag.[6]

$$Z^s_{i,t} = \gamma_0 + \gamma^s_1 Z^s_{i,t-1} + \gamma'^s_t (Z^s_{i,t-1} * \delta_t) + \delta_t + \mu^s_i + \epsilon_{i,t} \tag{3}$$

where γ^s_1 conditions the perceived shock s on previously experiencing shock s, γ'^s_t allows this persistence to vary by round, δ_t is a monthly time fixed effect and μ^s_i

[6]Our results are robust to additional lags.

is a household fixed effect. With a linear probability model, the coefficients have an intuitive interpretation: $p^s_{0,1} = \gamma^s_0 + \delta_t$ is the probability of experiencing the adverse effects of a given shock, conditional on not experiencing them previously. $p_{1,1} = \gamma^s_0 + \gamma^s_1 + \gamma'^s_t + \delta_t$ is the probability a shock's adverse effects will persist into the next period. γ^s_t and δ_t allow for a non-stationary process since the transition probability can change over time.[7]
We can present our estimated coefficients as a Markov Transition matrix:

	$Z^s_{i,t} = 0$	$Z^s_{i,t} = 1$
$Z^s_{i,t-1} = 0$	$p^s_{0,0} = 1 - (\gamma^s_0 + \delta_t)$ (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.

3.2 Estimating Shock Persistence

We estimate equation (3), the persistence of shocks over time. We take the four most frequent shocks: $S = \{$drought, flooding, crop disease illness$\}$ and regress them against their own values, lagged by one month. Table 5 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 $\hat{\gamma}^s_0$ and $\hat{\gamma}^s_1$ 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.[8]

With four shocks and 11 rounds[9], 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;

[7] 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.
[8] This is done by setting the relevant time dummy, i.e. $\delta_{May2017} = 0$ and $\gamma^s_{May2017} = 0$.
[9] We lose one round by construct due to the lag

February (round 9), the height of the hungry season; and May (round 12), when the harvest comes in (Malcomb et al., 2014). Tables 6, 7, 8 and 9 present these transition matrices across months for our four shocks of interest.

Recall that $\hat{p}^s_{1,1} = \hat{\gamma}^s_0 + \hat{\gamma}^s_1 + \hat{\gamma}^s_t + \delta_t$ is the persistence of shock s, the probability that a household continues experiencing its adverse effects one month later. As an illustration, from table 6a, 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 6b) and 86.1% in May (table 6c).

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 7a), by May (table 7c) 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 8. Figure 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 9a with $\hat{p}^s_{0,1} = 15.1\%$ but this rapidly climbs to 44.8% in table 9b and 41.9% in table 9c. It makes sense that the adverse effects of crop disease are most acute when the planted harvest is nearing maturation. Figure 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 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:

$$\hat{\rho}^s_{i,t} = \alpha_0 + \alpha_1 X_i + \zeta_{i,t} \tag{4}$$

allowing us to infer the correlation between these fixed effects and household characteristics $\frac{\delta \hat{\rho}^s_{i,t}}{\delta X_i} = \hat{\alpha}_1$.[10] Characteristics with a negative correlation

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

reduce the persistent effects of a shock, increasing a household's resilience.

We estimate equation (4) using the observed characteristics from the baseline. Figure 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.

4 Resilience as Distribution of Food Insecurity

An alternative to looking at the persistence of specific shocks is to think of resilience as the stochastic distribution in food insecurity outcomes $y_{n,t}$. As discussed earlier, 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. Households which are resilient should experience decreasing levels of CSI over time as they recover, while non-resilient households should experience persistently high or increasing levels of CSI.

We then 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. These changes in distribution can inform us about characteristics contributing to resilience.

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:

$$Y_t = F(Y_{t-1}, Z_t | X) \tag{5}$$

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.[11] X represents conditioning 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 $\psi_{t-1}(y_{t-1})$:

$$\psi_t(y_t) = \int p(y_t, y_{t-1})\psi_{t-1}(y_{t-1})dy_t \tag{6}$$

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:

$$F_t(y_t) = \int G(y_t, y_{t-1})F_{t-1}dy_t \tag{7}$$

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

$$G(y_t, y_{t-1}) := \mathbb{P}\{\beta_0 + \sum_{k=1}^{K} \beta_k y_{t-1}^k + \xi_t \leq y_t\} \tag{8}$$

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:

$$y_{i,t} = \beta_0 + \sum_{k=1}^{K} \beta_k y_{i,t-1}^k + Z_{i,t} + \delta_t + \epsilon_{i,t} \tag{9}$$

and plotting the predicted distribution. For robustness, we control for observable shocks with $Z_{n,t}$.[12] 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 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

[11] 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.

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

below the median value.

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:

$$y_{nt} = \alpha y_{n,t-1} + \eta_i + \upsilon_{nt} \tag{10}$$

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.

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.[13] As we observed in figures 3 and 4, there was an acute food crisis 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 10. 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.[14]

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.[15] 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 14a. 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.[16]

In order to interpret the results from table 10 more intuitively, 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 in figure 7. This is the expected change in CSI next month, averaged over the sample or relevant sub-sample. Estimating a higher order polynomial gives us a non-symmetrical distribution. The distribution of expected change in CSI is particularly right skewed for the first half of the year, as most households are experiencing a persistent food emergency. Even in the 2nd half of the year, most households can expect increasing levels of CSI, and therefore greater food insecurity in the future. However, a long, fat tail on the left suggests there are households who can expect diminishing levels of CSI, and therefore a reduced level of food insecurity.

We estimate equation (9) for sub-samples of the population to identify the defining characteristics of these resilient households. This conditions the

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

[14] 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.

[15] 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.

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

distribution of our expected outcomes on characteristics X_n. Tables 11, 12 13 and 14 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.

As before, in order to interpret these results intuitively we predict the change in CSI conditional on these characteristics and project the resultant distribution. 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 8 and 9. From figure 8a, 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 8b, 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 9a, 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 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 resilience by shifting the predicted distribution of ΔCSI are gender, access to land and owning a secondary house.

5 Resilience as Predictor of 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.

Though a wide array of popular supervised machine learning tools exist, the general premise is straightforward.[17] 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. 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. 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.[18]

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.[19] After this cleaning process, we were left with an $\mathbb{R}^d$ space of predictors, where d=79 variables.

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 $\lambda'\|\beta\|$.[20] The modified least squares operator is therefore

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

[18]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.

[19]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.

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

$$\min_{\beta \in \mathbb{R}^d} \left\{ \frac{1}{N} \sum_{i=1}^{N} (Y_{i,t} - \beta X_{i,t})^2 + \lambda \|\beta\| \right\} \tag{11}$$

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. We then compute the mean coefficient and its standard deviation and keep the 10 most significant variables.[21] We report these predictors in table 15. 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 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 $R^2 = 56.4\%$.

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

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.

$$\min_{js}[\min_{c_1} \sum_{x_i \in R_1(j,s)} (y_i - C_1)^2 + \min_{c_2} \sum_{x_i \in R_2(j,s)} (y_i - C_2)^2] \tag{12}$$

where

$$c_1 = \frac{1}{n}\sum_i (y_i | x_i \in R_1(j,s)) \text{ and } c_2 = \frac{1}{n}\sum_i (y_i | x_i \in R_2(j,s)) \tag{13}$$

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_j^b. 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 16. 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.[22] The quality of a households roof and whether anyone in the household is pregnant or nursing round of the top ten variables selected.

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

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 $R^2 = 55.6\%$.

Five of the top ten variables overlap or are very similar. Previous month's CSI is the best predictor in both cases, followed closely by geographic location as indicated by group village head. Other good predictors include the household's 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 of collecting monthly data from these sentinel sites.

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 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.

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.

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Tables

Table 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 2: **Household Co-variates**

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: **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 4: **Determinants of Missing Observations, Probit**

	Missing
Land Farmed (HA)	-0.0202*
	(0.0119)
Tropical Livestock Units	0.00741
	(0.00826)
Flood Plain	0.358***
	(0.0425)
Secondary House	0.295***
	(0.0512)
Age of HH Head	-0.000831
	(0.00147)
Education	0.00267
	(0.00576)
Gender	-0.0630
	(0.0548)
Chronically ill or Disabled	-0.0952
	(0.0582)
July	-0.892***
	(0.103)
August	-1.203***
	(0.120)
September	-1.089***
	(0.113)
October	-1.096***
	(0.114)
November	-0.736***
	(0.0970)
December	0.130
	(0.0807)
January	0.0834
	(0.0817)
February	-0.106
	(0.0836)
March	-0.274***
	(0.0857)
April	-0.128
	(0.0837)
May	-0.906***
	(0.109)
N	6215

The above were used to generate a Heckman style inverse Mills ratio $\hat{\lambda}$
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: **Lagged effect of Most frequent shocks, OLS**

	(1) Drought	(2) Flooding	(3) Illness	(4) 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 $\delta_{t=May2017} = 0$.
Clustered standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: **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 $\hat{\delta}_{Nov2016}$, where s=drought, in table 5, 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 $\hat{\delta}_{Feb2017}$, where s=drought, in table 5, 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 $\hat{\delta}_{May2017}$, where s=drought, in table 5, column (1)

Table 7: **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 5, 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 5, 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 5, column (2)
*though $\hat{\gamma}^{Flood}_1$ is insignificant, the sum of the two coefficients is significant

Table 8: **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 5, 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 5, 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 5, column (3)

Table 9: **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 5, 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 5, 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 5, column (4)

Table 10: **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 11: **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 12: **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 13: **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 14: **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 15: **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 16: **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

Table 17: **Most parsimonious specification from LASSO**

	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)

Out of sample performance on testing set (April, May): $R^2 = 56.4\%$

Bootstrapped standard errors in parentheses

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

Figures

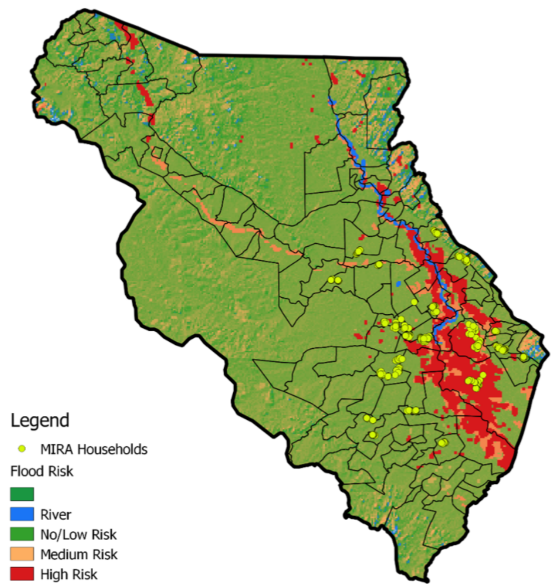


Figure 1: MIRA households and incidence of 2015 flooding from the Dartmouth Flood Observatory (Brakenridge and Anderson, 2004)

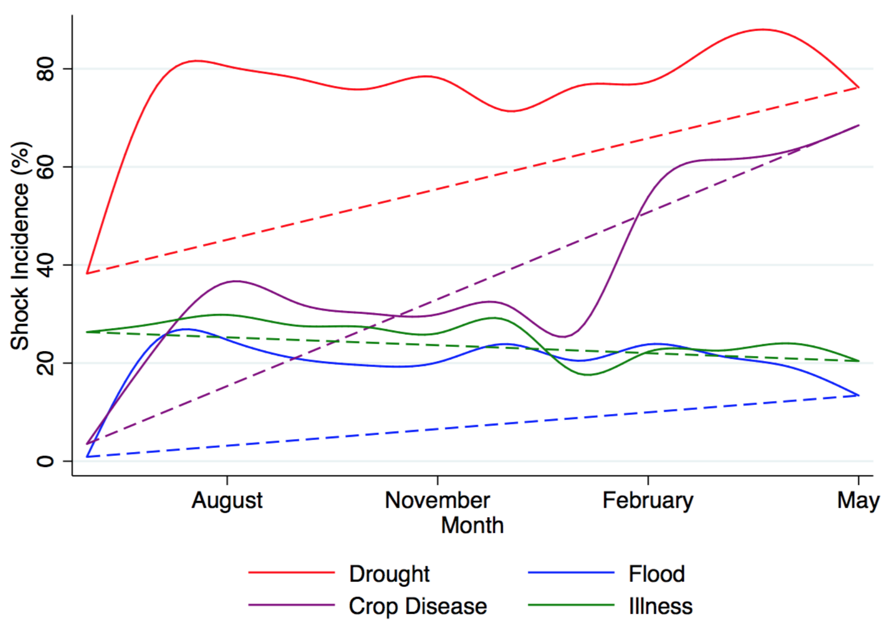
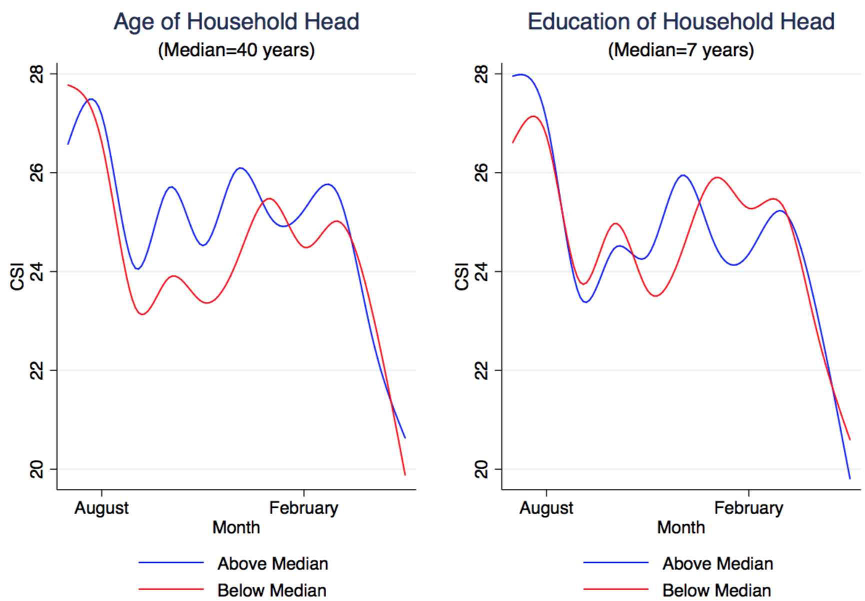
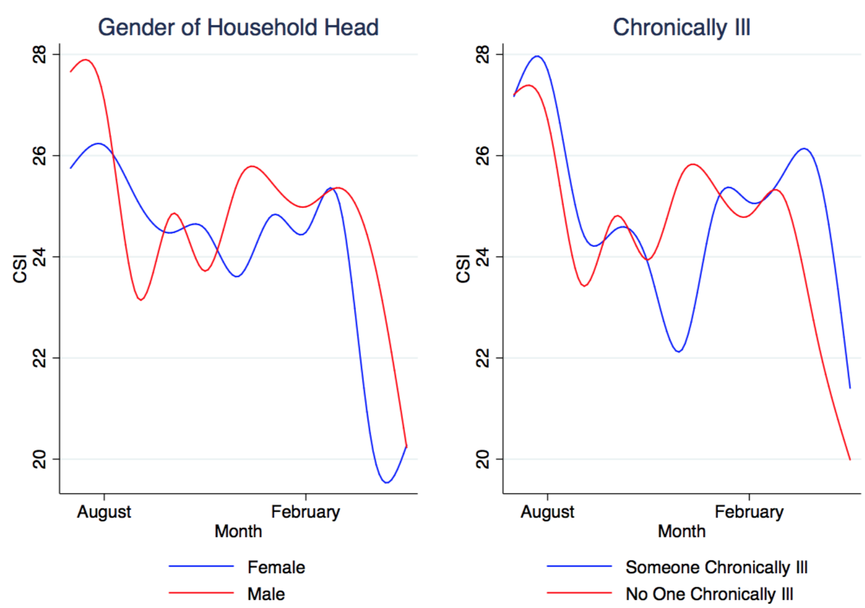


Figure 2: Most frequent shocks reported

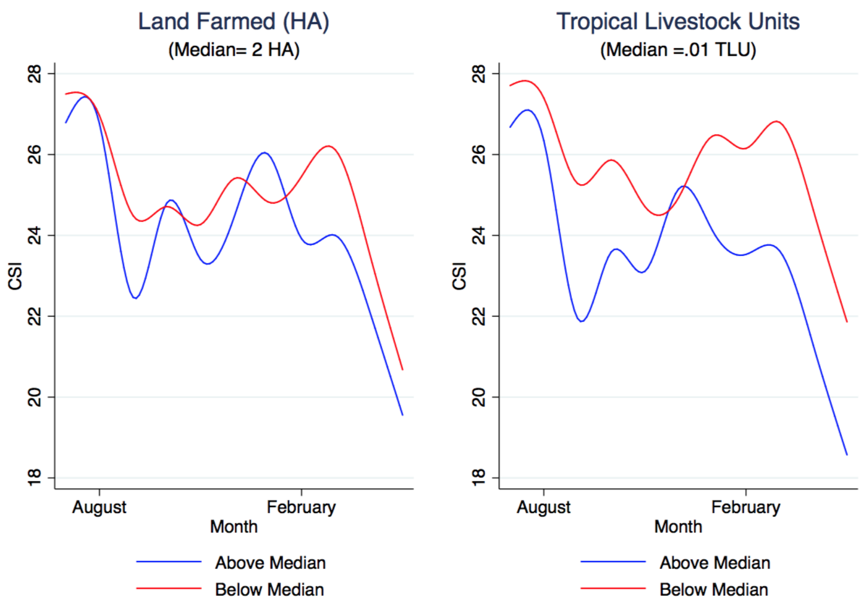


(a)

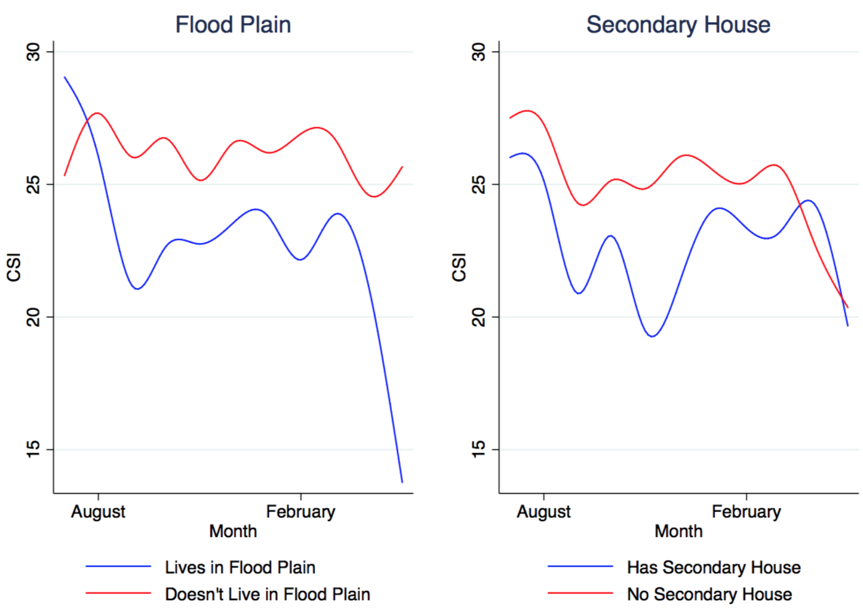


(b)

Figure 3: Trajectory of Coping Strategy Index disaggregated by demographic characteristics

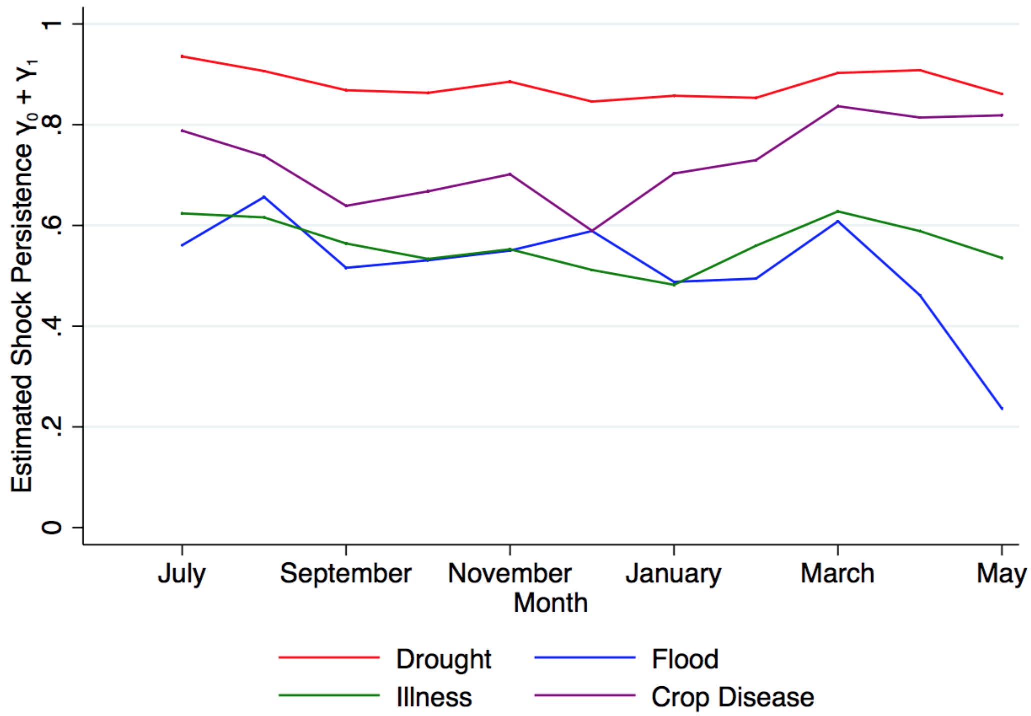


(a)

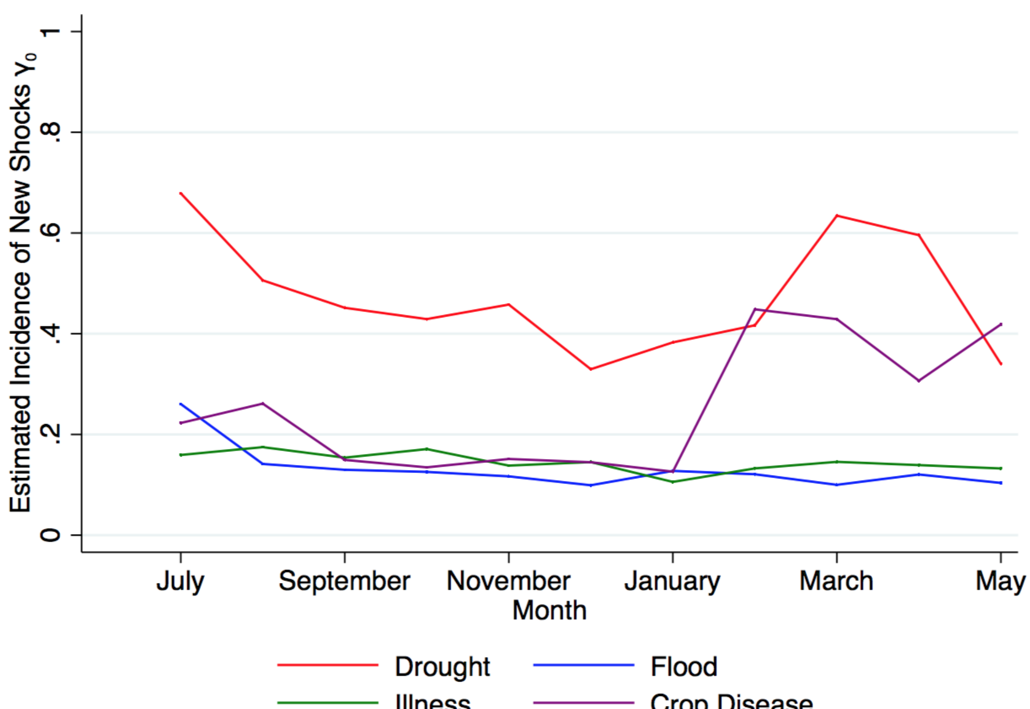


(b)

Figure 4: Trajectory of Coping Strategy Index disaggregated by assets and geographic characteristics



(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 5: Illustration of the parameters calculated from table 5 as they vary by round.

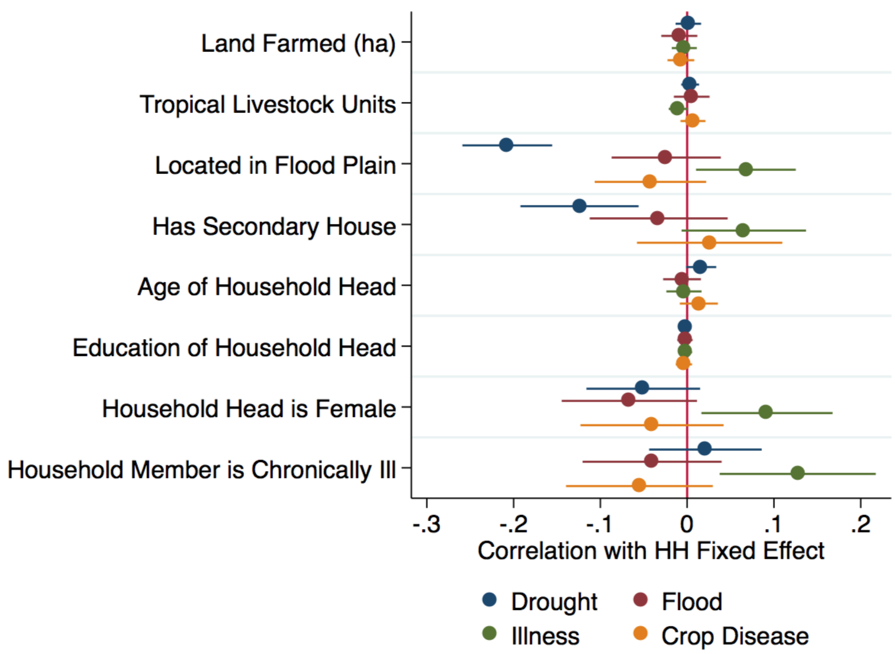


Figure 6: Correlation between estimated shock specific probability $\hat{\rho}^{s}_{i,t}$ and household characteristics (bootstrapped s.e)

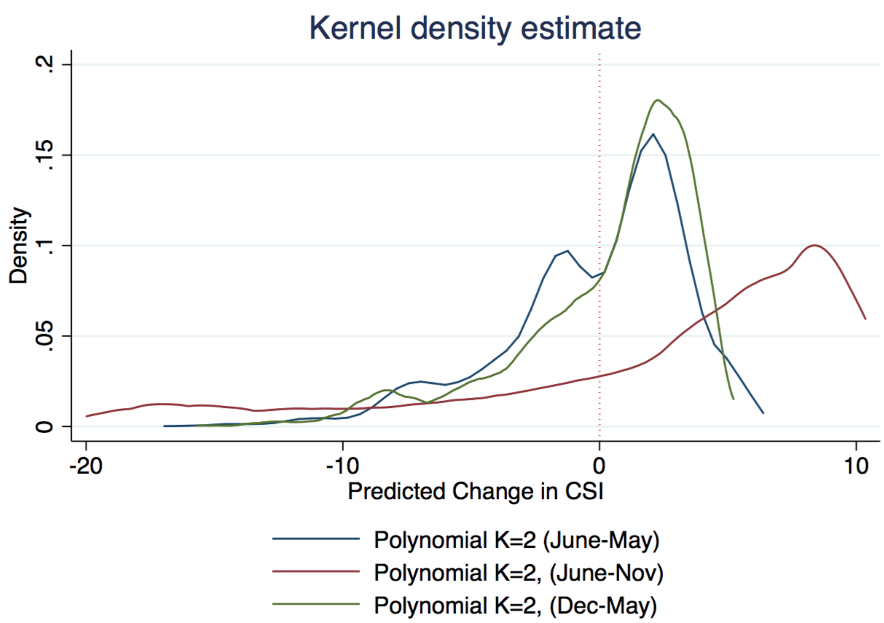
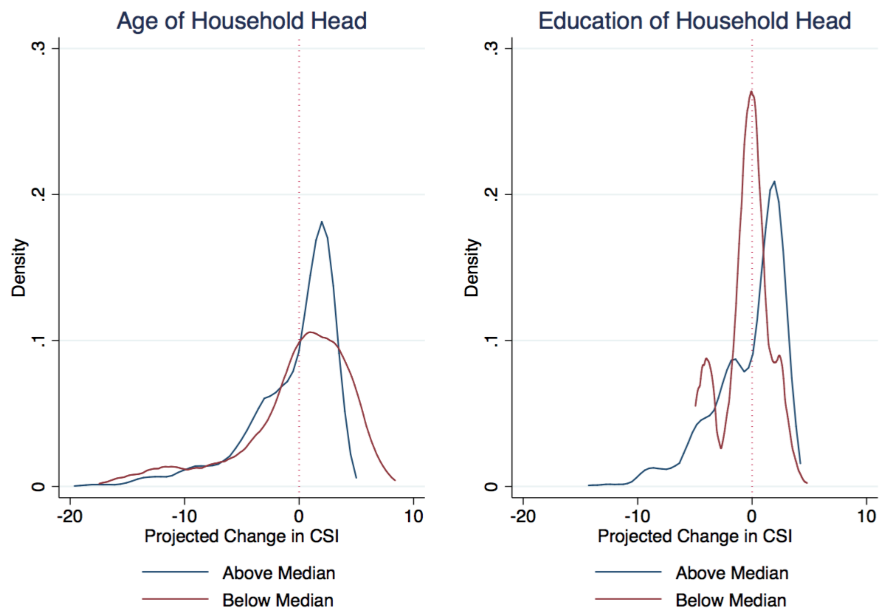
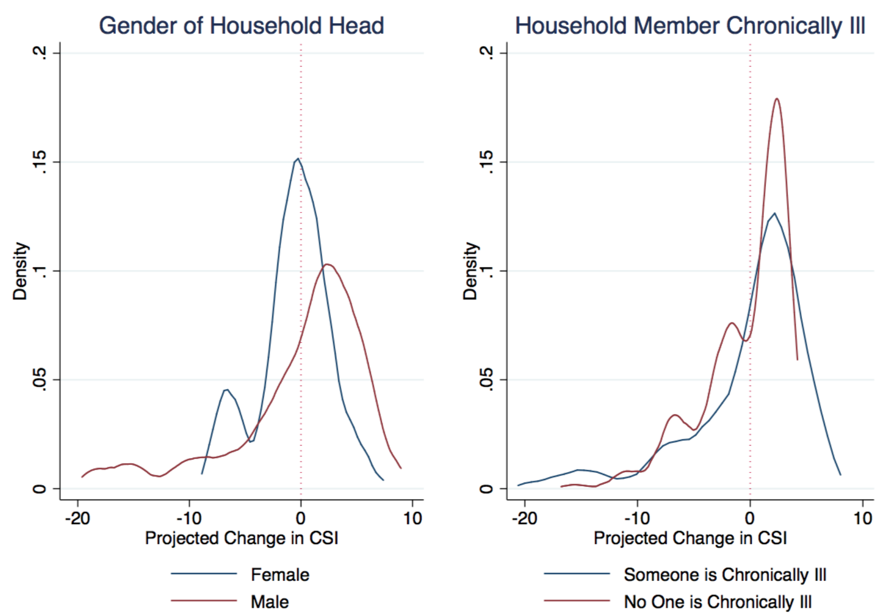


Figure 7: Predicted probability distribution functions for Δ CSI from table 10

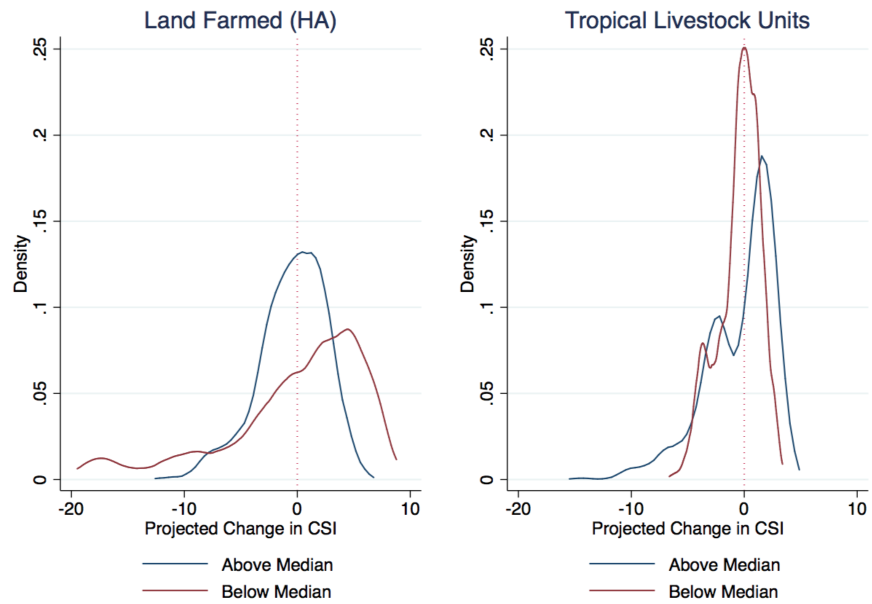


(a) Predicted from table 11, col (3) and (6)

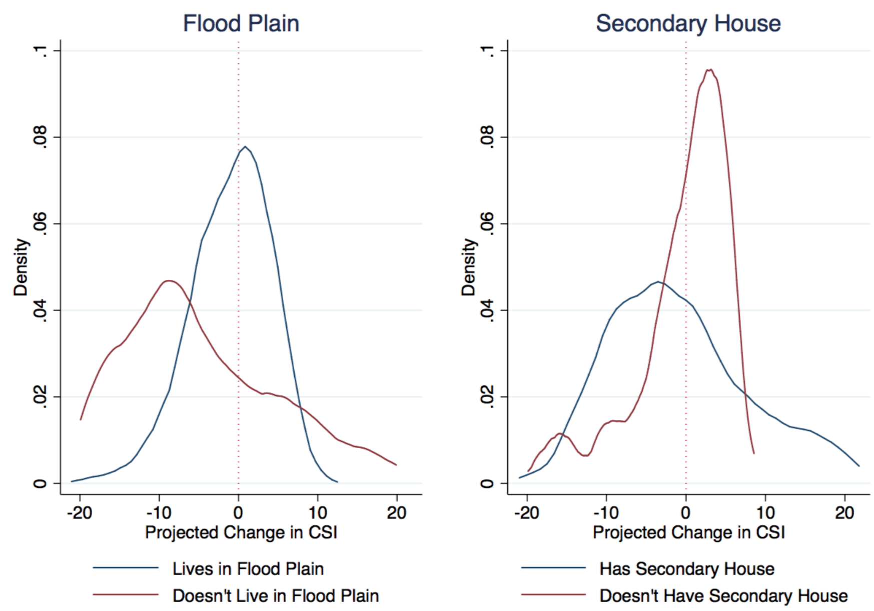


(b) Predicted from table 12, col (3) and (6)

Figure 8: Predicted probability distribution functions for Δ CSI for December through May, conditional on demographic characteristics



(a) Predicted from table 13, col (3) and (6)



(b) Predicted from table 14, col (3) and (6)

Figure 9: Predicted probability distribution functions for Δ CSI for December through May, conditional on assets and location

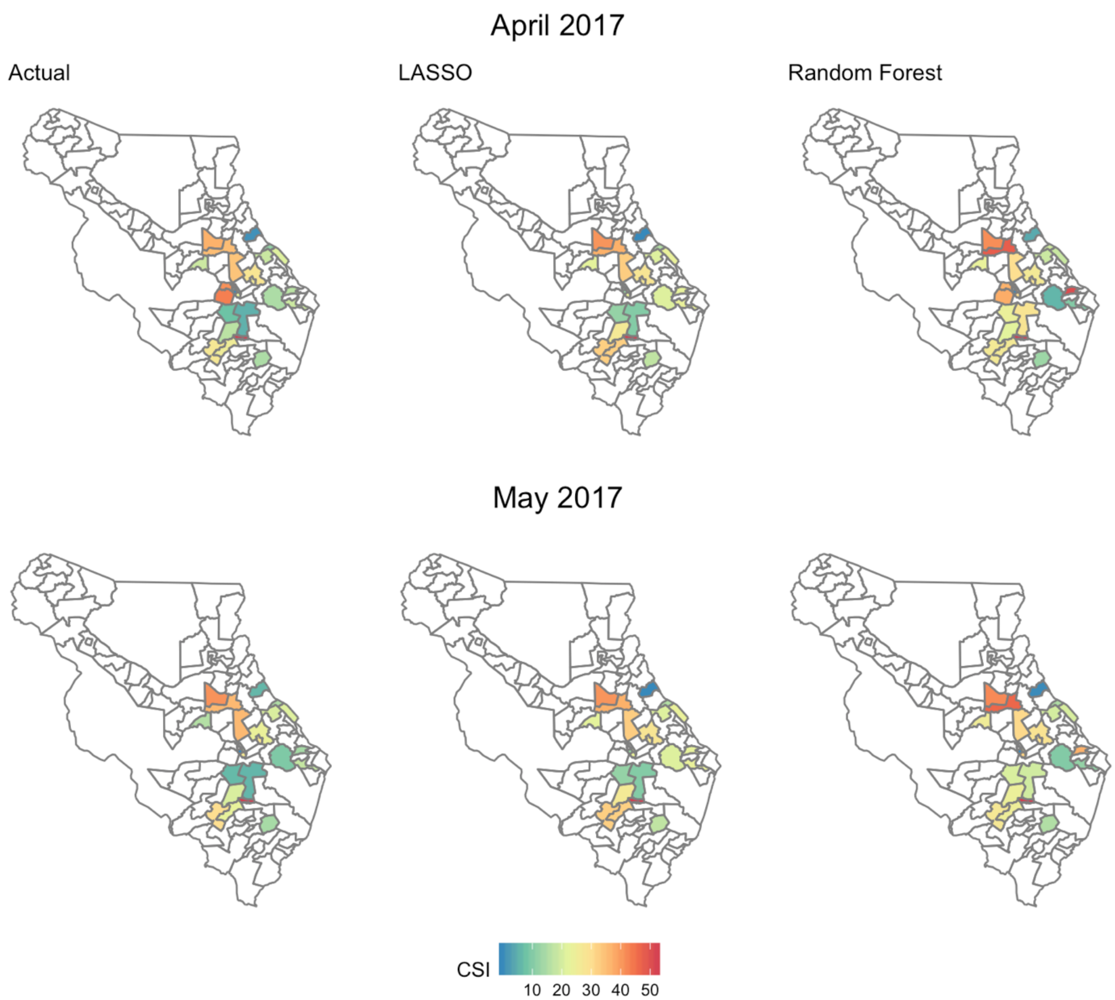


Figure 10: Actual and predicted CSI in April and May