SHOCK METRICS FOR RESILIENCE ANALYSIS:
AN INVESTIGATION OF THE RELATIONSHIP BETWEEN SUBJECTIVE AND OBJECTIVE INDICATORS

A Thesis

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ABSTRACT

As shocks become more prevalent, virulent, and widespread, their adverse consequences are expected to disproportionally affect those who are most vulnerable. The recent interest in resilience highlights the need for more precise measurements of shocks. This study investigates the extent to which subjective and objective measures of drought shocks are correlated. It also attempts to determine the factors, beyond “objective” measured rainfall, that determine households’ self-report of drought. First, I investigate whether type of employment, irrigation sources, and socioeconomic status explain the heterogeneity in drought reports. Second, I estimate the effects of the timing of interview on the probability of reporting a drought and the extent to which shock reports are path dependent. Using a panel of 1,298 households from India, the analysis reveals a negative but imperfect correlation between self-reported drought and measured rainfall. I find that wealthier households are more likely to report drought at low levels of rainfall. While rain dependent occupations are positively correlated with drought reports, I find no evidence of correlation with type of irrigation. The timing of survey interviews proves to be important: households interviewed during the rainy season are less likely to report a drought. I also find evidence for the path dependency of self-reports.

BIOGRAPHICAL SKETCH

Dieynab Diatta was born in Dakar, Senegal, and spent her most formative years abroad. At the age of 16, she attended high school in Norway at the United World College, where she obtained her International Baccalaureate diploma. She completed her Bachelor of Arts degree in Economics and International Studies at Macalester College. She later spent a year working as a consultant for the World Bank and the UN Economic Commission for Latin America and the Caribbean in Washington, DC. She then pursued a Master of Science degree in Applied Economics at Cornell University. She will be moving to Rome, Italy to work as a consultant for the UN Fund for Agricultural Development.

Pour Papa,

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I would like to express my deepest gratitude to my chair, Mark A. Constas, for inspiring the research that I have completed here, for his guidance, encouragement, and patience as I navigated different stages of the research process. He has not only helped me to become a seasoned researcher but has also shown great care for my professional and personal development. I am indebted to my other committee member, John F. Hoddinott, for guiding my research, providing feedback on my work, and his willingness to step in whenever necessary. I am grateful for all the hours they have committed to working with me on this research project, helping me to ask the right questions.

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Thank you to my family and friends for their support. I would like to thank my mother and father, who have provided me with great emotional support and heartfelt prayers. Thank you to my sister Marieme and my friend Leila for discussing with me the earliest formulations of my research ideas.

He who is not thankful to people is not thankful to God. All praises belong to God.

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Chapter I – Introduction

The increased occurrence of shocks and stressors in developing countries is a major hindrance to the sustainable well-being of households and communities. As the frequency and severity of shocks increases around the world, those in the most vulnerable regions, are expected to be disproportionally affected (UNISDR, 2015). Resilience as an area of study within development recognizes that sustainable development is tied to the capacity of people and communities to withstand and recover from recurrent shocks and stressors that disrupt their livelihoods. Constas et. al (2014, p. 4) define resilience as the "capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences." Barrett and Constas provide a similar definition working on a theory of development resilience (Barrett and Constas 2014). Both of these definitions imply ex ante and ex post actions taken to avoid and cope with the effects of shock exposure on well-being. At the core of the study of resilience, therefore, is understanding the properties of shocks and stressors, how they are measured empirically, and more important identifying the channels through which they affect people's well-being.

Efforts have been made to provide clear guidelines for shock measurement and to examine impacts of shocks. A report of the Food Security Information Network (FSIN) identifies six shock measurement principles, one of which is the need to incorporate both subjective and objective measurements of shocks in the study of resilience (Choularton et. al 2015). Both measures are important because while objective measures relate the mere occurrence of a shock, subjective measures add context and allow us to begin to understand the variations in well-being after exposure to a particular shock (Maxwell et al. 2015). Studies investigating the impact of shocks such as drought on a specific well-being outcome have used objective measures, including ground-station data that provide direct observation of rainfall, gridded data that interpolate rainfall values from ground stations to account for those that are missing, satellite data that infer rainfall measures from satellite image, or reanalysis data that combine these various methods (Dell, Jones, and Olken 2014). Self-reported shock variables are also relatively common in this literature. Research based on these measures uses them as primary variables or as proxies for a more "objective" truth without necessarily revealing complete understanding of their content. While progress has been made in the measurement of shocks, several important questions remain to be addressed. What determines the report of a shock? To what extent is the report of a shock correlated with the actual incidence of a shock? What do these self-reports tell us about households, beyond the binary information of the occurrence of shock?

This study examines the relationship between objective and subjective measures of drought and the determinants of subjective drought assessments. Objective measures reflect "verifiable observed phenomen[on] external to the individual" (Maxwell et al., 2015, p. 7) that do not depend on the experiences of individuals. Subjective measures, on the other hand, are highly contingent on personal narratives/experiences and capture the views, self-assessments, opinions, and perceptions of those who have expertise in a given area, whether technical or experiential. While an objective measure of shock might reveal the occurrence of a drought, as measured by rainfall deviations from a long-term mean, a subjective measure of that drought captures its perceived severity and impact through households' self-assessment of their experience of it (Maxwell et al. 2015). Nonetheless, as Maxwell et al. (2015) suggest, if we want to better understand *both* the actual and perceived severity of shocks, it is crucial that we incorporate subjective *and* objective measures in relevant analyses.

This thesis examines 1) how well self-reports of drought track objective measures of the same shock; and 2) whether the head of household's occupation, irrigation status, and the household's socioeconomic status influence self-reports of drought conditional on rainfall; and 3) the extent to which drought reports are sensitive to the timing of survey interviews and to previous self-reports of drought. I discuss the hypotheses related to each question in detail in the methods and results sections of the thesis. The contributions to the field are twofold. First, only one known study attempts to model as dynamic the relationship between objective and subjective measures (Shisanya and Mafongoya 2016). I take advantage of a unique four-year panel from rural India and estimate a dynamic autoregressive model to determine the relationship between current and past self-reports. Second, recognizing that rational beings are prone to priming, whereby people's perceptions are shaped what they know of the present (Kahneman 2012), I investigate the effect of weather status at the time of interviews on respondents' likelihood of reporting a shock. This will allow us to test the validity of retrospective shock reports as independent from current conditions. From a methodological perspective, the research also hopes to contribute to understanding factors that affect the accuracy of subjective reports of shocks. The study's contributions may be of interest to the research community interested in shock/resilience measurements and welfare dynamics, but also to development practitioners interested in recommendations that better inform practice.

The thesis is organized into four main chapters. The remainder of chapter I selectively examines literature on shocks to justify the present research. Chapter II describes the data and empirical strategy used. Chapter III presents the results of the analysis Chapter IV discusses the implications of the findings and offers avenues for future research.

1.1 Background: overview of the literature

To provide a background for the present research, I provide a brief overview of selected research on the subjective measurements of shocks. The aim here is consider 1) how shock measurement is central to resilience analysis, 2) the relationship between objective and subjective measurement.

1.1.1 Shocks in resilience analysis

The development-resilience literature reflects numerous calls to focus attention on the properties of shocks and stressors that are at the core of resilience analysis. In fact, Choularton et al. (2015) define six imperatives for shock measurements for the purpose of resilience analysis. First, as preliminary work, a thorough risk mapping of the area of study needs to be conducted to capture shock properties such as their type, intensity, and seasonality. Second, it is important to recognize that shocks have differential impacts at various scales and over different time periods. Therefore, their measurement should capture their effect not only at the household level at one point in time, as is often done in the literature, but also at the individual, community, and even national levels, over time. Third, shocks are rarely independent events; rather, individuals often deal with myriad shocks simultaneously, which makes understanding their interactions crucial. Fourth, shock measurements need to include both intensive shocks, which have slow onsets for a short period of time, and extensive shocks, which have lower intensity but are longer in duration. These different types of shocks might burden households differently and thus warrant attention. Fifth, conflict and political instability exacerbate shocks and should thus be taken into consideration. Sixth, both objective and subjective measures of shocks should be incorporated. The present thesis is concerned with this last principle of shock measurement, the inclusion of subjective and objective measures of shocks.

The subjective experience of a shock relates to an individual's assessment of the consequences of that shock on their welfare and the ensuing coping mechanisms adopted. Incorporating subjective indicators in the measurement of a drought, for example, goes beyond the immediate consequences such as crop failure or cattle loss to reveal the coping strategies adopted by households or lack thereof. It also considers the level of "shock fatigue" or complacency that households experience when faced with multiple repeated shocks. Therefore, subjective shock assessments are important because they provide a multidimensional perspective of risk that includes not only an individual's level of exposure to a risk, but more importantly their understanding of the risk, and their cognitive and material ability to mitigate (ex-ante) and cope (ex post) with the effects of that risk (Doss 2008).

1.1.2 Subjective vs. objective measures in the development literature

The interest in subjective measurements rests on the premise that individuals understand the risk factors that affect their lives better than "experts" do, thus allowing for a more bottom-up process (Jones and Tanner 2015). It is not a new concept; previous studies have focused on subjective measurements of well-being (Asadullah and Chaudhury 2012) and poverty and health (Crossley and Kennedy 2002), presenting, however, mixed evidence on how they relate to objective measures of welfare. While some studies found a positive association between income and subjective assessments of well-being (Mcbride

2001; Hagerty and Veenhoven 2003; Sacks, Stevenson, and Wolfers 2010), others have described the relation as nonexistent (Oswald and Wu 2011), especially in the long run (Easterlin et al. 2011).

One of the earliest studies of this relationship is work by Easterlin (1974). He documents what has been termed the "Easterlin Paradox," whereby individual income was found to be positively associated with subjective well-being (happiness), while growth in GDP had no effect on happiness at a national level. The literature documented a curvilinear relationship between income and subjective well-being. These studies suggest that while the relationship might be positive, beyond a certain threshold of wealth income has no effect on happiness (Veenhoven 1991; Inglehart 2000; Clark, Frijters, and Shields 2008). Subsequent studies have challenged this proposition. Deaton (2008) finds that when outliers are removed from the analysis, the relationship no longer holds. Similarly, using a longer time series, Easterlin (1995) also finds, in the case of Japan that the relationship does not hold. Studies by Banerjee, Deaton, and Duflo (2004) and Banerjee and Duflo (2007) report that those who are poor are less likely to self-report economic status corresponding to their actual income level and resources.

The health literature reveals similar mixed evidence. Using two waves of a nationally representative survey in England, Johnston, Propper, and Shields (2007) report low correlation between objective and self-reported measures of hypertension: while 34.7 percent of the sample was diagnosed with hypertension, only 7.1 percent reported being hypertensive. Similar results are found among Mexican patients, where 13 percent of patients who are actually hypertensive do not report it, and only 3 percent correctly report it (Parker et al. 2010). Discrepancies between these two measures vary depending on wealth. In England, the poorest were more likely to not report chronic hypertension when in fact they had it, compared to their wealthier counterparts (Johnston, Propper, and Shields 2007). It is important to study differences between these two ways of measuring because they can tell different stories about an outcome of interest. A study by Johnston et al. (2009) suggest that using self-reported health data led to an underestimation of the income-health gradient, whereas objective measures of the same conditions produced a large and statistically significant gradient. Nonetheless, such studies are often not uniform in their treatment of the subjective and objective variables, making any study comparison a hard task.

1.1.3 Subjective vs. Objective measures of drought

In comparison, studies on how self-reported weather shocks relate to objective measures are less extensive. Most studies focus on self-reported risks, which differ from shocks in that they represent the unrealized potential adverse effects of these shocks. There is conclusive evidence, both within the climate change literature (Loewenstein and Mather 1990; Melka et al. 2015; Shisanya and Mafongoya 2016) and that on risk and vulnerability (Volker et al. 2011; Smith, Barrett, and Box 2001; Doss et al. 2008) that while risks homogeneously affect communities, households within communities have heterogeneous responses in their perceptions of risk and characterizations thereafter. Only one study, to the best of my knowledge, explores the relationship between self-reported shocks and objective measures of the same shocks (Hunter, Gray, and Edwards, 2012). They find that self-reported drought had a higher correlation with financial indicators than did measured drought. Moreover, self-reported measures were more reflective of the socio-economic impact of rainfall deficits.

This points to an important gap in the literature and is the platform on which I base my thesis. Given the need for more precise measurements of shocks, I contribute to the literature by studying the relation between objective and subjective measures of drought. Very few studies look at the temporal correlation of shock reports. Only one recent study suggests a path dependency between previous and current shock reports (Shisanya and Mafongoya, 2016). That study finds that in general, farmers were accurate in their characterization of drought years, with a few miscategorizations noted which were due to a particular year being a carry-over from a previous year and not necessarily a drought year. In this thesis, I attempt to address this gap in the literature through an empirical study that was designed to examine the relationship between objective and subjective measures of shocks.

Chapter II - Data and Methods

2.1 Data

I use two data sources for this study. The first sets of data are from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). Household and subjective drought data were collected under ICRISAT's Village Dynamics in South Asia (VDSA) project, a multi-year (2009 – 2014) survey undertaken with a goal to "understand the dynamics of poverty in the rural economies of South Asia and the role of technologies, markets, institutions and policies in providing pathways out of poverty" (Rao et al. 2009). The project was spearheaded by ICRISAT in partnership with the International Rice Research Institute (IRRI), the National Centre for Agricultural Economics and Policy Research (NCAP), other partners of the National Agricultural Research Systems (NARS) in India, and the Socio Consult and Center for Policy Dialogue (CPD) in Bangladesh.

The VDSA survey covers 1,824 households in 42 villages in nine Indian states; – six in the SAT region: Andhra Pradesh, Gujarat, Karnataka, Madhya Pradesh, Maharashtra, Telangana; – three in East India: Bihar, Jharkhand, Odisha; – and 11 districts in Bangladesh. Districts from the Semi-Arid Tropics (SAT) region were selected from ICRISAT's pioneer Village Level Studies (VLS) project started in 1975. New districts were subsequently added based on soil and crop type, prioritizing districts where drought resistant crops are relatively important.[1]Representative villages in talukas/mandals (administrative areas at the sub-district level) were sampled, omitting any villages that

[1] These are ICRISAT's mandate crops: namely sorghum, pearl millet, pigeon pea, chickpea, groundnut, and more recently finger millet.

received substantial government support, or those located near towns or big urban centers (Rao et al. 2009). Within each village, households were selected based on landholding classification, with equal numbers of households randomly selected among landless, small, medium, and large landholders[2] in selected villages.

The present analysis uses the portion of the data from India. Although, data are available from 2009 for the SAT region, I use 2010 as the baseline given that data collection in East India did not start until 2010. At baseline, 1,526 households were interviewed. The same households were visited again in – 2011, 2012, 2013, and 2014. Newly formed households that separated from households originally in the data set, because of marriage, migration, or other reasons, were tracked if they were still within one of the sample villages. Moreover, new households were randomly selected from the census collected in 2009 at the beginning of the project, to replace any households that might have permanently migrated or those that were not available for interview during the data collection period. The sample attrition rate is 8.33 percent for the five rounds of data. Table 1 in Appendix A reports regression outputs for the potential effects on selection bias. In general, households that attrited were significantly less likely to own livestock or be headed by a member whose main occupation was agriculture. Attrition was also significantly less likely in the states of Jharkhand and Gujarat compared to Andhra Pradesh.

[2] Note that the land size cut off for each category was dependent on the geographical location under consideration. F or example, the cut off for large land was > 1.62 ha in the village of Agraharam in Andhra Pradesh, while it was > 3.24 in the village of Markabinahalli in Karnataka.

In 2014, Andhra Pradesh was split between the states of Andhra Pradesh and Telangana. As a result, the district of Mahbubnagar which belonged to Andhra Pradesh from 2010 to 2013, was under Telangana in 2014. I recoded the state to Telangana for the relevant households in all rounds. Households that were not present at baseline in 2010 are excluded from the analysis, as are as households that are missing one or more rounds of data (37 households). Households with missing data were not included, unless the data were easily filled with information from previous years of the survey. See Figure for a depiction of the sample selection criteria.

The final sample used in this analysis consists of four rounds (2010 – 2013) of a balanced panel of 1,298 households in 30 villages across nine states and 15 districts (see Figure 2 and Table 2 of Appendix A). Data for this are drawn from 1) a general household survey with information on household characteristics and asset ownership, 2) a consumption expenditure module, and 3) a shock module with information on shock experience, proactive / coping strategies undertaken, and income lost as a result.

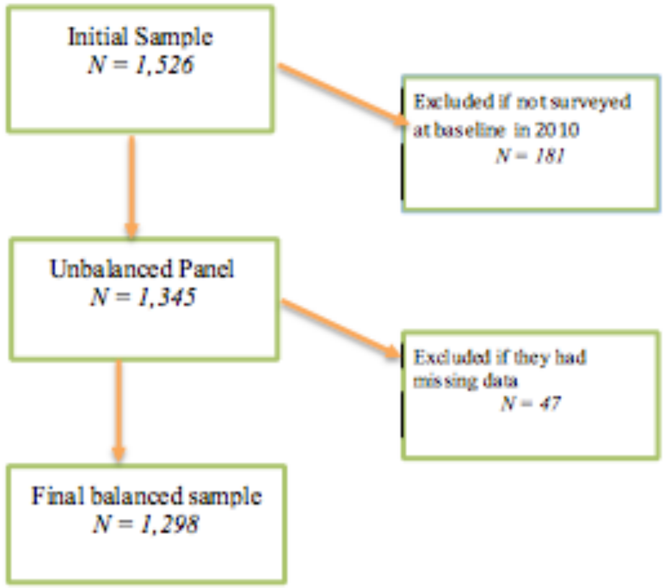

Figure 1 Sample selection chart

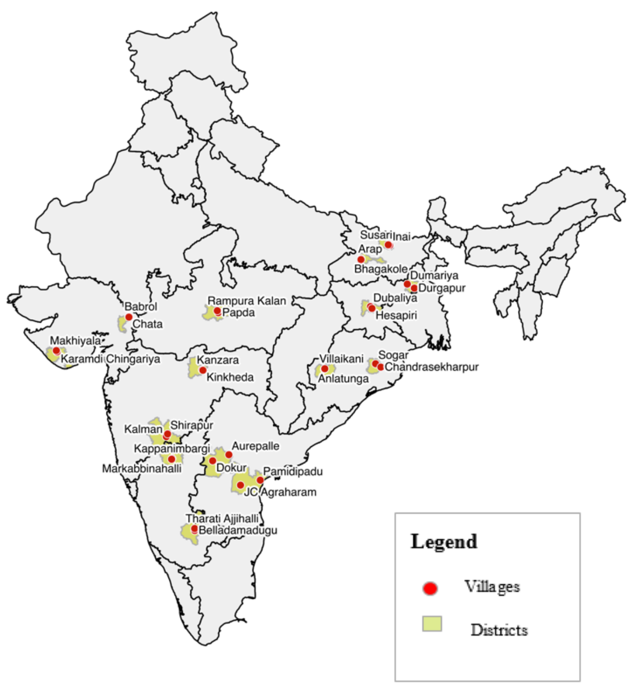

Figure 2 Geographical location of sample villages

Source: Author's own graph based on GIS data of village locations

2.2.1 Study Area

The study sample covers two agro ecological zones with distinct weather patterns. East India has a humid climate, while the SAT region has a more sporadic climate with features of both tropical and dry regions. Figure 3 below illustrates the variation in rainfall across the sample villages in 2011. The SAT region of India experiences annual precipitation in the range of 400 – 750 mm. The region is drought prone, with an erratic rainfall pattern coupled with extreme temperatures and a frequently late monsoon onset. The kharif, or rainy season, is characterized by the onset of the monsoon with agricultural soils rich in water but is a period of great production uncertainty due to the erratic rainfall pattern. In the sample SAT villages, the mean rainfall was 828 mm during the study, with a 25-year historical mean rainfall just below 800 mm. Weather is an important source of uncertainty in the region. East India (Bihar, Jharkhand, and Odisha), on the other hand is characterized by humid sub-tropical weather, with annual rainfall ranging between 1,000 and 2,500 mm. Figures 3 to 6 in Appendix B show rainfall patterns in the sample villages during the time of the study. In 2012, India experienced low levels of rainfall, which were 20 percent below the historical average. Drought was declared in three of the worst-hit states in the sample: Maharashtra, Karnataka, and Gujarat (Department of Agricultural Cooperation, 2012).

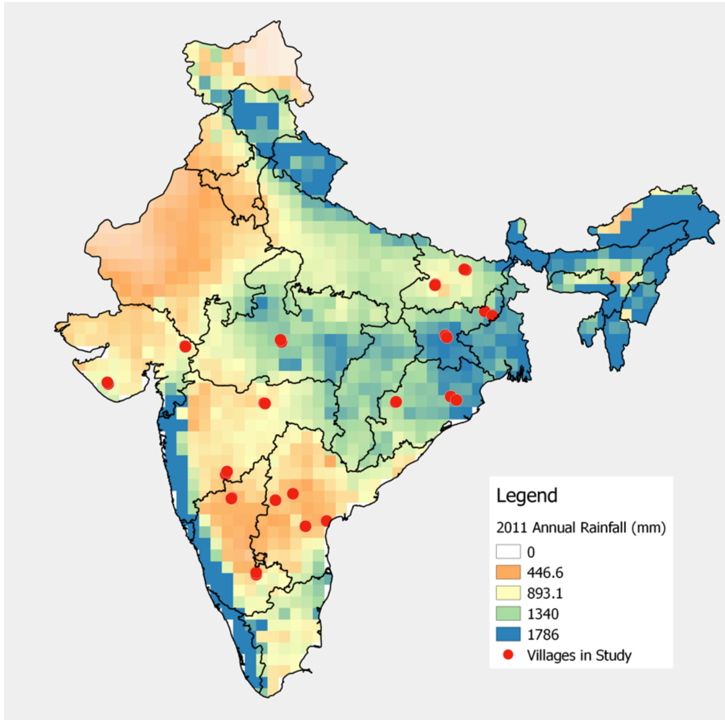

Figure 3 Rainfall pattern in sample villages (2011)

Source: Author's own graph based on rainfall datafrom the University of Delaware (NCAR, 2017)

2.2.2 Key variables

Self-reported shocks

The self-reported shock "subj_drought" is a binary variable indicating whether the household reported a "severe drought /flood / pest/diseases/ misfortune that affected [their] livelihoods in the last year." This variable is complemented with other self-reported variables indicating whether the household lost income as a result of the shock and amount lost, whether any coping strategies were adopted by the household (ranked in order of importance), and whether the household adopted activities in anticipation of the future climatic shocks. Box 1 in Appendix A details the survey questions in the shock module. In addition to the main subjective variable of interest (subj_drought), I construct two additional self-reported shock variables using the available information on shock reports:

- *drought_cop,* which is 1 if the household reported a drought *and* having adopted coping strategies in the aftermath of the drought, 0 otherwise.
- *drought_proac*, which is 1 if the household reported a drought *and* having adopted proactive measures bearing in mind future climatic shocks, 0 otherwise.

I include these different specifications of the subjective measure to investigate whether adding information to the self-reported variable might affect the relationship with the objective measures. Coping strategies reflect the set of actions taken ex post to mitigate the effects of a shock, while the adoption of proactive measures is an ex ante manifestation tied to the level of awareness and belief about climate change and the need for adaptation. These two components relate, respectively to a household's adaptive and absorptive capacity, which are key components of resilience (Constas et al., 2014).

Objective shock data

The "objective" rainfall data were obtained from the University of Delaware Air & Temperature database. The database contains global monthly measured precipitation (P, mm) between 1900 and 2014, interpolated to a 0.5 x 0.5 degree latitude/longitude grid (approximatively 30 miles or 50 km) obtained from various sources. The data for India were calculated from daily rainfall values interpolated from existing weather stations (NCAR, 2017).

One of the shortfalls of gridded data is that the location of interest can fall close to more than one grid. Therefore, I interpolate the monthly rainfall values using a bilinear weighting method and subsequently match them to village-level GIS coordinates. I calculate seasonal (rainy season and June/July average) and annual village-level rainfall. Using the annual rainfall, I define a drought if village rainfall is 75 percent of the historical 15-year mean or less:

$$Drought = \begin{cases} 1 \; if \; rainfall \leq 75\% \; of \; mean \\ 0 \; otherwise \end{cases}$$

I then compare this constructed drought indicator with drought variables as defined by the Indian government. The Indian Department of Agriculture and Cooperation under the Ministry of Agriculture uses a minimum of three of four indices for drought declaration: rainfall deficiency, the extent of area sown, a normalized difference vegetation index, and a moisture adequacy index (Department of Agriculture and Cooperation, 2009). In terms of rainfall, state governments' guidelines are that a drought is declared if the total rainfall in June and July is less than 50 percent of the mean rainfall for these two months, accompanied by negative impacts on soil moisture and vegetation, or if rainfall during the rainy season is less than 75 percent of the seasonal average with adverse impacts on vegetation and soil moisture. I construct two additional drought variables to match the definitions of the Indian government.

2.2.3 Summary statistics

Table 1 presents baseline summary statistics for the entire sample of variables used in the analysis. The average household has 5.49 members, with a dependency ratio of 67 percent, suggesting that for every two working adults in a household, there are at least three dependents under the age of 15 or over 65. Education levels are low within the households, with, on average, five years of formal education for the entire household and similar levels for the household head. Virtually all household heads are male (94 percent), and they are, on average, 48 years old. About 80 percent of household heads are employed in agriculture. I define "employed in agriculture" as either working on one's own farm or as agricultural laborer. Breaking down this group by specific occupation shows that half of the household heads are farmers (55 percent), while about 12 percent are farm laborers or farm servants (see Table 2). About 78 percent of the sample owns land, with an average landholding size of 3.05 acres per household. Livestock is owned by 71 percent of households, with 2.35 tropical livestock units (TLU) per household. Consumption expenditure data are adjusted to 2013 price levels using the 2013 consumer price index as the baseline to adjust for inflation. The average annual consumption is 70,000 rupees (USD 1,000), which is about 30 percent lower than the national average (Center for Monitoring Indian Economy, 2015).

Table 1 Summary statistics

Variable	Obs.	Mean	Std. Dev.
Household Characteristics			
Household size	1298	5.49	2.62
Household education (avg years)	1298	5.00	2.84
Dependency ratio (percent)	1298	67.00	69.41
Sex head (Male = 1)	1298	0.94	0.24
Age of head	1298	48.29	12.72
Education of head (years)	1298	5.49	2.62
Head employed in ag (yes =1)	1298	0.80	0.40
Productive capacity			
Land area owned (acres)	1298	3.04	6.61
Land area/ plot owned (acres)	1298	0.61	1.00
Irrigated land (percent of total)	1298	0.22	0.38
Owns livestock (yes =1)	1298	0.71	0.45
Tropical livestock units (TLU)	1298	1.68	2.04
Well-being indicators			
Total annual consumption (Rs.)	1298	70880	77749
Annual non-food consumption (Rs.)	1298	36744	69657
Annual food consumption (Rs.)	1298	34135	16093

Table 2 Occupation of the household head (baseline)

	Frequency	Percentage
Farming	713	54.93
Farm labor	147	11.33
Non-farm labor	126	9.71
Farm servant	9	0.69
Livestock	39	3.01
Business	51	3.93
Caste occupation	34	2.62
Salaried job	77	5.94
Domestic work	24	1.85
No work	40	3.08
Others	38	2.93

Table 3 shows that some of the baseline characteristics between households in the SAT and East India show are statistically different. Albeit significant, the differences in means are negligible for average household education, household size, male headedness, employment of head, and livestock ownership. Land area owned and share of land irrigated are substantially different between the two regions, with households in the SAT region owning twice the land holdings of East Indian households. Nonetheless, a smaller share of that land is irrigated compared to that of East India.

Table 3 Summary statistics by region (baseline)					
	East India		Semi-arid Tropics		
VARIABLES	N	Mean	N	Mean	T stat
Household size	468	5.880	830	5.263	***
Household education (years)	468	4.599	830	5.229	***
Sex head (Male = 1)	468	0.959	830	0.927	***
Age of head	468	47.94	830	48.48	
Education of head (years)	468	5.396	830	4.888	**
Head employed in ag (yes =1)	468	0.812	830	0.789	
TLU	468	1.663	830	1.69	
Owns livestock (yes =1)	468	0.799	830	0.667	***
Share of irrigated land (%)	468	0.327	830	0.157	***
Land area owned (acres)	468	1.627	830	3.829	***

T stat indicates whether the difference in means is significant
*** p<0.01, ** p<0.05, * p<0.1

2.2 Empiral Strategy

I begin the analysis with an investigation of the correlations between self-reported and measured drought. Using a linear probability model, I explore how the relationship between the two measures changes based on the definitions of the subjective and objective variables. Then I explore other factors beyond the measured rainfall that may explain the heterogeneity in self-reported drought. First, on the basis of similar explorations in the literature, I investigate whether differences in household characteristics, such as occupation of the household head, irrigation status, and socio-economic status influence drought reports once rainfall has been controlled for. Second, to contribute to the literature, I test the presence of "the interview priming effect" to see if weather conditions at the time of interviews affect the way that droughts are reported conditional on annual measured rainfall. Finally, using a dynamic panel model, I test the extent to which previous reports of drought influence subsequent reports.

2.2.1 How well do self-reported measures track objective measures of drought?

To investigate the relation between objective and subjective measures of shock, I estimate a linear probability model of the form:

$$\mathrm{Subj\_drought}_{idt} = \rho \mathrm{Objective}_{vt} + \beta X_{idt} + \tau_t + \delta + \varepsilon_{idt} \qquad (1)$$

where the dependent variable is a binary report of retrospective drought experience for household *i* in district *d* at time *t.* The variable "*Objective"* is the main independent variable of interest. It measures rainfall levels in village *v at* time *t*. Household characteristics *X* include information on household composition (size and dependency ratio), the household head (age, gender, whether employed in agriculture), the household's productive capacity (total land area, TLU), and the wealth quintile they belong to, which was defined from total household expenditure for each region and year. τ_t, δ, and ε_{idt} are time, districts fixed effects and a random error term, respectively. One of the drawbacks of the linear probability model is the possibility of predicting probability values outside the [0, 1] range, making inference at the tails of the cumulative density function difficult. However, as will be evident in the results section, the probabilities predicted by my models are bounded above by 0.5 with very few probabilities falling below 0. Therefore, I belief this will not cause too much bias.

Moreover, the linear probability model is easy to interpret and does not require the assumption of a specific functional form (Greene, 2012). To control for heteroscedasticity, I use cluster bootstrap standard errors at the district level in all models, unless otherwise specified.

Given similar rainfall conditions, why do we observe divergences in drought reports? First, it could be a simple matter of measurement errors in the subjective drought reports. Response bias plagues most household surveys. Households anticipating a payout might choose to paint a more gloomy picture of their situation, accentuating misfortunes and down playing gains. Moreover, people tend to remember sudden tragic events more vividly (Kahneman and Tversky, 1979) and, as a result, overestimate their frequency. To address these problems, I use the three self-reported variables described in the Data section: the report of drought, the report of drought and coping strategies, the report of drought and proactive measures. I expect to see a higher correlation between measured rainfall and the self-report of drought, compared to the other two measures.

Second, given that the rainfall data were interpolated at the village level, errors could exist relating to the accuracy of the rainfall stations and how far they are from the sample villages. It is, in fact, plausible that if a household is located at a higher altitude than the rainfall station that records precipitation for the village in which it lives, then a drought might be declared in that particular area based on the station reading, whereas the household did not necessarily experience it given its geographical and topological location. Most important, how is a drought defined? The definition of a drought is contingent on the type of drought that is referred to but also who gets to call it a drought (Hunter, Gray, and Edwards 2013). While most studies in the literature use annual rainfall values to construct drought variables (Dell, Olken, and Jones 2014), the Indian Department of Agriculture and Cooperation under the Ministry of Agriculture declares drought based on deficits in seasonal rainfall values (see the Data section for more details) (Department of Agricultural and Cooperation, 2009). Therefore, I investigate whether seasonal values correlate more with self-reports than do annual values of rainfall. Understanding the time of reference of self-reported drought is important; do households base drought assessments on the total annual rainfall in the previous year, or do reports reference average rainfall during the growing season when rainfall is most needed or during the harvest season after the impacts of the drought have materialized? Given that about 80 percent of heads of households in the sample are employed in agriculture and thus heavily depend on good rainfall during the growing seasons, I hypothesize that drought reports will correlate more with seasonal rainfall values than with annual values.

2.2.2 Beyond rainfall what other factors influence drought reports?

Once rainfall has been taken into consideration, are there other factors that explain heterogeneity in drought reports across households?

Differences in household characteristics

To identify heterogeneous subjective responses to common shocks, I interact household characteristics and measured rainfall and add it to equation (1):

$$\mathrm{Subj\_drought}_{idt} = \rho \mathrm{Objective}_{vt} + \beta X_{idt} + \partial \mathrm{Objective}_{vt} * X_{idt} + \tau_t + \delta + \varepsilon_{idt} \quad (2)$$

The coefficient of interest is ∂ which identifies the heterogeneity in self-reports by targetable household characteristics. I add the interaction term for three household variables: the main occupation of the household, the source of irrigation that the household uses, and their socioeconomic status. I hypothesize that households that are on the lower scale of socioeconomic status, those heavily dependent on agriculture, and those that rely on a rain-dependent irrigation source are more likely to report a drought, compared to their counterparts.

Interview priming effect

People tend to unconsciously allow an initial stimulus presented to them, in this case weather conditions at the time of interview, to influence responses to a later stimulus. This phenomenon is similar to priming and anchoring effects, which have been widely documented in the psychology literature (Kahneman and Tversky, 1979). I hypothesize that when respondents are administered the shock module during times of negative rainfall shocks, they are more likely to report a drought.

Path dependency of shock reports

To better inform our understanding of self-reports across time, I estimate a dynamic panel model using an Arellano-Bond estimator (Arellano and Bond, 1991), to measure the level of path dependency in shock reports as follows:

$$\mathrm{Subj\_drought}_{id,t} = \delta \mathrm{Subj\_drought}_{id,t-1} + \mathrm{Objective}_{v,t} + X_{id,t} + u_i + \tau_t + \delta + \varepsilon_{id,t} \quad (3)$$

where u_i is unobserved household effect. Lagged values of the self-reported shocks very likely correlate with the time-invariant unobserved household heterogeneity. To remedy this potential endogeneity, the Arellano-Bond estimator takes the first differences of regression (3) to obtain (4).

$$\Delta \mathrm{Subj\_drought}_{\mathrm{idt}} = \delta\Delta \mathrm{Subj\_drought}_{\mathrm{id,t-1}} + \rho\Delta \mathrm{Objective}_{\mathrm{vt}} + \beta\Delta \mathrm{X}_{\mathrm{idt}} + \tau_{\mathrm{t}} + \Delta\varepsilon_{\mathrm{idt}} \quad (4)$$

In this second stage, there is still a problem of endogeneity introduced by the correlation between the first difference of the lagged self-report variable and that of the error term. Recall that the first differences are as follows:

$$\Delta Subj\_drought_{id,t-1} = Subj\_drought_{id,t-1} - Subj\_drought_{id,t-1} \qquad (5)$$

$$\Delta\varepsilon_{\mathrm{id,t}} = \varepsilon_{\mathrm{idt}} - \varepsilon_{\mathrm{id,t-1}} \quad (6)$$

Controlling for household time invariant fixed effects, the model determines how previous drought reports affect current drought reports. Therefore, the δ coefficient on the lagged first difference is interpreted as the measure of the effect that previous drought reports have on current drought reports within a household across time. I use variation over time to estimate the parameter of interest and hypothesize a positive coefficient on the lagged drought report. Households that are affected by a drought in the previous year might be led to liquidate assets to cope with the effects of the shock. A year later, those households might still feel the effect of the shock depending on how many assets they had to sell off. Moreover, experiencing other shocks will exacerbate the perceived impact of the shock in the current year even when there is not actually a drought in a measured sense. I use four rounds of data, but I lose one round due to the first differencing. I allow for auto-correlated errors. To control for heteroscedasticity, I use robust standard errors at the district level.

Chapter III – Results

3.1 How well do self-reported measures track objective measures of drought?

Figures 4 and 5 illustrate self-reported shock distribution in East India and SAT between 2010 and 2013. The three most commonly reported shocks in East India are droughts, floods, and death of livestock. Drought is the most often reported shock, making up more than 55 percent of all shock reports in each year. Comparatively, shock reports in the SAT are less homogeneous. The SAT region is very shock prone with different shocks affecting households in any given year; shock distributions are more sporadic, exhibiting an unclear pattern. The three most common shocks reported are droughts, floods, and crop failure[3]. However, across the four years, droughts were the most important shock. In the entire sample, drought reports made up between 35 and 65 percent of all reports between 2010 and 2011. Moreover, while floods seem to have been important particularly for the SAT region, there was not enough variation in the responses to study. Therefore, I focus on self-reports of droughts.

[3] I aggregate crop loss due to pests / disease infestations and wild animals into one shock: crop failure.

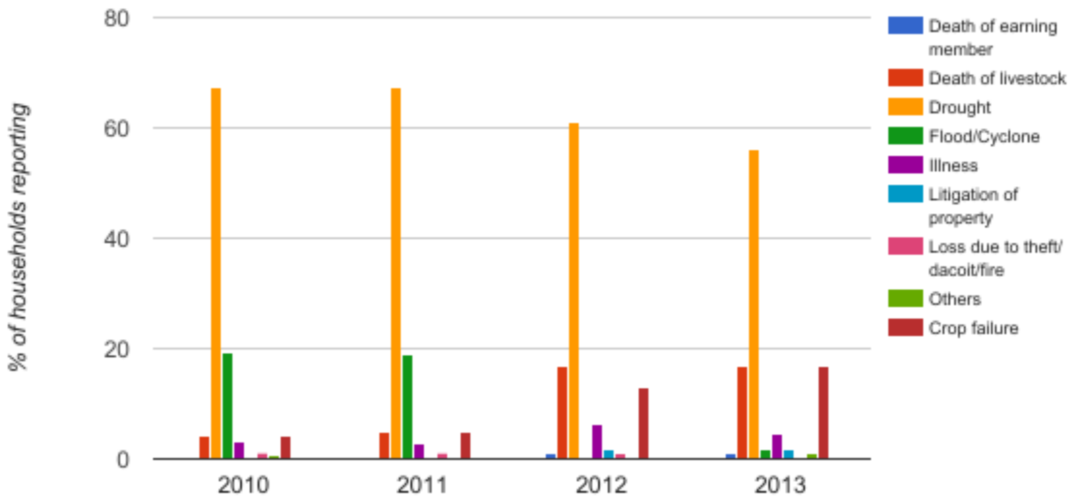

Figure 4 Shock distribution - East India

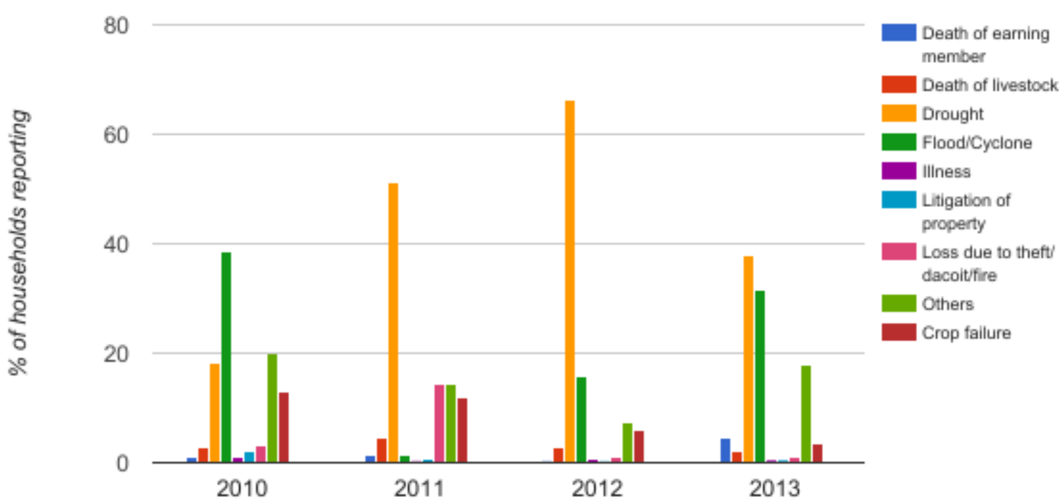

Figure 5 Shock distribution - SAT

Figure 6 illustrates the share of households that report being in drought compared to the share that are in drought according to the objective measure. A village is in drought, per my objective measure if annual village rainfall is 75 percent of the long-term mean or less. While 12 percent report having been affected by a drought, 18 percent are 'actually' in drought as determined by the objective measure. The correlation between the two measures is 0.2. In 2012, drought was declared in a number of states. During that year, 30 percent of households lived in an area affected by a drought, whereas only 21 percent reported having been affected by a drought. The correlation coefficient is higher in this case, at 0.4.

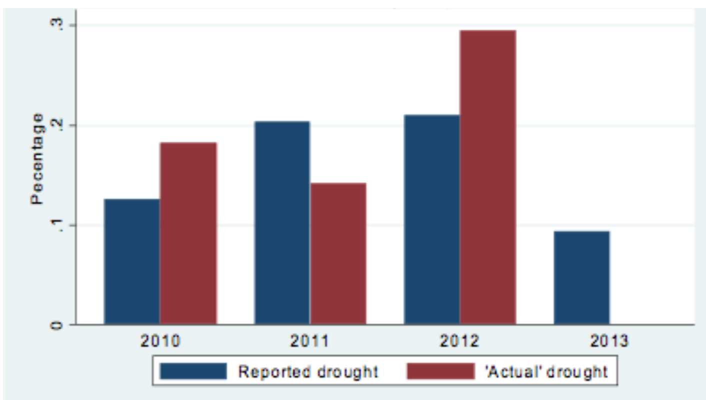

Figure 6 Subjective vs. objective measures of drought

More households reported having experienced droughts in 2011 and 2013, than were categorized as being in drought according to the objective measure. However, in 2010 and 2012 the opposite was true; fewer households reported droughts than were categorized as being in drought. In the pooled sample, the percentage of households that live in a drought stricken village but chose not to report is 11.3 percent, whereas 62.68 percent reported being affected by a drought while the village in which they live in did not qualify as being in drought as per the rainfall deficit from the long-term mean. See

Table 4 for a summary of these results. In general, households in the sample were more likely to report a drought even when there was no drought than to not report when there was a drought. This might indicate that there might be more factors at play when households report shocks. Section B below offers suggestions as to why that might be the case.

Table 4 Comparing objective and subjective measures

	Did you experience a drought?	
Objective rainfall	NO	YES
Rainfall > 75 % mean	88.68	62.68
Rainfall < 75 % mean	11.32	37.32

Next, I investigate whether measurement errors could be introduced due to the timing of reference of shock reports. When respondents are asked if they were negatively affected by a drought in the past year, they could be referring to the entire year or to a particular season of the year. Given that farming is such an important source of livelihood for most households in my sample, I hypothesize that their drought reports would be more correlated with rainfall values during the rainy season than annual rainfall values. As shown in Tables 5 and 6, I tested this hypothesis by exploring whether self-reported values are correlate more with seasonal or annual rainfall. In Table 6, the independent variables of interest are the annual rainfall, rainfall during the rainy season, and average rainfall during the months of June and July, in meters. The coefficient for the rainy season rainfall is similar in magnitude to that of the annual rainfall, however, it is less precise, yielding insignificant results with high standard errors. The coefficient for June/July is not significant, either. Similarly, as shown in Table 7, where I compare annual drought to drought during the rainy season and in June/July as defined by the

Indian government (see the Methods' section for these definitions), I find that the coefficients on the drought variable during the rainy season and in the months of June and July are not significant and have negligible effects on drought reports. In the meantime, living in a village affected by drought defined in annual terms increases the probability that a household reports a drought shock by 22.6 percent. The self-reported variable does not respond to changes in seasonal rainfall/drought rather, annual rainfall/drought seems to be more relevant in the assessment of drought reports. These results may seem counterintuitive given the high dependence on agricultural production in the sample villages; 80 percent of household heads are employed in agriculture. However, these findings indicate that while rainfall deficit during the rainy season is a precursor of bad harvest, the actual consequences only materialize during the harvest months, which may lead households to consider rainfall deficits over a longer period of time when reporting droughts. In light of these results, I rely on annual rainfall values instead of seasonal ones for the remainder of the study.

Table 5 Regression - Annual vs. Seasonal Rainfall (meters)

Dependent variable: Drought self-report (μ = 16%)

VARIABLES	Annual	Rainy season	June & July
Rainfall (meters)	-0.339**	-0.300	-0.516
	(0.119)	(0.414)	(0.359)
2011.year	0.0670	0.0789**	0.0819**
	(0.0398)	(0.0303)	(0.0295)
2012.year	0.0327	0.0811	0.0811
	(0.0858)	(0.104)	(0.104)
2013.year	-0.00769	-0.0363	-0.0148

	(0.0740)	(0.0702)	(0.0675)
Constant	0.290*	0.00613	0.0427
	(0.148)	(0.107)	(0.0970)
Observations	5,192	5,192	5,192
R-squared	0.072	0.035	0.039
Other controls: household characteristics, districts E			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Annual vs. seasonal rainfall (binary)

Dependent variable: Drought self-report (μ = 16%)

VARIABLES	Annual	Rainy season	June & July
Objective drought	0.226**	0.00997	0.00511
	(0.0989)	(0.0207)	(0.0264)
2011.year	0.0858**	0.0772**	0.0770**
	(0.0333)	(0.0308)	(0.0312)
2012.year	0.0556	0.0810	0.0810
	(0.0778)	(0.104)	(0.104)
2013.year	0.00406	-0.0358	-0.0367
	(0.0827)	(0.0715)	(0.0706)
Constant	-0.0965	-0.0572	-0.0563
	(0.0908)	(0.0809)	(0.0801)
Observations	5,192	5,192	5,192
R-squared	0.082	0.034	0.034
Other controls: household characteristics, districts FE			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Another way that measurement errors could be introduced is via the way that droughts are defined. I estimate whether different definitions of subjective and objective measures yield congruent results. In Table 7, I use two different objective variables. The first column uses annual rainfall in meters as the dependent variable. In column 2, drought is defined as a rainfall deficit of more than 25 percent of the long-term mean. There is a consistent coefficient on the objective shock in the range of 0.23 to 0.34, across the two specifications. Within a district, living in a village affected by drought increased the likelihood of reporting a drought by 34 percent with every additional meter of annual rainfall (or 1,000 mm). Next, when drought is defined as rainfall deviation from the mean, living in a drought stricken area raises the probability of reporting a drought by 22.6 (column 2 of Table 7). These results suggest that the correlation between self-reports and objectively measured drought is robust to how the latter is defined. For the remainder of the analysis, I use the annual rainfall values instead of the drought indicator because this variable is less prone to errors and distributional inaccuracies.

Table 7 Is the relationship contingent on specifications of the objective measure?

Dependent variable = Subjective drought (did you experience a drought) (μ = 16%)?

	(1)	(2)
Objective shock:	Annual Rainfall (m)	Drought
Objective shock	-0.339**	0.226**
	(0.119)	(0.0989)
2011.year	0.0670	0.0858**
	(0.0398)	(0.0333)
2012.year	0.0327	0.0556
	(0.0858)	(0.0778)
2013.year	-0.00769	0.00406
	(0.0740)	(0.0827)
Constant	0.290*	-0.0965
	(0.148)	(0.0908)
Observations	5,192	5,192
R-squared	0.072	0.082
Other controls: household characteristics, districts FE		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I carry out a similar exercise with the self-reported variables. I keep the objective measure constant and change the subjective measure. Table 8 reports the results of the analysis. In column 3, the dependent variable is whether the household reports a drought *and* having adopted proactive measures. These results are not significant. The questionnaire asked, "Did you adopt proactive measures bearing in mind future climatic shocks". The variable is bound to have errors given that the question is open ended and not tied to a specific shock. Moreover, only 9.8 percent of the sample reported a drought and adoption of proactive measures. The probability of reporting a drought *and* adopting a coping strategy (column 2) increases by 26.4 percent with every additional meter of annual rainfall while the probability to only report a drought increases by 33.9 percent (column 1), conditional on household characteristics and heterogeneous district effects. These results are intuitive. One would expect drought reports to be more dependent on rainfall than are reports the report of the adoption of coping strategies. Varying the subjective variable does, in fact, change the results, which indicates that the way that questionnaires on shock modules are drafted can greatly influence the outcome of the self-reported variable.

Table 8 Is the relationship contingent on specifications of the subjective variable?			
	(1)	(2)	(3)
Dependent variable is:	Reports drought (μ = 16%)	Reports drought & coping strategy (μ = 14%)	Reports drought & proactive measure (μ = 9.8%)
Rain (m)	-0.339**	-0.264**	-0.139
	(0.119)	(0.1000)	(0.0889)
2011.year	0.0670	0.0709*	0.0337
	(0.0398)	(0.0347)	(0.0374)
2012.year	0.0327	0.0812	-0.000301
	(0.0858)	(0.0735)	(0.0570)
2013.year	-0.00769	0.0328	-0.00176
	(0.0740)	(0.0634)	(0.0647)
Constant	0.290*	0.230***	0.0973
	(0.148)	(0.0743)	(0.115)
Observations	5,192	5,192	5,192
R-squared	0.072	0.078	0.024
Other controls: household characteristics, districts FE			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2 To what extent do household characteristics determine heterogeneity in drought reports?

To identify heterogeneous subjective responses to common shocks, I estimate a linear probability model including an interaction term of household characteristics and objective rainfall. I add the interaction term in separate regressions for three household characteristics: occupation of the household head, irrigation source, and socioeconomic status. My hypothesis is that wealthy households, those whose main source of income is farming, and those that employ a rain dependent irrigation source would be more likely to report a drought. Individual regression Tables for each of the three household characteristics can be found in Tables 9, 10, and 11.

The analysis suggests that household heads employed in agriculture, who are therefore more rain dependent for their livelihoods are more likely to report a drought at the same level of objective rainfall (see Table 9). Predicted probabilities are derived post-regression. As shown in figure 7, household heads involved in farming their own lands[4] are more sensitive to low levels of rainfall and are quicker to report a drought at low levels of annual rainfall. Farmers are 12.8 percent more likely to report a drought than non-farmers are, conditional on rainfall. At lower levels of rainfall, farming households are more likely to report drought most likely owing to the fact that their livelihoods are so intrinsically tied to the weather.

Table 9 Heterogeneous effects of the occupation of the household head

VARIABLES	(1)	(2)	(3)
Rainfall (m)	-0.339***	-0.333***	-0.383***
	(0.111)	(0.107)	(0.125)
Farm labor		-0.106***	-0.262***
		(0.0351)	(0.0974)
Non-farm labor		-0.111***	-0.261***
		(0.0271)	(0.0922)
Farm servant		-0.137**	-0.180
		(0.0555)	(0.265)
Livestock		-0.0332	-0.135
		(0.0265)	(0.121)
Business		-0.0715***	-0.0300
		(0.0211)	(0.0547)
Caste occupation		-0.0646**	-0.284***
		(0.0292)	(0.0687)
Salaried job		-0.0796**	-0.133
		(0.0367)	(0.128)
Education		-0.490***	-0.784
		(0.0207)	(0.837)
Domestic work		-0.0806***	-0.231**
		(0.0260)	(0.100)

[4] The survey questionnaire makes a distinction between farmers who own the land they farm and could employ others and farm laborers who do not own land but work in agriculture.

No work		-0.0598**	-0.169***
		(0.0265)	(0.0613)
Others		-0.0346*	-0.107
		(0.0199)	(0.0876)
Farm labor* Rainfall			0.163**
			(0.0798)
Non-farm labor * Rainfall			0.141**
			(0.0717)
Farm servant * Rainfall			0.0384
			(0.292)
Livestock * Rainfall			0.104
			(0.107)
Business * Rainfall			-0.0443
			(0.0589)
Caste occupation * Rainfall			0.229***
			(0.0866)
Salaried job * Rainfall			0.0531
			(0.116)
Education * Rainfall			0.222
			(0.586)
Domestic work * Rainfall			0.152*
			(0.0826)
No work * Rainfall			0.107**
			(0.0451)
Others * Rainfall			0.0748
			(0.0862)
Constant	0.469***	0.502***	0.552***
	(0.114)	(0.119)	(0.157)
Observations	5,192	5,188	5,188
R-squared	0.061	0.080	0.087
Other controls: year FE, district FE			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

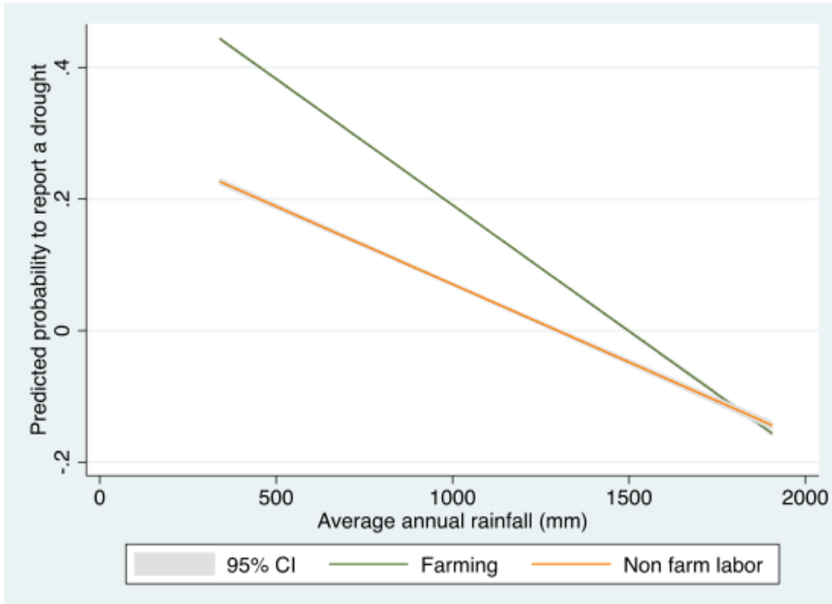

Figure 7 Predicted probabilities of reporting a drought: farmers vs. non-farm laborers

As shown in Table 10, the association between a household's main irrigation source and its likelihood of reporting a drought is inconclusive. The results do not offer much insight into how irrigation status might explain divergences in drought reports given the same rainfall realization. This is most likely due to the fact that it is not clear what the level of rain dependency of each of the different irrigation sources is unclear. In fact, the different irrigation sources are not easily ranked from less rain dependent to more rain-dependent as they seem to have both features in the sample villages.

Table 10 Heterogeneous effects of irrigation source			
VARIABLES	(1)	(2)	(3)
Rainfall (meters)	-0.339**	-0.333***	-0.248**
	(0.169)	(0.104)	(0.126)
Open well		0.139***	0.317***
		(0.0505)	(0.111)
Borewell		0.0695*	0.286**
		(0.0415)	(0.135)
Canal		0.105	0.166
		(0.0762)	(0.222)
Tank/pond		0.168	0.436
		(0.151)	(0.338)
Submersible pump		0.120*	0.167
		(0.0699)	(0.464)
River		0.0610	0.0364
		(0.0505)	(0.208)
Open well* Rainfall			-0.177
			(0.149)
Borewell* Rainfall			-0.251
			(0.155)
Canal* Rainfall			-0.0601
			(0.178)
Tank/pond* Rainfall			-0.278
			(0.277)
Submersible pump* Rainfall			-0.0478
			(0.309)
River* Rainfall			0.00467
			(0.210)
Constant	0.469***	0.401***	0.317**
	(0.165)	(0.113)	(0.142)
Observations	5,192	5,192	5,192
R-squared	0.061	0.093	0.103

Other controls: year FE, district FE
Omitted category: Rain-fed/No irrigation

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In terms of socioeconomic status, the results are more robust and point to a positive correlation between wealth and propensity to report a drought conditional on rainfall levels. Results can be found in Table 11. Contrary to the results of Barrett, Smith, and Box (2010) on self-reported drought risks for East African pastoralists, I find that poorer households are less likely than wealthier households to report a drought at low levels of rainfall realizations; the trend changes drastically beyond a threshold of 1,200 mm of rainfall in the SAT region. In East India, the threshold arises right around the mean annual rainfall for the region (see Figure 8). At rainfall values greater than the mean, households in the second wealth quintile are more likely to report a drought in the East India sample. This trend could occur given that, as reported in the summary statistics, the wealthiest are more likely to be agriculturists, and they are more affected by rainfall deficits. Moreover, for this group of households, marginal changes in rainfall can have a considerable impact on crop production, making them more sensitive to such changes.

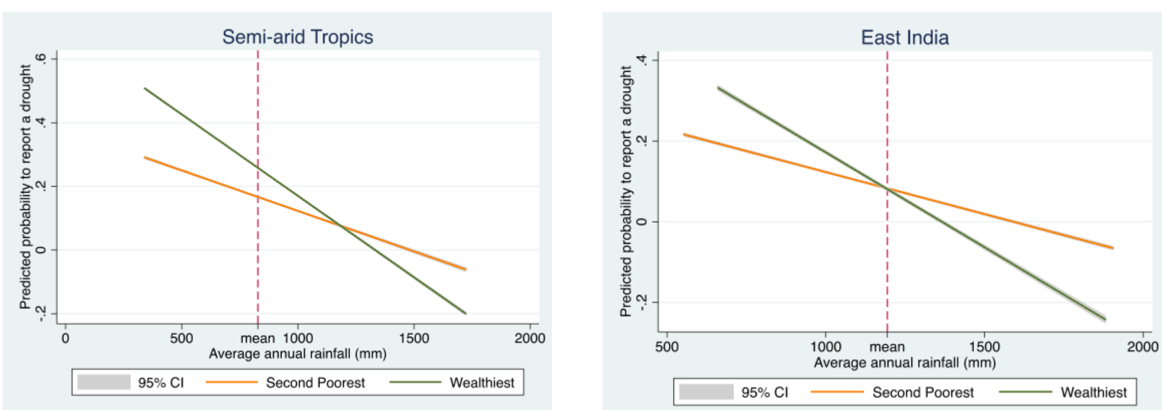

Figure 8 Predicted probabilities of reporting a drought by socio-economic status

Table 11 Heterogeneous effects of socio-economic status			
VARIABLES	(1)	(2)	(3)
Rainfall (m)	-0.339**	-0.330**	-0.485***
	(0.133)	(0.161)	(0.161)
Poorest		-0.114	-0.286**
		(0.0696)	(0.127)
Second quintile		-0.0635*	-0.304***
		(0.0383)	(0.103)
Third quintile		-0.0329	-0.189**
		(0.0303)	(0.0752)
Fourth quintile		-0.0150	-0.118*
		(0.0241)	(0.0645)
Poorest* Rainfall			0.190
			(0.123)
Second quintile* Rainfall			0.255**
			(0.109)
Third quintile * Rainfall			0.177**
			(0.0881)
Fourth quintile * Rainfall			0.120*
			(0.0654)
Constant			0.644***
			(0.149)
Observations	5,192	5,192	5,192
R-squared	0.061	0.071	0.085
Other controls: year FE, district FE Omitted category: wealthiest			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The coefficients on the year dummy for 2011 are significant in some of the models, suggesting that households were more likely to report 2011 as a drought year (see Tables 5, 6, and 7). There is not much evidence in the news media to suggest that 2011 was a particularly bad year. However, 2012, which is the year during which households would have responded to the shock module, was a drought year in many districts, especially in the SAT region (Maharashtra, Karnataka, and Gujarat). This could suggest that the drought conditions at the time of the interviews might have biased the responses about drought occurrence during the 2011 reference year. I discuss this "interview priming effect" below.

3.3 Interview priming effect

Next, I investigate the effect of the interview months on drought reports. During the study period, nearly 64 percent of all interviews were conducted in the months of July and August, while a quarter were conducted in September and a few in each of the other months of the year. In general, the interviews were conducted during the rainy season, right after planting. I investigate the effect of the interview month on the propensity to report. Table 12 provides the results of the analysis. I first include the level of rainfall during the month of the interview (column 2); however, the results are not significant. Then, in column 3, I include the month of the interview. The omitted month in the regression is January. The results suggest that households that responded to the shock module during the months of April, June, and October were less likely than those interviewed in January to report a drought once I controlled for district fixed effects and household characteristics. The results are sensitive to the cropping and planting patterns in the sample villages. January is towards the end of the harvest season and is characterized by low rainfall levels, while the rainy season begins in June. These results suggest that being interviewed at the beginning of the rainy season makes respondents less likely to report a drought, while households interviewed towards the end of the harvest season, when rainfall is low and farmers have fairly good confirmation of the impact of that year's weather shocks on their crops, are more likely to report drought. These findings have important implications for the design of shock modules that I discuss later.

Table 12 Interview priming effect			
VARIABLES	(1)	(2)	(3)
Rainfall (m)	-0.369***	-0.376**	-0.350**
	(0.109)	(0.150)	(0.164)
Rainfall interview (m)		0.180	
		(0.180)	
February			-0.0140
			(0.0587)
March			0.0332
			(0.0414)
April			-0.198*
			(0.103)
May			-0.0702
			(0.0447)
June			-0.250*
			(0.142)
July			-0.0337
			(0.0454)
August			-0.00419
			(0.0372)
September			-0.0451
			(0.0671)
October			-0.156***
			(0.0544)
November			-0.126
			(0.0863)
December			0.0448
			(0.0918)
Constant	0.344***	0.309**	0.371**
	(0.118)	(0.143)	(0.167)
Observations	5,192	5,192	5,192
R-squared	0.065	0.067	0.094

Other controls: district FE, household variables
Omitted: January

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.4 Path dependency of drought reports

To determine whether drought shocks are persistent, I estimate a dynamic panel model. Table 13 provides the results of the Arellano-Bond estimator. I test basic assumptions of the model. I test for first order serial correlation; the hypothesis is that there is no first order serial correlation. The test indicates that I can fail to reject the null of no serial correlation across all models. The second order serial correlation test could not be computed due to the limited length of the panel. In fact, the model includes only a one-year lag due to data limitations. Next, I test the exclusion restriction for the instruments used. Across all specifications, the Sargan test of over identified restrictions suggest that I can fail to reject the null hypothesis that the over identified instruments are valid. The coefficient of interest is the one on the lagged report. Drought report in the year prior increases the probability of reporting a drought. This holds in all three specifications of the model. A more intuitive interpretation of these results follows in Tables 14 through 18, where calculate conditional probabilities.

Table 13 Path dependency of shock reports			
VARIABLES	(1)	(2)	(3)
L.drought_report	0.518***	0.285***	0.310***
	(0.0670)	(0.0596)	(0.0523)
Rainfall (m)		-0.628***	-0.719***
		(0.0540)	(0.0709)
Year_2011			0.0371***
			(0.0126)
Year_2012			-0.0292*
			(0.0162)
Constant	0.0783***	0.722***	0.807***
	(0.0116)	(0.0514)	(0.0728)
Observations	2,596	2,596	2,596
Ar(1)	-10.174	-9.339	-10.938
Sargan test	84.83646	89.1507	91.21273

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

According the basic model in column 1, the probability that a household will report a drought at time is equal to the constant, 0.0783 or 7.83 percent. Conditional on reporting a drought in the previous year at, the probability to report a drought is 0.0783 + 0.518= 0.5963 or 59.6 percent (see Table 14). In column 2 of Table 13, I control for rainfall. Conditional on rainfall level at, and on reporting a drought in the previous year, the probability to report a drought at is 37.9 percent.

Table 14 Conditional probabilities - Model (1)		
	No drought at	Drought at
No drought at	92.2%	7.8%
Drought	40.4%	59.6%

Table 15 Conditional probabilities - Model (2)		
	No drought at t	Drought at t
No drought t-1	90.6%	9.4%
Drought t-1	62.1%	37.9%

Table 16 Conditional probabilities - Model (3)		
Year = 2010		
	No drought at	Drought at
No drought t-1	91.2%	8.8%
Drought t-1	60.2%	39.8%
Year = 2011		
	No drought at t	Drought at t
No drought t-1	91.2%	8.8%
Drought t-1	56.5%	43.5%
Year = 2012		
	No drought at t	Drought at t
No drought t-1	91.2%	8.8%
Drought t-1	63.1%	36.9%

Including the year of interview changes the results slightly. The omitted year in column 3 is 2010. The probability to report a drought at conditional on reporting at and on the level of rainfall is the highest in 2011 at 43.5 percent. In fact, reporting a drought in 2010, made it 3.71 percent more likely to also report a drought in 2011. However, reporting a drought in 2011, made it 2.9 percent less likely to also report the following year in 2012. Although this might seem counterintuitive, as noted earlier, the 2012 droughts induced the distribution of drought relief packages in several drought-affected districts, which would act to dampen the effect of the drought on household livelihood. These results suggest that shocks do persist over time, and the persistence is accentuated if the interview year is a drought year.

Chapter IV – Summary and Discussion

Summary of results

In this thesis, I set out to answer the following three questions: 1) how well do self-reports of drought relate to measured rainfall/drought; 2) can differences in employment of the household head, irrigation source, and self-reports explain heterogeneity in households' reports of drought once rainfall is controlled for; and 3) to what extent do self-reports depend on timing of the shock module and on past reports of drought?

I find that the self-reported values correlate with measured annual rainfall and drought variables defined therein, albeit not perfectly. Contrary to expectations, seasonal rainfall measures do not correlate well with self-reports of drought, but annual rainfall does, indicating that when households retrospectively answer questions in the shock module, they consider the level of rainfall during the entire previous year and not just rainfall during the rainy season. Results on the correlation between self-reports and measured annual rainfall are robust to how the objective variable is defined. Similar results were obtained with the use of measured drought defined as rainfall deficits of 25 percent or more from a long-term mean, compared to when drought is defined as annual rainfall values of one standard deviation below the long-term mean. However, different specifications of the self-reported variable yielded divergent results. Reports of drought and coping strategies had a lower association with measured rainfall, compared with reports of droughts only. These results make sense and suggest that more factors enter into the adoption of coping strategies. Experiencing a drought and reporting having adopted proactive measures against future climatic shocks had no association with rainfall levels.

I find that, beyond rainfall measured, the employment of the household head and household wealth are important determinants of self-reports of drought. Farmers were more likely than non-farmers to report having experienced a drought, conditional on rainfall levels. Wealthier households were also more likely than poorer households to report having been affected by a drought, up to a certain rainfall threshold. At rainfall levels beyond this threshold, poorer households had higher propensity to report a drought. These two results corroborate each other. In fact, wealthier households were also more often employed in agriculture. Unlike Hunter, Gray and Edwards (2013), I find no evidence of a relation between source of irrigation and self-reports. The lack of significance could have been due to limitations of my data; there is no clear indication of how rain dependent these irrigation sources are.

The timing of the shock-module questionnaires matters. I find that households interviewed during the rainy season were less likely to report a drought, while those interviewed during the harvest season were more likely to report a drought. Here, weather conditions at the time of the interviews had a priming effect on the report of past drought. More research needs to be undertaken to determine the effects of a more-encompassing range of interview-day weather conditions: the effects of precipitation, temperature, and their deviations from normal levels on responses to self-reported drought. There is a psychological aspect of subjective shocks that should not be ignored but, rather, captured to ensure our full understanding of subjective measurements. Moreover, the collection of accurate and unbiased self-reported values hinges on interviews being conducted in similar weather conditions (if our interest is in drought/weather shocks) over time, for the same households and across households at the same point in time. Failure to do so will result in heterogeneous responses that might have been avoided. Finally, I find evidence for the path dependency of self-reports. Drought shocks are persistent over time and their persistency is accentuated when there is a drought during the year of interview. These findings contribute to our understanding of the ways in which self-reports of drought relate to measures of drought and, more precisely, to the time of reference of self-reports vis-à-vis rainfall.

Implications for shock measurement

Given the abundance and ease of collection of self-reported indicators, a clear imperative exists to take advantage of the unique opportunity that such data present. However, such opportunity will not be seized unless and until we are aware of the precise measurement requirements of shocks and the potential sources of bias in the data-collection process. Self-reported data provide a nuanced understanding of shocks and their effects on household welfare and well-being over time that can be missed by measured rainfall. If we can ascertain, as the present analysis suggests, that shock perceptions are contingent on time of interview, then we need to ensure that shock modules control for potential bias, by standardizing the time of interview as best as possible both within and across households over time. This would allow for analysis that is less biased and, thus, more likely to appropriately influence policy.

In addition, given that shock reports correlate across time even when rainfall deficits have been considered indicates that the consequences of a shock persist from one year to the next. This is especially true if there are no significant "actual" drought conditions that would warrant such reports. In that sense, subjective assessments indicate the households that see themselves as most vulnerable to repeated shocks. In terms of practical implications, shock surveys should include questions on previous shock experiences, to capture this dimension. A current project on "Measuring Indicators for Resilience Analysis" (MIRA) by Catholic Relief Services and Cornell University, has undertaken part of these suggestions, including low-burden, high-frequency data collection of current and previous shocks. Similar efforts should follow.

Moreover, the importance of weather conditions at the time of interviews indicates that we can no longer study shocks in isolation; rather, their perceived effects are contingent on what is happening during both the time of reporting and the reference time (the previous year). In fact, the experience of other simultaneous shocks often exacerbates the perceived effects of a shock. The joint effect of both contemporaneous and past shocks can impose a heavy burden on households. Shock modules should then incorporate indicators that would capture the interaction of different shocks.

While a drought is a covariate shock affecting many households in an area, its impacts are varied and depend on an array of factors. This study has shown that a household's livelihood strategy, and wealth are important factors. In fact, I find that at low levels of rainfall, wealthier households are more likely to report a drought, whereas once annual rainfall reaches beyond 1300 mm, those that are poorer have a slightly higher probability of reporting a drought. These results have implications for the ways in which household surveys are designed. Household surveys should be representative of the socio-economic fabric of the area of study. Having respondents mostly from wealthier households would result in overstating the report of droughts, whereas when most of the participants are from lower socio-economic groups, the report would underestimate the reports of drought. This knowledge allows us to decipher the nuances of how drought affects people differently.

Implications for future research

In light of the findings and the noted limitations of the data and methods, future research should determine more accurate objective measures of drought. Better objective variables will take into consideration not only rainfall but also other weather indicators that are found to interact with rainfall in determining drought (Dell, Jones, and Olken, 2014). Such indicators might be data on temperature, moisture adequacy, and different indices that would allow more nuanced results for different types of droughts, whether agricultural, hydrological, or meteorological. Moreover, more accurate results can be elicited by paying closer attention to cropping patterns to determine the type of crops harvested, their water requirements, and the exact timing of their planting and harvest seasons. Future research on this topic should also explore the effect of government aid and/or social programs in influencing drought reports, especially just following a drought. In fact, the significant year effects throughout the analysis might hint at an important 'drought relief effect' that the study could not capture because of the poor quality of the data on drought relief/ government. Last, a longer study panel might be useful if we want to investigate the determinants of shock reports in the long term.

More research is also warranted on the experiences of common shocks, focusing on individual household members. This will be particularly important for large families comprising different family units with different employment trajectories. It is quite common in rural Indian villages to have large family structures that are made up of smaller families headed by the sons/daughters of the household heads. Furthermore, it is very likely that fathers and sons, while living under the same roof, are employed in different sectors and, thus, have different livelihood strategies. Yet, recording self-reported answers at the household level might underestimate, overestimate, or incorrectly specify self-reported values. It is therefore important to understand that household compositions are more complicated and nuanced than they might appear, which warrants a more targeted and individualized approach even within the same household.

Conclusion

The results reported here may have important implications in three respects. First, the results may inform the ways in which the measurement of shocks can be understood as having both objective and subjective properties. Second, the results may suggest the way objective and subjective measurement of shocks can be used as part of resilience analysis. Third, on a more practical level, the results demonstrate how the measurement of both subjective reports and objective indicators of shocks may help improve our ability to understand factors that affect ways in which shocks are experienced. For researchers and enumerators, these results are significant in that they may influence the way that shock module surveys for resilience measurement are designed. For development practitioners, the results may help build better connections between shock metrics and decision making about where and when interventions are most needed.

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APPENDIX A

Table 1. Probit results of the likelihood to leave the sample after baseline

Dependent: Does the household attrite after 2010? (Yes=1)		
VARIABLES	(1)	(2)
Household size	-0.0310	-0.0310
	(0.0323)	(0.0363)
Household education	-0.0278	-0.0452
	(0.0262)	(0.0292)
Age head of household	-0.000311	0.00212
	(0.00542)	(0.00606)
Sex of head (male =1)	-0.298	-0.515*
	(0.233)	(0.270)
Head employed in ag (yes=1)	-0.328**	-0.366**
	(0.165)	(0.181)
Owns land (yes =1)	-0.01000	0.100
	(0.194)	(0.217)
Owns livestock (yes =1)	-0.373**	-0.384**
	(0.161)	(0.183)
States (Andhra Pradesh base)		
Bihar		-0.369
		(0.289)
Gujarat		-0.182
		(0.272)
Jharkhand		-1.233**
		(0.479)
Maharashtra		-0.534**
		(0.251)
Odisha		-0.286
		(0.270)
Observations	1,345	996

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2. Household distribution within geographic area

Region	State	District	Village	HH number
Semi-Arid Tropics	Andhra Pradesh N = 76	Prakasam N =76	JC Agraharam	37
			Pamidipadu	39
	Gujurat N = 159	Junagadh N = 79	Makhiyala	39
			Karamdi Chingaraya	40
		Panchmahal N =80	Chatha	40
			Brabol	40
	Karnataka N = 160	Bijapur N = 80	Markabbinahalli	40
			Kapanimbargi	40
		Tumkur N = 80	Tharati	40
			Belladamadugu	40
	Maharashtra N = 264	Akola N = 112	Kanzara	62
			Kinkhed	50
		Solapur N = 152	Shirapur	88
			Kalman	64
	Madhya Pradesh N = 80	Raisen N = 80	Papda	40
			Rampur Kalan	40
	Telangana N = 116	Mahbubnagar N = 116	Dokur	48
			Aurepelle	68
East India	Bihar N = 160	Darbhanga N = 80	Inai	40
			Susari	40
		Patna N= 80	Baghakole	40
			Arap	40
	Jharkhand N = 160	Dumka N = 80	Dumariya	40
			Durgapur	40
		Ranchi N = 80	Dubaliya	40
			Hesapiri	40

	Odisha N = 160	Bolangir N= 80	Bilaikani	40
			Ainlatunga	40
		Dhenkanal N = 80	Chandrasekharpur	40
			Sogar	40

- "Did you experience any severe drought/flood/pest/diseases/misfortune that affected your livelihoods in the last year? The list of shocks is drought, flood/cyclone, pests and diseases, death of earning member, death of livestock, litigation of property, loss due to theft/dacoit/fire, wild boars, others (specify)
- Indicate the amount lost due to the said problems (in Rs. or % income).
- Did you adopt any coping mechanisms due to above said problems during last year? If yes, list the coping mechanisms adopted in order of importance.
- Did Government / any organization provide any assistance during drought/flood/pest/diseases/misfortune experienced during the last year? If yes, what type of assistance did you receive?
- Can you rank the individuals/institutions you approach in terms of how reliable they are in the event of a drought or flood?
- "Did you adopt any proactive measures keeping in mind future climatic shocks? If yes, what measures have been taken?

Box 1: Shock module Questionnaire

APPENDIX B

Fig 3. Rainfall pattern - long term

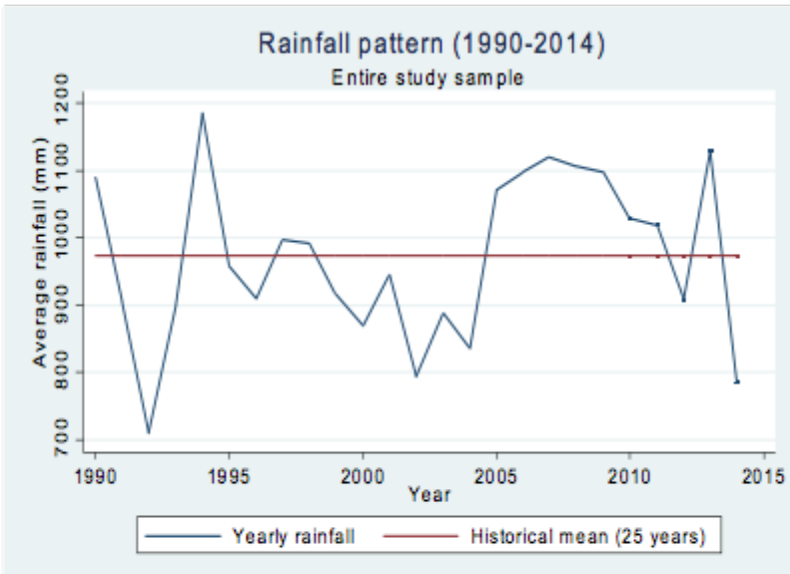

Fig 4. Rainfall pattern 2010-21014

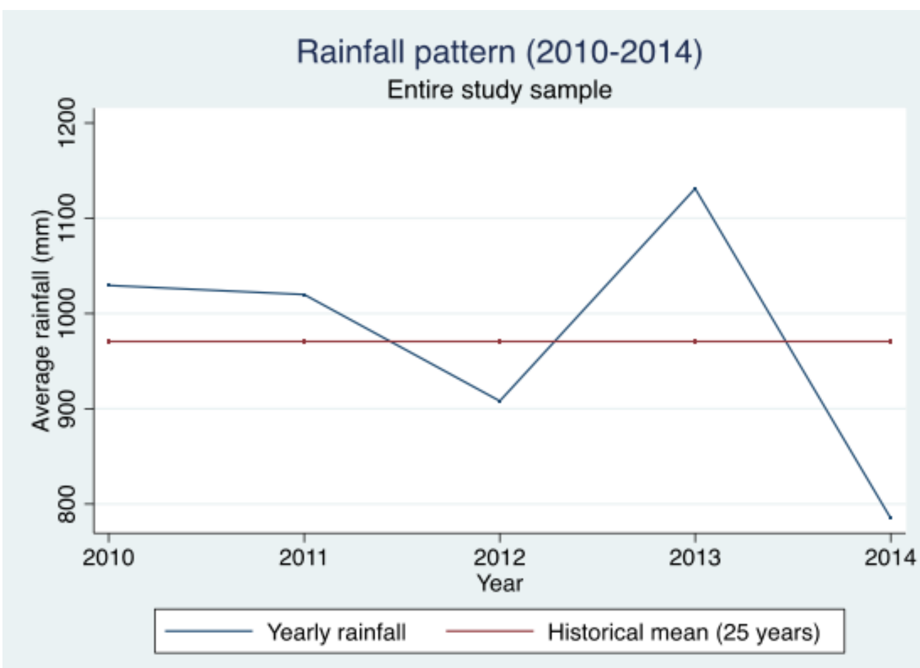

Fig 5. Rainfall pattern SAT vs East India (2010-21014)

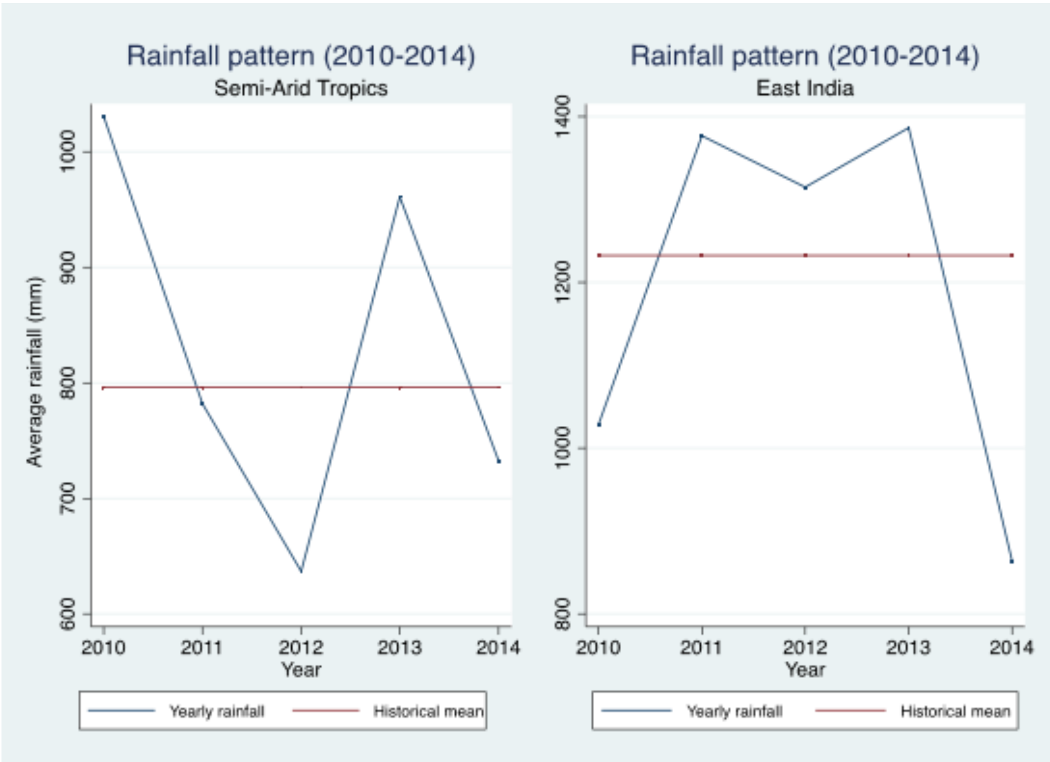

Figure 6. Rainfall pattern in SAT and East India 2010-2014