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Extreme weather events are expected to increase globally due to climate change thereby posing substantial risks to agricultural communities. The implications are especially high for tropical countries like India as the heavy dependence of agricultural sector to uncertain monsoons makes its agriculture highly vulnerable to weather variability and extremes. In this dissertation, we examine the vulnerability of agricultural systems in India to extreme weather events. To this end, we first develop an indicator of vulnerability using the partial moments model which captures two important dimensions of vulnerability - the likelihood of an agricultural system falling below some critical threshold as well as the extent of the loss below the threshold. We then demonstrate the usefulness of this

indicator for policymakers with an empirical application to India by examining both the vulnerability of crop yields to weather extremes as well as the household vulnerability to poverty. The estimation results using a panel data of rice yields from thirty Indian villages indicate that extreme and severe dry events have a positive and significant effect on vulnerability in rainfed farms but not in irrigated farms. These results provide evidence of irrigation as an adaptive mechanism for farmers. When examining agricultural household's vulnerability to poverty, we find similar effects of weather extremes with the household most vulnerable to poverty when exposed to an extreme dry event. We also find statistical evidence that crop diversification has a negative effect on vulnerability and is an important risk-mitigating tool employed by farm households. We next examine the vulnerability of Indian agriculture at a more aggregated level by exploiting a district-level panel data for forty years. Similar to the farm-level analysis, we find extreme and severe dry events to be the main drivers of vulnerability whereas irrigation and high-yield variety (HYV) seeds are found to increase resilience. We discuss the implications of our results for policymakers by examining the impacts under various hypothetical climate and technological scenarios.

Quantifying Vulnerability of Agricultural Systems in India to Weather Extremes

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Kedar Kulkarni, Author

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Chapter 1: Introduction

Evaluating the impacts of climate change on agriculture and its ability to adapt to changes in weather and weather variability poses an important challenge for agricultural researchers. In the recent years, following the United Nations guidelines, the discourse on climate change impacts in agricultural research has witnessed a paradigm shift. While the early research focused on average or aggregate physical and economic impacts, the growing reality of climate change coupled with the emergence of sustainable agriculture systems has seen a rise in studies that consider agricultural system performance in a multi-dimension setting. A central focus of this new literature has been on the vulnerability of agricultural systems to climate change. Vulnerability as a concept has long been a subject of study in the climate change literature with numerous agronomic studies documenting that growth and productivity of most crops are vulnerable to a number of critical thresholds, such as minimum and maximum temperatures, and availability of water. However, most of the existing economic studies have not yet addressed the vulnerability of agriculture in the sense of assessing the likelihood of crop yields or farm incomes falling below a critical threshold. Vulnerability assessments help in identifying the communities and regions most vulnerable to climate change, their ability to cope with adverse weather shocks and the factors driving their vulnerability. Policymakers can make use of this critical information to design interventions to reduce vulnerability.

In India, the heavy dependence of the agricultural sector to uncertain monsoons makes it highly vulnerable to weather variability and extremes (Fishman 2016; Auffhammer, Ramanathan, and Vincent 2012). Indeed, the frequency of extreme weather events, in particular floods, droughts and high maximum temperatures, has increased in the past fifty years in India as a result of climate change. Consequently, agricultural households are increasingly concerned about their exposure to these events as they play an important role in determining their welfare. For instance, extreme weather events such as droughts reduce surface water and groundwater supplies, affecting irrigation which in turn affects crop yields. The impacts from these events are often realized in the form of reduced crop sales and increase in production costs that can potentially reduce net farm income. Moreover, evidence shows adverse weather shocks also influence agricultural household decisions on child health and education (see for e.g., Jacoby and Skoufias 1997; Zimmermann 2020). The impact of changes in weather on crop yield and its variability therefore remains an important area of inquiry, as evident by the recent rise in the number of studies (Dinar et al. 1998; Mall et al. 2006; Cline 2007; Lobell, Schlenker, and Costa-Roberts 2011).

At the same time, farmers can adjust their practices to adapt to adverse weather events. One such practice is irrigation. For the past five decades, a focus of agricultural policy in India has been towards promoting green revolution technologies, particularly the adoption of high-yield seed varieties (HYV) and the increased use of irrigation and fertilizers, with the goal of improving agricultural productivity in order to meet the demands of rising population, national food security and poverty alleviation. Whilst the green revolution has helped India in achieving food self sufficiency, it has also resulted in a shift from traditional sustainable practices to modern practices that are arguably unsustainable in some dimensions, e.g., groundwater depletion.

Besides irrigation, market based instruments such as crop insurance enable agricultural producers to take ex-ante measures and adapt to extreme weather events. The Government of India (GoI) has introduced various crop insurance schemes since 1985 with the aim of providing financial support to the farmers in the event of failure of crops as a result of natural calamities. In virtually all these schemes, a farmer is entitled for claims if the actual yield for an insured crop falls short of a well specified 'guaranteed or threshold' yield in the event of a natural calamity. These facts have different implications for the producers and policymakers. On the one hand, producers are increasingly concerned about mitigating their losses from adverse weather events while maximizing profits, policymakers, on the other hand, are more concerned about designing effective insurance policies that to an extent are centered on the idea of crop yields falling below a threshold level in the presence of an adverse weather shock. Moreover, there are implications for food security as policymakers would like to avoid production falling below some critical threshold and take necessary actions to address threats to food insecurity.

In this dissertation, our main aim is to contribute to the development of methods for analysis of impacts of extreme weather events and technology on the vulnerability of agricultural systems. The methodological core of our study develops an indicator of vulnerability, defined here as the average absolute deviation below an appropriate reference level, to quantify the vulnerability of agricultural systems to extreme weather events. We show that this measure is able to capture both the likelihood of crop yields falling below a 'threshold yield' as well as the degree or the extent of the loss. We next demonstrate the usefulness of this measure in an assessment of the vulnerability of rice yields in India to extreme weather events. Lastly, we also emphasize on the general applicability of the vulnerability indicator with an investigation of the vulnerability of rural households in India to poverty.

The empirical analysis in this dissertation is based on the Village Level Dyanmics (VLS) agricultural database available through the International Crop Research Institute for Semi-Arid Tropics (ICRISAT). This database comprises of both district-level agricultural data as well as data from household farm surveys which allow us to examine the vulnerability with respect to a physical outcome such as crop yield as well as an economic outcome like household income. Furthermore, we are also able to exploit this database to conduct our analysis at both the farm level and district-level. The dissertation is organized as follows. Chapter 2 reviews the literature on modeling crop yields and vulnerability and states the contribution of our study. Chapter 3 presents a conceptual framework of vulnerability and an economic model of individual decision making under uncertainty. In Chapter 4, the threshold indicator of vulnerability is formally developed and hypotheses to be tested are outlined. Chapter 5 presents the empirical results using the farm-level dataset. In Chapter 6, the empirical results for the district-level vulnerability analyses is presented. Chapter 7 discusses the impact of technology and weather extremes on the vulnerability indicator in the future based on current biophysical and socioeconomic conditions.

Chapter 2: Literature Review

This chapter provides an overview of the existing literature on quantifying climate change impacts on agriculture. We outline the current state of practices in the economic literature on modeling the relationship between weather and agricultural output are determined. The research question undertaken in this study can be located within four strands of literature namely modeling production uncertainty in agriculture, impacts of climate change on agriculture, vulnerability and the choice of weather variables used in the quantification of climate change impacts.

2.1 Modeling Production Uncertainty in Agriculture

Modeling production uncertainty in agriculture is generally done by developing a stochastic production function. Crop output, y, is treated as a random variable at the time when inputs are chosen and the uncertainty in production enters primarily through a set of exogenous random factors, w, such as weather, pest damages, soil chemistry. Taken in the stochastic form, the agricultural production function can be written as $y = f(x, w)$ where y is a random variable that follows the distribution $\phi(y|x, \beta)$, parameterized by β. Under the expected-utility framework, the decision-maker with terminal wealth, W, maximizes her utility by choosing

x i.e. $\max_x EU(W + pf(x, w) - cx)$ where $E(.)$ is the expectation operator based on the subjective distribution, $\phi(w)$ and, p and c denote output and input prices, respectively.

A variety of approaches have been utilized in the past to empirically estimate the production function. Most of the early models characterize yield in a production function framework, specifying crop yields as a function of farm management inputs with the uncertain component, weather, considered in the error term. This can be largely attributed to the fact that weather data were not readily available. Prior to the key contribution by Just and Pope, the models commonly took the multiplicative and additive production specifications [1] . In their seminal work, Just and Pope (1978) showed that marginal effects of inputs are always increasing in the multiplicative model and are always zero in the additive model. In turn, they proposed the Just and Pope (J-P) specification that could identify the separate effects of inputs on the mean and variance of the output. Such a specification allowed for the categorization of marginal effects of inputs on the probability distribution of output as risk-reducing, risk-increasing or risk-neutral. Antle (1983) extended the Just and Pope specification, as it restricts the effect of inputs across higher moments, by proposing the 'flexible moment based' model. This approach relaxes any cross-moments restrictions i.e. the elasticity of exogenous variables with respect to variance does not restrict their elasticity with respect

[1]The multiplicative production function is specified as $y(x, w) = f(x).w$ where $E(w) = 1$. In the additive form of specification, the stochastic production function is $y(x, w) = f(x).w$ with $E(w) = 0$.

to skewness and kurtosis. Estimation of the different moments begins with the classical production function, the residuals of which are then squared and cubed to estimate higher moments such as variance and skewness. An important advantage of the moments-based model is that it provides a flexible approach to the estimation of risk preferences. The econometric model employed to estimate risk preferences does not restrict the impact of inputs on risk nor on the form of the utility function.

A different strand of literature has focused on modeling crop yield distributions in the context of crop insurance programs. The methods vary statistically. Studies using parametric methods reject the assumption of crop yield distributions being normal because of negative skewness and excess kurtosis (Day 1965; Ramirez 1997; Just and Weninger 1997; Atwood, Shaik, and Watts 2003). Some studies use a beta (Nelson and Preckel 1989; Hennessy, Babcock, and Hayes 1997; Hennessy 2011) and gamma (Pope and Ziemer 1984; Gallagher 1987) distribution to characterize crop yields because of their flexible nature to assume varying degrees of skewness and kurtosis. On the other hand, semi-parametric (Ker and Coble 2003) and non-parametric methods (Goodwin and Ker 1998; Tolhurst and Ker 2015) have been developed to overcome the restrictions of parametric models (for e.g. parametric form of distribution is the same across all locations). In addition, they are increasingly flexible in modeling in-sample crop yields while also capture features that parametric analyses hide (Ramsey 2020). Recently, a small body of literature has highlighted the importance of incorporating spatial and temporal information in crop yield modeling through empirical Bayes non-parametric methods (Ker and Goodwin 2000; Ozaki et al. 2008; Ker, Tolhurst, and Liu 2016; Park, Brorsen, and Harri 2019).

2.2 Climate Change Impacts on Agriculture

Motivated by an increase in scientific understanding of climate change, a particular body of literature has focused on modeling the relationship between weather, soil type and other exogenous controls on crop yields. Indeed, a range of methods have been developed that have contributed to our understanding of the impacts of climate change on agriculture. These methods can be broadly classified into four sections: Laboratory experiments, agronomic crop models, panel data analyses and cross-sectional analyses. Of these, the last two approaches rely on statistical techniques to estimate the relationship between weather or climate and agricultural output. These models link vectors of climate variables (C) and other exogenous controls (X) to an outcome (y) as in equation (2.1) [2] . Most of these studies do not explicitly include the farm management variables and are prone to misspecification bias. The functional form $f(.)$ is unknown to the econometrician and as economic theory provides little guidance on the shape of this relation, it remains an open empirical question.

[2] C may include averages of weather e.g., temperature, precipitation, wind speed. X may include several exogenous variables such as soil type, geography (e.g., elevation), population density and relevant location or time-specific dummies. The outcome of interest, y, is usually net revenues or crop yield.

$$y = f(C, X) \tag{2.1}$$

The cross sectional (Ricardian) technique examines equation (2.1) by regressing net revenue or land values on climate. It relies on the identification strategy that the cross-sectional variation observed in a particular climate allows the researcher to estimate the impact of climate on farmers' expected incomes. In its econometric estimation, it assumes a linear or semi-log specification as in equation (2.2) with the climatic variables specified in the quadratic form and a linear specification for all the other controls.

$$ln(y_{it}) = \beta_0 + \beta_1 C_{it} + \beta_2 C_{it}^2 + \alpha^{'} X_{it} + r_i + \epsilon_{it}; E(\epsilon_{i,t}|C_{it}, X_{it}) = 0 \tag{2.2}$$

where, i and t indicate the entity and time respectively, r is an entity-specific random effect and e is the residual that is normally distributed and uncorrelated with the exogenous variables. Perhaps, the most important advantage of the Ricardian approach is that it captures long-run adaptation to climate. Additionally, it also evaluates the effect of climate change on net revenue, thus providing a measure of welfare. In contrast, panel data weather studies, as discussed below, use crop yields as dependent variable and are not directly able to measure welfare. As such, numerous studies have utilized the Ricardian approach to estimate the impact of climate on agriculture (see Mendelsohn and Massetti 2017 for a complete list of studies).

However, Ricardian methods suffer from several issues. A first issue pertains to the functional form. Equation (2.2) with the quadratic approximation allows the separability of the climatic effect. With such a specification, the marginal effect of a climate variable, say precipitation, would solely depend on itself but not on other climatic variables such as temperature. One can relax this restriction by including an interaction term where the climatic variables are mutually dependent. A drawback of this approach is that it constraints the effects to assume very specific functional forms. There is no theoretical justification to assume such a particular functional form and is rather adopted for ease of estimation (Fezzi and Bateman 2015). A second empirical issue concerns that of omitted variable bias. Omitting variables such as irrigation technology and other variables (e.g., economic development, private investment) pose a threat to identification as the effect of climate on land values would absorb the unobserved contribution of irrigation technologies and the other variables (Deschênes and Greenstone 2007). For example, the use of irrigation to offset reduction in yield from rising temperatures is well documented (e.g., Tack and Ubilava 2015). As such, it is imperative to include the interactions between climate and other variables.

To overcome the problem of omitted variable bias in cross-sectional analyses, the use of panel data approach with fixed effects has been the preferred method in the last two decades. This approach investigates how the variation in weather across time affects the climate sensitivity of crop yields or net revenue (Blanc and Schlenker 2017). An advantage of the panel data method is its ability to control for unobservable time-invariant differences between groups and thus any variation observed is from the weather outcomes over time within a given spatial area. The regression equation takes the following form:

$$y_{it} = \alpha_i + \beta C_{it} + \gamma X_{it} + \theta_t + \epsilon_{it}; E(\epsilon_{it}|\alpha_i, \theta_t, X_{it}, C_{it}) = 0 \tag{2.3}$$

where i and t represent group and year respectively, α_i are the group-specific fixed effects that absorb all the time-invariant factors, whether observed or unobserved, between groups and θ_t are the time-fixed effects that capture the trends in the outcome data and thus isolate them from the idiosyncratic local shocks. The standard approach is to model crop-yields as a non-linear function of weather outcomes in a particular location and year and include location fixed-effects to capture the time-invariant factors (Blanc and Schlenker 2017)

Deschênes and Greenstone (2007) popularized this method by applying it to US agriculture and estimated the effect of random fluctuations in weather on farm net revenue. Following, an extensive set of studies have followed that rely on the reduced-form technique in equation (2.3) to estimate the effect of weather variation on different outcomes such as growth (Dell, Jones, and Olken 2009;Dell, Jones, and Olken 2012; Burke, Hsiang, and Miguel 2015), labor productivity (Deryugina and Hsiang 2014), human capital (Graff Zivin and Neidell 2012), energy demand

(Auffhammer and Mansur 2014), health (Deschênes and Greenstone 2011), conflict (Hsiang, Meng, and Cane 2011) and crop yields (Schlenker and Roberts 2009).

With the growing concerns about the effect of climate change on agriculture, there now exists a large literature that uses econometric panel methods to investigate the effects of weather variables on crop yield outcomes. This has also been made possible largely by the ready availability of agricultural data at the county and farm level, weather data as well as development of new sophisticated methods including the Geographic Information Systems (GIS). However, studies employing these methods have found inconsistent results of temperature, precipitation, and other weather variables on mean crop yields. The results vary between crops and locations. The effect of temperature on crop yields in the U.S. is shown to follow a non-linear pattern with temperatures above certain thresholds deemed to be harmful (Schlenker and Roberts 2009). Lobell, Schlenker, and Costa-Roberts (2011) find negative effects of temperature and positive effects of precipitation in warmer countries for major crops up to a particular threshold. Burke and Emerick (2016) exploit large variation in temperature and precipitation changes using U.S. county-level data and show corn and soybean yields respond negatively to multi-decadal changes in extreme heat. Various studies have been performed across the globe with similar conclusions (Carleton and Hsiang 2016; Auffhammer 2018). These studies primarily focus on temperature and precipitation and largely ignore other climatic variables such as humidity, wind speed, evaporation. Zhang, Zhang, and Chen (2017) appear to be one of the few econometric studies that show other climatic variables such as humidity, wind speed have a significant effect on crop yields.

Despite the advantages panel models offer in estimating climate change impacts on agricultural output, there exist several challenges for its adoption. Panel models may suffer from omitted variable bias, as in the cross-sectional approaches, if the time-varying factors are correlated with weather anomalies. While the fixed effects offer a solution to overcome time-invariant confounding factors, correlation between weather anomalies (e.g., hotter years are also drier) will wrongly attribute the effect of the correlated weather anomalies (temperature and precipitation) to one factor included. Thus, all weather anomalies must be included. In addition, other weather measures such as humidity, wind speed, solar radiation have been shown to influence water balance of a crop. Omission of these measures can produce biased results. Another important caveat of the panel models, as well as the cross-sectional models, is its inability to account for CO2 concentrations. As Schlenker and Roberts (2009) argue, accounting for CO2 concentrations is impossible as they evaporate quickly into the atmosphere and hence are statistically difficult to separate from the technological change.

While the Ricardian and panel methods have dominated the climate change impacts literature within the area of economics, most of the research outside the economics literature has used the integrated assessment framework to combine the climate projections and future socio-economic scenarios with process-based agronomic and livestock models. Crop simulation models embody a set of parameters related to crop growth processes that reflect the genetic characteristics of the crop type and variety. These models simulate the nonlinear effects of temperature, water, carbon dioxide (CO2), and nutrients, and their interactions with crop growth and yields, and they can incorporate explicit aspects of management such as altered planting dates, fertilization rates, and irrigation use. An important advantage of these models over the econometric models is their ability to incorporate the effects of future elevated CO2 on crop growth. The positive effects of a rise in atmospheric CO2 on crop yields is well documented (e.g. Antle et al. 2004). Because econometric models use observational data in their analysis, they are not able to incorporate the effects of CO2 and are likely to overestimate the adverse impacts or understate the positive impacts of climate change in the future (Antle and Stöckle 2017).

A second strand of literature focuses on modeling yield distributions to assess the distributional impacts. Most of the literature using the Ricardian and panel data models has focused on the mean economic impacts of climate change on crop yields. However, the impacts can differ substantially across regions and individuals. For instance, the aggregate economic impacts of climate on change on US agriculture are relatively small as compared to the impacts of climate change on the individual producers or consumers (McCarl and Reilly 2006). In order to go beyond the aggregate impacts, it is important to account for the asymmetrical nature of distributions in evaluating risk. While researchers in the past have considered the role of asymmetry in assessing risk, such as the safety first model (Roy 1952), mean-semivariance model (Markowitz 19599), exposure to downside risk (Bawa 1975; Menezes, Geiss, and Tressler 1980; Antle 1987; Modica and Scarsini 2005; Crainich and Eeckhoudt 2008), behavioral models (Kahneman and Tversky 1979), below target returns (Fishburn 1977) and the risk-value models (Jia, Dyer, and Butler 2001; Butler, Dyer, and Jia 2005; Routledge and Zin 2010), it is only recently that attention is being paid to risk associated with unfavorable events, such as climate change (Weitzman 2009; Tack and Ubilava 2015). One particular body of literature has focused on understanding the response of variability in temperature and precipitation on crop production. Employing the feasible generalized least square approach (FGLS) developed by Just and Pope (1978), various studies find variability in precipitation and temperature to significantly impact mean crop yields and crop yield variability, although the impacts differ across crop types and locations (Chen, McCarl, and Schimmelpfennig 2004; McCarl, Villavicencio, and Wu 2008; Isik and Devadoss 2006; Carew, Smith, and Grant 2009; Cabas, Weersink, and Olale 2010; Poudel and Kotani 2013). Also relevant is the recent literature on modeling yield distributions using higher moments. Tack, Harri, and Coble (2012) combine moment-based approach (Antle 1983) with maximum entropy techniques and examine the impacts of temperature and precipitation on the distribution of cotton yields in the US. Zhang and Antle (2018) use the partial moments model to investigate the climate vulnerability of winter wheat crops in the Pacific Northwest.

Quantile Regressions, first proposed by Koenker and Bassett Jr (1978), can be seen as a compromise between parametric and non-parametric methods and provide a distribution-free approach to estimating conditional densities. Several studies have examined the crop yield distributions using quantile regressions. Barnwal and Kotani (2013) use quantile regressions to assess the sensitivity of rice yields in Andhra Pradesh to climate change and find the effect to be more profound in lower quantiles. Krishnamurthy (2011) employs a panel data quantile regression methodology to evaluate the impacts of climate change on rice and wheat yields and finds the effect to be largely negative. Sanglestsawai, Rejesus, and Yorobe Jr (2015) measure the impact of Bt corn on crop yields in the Phillippines using an instrumental variable quantile regression and find differences in the impact of Bt technology over different quantiles of the corn yield distribution. Similarly, Chavas and Shi (2015) use conditional quantile regressions to show the heterogenous benefits of genetically modified seed technology on crop yields in Wisconsin. Chavas et al. (2019) study the impacts of weather on crop yield distributions in Italy using a quantile autoregression model and find asymmetric effects of extreme weather on lower and upper tail of the distribution.

2.3 Vulnerability

In the past decades, vulnerability assessments have gained importance following the United Nations Framework Convention on Climate Change (UNFCCC) guidelines "The specific needs and special circumstances of developing country Parties, especially those that are particularly vulnerable to the adverse effects of climate change, and of those Parties, especially developing country Parties, that would have to bear a disproportionate or abnormal burden under the Convention, should be given full consideration" (United Nations, 1992). This has resulted in a growth in research on understanding vulnerability and climate change vulnerability assessments (See Tonmoy, El-Zein, and Hinkel 2014; Giupponi and Biscaro 2015 for a thorough review).

The term *vulnerability* is found in different disciplines and in different contexts. The Cambridge dictionary defines vulnerability as '*able to be harmed or attacked*'. Because the target population and methodology differ between sciences, there is no one globally accepted definition of vulnerability within the vulnerability assessment literature. Disciplines rather focus on narrowing down the scope of vulnerability and accordingly present a metric for it. In economics, and in general, vulnerability means '*the risk of being harmed, wounded (negatively affected) by unforeseen events*' (Guillaumont 2009). Vulnerability may thus be viewed as the increased sensitivity to shocks or a greater susceptibility to shocks of an adverse nature. In tropical economies like India, where the susceptibility to shocks, especially related to adverse weather conditions (e.g., floods or droughts), is high, it is critical to assess the extent to which individuals are affected by such shocks. This issue is further complicated by the idiosyncratic nature of these shocks i.e., it affects certain regions or individuals more than others. In a recent study of the US agriculture, Antle and Capalbo (2010) note that climate change will likely have important distributional impacts across regions and the type or size of farms. Small farms are less specialized and more diversified in their mix of crops and depend to a larger extent on non-farm sources of incomes. As a result, they are less impacted by climate change as compared to larger farms who tend to be highly specialized and vulnerable to climate changes. However, large farms are also financially stronger and depend on market-based risk management tools as well as on government subsidies. One important implication from this discussion is that while individuals are interested in managing their vulnerability to climate change, policymakers are more concerned about the distributional impacts i.e., the various populations that are expected to be vulnerable to climate change so as to target intervention.

Various disciplines have proposed and applied numerous quantitative techniques to measure vulnerability. Perhaps, the most common method is to quantify vulnerability using a set or composite of proxy indicators (Moss, Brenkert, and Malone 2001; Kaly et al. 2002; Wheeler 2011). This approach combines various factors of an entities (e.g., region or country) exposure to a shock and its ability to recover from it. In contrast, the vulnerability literature in economics quantifies vulnerability within a micro-theoretic framework i.e., vulnerability of each individual in an entity is calculated and then individual vulnerabilities are aggregated to form the entity's vulnerability [3] . In economics, vulnerability has mainly been conceptualized in the context of poverty and defined as the risk of being poor or becoming poor. There exist three principal approaches in

[3]This approach is analogous to the measurement of poverty, where a society's poverty is the aggregate sum of individual poverty levels (see Sen 1976)

quantifying vulnerability to poverty – vulnerability as expected poverty (VEP), vulnerability as low expected utility (VEU) and vulnerability as uninsured exposure to risk (VER) (Hoddinott and Quisumbing 2010).

The VEP and VEU approaches measure individual vulnerability around a reference level. Individual vulnerabilities are then aggregated to arrive at a measure of society's vulnerability. In the VEP, vulnerability is mainly conceptualized as a risk concept i.e. as the expected value of suffering from a shock below a certain target threshold (Fishburn 1977), which is essentially the poverty line in this case. Some early studies using this approach include Suryahadi, Sumarto, and Pritchett (2000) where they define vulnerability as the probability of falling below the poverty line in any three consecutive time periods in the future. Following, studies such as Chaudhuri, Jalan, and Suryahadi (2002) and Kamanou and Morduch (2002), Christiaensen and Subbarao (2005) measured vulnerability within the VEP framework. In this approach, vulnerability to poverty of the individual j in time period t, is defined as the expected value of the FGT poverty index over the state of nature he faces in time period $t+1$. The VEU approach, instead, bases itself on the expected utility theory and defines vulnerability as the difference between the utility of obtaining a reference level of consumption under certainty (e.g. as defined by the poverty line) and the expected utility of consumption (Ligon and Schechter 2003). Calvo and Dercon (2005) provide a measure of vulnerability also based on the expected utility theory where individual vulnerability is an assessment of the magnitude of the threat that the individual will experience episodes of poverty in the future. The VER approach is based on the consumption smoothing and risk-sharing literature where vulnerability is defined by the extent to which a negative shock causes a household to deviate from expected welfare (Gerry and Li 2010). While the VEU and VEU are forward-looking approaches i.e., they perform an ex-ante assessment of future poverty, VER is an ex-post assessment of the extent to which a negative shock caused a welfare loss.

Besides the three principle approaches, recent studies have measured vulnerability within the reference-utility theory framework such as in Günther and Maier (2014). In there, poverty is measured as a function of current consumption level as well as the losses and gains with respect to a reference utility level. Other studies have quantified vulnerability within the mean-risk dominance criterion. For instance, Chiwaula, Witt, and Waibel (2011) provide a measure of vulnerability where they identify an individual is vulnerable if the poverty line, Z, is greater than the difference between mean and standard deviation of income, y i.e. $Z > E(\bar{y_i}) - \sigma_y$. Gallardo (2018) extends this approach and uses the downside mean semi-deviation as the risk parameter, γ, such that an individual is vulnerable to poverty if $Z > E(\bar{y_i}) - \sigma_y$, $\gamma \in (0, 1]$.

A particular focus of this research is on measuring the economic vulnerability of agricultural systems to extreme weather events. As such, it follows the Foster-Greer-Thorbecke poverty indicator concept and defines vulnerability as the absolute deviation below a certain reference level. This indicator of vulnerability is discussed in detail in chapter 4. There are three important reasons for why this measure is relevant for this study. Firstly, a measure of vulnerability has to capture downside risk i.e., shortfalls from a given reference point. This is crucial because the relevant risk in vulnerability assessments is primarily concerned with the inability to manage adverse shocks. In contrast, upward gains are not important because they are innocuous and do not contribute to losses in welfare or mitigate downside risk. Secondly, the vulnerability indicator must be necessarily forward-looking. Individuals and policymakers are increasingly concerned about the future and thus a measure that informs them about the potential deprivations in the future is of primary importance. Thirdly, the measure of vulnerability should account for the fact that vulnerability is an individual specific concept in the sense that each individual's perception of risk is different and thus same shortfalls from the reference level may reflect different levels of vulnerability.

An important distinction has to be made between the vulnerability indicator used in this study from the existing methods in the poverty literature as discussed above. While the indicator is analogous to a measure of vulnerability as expected poverty (VEP), it differs mainly in its assumption of the reference line. Most of the studies under the VEP framework assume a probability threshold of 0.5. However, such a fixed threshold can have different implications on risk and vulnerability. Instead, in this study, an argument is made for considering an absolute threshold of vulnerability. The primary motivation for this comes from the fact that individuals and policymakers are more concerned about survival. For instance, a farm owner with a mortgage is increasingly concerned about not going insolvent. Further, as will become apparent in the next section, the VEP measures are expected values of the FGT indices and therefore cannot measure the magnitude of losses (i.e., depth of the fall below the reference line). In other words, the FGT indices are by construction relative measures. However, Antle et al. (2004) show that absolute and relative measures of vulnerability can result in different conclusions for policymakers. The VEU approach, on the other hand, comes with the caveat that it requires the researcher to assume specific functional form for the utility function, which is assumed to be the same for all individuals. However, individual preferences differ with individuals. Furthermore, it also has the shortcoming of having a symmetric view of risk. The vulnerability indicators under the mean deviation and reference dependent utility theory measures suffer from the same criticism as the VEU approach in that they do not capture asymmetrical nature of risk and depend on the researcher's choice of utility functional form as well as the gain-loss functions respectively. Although the downside semi-deviation measure is able to capture asymmetric risk, it is dependent on the arbitrary nature of the risk aversion parameter as well as the assumption of linear relationship between the mean and the risk parameter. In turn, the vulnerability indicator used in this study provides a flexible way to capture the asymmetric nature of risk and measures both the probability and severity of expected losses below some reference level. Lastly, in the climate change impacts literature, the prevalent statistical models discussed earlier, have not addressed the vulnerability of agriculture (i.e., the likelihood of production or revenues falling below a certain threshold) as these studies rely on aggregated data and are able to only assess the impacts on the total production. The issue is further intensified as climate change is likely to have important distributional impacts, across regions and farms. By using highly aggregated data, many economic studies are unable to capture this heterogeneity. A recent study by the AgMIP team in Africa and South Asia demonstrates the importance of quantifying heterogeneity in vulnerability assessments of climate change and shows that in heterogeneous populations, the average economic impact is a poor measure of vulnerability (Rosenzweig et al. 2014). In the past decade, some progress has been made in quantifying agricultural production vulnerability (Antle et al. 2004) as well as in econometric methods of investigating the effects of climate change on yield distributions at a regional scale (Tack, Harri, and Coble 2012; Zhang and Antle 2018)

2.4 Weather Variables in Climate Change Impacts Literature

The fourth body of literature related to our work is on modeling the crop yield-water relationship. Most of the current literature on climate change impacts has focused on using some measures of precipitation and temperature to model crop yields as a function of weather. However, the importance of temperature anomalies, water deficit periods and other climatic variables like humidity, solar radiation and wind speed on crop growth has been long acknowledged in the agronomic literature (Xu, Twine, and Girvetz 2016; Siebert et al. 2017). Besides, few studies have focused on quantifying extreme weather events such as droughts and flood. This is partly because there is no universally accepted definition of what constitutes a drought or flood. Various studies use different indices and metrics to capture these extreme weather events. Composite drought indices like the Palmer Drought Index (PDSI), Standard Precipitation Index (SPI) and Standard Precipitation and Evapotranspiration Index (SPEI) have gained popularity in the past years as they consider the joint effects of temperature, precipitation, potential evaporation and better capture the soil moisture and water relationship. In the U.S, most of the policymakers rely on the US Drought Monitor (USDM), which is shown to capture the negative impacts of droughts on crop yields (Kuwayama et al. 2019). Ortiz-Bobea et al. (2019) use a measure of soil moisture using the North American Land Data Assimilation System (NLDAS) dataset to highlight the importance of intraseasonal timing of water availability on crop yield variability.

2.5 Contributions

This dissertation makes several contributions to the literature. The main goal of this paper is to contribute to the development of methods for analysis of impacts of extreme events, such as extreme weather associated with climate change, on outcome variables such as crop yields or farm income. To this end, we make both methodological and empirical contributions. Firstly, on the methodological front, we develop a measure of climate vulnerability using the partial moments model of Antle (2010). Our proposed vulnerability indicator is closely related to the Foster, Greer, and Thorbecke (1984) (FGT) poverty indicator concept in that both measures capture the deviation below a well-defined reference level. However, the FGT indicator measures the relative vulnerability while the vulnerability indicator presented here is an absolute measure. Absolute and relative measures of vulnerability can have different implications on the outcome variables. For instance, Antle et al. (2004) use both relative and absolute measures of vulnerability to test the hypothesis of a negative relationship between resource endowments and vulnerability and find this to be true only for absolute measures but not for relative measures. To further elaborate the difference, consider two farms A and B with incomes of USD1000 and USD1500 respectively. With climate change, assume farm A experiences a loss of 10% in its income while farm B loses 15%. Using a relative measure of vulnerability, farm B would be considered more vulnerable. However, under an absolute measure of vulnerability, say with USD 950 as the threshold, farm A would be vulnerable, whereas farm B would not.

Secondly, we contribute to the existing literature on the effects of weather and climate on agricultural outcomes. While there exists a large body of literature on analyzing the impact of climatic factors and weather effects on agricultural outcomes, virtually all of these studies focus on the mean economic impacts of weather and climate on crop yields and use these estimates to predict the aggregate effect of climate change on crop yields. At the same time, the critical role of weather in production risk is well-documented. Yet, the quantitative evidence on the effects of weather on crop yields distribution is scarce. The vulnerability indicator developed using the partial moments approach and a threshold indicator is able to fill these gaps and is advantages for two reasons. Firstly, this indicator takes into account both the average and distributional impacts of weather on crop yields. Secondly, and more importantly, this indicator is able to capture the shortfall from the '*threshold yield*'. In other words, it is a measure of the expected '*yield gap*' resulting from the occurrence of an extreme weather event i.e., the magnitude of an adverse outcome.

Thirdly, we contribute to the growing literature on characterizing the crop yield-water relationship. Agronomic science shows that the role of intra-seasonal timing of environmental stress in crop yield determination is crucial (Smith et al. 1999; Fageria, Baligar, and Clark 2006). To this end, we look at the temporal variation in the climatic water balance throughout the growing season. This enables us to exploit the periods during which agricultural growth is most sensitive to adverse weather conditions.

A final contribution is related to the climate indicator employed in the characterization of the crop yield-water relationship. Most of the climate change impacts literature in economics has focused on precipitation or temperature. Yet, we know other weather measures such as humidity, solar radiation, wind speed influence the water balance of a crop. As such, we use the Standardized Precipitation Evapotranspiration Index (SPEI) that considers the joint effects of precipitation, temperature, solar radiation, humidity and wind speed. The SPEI index is the difference between precipitation and potential evapotranspiration, i.e., the net balance of water, which is standardized. The index is expressed in units of standard deviations from the long-run average, so that a positive (negative) value in a given month means an above (below) normal water balance. The water balance is important for vegetation activity. A lower balance reduces plant growth and hence negatively affects agricultural production. The SPEI index is a useful measure in this study for two reasons. Firstly, the index captures the climatic water balance i.e., the difference between water supply (e.g., precipitation) and water demand (e.g., runoff, potential evapotranspiration). We can therefore adequately represent various weather events such as agricultural droughts (i.e., excess water demand) and floods (i.e., excess water supply) using the SPEI index. Secondly, it allows us to capture the timing and severity of the event. Exploiting the timing of the occurrence of the event as well as the magnitude of it allows us to capture the vulnerability of crops during the crop growth phase.

Chapter 3: A Conceptual Framework of Vulnerability

3.1 Conceptual Framework

The literature on conceptualizing vulnerability has stressed on linking three important elements – exposure, sensitivity and adaptive capacity (Parry et al. 2007). We present a conceptual framework of vulnerability which incorporates these three elements. Our conceptual framework builds on the model of Hoddinott and Quisumbing (2010) and comprises four components – 'environment', 'assets', 'activities' and 'outcomes'. Environment describes the conditions in which a household and product markets function. All the households are endowed with assets which when combined with other assets, or by themselves, produce an outcome. These assets can also be distributed across various activities and is conditioned by the environment in which the household's function. The outcome resulting from the allocation of assets to various activities within a given environment is a determinant of household's welfare. Figure 3.1 shows the linkage between households, product markets and outcomes, and the sources of risk faced by them. A household's vulnerability is embedded in this chain and depends on the likelihood of the shock occurring, the nature of the shock, the extent of the shock on household's welfare and its coping mechanisms. Vulnerability is intrinsic to this linkage and can be considered as the '*risk chain*'.

We now expand on the above framework by considering a new household in a rural setting. This household functions within four environments – natural, economic, political, and social. The natural environment refers to events arising from the nature such as the amount of rainfall, temperature, soil quality and distance to markets. The social environment describes the behavioral norms and social cohesion for the existence of the household. The political environment captures the rules and laws as well as the mechanisms by which the rules are set. Lastly, the economic environment refers to the policies and technological growth that affect the product markets as well as the household's returns on assets. These environments vary between the local, regional, national, and global levels. Households work within these environments and are endowed with assets. These assets can be categorized into physical assets (livestock, machinery, and land), human assets (labor, skills, and knowledge), financial assets (cash, checking accounts, mortgages) and social assets (networks, social trusts, cooperatives). Figure 3.1 shows that the household allocates its endowments across various activities e.g., agricultural, and non-agricultural activities. Moreover, the household chooses to allocate its endowments across activities to maximize its expected returns from them. Outcomes (e.g., farm production) are then a result of household allocation decisions across activities.

The environment within which the households reside can be considered to be sources of risk. Any shock that impacts households emerge from one or more of the four environments. For instance, floods and droughts are natural sources of risk whereas civil wars can be considered to be social or political sources of risk. Furthermore, the shocks can be either idiosyncratic or covariant in nature. A death of the household head is an example of an idiosyncratic shock i.e., restricted to that particular household while a flood or drought can be considered to be a covariate shock i.e., common to all the households. The complex relationship between household's assets and its allocation to activities and the outcome is affected by the realization of the shock. For example, a natural shock such as flood or droughts can adversely affect household's physical assets such as agricultural land and in turn impact crop yields or production which would lead to a dramatic fall in household income, a measure of welfare. The household could respond to this shock by reallocating its assets e.g., shifting labor from farm activities to non-farm activities, selling some of its assets etc.

Several implications can be drawn based on this framework for quantifying vulnerability. Firstly, it is imperative to know the various components and sources of risk affecting rural households. In India, majority of the rural households depend on agriculture as a means of subsistence. Although, there is considerable growth in the off-farm employment, on-farm activities still constitute a major source of household income. A natural shock like drought directly impacts crop yields as well as local prices thereby affecting household income. Secondly, agriculture has performed differently in different parts of India. Using national averages and to some extent state averages is useful in understanding overall growth and progress but these measures are not informative enough to frame policies as they do not capture the heterogeneity in agricultural systems. Any such analysis therefore must conduct at the sub-national level. In recent years, availability of data at the district level as well as at the household level imply the unit of analysis can be either a district or farm. Lastly, these facts suggest that we need a model that can capture the complex interactions between biophysical and management processes that jointly determine the production outcomes.

3.2 Output distributions, weather extremes and partial moments

In this section, we adopt the partial moment-based model developed by Antle (2010) to illustrate the impact of extreme weather events on output distributions. This framework is useful in formulating an economic model and in quantifying vulnerability and in the description of our econometric strategy presented below.

Following Antle (2010), production is defined as a stochastic process, $y = f(x, SPEI)$ determined by complex interactions between management decisions, x and exogenous random events such as weather, $SPEI$. Figure 3.2 describes the process that generates output distribution and its relation to inputs and climate. The positive horizontal axis represents the weather generated from a climate in a particular location, denoted by $\chi(SPEI|\theta)$, where θ parameterizes the climate, expressed in the form of climatic variables such as a multi-scalar drought index, $SPEI$. The positive vertical axis measures output per unit of land (yield) with the upper bound, $\bar{y}$, defined as the maximum output per hectare determined by the crop's genetic potential. The negative horizontal axis measures the probability density of output given inputs, x, denoted as $\phi(y|x)$.

Figure 3.2 shows two production relationships, $f(x_A, SPEI)$ and $f(x_B, SPEI)$, generating two different output distributions, $\phi(y|x_A)$ and $\phi(y|x_B)$ respectively. Consider a low level of input such as high yield seed variety which responds strongly to normal SPEI. Distribution A corresponds to this case. In this case, the mass of the output distribution is concentrated at low output levels and is right-skewed. Distribution B is obtained when an input is applied at a high level such as HYV seed. In this case, mass of the output distribution is concentrated at high output levels and is left-skewed. Further, different types of inputs and the interactions between them can also have different effects on the mean and variance of the output distributions. For instance, if an input is applied increasingly, it can change the output distribution from a positively skewed to a more symmetrical shape but with an increased mean and variance. The characterization of yield distributions in figure 3.2 indicates that changes in inputs are likely to have different effects on the positive and negative tails of distributions as well as various quantitative and qualitative effects on the shape of the distribution. Antle (2010) shows that a flexible model can quantify the effects of inputs on output distributions. In other words, it can capture the different effects of an input on the positive and negative tails of the distribution.

In the next section, we formalize our conceptual framework into an economic model at the household level using the decision-making under uncertainty framework with the objective of formally understanding how extreme weather events impact agricultural households' vulnerability.

3.3 Economic Model

The scope of this section is to formalize the conceptual framework discussed in the above section into an economic model at the household level. The economic model for measuring vulnerability is developed on the basis of decision-making under uncertainty framework with the objective of formally understanding how extreme weather events affect agricultural households' vulnerability.

For simplicity, we first consider a farm with a production technology where production is a single period process for a single output and then generalize. Across the process, farmer chooses various inputs and capital, weather occurs, and finally output is realized. Thus, the production process is realized by random weather variables.

Consider a production function

$$y = f(x, z, w, \epsilon; \alpha) \tag{3.1}$$

where y is crop yield per hectare, w is a vector of inputs use and farm management, z is a vector representing fixed farm factor such as land, human capital, w captures weather which consists of anticipated weather event, w^a and unanticipated weather event, w^u , α is a vector parameter of interest and ϵ are any other unanticipated random shocks.

We assume that i) the production function is strictly concave and twice differentiable in input use; ii) the unanticipated shocks are jointly distributed in a particular location at a specified time interval according to $\chi(w^u, \epsilon|\theta)$ where θ is interpreted as the micro-climate parameters of at an individual farm and output, y, follows a distribution, $y \sim \phi(y|x, z, w^a, \theta)$; iii) price of input use, c, is predetermined and normalized by the output price and; iv) farmers are risk-averse.

Define by $U(\pi, \beta)$ the utility function, parametrized by β, and the net return function, $\pi(c, z, x, w^a, \alpha, \theta) = f(x, z, w^a, \theta; \alpha) - cx$. The goal of the risk-averse farmer is to maximize her expected utility by choosing x,

$$\max_x E[U(\pi, \beta)|c, x, z, w^a, \theta, \alpha)] = \int \int U[f(x, z, w^a, \alpha) - cx]\, \chi(w^u, \epsilon)\, dw^u\, d\epsilon \quad (3.2)$$

The solution to this maximization problem is $x(c, z, w^a, \alpha, \beta, \theta) \equiv x(\gamma)$ where $\gamma = (c, z, w^a, \alpha, \beta, \theta)$ are the micro-parameters.

In the next chapter, we build upon the conceptual framework and economic model to define a threshold indicator of climate vulnerability of agricultural systems and show how the partial moments model can be used to construct this indicator.

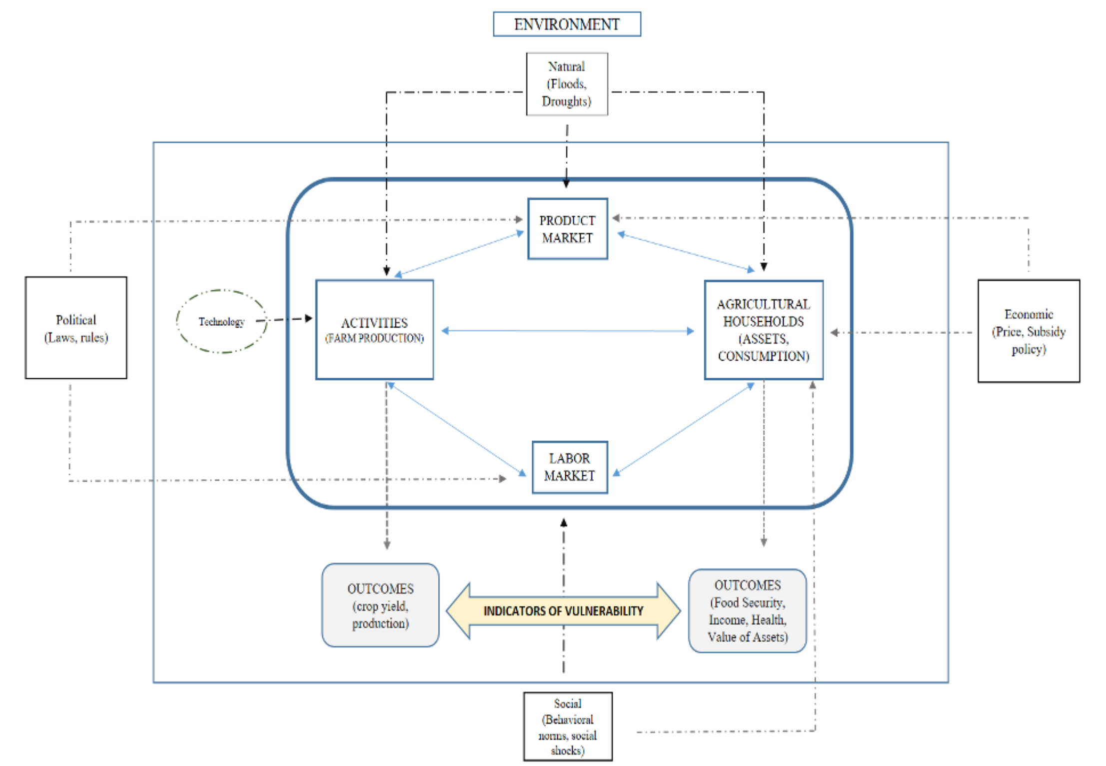

Figure 3.1: A Conceptual Framework of Vulnerability (Based on Hoddinott and Quisumbing, 2003)

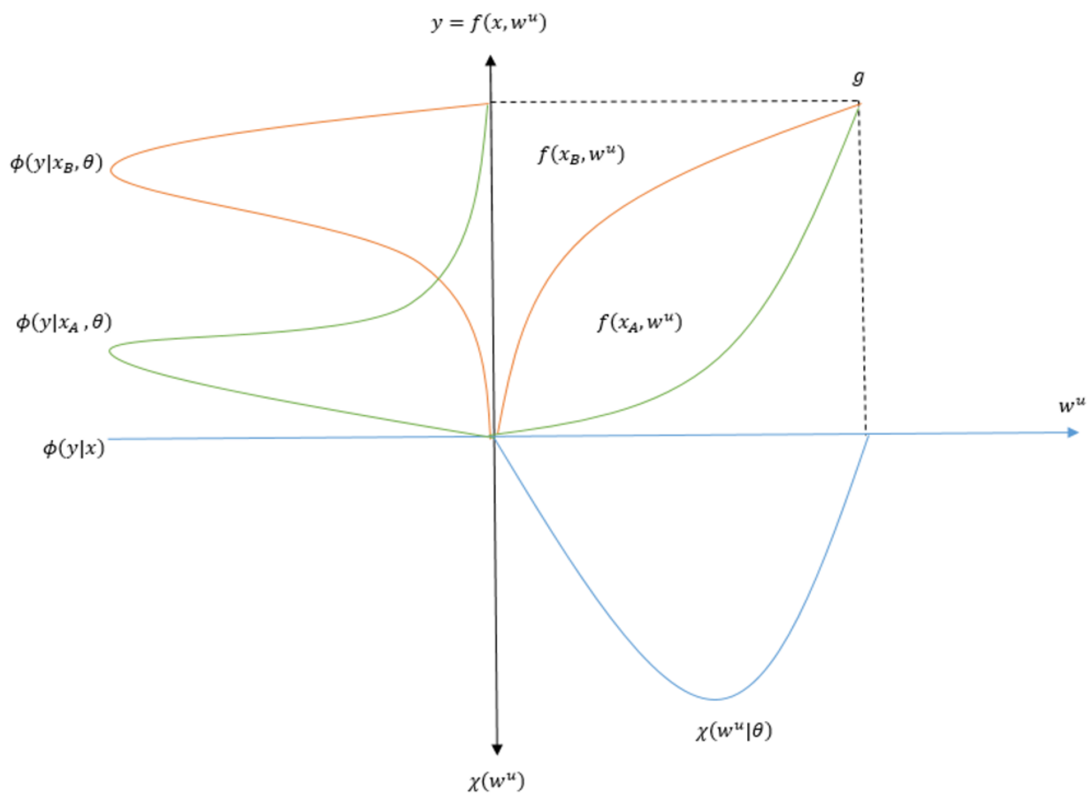

Figure 3.2: Output distribution properties determined by production functions with management inputs (x) and random variable (SPEI). Source: Antle (2010)

Chapter 4: Measuring Vulnerability

4.1 Vulnerability Indicator

The term ’vulnerability’ is found in different disciplines and in different contexts. While the Cambridge dictionary defines vulnerability as ‘able to be harmed or attacked’, because the target population and methodology differ between sciences, there is no one globally accepted definition of vulnerability within the vulnerability assessment literature. Disciplines rather focus on narrowing down the scope of vulnerability and accordingly present a metric for it. In economics, vulnerability has been primarily conceptualized in the context of poverty. In the vulnerability to poverty literature, the most common measure is that of vulnerability as expected poverty (VEP) because it meets the desirable properties inherent to the Foster-Greer-Thorbecke (FGT) poverty measures, including symmetry, replication invariance, subgroup consistency and decomposability (Foster, Greer, and Thorbecke 1984). Simply put, the vulnerability to expected poverty can be considered to be the expected value of the FGT measure and is defined as the likelihood of falling below a critical threshold e.g. poverty line, consumption threshold (Suryahadi, Sumarto, and Pritchett 2000; Chaudhuri, Jalan, and Suryahadi 2002). Ligon and Schechter (2003) use a similar idea of ‘*poverty line*’ and define vulnerability to poverty as the difference between the utility derived from a non-vulnerable level of certainty-equivalent consumption and the expected utility of consumption. A more general definition often found in the literature on vulnerability as exposure to poverty is that of '*vulnerability is the risk of becoming poor or at risk of remaining poor*' (Christiaensen and Subbarao 2005; Calvo and Dercon 2013; Chiwaula, Witt, and Waibel 2011). In contrast, vulnerability as exposure to risk concerns an individual's inability to smooth consumption over time (Ravallion and Chaudhuri 1997; Glewwe and Hall 1998; Jalan and Ravallion 1999; Dercon and Krishnan 2000; Amin, Rai, and Topa 2003). An alternate definition of exposure to risk is proposed by Povel (2015) who uses an approach to exposure to downside risk to capture the asymmetric view of risk and defines vulnerability as the "*resilience against a shock*".

The FGT class of poverty measures can be defined as $P_\alpha = \frac{1}{n}\sum_{i=1}^{q}(\frac{z-y_i}{z})^\alpha$ where z is the poverty line, y_i is the i^{th} individual's lowest income, n is the total population, q is the number of persons who are poor, and $\alpha \geq 0$ is a "poverty aversion" parameter. In the continuous case, the FGT indicator is $P_\alpha = \frac{1}{n}\int_0^z(\frac{z-y_i}{z})^\alpha\,\phi(y)\,dy$ where $q = \int_0^z\,\phi(y)\,dy$. For $\alpha = 0$, P_0 = $\frac{q}{n}$ is the proportion below the poverty line or simply the headcount ratio; for $\alpha = 1$, $P_1 = \frac{1}{n}\int_0^z(\frac{z-y_i}{z})\,\phi(y)\,dy$, is the poverty gap measure and for $\alpha = 2$, $P_2 = \frac{1}{n}\int_0^z(\frac{z-y_i}{z})^2\,\phi(y)\,dy$ is the expected severity of the poverty. Note that we can re-write $P_1 = \frac{1}{n}\int_0^z\,\phi(y)\,dy$ - $\frac{1}{n}\int_0^z\frac{y}{z}\,\phi(y)\,dy = \frac{q}{n}\left[\frac{z-\bar{y}}{z}\right]$ where $\bar{y} = \frac{1}{q}\int_0^z\,y\,\phi(y)\,dy$ is the average income of the poor.

Following the FGT measures of poverty, we can construct a family of vulnerability measures. We define a threshold indicator of climate vulnerability as the average absolute deviation below some reference level, $I(x,r,\theta) = \int_0^r (r-y)\,\phi(y|x,\theta)\,dy$ where I is a threshold indicator of the climate vulnerability at an individual farm, y is an economic outcome (e.g. crop yield) from the output production and r is a reference level. This indicator can be presented as an ex-ante risk measure based on a stochastic distribution and is closely related to concepts in the finance literature such as the lower partial moments.

The vulnerability indicator, I, used above captures absolute vulnerability in the sense of the average amount the vulnerable person are below r i.e. an absolute deviation from a reference level whereas the FGT indicator measures the relative vulnerability. Note that, analogous to the FGT poverty gap indicator, we can express the vulnerability indicator in relative terms as $I(x,r,\theta) = \int_0^r \left[\frac{r-y}{r}\right] \phi(y|x,\theta)\,dy$. However, absolute and relative measures of vulnerability can have different implications for vulnerability. For instance, Antle et al. (2004) use both relative and absolute measures of vulnerability to test the hypothesis of a negative relationship between resource endowments and vulnerability and find this to be true only for absolute measures but not for relative measures. To further elaborate this concept, consider two farms, A and B, with incomes of \$1000 and \$1500 respectively. With climate change, say, farm A experiences a loss of 10% in its income while farm B loses 15%. Using a relative measure of vulnerability, farm B would be considered more vulnerable. However, under an absolute measure of vulnerability, with \$950 as the absolute threshold, farm A would be more vulnerable. Thus, it matters what measure of vulnerability is considered.

To further see the intuitive appeal of the FGT indicator, define $\Phi(x, r, \theta) = \int_0^r \phi(y|x, \theta)\, dy$ as the probability of an individual being vulnerable i.e. the probability of crop yield falling below an appropriate reference level and $[r - \eta_1(x, r, \theta)]$ as the degree of vulnerability i.e. the average amount the crop yield is below the reference level for the vulnerable individual or the expected yield gap where $\eta_1(x, r, \theta) = \int_0^r y\, \phi(y|x, \theta)\, \Phi(x, r, \theta)^{-1}\, dy$ is the first-order lower partial moment. Then the vulnerability indicator can be written as

$$I(x, r, \theta) = \int_0^r (r - y)\, \phi(y|x, \theta)\, dy \tag{4.1}$$

$$= \Phi(x, r, \theta) \int_0^r (r - y)\, \phi(y|x, \theta)\, \Phi(x, r, \theta)^{-1}\, dy \tag{4.2}$$

$$= \Phi(x, r, \theta)[r - \eta_1(x, r, \theta)] \tag{4.3}$$

Note that the FGT poverty gap measure ($\alpha = 1$) above can also be expressed as the product of the headcount ratio as well as the average income gap of the poor. The intuitive appeal of the FGT poverty gap measure is also seen in Figure 4.1 as it combines the two important dimensions of vulnerability - the probability of vulnerability and the expected yield gap. The upper left quadrant in Figure 4.1 shows the impact of a change in climate on vulnerability. Climate change, realized in the form of more frequent occurrences of extreme weather events (e.g. droughts in this case), can be represented in the shift of the parameter θ to θ'. As a result, the output distribution is negatively affected and shifts left from $\phi(y|x, \theta)$ to $\phi(y|x, \theta')$, reducing the mean and shifting the higher-order moments. Note that increase in frequency of extreme weather events has an asymmetric effect on the tails of the output distribution. It shifts the mass of the output distribution concentration from the upper tail and reduces the negative skewness. With climate change, interpreted here as the increase in frequency of extreme weather events such as droughts, vulnerability to extreme weather event increases, i.e. from, $I(x, r, \theta) = \Phi(x, r, \theta)[r - \eta_1(x, r, \theta)]$ to $I(x, r, \theta'] = \Phi(x, r, \theta')[(r - \eta_1(x, r, \theta')]$. In other words, both the proportion of the population below the reference level (Φ) and the expected yield gap ($r - \eta_1$) is greater with climate change.

4.2 Hypotheses

In this section, we use the indicator of vulnerability developed here and the conceptual framework from chapter three to outline the testable hypotheses.

(a) *Extreme weather events increase the vulnerability of agricultural systems as well as households*

Extreme weather events such as drought and floods are expected to lower crop yields and thus increase the vulnerability of the farms. The main channel through which this is expected to occur is due to lack of availability of water (or the excess of it) during the growing season cycle thereby impeding crop growth. Moreover, since most of the rural households depend on agriculture for their livelihood, decrease in yields as a result of extreme weather event is likely to lower household income which in turn is expected to increase their vulnerability to income.

(b) *Irrigation technologies decrease the vulnerability of agricultural systems and households*

Adoption of irrigation technologies and expansion over rain-fed croplands is an effective adaptation strategy. Farm managers are likely to adapt these measures as a response to increasing temperatures and heat stress faced by the crops. Further, the greater the share of irrigated area across all the farms in the households, the lower is the household's vulnerability.

(c) *High-Yield Variety Seeds decrease the vulnerability of agricultural systems and households.*

The use of high-yield variety (HYV) seeds by farmers is mainly done with the aim of achieving higher yields. It is thus likely that adoption of these modern variety seeds will result in the households becoming less vulnerable in the event of a good harvest. However, the HYV seeds require much higher water intake and are also less resilient to droughts and heat stress. Thus, in the event of an extreme weather event, HYV crops are likely to be more sensitive and increase the vulnerability of the households.

(d) *Vulnerability of the households differs by farm-size with marginal farms more vulnerable than small and medium scaled farms.*

Farm size is expected to be a significant predictor of a household's vulnerability. Most of the marginal farms are rainfed and thus likely to be more vulnerable in the event of a drought or flood. On the other hand, small and medium scaled farms are adopters of HYV and irrigated which makes them more resilient to an extreme weather event.

(e) *Crop diversity increases the resilience of households*

Households can diversify their farm income sources by planting multiple crops in a season thereby decreasing their vulnerability to income loss from weather extremes.

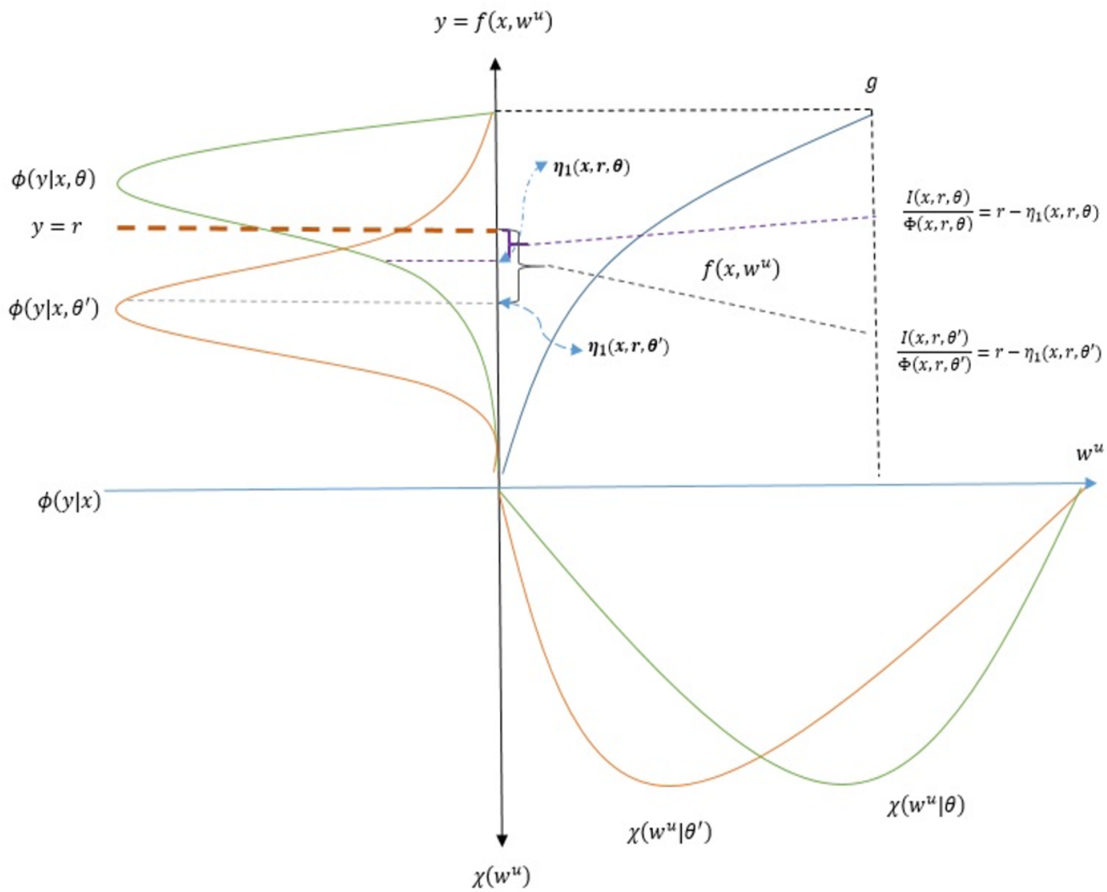

Figure 4.1: A conceptual framework of the impact of extreme weather events on the output distribution (Based on Zhang and Antle, 2018)

Chapter 5: Empirical Analysis – Households

The conceptual framework of vulnerability developed in chapter 3 highlights the linkage between households, product markets and outcomes, and the various sources of risk faced by them. A household' vulnerability is embedded in this chain and is dependent on the likelihood of the shock occurring, the nature of the shock, the extent of the shock on household's welfare and its coping mechanisms. For a developing and agricultural-intensive country like India, agricultural shocks constitute an important source of risk for majority of the rural households. In particular, its heavy dependence on rainfall renders these households vulnerable in the event of a natural calamity such as a drought or flood. This can often result in a wide variability in their income. If the households lack sufficient coping mechanisms, such as assets or insurance, the impact of such extreme events can extend beyond just the lowering of physical capital like crop yields or income and lead to irreversible losses such as reduced consumption or low investments in health and education (Jacoby and Skoufias 1997; Zimmermann 2020). Consequently, households can find themselves in a poverty trap (Morduch 1994; Carter and Barrett 2006). Examining the impact of changes in weather on agricultural outcomes therefore remains an important area of inquiry, especially from the perspective of policymakers. It is thus desirable for the policymakers to identify the households and communities most vulnerable to weather shocks and their adapting capacity. This information can be useful in designing policies that are directed at reducing vulnerability and in turn poverty. Moreover, the implications extend towards other human dimensions such as food insecurity and child malnutrition as policymakers would like to avoid production falling below some critical threshold and take necessary actions to address threats to food insecurity.

In this chapter, we examine the vulnerability of rural households in India to extreme weather events. The specific goal is to investigate how extreme weather events impact the vulnerability of crop yields as well as household income. To this end, we employ the climate indicator of vulnerability developed in earlier chapters, defined as the absolute deviation below an appropriate reference level, to a farm-level panel dataset from thirty Indian villages and empirically evaluate how extreme weather events affect the likelihood of crop yields falling below a critical threshold as well as the likelihood of a household falling below the poverty line. This distinction is important for two reasons. On one hand, although there has been a rise in off-farm employment, agriculture still constitutes a major source of income for most rural households. Thus, understanding how adverse weather shocks affect the vulnerability of household to poverty is of interest. On the other hand, quantifying the vulnerability of crop yields to weather extremes seems relevant since agriculture forms a means of subsistence for most rural household. Moreover, crops such as wheat and rice are staple in the country but also essential for trade as India is a net exporter of these crops. A natural shock like drought can directly impact crop yields as well as local prices thereby affecting household income. In the absence of a well-integrated market, weather shocks can also result in an increase in agricultural prices. Consumers will be hurt but producers might benefit through increased revenues which may partially offset their losses in crop yields. Cline (1992) suggests in order to capture losses in producer and consumer welfare, analyzing agricultural yields is preferable. While income and consumption indicators seem to be predominantly used in measuring vulnerability, the use of physical outcomes such as crop yields is scarce.

The rest of the chapter proceeds as follows. In the next section, we present the data sources used for the econometric analyses. In section 5.2, we present the econometric model and the results from the econometric analysis of the impact of extreme weather events on the vulnerability of crop yields. Section 5.3 present the econometric analysis and results for household vulnerability to poverty. Finally, section 5.4 concludes.

5.1 Data Sources

5.1.1 Agricultural Data

The main data source for the farm-level analyses comes from the Village Dynamics in South Asia (VDSA) micro level panel dataset generated by the International

Crops Research Institute for the Semi-Arid Tropics (ICRISAT) in partnership with Indian Council of Agricultural Research (ICAR) Institutes. This dataset includes household level survey data collected in three periods – First-Generation VLS (1975-1981), Second Generation VLS (2001-2009) and Second-Generation SAT (2009-2015). For our study, we use the Second-Generation SAT data which was collected between 2009 and 2015 in 30 villages of 9 states of India (Andhra Pradesh, Bihar, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra, Odisha, and Telangana). [1]

Note that the VDSA data consists of production and input use data for each parcel utilized by the household. For instance, a household could cultivate a farm with four rice parcels and information relating to input use, management and output was collected for each of the four rice parcels. The dataset also uniquely identifies each parcel over time. As such, we are able to construct a parcel-level panel data set from the VDSA survey data. As noted in earlier section, we run our empirical models using parcel-level observations and account for parcel-level fixed effects. Another advantage of this dataset is the data quality. These data are collected for two main growing seasons in India – Kharif and Rabi. This is particularly important for our study since the effect of weather variables on crop output is likely to vary by season. The data are also collected using a strategic sampling and survey methodology that ensure data accuracy. ICRISAT intensively trains village resident investigators who revisit the households on a regular basis to

[1] Further documentation on the sampling procedure and questionnaires can be found at http://vdsa.icrisat.ac.in/vdsa-microdoc.aspx

collect information about household consumption, farm inputs and outputs. Another major concern for our analysis pertains to the irrigation of the cultivated parcels. The dataset used in this study captures the area of parcel irrigated by each household. However, one potential issue is the availability of irrigated water during the growing season on each parcel. This information is not contained in our dataset and is particularly of concern because of the high rate of groundwater depletion in India. As such it could be the case that area irrigated on a parcel of land may not equate to sufficient availability of groundwater for irrigation on that parcel. Nevertheless, for the purpose of our study, we do not assume this to be the case and consider a cultivated parcel to be irrigated (dummy = 1) if the share of the parcel area irrigated is greater than 15% and not irrigated (dummy = 0) otherwise. We then run our models separately for irrigated and non-irrigated parcels. Table 5.1 provides descriptive statistics for the "economic and farm variables" included in the empirical model for crop yield analysis.

For the examination of vulnerability of households to poverty, we build on the parcel-level dataset and construct a panel which uniquely identifies each household over time. Our main variable of interest is the household income from agriculture. To construct this variable, we take the net of total revenue from the sale of all crops and farm expenditure on all parcels of land while discounting for any family labor. Lastly, we use the Simpson Crop Diversity Index [2] to capture spatial diversity, that is the amount of crop diversity found across

[2]Simpson Index = $1 - \sum_{i=1}^{n} {p_i}^2$ where p is the area share occupied by i^{th} crop in the household

all the cultivated parcels of the household. This index is included to capture the effects of any diversification strategy employed by the households and is calculated for each household based on the share of the area planted with each crop. A score of 1 on the index indicates full diversification and a zero score is indicative of a monocropping household. Other commonly employed measures of spatial diversity in agronomic literature include the Shannon and Herfindahl Index. While the latter is simply equal to one minus the Simpson Index, the former is the reciprocal of Simpson Index. Most researchers use these indices flexibly as there exists little justification for choosing one over the other. Table 5.2 provides descriptive statistics for the "economic and farm variables" included in the empirical model.

5.1.2 Weather Data

The data for weather variables in this study comes from the Climate Research Units (CRU) high-resolution gridded dataset developed by the UK's Natural Environment Research Council (NERC) and the US Department of Energy. The CRU TS 4.00 provides information on total average monthly precipitation and potential evapotranspiration on a 5-degree X 5-degree latitude-longitude grid for the years 1901-2018. We use the gridded data to construct the Standard Precipitation and Evapotranspiration Index (SPEI) using the R module developed by Vicente-Serrano, Beguería, and López-Moreno (2010) for each village for the period 2009-2015 (see appendix for a detailed explanation). We then use a geo-spatial software to aggregate the SPEI data to the village level and calculate the average of the points located inside the village boundaries. Thus, the weather variables in this study are at the village level and reported at a monthly time scale for all the years covered in the Second-Generation SAT dataset. This weather data is then merged with the VDSA data, which is then used for our empirical analyses. Table 5.1 and Table 5.2 provide the descriptive statistics for the "weather variables" included in the empirical model for the parcel and household analysis, respectively.

5.2 Vulnerability of Crop Yields to Weather Extremes

To meet the growing demands of rising population, national food security and poverty alleviation, India's agricultural policy over the past five decades has been geared towards advancing green revolution technologies, particularly the adoption of high-yield seed varieties (HYV) and the increased use of irrigation and fertilizers, with the goal of improving agricultural productivity. Two crops – Rice and Wheat – were the beneficiaries of this revolution which resulted in India becoming a net exporter of these food grains. Whilst the green revolution has helped India in achieving food self-sufficiency, it has also resulted in a shift from traditional sustainable practices to modern practices that are arguably unsustainable in some dimensions, e.g., groundwater depletion.

In this section, the focus of our analysis is mainly on rice production in the Kharif (Monsoon) season. This is because rice is a water-intensive crop and is particularly vulnerable to vagaries in weather. Moreover, rice is a staple food in the region of South Asia with the crop accounting for 7% of the total land under cultivation. Thus, there are implications for food security as climate change is expected to negatively impact rice yields in India (Auffhammer, Ramanathan, and Vincent 2012). To this end, we examine the vulnerability of rice yields in rural India to extreme weather events. Recall from chapter 3 that the climate indicator of vulnerability is

$$\begin{aligned} I(x, r, \theta) &= \int_0^r (r - y)\, \phi(y|x, \theta)\, dy \\ &= \Phi(x, r, \theta)[r - \eta_1(x, r, \theta)] \end{aligned} \tag{5.1}$$

where I is a threshold indicator of the vulnerability at an individual farm or household, y is an economic outcome (e.g., crop yield), x are farm input and r is the reference level. The goal here is then to show how extreme weather events (θ) and green revolution technologies (x) affect vulnerability (I). At the farm level, the indicator, I, captures the probability of being vulnerable i.e., the likelihood of a farm unit falling below the threshold level of yield, $\Phi(x, r, \theta)$ as well as the expected yield gap, $[r - \eta_1(x, r, \theta)]$ i.e., how much is the fall below the threshold yield.

5.2.1 Threshold Yield

While theory provides little guidance on what should be the reference level of yield, studies on poverty and vulnerability to poverty serve as a starting point. In the poverty literature, a common threshold measure is that of a poverty line. Poverty is then considered to be some function of a shortfall of current income or consumption expenditures from a poverty line. Furthermore, the concept of threshold yield has long been of interest for designing optimal insurance policies in India. The Government of India (GoI) has introduced various crop insurance schemes since 1985 with the aim of providing financial support to the farmers in the event of failure of crops as a result of natural calamities. In virtually all of these schemes, a farmer is entitled for claims if the actual yield for an insured crop falls short of a well specified 'guaranteed or threshold' yield in the event of a natural calamity.

We borrow these ideas and analogously define a 'threshold yield'. Vulnerability to extreme weather events can then be considered to be the likelihood of crop yields falling below this threshold. The measure of threshold yield defined here based on an area-based average of yield histories for the chosen insured unit, which is usually the village. To this end, we utilize two reference measures in our analysis. Our first measure of threshold yield, r_1, is the average of the village yield for the 2009-2014 survey years multiplied by the 60% to account for a high-risk area. Our second measure of threshold yield r_2 is simply the mean village yield over the sample period.

5.2.2 Estimation Strategy

We estimate a binary dependent variable model as in equation (5.2).

$$P_{ijvt} = \alpha_{ijvt} + \beta\, W_{vt} + \gamma\, X_{ijvt} + \theta\,(W_{svt} * X_{ijvt}) + \lambda_t, \delta\, g_{st} + u_{ijvt} \tag{5.2}$$

$$E(u_{ijvt}\,|\,\alpha_i\,, W_{vt}\,, X_{ijvt}\,, \lambda_t\,, g_{st}\,) = 0$$

Where, P_{ijvt} is a binary variable that takes the value of 1 if the parcel i of farm j in village v is vulnerable and 0 otherwise. We define a parcel to be vulnerable if the observed rice yield in parcel i of farm j falls below the threshold yield in the Kharif growing season of the year t.

The main regressor of interest, W_{vt}, is a vector of adverse weather shocks in the growing season for year t in village v. We exploit the Standard Precipitation Evapotranspiration Index (SPEI) to construct two original measures of weather shocks. Our first measure is the exposure to a drought and flood over the Kharif growing season. The rice growing season in India spans on an average 150 days, with the Kharif season extending from June to October. There are three main crop growing phases during each season – Vegetative, Reproductive and Ripening – with each phase having its own water demand. Agronomic science has shown that the role of intra-seasonal timing of water stress is particularly crucial in crop yield determination. To this end, we look at the temporal variation in the climatic water balance throughout the growing season. This enables us to exploit the periods during which the crop growth is most sensitive to adverse weather conditions. Here, we define two adverse weather conditions – D, droughts and F, Floods – based on the SPEI [3]. The variable D takes the value of 1 if SPEI falls below -1, and 0 otherwise for a given month in village v of year t. Similarly, F equals 1 if SPEI is above 1, and 0 otherwise for a given month in village v of year t. Having defined a drought month, our final measure of exposure to a drought is computed as the number of months each village faces a drought in each of the k growing phases in season s during the year t, where $k = 1$ represents the vegetative phase and $k = 2$ is indicative of the reproductive and ripening phase[4]. For example, the variable D_{1vt} represents the number of droughts faced by the village v in the growing season of year t for the vegetative phase. Similarly, a measure of exposure to a flood is constructed. The vector of weather variables is then $W_{1vt} = (D_{kvt}, F_{kvt})$ for $k = 1, 2$

Our second measure of weather shock captures the intensity of the weather shock during the growing season. The intensity of the weather shock in a given month depends on what value SPEI reaches. Based on the SPEI classification index, we construct six intensity bins - Extreme Dry (ED), Severe Dry (SD), Moderate Dry (MD), Severe Wet (SW), Moderate Wet (MW) and Extreme Wet (EW). Each bin

[3]Note that these weather variables are only available at the village level and not at the parcel level.

[4]For the Kharif season, the vegetative phase lasts three months beginning in June and ending in August. The reproductive phase is for six weeks, the beginning of September to mid-October and the ripening phase consists of four weeks, mid-October to mid-November. Since the climate data is only available at the month-by-year level, we consider two phases where the vegetative phase comprises of the months, June to August, and the reproductive and ripening phase comprising the months, September to November

takes a value of 1 if the village experiences that weather event and 0 otherwise. For instance, a village is considered to experience a "severe drought" if the value of SPEI falls below -1.5. The normal weather bin is taken as the reference bin and as such is excluded from our regressions to avoid the dummy variable trap. Our final intensity measure is then computed as the number of months each village experiences an intense weather event over the growing season. For example, the variable SD_{vt} represents the number of months in which village v faced a severe drought event over the growing season cycle in the year. The vector of weather variables is then $W_{2vt} = (ED_{vt}, SD_{vt}, MD_{vt}, MW_{vt}, SW_{vt}, EW_{vt})$

X is a vector of farm inputs and sociodemographic variables. The input application variables included are fertilizer use (in kg/ha), pesticide use (in kg/ha), HYV dummy, and labor (in days/ha). Sociodemographic and farm characteristics included in the specification are: land tenure status, age, and education of household head (in no. of years), and farm size. Land tenure status is represented by a dummy variable Own where this variable is equal to 1 if the land is owned, and it is zero otherwise. Parcel size is captured by the dummy Small Parcel[5] where the variable takes the value of 1 if the parcel area is greater than 1 ha and zero otherwise.

The term, α_i, captures parcel-level fixed effects which allows us to control for

[5]The VDSA documentation classifies farms into five categories based on the area cultivated i.e. marginal farms (< 1 Ha), small farms (1 Ha to 2 Ha), semi-medium farms (2 Ha to 5 Ha), medium farms (5 Ha to 10 Ha) and large farms (> 10 Ha). Categorization of parcels is done accordingly where parcels less than 1 Ha are marginal parcels and those greater than 1 Ha small parcels. Since the maximum parcel size in our sample is around 3 Ha, we only consider two types of parcels

potential endogeneity caused by time-invariant parcel-level unobservable that are constant over time, yet different across entities (e.g., distance to the market, slope, unobserved farmer's management ability). Estimation of equation (5.2) using a fixed-effect model will generate consistent parameter estimates. Alternatively, one could use a random effect model using the approach proposed by Mundlak (1978). Year fixed effects (λ_t) capture any common time trends across villages within a given year, including aggregated demand shocks, price shocks and regional policies and programs. We further include a state-specific linear time trend, g_{st}, controlling for the fact that yields are upwards trending over time. Finally, u_{ijvt} is the parcel-level idiosyncratic error term, and β, γ, and θ are the parameter vectors to be estimated.

Our identification strategy relies on the fact that probability of a parcel of farm being vulnerable to weather events is a function of observed farm characteristics and its exposure to weather shocks. Validity of β rests crucially on the assumption that its estimation will produce unbiased estimates of β. Unbiasedness requires $E(u_{ijvt} \,|\, \alpha_i\,, W_{vt}\,, X_{ijvt}\,, \lambda_t\,, g_{st}\,) = 0$. By conditioning on parcel-level fixed effects, year fixed effects and a state specific time trend, β is identified from farm-specific weather shocks after controlling for other non-weather shocks common to all farms in the village. A shortcoming of this approach is that all the fixed effects are likely to magnify the importance of misspecification due to measurement error, which generally attenuates the estimated parameters.

Next, we use a two-step procedure to estimate the yield gap. In the first step, we estimate the mean production function using a flexible functional form as in equation 5.3. Next, the residuals from the estimation of the mean function are used to compute the lower partial moment and input elasticities with respect to the lower partial moment are then estimated.

$$q_{ijvt} = f(W_{vt}, X_{ijvt}, \delta_{ij}, \lambda_t, g_{st}; \Omega) + V_{ijvt} \tag{5.3}$$

The estimation of equation (5.3) poses atleast two econometric challenges. Firstly, specification of the mean function is important to the properties of the partial moments estimation, which is based on the residuals, V, of equation (5.3). Ideally, we would like $f(.)$ to provide a flexible representation of the effects of farm inputs and weather on crop yield. Equation (5.3) employs a flexible functional form that relaxes the embedded restrictions of the moments in the multiplicative error model and the additive error model with multiplicative heteroscedasticity (see Antle, 1983). In this context, we follow Antle (2010) and specify the mean function as $q_{ijvt} = g[f(.)] + V_{ijvt}$ for the additive error model where $f(.)$ is a function that is quadratic in the logs of the inputs and g $[.]$ is specified as an exponential function. In a recent study, Tack, Harri, and Coble (2012) suggest an alternative procedure in the form of estimating zero-order moments. However, note that this method still does not overcome the bias issue. Recall, the variance of a random variable can be written as the difference between the zero-order second moment and mean squared. Thus, a biased estimate of mean still enters this equation and further contaminates the distribution since the residuals are taken to the square and used for estimating the variance.

A second econometric issue concerns potential endogeneity of inputs. It is likely that adoption of irrigation and high variety technologies as well as application of fertilizers during the growing season may be correlated with farmers' unobserved heterogeneity such as their ability to gather information on weather and new technologies. This can lead to biased and inconsistent estimates of Ω in equation (5.3) because of omitted variable bias. We therefore need to account for time invariant parcel specific characteristics. In the case of panel data, one can re-write the error term, V, in equation (5.3) as $V_{ijvt} = I_{ij} + k_{hvt}$ where I_{ij} is the time-invariant unobserved characteristics of the i^{th} parcel of farm j.

The use of a fixed-effect model to estimate equation (5.3) will generate consistent parameter estimates. Alternatively, one could use a random effect model using the approach proposed by Mundlak (1978). Denote by $\bar{X_{ij}}$ the mean of the time-varying explanatory variables of i^{th} parcel of the j^{th} farm in equation (5.3). Following Mundlak, specify $I_{ij} = \bar{X_{ij}}\tau + l_{ij}$ where τ is a vector of parameters capturing any correlation between the unobservable parcel level specific effects and the explanatory variables, and l_{ij} is an idiosyncratic error term uncorrelated with $\bar{X_{ij}}$. Then, for the parcel i of farm k at time t, substituting $V_{ijvt} = I_{ij} + k_{hvt}$ and $I_{ij} = \bar{X_{ij}}\tau + l_{ij}$ into equation (5.3), we get

$$q_{ijvt} = f(W_{vt}, X_{ijvt}, \lambda_t, g_{st}; \Omega) + \bar{X_{ij}}\,\tau + \eta_{1jvt} \tag{5.4}$$

where $\eta_{1jvt} = l_{ij} + k_{hvt}$ and η_{1jvt} is iid $(0, (\sigma_{\eta_1})^2)$ and $\bar{X_{ij}}\,\tau$ controls for the relevant farm-specific unobserved heterogeneity. Equation (5.4) is the one used in the estimation of the mean function yielding consistent estimates of Ω.

A limitation of including the fixed effects or the correlated random effects approach is that it imposes an additive structure to the model i.e., the time invariant parcel specific characteristics are additively separable. For instance, suppose the heterogeneity in farmers' ability, I_{ij}, is the unobserved farmer skill level. Consider a simple panel model $y_{ij} = f(X_{ij}, I_{ij}) + e$. If $f(.)$ is additively separable in X and I, then the model takes the form $y_{ij} = I_{ij} + X_{ij}\ \beta + e_{ij}$. Here, the use of fixed effects or correlated random effects model would cause I_{ij} to cancel out. In such a case the econometrician is not able to capture the heterogeneity of the farmers' skill effect. More precisely, this restricts the marginal effect of X with respect to y, $\frac{\partial f(X,I)}{\partial y} = \frac{\partial f(X)}{\partial y}$, to be same across all individual units for the same observed X. On the other hand, if $f(.)$ is non separable in X and I, this allows the effect of X on Y to differ across individuals for the same observed X i.e., $\frac{\partial f(X,I}{\partial y} = \frac{\partial f(X,I)}{\partial y}$.

The residuals from the estimation of the mean function, η_{1jvt} are then used to estimate the lower partial moment as in equation (5.5). Specifically, we only consider the residuals for those parcels that are vulnerable i.e., below the threshold level of yield and use them to compute the lower partial moment. Alternatively, one could difference out the threshold level of yield from the realized crop yield to construct the lower partial moment, η_{1jvt}. This is advantageous as it enables one to avoid the problem of mis-specifying the mean-function and the consequences of it on the estimation of higher order moments.

$$\eta_{1jvt} = f(W_{vt}, X_{ijvt}, \lambda_t, g_{st}; \Psi) + \mu_{ijvt} \tag{5.5}$$
$$E(\mu_{ijvt} | W_{vt}, X_{ijvt}, \lambda_t, g_{st}) = 0$$

We estimate the lower partial moment in equation (5.5) by taking the negative of it so that interpretation of coefficients is simpler. A positive coefficient implies an increase in the lower partial moment. Note that with panel data, equation (5.5) would also have a parcel-specific component. Again, we use the Mundlak approach to control for potential endogeneity in the estimation of the lower partial moment which then generates unbiased estimates of Ψ .

The vulnerability indicator can then be computed as in equation (5.6) based on the estimates from equation (5.2) and (5.5).

$$\hat{I_{jvt}} = \hat{P_{ijvt}} (r - \hat{\eta_{1jvt}}) \tag{5.6}$$

5.2.3 Results

In this section, we report the effects of weather variables and farm inputs on the vulnerability of rice yields. We first discuss the effects on the probability of rice yields falling below the threshold yield. Table 5.3 reports the estimation results for the weather variables, W_1 and W_2, on the two dimensions of vulnerability. Next, in Table 5.4, we present the results of the effects of farm input variables.

Effects of the weather variables on the vulnerability of rice yields

The fully specified model is based on the equation (5.2) and (5.5). Columns (1) and (3) of Table 5.3 presents the marginal effects for the fully specified model for irrigated and non-irrigated parcels respectively on the probability measure. In Columns (2) and (4) of Table 5.3, we present the marginal effects for our model on the lower partial moment. This model includes the first set of weather variables, W_1, farm inputs as controls and their relevant interactions with W_1. It also includes farm and household characteristics, parcel, and year fixed effects as well as a state-specific linear time trend. The standard errors are clustered at the village level to account for correlations between the parcels within a farm and any potential correlations among farms within a village. In columns (5) and (7) of Table 5.3 we present the marginal effects on the probability measure for the irrigated and non-irrigated parcels respectively with W_2 as our weather measure. Columns (6) and (8) of Table 5.3 show the marginal effects on the lower partial moment.

Examination of the weather parameters shows that occurrence of a drought during the reproductive and ripening phase positively and significantly impacts the probability of being vulnerable for rainfed farms. Rice is a plant which has a high demand for water, particularly during the reproductive stage. As a result, experiencing an additional month of drought during this phase results in the parcel being vulnerable by 18 percentage points. Similarly, experiencing an additional month of flood during this phase increases the likelihood of falling below the threshold yield by 12 percentage points. We interpret this as an excess availability of soil moisture which might cause losses in yield if the excess water cannot be removed because of poor drainage. On the other hand, we do not find any significant effects of an occurrence of a drought or flood on the likelihood of being vulnerable in irrigated farms. Thus, irrigation here can be seen as an adaptive tool farmers employ to substantiate for any deficiency in precipitation.

The parameters for the weather variables in Table 5.3 present a similar story. We find that the intensity of the event matters in addition to the timing of the event. The coefficient estimates for the extreme, severe, and moderately drought variables are all positive and statistically significant, indicating that a parcel's exposure to an additional month of dry weather event increases the likelihood of rice yield falling below the threshold compared to a normal weather event. Further, the magnitude of this positive impact is largest for an extreme drought followed by severe and moderate drought. However, we do not find any significant effects for moderate or extreme flood events.

We next turn to the results of the estimation of the lower partial moment as specified in the equation (5.5). These sets of results provide further evidence of the effects of weather on vulnerability. Occurrence of an additional month of drought during the vegetative phase has a positive but insignificant effect on the yield gap in both irrigated and rainfed farms. In contrast, an additional month of drought during the ripening and reproduction phase significantly increases the yield gap in both set of farms with the effect being higher in the rainfed farms. In the case of the intensity of the weather events, we find that extreme and severe droughts have a positive and significant effect on the yield gap irrespective of whether the farm is irrigated or not. However, the effect of moderate drought on the yield gap is found to be negative on irrigated farms but positive for rainfed farms. One way to interpret this result is that for those parcels that are vulnerable, irrigation serves as a tool in mitigating the loss in crop yields from moderate drought events but not in severe and extreme droughts.

Figure 5.1 and 5.2 plots the SPEI bin coefficients from equation (5.1) on the vulnerability of rice yields to weather extremes. The normal bin was chosen as the omitted bin so that the coefficients are interpreted as the marginal effect of experiencing an additional weather event relative to a normal one. The graph provides further evidence on the non-linear effects of weather on crop yields. For instance, Schlenker and Roberts (2009)) find a nonlinear relationship between temperatures and productivity with crop yields increasing modestly until a threshold temperature and then declining. However, one limitation of their study is that they do not include farm inputs (e.g., fertilizers) and other climatic variables (e.g., precipitation) which are known to impact productivity. Our analysis overcomes these limitations as we control for farm management as well as capture the join effects of temperature, precipitation, and other climatic variables through the SPEI Index. As in Schlenker and Roberts (2009), we find threshold effects of weather variables on crop yields with the probability of falling below r_1 increasing ex-ante with a shift in the distribution of SPEI towards a higher frequency of extreme events. Moreover, these results are also consistent with the agronomic literature showing the adverse effects of high temperatures and precipitation on rice yields (Vogel et al. 2019; Welch et al. 2010)

Effects of farm inputs on the vulnerability of rice yields

HYV's effect on vulnerability is likely to depend on whether the parcel is irrigated or not. This is because cultivation of HYV seeds requires intensive use of fertilizer and pesticide application as well as adequate availability of water. Under these conditions, one would expect HYV to decrease the vulnerability of rice yields on irrigated farms but not on rainfed farms. The marginal effect of HYV seed, as seen in Table 5.4, on the probability measure as well as the yield gap confirm this hypothesis. Irrigated farms that employ HYV seeds reduce the likelihood of crops falling below the threshold yield by 9 percentage points while also decreasing the yield gap by 57% as opposed to irrigated farms employing traditional seeds. On the other hand, rainfed farms are much more vulnerable when employing

HYV seeds. This is possibly due to deficiencies in water availability combined with the intensive use of fertilizers and pesticides on rainfed farms which are likely to exacerbate the effects of High Variety Seeds.

With respect to fertilizers, the results suggest that on average, usage of an additional ton of fertilizer per hectare results in a 25 percentage points decrease in the probability of the parcel being vulnerable. On the contrary, the effect of fertilizer use on the yield gap is positive and statistically significant thereby suggesting that crop productivity in the presence of fertilizers is low for vulnerable parcels. One possible reason for this lies in the fact that farmers in India are often awarded large subsidies in fertilizers and as such they tend to apply more of it than the recommended rates with the hope of achieving higher yields. Thus, if the soil fertility is low and inadequate availability of water, fertilizers can have a detrimental effect on productivity. In the case of pesticides, we find the effect to be opposite. On one hand, pesticides increase the likelihood of not meeting the critical threshold for both irrigated and rainfed parcels, while on the other hand, application of pesticides has a statistically positive effect on the yield gap for irrigated farms but a significant and negative effect for rainfed farms. Multiple reasons can explain this phenomenon. For instance, pesticide use can adversely impact farmers' health which in turn can reduce labor productivity (Antle and Pingali 1994). Further, higher usage of fertilizers without proper pesticide application can result in lower rice yields. Finally, heavy treatment of soil with pesticides can contaminate groundwater, a major source of irrigation in

Indian agriculture, while also causing a decline in soil microorganisms.

Finally, the effect of labor on the yield is statistically significant and positive on both irrigated and non-irrigated farms. This is largely due to the declining marginal productivity of labor in hotter conditions. We also find the area of parcel cultivated to be a significant factor in explaining vulnerability. Specifically, small parcels under irrigation are found to be less vulnerable than under rainfed ones.

5.3 Vulnerability of Households to Poverty

In this section, we turn our focus to the analysis of household' vulnerability to poverty. The goal is to investigate the factors determining household's vulnerability to poverty. We follow the poverty literature in economics and define vulnerability to poverty as the likelihood of falling below a certain income threshold (e.g., poverty line). Consider the vulnerability indicator developed in chapter 3.

$$\begin{aligned} I(x,T,\theta) &= \int_0^T (T-y)\,\phi(y\,|\,x,\theta)\,dy \\ &= \Phi(x,T,\theta)\,[T-\eta_1(x,T,\theta)] \end{aligned} \tag{5.7}$$

where I is a threshold indicator of the vulnerability at an individual household,

y is household income, x are household characteristics and T is the reference income level. The goal here is then to show how extreme weather events (θ) and green revolution technologies (x) affect vulnerability (I). Then, I captures the probability of being vulnerable i.e., the likelihood of a household falling below the poverty line, $\Phi(x, T, \theta)$ as well as the expected poverty gap, $[T - \eta_1(x, T, \theta)]$ i.e., how much is the fall below the poverty threshold.

5.3.1 Threshold Income

The threshold level of income considered here is based on the concept of a poverty line as defined in the vulnerability to poverty literature. Here, we consider two measures of threshold income. The first measure, T_1, is based on the international poverty line, currently set at USD 1.90 a day. Since our unit of household income is in Indian Rupees, the 2009 exchange rate of 1USD = INR 46.5268 was used as a conversion measure. Our second measure, T_2, is based on the 2014 rural poverty line recommendation of INR 972 per month by the Indian Government appointed Rangarajan Committee.

5.3.2 Estimation Strategy

We estimate a binary dependent variable model as in equation (5.8).

$$H_{ivt} = a_i + b\,W_{vt} + c\,X_{ivt} + d\,W_{vt} * X_{ivt} + \Lambda_t + \Delta\,g_{st} + \xi_{ivt} \tag{5.8}$$

$$E(\xi_{ivt}\,|W_{vt}\,, X_{ivt}\,, \Lambda_t\,, g_{st}] = 0$$

Where, H_{ivt} is a binary variable that takes the value of 1 if the household i in village v is vulnerable and 0 otherwise. We define a household to be vulnerable if the observed household income (net of farm revenue and farm expenditure) in falls below the threshold income in the kharif growing season of the year t.

We use the weather intensity bins, W_2, as our main regressor of interest in our model. X is a vector of farm inputs and household characteristics. The input application variables included are share of HYV area under use (in percentage), share of irrigated land (in percentage), cultivated area (in percentage) and crop diversity, as captured by the Simpson Index.

Sociodemographic and farm characteristics included in the specification are: age of the household head, education of the household head, gender of the household hold, caste of the household, a dummy each for primary occupation of the household head, whether the household owned the plot or leased out and if it employed high value machinery, family size of the household, distance to the nearest market, number of animals owned, cash transferred received, loan received and value of farm implements.

The term, a_i, captures household-level fixed effects which allows us to control for potential endogeneity caused by time-invariant household-level unobservable that are constant over time, yet different across entities (e.g., distance to the market, slope, unobserved farmer's management ability). Year fixed effects (Λ_t) capture any common time trends across villages within a given year, including aggregated demand shocks, price shocks and regional policies and programs. We further include a state-specific linear time trend, g_{st}, controlling for the fact that yields are upwards trending over time. Finally, ξ_{ivt} is the household-level idiosyncratic error term, and b, c, and d are the parameter vectors to be estimated.

Our identification strategy relies on the fact that probability of a household being vulnerable to weather events is a function of observed farm characteristics and its exposure to weather shocks. Validity of b,c and d rests crucially on the assumption that its estimation will produce unbiased estimates of b, c and d respectively. Unbiasedness requires $E(\xi_{ivt}\,|W_{ivt}\,, X_{ivt}\,, \Lambda_t\,, g_{st}] = 0$. By conditioning on household fixed effects, year fixed effects and a state specific time trend, b is identified from household specific weather shocks after controlling for other non-weather shocks common to all farms in the village.

Define by π the net income from all farm activities. Then, our estimation of the T - π, income gap, proceeds in two steps. First, we estimate the mean income function using a flexible functional form in equation (5.9). Again, the estimation of equation (5.9) is likely to suffer from the challenges of endogeneity and misspecification. Similar to the estimatin of the rice yield function, we specify the mean income function in a flexible form and apply the mundlak instrument to account for unobserved heterogeneity such as in equation (5.10) which is then used to generate consistent estimates of. Next, we consider the residuals for only those households that are vulnerable i.e. whose observed income during the kharif growing season is below the poverty line and use it to compute the lower partial moment, ζ as in equation (5.11).

$$\pi_{ivt} = f(W_{vt}, X_{ivt}, \Lambda_t, g_{st}; \omega) + \nu_{ivt} \tag{5.9}$$
$$E(\nu_{ivt} \,|\, W_{vt}\, X_{ivt}\, \Lambda_t\,, g_{st}\,) = 0$$

$$\pi_{ivt} = f(W_{vt}, X_{ivt}, \Lambda_t, g_{st}; \omega) + \bar{X_{ivt}}\, M + \upsilon_{ivt} \tag{5.10}$$
$$E(\upsilon_{ivt} \,|\, W_{vt}\, X_{ivt}\, \Lambda_t\,, g_{st}\,) = 0$$

$$\zeta_{ivt} = f(W_{vt}, X_{ivt}, \Lambda_t, g_{st}; \rho) + \Upsilon_{ivt} \tag{5.11}$$
$$E(\Upsilon_{ivt} \,|\, W_{vt}\, X_{ivt}\, \Lambda_t\,, g_{st}\,) = 0$$

5.3.3 Results

In this section, we report the estimation results for our fully specified model in equation (5.8) and (5.11) of weather variables and farm inputs on the vulnerability of households. We first present the results of the effects of the weather variables on the vulnerability indicator based on the global poverty line (USD 1.9 per day). We next discuss the effects of household characteristics on the two dimensions of the indicator. These estimates are shown in Table 5.5 and Table 5.6, respectively. We report the estimation results for the reference income level of INR 972 per month in the appendix.

Effects of the weather variables on the vulnerability of household to poverty

Results of the linear probability model based on the global poverty line as displayed in column (1) and (2) of Table 5.5 show that extreme and severe droughts significantly impact household's vulnerability to poverty. Particularly, the effect is largest for extreme droughts. Experiencing an additional month of extreme drought results in the likelihood of household income falling below the poverty line by 13 percentage points. On the other hand, moderate weather events have the opposite effect. Similar results are seen of the effects of weather on the lower partial moment. Further, the results are robust to various measures of reference income levels as evident from the results based on the second threshold measure in appendix. Figure 5.3 and Figure 5.4 plot the estimated marginal effect of weather bins on the probability measure as well as the poverty gap. The normal bin was chosen as the omitted bin so that the coefficients are interpreted as the marginal effect of an additional month of weather event relative to a normal one. As in the case of crop yields, we find non-linear effects of weather variables on household's vulnerability to poverty.

Effects of household characteristics on vulnerability to poverty

With respect to the farm and household characteristics, we find crop diversity and Green Revolution Technologies to be the most important determinants of vulnerability. Households see crop diversification as a risk management strategy by maintaining a diverse portfolio of crops cultivated that reduces the risk of crop failure or in the realization of a sub-optimal yield in the presence of adverse weather events. Adoption of HYV seeds and irrigation are other ways that households reduce their vulnerability since adoption is likely to result in higher yields and thereby incomes. Finally, we also find the caste of the household to significantly affect vulnerability. This is likely due to the credit and knowledge constraints faced by a lower caste households.

5.4 Conclusions

This chapter examines the vulnerability of households to extreme weather events. Applying the vulnerability indicator to a panel data of rice yields from thirty Indian villages, the results suggest that extreme and severe droughts have a positive and significant effect on vulnerability. In addition, the results also show that the timing of the extreme weather event is crucial with the reproductive phase of the crop growing period being the most sensitive to weather extremes.

When examining the household's vulnerability to poverty, the effects of weather extremes are similar with the household most vulnerable when exposed to an extreme drought. Lastly, the results also provide evidence of irrigation as an adaptive mechanism for farmers. The effects of farm inputs and household characteristics provide a further insight into the factors that cause a parcel or household to be vulnerable. Results show that fertilizers make the farms more resilient to weather extremes whereas pesticide application is shown to increase vulnerability. HYV seeds are shown to make farms more resilient in the presence of irrigation through the way of increased crop yields but on the other hand also cause them to be more vulnerable under rainfed conditions. Finally, smaller farms are more resilient than marginal farms. When looking at the household's vulnerability to poverty, the results indicate crop diversification to be an important tool in reducing vulnerability.

Finally a quick comparison of the results from the estimation of vulnerability of rice yields and income to weather extremes suggests that for subsistence households that largely depend on agricultural output as a major source of income, understanding the factors affecting farms' vulnerability to crop yields can provide useful information about the household's vulnerability to poverty.

Table 5.1: Descriptive Statistics for the Farm Inputs and Weather Variables in the Parcel-level dataset

Variables	Unit/Description	N	Mean	SD	Min	Max
Extreme Dry	No. of months where $SPEI \leq -2.0$ over the growing season	6616	0.01	0.11	0	1.00
Severe Dry	No. of months where $-2.0 < SPEI \leq -1.5$ over the growing season	6616	0.24	0.53	0	2.00
Moderate Dry	No. of months where $-1.5 < SPEI \leq -1.0$ over the growing season	6616	0.64	0.81	0	3.00
Moderate Wet	No. of months where $1.0 < SPEI \leq 1.5$ over the growing season	6616	0.58	0.71	0	3.00
Severe Wet	No. of months where $1.5 < SPEI \leq 2.0$ over the growing season	6616	0.34	0.62	0	2.00
Extreme Wet	No. of months where $SPEI > 2.0$	6616	0.04	0.20	0	1.00
Drought - Veg	No. of months where $SPEI < -1$ in the vegetative phase	6616	0.62	0.88	0	3.00
Drought - RR	No. of months where $SPEI < -1$ in the reproductive and ripening phase	6616	0.18	0.38	0	1.00
Flood - Veg	No. of months where $SPEI > 1$ in the vegetative phase	6616	0.41	0.54	0	2.00
Flood - RR	No. of months where $SPEI > 1$ in the reproductive and ripening phase	6616	0.47	0.50	0	2.00
HYV	Dummy = 1 if parcel uses improved/Hybrid seed	6616	0.72	0.45	0	1.00
Irrigated	Dummy = 1 if parcel is irrigated	6616	0.58	0.49	0	1.00
Fertilizers	Application in Kg/Ha	6616	123.20	154.79	0	765.70
Pesticide	Application in Kg/Ha	6616	0.31	2.74	0	123.50
Family Female Labor	Days/Ha	6616	4.34	10.14	0	202.75
Family Male Labor	Days/Ha	6616	9.18	13.14	0	171.53
Hired Male Labor	Days/Ha	6616	3.22	6.13	0	72.68
Hired Female Labor	Days/Ha	6616	7.90	11.22	0	119.38
Household Age	Age of the household head	6593	51.93	13.16	18	88.00
Household Education	Number of years of education of the household head	6568	6.30	4.93	0	19.00
Household Gender	Dummy=1 if household head if female	6597	0.05	0.22	0	1.00
Own Parcel	If Parcel is owned by the household	6616	0.93	0.25	0	1.00
Parcel Size	Ha	6616	0.26	0.32	.003	4.86
Small Parcel	Dummy=1 if Parcel is Small	6616	0.03	0.18	0	1.00
Soil Depth	Soil depth of the parcel in mm	6341	162.93	143.85	0	914.00
Soil Fertility	$1 =$ Very poor, 2 =Poor, $3 =$ Good and $4 =$ Very good	6507	3.14	0.70	1	4.00
Caste	Dummy=1 if lower caste	6616	0.15	0.36	0	1.00

Table 5.2: Descriptive Statistics for the Farm Inputs and Weather Variables in the Household-level dataset

Variables	Units/Definition	N	Mean	SD	Min	Max
Extreme Dry	No. of months where $SPEI > -2.0$	5363	0.04	0.20	0	1.00
Severe Dry	No. of months where $-2.0 < SPEI \leq -1.5$	5363	0.21	0.47	0	2.00
Moderate Dry	No. of months where $-1.5 < SPEI \leq -1.0$	5363	0.54	0.73	0	3.00
Moderate Wet	No. of months where $1.0 < SPEI \leq 1.5$	5363	0.63	0.71	0	3.00
Severe Wet	No. of months where $1.5 < SPEI \leq 2.0$	5363	0.46	0.72	0	4.00
Extreme Wet	No. of months where $SPEI > 2.0$	5363	0.14	0.42	0	3.00
Crop Diversity	Simpson Diversity Index	5363	0.22	0.25	0	0.96
Share of HYV Area Planted	Share of area under HYV use	5363	0.63	0.42	0	1.00
Share of Irrigated Area	Share of area irrigated	5363	0.36	0.44	0	1.00
Total Area Cultivated	Total area cultivated by household in Ha	5363	1.44	2.04	0	31.17
Household Head Age	Age of the head of the household	5358	49.79	12.51	16	90.00
Household Head Education	No. of years of education of the household head	5350	5.38	4.71	0	19.00
Household Head Gender	Gender of the household (1=Female, 0=Male)	5359	0.05	0.21	0	1.00
Main Occupation	Dummy=1 if primary occupation is agriculture	5363	0.74	0.44	0	1.00
Own Plot	Dummy=1 if the household owns the parcels	5363	0.94	0.23	0	1.00
Leased In	Dummy=1 If the household leased in the parcels	5363	0.15	0.36	0	1.00
High Value Machinery	Dummy=1 if the household uses high value machinery	5352	0.82	0.38	0	1.00
Family Size	Number of members in the household	5363	5.58	2.63	1	26.00
Market Distance	Distance to Market in km	5363	11.44	6.64	0	52.00
Caste	Dummy=1 if household belongs to lower caste	5363	0.17	0.37	0	1.00
Loan Received	Total loan received by the household in INR Lakhs	5363	0.02	0.18	0	8.00
Cash Received	Total Cash Received by the household in INR Lakhs	5363	0.01	0.10	0	5.00
Value of Assets	Total value of household assets in INR Lakhs	5363	0.03	0.28	0	15.00
Value of Farm Implements	Total value of household farm implements (in INR lakh)	5363	0.02	0.25	0	15.00
Animal Value	Total value of all animals in the household (in INR lakh)	5363	0.03	0.10	0	1.95
Animals Owned	Total No. of animals owned by the household	5363	0.98	4.15	0	128.00

Table 5.3: Effects of Weather Variables on Parcel Vulnerability with respect to the threshold, r_1

	Model 1				Model 2			
	Irrigated		Rainfed		Irrigated		Rainfed	
	Φ	η_1	Φ	η_1	Φ	η_1	Φ	η_1
Drought - Veg	-0.004	-0.010	0.074	0.081				
	(0.036)	(0.037)	(0.066)	(0.059)				
Drought - RR	-0.011	0.181**	0.341***	0.585*				
	(0.038)	(0.082)	(0.116)	(0.278)				
Flood - Veg	0.022	-0.061	0.279*	-0.558				
	(0.051)	(0.085)	(0.142)	(0.083)				
Flood - RR	0.003	0.126***	-0.370***	0.305*				
	(0.041)	(0.044)	(0.080)	(0.152)				
Extreme Dry					-0.184*	0.484***	0.012***	0.037***
					(0.104)	(0.145)	(0.005)	(0.007)
Severe Dry					0.002	0.111*	0.012***	0.023***
					(0.034)	(0.067)	(0.003)	(0.005)
Moderate Dry					-0.015	0.053*	-0.009**	0.018***
					(0.104)	(0.145)	(0.005)	(0.007)
Moderate Wet					-0.009	0.029	-0.003***	0.026***
					(0.019)	(0.022)	(0.001)	(0.005)
Severe Wet					0.002	0.041	0.003	-0.002
					(0.018)	(0.040)	(0.002)	(0.003)
Extreme Wet					0.147	-0.175	0.000	-0.086***
					(0.166)	(0.269)	(0.003)	(0.016)
Observations	3854	2762	663	365	3854	2762	663	365
R^2	0.661	0.658	0.901	0.879	0.702	0.648	0.905	0.910
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability for irrigated and rainfed parcels based on two models. Robust standard errors clustered at the village level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the weather variables by growing phases. Model 2 replaces the growing phases weather variables with weather bins. Both models include interaction between farm inputs and weather variables.

Table 5.4: Effects of Farm Inputs on Parcel Vulnerability with respect to the threshold, r_1

	Model 1				Model 2			
	Irrigated		Rainfed		Irrigated		Rainfed	
	Φ	η_1	Φ	η_1	Φ	η_1	Φ	η_1
HYV	-0.082***	-0.021	-0.051	-0.960***	-0.089***	-0.004	-0.572*	5.251***
	(0.015)	(0.076)	(0.039)	(0.122)	(0.031)	(0.084)	(0.309)	(0.063)
Fertilizers	-0.227	-0.322*	-0.001***	-0.019***	-0.253**	-0.127	0.074**	1.852***
	(0.090)	(0.138)	(0.000)	(0.002)	(0.100)	(0.138)	(0.028)	(0.022)
Pesticide	0.019***	0.109	0.438***	0.002***	0.024***	0.106**	0.323***	-0.891***
	(0.006)	(0.068)	(0.036)	(0.000)	(0.005)	(0.042)	(0.085)	(0.168)
Family Female Labor	-0.005	0.002*	-0.067***	0.276***	-0.006***	0.001	0.130***	0.498***
	(0.003)	(0.001)	(0.011)	(0.032)	(0.002)	(0.001)	(0.029)	(0.033)
Family Male Labor	-0.001	-0.004***	0.001	0.094***	-0.000	-0.004**	0.403**	0.199***
	(0.001)	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)	(0.127)	(0.032)
Hired Female Labor	-0.005***	-0.003***	-0.016*	-0.010	0.002	-0.009***	0.163***	-0.008***
	(0.001)	(0.001)	(0.009)	(0.017)	(0.002)	(0.002)	(0.034)	(0.000)
Hired Male Labor	0.001	-0.010***	-0.014	-0.061***	-0.004***	-0.003**	0.352***	0.169***
	(0.002)	(0.002)	(0.010)	(0.012)	(0.001)	(0.001)	(0.026)	(0.000)
Small Parcel	-0.309**	0.175	-0.033	-1.708***	-0.322**	0.325*	-1.975***	1.651**
	(0.142)	(0.175)	(0.029)	(0.116)	(0.156)	(0.196)	(0.760)	(0.699)
Observations	3854	2762	663	365	3854	2762	663	365
R^2	0.661	0.658	0.901	0.879	0.702	0.648	0.905	0.910
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parcel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the farm input variables on the two dimensions of vulnerability for irrigated and rainfed parcels based on two models. Robust standard errors clustered at the village level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the weather variables by growing phases. Model 2 replaces the growing phases weather variables with weather bins. Both models include interaction between farm inputs and weather variables.

Table 5.5: Effects of Weather Variables on Household Vulnerability based on the threshold, T_1

	Φ	η_1
Extreme Dry	0.140***	0.523***
	(0.031)	(0.091)
Severe Dry	0.071***	0.172***
	(0.016)	(0.051)
Moderate Dry	-0.026**	0.015
	(0.010)	(0.035)
Moderate Wet	-0.022***	-0.037
	(0.009)	(0.031)
Severe Wet	-0.020**	-0.018
	(0.009)	(0.039)
Extreme Wet	0.052***	0.181***
	(0.015)	(0.068)
Observations	5339	2276
R^2	0.139	0.162
State Time Trend	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes

Notes: The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability. Robust standard errors clustered at the household level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. All regressions include household characteristics as controls and interaction with weather variables.

Table 5.6: Effects of Farm Characteristics on Household Vulnerability based on the threshold, T_1

	Φ	η_1
Share of HYV Area Planted	-0.048**	0.043
	(0.020)	(0.055)
Share of Irrigated Area	-0.092***	0.138*
	(0.024)	(0.077)
Total Area Cultivated	-0.033***	0.168***
	(0.011)	(0.064)
Crop Diversity	-0.229***	-0.150
	(0.039)	(0.128)
Caste	0.190***	0.218**
	(0.060)	(0.088)
Observations	5339	2276
R^2	0.139	0.162
State Time Trend	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes

Notes: The table displays coefficient of marginal effects for all the farm inputs and household characteristics on the two dimensions of vulnerability. Robust standard errors clustered at the household level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. All regressions include household characteristics as controls and interaction with weather variables.

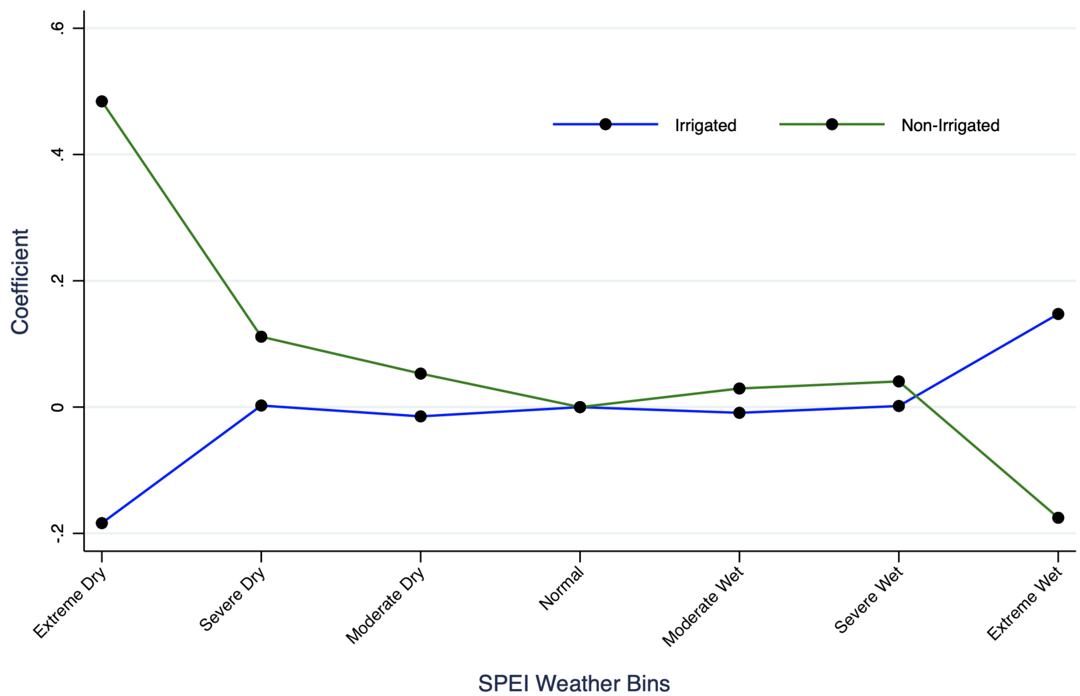

Figure 5.1: Estimated Impact of an extreme weather event on the probability of rice yield falling below the threshold, r_1, relative to a normal event

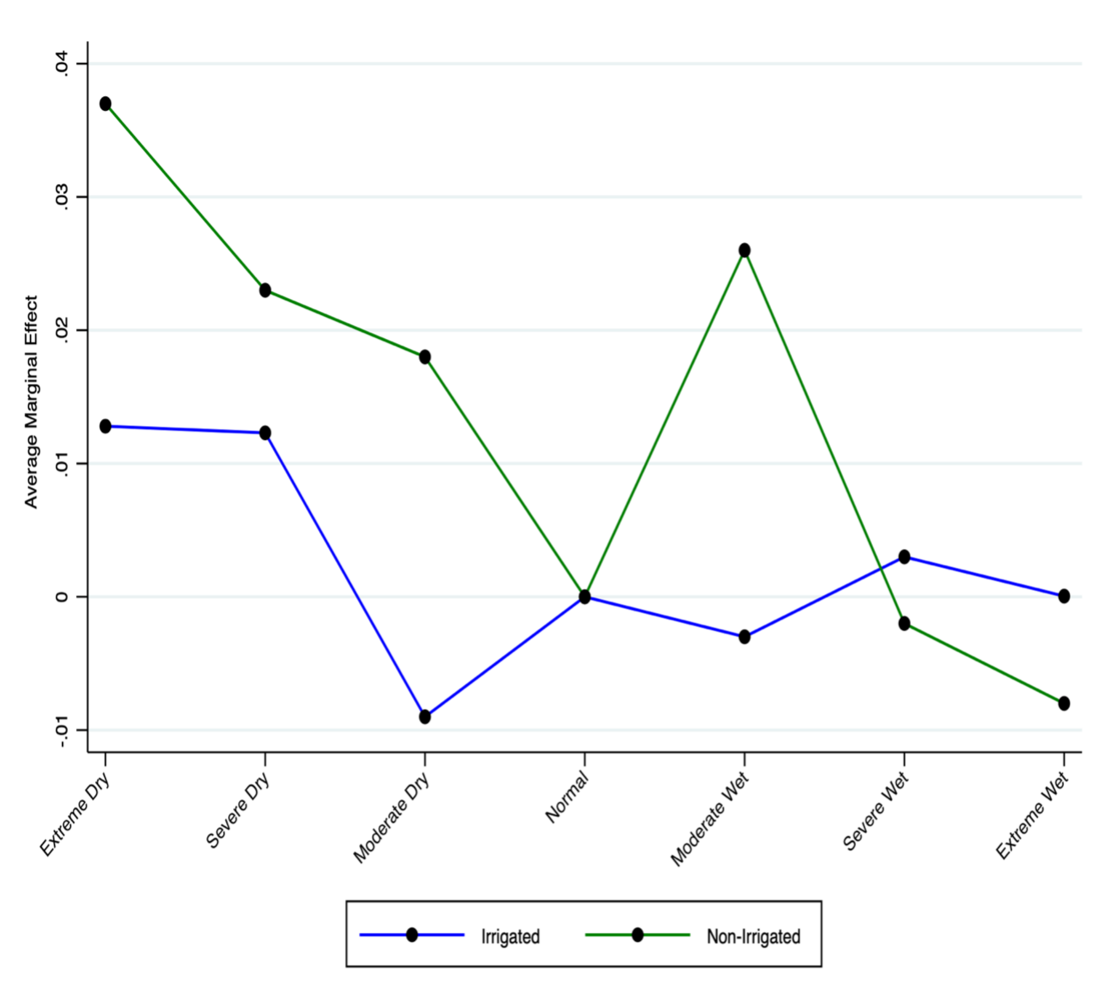

Figure 5.2: Estimated Impact of an extreme weather event on the yield gap based on r_1, relative to a normal event

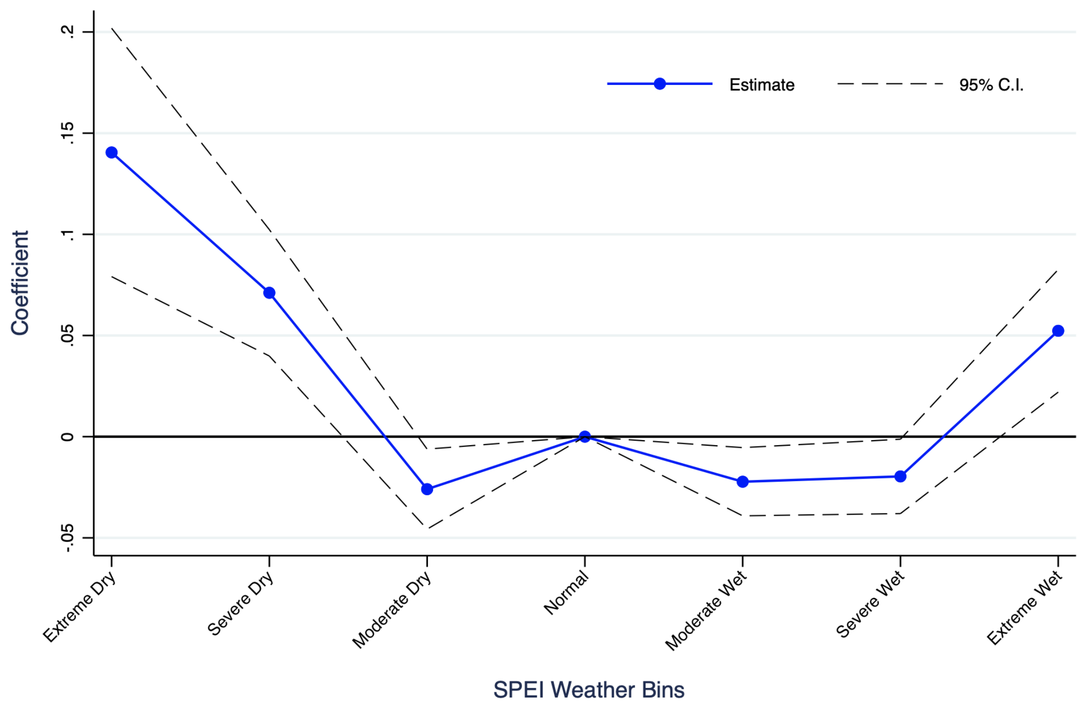

Figure 5.3: Estimated Impact of an extreme weather event on the probability of household falling below the poverty line, T_1, relative to a normal event

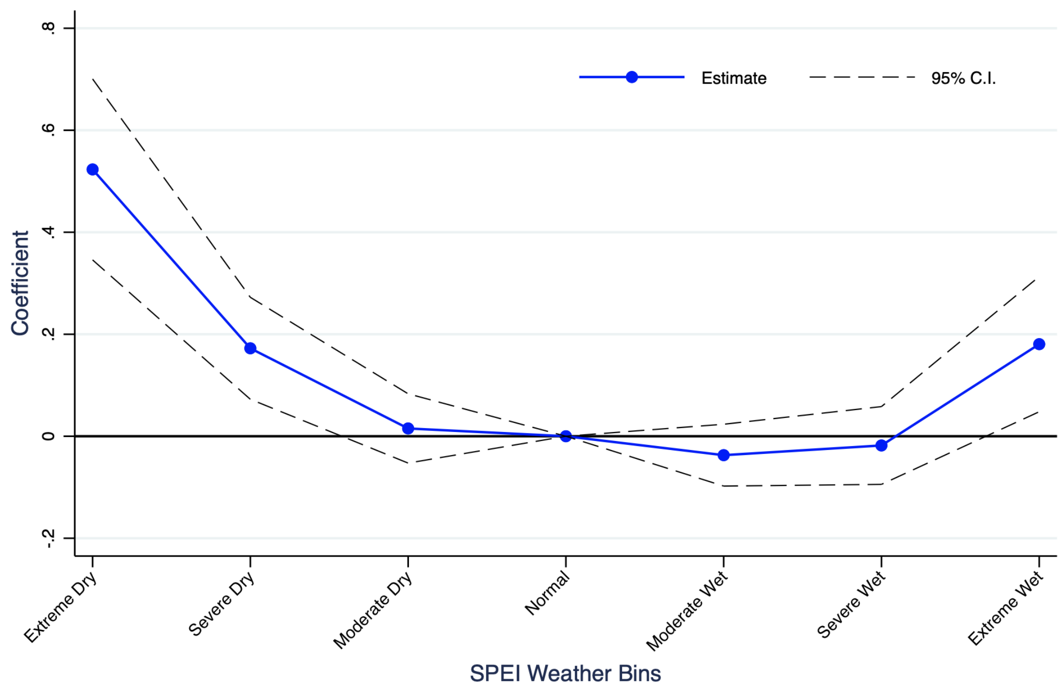

Figure 5.4: Estimated Impact of an extreme weather event on the poverty gap based on T_1, relative to a normal event

Chapter 6: Empirical Analysis – Districts

The economic model presented in chapter 3 is for an individual farm, i. However, the unit of analysis of this study is a district. To obtain the district-level yield, we can simply aggregate the yield at each individual farm, i. Mathematically,

$$Y = \sum_{i=1}^{N} y_i = \sum_{i=1}^{N} f(x(\gamma_i), z_i, w_i^{\alpha}, w_i^{u}, \epsilon_i, \alpha) \tag{6.1}$$

where Y is the district yield for N farms in the district.

The micro-parameters γ vary across space and time and are themselves realizations of a macroworld. District-level yield, Y, can then be considered to be a random variable that varies according to the physical characteristics of a district, its micro-parameters and other unobservable random shocks such that it follows a distribution, Y $\sim \phi(\gamma, w^u, \epsilon|\delta)$ where δ parameterizes the distribution of micro parameters and shocks in the district.

Define by $\mu_1(\delta)$ the mean of the district-yield distribution where

$$\mu_1(\delta) = E(Y|\delta) = \int\int\int \sum_i f(x(\gamma_i), z_i, w_i^{\alpha}, w_i^{u}, \alpha)\, \phi(\gamma, w^u, \epsilon|\delta)\, d\gamma\, dw^u\, d\epsilon \tag{6.2}$$

Recall, the vulnerability indicator is

$$
\begin{aligned}
I(X, R, \theta) &= \int_0^r (R - Y)\, \phi(Y|X, R, \theta)\, dY \\
&= \Phi(X, R, \theta)[r - \eta_1(X, R, \theta)]
\end{aligned} \tag{6.3}
$$

where I is an indicator of vulnerability at the district level, X are district aggregated farm inputs, Y is the district yield and R is the reference level of yield. Measured at the district level, I then captures the proportion of population vulnerable to extreme weather events, $\Phi(X, R, \theta)$ as well as the expected yield gap, [$R - \eta_1(X, R, \theta)$].

6.1 Data Sources

6.1.1 Agricultural Data

We use agricultural data from the Village Dynamics in South Asia Meso Dataset (VDSA) obtained through the Tata-Cornell district level database (DLD). The dataset includes information on annual agricultural production and acreage, by crops, for 307 districts in 19 states for the years 1961- 2011. We drop two states – Kerala and Assam - from our sample owing to missing data and our final dataset includes 292 districts in 17 states. We particularly focus on rice since it is a major staple crop in India and heavily susceptible to extreme events. We also procure data on farm characteristics, labor, and technology. The dataset thus is a panel of

292 districts for 40 years. We present summary statistics of our sample in Table 6.1, firstly for all the districts pooled together and then separately for vulnerable and non-vulnerable districts, computed based on the reference level R_1. The key outcome variable in our analyses is annual rice yield measured in tons per hectare. Our main explanatory variables include acreage (hectares), labor (Number per hectare), fertilizers (Tons), Irrigation (percentage of total land irrigated) and High Yield Variety Area (as percentage of total area planted).

6.1.2 Weather Data

We use weather data from the Climate Research Unit's (CRU) high-resolution gridded dataset developed by the UK's Natural Environment Research Council (NERC) and the US Department of Energy. The CRU TS 4.00 provides information on total average monthly precipitation and potential evapotranspiration on a 5-degree X 5-degree latitude-longitude grid for the years 1901-2010. We use the gridded data to construct the Standard Precipitation and Evapotranspiration Index (SPEI) using the R module developed by Vicente-Serrano, Beguería, and López-Moreno (2010) for each district for the period 1970-2010 (see appendix for a detailed explanation). This is accomplished by overlaying a land use map on the CRU TS dataset for each grid cell within 100 kilometers of each district's geographical center using inverse distance weighting. Our key indicator is the growing season SPEI, computed by averaging monthly SPEI over the growing season months (June-September). The SPEI index can be calculated at various timescales such as 1, 3, 6, 12 and 24 months, which represent different types of droughts. Usually, a 3-month or 6-month timescale is used for agricultural drought, while a 12-month or 4-month timescale is suitable for capturing hydrological drought (Mishra and Singh 2010). Figures A2 - A5 shows the spatial distribution of 3-month average SPEI for the growing season months, June to September.

We use the SPEI classification index to further exploit our growing season SPEI variable and subsequently construct seven SPEI bins. These bins represent various degrees of wet and dry weather events i.e., extreme, severe, moderate and normal. Each bin is assumed to take a value of 1 if the district experiences that particular weather event and 0 otherwise. For instance, a district is considered to experience an "extreme" dry event (or extreme drought) in that particular year if the value of SPEI < -2.0. We consider the normal weather bin to be the reference bin and exclude it from our regressions to avoid the dummy variable trap. The interpretation of the coefficients of SPEI bins is relative to the reference bin. For example, the coefficient on the extreme weather bin would represent how much crop yields decrease (or increase) if there was a certain distribution of weather and the district experienced an extreme weather event for that growing season instead of a normal weather event.

6.2 Vulnerability of District Crop Yields to Weather Extremes

6.2.1 Threshold Yield

We consider four measures of threshold yield. Our first measure of threshold yield, R_1, is based on the Prime Minister Fasal Bima Yojna (PMFBY) insurance scheme. To construct this measure, we first calculate, for each district, an expected yield (EY) based on a seven-year moving average of rice yields. The threshold yield is then set at 70, 80 and 90 percent of EY based on coefficient of variation for yields in the ranges of greater than 30%, 16 to 30% and 15% or less, respectively. This can be considered to be a weighted measure of the threshold yield accounting for "low", "medium" and "high" risk areas respectively. For our second measure, R_2,we consider only the EY as our threshold yield. The third measure of threshold yield, R_3, is derived from the National Agricultural Insurance Scheme (NAIS) wherein the EY is the three-year moving average and threshold yields are set at 60%, 80% and 90% of the EY based on the coefficient of variation for yields as in the PMFBY. Our fourth and final measure of threshold yield, R_4 is set as the mean of the first quantile, q = (0, 15], to account for exposure to downside risk

6.2.2 Estimation Strategy

We estimate a binary dependent variable model as in equation (6).

$$D_{dt} = X'_{dt}\,\beta_1 + \beta_2\,SPEI_{dt} + X'_{dt} * SPEI_{dt}\,\beta_3 + \delta_d + \lambda_t + g_{st} + u_{dt} \tag{6.4}$$
$$E(u_{dt}|X_{dt}, SPEI_{dt}, \lambda_t, g_{st}, \delta_d) = 0$$

Where D_{dt} is a binary variable that takes the value of 1 if the district is vulnerable and 0 otherwise. A district is considered to be vulnerable if the observed rice yield is below the threshold yield in a particular year. X is a $1xK$ matrix of observable determinants of crop yields $-$ Fertilizer, labor, share of HYV area, share of irrigated area and β_1 is a $Kx1$ matrix of parameters. β_1, β_2, and β_3 are the main parameters of interest while SPEI captures growing season (June to September) climatic water balance. We account for unobserved district-specific time invariant determinants of crop yields by including a district fixed effect δ_d. We also include a time dummy, λ_t, to capture any common time trends across districts within a given year, and include a state-specific linear time trend, g_{st}, controlling for the fact that yields are upward trending over time. Finally, u_{dt} represents stochastic error term.

Our identification strategy relies on the fact that probability of an agricultural district being vulnerable to extreme weather events is a function of observed farm characteristics and its exposure to weather shocks. Validity of β_1, β_2 and β_3 rests crucially on the assumption that its estimation will produce unbiased estimates of β_1, β_2 and β_3. Unbiasedness requires $E[u_{dt}|SPEI_{dt}, X_{dt}, \delta_d, g_{st}, \lambda_t] = 0$. By conditioning on district fixed effects, year fixed effects and a region specific time trend, our parameters are identified from district-specific weather shocks after controlling for other non-weather shocks common to all districts. A shortcoming of this approach is that all the fixed effects are likely to magnify the importance of mis-specification due to measurement error, which generally attenuates the estimated parameters.

We estimate equation (6.4) using a linear probability model (LPM). This estimation technique has several advantages. Firstly, it allows us to control for district-specific time-invariant characteristics such as soil quality. Secondly, the interpretation of the parameters is simpler when average marginal effects are considered. For instance, a one-SD increase in SPEI increases the probability of being vulnerable by 100 x β_2 percentage points. However, LPMs are susceptible to criticism because they can produce coefficients that will predict outcomes outside the [0, 1] interval. While discrete choice models such as logit and probit can overcome this issue, with large sample sizes, LPMs perform quite similarly to discrete choice models.

Estimation of the yield gap measure, $R - \eta_1(X, R, \theta)$ requires a characterization of the probability distribution of crop yield. To this end, we use a moment-based approach as it provides a general parametrization of the moments of the crop yield distribution. A second motivation in using the moment-based model pertains to the fact that multiplicative-error production models as well as additive-error models with multiplicative heteroscedasticity (e.g. Just-Pope

Production function) impose arbitrary restrictions on the relationship between inputs and the probability distribution of the output, as shown by Antle (1989).

Our estimation of the yield gap proceeds in two steps. First, we estimate the mean production function using a flexible functional form in equation (7). Next, the residuals from the estimation of the mean function are used to compute the lower partial moment and input elasticities with respect to the lower partial moment are then estimated as in equation (6.7).

$$\begin{aligned} Y_{dt} &= f(X_{dt}, SPEI_{dt}, \lambda_t, g_{st}; \alpha) + \epsilon_{dt} \\ E(\epsilon_{dt} | X_{dt}, SPEI_{dt}, \lambda_t, g_{st}) &= 0 \end{aligned} \tag{6.5}$$

The estimation of equation (6.5) poses two econometric challenges. Firstly, specification of the mean function is important to the properties of the partial moments estimation, which is based on the residuals from equation (7). Ideally, we would like $f(X_{dt}, SPEI_{dt}, \lambda_t, g_{st}, \alpha)$ to provide a flexible representation of the effects of farm inputs and weather on crop output. Equation (7) employs a flexible functional form that relaxes the embedded restrictions of the moments in the multiplicative error model and the additive error model with multiplicative heteroscedasticity (see Antle (1983)). In this context, we follow Antle (2010) and specify the mean function as $y_{dt} = g[h(X_{dt}, SPEI_{dt}, \lambda_t, g_{st}; \alpha)] + \epsilon_{dt}$ for the additive error model where $h(.)$ is a function that is quadratic in the logs of the inputs and $g[.]$ is specified as an exponential function.

A second econometric issue concerns potential endogeneity of inputs. It is likely that adoption of irrigation and high variety technologies as well as application of fertilizers during the growing season may be correlated with farmers' unobserved heterogeneity such as their ability to gather information on weather and new technologies. This can lead to biased and inconsistent estimates of α in equation (6.5) because of omitted variable bias. Studies in the past (e.g. Chavas and Di Falco 2012; Mukasa 2018) have addressed this problem by specifying the error term, $\epsilon_{dt} = \delta_d + \eta_{1dt}$ where δ_d captures the time invariant unobserved characteristics of the d^{th} district. Estimation of equation (6.5) using a fixed-effects model will then generate consistent parameter estimates as long as the effect of the unobservable is time-invariant and additive. However, it is possible that many district specific unobservable such as soil moisture, field slope, farmers' skills and ability could interact with inputs and enter the production function in a non-linear form. Then, equation (6.5) takes the form,

$$
\begin{aligned}
Y_{dt} &= f(X_{dt}, SPEI_{dt}, \delta_d, \lambda_t, g_{st}; \alpha) + \eta_{1dt} \\
E(\eta_{1dt} &| X_{dt}, SPEI_{dt}, \lambda_t, g_{st}, \delta_d) = 0
\end{aligned}
\tag{6.6}
$$

We estimate the lower partial moment in equation (6.7) by taking the negative of the residuals from equation (6.6). This makes the interpretation of coefficients simpler as a positive coefficient is an increase in the lower partial moment.

$$\eta_{1dt} = f(X_{dt}, SPEI_{dt}; \zeta) + e_{dt}; E(e_{dt}|X_{dt}, SPEI_{dt}) = 0 \tag{6.7}$$

The vulnerability indicator can then be computed based on the estimates from equation (6.4) and (6.7) as

$$\hat{I_{dt}} = \hat{D_{dt}}\,(R - \hat{\eta_{1dt}}) \tag{6.8}$$

6.2.3 Results

In this section, we report the effects of climate and technology on the vulnerability of rice yields. Table 6.2 reports the marginal effects of weather variables based on the linear probability model for the fully specified model in equation (6.4) and the lower partial moment in equation (6.7). Next, in Table 6.3 we present the results of the marginal effects of inputs on the vulnerability indicator. Appendix presents the results of the estimation of the linear probability model and lower partial moments model for the other three reference levels,R_2, R_3 and R_4.

Effects of climate and inputs on the probability of rice yields falling below the vulnerability threshold, R_1

Column (1) and (2) of Table 6.2 reports estimates for the growing season SPEI. We find that one SD increase in SPEI during the growing season results in a 7 percentage points decrease in the likelihood of falling below the threshold. When exploring the intensity of the weather events, the coefficient estimates for the extreme, severe, and moderately dry variables are all shown to be positive and statistically significant, indicating that occurrence of a dry weather event increases the likelihood of rice yield falling below the threshold compared to a normal weather event. Further, the magnitude of this positive impact is larger for extreme dry event with the probability of falling below the threshold ranging from 22 to 57 percentage points depending on the chosen threshold level of yield. On the other hand, we find moderate and severely wet events significantly decrease the probability of falling below the threshold.

Figure 6.1 plots the SPEI bin coefficients from equation (6.4) on the probability of being vulnerable. The normal bin was chosen as the omitted bin so that the coefficients are interpreted as the marginal effect of experiencing an extreme weather event relative to a normal one. The graph demonstrates that, all else equal, the likelihood of crop yields falling below the reference, r, is the highest for extreme dry events followed by severe and moderate dry.

In column (3) and (4) of Table 6.2, we report the estimates for "Drought" and "Flood" weather events where the variables respectively take the value of 1 if SPEI < -0.99 and SPEI $> +0.99$ and 0 otherwise. We consider the base category to be the normal event (i.e., $-0.99 < SPEI < 0.99$). The coefficient corresponding to the "flood" is statistically significant and negative indicating that relative to a "normal" event, a "flood" reduces the likelihood of falling below the threshold by approximately 2 percentage points. In the case of a "drought", we see that its occurrence increases the probability of falling below the threshold by 16 percentage points.

These results provide further evidence on the non-linear effects of weather on crop yields. For instance, Schlenker and Roberts (2009) use county level agricultural data in the US and find a nonlinear relationship between temperatures and productivity with crop yields increasing modestly until a threshold temperature and then declining. However, one limitation of their study is that they do not include farm inputs (e.g., fertilizers) and other climatic variables (e.g., precipitation) which are known to impact productivity. Our analysis overcomes these limitations as we control for farm management as well as capture the join effects of temperature, precipitation, and other climatic variables with our SPEI variable. Similar to Schlenker and Roberts, we find threshold effects of weather variables on crop yields with the probability of falling below R increasing ex-ante with a shift in the distribution of SPEI towards a higher frequency of extreme events. Moreover, these results are also consistent with the agronomic literature showing the adverse effects of high temperatures and precipitation on rice yields (Vogel et al. 2019)

We now examine the effects of SPEI on the lower partial moment of the rice yield distribution. In interpreting the lower partial moment, keep in mind that it is estimated as the negative of the residuals so that a positive coefficient is an increase in the lower partial moment. The coefficient of SPEI growing season maintains a negative sign as expected. A one standard deviation increase in this variable is associated with a 2.3 percentage point reduction in the lower partial moment. In other words, reducing the climatic water balance has a positive impact on the expected yield gap as it decreases the distance between the threshold and the fall from the threshold. Column (4) reports the results for "drought" and "flood" events with droughts increasing the yield gap by 2% relative to a normal event while a wet event reduce this gap by 9% relative to a normal event. The estimates from column (2), (4) and (6) further provide evidence of the effects being robust to different specifications of the SPEI variable. Column (6) in Table 6.2 reports the results of estimation of the lower partial moment model for the SPEI bins. The results show extreme, severe, and moderate dry events increase the lower partial moment with the effect larger for the extreme dry events. On the contrary, we find moderate, severe, and extreme wet events decrease the lower partial moment with the effect being larger for extreme wet events. Similar results are observed when SPEI bins are interacted with the management variables.

Figure 6.2 plots the SPEI bin coefficients on the expected yield gap. The normal bin was chosen as the omitted bin so that the coefficients are interpreted as the marginal effect of experiencing an extreme weather event relative to a normal one. The graph demonstrates that, all else equal, extreme and severe dry events increase the extent of the crop yield loss from the threshold level relative a normal event. We also observe similar effects for severe wet events, but extreme wet events decrease the expected yield gap, contrary to our expectations.

Examination of the elasticities of the technology variables indicates that both irrigation and HYV seeds decrease the likelihood of the rice yields falling below the threshold. In particular, a doubling of the area under irrigation reduces the probability in the range of 3-5 percentage points while a doubling of the HYV area decreases the likelihood of the fall in the range of 2-9 percentage points. These results suggest that both irrigation and HYV area act as efficient management techniques to increase resilience of an agricultural system. Further, we do not find any significant effect of fertilizer use on the probability and expected yield gap measure across all our specifications. This is partly because the fertilizer measure in our analyses is interpolated for the rice yield from annual measures and is at best a proxy. Finally, the effect of labor on the probability measure is positive for females but we do not attain significant results for male labor. However, we find a similar effect of labor on the lower partial moment.

6.3 Conclusions

This chapter examines the vulnerability of agricultural districts in India to extreme weather events. Applying the vulnerability indicator to a panel data of rice yields from 292 Indian districts, we find that the SPEI index has a negative and significant impact on the vulnerability of rice yields. We further use this index to exploit the temporal variation in growing season water stress levels. Our results indicate that very high and low water stress levels, as captured by the extreme wet and dry events on the SPEI index, significantly increase the vulnerability of rice yields. This finding suggests that the SPEI index contains information regarding impacts of climatic water balance and intra-seasonal timing of water stress on crop yields and serves as evidence in support of quantifying the impacts of extreme weather events on crop yields.

Our analysis also sheds light on the sensitivity of the indicator to various reference levels. The results in table consider the threshold yield as modeled in the PMFBY insurance scheme. However, in tables we present the results for other potential threshold levels of yield. The results indicate that our measure of vulnerability is highly sensitive to the chosen threshold. This has important implication for policymakers, especially with respect to the crop insurance programs. For example, our vulnerability indicator can be used to estimate the effects of future climate impacts for different reference level yields and use these estimates to frame appropriate crop insurance policies to mitigate the expected losses in yield.

Table 6.1: Summary Statistics

	All-India			*Vulnerable*			*Non-Vulnerable*		
	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.
Rice Yield (T/Ha)	11896	1.44	0.92	1787	0.74	0.67	10109	1.56	0.90
Rice's share of total area planted (%)	11896	22.51	22.70	1787	18.88	23.03	10109	23.15	22.58
Share of Irrigated Area (%)	11200	46.58	40.42	1718	35.13	37.99	9482	48.66	40.50
Fertilizers (T/Ha)	11542	0.03	0.05	1741	0.02	0.03	9801	0.03	0.05
Share of HYV area planted (%)	8871	43.89	38.27	1348	34.51	36.97	7523	45.57	38.25
Male Labor (No./Ha)	11112	0.28	0.26	1533	0.30	0.35	9579	0.28	0.24
Female Labor (No./Ha)	11112	0.19	0.21	1533	0.22	0.27	9579	0.19	0.19
Growing Season SPEI	11926	-0.10	0.95	1787	-0.54	0.92	10139	-0.02	0.93

Ha = hectares, HYVs = High yield variety seeds, SPEI Index calculated for growing season months i.e. June, July, August and September. Source: Authors' own calculation from the VDSA District Meso database

Table 6.2: Effects of Weather Variables on District Vulnerability with respect to the threshold, R_1

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Growing Season SPEI	-0.076***	-0.016				
	(0.006)	(0.010)				
Drought			0.155***	0.019		
			(0.016)	(0.016)		
Flood			-0.035***	-0.043		
			(0.008)	(0.033)		
Extreme Dry					0.384***	0.110***
					(0.080)	(0.041)
Severe Dry					0.231***	0.037
					(0.025)	(0.023)
Moderate Dry					0.130***	0.010
					(0.018)	(0.019)
Moderate Wet					-0.048***	-0.062*
					(0.010)	(0.033)
Severe Wet					-0.006	-0.052
					(0.015)	(0.062)
Extreme Wet					-0.009	-0.352***
					(0.041)	(0.105)
Observations	7664	1039	7664	1039	7664	1039
R^2	0.214	0.541	0.219	0.551	0.230	0.571
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include farm inputs (Share of Irrigated Area, Share of HYV area, Share of Rice area, Male and Female Labor) and their interactions with weather variables.

Table 6.3: Effects of Farm Inputs on District Vulnerability with respect to threshold R_1

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Share of Irrigated Area	-0.104**	-0.119**	-0.113**	-0.126**	-0.100**	-0.116**
	(0.044)	(0.058)	(0.045)	(0.058)	(0.045)	(0.055)
Share of HYV area planted	-0.063***	0.032	-0.067***	0.031	-0.061***	0.036
	(0.020)	(0.037)	(0.020)	(0.037)	(0.020)	(0.038)
Share of Rice Area	0.094	0.053	0.054	0.002	0.085	0.055
	(0.154)	(0.227)	(0.159)	(0.220)	(0.158)	(0.215)
Male Labor	0.417***	0.252	0.421***	0.279	0.431***	0.171
	(0.152)	(0.204)	(0.154)	(0.222)	(0.146)	(0.391)
Female Labor	-0.001	0.197	0.031	0.145	0.008	0.201
	(0.147)	(0.177)	(0.149)	(0.177)	(0.144)	(0.244)
Observations	7664	1039	7664	1039	7664	1039
R^2	0.214	0.541	0.219	0.551	0.230	0.571
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the farm input variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include interaction between farm inputs and weather variables.

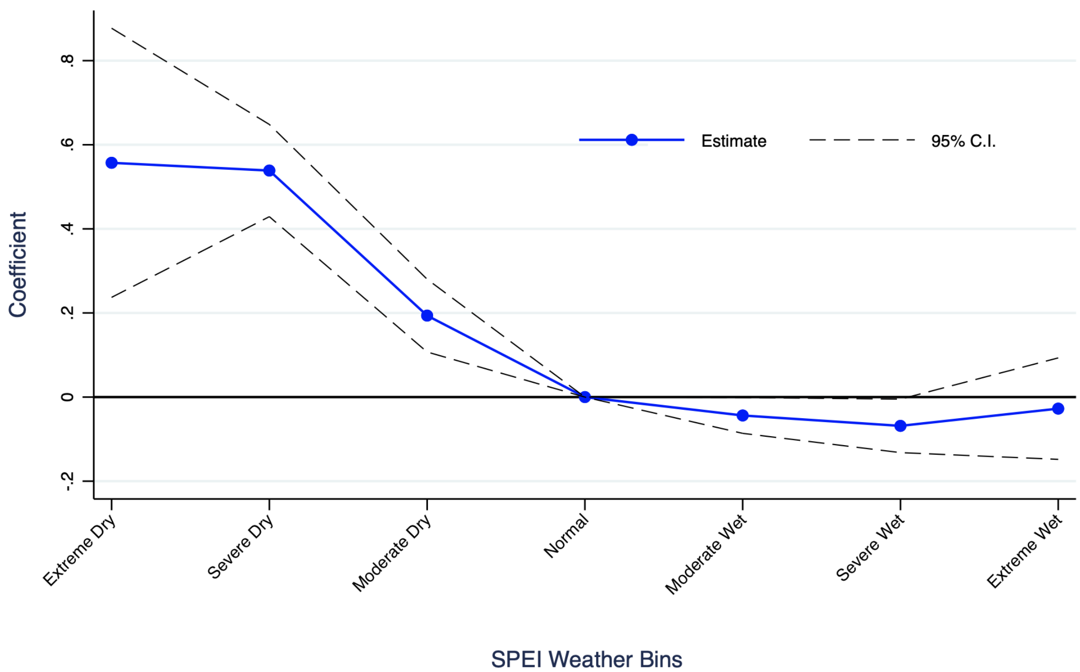

Figure 6.1: Estimated Impact of an extreme weather event on the probability of district rice yields falling below the threshold, R_1, relative to a normal event

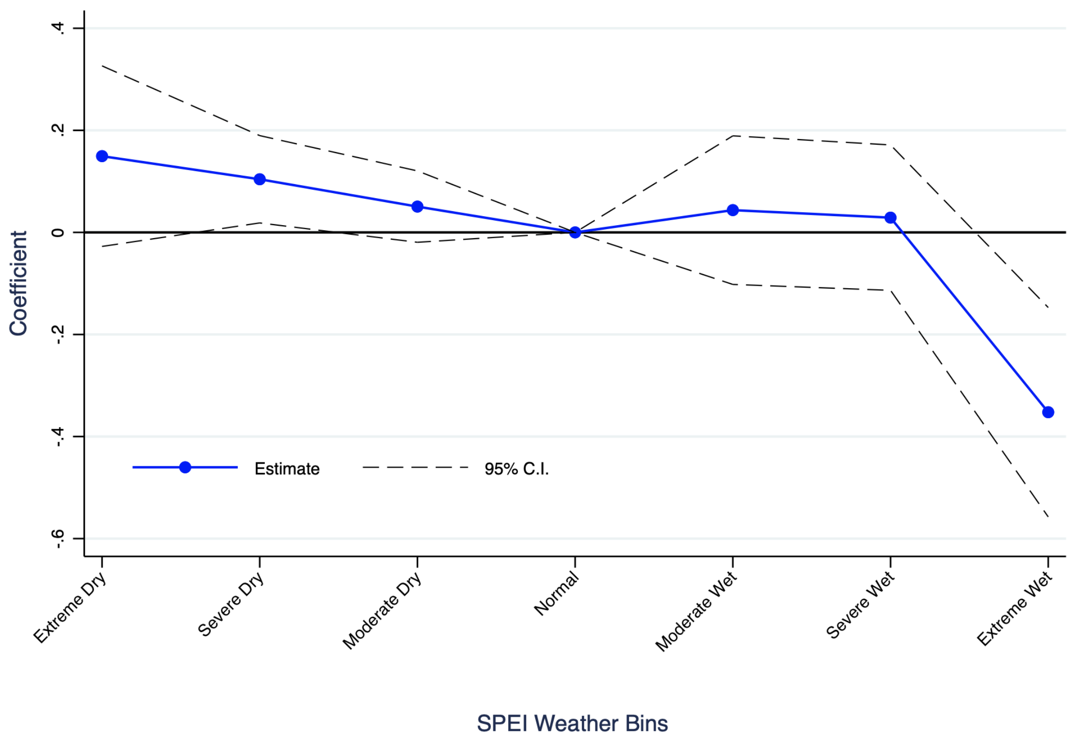

Figure 6.2: Estimated Impact of an extreme weather event on the district yield gap with respect to the threshold, R_1, relative to a normal event

Chapter 7: Discussion

Extreme weather events are expected to increase globally due to climate change thereby posing substantial risks to agricultural communities. The implications are especially high for tropical countries like India as the heavy dependence of agricultural sector to uncertain monsoons makes its agriculture highly vulnerable to weather variability and extremes. In this dissertation, we examine the vulnerability of agricultural systems in India to extreme weather events. To this end, we first develop an indicator of vulnerability using the partial moments model which captures two important dimensions of vulnerability - the likelihood of an agricultural system falling below some critical threshold as well as the extent of the loss below the threshold. We then provide an empirical application by examining the vulnerability of crop yields to weather extremes as well as the household vulnerability to poverty. The estimation results using a panel data of rice yields from thirty Indian villages indicate that extreme and severe droughts have a positive and significant effect on vulnerability in rainfed farms but not in irrigated farms. These results provide evidence of irrigation as an adaptive mechanism for farmers. When examining the household's vulnerability to poverty, we find similar effects of weather extremes with the household most vulnerable to poverty when exposed to an extreme drought. We also find statistical evidence that crop diversification has a negative effect on vulnerability and is an important risk-mitigating tool employed by farm households. We next examine the vulnerability of Indian agriculture at a more aggregated level by exploiting a district-level panel data for forty years. Similar to the farm-level analysis, we find extreme and severe droughts to be the main drivers of vulnerability whereas irrigation and high-yield variety (HYV) seeds are found to increase resilience.

Several implications can be drawn based on this set of results. Firstly, the findings from the farm level analysis demonstrate that in examining the effect of weather variables, particularly extremes, on crop outcomes, it is vital to capture both the timing and intensity of the event. The use of a composite climate index such as SPEI is favorable in such assessments. Secondly, the results highlight the potential adaptive mechanisms that farmers and households utilize to mitigate losses from such events. Two tools stand out in particular - Irrigation and Diversification. Providing access to better irrigation and irrigated technologies and efforts aimed at diversification are key strategies for policymakers to consider. A third implication relates to the spillover effects of weather extremes on important human development indicators. The results from the farm and household analysis show that extreme weather events have similar effects on the vulnerability of crop yields as well as income. Indeed, rural households in India heavily depend on agriculture for their livelihood. It is thus plausible that the effects of extreme events may extend beyond agricultural outcomes to health and education. The vulnerability indicator developed using the partial moments model presents an opportunity for researchers and policymakers to advance the empirical knowledge on the effects of weather extremes on different human development indicators. The applicability of the vulnerability indicator in examining questions related to the chronic undernutrition and early childhood education is one such area of potential interest. A final implication relates to the impact of change in climate and improvement in technologies on vulnerability. Policymakers are likely to be interested in identifying the communities vulnerable to changes in environmental conditions and technologies so as to target intervention. The remainder of this chapter discusses the implications of the vulnerability indicator for policymakers under different climate and technological scenarios.

7.1 Simulations

In this section, we simulate the impact of weather extremes on the vulnerability of agricultural systems under various hypothetical climate and technological scenarios. To simulate the ex-ante distribution of the vulnerability indicator, we first predict the two components of the distribution using the estimates from the farm-level analysis. We then recover the underlying probability density function using non-parametric estimation methods. We consider three specific scenarios as part of the simulations. First, we consider the impact of an improvement in technology on the distribution under current climate. Secondly, we examine the effect of farm size and technology using a set of improved technology and no technology under the current climate. Finally, we consider the impact on the distribution from a change in climate and under current and a better set of technology.

7.1.1 Simulations at the Farm and Household Level

Effect of Technology on Vulnerability

Figure 7.1 shows the effects of technology on the distribution of the vulnerability indicator. The two technological situations considered here are with and without an improved set of technology where a technological set comprises of application of improved or hybrid variety of seeds and irrigation. The two distributions clearly highlight the differential effects of technology and the absence of it on the vulnerability indicator. Vulnerability is shown to decrease on average in the presence of technology. The distribution is also less skewed with the mass of the output distribution concentrated at the mean and thin tails. On the contrary, the distribution with no technology has a much higher variance, fatter tails and relatively higher mean. These two observations are suggestive of the fact that farms utilizing improved technology are , on average, less vulnerable.

Effect of Farm Size on Vulnerability

Figure 7.2 shows the effects of farm size on the distribution of the vulnerability indicator. Specifically, we consider marginal farms under two sets of hypothetical scenarios. This is because the results from the farm level analysis show that marginal farms are more vulnerable than small farms. We assess the vulnerability based on the marginal farms with current technology. We then consider the situation where the marginal farms are assumed to have better technologies. It is apparent that the adapting better technologies results in the marginal farms being less vulnerable. The distribution in the case of marginal farms with the current set of technology is asymmetric with a higher mean and is highly skewed to the right. On the other hand assuming better technologies results in a shifting of the mean to the left implying a decrease in vulnerability.

Effect of Weather Extremes on Vulnerability

Figure 7.3 shows the effects of a change in climate on the distribution of the vulnerability indicator. Three set of conditions are considered. The first set pertains to the use of current technology under droughts. Next, we simulate the climate such that the frequency of droughts is greater. We then consider the effects of adopting better technology under this new climate and the effects of continuing to use the current set of technology. In the first case, we clearly see the variance of vulnerability is higher and the tails are much fatter. The distributions under a new set of climate indicate an increase in vulnerability relative to the current climate. This is because droughts adversely affect the distribution by pushing the mean to the right and increasing the negative skew thus resulting in thinner tails as the mass of the distribution is now concentrated on the positive tail. When comparing the distributions under the new climate with respect to technologies, we see that the average vulnerability is lower for farms adopting newer technologies.

7.1.2 Simulations at the District Level

Effect of Technology on Vulnerability

The district level simulations present a slightly different story than the farm level ones as now we are able to capture the heterogeneity in agricultural systems across the country. We consider the effect of adopting improved technology on vulnerability. The simulations in figure 7.4 show that vulnerability is greater, on average, for districts with a higher share of irrigated and HYV area. However, when one takes into account HYV share and irrigation separately, the results indicate that HYVs are a risky prospect and adopting only HYVs in fact would result in a increase in vulnerability. This further strengthens the conclusion from the farm and district level analysis where we find the effect of HYVs is exacerbated in the absence of adequate water. On the other hand, adopting only irrigation technology decreases vulnerability as expected.

Effect of Weather Extremes on Vulnerability

Figure 7.5 and Figure 7.6 show the effects of a change in climate on the distribution of the district vulnerability indicator. In figure 7.5, we show the effects of current technology when exposed to droughts. Next, we simulate the climate such that the frequency of droughts is greater. We then consider the effects of adopting better technology under this new climate and compare it to effects of continuing to use the current set of technology. In the first case, we clearly see the mean of the distribution under irrigation and both irrigation and HYV is lower indicating that vulnerability decreases under this technology set if the district faces an additional drought. We further find vulnerability to be greater with the mean highest when using current set of technology. vulnerability is higher and the tails are much fatter. The distributions under a new set of climate indicate an increase in vulnerability relative to the current climate. This is because droughts adversely affect the distribution by pushing the mean to the right and increasing the negative skew thus resulting in thinner tails as the mass of the distribution is now concentrated on the positive tail. When comparing the distributions under the new climate with respect to technologies, we see that the average vulnerability is lower for farms adopting both set of technologies but higher when adopting only HYV. These results further provide evidence on the complementary effect of HYVs with irrigation. The main implication for policymakers is that in the event of a drought, the use of hybrid varieties decreases vulnerability if better irrigation facilities are available. If not, the effect is exacerbated.

7.2 Conclusions

In interpreting these findings, it is important to note that the statistical methods do not take in account other factors such as CO2 fertilization effects. The simulations presented here also do not consider changes in political and socioeconomic conditions which are an important component for vulnerability assessment as noted in chapter three. Further research is needed to examine the effects of CO2 fertilization and design scenarios that consider changes in biophysical and socioeconomic conditions. Process-based approaches can offer a viable solution. Furthermore, in accounting for the effects of irrigation, a strong assumption is made about the groundwater availability in the future. Climate change and over-exploitation of water resources is likely to reduce the availability of it and as such the results presented here are at best conservative measures. It is also well-documented that the impacts of climate change will be disproportionate, with the marginalized groups severely affected (Van Aelst and Holvoet 2016). While the results from the analysis provide some evidence of it, further research is needed to test vulnerability across socio-economic groups as well as on various indicators of human development. The model constructed and parameterized in this dissertation provide a foundation to explore these questions.

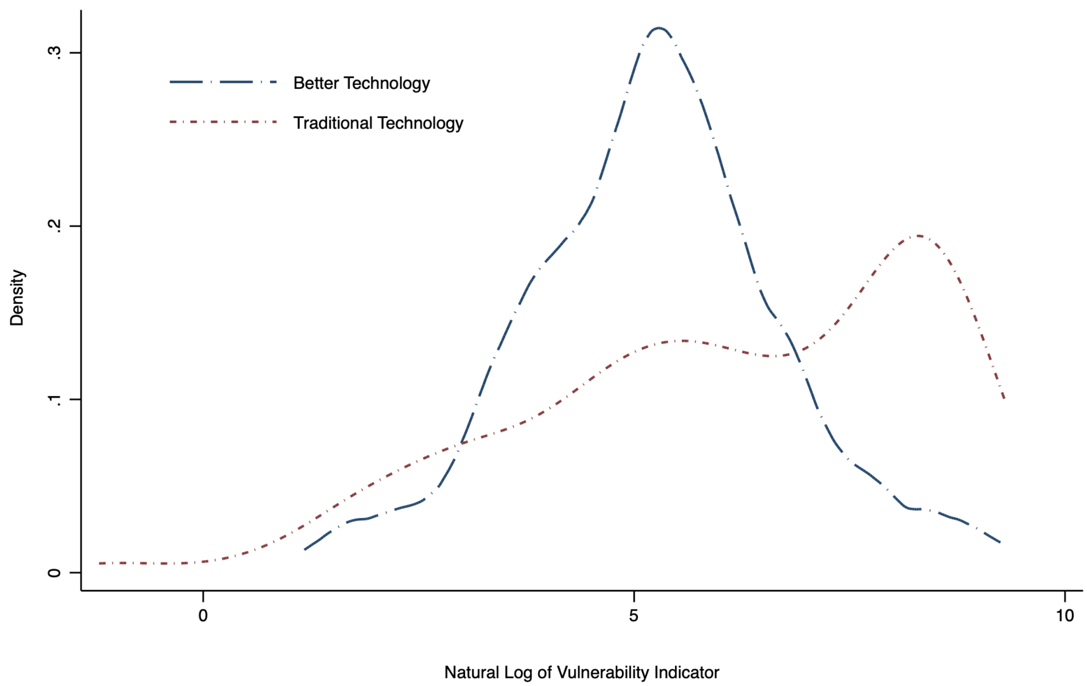

Figure 7.1: Non-parametric estimation of the effect of technology on the distribution of vulnerability indicator

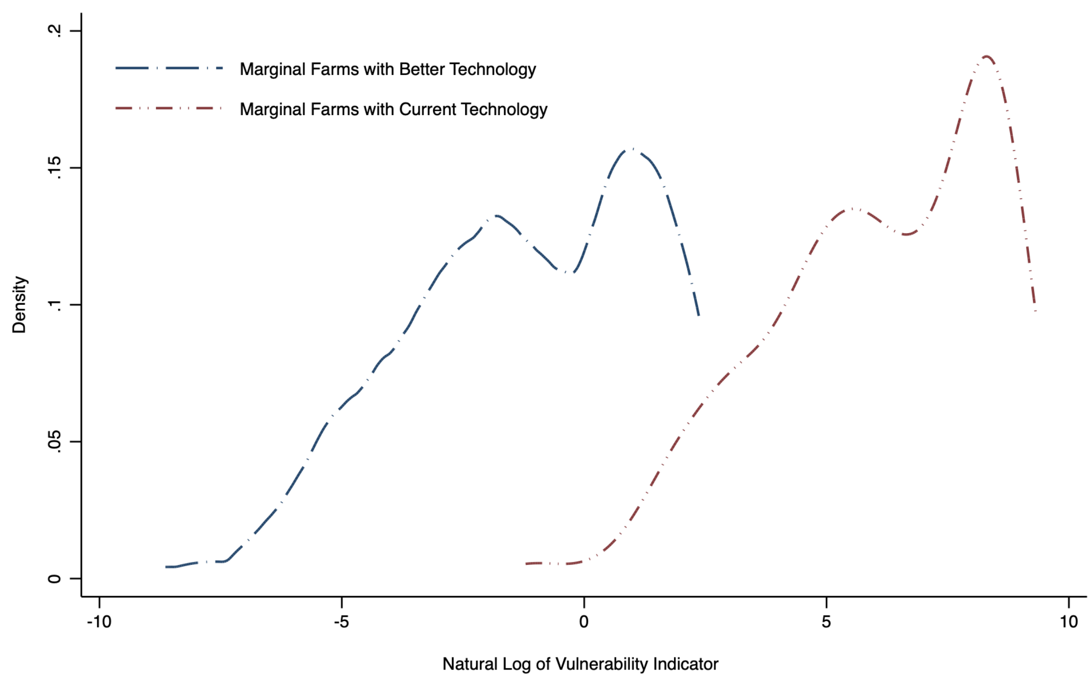

Figure 7.2: Non-parametric estimation of the effect of technology and farm size on the distribution of vulnerability indicator

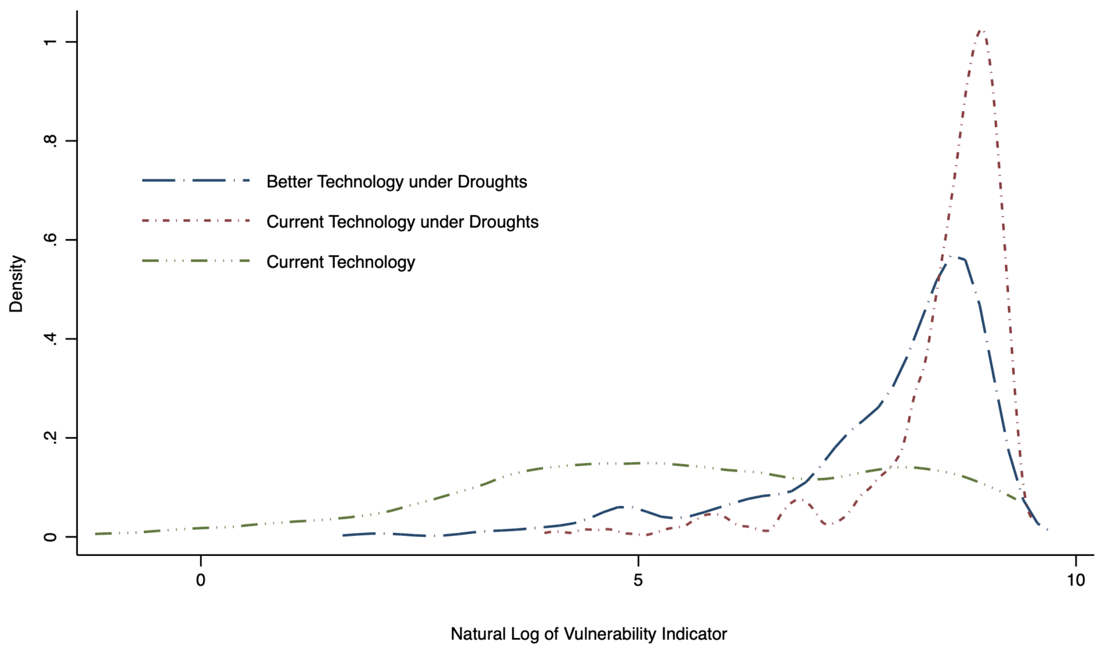

Figure 7.3: Non-parametric estimation of the effect of droughts on the distribution of vulnerability indicator

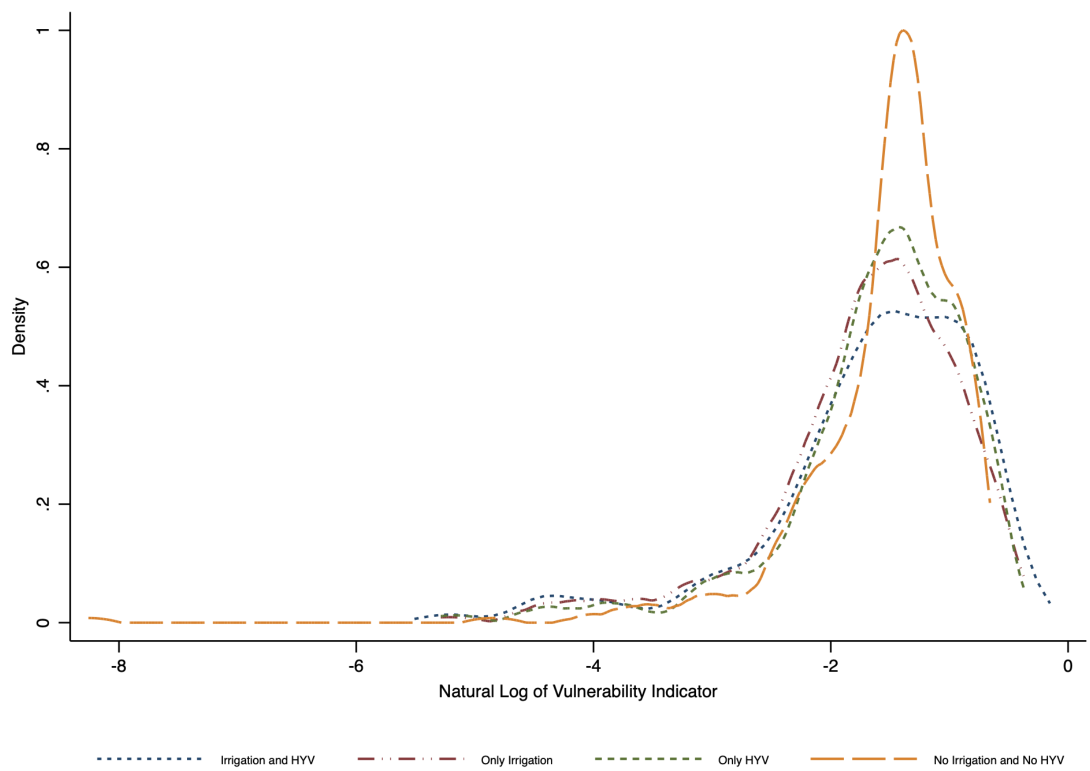

Figure 7.4: Non-parametric estimation of the effect of technology on the distribution of district vulnerability indicator

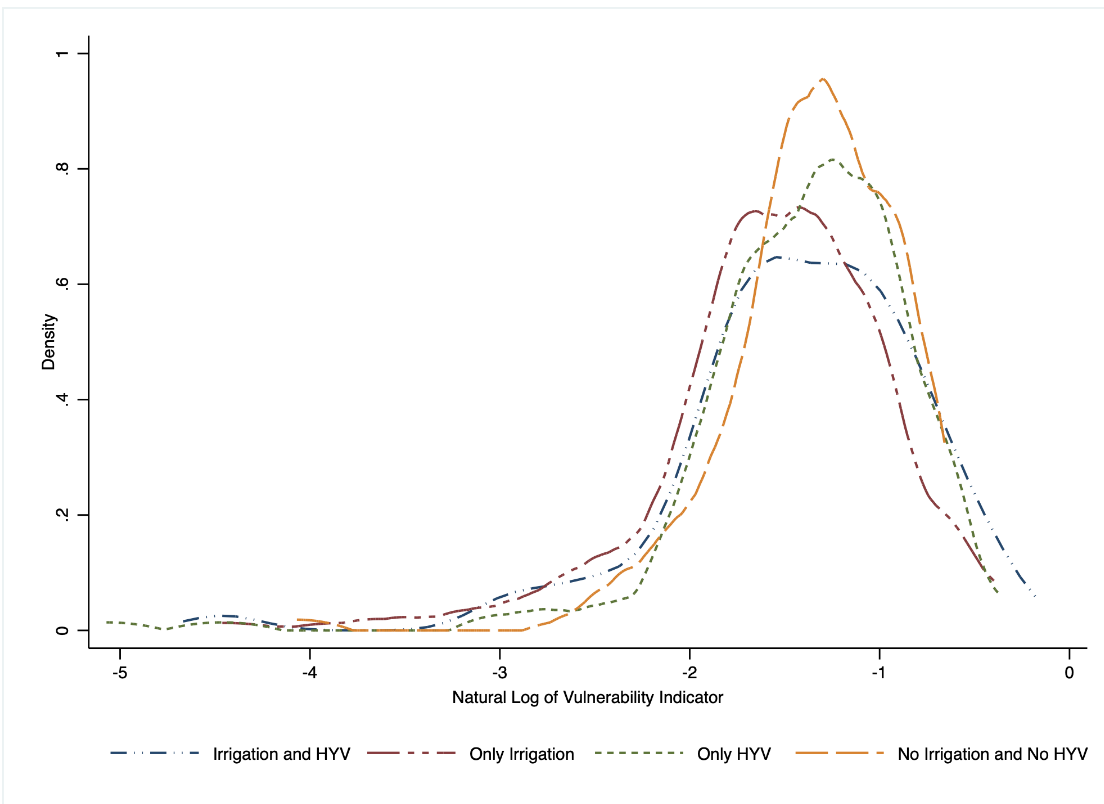

Figure 7.5: Non-parametric estimation of the effect of increased technology on the distribution of district vulnerability indicator when exposed to droughts under the current climate

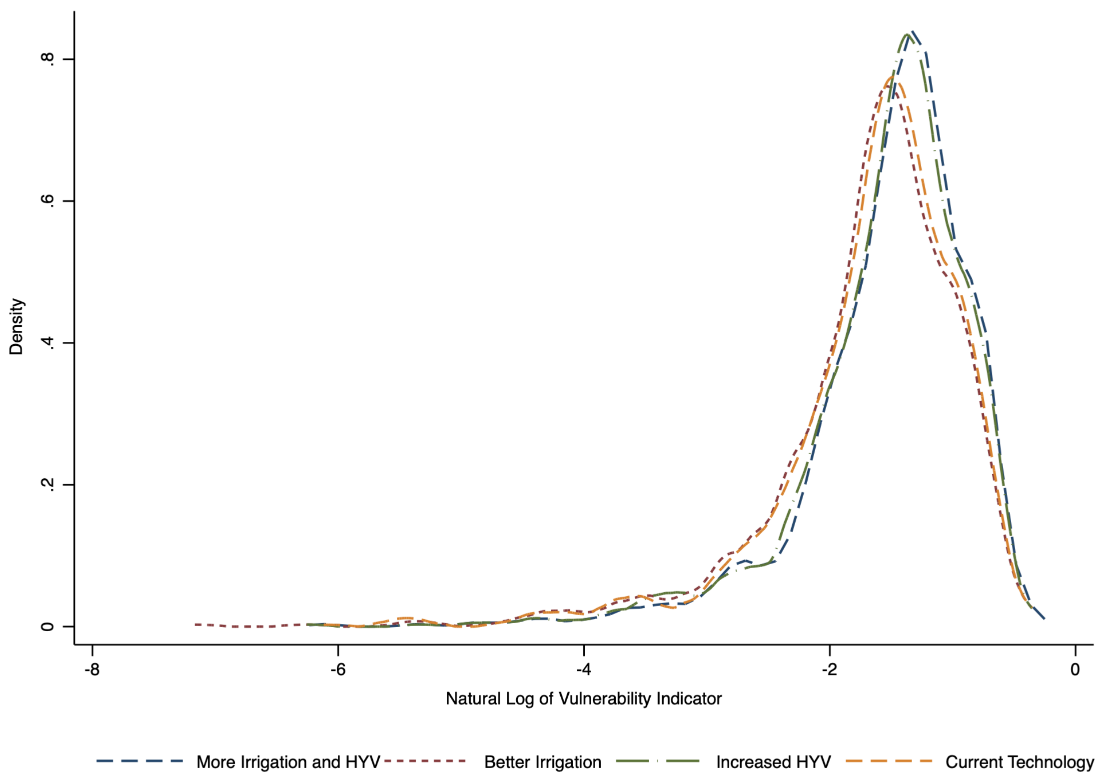

Figure 7.6: Non-parametric estimation of the effect of increased technology on the distribution of district vulnerability indicator when exposed to droughts under a new climate

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APPENDICES

Appendix A: Standard Precipitation Evapotranspiration Index

The methodology proposed here uses standardized measures of weather. The standardized precipitation index (SPI), first introduced by McKee et al. (1993), is based on conversion of the precipitation data to probabilities by using gamma distribution, the results of which are then used to determine the intensity, duration, and frequency of drought at given time scale. The common advantage of the SPI is its multi-temporal character. Such a feature is essential for assessing drought impacts owing to its flexibility and ease in operation in practical drought monitoring. However, the main criticism of the SPI is that its calculation is based on only precipitation data. The Palmer Drought Severity Index (PDSI) is based on a water balance equation taking into account precipitation, moisture supply, runoff and evaporation demand at the surface level. According to Vicente-Serrano, Beguería, and López-Moreno (2010), although some of the weaknesses of the PSDI have been solved by Wells, Goddard, and Hayes (2004), the main weakness of the PDSI identified by Guttman (1998) has not been addressed: the fixed temporal scale between 9 to 12 months and the fact that PDSI values are affected by conditions up to four years in the past.

Since climate change involves both changes in precipitation and temperature, an index accounting for the influence of temperature and precipitation is desired.

Recently, Vicente-Serrano, Beguería, and López-Moreno (2010) proposed the standardized precipitation evapotranspiration index (SPEI) which is the difference between precipitation and potential evapotranspiration, i.e. the net balance of water, which is standardized. SPEI is expressed in units of standard deviations from the long-run average, so that a positive (negative) value in a given month means an above (below) normal water balance. The water balance matters primarily for vegetation activity: A lower balance reduces plant growth (Vicente-Serrano et al. 2012) and hence agricultural output. As both temperature and precipitation have an impact on agricultural production and the livelihood of rural populations, considering SPEI index as the standardized measure of weather is more sensible. This index further offers the opportunity to easily characterize average production under locally and frequency-defined weather scenarios. As the framework is very simple, it can easily be extended to partial and quantile moments of different agricultural systems at different intervals of the population distribution.

Constructing the SPEI

This study uses the R program routines developed by Vicente-Serrano, Beguería, and López-Moreno (2010); Beguería et al. (2014) to manually construct the SPEI based on monthly precipitation and temperature data from 1966-2011 obtained from the Climatic Research Unit, University of East Anglia. The computation involves:

- Compute the climatic water balance, D, defined at the monthl level as the difference between precipitation and potential evapotranspiration (PET). Since no direct data on PET is available, the PET is calculated using the Thornthwaite method.
- The climatic water balance, D, is aggregated at different time scales (1, 3, 6, 12) and a kernel function is applied to the data which allows the incorporation of information from previous time steps into the calculation of the current step.
- The time series is standardized according to a log-logistic distribution whose parameters are estimated by the L-moment procedure. The probability distribution function of D according to the log-logistic is

$$F(x) = \left[1 + \frac{\alpha}{x-\gamma}^{\beta}\right]^{-1}$$

  SPEI is calculated as the standardized values of F(x). By construction, it has a mean 0 and a standard deviation of 1 in a given district over the historic sample i.e. 1966-2011. Figure A.1 plots the extreme weather events over the sample period.
- For estimation purposes, only the growing season SPEI is considered by averaging the monthly SPEI over the growing season months i.e. May to October.

Interpreting SPEI

One can read the parameter estimates on SPEI in terms of standard deviation i.e. a net 'climatic balance of water' one standard deviation away from normal causes a change of $\beta\%$ in the productivity of rice per hectare. The fact that the SPEI is standardized implies that the climatic water balance is measured in terms of local frequencies. This helps sorts another source of unobserved heterogeneity: typically, one can assume that a given level of net balance of water is going to have a heterogeneous impact across the country. The standardization implies that we are comparing the net balances of water in terms of their local frequency so that passing from 0 to 1 on the SPEI scale means the same across the country, i.e. a 1 SD compared to normal conditions.

Table A.1: Classification of extreme weather events based on SPEI

Condition	**SPEI**
Extreme Wet	≥ 2.0
Severe Wet	[1.5, 2.0)
Moderate Wet	[1.0, 1.5)
Normal	(-1.0, 1.0)
Moderate Dry	(-1.5, -1.0]
Severe Dry	(-2.0, -1.5]
Extreme Dry	≤ 2.0

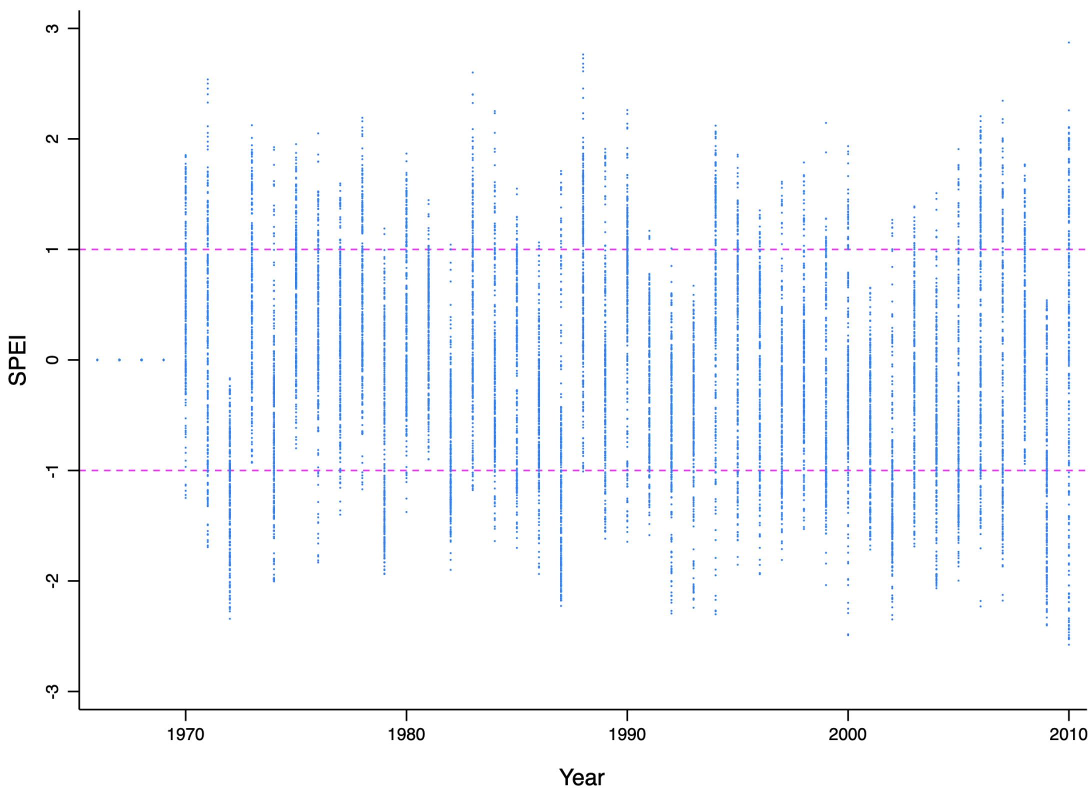

Figure A.1: Extreme Weather Events in India (1966-2011) as captured by the SPEI Index

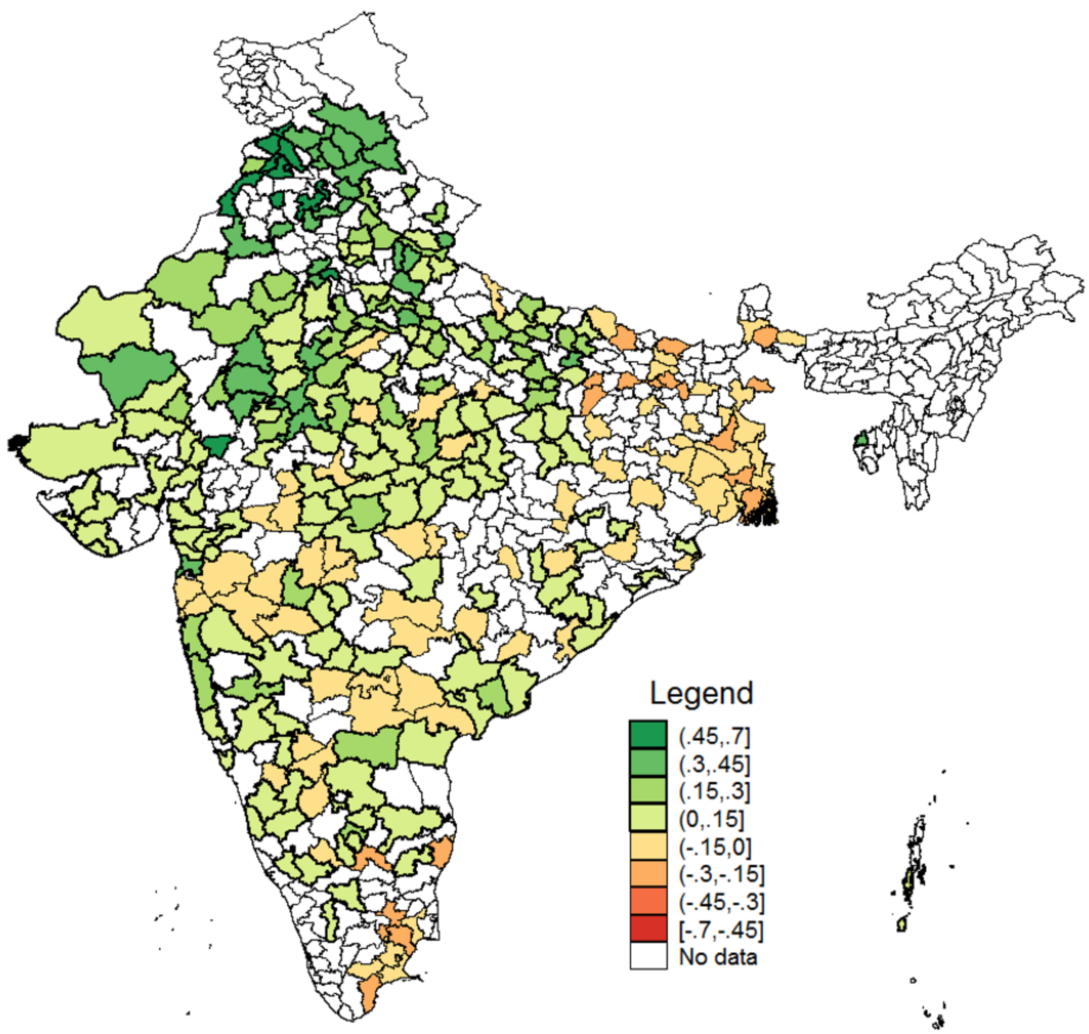

Figure A.2: Spatial distribution of average SPEI (1966-2010) for the month of June

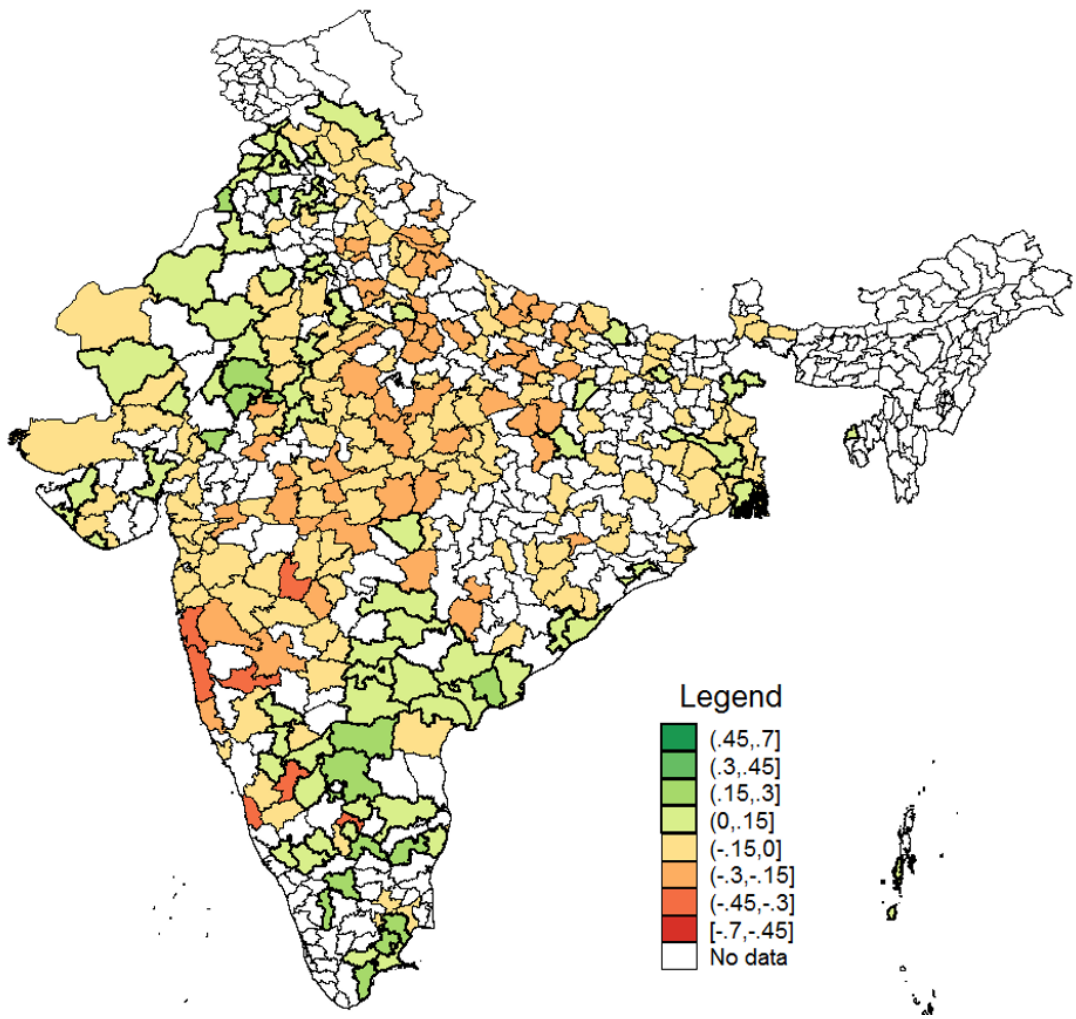

Figure A.3: Spatial distribution of average SPEI (1966-2010) for the month of July

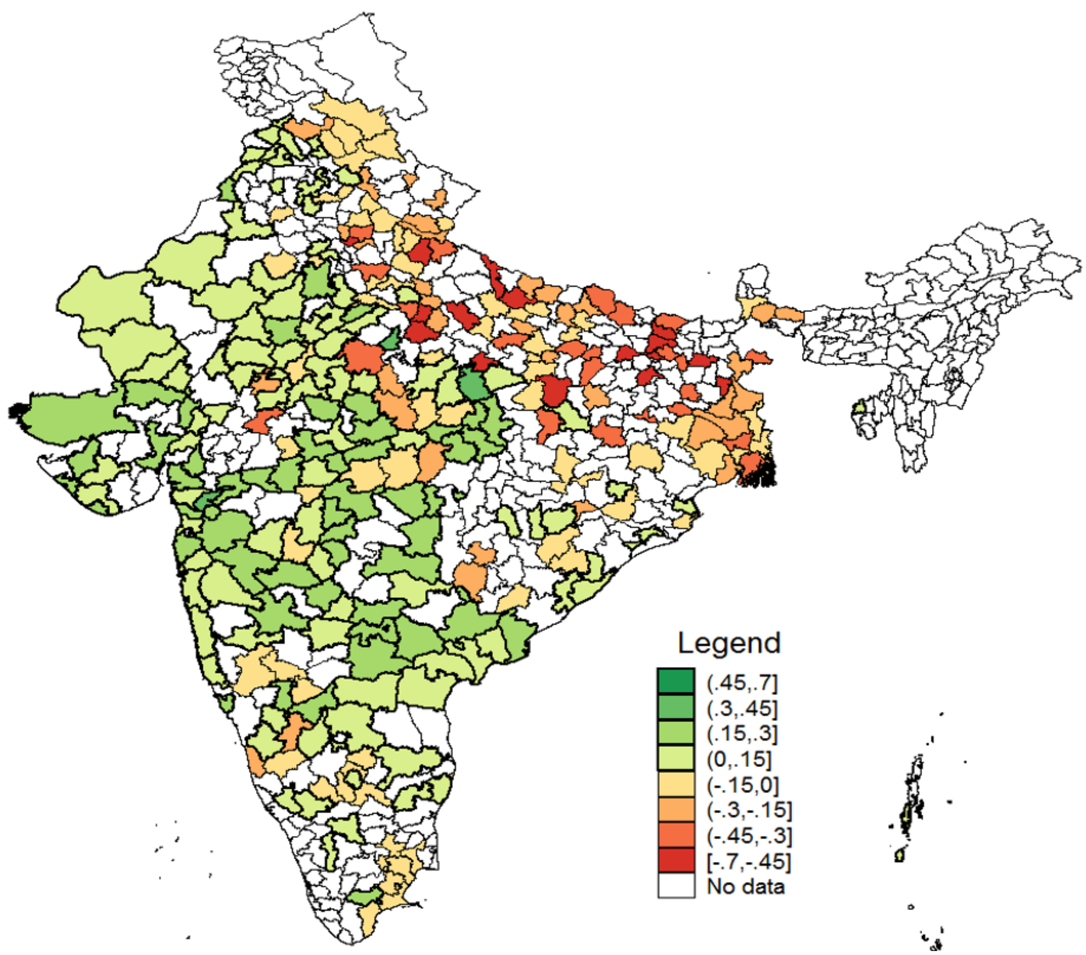

Figure A.4: Spatial distribution of average SPEI (1966-2010) for the month of August

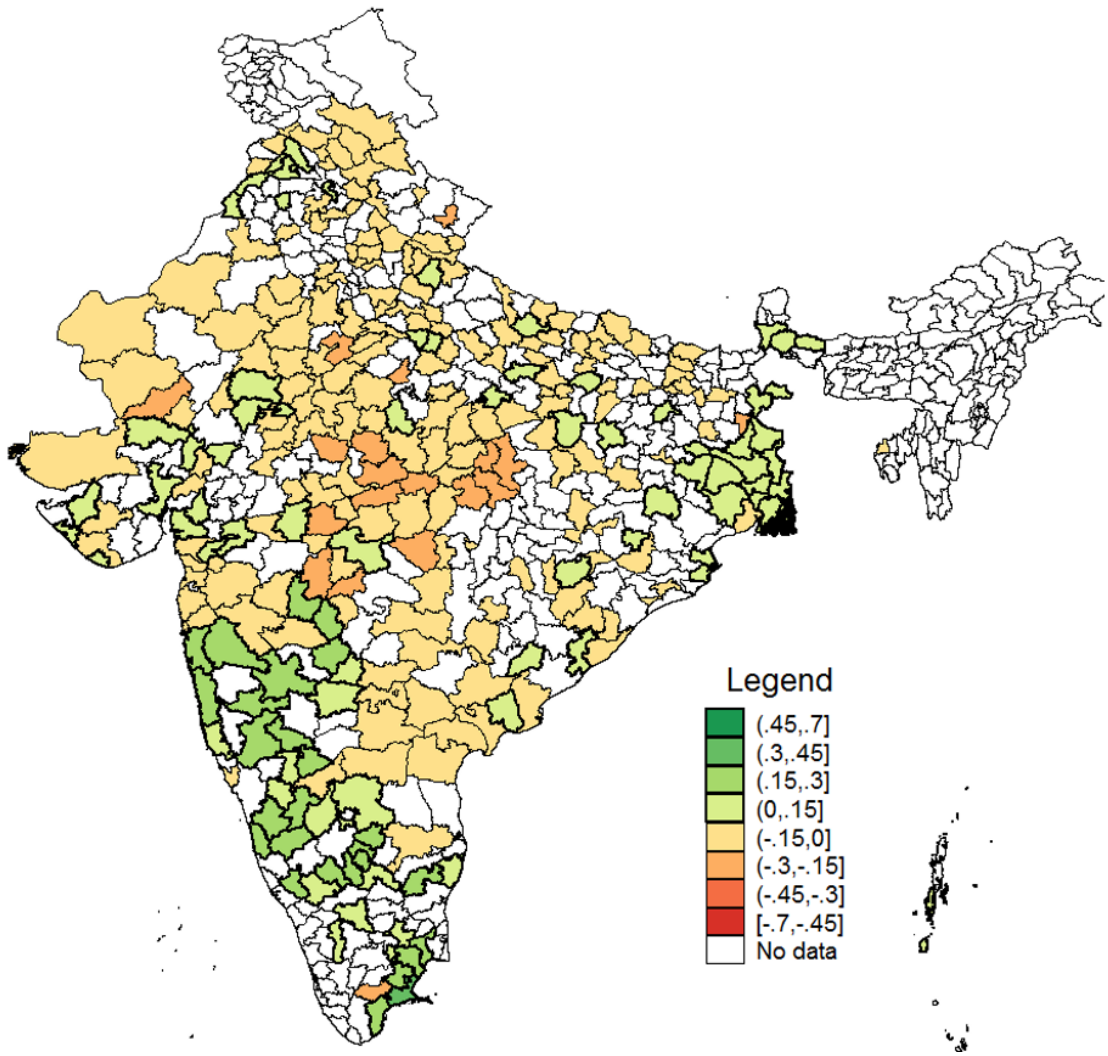

Figure A.5: Spatial distribution of average SPEI (1966-2010) for the month of September

Appendix B: Estimation Based on Alternative Reference Points

Table B.1: Effects of Weather Variables on Household Vulnerability based on the threshold, T_2

	Φ	η_1
Extreme Dry	0.132***	0.473***
	(0.031)	(0.086)
Severe Dry	0.093***	0.186***
	(0.014)	(0.044)
Moderate Dry	-0.026***	-0.012
	(0.010)	(0.034)
Moderate Wet	-0.019**	-0.049*
	(0.008)	(0.027)
Severe Wet	-0.016*	-0.048
	(0.009)	(0.035)
Extreme Wet	0.006	0.220***
	(0.015)	(0.068)
Observations	5339	3145
R^2	0.149	0.154
State Time Trend	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes

Notes: The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability. Robust standard errors clustered at the household level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. All regressions include household characteristics as controls and interaction with weather variables.

Table B.2: Effects of Farm Characteristics on Household Vulnerability based on the threshold, T_2

	Φ	η_1
Share of HYV Area Planted	-0.045**	0.002
	(0.019)	(0.054)
Share of Irrigated Area	-0.088***	0.031
	(0.024)	(0.072)
Total Area Cultivated	-0.055***	0.086
	(0.014)	(0.055)
Crop Diversity	-0.180***	-0.347***
	(0.037)	(0.111)
Caste	0.011	0.359***
	(0.055)	(0.101)
Observations	5339	3145
R^2	0.149	0.154
State Time Trend	Yes	Yes
Year FE	Yes	Yes
Household FE	Yes	Yes

Notes: The table displays coefficient of marginal effects for all the farm inputs and household characteristics on the two dimensions of vulnerability. Robust standard errors clustered at the household level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. All regressions include household characteristics as controls and interaction with weather variables.

Table B.3: Effects of Weather Variables on District Vulnerability with respect to the threshold, R_2

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Growing Season SPEI	-0.081***	-0.050***				
	(0.008)	(0.006)				
Drought			0.167***	0.086***		
			(0.018)	(0.013)		
Flood			-0.041***	-0.023		
			(0.015)	(0.015)		
Extreme Dry					0.340***	0.167***
					(0.062)	(0.040)
Severe Dry					0.221***	0.112***
					(0.028)	(0.021)
Moderate Dry					0.149***	0.073***
					(0.019)	(0.015)
Moderate Wet					-0.055***	-0.031*
					(0.017)	(0.018)
Severe Wet					-0.020	-0.016
					(0.026)	(0.022)
Extreme Wet					-0.151**	0.144***
					(0.062)	(0.054)
Observations	7664	2583	7664	2583	7664	2583
R^2	0.202	0.378	0.209	0.381	0.214	0.389
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include farm inputs (Share of Irrigated Area, Share of HYV area, Share of Rice area, Male and Female Labor) and their interactions with weather variables.

Table B.4: Effects of Farm Inputs on District Vulnerability with respect to threshold R_2

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Share of Irrigated Area	-0.116**	-0.062	-0.124**	-0.068	-0.115**	-0.062
	(0.054)	(0.048)	(0.055)	(0.049)	(0.056)	(0.050)
Share of HYV area planted	-0.091***	-0.030	-0.092***	-0.028	-0.089***	-0.021
	(0.030)	(0.022)	(0.030)	(0.022)	(0.030)	(0.022)
Share of Rice Area	0.083	-0.008	0.061	-0.068	0.068	-0.008
	(0.195)	(0.158)	(0.200)	(0.161)	(0.201)	(0.169)
Male Labor	0.323*	0.373*	0.318	0.395**	0.327*	0.382*
	(0.190)	(0.190)	(0.195)	(0.192)	(0.193)	(0.199)
Female Labor	0.305*	0.012	0.340*	0.004	0.323*	0.021
	(0.183)	(0.167)	(0.185)	(0.168)	(0.184)	(0.172)
Observations	7664	2583	7664	2583	7664	2583
R^2	0.202	0.378	0.209	0.381	0.214	0.389
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the farm input variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include interaction between farm inputs and weather variables.

Table B.5: Effects of Weather Variables on District Vulnerability with respect to the threshold, R_3

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Growing Season SPEI	-0.069***	-0.024**				
	(0.006)	(0.011)				
Drought			0.153***	0.027		
			(0.016)	(0.018)		
Flood			-0.027***	-0.060		
			(0.009)	(0.038)		
Extreme Dry					0.455***	0.150***
					(0.082)	(0.049)
Severe Dry					0.229***	0.044
					(0.028)	(0.032)
Moderate Dry					0.122***	0.007
					(0.018)	(0.019)
Moderate Wet					-0.042***	-0.079
					(0.010)	(0.057)
Severe Wet					-0.000	-0.062
					(0.017)	(0.067)
Extreme Wet					-0.060	2.758***
					(0.038)	(0.922)
Observations	7664	1040	7664	1040	7664	1040
R^2	0.200	0.523	0.205	0.537	0.217	0.554
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include farm inputs (Share of Irrigated Area, Share of HYV area, Share of Rice area, Male and Female Labor) and their interactions with weather variables.

Table B.6: Effects of Farm Inputs on District Vulnerability with respect to threshold R_3

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Share of Irrigated Area	-0.075	-0.073	-0.084*	-0.079	-0.075	-0.051
	(0.046)	(0.060)	(0.047)	(0.058)	(0.048)	(0.058)
Share of HYV area planted	-0.051***	0.046	-0.054***	0.045	-0.050***	0.053
	(0.018)	(0.046)	(0.018)	(0.047)	(0.018)	(0.048)
Share of Rice Area	0.079	0.071	0.039	-0.001	0.052	0.113
	(0.148)	(0.167)	(0.150)	(0.178)	(0.150)	(0.196)
Male Labor	0.306***	0.291	0.318**	0.343	0.359***	0.221
	(0.115)	(0.246)	(0.125)	(0.255)	(0.116)	(0.381)
Female Labor	0.116	-0.010	0.149	-0.079	0.105	0.013
	(0.109)	(0.193)	(0.116)	(0.192)	(0.116)	(0.232)
Observations	7664	1040	7664	1040	7664	1040
R^2	0.200	0.523	0.205	0.537	0.217	0.554
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the farm input variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include interaction between farm inputs and weather variables.

Table B.7: Effects of Weather Variables on District Vulnerability with respect to the threshold, R_4

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Growing Season SPEI	-0.049***	-0.023**				
	(0.005)	(0.012)				
Drought			0.102***	0.027*		
			(0.014)	(0.016)		
Flood			-0.014	-0.024		
			(0.009)	(0.033)		
Extreme Dry					0.358***	0.169
					(0.077)	(0.227)
Severe Dry					0.178***	0.027
					(0.024)	(0.025)
Moderate Dry					0.068***	0.020
					(0.015)	(0.020)
Moderate Wet					-0.013	0.001
					(0.011)	(0.040)
Severe Wet					-0.020	-0.048
					(0.014)	(0.073)
Extreme Wet					0.051	-0.094
					(0.057)	(0.061)
Observations	7664	808	7664	808	7664	808
R^2	0.224	0.620	0.228	0.627	0.242	0.653
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the weather variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include farm inputs (Share of Irrigated Area, Share of HYV area, Share of Rice area, Male and Female Labor) and their interactions with weather variables.

Table B.8: Effects of Farm Inputs on District Vulnerability with respect to threshold R_4

	Model 1		Model 2		Model 3	
	Φ	η_1	Φ	η_1	Φ	η_1
Share of Irrigated Area	-0.125***	-0.218**	-0.140***	-0.235**	-0.115**	-0.221**
	(0.044)	(0.105)	(0.043)	(0.104)	(0.056)	(0.106)
Share of HYV area planted	-0.079***	-0.022	-0.082***	-0.028	-0.089***	-0.028
	(0.021)	(0.057)	(0.021)	(0.061)	(0.030)	(0.070)
Share of Rice Area	0.042	-0.028	-0.006	-0.119	0.068	-0.049
	(0.116)	(0.200)	(0.119)	(0.211)	(0.201)	(0.216)
Male Labor	0.314***	0.191	0.322***	0.281	0.327*	0.224
	(0.092)	(0.212)	(0.096)	(0.199)	(0.193)	(0.219)
Female Labor	-0.085	-0.013	-0.049	-0.083	0.323*	-0.112
	(0.097)	(0.196)	(0.098)	(0.196)	(0.184)	(0.207)
Observations	7664	808	7664	808	7664	808
R^2	0.224	0.620	0.228	0.627	0.214	0.653
State Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: (a) The table displays coefficient of marginal effects for all the farm input variables on the two dimensions of vulnerability based on three models. Robust standard errors clustered at the district level in parentheses. Stars indicate significance *** $p < 0.01$ ** $p < 0.05$ *$p < 0.10$. (b) The different models are as follows. Model 1 includes the growing season SPEI specified in the quadratic as the main weather variable. Model 2 replaces SPEI growing season with weather dummies (Drought and Flood) and Model 3 includes the six weather bins instead of the two weather dummies. All three models include interaction between farm inputs and weather variables.

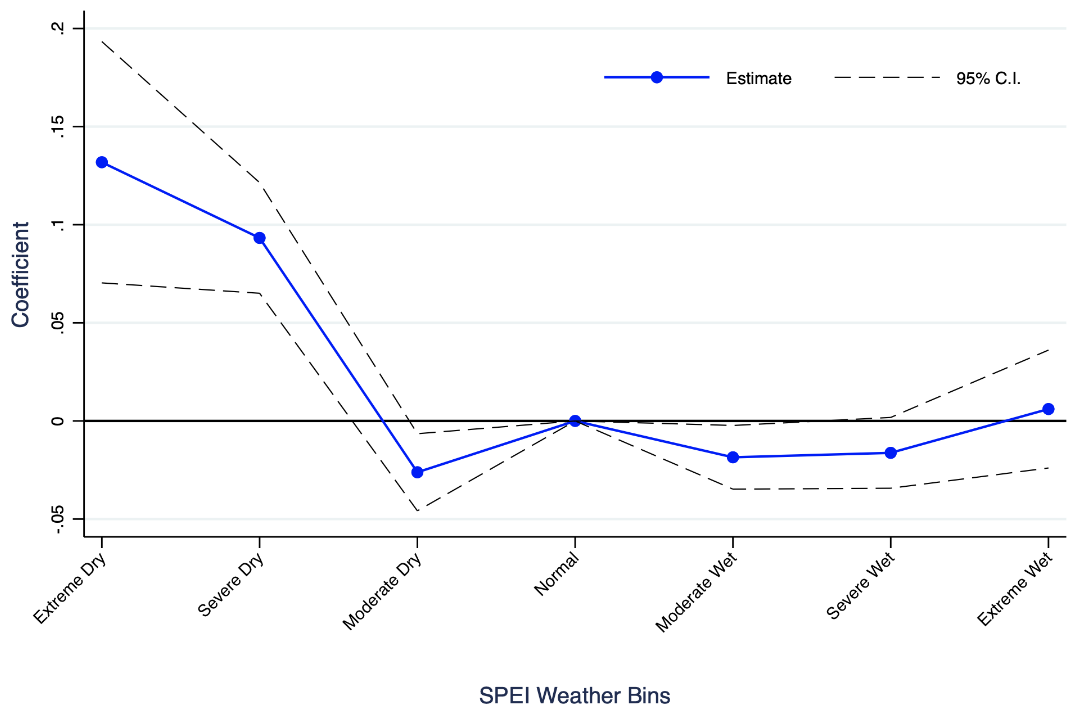

Figure B.1: Estimated Impact of an extreme weather event on the probability of household falling below the poverty line, T_2, relative to a normal event

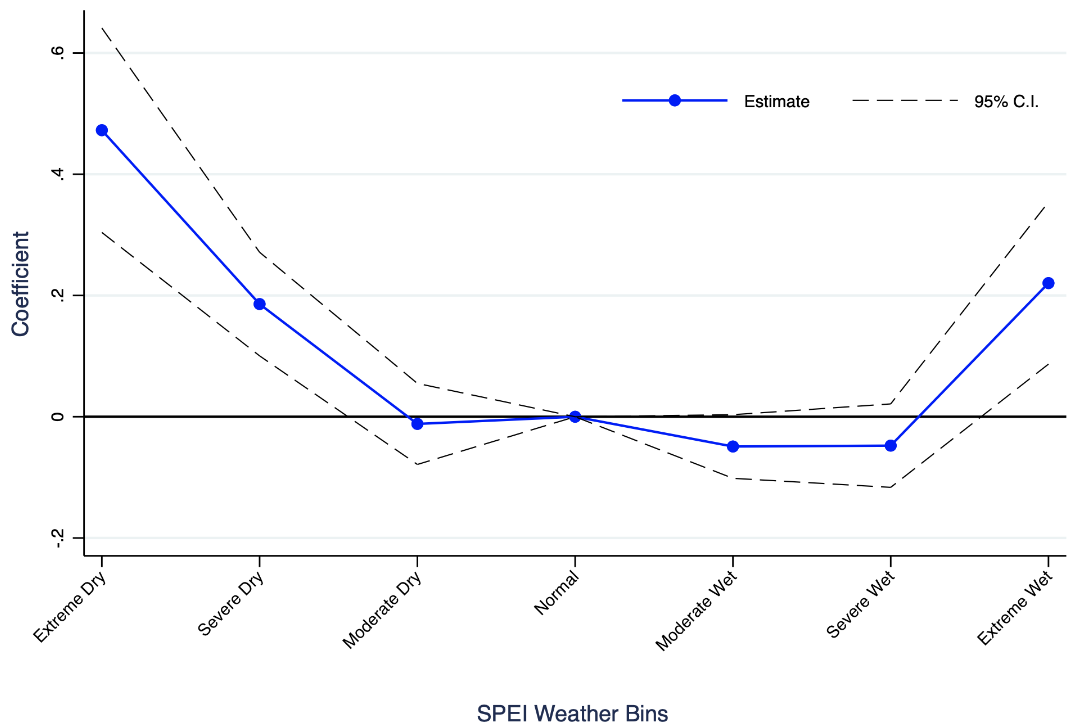

Figure B.2: Estimated Impact of an extreme weather event on the poverty gap based on T_2, relative to a normal event

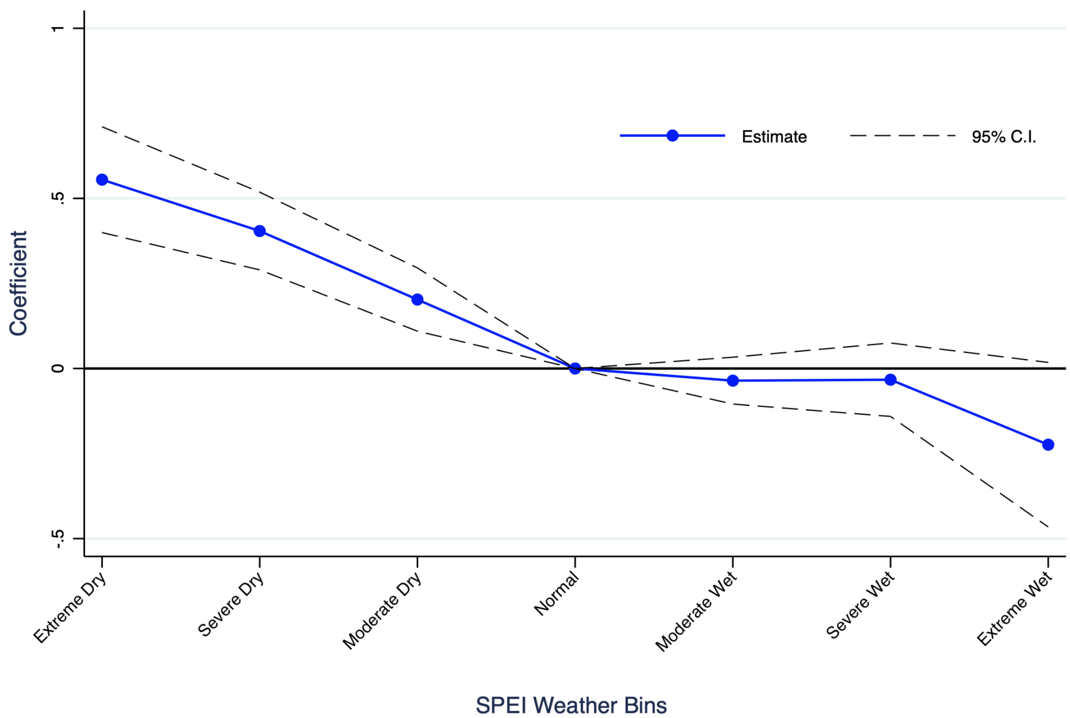

Figure B.3: Estimated Impact of an extreme weather event on the probability of district rice yields falling below the threshold, R_2, relative to a normal event

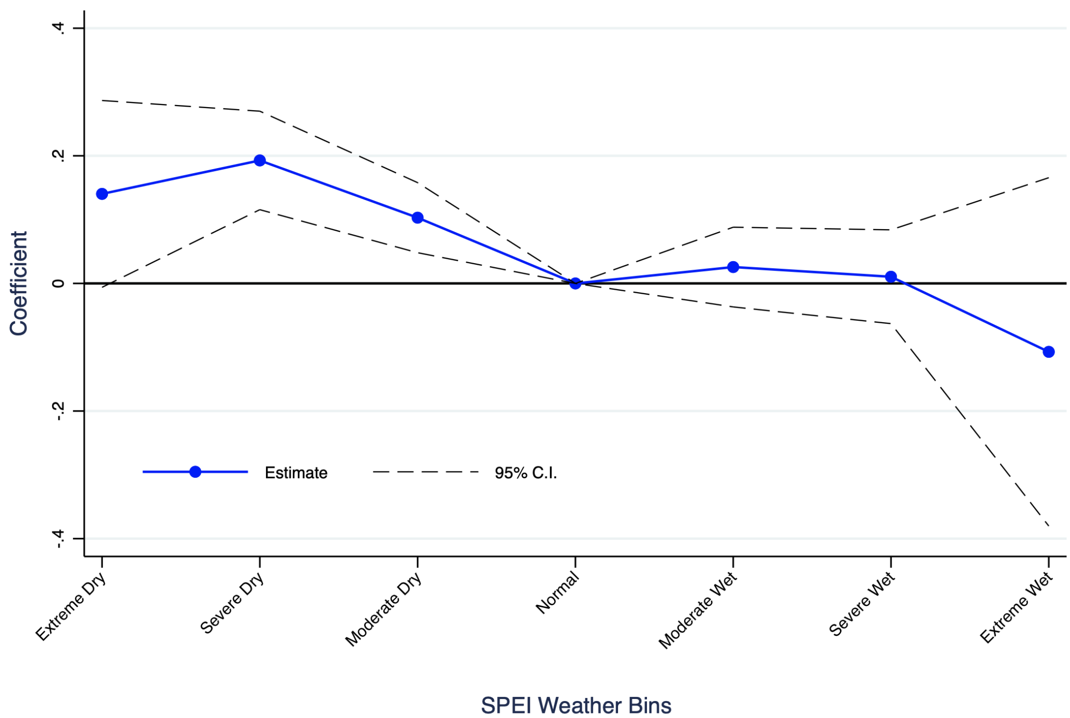

Figure B.4: Estimated Impact of an extreme weather event on the district yield gap with respect to the threshold, R_2, relative to a normal event

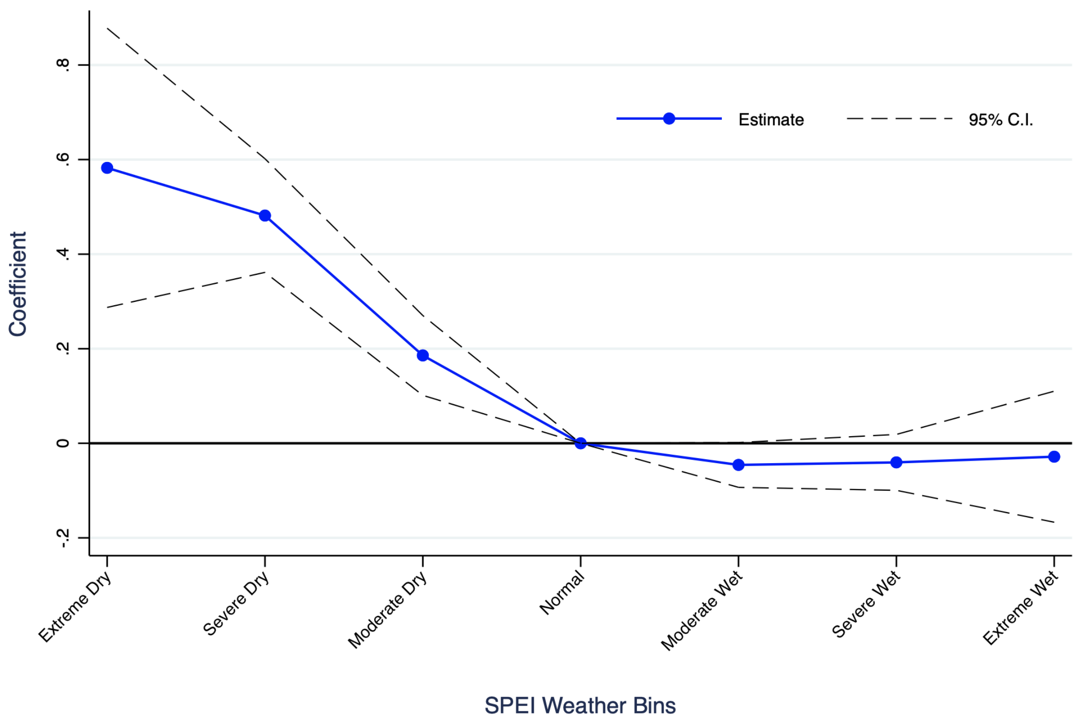

Figure B.5: Estimated Impact of an extreme weather event on the probability of district rice yields falling below the threshold, R_3, relative to a normal event

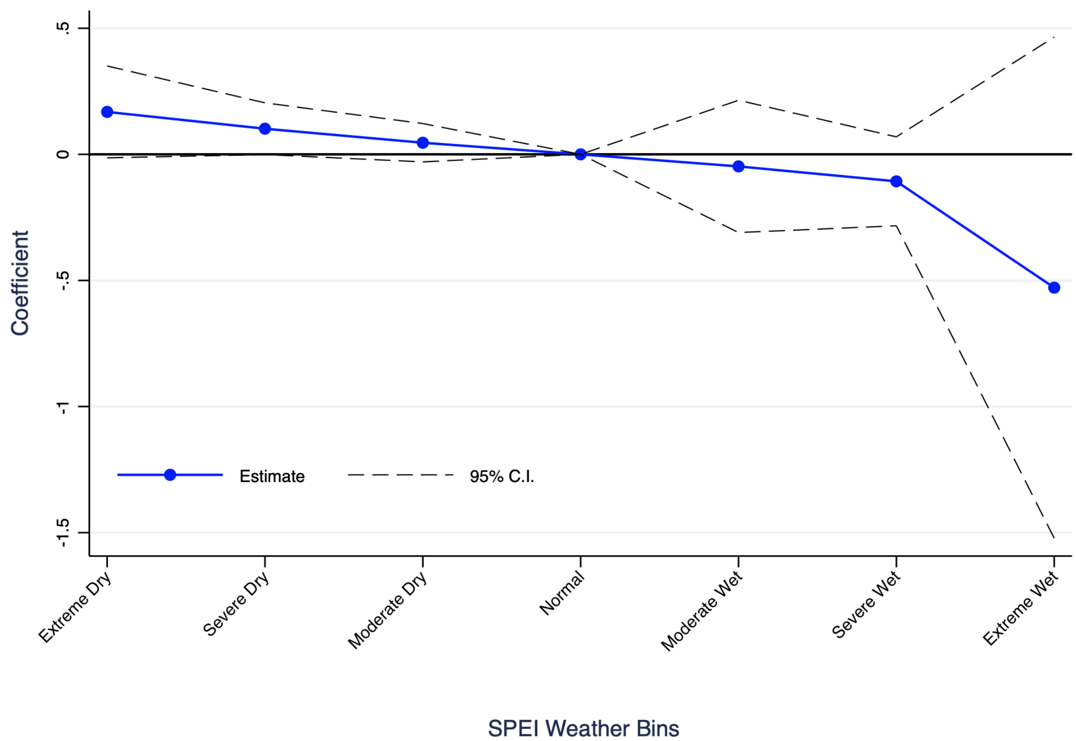

Figure B.6: Estimated Impact of an extreme weather event on the district yield gap with respect to the threshold, R_3, relative to a normal event

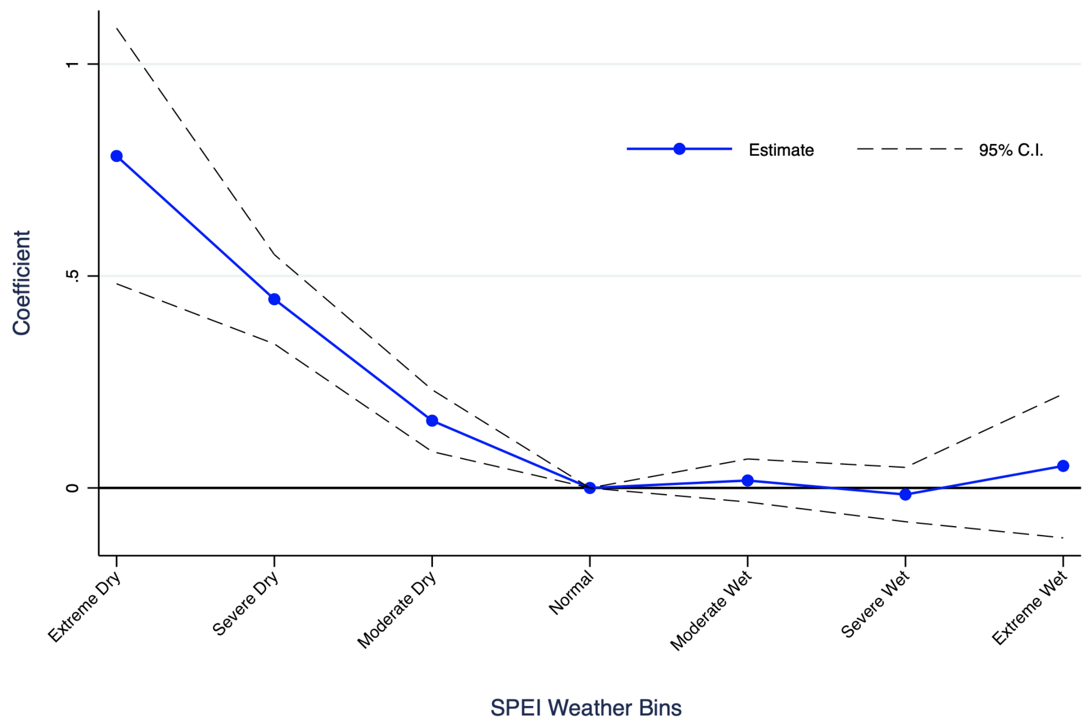

Figure B.7: Estimated Impact of an extreme weather event on the probability of district rice yields falling below the threshold, R_4, relative to a normal event

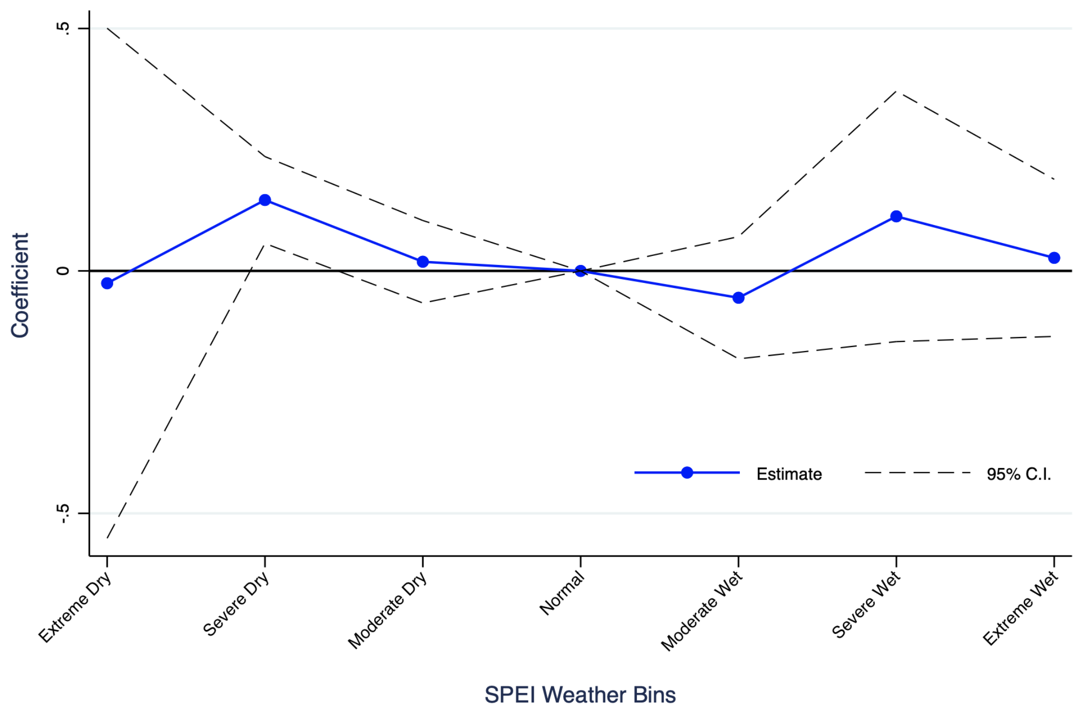

Figure B.8: Estimated Impact of an extreme weather event on the district yield gap with respect to the threshold, R_4, relative to a normal event