Quantifying Vulnerability of Crop Yields in India to Weather Extremes*

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Abstract

Most of the existing climate change impacts studies on agriculture focus on mean economic impacts and neglect distributional and other dimensional impacts of climate change. In this paper, we develop an indicator of 'climate vulnerability' which allows us to quantify both the likelihood of a loss in crop yields and the extent of the loss associated with extreme weather events. We then demonstrate the utility of this indicator by applying it to a panel data from India for the period 1970-2011. Specifically, we use the partial moments model to examine the effects of extreme weather events on the vulnerability of rice yield distribution. Our results show that extreme dry and wet weather events significantly increase the vulnerability of agricultural systems while irrigation and high-yield variety (HYV) seeds are found to increase resilience thereby reducing agricultural systems' vulnerability to weather extremes. Further, we also find vulnerability to be greater for female labor as compared to male labor. We discuss the implications of our results for policymakers, especially in the context of crop insurance programs.

Keywords: Vulnerability, crop yields, weather extremes, partial moments, India
JEL Codes: C5, O13, Q12, Q54

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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 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 towards assessing the vulnerability of agricultural systems to climate change. 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 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. 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 paper, we develop an indicator of 'climate 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. To this end, we examine the impact of extreme weather events and green revolution technologies on the vulnerability of agricultural systems.

Our analysis is based on a panel dataset on agricultural yields for 292 Indian districts for the period 1970 – 2010, merged with an original measure of the growing season Standard Precipitation Evapotranspiration Index (SPEI) which captures the monthly climatic water balance i.e. difference between precipitation and potential evapotranspiration. We exploit the SPEI index using a flexible binning approach to account for weather extremes and quantify their impacts on crop yields. Our estimation strategy proceeds in two stages. Firstly, to quantify the likelihood of crop yields falling below a reference level, we estimate a linear probability model with fixed effects while controlling for district-level unobservables. In the second stage, we estimate the mean production function using a flexible functional form, the residuals of which are used to compute the lower partial moment. Finally, we estimate the effects of extreme weather events and technology on the lower partial moment to capture the expected yield gap i.e. the extent of the loss from the reference level.

Our paper 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 climate change and technology on yield variability. 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-Greek Thorbecke (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 $1000 and $1500 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 $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. Exploring both the aggregate and distributional impacts of weather on the distribution of crop yields is a major objective of this study. We use the partial moments model of Antle (2010) to define an indicator of climate vulnerability as the average absolute deviation below a well-defined reference level i.e., the first order lower partial moment of an outcome distribution. There are two advantages of using such a measure. 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. An additional contribution is related to the climate indicator employed in the characterization of the crop yield-water relationship. Most of the climate change literature 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 severity of the event.

The paper proceeds as follows. In section 2, we briefly review the literature. In section 3 we discuss the vulnerability concepts and present an indicator of vulnerability for our analyses. Section 4 describes our empirical strategy and provides a summary of data. Section 5 presents the empirical results and section 6 concludes.

2 Literature Review

Our study builds on four volumes of literature. Firstly, our work is closely related to the literature investigating the impacts of climate change on agriculture. The main focus of these studies is on modeling the relationship between weather, soil type and other exogenous controls on crop yields or farm revenues. Two major methodologies include the (i) cross-sectional or Ricardian analyses and (ii) panel data analyses. Ricardian models (Mendelsohn, Nordhaus, and Shaw 1994, 1996) estimate the impact of climate on net revenue or land values. A major advantage of these models is its ability to capture long-run adaptation to climate. However, there are several shortcomings of the Ricardian analyses. One issue pertains to that of functional form. Typically, a quadratic approximation is employed allowing for the separability of the climatic effect. Some studies have relaxed 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 a particular functional form and is rather adopted for ease of estimation (Fezzi and Bateman 2015). A second empirical concern is related to the omitted variable bias as they do not account for the unobserved heterogeneity. Time-independent location specific-factors such as farmers' skills and soil quality when not observed pose a serious threat to identification resulting in biased estimates.

Panel data methods overcome some of the shortcomings of the Ricardian analyses and therefore have gained popularity in the climate change impacts literature in the past two decades (e.g. Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Lobell, Schlenker, and Costa-Roberts 2011; Fisher et al. 2012). Application of panel data methods with fixed effects allows the econometrician to account for unobservable time-invariant differences and therefore any variation observed is from the weather outcomes over time within a year for the spatial unit of analyses. Like Ricardian models, panel data methods

are also prone to omitted variable bias. While fixed effects offer a solution to overcome time-invariant confounding factors, correlation between weather anomalies (e.g. hotter years are also drier) can wrongly attribute the effect of the correlated weather anomalies to one factor included. In addition, other weather measures such as humidity, wind speed, solar radiation have been shown to influence water balance of a crop and therefore exclusion of these measures can produce biased results (Zhang, Zhang, and Chen 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 1959), 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. Several studies have also used quantile regressions to model yield distributions. Developed by Koenker and Bassett Jr (1978) quantile regressions provide a distribution free approach to estimating conditional densities and can be seen as somewhat of a compromise between parametric and non-parametric methods. 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. Chavas et al. (2019) study the impacts of weather on crop yield distributions using a quantile autoregression model and find asymmetric effects of extreme weather on lower and upper tail of the distribution.

The third body of literature related to our work is on vulnerability and its measurement. 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 exposure to a shock and its ability to recover from it. While the indicator approach is useful in exploring conceptual frameworks, one limitation is that there is considerable subjectivity in the selection of their variables and often results in a lack of correspondence between the conceptual definition of vulnerability and its metric (Luers et al. 2003). 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 principle approaches in 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). In the VEP approach, vulnerability is mainly conceptualized as a risk concept i.e. as the expected value of suffering from a shock below a certain target threshold, which is usually the poverty line. The VEP measures can be considered to be expected values of the Foster, Greer, and Thorbecke (1984) (FGT) indices. Early studies use this approach to define vulnerablity as the probability of falling below the poverty line in any three consecutive periods (Suryahadi, Sumarto, and Pritchett 2000; Chaudhuri, Jalan, and Suryahadi 2002; Kamanou and Morduch 2002; Christiaensen and Subbarao 2005). 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). Finally, 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). Recently, some studies have quantified vulnerability within the reference utility theory framework (Kahneman and Tversky 1979). 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 theory.

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.

3 Vulnerability

The literature on conceptualizing vulnerability has stressed on linking three important elements – exposure, sensitivity and adaptive capacity (Parry et al. 2007). In appendix A, we present a conceptual framework of vulnerability which incorporates these three elements. Figure 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.

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. In India, agricultural markets are not well integrated. If weather shocks lead to an increase in agricultural prices, it will hurt consumers and 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. A second implication for our study thus lies in testing the usefulness of crop yields as an indicator of vulnerability in vulnerability assessments. Thirdly, 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 are not able to capture the heterogeneity in agricultural systems. As such our unit of analysis is a district for two specific reasons – a) we are able to account for the heterogeneity in agriculture and b) most of the agriculture planning and program implementation is done at the district-level and so from the perspective of the policymaker, it is useful to consider an aggregate indicator of vulnerability. These facts suggest that to understand a household's vulnerability to extreme weather events, we need a model to capture the complex interactions between biophysical and management processes that jointly determine production outcomes. To this end, we adopt the framework described in 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, $y = f(x, w^u)$ determined by complex interactions between management decisions, x and exogenous random events, w^u. Figure 2 describes the process that generates output distribution and its relation to inputs and climate. The positive horizontal axis represents the weather

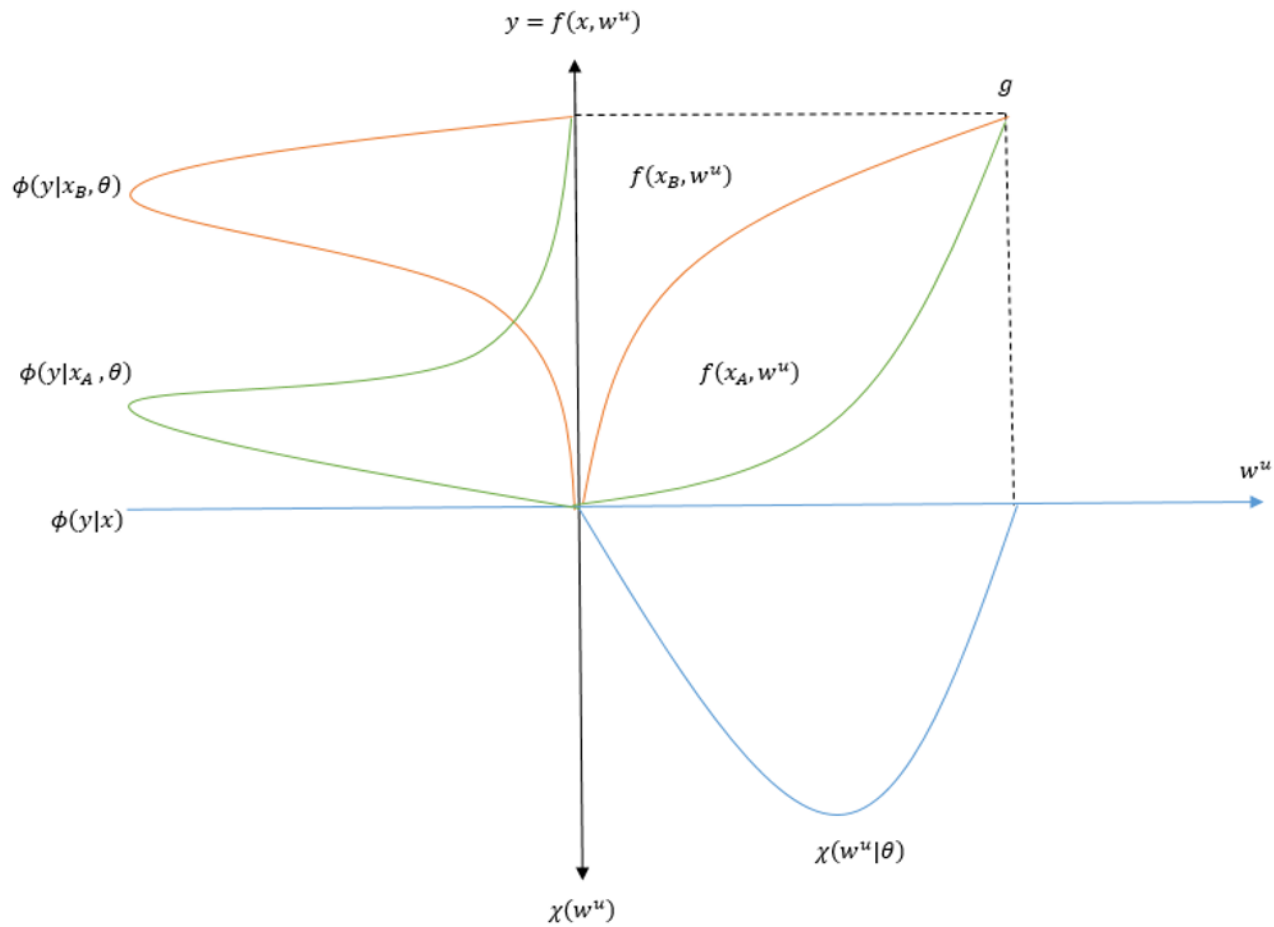

Figure 2: Output distribution properties determined by production functions with management (x) inputs and random inputs (w^u). Source: Based on Antle (2010)

generated from a climate in a particular location, denoted by $\chi(w^u|\theta)$, 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, g, 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 $\phi(y|x, \theta)$.

Figure 2 shows two production relationships, $f(x_A, w^u)$ and $f(x_B, w^u)$, generating two

different output distributions, $\phi(y|x_A, \theta)$ and $\phi(y|x_B, \theta)$ 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 fertilizers. 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 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.

In the next subsection, we use this framework 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 according to the conceptual framework presented here. However, before we define and quantity vulnerability, we formalize our conceptual framework into an economic model at the household level (see appendix B) using the decision-making under uncertainty framework with the objective of formally understanding how extreme weather events affect agricultural households' vulnerability. We then aggregate the economic model at the district level and use it to guide our econometric analyses.

3.1 Measuring Vulnerability

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 ith 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

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

$$= \Phi(x,r,\theta) \int_0^r (r-y)\,\phi(y|x,\theta)\,\Phi(x,r,\theta)^{-1}\,dy \tag{2}$$

$$= \Phi(x,r,\theta)[r - \eta_1(x,r,\theta)] \tag{3}$$

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 3 as it combines the two important dimensions of vulnerability - the probability of vulnerability and the expected yield gap. The upper left quadrant in figure 3 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.

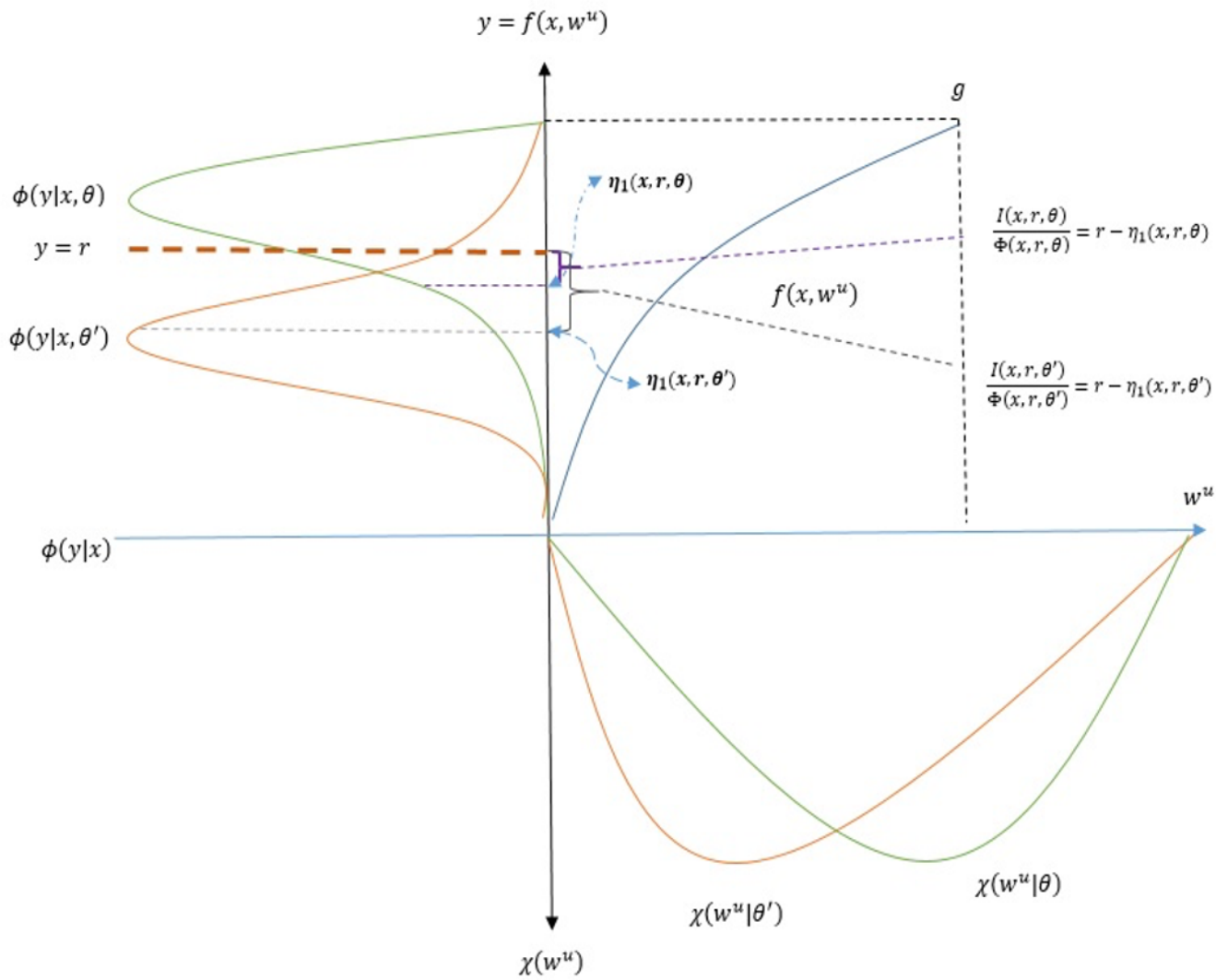

Figure 3: A conceptual framework of the impacts of extreme weather events on the output distribution.
Source: Based on Zhang (2016)

4 Estimation Strategy

The economic model presented in appendix B 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,

$$Y = \sum_{i=1}^{N} y_i = \sum_{i=1}^{N} f(x(\gamma_i), z_i, w_i^{\alpha}, w_i^{\mu}, \epsilon_i, \alpha) \tag{4}$$

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 $\sim \phi(\gamma, w^{\mu}, \epsilon|\delta)$ where δ parametrizes the distribution of micro parameters and shocks in the district.

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

$$\mu_1(\delta) = E(Y|\delta) = \int\int\int \sum_i f(x(\gamma_i), z_i, w_i^{\alpha}, w_i^{\mu}, \alpha)\, \phi(\gamma, w^{\mu}, \epsilon|\delta)\, d\gamma\, dw^{\mu}\, d\epsilon \tag{5}$$

The higher central moments of the distribution are $E[Y - \mu_1(\delta)^k|\delta] \equiv \mu_1(k)$ for $k > 1$

Measured at the district level, the vulnerability indicator in equation (3) then captures the proportion of population vulnerable to extreme weather events, $\Phi(x, r, \theta)$ as well as the expected yield gap, $[\, r - \eta_1(x, r, \theta)\,]$. In this section, we present an econometric strategy for estimating these two dimensions of vulnerability using a linear probability model and partial moments model, respectively.

4.1 Estimating $\Phi(x, r, \theta)$

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

$$D_{dt} = X'_{dt}\,\beta_1 + \beta_2\,SPEI_{dt} + X'_{dt} * SPEI_{dt}\,\beta_3 + \delta_d + \lambda_t + g_{st} + u_{dt};\; E(u_{dt}|X_{dt}, SPEI_{dt}, \lambda_t, g_{st}, \delta_d) = 0 \tag{6}$$

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) 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.

4.2 Estimating $r - \eta_1(x, r, \theta)$

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 (9).

$$y_{dt} = f(X_{dt}, SPEI_{dt}, \lambda_t, g_{st}; \alpha) + \epsilon_{dt};\ E(\epsilon_{dt}|X_{dt}, SPEI_{dt}, \lambda_t, g_{st}) = 0 \tag{7}$$

The estimation of equation (7) 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 (7) 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 dth district. Estimation of equation (7) 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 (7) takes the form,

$$y_{dt} = f(X_{dt}, SPEI_{dt}, \delta_d, \lambda_t, g_{st}; \alpha) + \eta_{1dt} \tag{8}$$

where $E(\eta_{1dt}|X_{dt}, SPEI_{dt}, \lambda_t, g_{st}, \delta_d) = 0$ and $corr(X_{dt}, \delta_d) \neq 0$, $corr(SPEI_{dt}, \delta_d) \neq 0$.

We estimate the lower partial moment in equation (9) by taking the negative of the residuals from equation (8). This makes the interpretation of coefficients simpler as a positive coefficient is an increase in the lower partial moment.

$$\eta_{1dt} = f(X_{dt}, SPEI_{dt}; \zeta) + e_{dt}; E(e_{dt}|X_{dt}, SPEI_{dt}) = 0 \tag{9}$$

The vulnerability indicator can then be computed based on the estimates from equation (8) and (9) as

$$\hat{I} = (X'_{dt}\,\hat{\beta}_1 + \hat{\beta}_2\,SPEI_{dt} + \hat{\beta}_3\,X'_{dt} * SPEI_{dt})(r - X'_{dt}\,\hat{\zeta} - SPEI_{dt}\,\hat{\zeta}) \tag{10}$$

4.3 Estimating High-order moments

As figures 2 and 3 illustrate, input use and climate variables can have differential effects on the upper and lower tails of the distribution and therefore on vulnerability. To demonstrate the empirical relevance of these hypothetical distribution, Figure A3 shows the kernel densities of district rice yields for vulnerable and non-vulnerable groups based on an appropriate reference level, r. The output distribution for the non-vulnerable group is skewed to the right with the mass of the distribution concentrated at the positive tail. An increase in extreme weather events pushes the mean of the distribution to the left, below r, while also resulting in more mass concentrated on the negative tail. Thus, the proportion of population below r is greater as well as the yield gap. This graphical analysis suggests that we need an econometric model that is flexible enough to differentiate the effects of individual inputs on the different tails of the rice yield distribution. Indeed, recent studies have applied the partial moments model to test the asymmetric effects of inputs on the

output distribution (see for e.g., Zhang and Antle 2018). As such, we use the residuals from the mean production function in equation (8) to construct the high-order central and partial moments.

The high-order central moments of the distribution can be specified as

$$\eta_{1dt}^{j} = \mu_j(X_{dt}, SPEI_{dt} + v_{dt});\ E(v_{dt}|X_{dt}, SPEI_{dt}) = 0, j = 2, 3 \tag{11}$$

and the partial-moment functions are

$$|\eta_1|_{dt}^{j} = \mu_j(X_{dt}, SPEI_{dt} + v_{ndt});\ E(v_{ndt}|X_{dt}, SPEI_{dt} = 0, j = 2, 3\, for\, y_{dt} < r \tag{12}$$

$$|\eta_1|_{dt}^{j} = \mu_j(X_{dt}, SPEI_{dt} + v_{pdt});\ E(v_{pdt}|X_{dt}, SPEI_{dt}) = 0,\ j = 2, 3\, for\, y_{dt} > r \tag{13}$$

4.4 Threshold Yield

An important element in the vulnerability indicator presented in section 3 is the reference level, r. While theory provides little guidance on what should be this threshold level, studies on poverty and vulnerability to poverty can 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. We borrow this idea from this literature 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.

We consider four measures of threshold yield. The first three measures of threshold yield are motivated by the various crop insurance schemes. 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.

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.

4.5 Data

4.5.1 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 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).

4.5.2 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 et al. (2010) for each district for the period 1970-2010 (see section A3 of 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). Figure A2 shows the spatial distribution of average SPEI for the growing season months, June to September.

Table 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

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

We use the SPEI classification index [1] 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 events.

5 Results

In this section, we report the effects of climate and technology on the vulnerability of rice yields. We first discuss the effects of technology and climate on the probability of rice yields falling below r_1. Table 2 reports the estimation the linear probability model estimates as in equation (6). Next, in Table 3 we present the results of the estimation of the first lower partial moments model. In this discussion, results are based on the reference level, r_1. We next report the effects of climate and technology on the mean and high-order moments of rice yield distributions, using r_1 as the reference level, in Table 4 and discuss the implications for our vulnerability indicator. Appendix D presents the results of the estimation of the linear probability model and lower partial moments model for the other

[1] According to the SPEI classification index, if 1.0 <SPEI< 1.0, weather conditions are normal. If +1.0 <SPEI< 1.5, weather condition is moderately wet. For +1.5 <SPEI< 2.0, conditions are severely wet and SPEI $\geq +2.0$, it is extremely wet. Similarly, $-1.5 <$ SPEI < -1.0 indicates a moderately dry condition, for $-2.0 <$ SPEI < -1.5, conditions are severely dry and for SPEI$\leq$ -2.0, extremely dry.

three reference levels, r_2, r_3 and r_4. Appendix D also discusses the effects on the mean and high-order moments of rice yield distributions for the other reference levels.

Effects of climate and inputs on the probability of rice yields falling below the vulnerability threshold, r_1

Column (1) and (2) of Table 2 include SPEI bins with no interactions and interactions with the farm management variables, respectively. The coefficient estimates for the extreme, severe and moderately dry variables are all 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 4 plots the SPEI bin coefficients from equation (7) 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) of Table 2, we include the average growing season SPEI measure instead of bins without any interactions and introduce the SPEI measure in the quadratic form in column (4). Column (5) of Table 2 reports the estimate with the quadratic specification of SPEI along with the interactions. We find that a fall in SPEI from 0 (long-run average) to -1 (one standard deviation below the long-run average) increases the probability of

Table 2: Estimates of the Linear Probability Model with reference level, r_1

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable - Probability of Being Vulnerable					
Semi-Elasticities						
Irrigation	-0.161***	-0.039***	-0.168***	-0.173***	-0.164***	-0.166***
	(0.048)	(0.005)	(0.050)	(0.051)	(0.049)	(0.047)
HYV	-0.042*	-0.017**	-0.044*	-0.038+	-0.041*	-0.040*
	(0.020)	(0.006)	(0.020)	(0.021)	(0.020)	(0.019)
Fertilizers	-0.012	-0.004	-0.008	-0.011	-0.012	-0.009
	(0.013)	(0.003)	(0.013)	(0.013)	(0.012)	(0.013)
Male Labor	0.223***	0.006	0.234***	0.231***	0.222***	0.211***
	(0.057)	(0.007)	(0.058)	(0.058)	(0.058)	(0.053)
Female Labor	-0.035	0.027***	-0.042	-0.044	-0.043	-0.028
	(0.038)	(0.006)	(0.039)	(0.038)	(0.038)	(0.036)
Share of Rice Area	0.149+	-0.016***	0.121	0.117	0.133+	0.126+
	(0.078)	(0.005)	(0.075)	(0.075)	(0.076)	(0.076)
Marginal Effects						
Extreme Dry	0.375***	0.508***				
	(0.087)	(0.055)				
Severe Dry	0.108**	0.341***				
	(0.034)	(0.019)				
Moderate Dry	0.118***	0.174***				
	(0.026)	(0.012)				
Moderate Wet	-0.033*	-0.058***				
	(0.013)	(0.013)				
Severe Wet	0.010	-0.039*				
	(0.022)	(0.018)				
Extreme Wet	-0.030	-0.073				
	(0.038)	(0.069)				
Growing Season SPEI			-0.047***	-0.050***	-0.056***	
			(0.008)	(0.006)	(0.007)	
Dry						0.160***
						(0.023)
Wet						-0.025*
						(0.011)
Constant	-0.080	0.133***	-0.026	0.010	-0.026	-0.063
	(0.089)	(0.010)	(0.084)	(0.084)	(0.086)	(0.084)
N	7698	7698	7698	7698	7698	7698
R-Squared Overall	0.056	0.118	0.058	0.073	0.078	0.074
R-Squared Within	0.162	0.110	0.154	0.175	0.184	0.190

Note: Column(1) and (3) do not include interactions between inputs and weather variables. Columns (2), (4) , (5) and (6) include interactions. Growing season SPEI specified in the quadratic in column (5) and in column (6) replaced with Dry (SPEI < -0.99) and Wet (SPEI$>$ 0.99) dummies. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means while estimates for weather variables are marginal effects. Robust standard errors in parentheses clustered at the district level. Stars indicate significance *** p<0.001 ** p<0.01 * p<0.05 + p<0.10

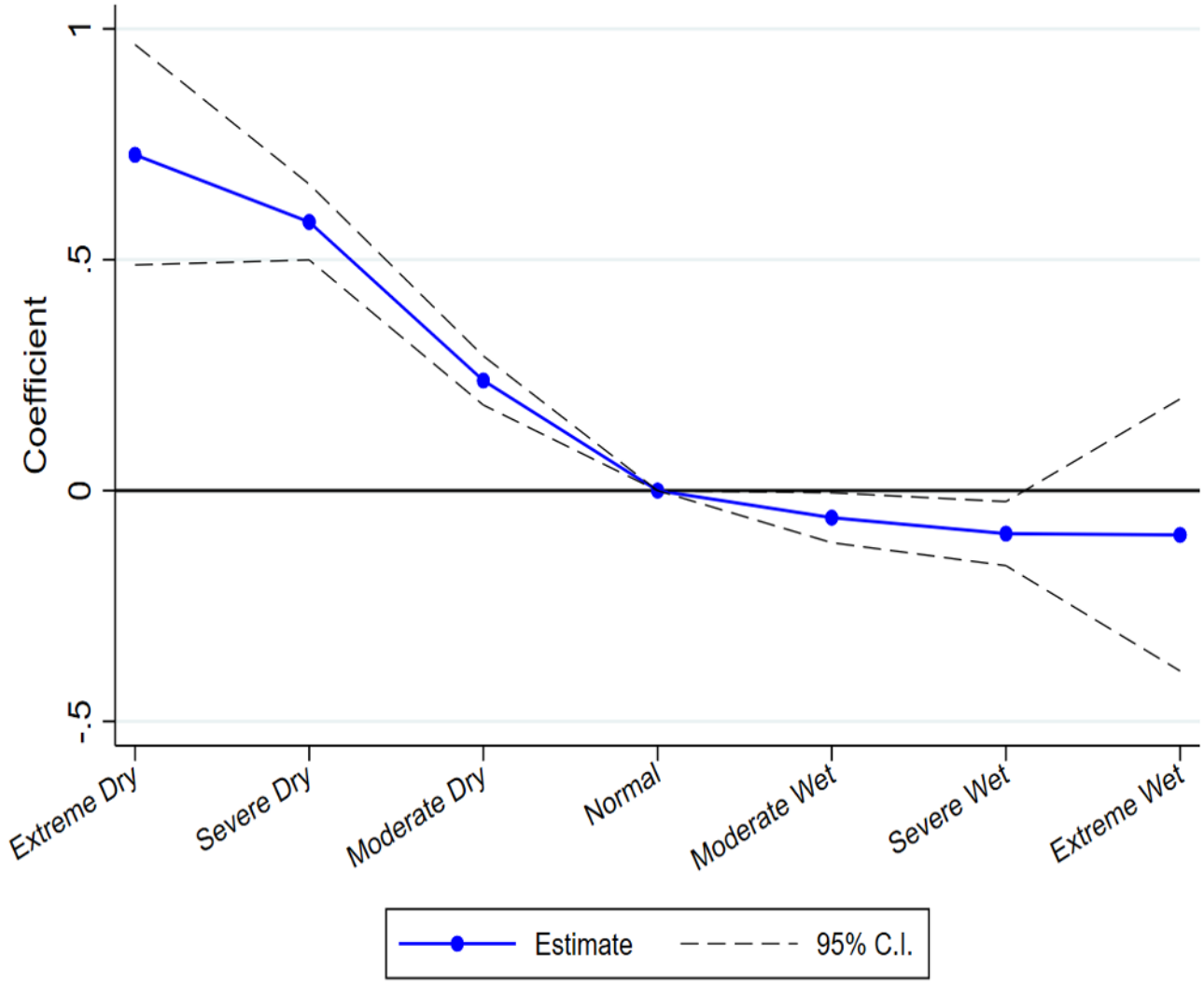

Figure 4: Estimated impact of an extreme weather event on the probability of falling below r relative to a normal event

falling below the threshold in a range of 3 – 5 percentage points. Finally, column (6) of Table 2 reports the estimates for "Dry" and "Wet" 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 "wet" event is statistically significant and negative indicating that relative to a "normal" event, a "wet" event reduces the likelihood of falling below the threshold by approximately 2 percentage points. In the case of a "dry" event, 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) 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; Welch et al. 2010).

Effects of climate and inputs on the yield gap

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. Column (1) in Table 3 reports the results of estimation of the lower partial moment model for the SPEI bins in the absence of any interactions with management variables. 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 5 plots the SPEI bin coefficients from equation (2c) 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.

In column (3), we replace the bins with the average growing season SPEI measure and interact this measure with management variables in column (4). 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 (5) reports the results for "dry" and "wet" events with dry events 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 (3)-(5) further provide evidence of the effects being robust to different specifications of the SPEI variable.

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 of the

Table 3: Estimates of the First Lower Partial Moment with reference level, r_1

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: First Lower Partial Moment				
Semi-Elasticities					
Irrigation	-0.131*	-0.093	-0.124+	-0.141+	-0.114
	(0.062)	(0.089)	(0.064)	(0.081)	(0.087)
HYV	-0.030	-0.046	-0.034	-0.018	-0.028
	(0.028)	(0.053)	(0.027)	(0.047)	(0.055)
Fertilizers	0.011	0.005	0.011	0.006	-0.007
	(0.013)	(0.028)	(0.014)	(0.031)	(0.029)
Male Labor	0.050	0.179	0.063	0.026	0.150
	(0.073)	(0.114)	(0.075)	(0.073)	(0.095)
Female Labor	0.101*	0.066	0.094*	0.051	0.075
	(0.042)	(0.065)	(0.042)	(0.048)	(0.060)
Share Rice	0.109	0.065	0.101	0.162+	0.124
	(0.090)	(0.101)	(0.094)	(0.088)	(0.089)
Marginal Effects					
Extreme Dry	0.146*	0.094			
	(0.068)	(0.067)			
Severe Dry	0.029	0.057+			
	(0.024)	(0.030)			
Moderate Dry	0.004	-0.015			
	(0.018)	(0.018)			
Moderate Wet	-0.079	-0.151***			
	(0.052)	(0.031)			
Severe Wet	-0.060	-0.202*			
	(0.057)	(0.097)			
Extreme Wet	-0.359***	-0.320+			
	(0.095)	(0.186)			
Growing Season SPEI			-0.023+	-0.029*	
			(0.013)	(0.013)	
Dry					0.025
					(0.021)
Wet					-0.093**
					(0.034)
Observations	1040	1040	1040	1040	1040
R-Squared	0.33	0.44	0.31	0.36	0.38

Note: Column(1) and (3) do not include interactions between inputs and weather variables. Columns (2) (4) and (5) include interactions. Growing season SPEI specified in the quadratic in column (4) and in column (5) replaced with Dry (SPEI < -0.99) and Wet (SPEI > 0.99) dummies. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means while estimates for weather variables are marginal effects. Robust standard errors in parentheses clustered at the district level. Stars indicate significance *** p< 0.001 ** p< 0.01 * p< 0.05 + p< 0.10

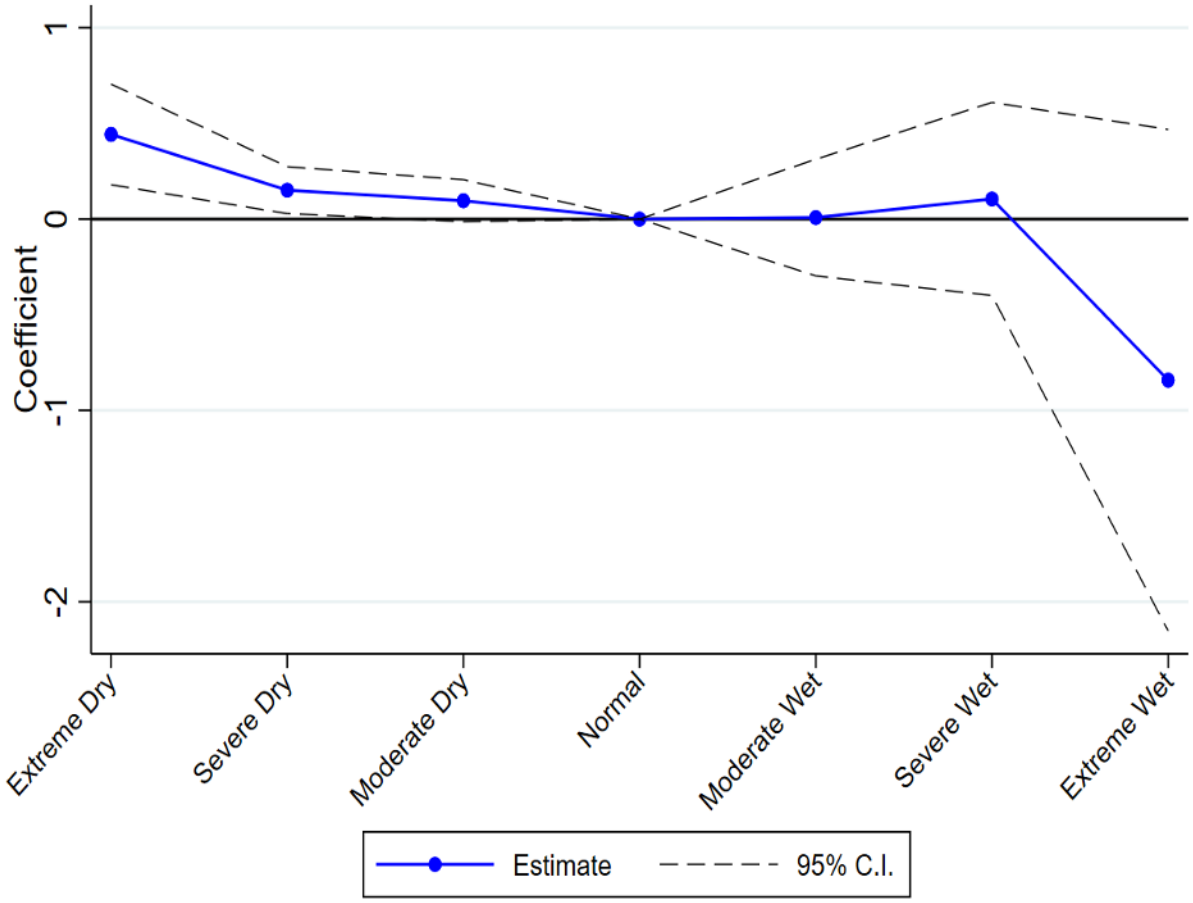

Figure 5: Estimated Impact of an extreme weather event on the yield gap relative to a normal event

fact that 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 males. We find similar effect of labor on the lower partial moment.

The high-order moment effects of climate and inputs

To better understand the effects of climate variables on vulnerability, we consider the high-order moments of the rice yield distribution. We obtain consistent residuals from the

rice yield function estimation with a flexible form and estimate equations. Table presents elasticities of the high-order moment function estimates for the four different reference yields. Examination of the parameters in Table 4 indicates that extreme and severe dry events are mean and variance reducing if the first two moments are considered. However, with respect to the partial moments, we find extreme dry events strongly increase the negative skewness while decreasing the mass in the positive tail of the distribution. On the contrary, we find moderate dry events to increase the positive skew of the distribution. With respect to the wet variables, the mean and full second moment indicate moderate and severe wet events are mean-increasing and risk-reducing.

The partial moments, however, present a different picture. The effect of moderate wet events is strongly negative on both the lower and upper tail of the distribution with the effect being larger on the lower tail. This indicates that moderate wet events truncate the negative tail reducing the negative skewness while also reducing the mass in the upper tail of the distribution. Our findings are similar for the severe and extreme wet events that is they reduce the negative skew of the distribution.

We next turn to the effects of technology and labor on the higher-order moments of the output distribution. The mean elasticities for irrigation suggest that a doubling of the area under irrigation results in an increase in rice yield by about 3 tons per hectare. Further, the full second moment suggests that irrigation negatively affects the variance of the yield distribution implying irrigation is risk-reducing, as one would expect. We find asymmetric effects of irrigation on the upper and lower tail with the effect being large and statistically significant on the second and third lower partial moment resulting in a large reduction in skewness. This suggests that on one hand irrigation improves the crop yield-water relationship by reducing the soil moisture deficit. On the other hand, irrigation shifts the mass of the distribution positively towards the 'genetic potential, g' through increased input use such as fertilizers.

Table 4: Estimates of Full- and Partial-Moment Function Parameters for Rice Yield Production with reference level, r_1

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Full 2nd	Lower 2nd	Upper 2nd	Lower 3rd	Upper 3rd
Elasticities						
Irrigation	0.028**	-0.117*	-1.645***	0.082	3.254***	1.693+
	(0.009)	(0.058)	(0.219)	(0.069)	(0.970)	(0.993)
HYV	0.053***	0.158**	3.681***	0.024	6.197***	4.022***
	(0.008)	(0.061)	(0.537)	(0.021)	(1.636)	(0.775)
Fertilizers	0.066**	0.041	-2.022**	0.097	-1.608	0.140
	(0.025)	(0.257)	(0.661)	(0.182)	(1.444)	(0.542)
Male Labor	0.015	-1.794*	-22.345***	-1.375*	-27.702**	-10.717***
	(0.085)	(0.827)	(4.723)	(0.547)	(9.674)	(1.858)
Female Labor	-0.072+	1.019+	29.765***	0.513*	42.170**	3.685***
	(0.040)	(0.582)	(5.244)	(0.243)	(13.473)	(0.841)
Share of Rice Area	-0.043	-0.698+	1.411	-0.634**	0.072	1.505+
	(0.038)	(0.371)	(1.040)	(0.237)	(1.808)	(0.798)
Extreme Dry	-1.238**	-0.976+	6.062***	-0.188	7.253**	0.234
	(0.384)	(0.528)	(1.126)	(0.171)	(2.309)	(0.381)
Severe Dry	-0.174***	-0.584	5.703***	-0.178	6.755**	0.433
	(0.036)	(0.482)	(1.042)	(0.182)	(2.255)	(0.333)
Moderate Dry	-0.071**	0.045	-1.076**	0.088	-1.607+	0.338*
	(0.024)	(0.167)	(0.411)	(0.113)	(0.899)	(0.170)
Moderate Wet	0.028+	-0.749***	-4.888***	-0.040	-12.808	-0.395*
	(0.017)	(0.218)	(1.463)	(0.081)	(8.682)	(0.193)
Severe Wet	0.077*	-0.083	-27.604***	-0.086	-43.884***	-0.184
	(0.034)	(0.331)	(3.887)	(0.134)	(11.846)	(0.296)
Extreme Wet	-0.035	-7.625***	-16.433***	-0.010	-27.731**	-0.194
	(0.144)	(0.528)	(2.914)	(0.218)	(8.669)	(0.446)
Observations	7698	7698	1040	6658	1040	6658
R-Squared	0.90	0.83	0.90	0.68	0.98	0.95

Note: All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Elasticities reported with robust standard errors clustered at the district level in parentheses. Stars indicate significance *** p< 0.001 ** p< 0.01 * p< 0.05 + p< 0.10

With respect to HYV, interesting findings emerge from the estimates of the lower and upper partial moment. While HYV is mean and variance increasing, it has a positive effect on the upper and lower partial moments, with the effect seen to be larger on the lower tail of the distribution. This points to the fact that, on one hand, HYV extends the positive tail of the distribution, while on the other hand, it truncates the negative tail of the distribution thereby increasing skewness.

Investigating the effect of labor on the mean and high-order moments, we find that male labor negatively affects the variance and is risk-decreasing. However, the partial moment functions present a different picture. Male labor has a negative and statistically significant effect on both the positive and negative tails of the distribution. Further, this effect is larger on the lower tail resulting in a large reduction in skewness with the distribution more positively skewed. On the other hand, the estimates for female labor have exactly the opposite signs to that of male labor, with the magnitude larger for the lower third partial moment implying that female labor increases the negative skewness of the distribution.

In conclusion, these results have important implications on the proposed vulnerability indicator. In the case of extreme weather events, we find extreme weather events to have a significant impact on vulnerability to losses in the crop yields. In particular, extreme dry events increase both the likelihood of crop yields falling below the threshold as well as the extent of the fall thereby increasing vulnerability. Similar effect is seen for severe and moderately dry weather events, albeit with a lower magnitude. On the other hand, moderate and severe wet events decrease vulnerability by reducing the probability of falling below the threshold as well as the average distance between the threshold and the fall from the threshold. Moreover, irrigation and HYV technology are shown to increase resilience by virtue of acting as adaptive mechanisms against extreme weather shocks. The results also show that partial moments model provide a better insight into understanding the effects of extreme weather events on the rice yield distribution and show that weather

extremes and inputs have asymmetric effects on the positive and negative tails of the distribution consistent with previous research (Antle 2010; Zhang and Antle 2018).

6 Conclusion

Extensive research has been done on modeling the link between climatic conditions and agricultural outcomes (Mendelsohn, Nordhaus, and Shaw 1994; Deschênes and Greenstone 2007; Lobell, Schlenker, and Costa-Roberts 2011; Schlenker and Roberts 2009). Of particular importance is the impact of climate change on agriculture in developing countries like India, where it is a primary source of livelihood. However, the literature to date has mostly focused on the mean economic impacts of climate change and neglected the vulnerability of agriculture in the sense of assessing the likelihood of production falling below a critical threshold. In this paper, we develop an indicator of 'climate vulnerability' which allows us to quantify both the likelihood of a loss in crop yields and the extent of the loss associated with extreme weather events. We then demonstrate the utility of this indicator by applying it to a panel of agricultural outcomes from India and estimate the effects of extreme weather events, as captured by SPEI, on the vulnerability of rice yield distribution.

Using regression specifications that includes average growing season SPEI as well as the severity of the weather events, 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 concept of reference level. 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 the estimates to frame appropriate crop insurance policies so as to mitigate the expected losses in yield.

Finally, there are several ways in which future work could build upon. Firstly, we focus on district-level yields that are to an extent aggregated and conceal the effects of extreme weather events and technology on individual farms. Future work could examine the vulnerability of individual farms using farm survey data. Secondly, our results provide weak evidence of vulnerability across gender groups. It is well documented that the impacts of climate change will be disproportionate, with the marginalized groups severely affected (Van Aelst and Holvoet 2010). Future research using detailed household survey data should test for difference in vulnerability across socio-economic groups.

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Appendix A. Conceptual Framework of Vulnerability

In this section, we develop a conceptual framework of vulnerability by linking households' product markets and outcomes, and the sources of risk faced by them. Vulnerability is intrinsic to this linkage and can be considered as the "risk chain". 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.

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 the aforementioned 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 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 so as 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.

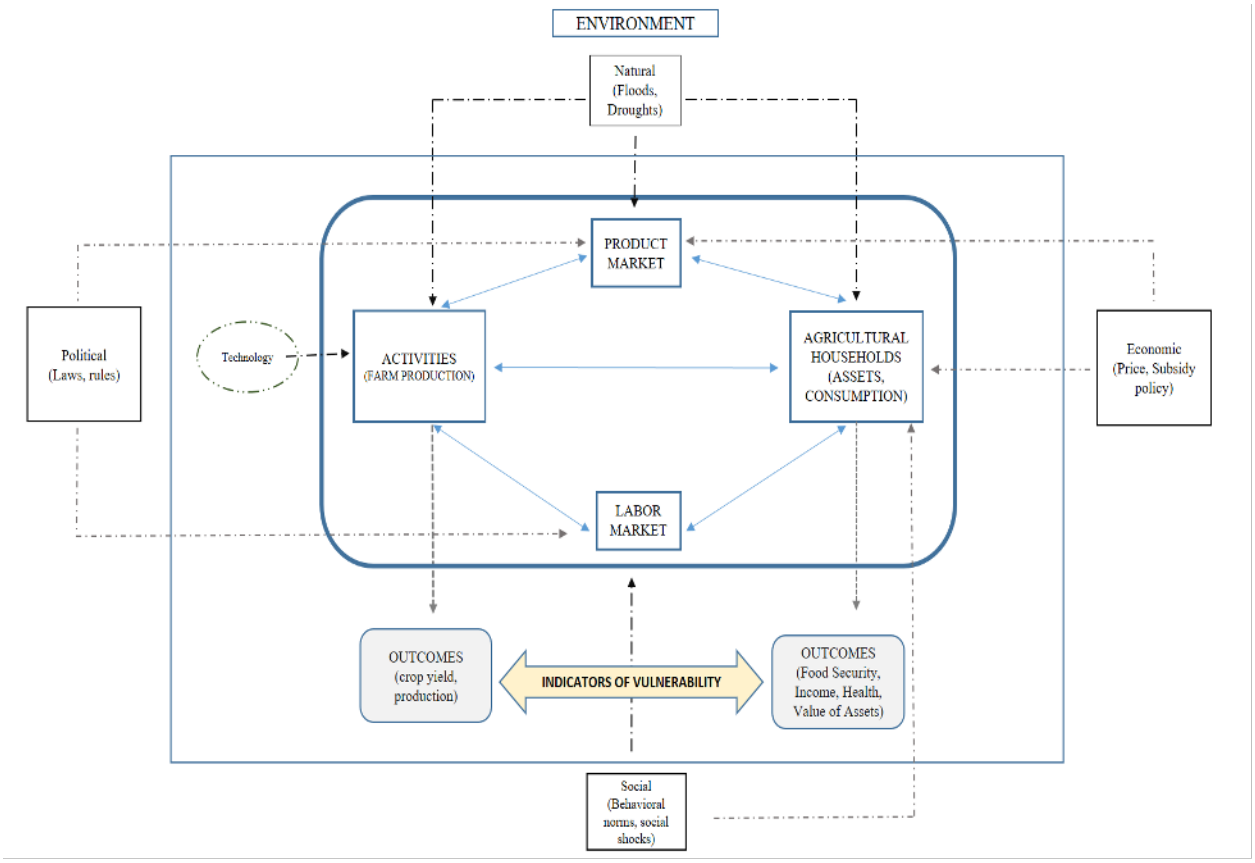

Figure 1: A Conceptual Framework of Vulnerability (Based on Hoddinott and Quisumbing, 2003)

Appendix B. Economic Model

The scope of this section is to formalize the conceptual framework discussed in Appendix A 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

$$y = f(x, z, w, \epsilon; \alpha) \tag{14}$$

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,

$$\max_x E[U(\pi, \beta)|c, x, z, w^a, \theta, \alpha)] = \int\int U[f(x, z, w^a, \alpha) - cx]\, \chi(w^u, \epsilon)\, dw^u\, d\epsilon \tag{15}$$

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.

Appendix C: 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.

- 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 β% 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 A1: Drought and Flood Classification based on SPEI

Condition	SPEI
Extreme Flood	$\geq$2.0
Severe Flood	[1.5,2.0)
Moderate Flood	[1.0, 1.5)
Normal	(-1.0, 1.0)
Moderate Drought	(-1.5, -1.0]
Severe Drought	(-2.0, -1.5]
Extreme Drought	$\leq$2.0

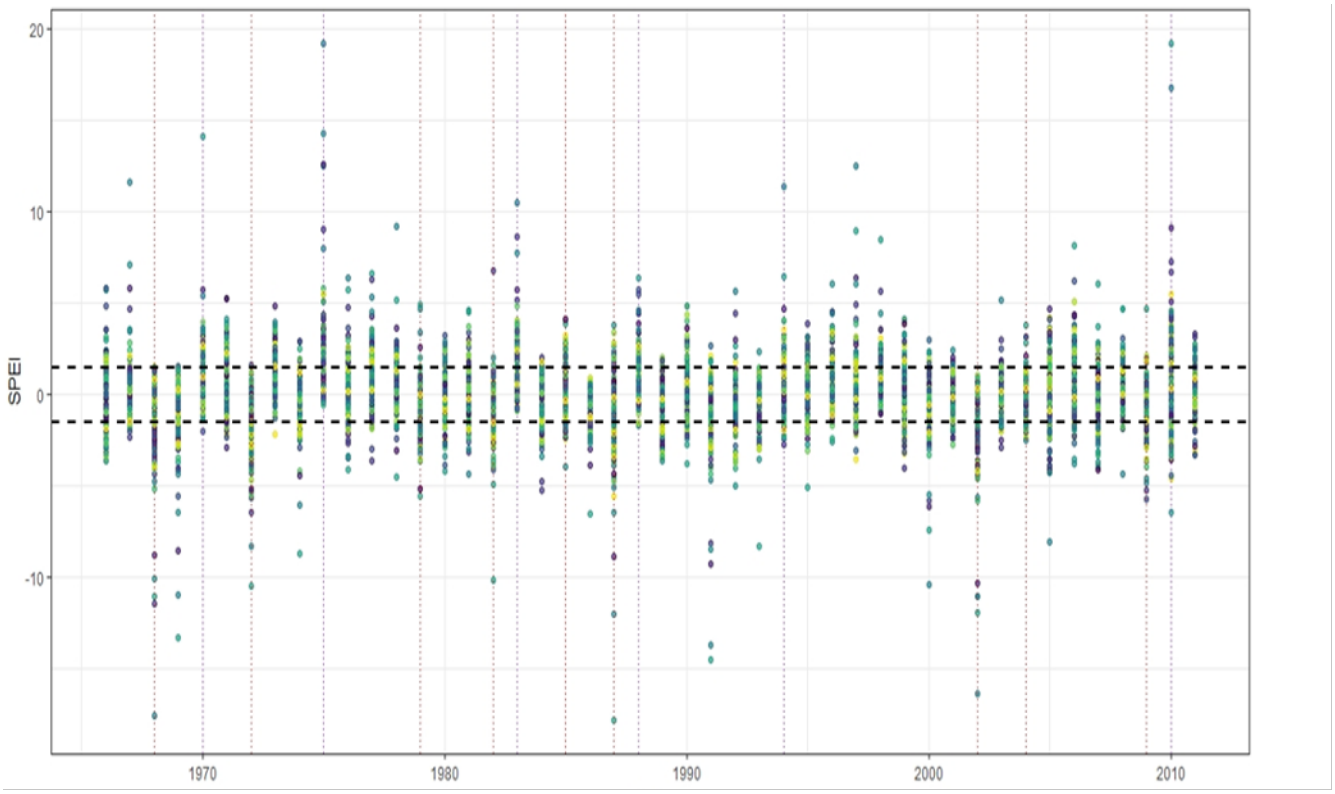

Figure A1: Extreme Weather Events in India (1966-2011) as captured by the SPEI Index

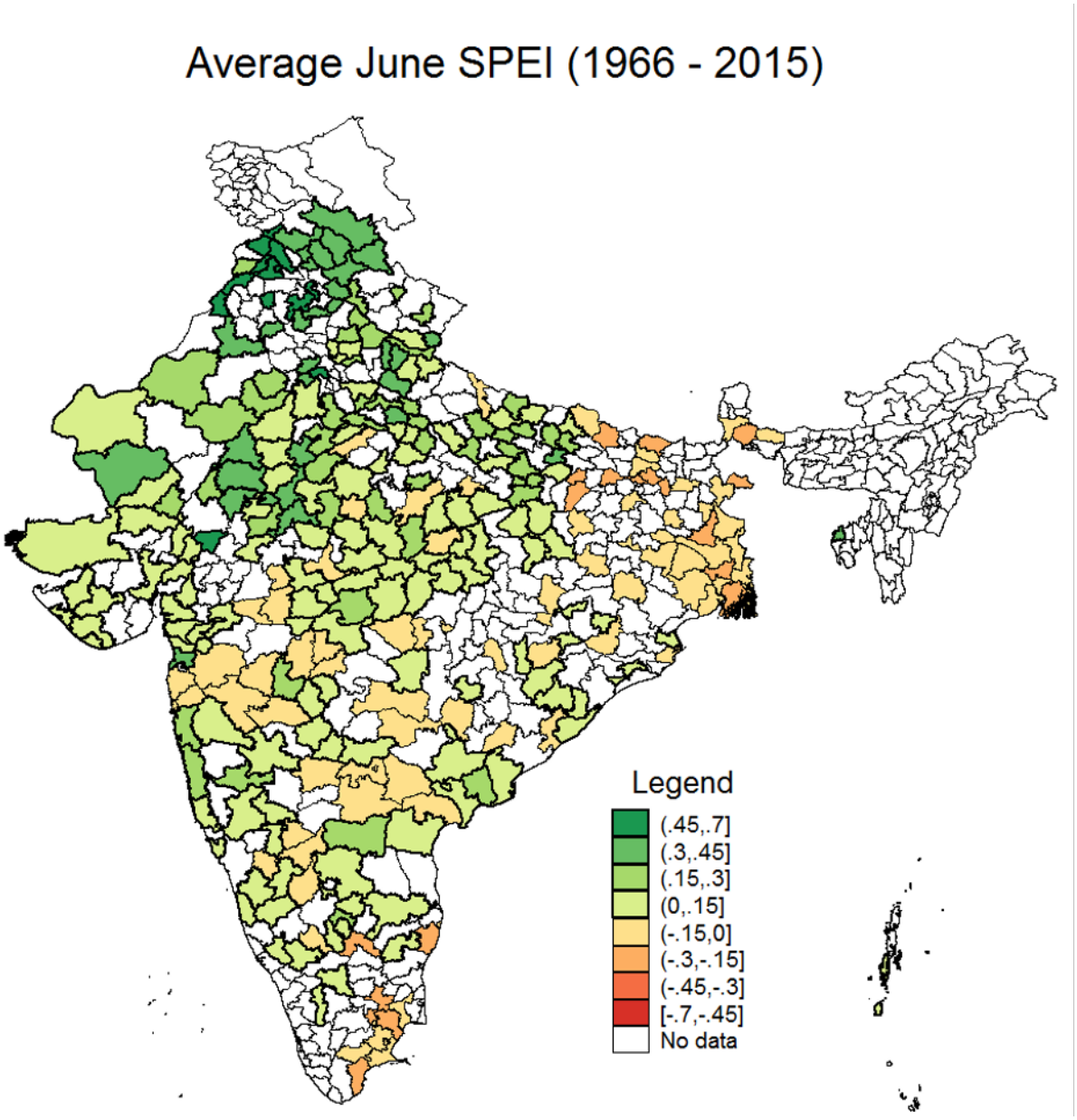

Figure A2.1: Spatial distribution of average SPEI for June

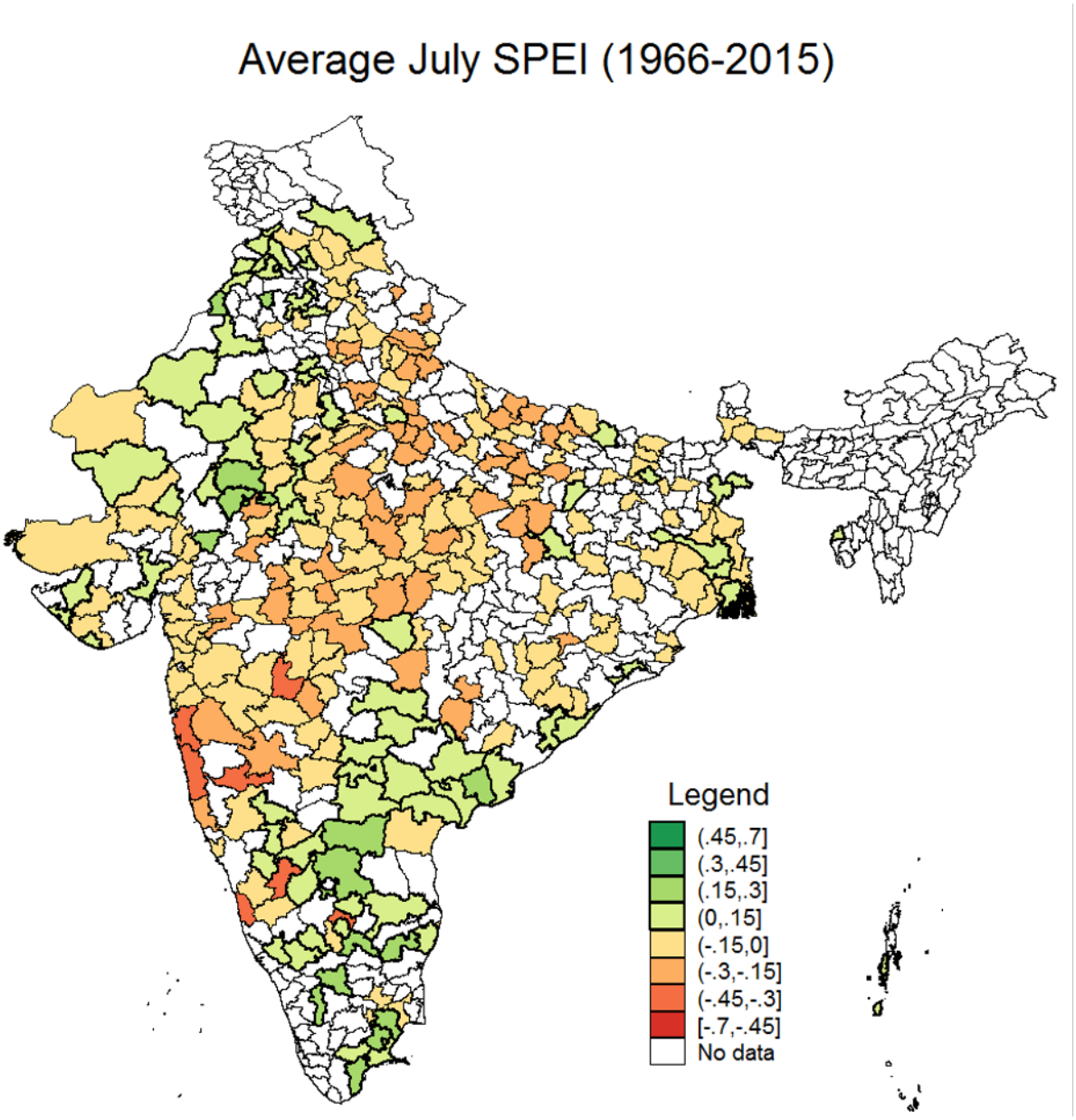

Figure A2.2: Spatial distribution of average SPEI for July

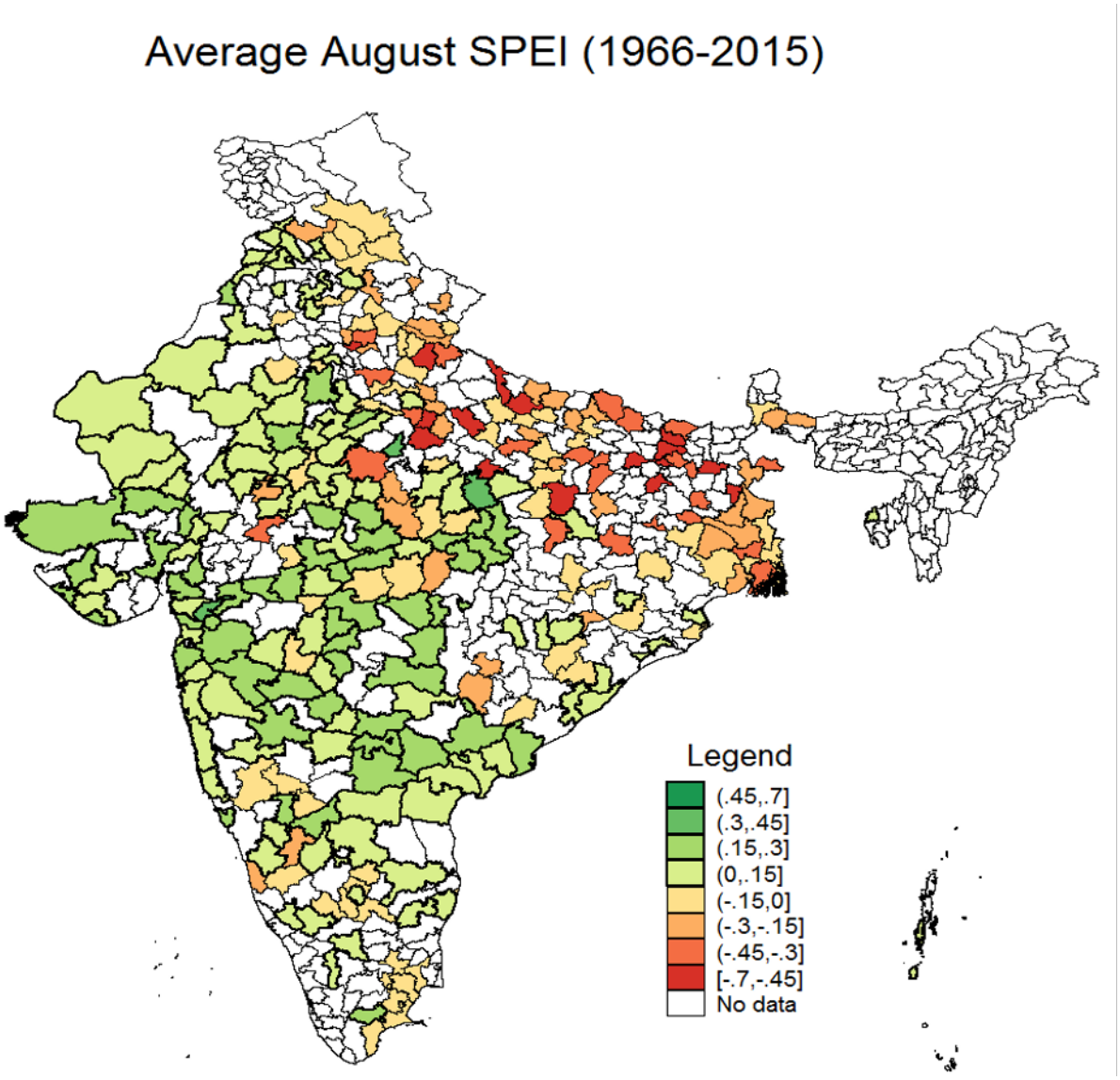

Figure A2.3: Spatial distribution of average SPEI for August

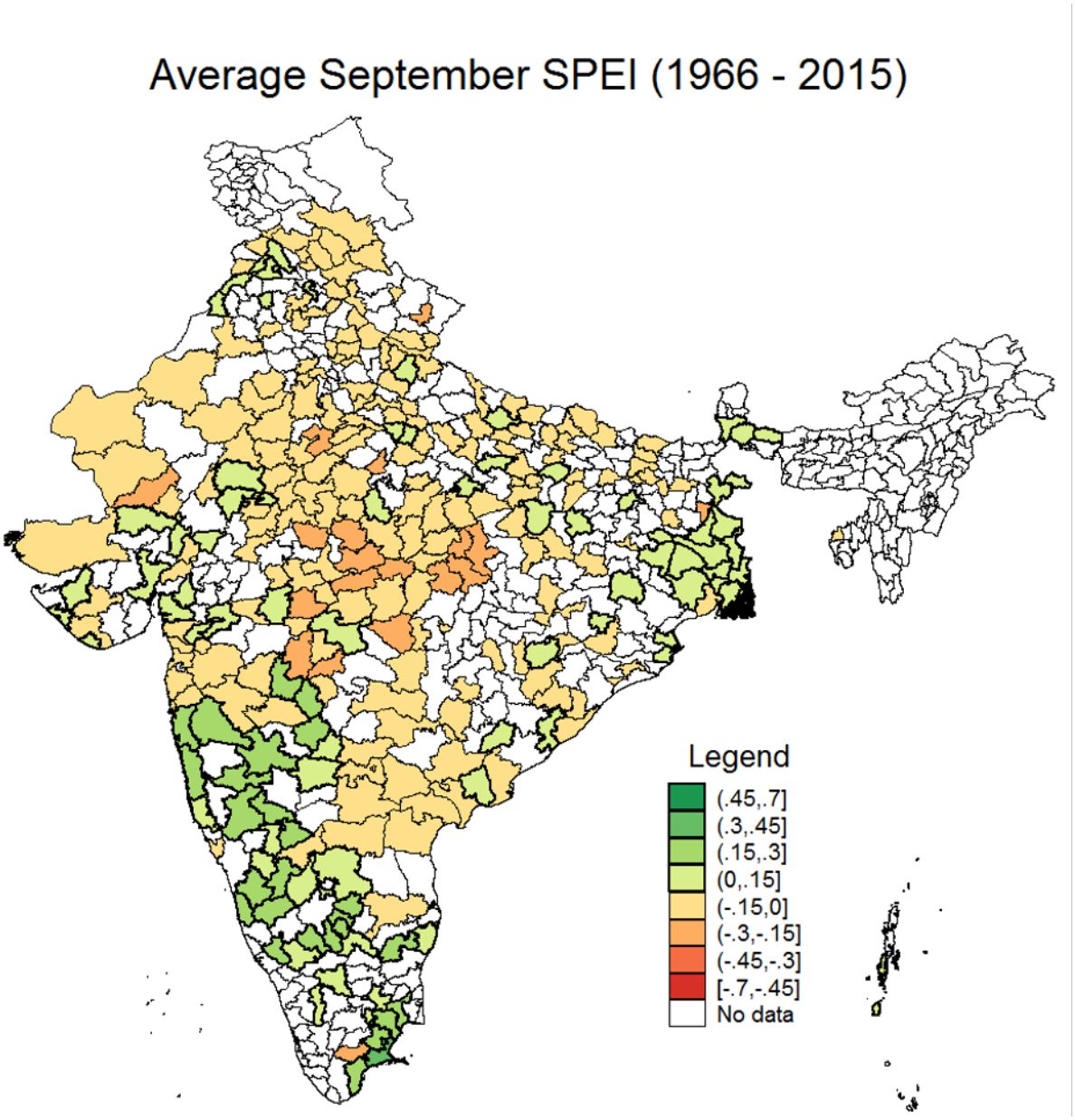

Figure A2.4: Spatial distribution of average SPEI for September

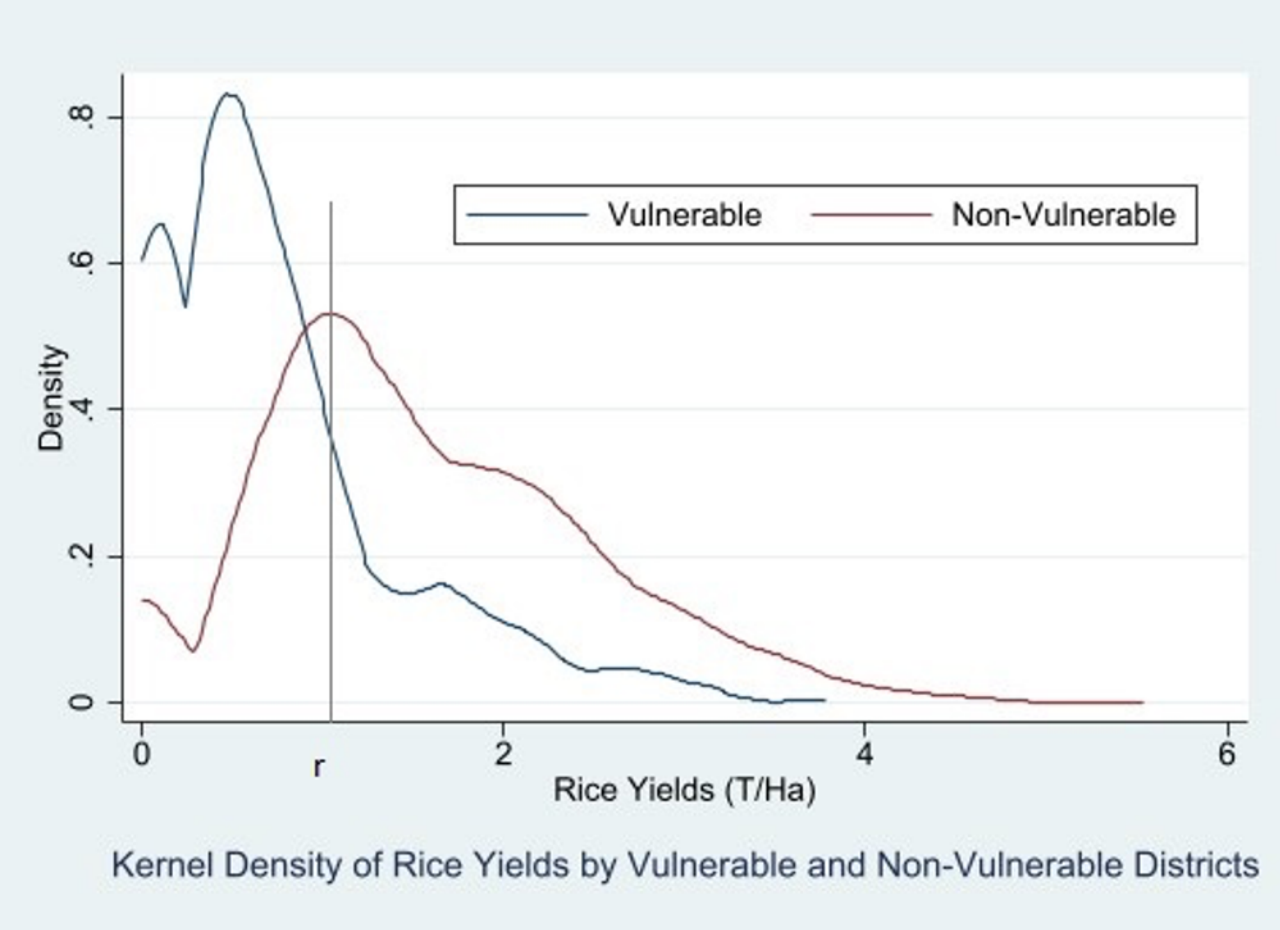

Figure A3: Kernel densities of rice yield for vulnerable and non-vulnerable districts based on the reference level, r_1

Appendix D: Estimation Results for reference level, r_2, r_3 and r_4

A2. Effects of extreme weather events and technology on vulnerability of rice yields for different reference levels

Table A2: Estimates of the Linear Probability Model with reference level, r_2

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Semi-Elasticities						
Irrigation	-0.0823	-0.0552***	-0.0898	-0.0938	-0.0852	-0.0908
	(-1.38)	(-7.39)	(-1.48)	(-1.56)	(-1.42)	(-1.56)
HYV	-0.0801**	0.00137	-0.0800**	-0.0725**	-0.0752**	-0.0699**
	(-2.98)	(0.16)	(-2.96)	(-2.67)	(-2.82)	(-2.62)
Fertilizers	-0.0328	-0.00818*	-0.0292	-0.0354+	-0.0363+	-0.0307
	(-1.41)	(-2.12)	(-1.26)	(-1.67)	(-1.73)	(-1.32)
Male Labor	0.174*	0.0114	0.186**	0.191**	0.181*	0.166*
	(2.49)	(1.18)	(2.67)	(2.67)	(2.52)	(2.35)
Female Labor	0.0228	0.0385***	0.0149	0.0120	0.0124	0.0325
	(0.50)	(4.76)	(0.33)	(0.26)	(0.27)	(0.68)
Share of Rice Area	0.0465	-0.0307***	0.0210	0.0166	0.0319	0.0239
	(0.51)	(-4.69)	(0.24)	(0.19)	(0.37)	(0.27)
Marginal Effects						
Extreme Dry	0.228**	0.512***				
	(2.82)	(6.65)				
Severe Dry	0.177***	0.381***				
	(4.19)	(14.39)				
Moderate Dry	0.122***	0.237***				
	(4.03)	(13.99)				
Moderate Wet	-0.0623**	-0.0960***				
	(-2.64)	(-5.37)				
Severe Wet	-0.0398	-0.0607*				
	(-1.16)	(-2.39)				
Extreme Wet	-0.0435	-0.236*				
	(-0.74)	(-2.47)				
SPEI			-0.0552***	-0.0589***	-0.0641***	
			(-5.08)	(-5.80)	(-6.28)	
Dry						0.203***
						(7.60)
Wet						-0.0554**
						(-2.85)
N	7698	7698	7698	7698	7698	7698

Note: Column (1) includes SPEI bins with no interactions, Column (2) includes SPEI bins and its interactions with X, column (3) includes average growing season SPEI with no interactions, column (4) includes average growing season SPEI in the quadratic, column (5) includes average growing season SPEI and its interactions with X, column (6) includes Dry (SPEI < -0.99) and Wet (SPEI > 0.99) dummies and their interactions with X. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means. T-Statistics below parameters in parentheses *** p<0.001, ** p<0.01, * p<0.05 + p<0.10

Table A3: Estimates of the First Lower Partial Moment with reference level, r_2

Variables	(1)	(2)	(3)	(4)	(5)
Semi-Elasticities					
Irrigation	-0.192***	-0.223***	-0.209***	-0.249***	-0.236***
	(-3.68)	(-3.65)	(-3.91)	(-4.19)	(-3.91)
HYV	-0.0278	-0.0357	-0.0256	-0.0463	-0.0359
	(-1.23)	(-0.96)	(-1.17)	(-1.29)	(-0.98)
Fertilizers	0.0172	0.0201	0.0198	0.0161	0.0198
	(1.41)	(1.08)	(1.58)	(0.89)	(1.05)
Male Labor	0.190**	0.129	0.182**	0.125+	0.137+
	(2.87)	(1.61)	(2.83)	(1.89)	(1.74)
Female Labor	0.00263	0.0353	0.00421	-0.0126	0.0319
	(0.06)	(0.70)	(0.10)	(-0.31)	(0.65)
Share of Rice Area	0.0692	0.127*	0.0435	0.129*	0.110*
	(1.28)	(2.25)	(0.81)	(2.28)	(1.97)
Marginal Effects					
Extreme Dry	0.239***	0.172*			
	(4.14)	(2.56)			
Severe Dry	0.0725***	0.0893***			
	(3.63)	(3.67)			
Moderate Dry	0.0634***	0.0545***			
	(3.81)	(3.38)			
Moderate Wet	-0.0286	-0.0911***			
	(-1.14)	(-4.21)			
Severe Wet	0.0368	-0.0136			
	(1.42)	(-0.57)			
Extreme Wet	-0.0333	0.264+			
	(-0.39)	(1.85)			
SPEI			-0.0381***	-0.0454***	
			(-5.53)	(-7.12)	
Dry					0.0705***
					(4.84)
Wet					-0.0518**
					(-3.16)
N	2553	2553	2553	2553	2553

Note: Column (1) and (3) do not include interactions between inputs and weather variables. Columns (2) (4) and (5) include interactions. Growing season SPEI specified in the quadratic in column (4) and in column (5) replaced with Dry (SPEI < -0.99$) and Wet (SPEI >0.99$) dummies. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means while estimates for weather variables are marginal effects. T-statistics in parentheses. Stars indicate significance *** p<0.001, ** p<0.01, * p<0.05 + p<0.10

Table A4: Estimates of the full and partial moment function for rice yield production for r_2

Variables	Mean	Full 2nd	Lower 2nd	Upper 2nd	Lower 3rd	Upper 3rd
Irrigation	0.028***	-0.117**	-0.312	0.209	-8.563***	3.282
	(0.009)	(0.058)	(0.186)	(0.174)	(0.756)	(1.811)
HYV	0.053***	0.158**	2.990***	1.200***	0.838***	13.770***
	(0.008)	(0.061)	(0.415)	(0.386)	(0.129)	(2.807)
Fertilizers	0.066**	0.041	-2.807***	1.144**	-13.276***	-0.391
	(0.025)	(0.257)	(0.822)	(0.422)	(1.328)	(0.696)
Male Labor	0.015	-1.794**	1.144	-1.781	-3.432	-29.966***
	(0.085)	(0.827)	(0.805)	(1.143)	(1.485)	(4.861)
Female Labor	-0.072+	1.019+	8.591***	1.594	44.117***	11.848***
	(0.040)	(0.582)	(1.384)	(0.873)	(3.241)	(1.656)
Share of Rice Area	-0.043	-0.698+	1.454	-1.264*	2.687	6.939***
	(0.038)	(0.371)	(0.846)	(0.584)	(1.583)	(2.125)
Extreme Dry	-1.238***	-0.976+	1.642***	0.105	6.920***	1.215*
	(0.384)	(0.528)	(0.402)	(0.270)	(1.076)	(0.548)
Severe Dry	-0.174***	-0.584	-0.429+	0.295	4.186***	0.394
	(0.036)	(0.482)	(0.235)	(0.195)	(0.696)	(0.412)
Moderate Dry	-0.071**	0.045	-0.120	0.409***	3.660***	0.606
	(0.024)	(0.167)	(0.196)	(0.134)	(0.411)	(0.389)
Moderate Wet	0.028+	-0.749***	-3.216***	0.015	-12.940***	-0.386
	(0.017)	(0.218)	(0.436)	(0.144)	(1.008)	(0.338)
Severe Wet	0.077**	-0.083	-0.268	0.415+	3.468***	0.898*
	(0.034)	(0.331)	(0.532)	(0.215)	(0.529)	(0.408)
Extreme Wet	-0.035	-7.625***	-8.515***	-0.412	-11.770***	2.656***
	(0.144)	(0.528)	(1.042)	(0.350)	(0.970)	(0.802)

Note: All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Elasticities reported with robust standard errors clustered at the district level in parentheses. Stars indicate significance *** p<0.001, **p<0.01, *p<0.05, +p<0.10

Table A5: Estimates of the Linear Probability Model with reference level, r_3

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Semi-Elasticities						
Irrigation	-0.137***	-0.0284***	-0.147***	-0.151***	-0.141***	-0.151***
	(-3.56)	(-5.28)	(-3.72)	(-3.73)	(-3.55)	(-3.91)
HYV	-0.0401+	-0.0166**	-0.0415*	-0.0380+	-0.0412*	-0.0352+
	(-1.91)	(-2.71)	(-1.97)	(-1.82)	(-2.00)	(-1.68)
Fertilizers	-0.0125	-0.00508+	-0.00908	-0.0140	-0.0151	-0.0110
	(-0.71)	(-1.82)	(-0.50)	(-0.86)	(-0.95)	(-0.60)
Male Labor	0.180***	-0.0101	0.193***	0.202***	0.191***	0.178***
	(4.31)	(-1.45)	(4.56)	(4.47)	(4.39)	(3.92)
Female Labor	-0.0195	0.0305***	-0.0263	-0.0282	-0.0278	-0.00829
	(-0.82)	(5.24)	(-1.07)	(-1.14)	(-1.17)	(-0.33)
Share of Rice Area	0.156*	-0.000694	0.126+	0.111+	0.128*	0.124+
	(2.32)	(-0.15)	(1.95)	(1.77)	(2.02)	(1.92)
Marginal Effects						
Extreme Dry	0.405***	0.563***				
	(4.30)	(10.13)				
Severe Dry	0.145***	0.351***				
	(3.61)	(18.37)				
Moderate Dry	0.0986***	0.173***				
	(3.59)	(14.19)				
Moderate Wet	-0.0301*	-0.0519***				
	(-2.07)	(-4.03)				
Severe Wet	0.01000	-0.0349+				
	(0.39)	(-1.90)				
Extreme Wet	-0.0113	-0.120+				
	(-0.28)	(-1.73)				
SPEI			-0.0428***	-0.0456***	-0.0515***	
			(-5.31)	(-6.93)	(-7.70)	
Dry						0.165***
						(7.48)
Wet						-0.0250*
						(-2.33)
N	7698	7698	7698	7698	7698	7698

Note: Column (1) includes SPEI bins with no interactions, Column (2) includes SPEI bins and its interactions with X, column (3) includes average growing season SPEI with no interactions, column (4) includes average growing season SPEI in the quadratic, column (5) includes average growing season SPEI and its interactions with X, column (6) includes Dry (SPEI < -0.99) and Wet (SPEI > 0.99) dummies and their interactions with X. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means. T-Statistics below parameters in parentheses *** p<0.001, ** p<0.01, * p<0.05 + p<0.10

Table A6: Estimates of the First Lower Partial Moment with reference level, r_3

Variables	(1)	(2)	(3)	(4)	(5)
Semi-Elasticities					
Irrigation	-0.0268	0.0346	-0.0217	0.000602	0.0198
	(-0.39)	(0.51)	(-0.32)	(0.01)	(0.29)
HYV	0.00939	-0.0476	0.00864	-0.0181	-0.0266
	(0.46)	(-1.31)	(0.43)	(-0.54)	(-0.79)
Fertilizers	-0.0137	-0.00528	-0.0113	-0.00749	-0.00646
	(-1.23)	(-0.25)	(-0.95)	(-0.34)	(-0.30)
Male Labor	0.164*	0.0348	0.150+	0.112+	0.111+
	(2.10)	(0.42)	(1.84)	(1.72)	(1.69)
Female Labor	-0.0143	0.0748	-0.0194	-0.0279	0.0293
	(-0.26)	(1.26)	(-0.34)	(-0.60)	(0.57)
Share of Rice Area	0.122*	0.217**	0.101+	0.137**	0.143*
	(2.03)	(3.13)	(1.78)	(2.59)	(2.50)
Marginal Effects					
Extreme Dry	0.176**	0.150**			
	(2.80)	(2.62)			
Severe Dry	0.0381	0.0680+			
	(1.29)	(1.91)			
Moderate Dry	0.0238	0.00235			
	(1.28)	(0.13)			
Moderate Wet	-0.0656	-0.0867+			
	(-1.26)	(-1.67)			
Severe Wet	0.0573	-0.0524			
	(1.04)	(-0.82)			
Extreme Wet	-0.109	3.986*			
	(-0.59)	(2.28)			
SPEI			-0.0234*	-0.0372***	
			(-2.23)	(-3.76)	
Dry					0.0560*
					(2.19)
Wet					-0.0585
					(-1.50)
N	1045	1045	1045	1045	1045

Note: Dependent variable is lower partial moment constructed as negative of residuals from eq (2c). Column (1) includes SPEI bins with no interactions, Column (2) includes SPEI bins and its interactions with X, column (3) includes average growing season SPEI with no interactions, column (4) includes average growing season SPEI and its interactions with X, column (5) includes Dry (SPEI < -0.99) and Wet (SPEI > 0.99) dummies and their interactions with X. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means. T-Statistics below parameters in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table A7: Estimates of the full and partial moment function for rice yield production using r_3 as the reference level

Variables	Mean	Full 2nd	Lower 2nd	Upper 2nd	Lower 3rd	Upper 3rd
Irrigation	0.028***	-0.117**	8.636***	0.674**	18.354	6.653***
	(0.009)	(0.058)	(1.240)	(0.245)	(26.366)	(1.041)
HYV	0.053***	0.158**	3.289***	0.108**	36.131	4.018***
	(0.008)	(0.061)	(0.503)	(0.042)	(51.735)	(0.548)
Fertilizers	0.066**	0.041	-11.765***	0.234	-20.527	1.052*
	(0.025)	(0.257)	(1.664)	(0.165)	(22.692)	(0.511)
Male Labor	0.015	-1.794**	62.609***	-4.485***	31.748	-14.158***
	(0.085)	(0.827)	(8.358)	(1.087)	(45.264)	(1.690)
Female Labor	-0.072+	1.019+	-1.578***	1.228***	39.041	4.454***
	(0.040)	(0.582)	(0.454)	(0.403)	(51.939)	(0.686)
Share of Rice Area	-0.043	-0.698+	19.243***	0.069	-5.328	1.090
	(0.038)	(0.371)	(2.973)	(0.296)	(14.321)	(0.704)
Extreme Dry	-1.238***	-0.976+	13.803***	-0.634*	30.393	-0.855***
	(0.384)	(0.528)	(1.956)	(0.271)	(43.158)	(0.279)
Severe Dry	-0.174***	-0.584	-2.356***	-0.007	29.619	1.093**
	(0.036)	(0.482)	(0.468)	(0.200)	(43.704)	(0.412)
Moderate Dry	-0.071**	0.045	-11.875***	0.030	5.482	0.380*
	(0.024)	(0.167)	(1.581)	(0.141)	(8.833)	(0.186)
Moderate Wet	0.028+	-0.749***	-35.232***	-0.196**	-58.903	-0.424*
	(0.017)	(0.218)	(4.995)	(0.081)	(76.580)	(0.197)
Severe Wet	0.077**	-0.083	18.994***	-0.271+	52.378	0.028
	(0.034)	(0.331)	(2.293)	(0.143)	(76.895)	(0.290)
Extreme Wet	-0.035	-7.625***	-44.367***	-3.286***	-18.196	-6.526***
	(0.144)	(0.528)	(7.270)	(0.680)	(25.494)	(0.672)

Note: All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Elasticities reported with robust standard errors clustered at the district level in parentheses. Stars indicate significance *** p<0.001, **p<0.01, *p<0.05, +p<0.10

Table A8: Estimates of the Linear Probability Model with reference level, r_4

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Semi-Elasticities						
Irrigation	-0.180***	0.0332***	-0.188***	-0.200***	-0.195***	-0.196***
	(-3.71)	(5.52)	(-3.85)	(-4.03)	(-3.98)	(-4.04)
HYV	-0.0728***	-0.0875***	-0.0752***	-0.0687**	-0.0703**	-0.0731***
	(-3.34)	(-12.81)	(-3.41)	(-3.05)	(-3.15)	(-3.30)
Fertilizers	-0.0281**	-0.0280***	-0.0261**	-0.0287**	-0.0292**	-0.0275**
	(-2.90)	(-8.98)	(-2.68)	(-2.99)	(-3.05)	(-2.77)
Male Labor	0.133**	0.0286***	0.142**	0.145**	0.140**	0.136**
	(2.74)	(3.69)	(2.95)	(3.05)	(2.91)	(2.90)
Female Labor	-0.0548	-0.0262***	-0.0605+	-0.0572	-0.0570	-0.0484
	(-1.48)	(-4.03)	(-1.67)	(-1.58)	(-1.55)	(-1.32)
Share of Rice Area	0.0940	0.0261***	0.0741	0.0643	0.0731	0.0728
	(1.53)	(4.96)	(1.25)	(1.07)	(1.23)	(1.18)
Marginal Effects						
Extreme Dry	0.320***	0.387***				
	(3.40)	(6.25)				
Severe Dry	0.0825*	0.254***				
	(2.16)	(11.91)				
Moderate Dry	0.0564**	0.116***				
	(2.66)	(8.53)				
Moderate Wet	-0.0430**	-0.0310*				
	(-2.99)	(-2.16)				
Severe Wet	-0.0253	-0.0329				
	(-0.91)	(-1.61)				
Extreme Wet	0.00379	-0.0428				
	(0.06)	(-0.56)				
SPEI			-0.0360***	-0.0399***	-0.0429***	
			(-5.42)	(-5.61)	(-5.67)	
Dry						0.105***
						(4.61)
Wet						-0.0409*
						(-2.50)
N	7698	7698	7698	7698	7698	7698

Note: Column (1) includes SPEI bins with no interactions, Column (2) includes SPEI bins and its interactions with X, column (3) includes average growing season SPEI with no interactions, column (4) includes average growing season SPEI in the quadratic, column (5) includes average growing season SPEI and its interactions with X, column (6) includes Dry (SPEI < -0.99) and Wet (SPEI > 0.99) dummies and their interactions with X. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means. T-Statistics below parameters in parentheses *** p<0.001, ** p<0.01, * p<0.05 + p<0.10

Table A9: Estimates of the First Lower Partial Moment with reference level, r_4

Variables	(1)	(2)	(3)	(4)	(5)
Semi-Elasticities					
Irrigation	-0.116+	-0.127+	-0.116+	-0.111	-0.134+
	(-1.82)	(-1.69)	(-1.82)	(-1.42)	(-1.72)
HYV	-0.0435+	-0.0232	-0.0433+	-0.0298	-0.0195
	(-1.70)	(-0.93)	(-1.68)	(-1.11)	(-0.80)
Fertilizers	0.00287	0.00333	0.00326	-0.00264	-0.00422
	(0.42)	(0.18)	(0.50)	(-0.14)	(-0.21)
Male Labor	0.0284	0.138+	0.0341	0.0864	0.121+
	(0.47)	(1.82)	(0.58)	(1.34)	(1.68)
Female Labor	0.0643	0.0446	0.0549	0.0595	0.0523
	(1.59)	(1.01)	(1.41)	(1.49)	(1.13)
Share of Rice Area	-0.0312	-0.0362	-0.0152	-0.0489	-0.0404
	(-0.47)	(-0.42)	(-0.21)	(-0.64)	(-0.49)
Marginal Effects					
Extreme Dry	0.0528	-0.0643			
	(0.81)	(-0.74)			
Severe Dry	0.0446+	0.0476+			
	(1.93)	(1.86)			
Moderate Dry	0.0281	0.0314			
	(1.35)	(1.41)			
Moderate Wet	-0.0433+	-0.0138			
	(-1.66)	(-0.53)			
Severe Wet	-0.0121	-0.0503			
	(-0.35)	(-1.47)			
Extreme Wet	-0.183+	-0.448			
	(-1.93)	(-1.28)			
SPEI			-0.0248**	-0.0258**	
			(-2.89)	(-2.76)	
Dry					0.0286+
					(1.69)
Wet					-0.0392+
					(-1.71)
N	1353	1353	1353	1353	1353

Note: Dependent variable is lower partial moment constructed as negative of residuals from eq (2c). Column (1) includes SPEI bins with no interactions, Column (2) includes SPEI bins and its interactions with X, column (3) includes average growing season SPEI with no interactions, column (4) includes average growing season SPEI and its interactions with X, column (5) includes Dry (SPEI < -0.99) and Wet (SPEI > 0.99) dummies and their interactions with X. All regressions weighted by average cropland area and include district and year fixed effects as well as a state-specific linear time trend. Semi-elasticities reported for inputs computed at sample means. T-Statistics below parameters in parentheses *** p<0.001, ** p<0.01, * p<0.05, + p<0.10

Table A10: Estimates of the full and partial moment function for rice yield production using r_4 as the reference level

Variables	Mean	Full 2nd	Lower 2nd	Upper 2nd	Lower 3rd	Upper 3rd
Irrigation	0.028***	-0.117**	-1.932+	-0.168***	-2.602	-0.161***
	(0.009)	(0.058)	(1.024)	(0.047)	(1.806)	(0.065)
HYV	0.053***	0.158**	-0.122	-0.009	-0.166	0.072
	(0.008)	(0.061)	(0.083)	(0.022)	(0.125)	(0.043)
Fertilizers	0.066**	0.041	-1.477*	0.393	-2.239*	0.714
	(0.025)	(0.257)	(0.656)	(0.285)	(1.020)	(0.482)
Male Labor	0.015	-1.794**	1.417	-0.511*	2.716	-1.166***
	(0.085)	(0.827)	(3.038)	(0.229)	(4.	(0.367)
Female Labor	-0.072+	1.019+	2.454	-0.100	3.649+	0.251
	(0.040)	(0.582)	(1.701)	(0.171)	(2.084)	(0.362)
Share of Rice Area	-0.043	-0.698+	-0.217	-0.370	-0.176	-0.447
	(0.038)	(0.371)	(0.780)	(0.368)	(1.150)	(0.660)
Extreme Dry	-1.238***	-0.976+	19.142+	0.156	7.264***	0.123
	(0.384)	(0.528)	(11.086)	(0.118)	(0.872)	(0.107)
Severe Dry	-0.174***	-0.584	11.360	-0.037	4.441***	0.089
	(0.036)	(0.482)	(7.067)	(0.100)	(0.813)	(0.093)
Moderate Dry	-0.071**	0.045	-0.756+	0.087	-1.139+	0.074
	(0.024)	(0.167)	(0.404)	(0.060)	(0.617)	(0.091)
Moderate Wet	0.028+	-0.749***	-0.610	0.202***	-0.919	0.111
	(0.017)	(0.218)	(0.882)	(0.055)	(1.025)	(0.079)
Severe Wet	0.077**	-0.083	-94.630	0.191*	-4.130*	0.139
	(0.034)	(0.331)	(62.277)	(0.083)	(1.946)	(0.142)
Extreme Wet	-0.035	-7.625***	-131.206+	-22.037***	-10.292***	-24.590***
	(0.144)	(0.528)	(81.396)	(2.503)	(2.206)	(2.616)

Note: All regressions include district and year fixed effects as well as a state-specific linear time trend. Elasticities reported with robust standard errors clustered at the district level in parentheses. Stars indicate significance *** p<0.001, **p<0.01, *p<0.05, +p<0.10