ABSTRACT

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Global climate change has large impact on agriculture. The three essays in this dissertation study how temperature warming affects on various crops in different regions.

In Chapter 2, we study the relationship between yields of modern rice varieties and three major weather variables — maximum temperature, minimum temperature, and precipitation. Data from a long-running farm-level survey in the Philippines, with rich information on planted rice varieties, allows us to estimate fixed effect econometric models of rice yields. We find that increases in temperature, especially minimum temperatures, have substantial negative impacts on rice yields. Yield response to temperatures varies across different varietal groups. Early modern varieties, bred primarily for higher yields, pest resistance, and/or grain quality traits, demonstrate improved heat-stress resistance relative to traditional varieties. Moreover, the most recent varietal group bred for better tolerance to abiotic stresses are even more resilient to warming temperatures. These results provide some evidence that public investments in breeding rice varieties more tolerant to warming temperatures have been successful, and continued investments in these breeding efforts are warranted.

Chapter 3 explores how warming temperatures influence corn yield response to planting density. Using 1990-2010 field trial data from Wisconsin and econometric models with a variety of specifications, we find that warming temperatures reduce the yield benefits of increasing planting density. However, these adverse warming effects are smaller for genetically-modified (GM) corn varieties with rootworm (RW) resistant traits. Consistent with previous studies, these results support the notion that varietal improvements through genetic modification may have paved the way for higher planting densities in US corn production. Moreover, our results imply that expected in-season temperatures are important considerations when making planting density decisions.

Chapter 4 examines whether crop insurance participation rate influences the impact of extreme heat on yield risk (i.e., yield variance, skewness, and kurtosis). We utilize a parametric moment-based method and county-level panel data to evaluate how crop insurance participation affects the relationship between warming temperatures and the moments of crop yield distributions. Our results indicate that the yield risk increasing effect of warming is further magnified under high levels of crop insurance participation. Not only does the moral hazard effect of crop insurance adversely impact mean yields under climate change, but it also influences the extent by which warming affects yield variability over time. This supports the notion that crop insurance can serve as a disincentive for climate change mitigation in agriculture.

Essays on The Effects of Warming Temperatures in Agriculture

by
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DEDICATION

To my parents Hao Wang and Xinfeng Liu.

BIOGRAPHY

The author was born in the city of Jinan, Shandong Province, China in 1991. In 2014, she received his bachelor's degree in Economics from Hainan Normal University, China. she then studied at University of Texas at Austin and received her master's degree in Economics in 2015. From 2015 to 2020, the author worked under the supervision of Dr. Roderick Rejesus in North Carolina State University, USA.

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TABLE OF CONTENTS

CHAPTER

1 INTRODUCTION

Agriculture is one of the sectors that is the most affected by climate change. As the climate continues to warm up, the impacts on agricultural production become more severe, farmers face more challenges in mitigating the negative effects of climate warming and improving production sustainability under such circumstances. The goal of my dissertation is to explore the influence of three factors i.e. adopting newly released crop varieties, adjusting planting density, and crop insurance participation on the sensitivity of crop yield to warming.

In Chapter 2, we attempt to explore the effectiveness of developing and adopting new rice varieties in addressing the climate change challenge in rice production. For this purpose, we use farm-level survey data collected from Central Luzon area in the Philippines in the period from 1966 to 2016. The model we use includes climate-MV interaction terms. Such model helps us to disentangle the warming effects on rice yields by allowing for identifying varietal-group-specific warming effects. It gives us insight into which rice varietal group is most effective in mitigating the adverse effects of warming temperatures and whether the recently released modern varieties mitigate or aggravate the impacts of heat on rice production. Another contribution of this paper is that the data set we use in our analysis is farm-level panel data rather than aggregate rice production data or experimental field trial data commonly used by other research. Such data enables us to better examine rice growth response to warming under actual farmer-managed field conditions.

This chapter is structured as follows. Section 2.2 introduces the empirical setting and data sources, as well as discusses pertinent background on rice varietal development in the Philippines. Section 2.3 illustrates the modeling framework that examines the heterogeneity in the resilience of each varietal group's yield with respect to weather variables. Section 2.4 explains the estimation results. Section 2.5 provides various robustness checks and Section 2.6 discusses the conclusions.

In Chapter 3, we switch to the impacts of plant density on corn production. Previous literature has provided abundant evidence for the contribution of increasing plant density to crop production increases. However, this positive effect of plant density increases can be influenced by climate warming. To determine how the response of yield to plant density increases is affected by warming temperature, we merge a plot-level field trial data collected by the University of Wisconsin over the period 1990-2010 with publicly available weather data and estimate regression models with plant density-temperature interaction terms. In addition, we explore how GM traits influence corn yield response to increases in planting density as the temperature is heating through estimating models including GM traits-plant density-temperature interaction terms.

Chapter 3 proceeds as follows. First, we provide a detailed description of the data sources and our empirical approach that allows us to examine how corn yield responds to changes in plant density under different temperatures and/or GM traits in Section 3.2. This is followed by a thorough discussion of estimation results (Section 3.3) and various robustness checks (Section 3.4). Lastly, conclusions, important implications, and potential avenues for future research are presented in Section 3.5.

Chapter 4 attempts to address the question of whether crop insurance adoption influences the effect of warming temperatures on crop yield and yield risk. We are particularly interested in exploring if increasing crop insurance participation would result in larger increases in the yield risk response to extreme heat. To accomplish the goals, we use a county-level panel data set including information on crop (corn and soybeans) yield, weather, and crop insurance participation rate and estimate stochastic production functions through using parametric moment-based estimation procedures to determine whether the relationship between extreme heat and all four moments of the yield distribution (e.g, mean, variance, skewness, kurtosis) is affected by crop insurance use.

Chapter 4 is organized as follows. Section 4.2 describes the county-level panel data utilized in the study. Section 4.3 describes the parametric moment-based estimation procedures and the empirical specification. Section 4.4 discusses the estimation results. Section 4.5 provides several robustness checks, the instrumental variable method, and the cost of risk calculated based on estimates of the main model. Section 4.6 concludes.

CHAPTER

2

QUANTIFYING THE YIELD SENSITIVITY OF MODERN RICE VARIETIES TO WARMING TEMPERATURES: EVIDENCE FROM THE PHILIPPINES

This chapter examines the relationship between yields of modern rice varieties and three major weather variables — maximum temperature, minimum temperature, and precipitation. We use a long-running farm-level survey data in the Philippines, with rich information on planted rice varieties and propose fixed effect econometric models, to identify the warming effects on yields of different rice varieties. The results show that increases in temperature, especially minimum temperatures, have substantial negative impacts on rice yield and the most recent varietal group bred for better tolerance to abiotic stresses are even more resilient to warming temperatures compared to traditional varieties and earlier modern varieties. These results provide some evidence that public investments in breeding rice varieties more tolerant to warming temperatures have been successful, and continued investments in these breeding efforts are warranted.

2.1 Introduction

Rice is the most important food crop in the world, with nearly half of the world's population relying on it for sustenance every day. It is the main staple food across a number of Asian countries, and it is also becoming an increasingly important food crop in Africa and Latin America ([Cha17]). Over 144 million farms cultivate rice across an area of about 167 million hectares (ha) in more than 100 countries ([FAO19]). Rice-based farming systems have also been the main source of income for a large proportion of rural farmers located in a number of developing countries ([Cha17]).

Given the importance of rice as a major staple food and a source of income for farmers worldwide, a key challenge is to find strategies that would maintain or improve rice productivity in the future even in the presence of climate change. Based on the recent climate assessment reports of the Intergovernmental Panel on Climate Change (IPCC), global warming has intensified over the last 50 years and this warming trend is predicted to persist in the future (see the Figure S2.1). A warming climate has the potential to adversely affect rice yields and rice quality ([Pen04]; [Iiz06]; [Lym13]; [Kaw16]). For example, extremely high temperatures can lead to spikelet sterility and consequently reduce rice yields ([Ngu14]; [Bhe16]). These adverse warming effects then have the potential to compromise food security in countries that rely on it as a food staple.

One strategy that may help address the climate change challenge in rice production is the development and use of newer rice varieties that are better able to adapt to a progressively warming climate. Over the years, development and adoption of new rice varieties have been utilized to overcome a variety of production challenges that have historically arisen in this sector. Since the Green Revolution in the 1960s, there have been development and consequent adoption of several generations of modern rice varieties (MVs) aimed at addressing various production challenges such as lodging, low fertilizer responsiveness, pest problems, and adverse weather conditions (see next section for more details). The release and subsequent adoption of these MVs have led to remarkable increases in rice yields over time ([Bar85], [Hay94], [Ots94], [Est06]), especially as compared to the traditional rice varieties (TVs), which was the only rice varietal group available prior to the Green Revolution.

With this history of rice varietal development over time, it is likely that there is heterogeneity in each variety's (or varietal group's) yield response to weather variables. The objective of this study is to determine the yield response of different rice varietal groups to warming temperatures. To achieve this objective, we utilize farm-level survey data collected every four to five years from 1966 to 2016 in the Central Luzon region of the Philippines ([Moy15]; [Lab15]). Examining the Philippine case is especially relevant since it is one of the top ten rice-producing countries in the world ([FAO19]), and the pattern of varietal adoption in this country is representative of other major rice-producing countries like India, Indonesia, Bangladesh, and Vietnam ([Bre11]; [Pan12]). Since farmers are tracked over time in the data set utilized, we are able to develop fixed effects econometric models, which then allows us to identify "varietal-group-specific" yield response to several weather variables (e.g., minimum temperature, maximum temperature, and precipitation).[1] Therefore, the study results provide interesting insights as to the effectiveness of prior rice varietal development efforts,

[1]As noted in [Lau08] and [Lab15] there are numerous specifically-named MVs that have been released in the Philippines since 1966 and it would have been impossible to estimate yield response to weather changes for each of these specifically-named rice varieties. Hence, in this study, we focus on the yield response of varietal groups (as further defined below) to weather variables.

specifically in terms of mitigating the adverse impacts of climate change.

Due to concerns about the effect of climate change on agriculture, there is now a large literature that has used econometric methods to examine how weather variables influence crop yield outcomes (See, for example, [Auf06], [Wel10]; [Sar12]; [Lym13] and [Kaw16] for rice; [Sch09] for corn; [Tac15b] for wheat). There is also another strand of literature that explores the determinants and economic impacts of particular climate change adaptation practices for different crops (See: [Che14]; [Wan10]; [Der09]; [DF11]; [But13]; [Hua15]). Despite this rich literature on climate change adaptation and climate change effects on yields, to the best of our knowledge, there has been a limited number of studies that investigated how the yield impact of weather variables may vary depending on the rice variety, or the rice varietal group, used by farmers. [Tac16], using a long time-series of field trial data in the U.S., examined variety-specific yield response to higher temperatures for wheat, but not for rice. [Has16] examined how the yield response of TVs differ from high yielding rice varieties (HYVs), using more aggregate region-specific data from Bangladesh. We have not found any study that has used individual farm-level data to econometrically examine the relationship between rice varietal use and yield response to weather variables.

Our main contribution is to disentangle the warming effects on rice yields by allowing for econometrically identifying varietal-group-specific effects. This is important because it will allow us to know which rice varietal group is most effective in mitigating the adverse effects of warming temperatures and whether the older MVs had some climate change mitigation features. Although not all previously released rice MVs are widely used anymore ([Lab15]), it is still important to determine whether these older varietal groups have historically contributed to climate change mitigation, especially because they were not specifically bred for this purpose (see more discussion on this issue below). If these climate change mitigation effects are present for these earlier MVs, then these are important "spillover" rice breeding effects that need to be recognized. But more importantly, given that newer rice varieties were developed to be more tolerant to adverse climatic conditions, providing empirical evidence to show the climate change mitigation effects of these newer varieties on farmers' fields allows one to see whether more recent breeding efforts to produce "climate-change-tolerant-traits" has indeed been successful.

The second contribution is that we exploit actual farm-level panel data in our analysis, rather than using more aggregate rice production data (e.g., district-level, province-level) or experimental field trial data, which are the two most commonly used data types in previous literature. The novel data set used in this study allows one to better examine rice yield response under actual farmer-managed field conditions. The data set used is also unique in terms of the decades-long time period it spans, which is relatively rare in terms of the few climate-change studies that utilize individual farm-level data sets. Furthermore, the farm-level data set we use also has rich information on the rice varieties used, as well as the other inputs utilized by the grower (e.g., fertilizer, insecticide). Much of the individual data sets used for climate-change studies in the past do not have rich varietal information that would allow one to estimate variety-specific (or varietal-group-specific) yield response to weather variables. Disregarding heterogeneity in the yield response of specific rice varieties may lead to inaccurate inferences regarding the yield effects of warming. Hence, having this unique and novel data set gives us the rare opportunity to study the interactions of rice varietal traits and the environment it grows in, over a long period of time.

The rest of this chapter is organized as follows. Section 2.2 introduces the empirical setting and data sources, as well as discusses pertinent background on rice varietal development in the Philippines. Section 2.3 illustrates the modeling framework that examines the heterogeneity in the resilience of each varietal group's yield with respect to weather variables. Section 2.4 explains the estimation results. Section 2.5 provides various robustness checks and Section 2.6 discusses the conclusions.

2.2 Empirical Setting and Data Sources

The empirical setting for this study covers six major rice-producing provinces from two administrative regions in the Philippines: (a) La Union and Pangasinan provinces in Region I (called the Ilocos region), and (b) Nueva Ecija, Pampanga, Bulacan, and Tarlac provinces in Region III (usually called the Central Luzon region). For the purpose of this study (and consistent with [Lab15]), the six provinces in the study area are collectively referred to here as Central Luzon. In 2013, the total harvested area in the six provinces was 0.9 million ha, with the majority of these under irrigation (82%). The average rice yield in the study area was 4.7 tons per ha, per cropping season in 2013, which is slightly higher than the national average. Rice is planted twice a year: (a) the wet season (WS) production that ranges from May/June to September/October, and (b) the dry season (DS) production that ranges from November/December to March/April ([Moy15]). The average farm size in the study area is around 1 ha ([Moy15]). Like many other countries of the world, the Philippines (and the study area under consideration) have experienced significant warming trends over the years. Estimates from the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) suggest that, between 1951 to 2010, average maximum and minimum temperatures in the Philippines have increased by 0.36°C and 1.0°C, respectively.

As previously mentioned, Philippine rice varietal development and utilization roughly follows the pattern for other major rice-producing countries in Asia ([Bre11]; [Pan12]). The first-generation MVs (called MV1) were released from the mid-1960s to the mid-1970s, which included the IR5 to IR34 varieties developed by the International Rice Research Institute (IRRI) and the C4 series developed by the University of the Philippines (UP). Specifically, the release of IRRI's IR8 variety in the Philippines and India is widely considered as the event that ignited the Green Revolution for rice production. Compared to TVs, MV1 achieved higher yields primarily due to their resistance to lodging, their ability to make more efficient use of solar energy, and their responsiveness to fertilizer ([Lau08]). Although MV1 are typically higher-yielding (relative to TVs) they were more susceptible to pests and diseases. The second-generation MVs (called MV2) were released in the mid-1970s to mid-1980s and included such IRRI-developed varieties like IR36 to IR62. These MV2 varieties incorporated multiple pest and disease resistance traits (relative to MV1). The third-generation MVs (called MV3) were developed and released between the mid-1980s to the late-1990s, and incorporated better grain quality and stronger host plant resistance ([Lau08]). Lastly, the fourth-generation MVs (called MV4) were released after 1995. In this period, public rice breeding programs started to focus on the research and development of varieties specifically for adverse rice production environments, such as those subject to salinity, floods, and drought ([Lab15]).[2]

The main data source utilized for this study is from the so-called "Central Luzon Loop Survey" or simply the "Loop Survey." It is called the "Loop Survey" because of the sampling strategy used, where the farm households included in the sample are located along the loop of the main highway that passes through the six provinces (Figure 2.1). Face-to-face interviews were conducted to collect various socio-demographic, input use, and rice production information from the sample respondents (See [Moy15] for more details on how the survey was conducted over the years and the different sets of information collected). The loop survey data included WS information for the following cropping years: 1966, 1970, 1974, 1979, 1982, 1986, 1990, 1994, 1999, 2003, 2008, 2011 and 2015; while DS information was available for 1967, 1971, 1975, 1980, 1987, 1991, 1995, 1998, 2004, 2007, 2012 and 2016.

Note that the loop survey collected production and input use data for each parcel (or field) the farmers have (i.e., there could be three rice parcels for a particular farm household, and input use information, say on fertilizer, was collected for each of the three parcels, where the input applied for each parcel may vary). However, there was no unique identifier used to consistently track parcels over time. Hence, only a farm-level panel data set can be constructed with the loop survey since only the farm households can be uniquely tracked over time (and not the parcels for each farm household). Nevertheless, we still "carry-over" the parcel level data rows (for each farm household) and run our empirical models using parcel-level observations. But, as discussed further in the next section, we can only account for farm-level fixed effects (and not parcel-level fixed effects) given the data structure described here.

As noted above, the loop survey includes data for two growing seasons (DS and WS). It is likely that the rice yield effect of weather variables varies by season. From 1966 to 1975, only around 20% of farmers in the Central Luzon region can plant a DS rice because of the lack of irrigation. For this reason, our DS sample has a relatively small number of observations. Given the limited size of the dry season data, we focus on the analysis of the WS data. Another major concern is that yield response to weather variables and input use are likely to vary depending on whether the farm is irrigated or not. Thus, pooling them together and fitting the model for this kind of pooled data is inappropriate. With the construction and operation of large scale irrigation systems and wide use of small pumps for irrigation, the population of farmers having access to irrigated water was growing rapidly for the period considered. In the data set we used for empirical analysis, 79% of observations are irrigated operations. For this reason, in this study, the sample of interest was limited to irrigated rice production planted in the WS.

[2]As noted in [Lab15], there was an additional varietal group called MV5 that refers to modern rice varieties released after 2005. However, these varieties do not have substantially different characteristics relative to MV4. Hence, MV4 and MV5 are considered as the same varietal group–recent MVs in this study.

Aside from the loop survey data, we also collected monthly average of daily values for minimum temperature (in °C) and maximum temperature(in °C), and monthly total precipitation (in mm/month)) from the following sources: (a) the WorldClim data (version 1.4) for 1960-1990, and (b) the University of East Anglia's Climatic Research Unit (CRU) data (version 3.23) for years 1990-2016.[3] Since these data sets are at higher spatial resolutions (i.e., 0.5-degree resolutions for the CRU data), a climate downscaling tool (called ClimDown) was used to produce climatic data corresponding to the municipality level[4] where each loop survey household is located (See [Mos14] for more information on this downscaling process). Therefore, the climate data in this dataset are at the municipality level and reported at a monthly time-scale for the years covered in the loop survey. This climate data were then merged to the loop survey data in order to have one unified data set to run our empirical models.

2.3 Modeling Framework

We use multivariate regression methods to estimate econometric models of the following general form:

$$\ln(y_{ijmt}) = \alpha_j + f(\mathbf{tmin}_{kmt}, \mathbf{tmax}_{kmt}, \mathbf{prec}_{mt}, \mathbf{V}_{ijmt}; \delta, \beta, \psi) + \gamma \mathbf{X}_{ijmt} + \eta t + \varepsilon_{ijmt} \tag{2.1}$$

where $\ln(y_{ijmt})$ is the natural log of rice yield y (in kg/ha) for parcel i and farm j, located in municipality m, for year t. The other terms in Equation (2.1) are described as follows. The parameter α_j accounts for unobservable time-invariant farm-level fixed effects such as soil quality and farmer management ability. The function $f(\cdot)$ is what we call the climate function that includes the following explanatory variables: (a) a vector of weather variables: municipality-level maximum and minimum temperature for a particular kth growing phase, as well as cumulative growing season precipitation; and (b) a vector of parcel-level rice varietal group dummy variables $\mathbf{V}_{ijmt}$.

For the purpose of having a more parsimonious model (and more easily interpretable results), we classify the hundreds of varieties in the Loop Survey data set into three main varietal groups: the "TV" group, the "Early MVs" group, and the "Recent MVs" group.[5] The TV group is the omitted category in the regressions, which includes the varieties prior to the Green Revolution. Rice varieties commonly considered as MV1, MV2 and MV3 are included in the "Early MVs" group, where "Early MV" is a dummy variable equal to one if the rice variety planted is either considered as MV1, MV2, or MV3, zero otherwise. In addition, rice varieties commonly classified as MV4 and MV5 are included in the "Recent MVs" group, where it is represented as a dummy variable equal to one if the rice variety planted is commonly considered as "Recent MVs", zero otherwise.

The term $\mathbf{X}_{ijmt}$ is a vector of control variables that include parcel-level input applications (e.g.,

[3] See http://wwwww.worldclim.org/version1 for the WorldClim data and https://crudata.uea.ac.uk/cru/data/hrg/ for the CRU data. For more information on how these two data sets were constructed see [Hij05] and [Har14], respectively.

[4] Administrative unit data were collected from the Global Administrative Areas (GADM) database located at http://www.gadm.org.

[5] This means that, for the purpose of parsimony, we did not use the more common MV1 to MV5 varietal group classification as described in the previous section (and as utilized in previous studies like [Lau08] and [Lab15]).

fertilizer use, pesticide applications, and labor), as well as other farmer/farm socio-demographic characteristics (e.g., age, education, land tenure). The term ηt is a linear time trend that is common to all farms in the sample and, in previous studies, it typically represents technological evolution. However, note that the use of rice varietal group dummies in the specification allows us to separate at least the "varietal development" part of the technological change from this time trend. The term ε_{ijmt} is the parcel-level idiosyncratic error term, and δ, β, ψ, and γ are parameter vectors to be estimated.

Note that the farm-level fixed effects (α_j) allow one to control for potential endogeneity caused by farm-level, time-invariant unobservables that do not vary across parcels within a farm (i.e., like unobserved farmer management ability). Given that farm size in our data only averages around 1 to 2 hectares, it is reasonable to expect that these farm-level fixed effects adequately control for potential endogeneity caused by time-invariant unobservables. Furthermore, we cluster standard errors at the village level to account for potential correlations among the parcels within a farm and the spatial correlations among farms within a village.

2.3.1 Climate Function Specification

To estimate Equation (2.1), the function $f(\mathbf{tmin}_{kmt}, \mathbf{tmax}_{kmt}, \mathbf{prec}_{mt}, \mathbf{V}_{ijmt}; \delta, \beta, \psi)$ needs to be specified. The weather variables used are minimum temperature ($tmin$), maximum temperature ($tmax$), and precipitation ($prec$), which are the same weather variables typically used in previous studies ([Wel10]; [Has16]).[6] Note however that these weather variables were only available at the municipality level (m), and not at the farm or parcel level. As discussed further below, we also run an alternative specification with the following weather variables: $tavg$, dtr, and $prec$. In this case, the variable $tavg$ is mean temperature (in °C), dtr represents the diurnal temperature range (which is equal to the difference between $tmax$ and $tmin$), and $prec$ is cumulative precipitation fo the entire season (as previously defined). This alternative specification is also used in [Wel10].

In our main empirical specification, we use $tmin$ and $tmax$ by k growing phase, instead of by month. We decided to do this in order to have a parsimonious specification to facilitate estimation and for ease of interpretation. Since our focus is on the WS, it is important to note that this growing season spans 3-6 months and the lengths of the growing season vary across provinces. One can then designate the main growing phases in each season as $k = 1, 2, 3$, where 1 = vegetative phase, 2 = reproductive phase, and 3 = ripening phase. For example, $tmax_{3mt}$ would represent the maximum temperature for the ripening phase ($k = 3$).

However, the raw climate data set only contain the monthly average of daily minimum temperatures and maximum temperatures, as well as the monthly cumulative precipitation (i.e., the sum of daily observations within a month). To construct weather variables by growing phase, we need to assign the monthly weather values to each growing phase for each year and across all provinces in the survey data. Therefore, data on the "rice growing windows" (i.e., the dates from planting to har-

[6] Minimum temperature is normally associated with nighttime temperatures and maximum temperature is associated with daytime temperatures. [Wel10] have shown that these two variables may have differing effects on rice yields.

vesting) for each growing season in the data are required. For this purpose, we utilized the RiceAtlas ([Lab17]), which contains the planting and harvesting dates for all of the provinces covered by the Central Luzon Loop Survey. (See Table 2.3 for average maturity and growing phase lengths provided by RiceAtlas.) However, the RiceAtlas mainly focuses on the "growing windows" from 1979 onwards, while the Loop survey data covers a longer period of time (i.e. from 1966 to 2016). Information about "growing windows" for the earlier years of the Loop survey is not available. Thus, we needed to make reasonable assumptions about the months to include in each phase for earlier years of the Loop survey data. Before 1979, when TVs and MV1 are the major varieties adopted, growing seasons typically lasted around 5 to 6 months, and the wet season starts around June and ends in November. The vegetative phase usually lasts 75-95 days (i.e., 3 months), with the duration of both the reproductive and ripening phases around one month (see http://www.knowledgebank.irri.org/step-by-step-production/pre-planting/crop-calendar). Based on the information above, for the years prior to 1979, we take the average weather values from June to September as the vegetative phase value, the average of September and October as the reproductive phase value, and the average of October and November as ripening phase value. With the adoption of MV2, the average growth period declined from about 150 days in the 1960s and 1970s to about 110-120 days in the 1980s and 1990s ([Moy15]). For growing seasons after 1979, the RiceAtlas provides accurate planting and harvesting dates, and we, therefore, use this information to properly assign the monthly weather values to appropriate growing season phases for these years.

Another major component of the climate function $f(\cdot)$ is the rice varietal group dummies ($\mathbf{V}_{ijmt}$). In this study, we designate TV as the base group (e.g., the omitted category) and then use the notation V^r to represent the 2 other varietal groups we defined in the previous section (i.e., $r = 1,2$ corresponds to 1 = "Early MVs" and 2 = "Recent MVs", respectively. The area planted to each varietal grouping (for each survey year) is presented in Figure 2.2.

Given the notations discussed above, the climate function $f(\cdot)$ can then be fully specified as follows:

$$\begin{aligned}\sum_{r=1}^{2}\beta^r\mathbf{V}^r_{ijmt} + \sum_{k=1}^{3}\delta_{1k}\mathbf{tmin}_{kmt} + \sum_{k=1}^{3}\delta_{2k}\mathbf{tmax}_{kmt} + \delta_3\mathbf{prec}_{mt} + \delta_4(\mathbf{prec}_{mt})^2 + \\ \sum_{k=1}^{3}\sum_{r=1}^{2}\psi^r_{1k}(\mathbf{tmin}_{kmt}\times\mathbf{V}^r_{ijmt}) + \sum_{k=1}^{3}\sum_{r=1}^{2}\psi^r_{2k}(\mathbf{tmax}_{kmt}\times\mathbf{V}^r_{ijmt}) + \\ \sum_{r=1}^{2}\psi^r_3(\mathbf{prec}_{mt}\times\mathbf{V}^r_{ijmt}) + \sum_{r=1}^{2}\psi^r_4((\mathbf{prec}_{mt})^2\times\mathbf{V}^r_{ijmt})\end{aligned} \tag{2.2}$$

Quadratic precipitation terms is added to the climate function to allow for nonlinear precipitation effects, which is similar to the specification used in previous research ([Tac15b], [Lob11], [Sch10a]). The climate-MV interaction terms make it possible to examine whether there is heterogeneity in each varietal groups' response to weather variables.

2.3.2 Specification of Control Variables

The next component of Equation (2.1) that needs to be specified is the vector $\mathbf{X}_{ijmt}$, which accounts for a number of control variables such as parcel-level input applications and other socio-demographic farm characteristics. Including these variables in the specification allows us to control for observable time-varying factors that can influence rice yields, thereby improving the accuracy and efficiency of our estimations.

The input application variables included in the specification are: fertilizer applications (in kg/ha), labor use (in man-days/ha), insecticide use, and land size(ha). These are considered as major determinants of rice yields ([Moy15]). Socio-demographic characteristic included in the specification is land tenure status, age, education of household head (in no. of years), number of family members whose primary job is farming, and secondary job is farming. Land tenure status is represented by a dummy variable "Own" where this variable is equal to 1 if the land is owned, and it is zero otherwise (e.g., share tenant, fixed rent leaseholder, or other tenurial arrangements). Table 2.1 provides descriptive statistics for the "economic variables" included in the empirical model, and Table 2.2 presents the summary statistics for the weather variables.

2.3.3 Marginal Effects

One of the main goals of this chapter is to investigate heterogeneity in the yield response of different rice varietal groups to weather variables. The yield response is measured by the marginal effect of changes in weather variables on rice yield. Given the climate function specified in Equation (2.2), the marginal effect of minimum and maximum temperatures can be calculated using the following:

$$\frac{\partial y}{\partial \mathbf{tmin}_k} = \delta_{1k} + (\psi^r_{1k} \times \mathbf{V}^r_{ijmt}), \tag{2.3}$$

$$\frac{\partial y}{\partial \mathbf{tmax}_k} = \delta_{2k} + (\psi^r_{2k} \times \mathbf{V}^r_{ijmt}) \tag{2.4}$$

where $\mathbf{V}^r_{ijmt}$ is the parcel-level rice varietal group dummy variables. For example, suppose the rice variety adopted belongs to the "Early MVs" group, then $\mathbf{V}^1_{ijmt} = 1$. In this case, the marginal yield effect of a one-unit change in the minimum (maximum) temperature for the kth phase is $\delta_{1k} + \psi^r_{1k}$ ($\delta_{2k} + \psi^r_{2k}$) (i.e., the coefficient associated with the weather variable plus the coefficient associated with the interaction of the weather variables and the varietal grouping dummy). Because TV is designated as the base varietal grouping, the marginal effects of weather variables $\mathbf{tmin}_{kmt}$ and $\mathbf{tmax}_{kmt}$ on TV rice yield are δ_{1k} and δ_{2k}, respectively. On the other hand, the marginal effect of growing season cumulative precipitation is:

$$\frac{\partial y}{\partial \mathbf{prec}} = \delta_3 + (2 \times \delta_4 \times \mathbf{prec}) + (\psi^r_3 \times \mathbf{V}^r_{ijmt}) + (2 \times \psi^r_4 \times \mathbf{prec} \times \mathbf{V}^r_{ijmt}) \tag{2.5}$$

The simple marginal effect expressions in Equations (2.3) and (2.4) can easily be interpreted if there are only a few weather variables to consider for each growing phase and if there are only one or two rice varietal groups. However, as seen in Equations (2.3) and (2.4) above, our empirical model includes six "temperature-growing-phase" variables for each of two MV groups. Given the number of parameters involved, drawing sensible and consistent inferences using the simple marginal effect expressions in Equation (2.3) and (2.4) would be difficult and complex. As such, for ease of interpretation and to facilitate making inferences, we focus on estimating the marginal effect of a particular "warming scenario", where we are interested in the cumulative marginal effect of a 1°C increase in both $tmin$ and $tmax$ in all three rice-growing phases (or for a particular phase).[7] The marginal effect of this specific "warming scenario" can then be calculated respectively for the TVs, Early MVs, and Recent MVs as follows:

$$\sum_{k=1}^{3} \frac{\partial y \mid V = \text{TV}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \text{TV}}{\partial \mathbf{tmax}_k} = \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} \tag{2.6}$$

$$\begin{aligned} \sum_{k=1}^{3} \frac{\partial y \mid V = \text{Early MVs}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \text{Early MVs}}{\partial \mathbf{tmax}_k} = \\ \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} + \sum_{k=1}^{3} \psi_{1k1} + \sum_{k=1}^{3} \psi_{2k1} \end{aligned} \tag{2.7}$$

$$\begin{aligned} \sum_{k=1}^{3} \frac{\partial y \mid V = \text{Recent MVs}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \text{Recent MVs}}{\partial \mathbf{tmax}_k} = \\ \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} + \sum_{k=1}^{3} \psi_{1k2} + \sum_{k=1}^{3} \psi_{2k2} \end{aligned} \tag{2.8}$$

From these equations, we can calculate the warming yield response of Early MVs and the Recent MVs as compared to TVs. This allows us to make inferences on whether or not the Early MVs and/or Recent MVs are more resilient to warming temperatures relative to the TVs.

On the other hand, for calculating the impact of cumulative precipitation ($prec$), we can directly derive the marginal effect because we utilize a single cumulative growing-season precipitation variable in the specification, instead of precipitation in each of the three growing phases. For example, the estimated marginal effect of a 1mm increase in the cumulative precipitation for the TVs, Early MVs, and Recent MVs can be calculated as follows:

$$\frac{\partial y \mid V = \text{TV}}{\partial \mathbf{prec}} = \delta_3 + 2 \times \delta_4 \times \mathbf{prec} \tag{2.9}$$

$$\frac{\partial y \mid V = \text{Early MVs}}{\partial \mathbf{prec}} = \delta_3 + 2 \times \delta_4 \times \mathbf{prec} + \psi_{31} + 2 \times \psi_{41} \times \mathbf{prec} \tag{2.10}$$

$$\frac{\partial y \mid V = \text{Recent MVs}}{\partial \mathbf{prec}} = \delta_3 + 2 \times \delta_4 \times \mathbf{prec} + \psi_{32} + 2 \times \psi_{42} \times \mathbf{prec} \tag{2.11}$$

Given that a squared precipitation term and its interaction with the varietal group dummy are

[7] Even though the specific "warming scenario" discussed here is mainly for the purpose of facilitating interpretation, it is important to note that minimum and maximum temperatures in the Philippines tend to move together and are usually positively correlated (See [Wel10]; [Pen04]). Our data also supports this behavior (See Supplementary Figure S2.2 and Supplementary Table S2.3). Therefore, the base "warming scenario" examined here is still is fairly reasonable based on this positive correlation between $tmin$ and $tmax$. Nevertheless, given that minimum and maximum temperatures are likely not to move together in *exactly* 1°C intervals in reality, we also explore marginal effects for the case where $tmin$ and $tmax$ changes based on projections from climate models (See Section 2.4 below).

included in Equation (2.2), the marginal impacts of precipitation in Equations (2.9) to (2.11) are a function involving the value of $prec$. In this study, we calculate the marginal impact of cumulative precipitation at the mean of $prec$. In addition, we also measure and report the marginal effect of a 1 standard deviation increase in precipitation (at the mean of $prec$).

2.4 Estimation Results

The fully specified empirical model for this study is primarily based on Equations (2.2) and (2.2) above. However, in this section, we also present estimation results from four other more parsimonious models, which then build towards the full specification results from Equations (2.2) and (2.2). The first parsimonious model (Model 1) is our baseline where we do not include the interaction terms between the temperature variables and the varietal group dummies, for all three growing phases. In Model 1, we only include the interaction of $tmin$ for the vegetative growth phase with the varietal group dummies, and the interaction of $tmax$ for the ripening phase with the varietal group dummies.[8] In addition, the baseline model also includes the $tmin$ and $tmax$ variables in all phases individually, the fixed effects, and the time trend. The second parsimonious model (Model 2) includes the interactions of the $tmin$ and $tmax$ variables in all growing phases (e.g., the vegetative, reproductive, and ripening phases), instead of just the varietal group interactions with the vegetative phase $tmin$ and the ripening phase $tmax$, plus the remaining variables in Model 1. Next, the third parsimonious model (Model 3) adds on the $prec$ and squared $prec$ terms to Model 2. The fourth parsimonious model (Model 4) then includes all variables of Model 3 and adds the interactions of $prec$ and squared $prec$ with varietal grouping dummy variables. Lastly, the fully specified model is Model 5, where all the economic variables (i.e., input application variables and socio-economic variables) are included in the specification, in addition to the variables in Model 4 (i.e., this is the full expressions from Equations (2.2) and (2.2)). The parameter estimates for all of these models are presented in Supplementary Table S2.1 in Appendix A.

The pertinent marginal effects for Models 1 to 5 under a variety of warming scenarios are presented in Table 2.4.[9] Marginal effects for the "baseline" model (Model 1) and the corresponding P-values are in columns 2 and 3. Model 2 results are presented in columns 4 and 5. Marginal effects and their P-values for Model 3 are in columns 6 and 7. Marginal effects and their P-values for Model 5 are in columns 8 and 9. Lastly, the marginal effects and their P-values based on the full specification are shown in columns 10 and 11.

[8]The vegetative rice-growing phase $tmin$ and the ripening phase $tmax$ were chosen in this baseline model based on a preliminary run of the empirical model without any interactions, but including all the individual $tmin$ and $tmax$ variables in all phases (i.e., vegetative, reproductive, and ripening phases). In this preliminary run, the parameters associated with the $tmin$ in the vegetative phase and $tmax$ in the ripening phase are the largest. Therefore, this preliminary run suggests that $tmin$ during the vegetative phase and $tmax$ during the ripening phase had the largest impact on rice yields. Therefore, we decided to have an initial parsimonious baseline model that only include the climate-varietal-group interactions for these two variables.

[9]The warming scenario considered in Table 2.4 is a 1°C increase in $tmin$ and $tmax$. We also provide the marginal effects for a warming scenario that increases $tmin$ and $tmax$ by 1 standard deviation in Supplementary Table S2.2 and Supplementary Figure S2.3 in Appendix A. The pattern of results in both cases are similar.

For all model specifications, a warming scenario that increases $tmin$ and $tmax$ by 1°C in all growing phases substantially reduces rice yields, though some of the estimated warming effects are not statistically significant at the usual levels of significance (i.e., see warming scenario in the top panel of Table 2.4). The magnitudes of our marginal effects range from -6.6% (for Recent MVs in the "baseline" model) to -27.5% (for the TVs under Model 3). Results presented in the other two warming scenarios, where only $tmin$ or $tmax$ are increased separately by 1°C (see middle panels of Table 2.4), indicate that $tmin$ is the likely source of the observed negative yield impact of warming. This result is consistent with results from [Wel10] where $tmin$ effects were also found to be the stronger determinant of rice yield losses due to warming temperatures. It is also important to note that the estimated adverse warming effects observed in Model 3 and Model 4 became higher (relative to the effects in Models 1 and 2), as one controls for precipitation and its interactions. However, the observed marginal effects in Model 5 are lower than the estimates in Models 3 and 4 after a set of economic variables are added to the specification. This suggests that controlling for precipitation and possible time-varying confounding factors may be important in our empirical context.[10]

Another important result from Table 2.4 is the heterogeneity of the warming impacts across the three varietal groups examined. In Figure 2.3, we graphically present the marginal percentage yield effects of the main warming scenario (e.g, a 1°C increase in both $tmin$ and $tmax$ across the vegetative, reproductive, and ripening phases) for the three varietal groups. For all five model specifications, the warming impact is lowest for the Recent MVs varietal group.[11] This result provides some farm-level evidence that rice breeding efforts to improve tolerance to abiotic stresses have indeed resulted in more resilience to warming temperatures. In addition, we observe in Figure 2.3 that the negative warming effect on yields is smaller for the Early MVs as compared to the TVs (across all model specifications). This is suggestive of a "spillover" warming tolerance effect from early rice breeding efforts that were targeted primarily for increasing yields, improving pest resistance, and/or enhancing quality traits (rather than enhancing tolerance to abiotic stresses).

Next, we utilize the parameter estimates from our fixed-effect models to investigate how projected future climate change will likely influence potential rice yields of the three varietal groups examined in this study.[12] To complete this climate projection and rice yield simulation exercise, we utilize the projected climate change values from PAGASA, the main meteorological government agency in the Philippines. The climate change values from PAGASA are the projected change in sea-

[10] It should be noted here that although including farm inputs in the specification can help control for confounding factors, it can also raise endogeneity concerns especially if there are parcel-level unobservables not adequately controlled for by the farm-level-fixed effects. Nonetheless, this concern is mitigated by the result that the magnitudes of the estimated effects in Models 3 to 5 are roughly similar.

[11] In Figure 2.3, there are clear variations in the estimated magnitudes of the marginal effects. However, the confidence bands do not clearly suggest that the marginal effects are statistically different across varietal groups. This may simply be due to sample size limitations in the data and perhaps test power issues, which we believe does not wholly invalidate the inferences made.

[12] Simulating the effect of projected future climate on rice yields also provides additional insights relative to the 1°C warming scenario examined in Table 2.4 since this simulation exercise does not implicitly assume that $tmin$ and $tmax$ change by the same amount (i.e., dtr is not assumed to be constant in the future climate projections).

sonal minimum temperature, maximum temperature, and precipitation from the average over the period 1971-2000 to the average over the period 2011-2040. These projected changes are generated based on the statistical downscaling of three global climate models (GCMs): (1) the BCM2, (2) the CNCM3, and (3) MPEH5; and two plausible emissions scenarios: (1) the A1B emission scenario, and (2) the A2 emission scenario.[13]

The projected changes in $tmin$ and $tmax$ and $prec$ for each of the six provinces in this study are presented in Supplementary Table S2.4, Supplementary Table S2.5, and Supplementary Table S2.6. In addition, the summary statistics for the average across the six Loop survey provinces by growing phase (in the WS) are provided in Supplementary Table S2.7. Note that Supplementary Table S2.7 shows that both $tmin$ and $tmax$ are predicted to increase in the future. Under most of the "emission-scenario-GCM-growing phase" combinations examined, the magnitudes of the changes in $tmin$ and $tmax$ are similar (which validates the original "warming scenario" examined above). However, specifically under the"A1B-CNCM3-Vegetative Phase" combination and the"A2-CNCM3-Vegetative Phase" combination, the incremental increase in $tmin$ is double that of the increase in $tmax$, which typically leads to relatively different climate predictions under CNCM3 model (as compared to the other two GCMs).

The percentage change in rice yields due to the projected temperature changes are presented in Figure S2.4 and Figure S2.5 for the fully specified model (Model 5), and the detailed yield effects for all models are presented in Supplementary Table S2.8. In general, our results suggest that the Recent MVs yields are still the ones that are more tolerant to projected warming temperatures for most of the GCM-emission-scenario combinations examined (with the exception of the results from the CNCM3 projection model). Results from this analysis also suggest that Early MVs exhibit better tolerance to projected warming temperatures (as compared to the TVs). These climate projection results are consistent with the earlier analysis from the warming scenario examined (Table 2.4).

So far, we have focused on the differential warming impacts across different varietal groups using both the warming scenario and climate projection models. Precipitation effects have not been discussed. In Figure S2.7, we also show the marginal rice yield response due to a 1 standard deviation increase in growing season cumulative precipitation $prec$ (evaluated at the mean of $prec$). Increases in $prec$ (at the mean) tend to reduce yields of all three varietal groups. Among the three varietal groups, the estimated reduction in the Recent MVs yield is the smallest. These estimates indicate that the Recent MVs is the rice varietal group that is more tolerant to increases in cumulative precipitation. Although, it should be noted that the Early MVs also exhibit resilience to

[13]Note that GCMs are powerful computer programs that use physical processes to replicate, as accurately as possible, the functioning of the global climate system ([Com07]. The BCM2 model was established by the Bjerknes Centre for Climate Research. On the other hand, the CNCM3 GCM was developed by the Météo-France (Centre National de Recherches Météorologiques). Lastly, the MPEH5 was developed by the Max Planck Institute for Meteorology. These three GCMs are considered the most effective at simulating climate for the Philippines ([Tol16]).

On the other hand, the A1B and A2 are two emissions scenarios used in the regional climate projections of the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) and were generated by the Geophysical Fluid Dynamics Laboratory (GFDL) model. The A1 family of scenarios assumes a more integrated world and A1B is based on a balanced technological emphasis on all energy sources. The A2 scenarios, on the other hand, assumes a more divided world.

increases in cumulative precipitation (as compared to the TVs).

2.5 Robustness Checks

As a robustness check, we also estimate similar models as described in Equations (2.2) and (2.2), but instead of $tmin$ and $tmax$, as the two main temperature variables considered, we instead utilize average temperature ($tavg$) and diurnal temperature range (dtr). Cumulative precipitation $prec$ is still included in this robustness check specification (with both linear and quadratic terms). We still follow the approach from the previous section where we examine four parsimonious models (Models 1-4) and build-up to a fifth full model specification.[14]

The estimated marginal yield effects of $tavg$ and dtr for various warming scenarios and model specifications are presented in Table 2.5 (and regression results for the specifications are in Supplementary Table S2.9 in Appendix A). In addition, the marginal effects of a 1°C increase in $tavg$ are graphically shown in Figure 2.4. Our results indicate that increases in $tavg$ negatively impact rice yields. However, the magnitudes of the marginal effects for $tavg$ is smaller than the ones in the previous section for $tmin$ and $tmax$. In addition, a good number of these marginal effects are statistically insignificant, which is consistent with previous studies ([Wel10]). This is because, for most varietal groups in nearly all specifications, $tmin$ and $tmax$ have opposing rice yield impacts. Thus, the opposing temperature impacts may partly cancel each other out. On the other hand, the marginal effect of dtr is positive (See Table 2.5 (middle panel) and Supplementary Figure S2.8). Note that an increasing dtr means that $tmax$ is increasing faster than $tmin$, while a decreasing dtr means that $tmin$ is growing faster than $tmax$. Thus, the positive marginal effect for dtr supports the notion that increasing $tmin$ has a negative impact on rice yields (i.e., consistent with our main specification results in the previous section).

Under all five model specifications, the percentage negative yield impact of $tavg$ is the highest for TVs and the lowest for the Recent MVs. This result is consistent with the conclusion we made based on the models above involving $tmin$ and $tmax$, which provides further evidence as to the effectiveness of the breeding work done to develop MV4 and MV5. In addition, Figure S2.9 shows the marginal yield impacts of $prec$ at the mean for the model using $tavg$ and dtr, which also shows the robustness of the precipitation mitigation effect of the Recent MVs from the earlier regression runs.

Another robustness check is running separate regressions by varietal groups. The dataset was divided into three subsamples by varietal groups. We constructed a model specification including linear terms for $tmin$ and $tmax$, linear and quadratic terms for $prec$, and applied this specification to each varietal group subsample. The estimated impacts of a +1°C warming scenario and a 1 standard deviation increase in $prec$ for each varietal group subsample are seen in Supplementary

[14]One subtle difference to note in the baseline model here (Model 1) is that the interactions considered are only for: (a) $tavg$ in the reproductive phase, and (b) dtr in the vegetative phase. As in the previous section, this choice was made since preliminary runs of specifications without interactions indicate that the estimated coefficients associated with reproductive phase $tavg$ and vegetative phase dtr are the highest (among the $tavg$ and dtr coefficients for all three growing phases separately).

Table S2.10 and the parameter estimates are reported in Supplementary Table S2.11. In addition, we graphically show the impact of a 1°C warming scenario based on the separate regression runs in Supplementary Figure S2.10, while the impact of a 1 standard deviation increase in $prec$ is provided graphically in Supplementary Figure S2.11. Note that in Supplementary Figure S2.10, we only plot the confidence interval for early MVs and recent MVs because of the large confidence interval for the TV group (which is likely due to the small sample size), and this does not easily fit the scale of the figure. Even though the significance of estimated marginal effects largely decline in these subsample runs due to the small sample sizes (especially for TVs), the mitigation effect observed for the Recent MVs is still present.

Since the roll-out and use of the different varieties occurred sequentially through time (i.e., TVs in earlier years, followed by the release of Early MVs, and then Recent MVs in more recent years), one other approach to check the robustness of results is by running a specification without varietal group dummy interactions with weather, but instead interacting the weather variables (by growing phase) with the time trend. Parameter estimates from this alternative specification are reported in Supplementary Table S2.12.[15] In this specification, varietal development is embedded in the time trend (along with other rice technologies evolving over time). Hence, if varietal development is the main driver of rice technological change, then we would expect a pattern where the adverse effect of warming would be larger in earlier years (where TV is predominant) and it would then slowly decrease over time as more MVs are released. More recent years will have smaller negative warming effects than earlier years given the release of MV4 and MV5. This pattern is indeed verified and shown in Supplementary Figure S2.12 in Appendix A, which supports the robustness of our earlier results.

Another robustness check we conducted is to examine a specification with both: (a) varietal group interactions with the weather and (b) time trend interactions with the weather. Compared to the specification in the previous paragraph, this last specification separates out the warming effect of varietal groups from the warming effect due to other technologies. Parameter estimates from this specification are reported in Supplementary Table S2.13 and the pertinent marginal effects are presented in Supplementary Figure S2.13. Results from this last robustness check are still consistent with the main pattern of results from the previous analysis, where the adverse warming effect is smaller for the recent MVs relative to the earlier MVs and the TVs.

The number of observations for TV is relatively small and available only at the beginning several years of the study period (see Figure 2.2). For this reason, estimates related to TV have large standard errors and are insignificant in the major model. Due to the difficulty of getting efficient estimators for

[15]Specifically, results from Model 3 and Model 4 in Supplementary Table S2.12 are the ones that coincide with the specification and results described here. We also present results from another two specifications (Model 1 and Model 2) where there are no varietal group interactions with the weather and no time trend interactions with the weather. This is the case where one has no data on varietal groups and it is assumed that the marginal effect of warming is constant. In this case, the estimated marginal impact of 1°C warming scenario is -15.3% from Model 1 and -11.5% from Model 2. Hence, in this naive specification, we do not adequately capture the heterogeneity in the warming effects (e.g., the larger warming effects on TVs) and further highlights the importance of having varietal data when exploring climate change impacts in agriculture.

TV, we estimate the model without observations for TV to compare the resilience of early MVs and recent MVs to weather changes. Column 9 in Table S2.15 shows the warming impacts on early MVs and recent MVs estimated by the major model dropping TV from the data. 1°C warming scenario results in a larger reduction in the yield of early MVs than the recent MVs.

Even though the classification of MV5 is completely based on the year of release rather than the characteristics different from the previous generation of modern varieties. It is still interesting to see how their resistances to weather variables are different. For this reason, we separate recent MVs into MV4 and MV5 and estimate the coefficients for them separately. The marginal impact of warming and precipitation change estimated from these models are provided by Table S2.18 and Table S2.19. According to the results, both MV4 and MV5 are shown to be more resistant to 1°C warming than the earlier varieties and the temperature resilience for MV5 is slightly higher than but close to MV4.

Other robustness checks include estimating the effects of precipitation for three growing phases rather than the entire growing season, adopting "fixed" growing phase windows (assume each of the vegetative, reproductive and ripening phase takes two months), interacting input variables with varietal group dummies, interacting maximum temperature, precipitation and varietal group dummies and run regressions with a variety of specifications for time control: models controlling for cubic time trends, year fixed effects, and province-specific time trends. Results from these alternative models also support the conclusion made from our major analysis. (see Table S2.14 and Table S2.15)

2.6 Conclusions

The main objective of this chapter is to investigate whether modern rice varieties (MVs) mitigate the adverse yield impacts of climate change, especially the more recent varieties (MV4 and MV5) specifically bred to be more tolerant to abiotic stresses. By merging Philippine farm-level survey data (from 1966-2016) with monthly, municipality-level climate data, we are able to estimate fixed effect econometric models with "weather-varietal group" interactions and assess whether there is heterogeneity in the warming effects across different rice varietal groups. Results from the analysis indicate that modern rice varieties mitigate the detrimental effects of warming on rice yields, and there is evidence that rice varieties in the recent MVs varietal group indeed tend to be more resilient to a warming climate relative to the earlier rice MVs. Although early modern varieties were not specifically developed to address climate change and other abiotic stresses, we find that they in fact partially mitigate the negative yield effects of warming. The presence of some climate change mitigation effects for these early modern rice varieties can be considered a "spillover" benefit from rice breeding efforts that were not specifically targeted to improve resilience to climate change. Moreover, the stronger climate change mitigation effects for recent MVs provides evidence that there are indeed direct yield benefits from rice-breeding efforts to improve tolerance to abiotic stresses.

Findings from our study suggest that public rice breeding efforts to develop rice varieties with "high-temperature tolerance traits" is essential to the maintenance of past rice yield gains, especially in a future with global warming. This implies that future public investments in breeding for abiotic stress tolerance is important for ensuring food security and in reducing climate-change-induced production risks faced by rice farmers in developing countries. Even though we provide some evidence on the success of recent breeding efforts to increase resilience to abiotic stress, our results for rice producers in the Central Luzon region of the Philippines still show that rice yields will be negatively affected by future climate change even when using MV4 and MV5. Hence, there should be continued research investments in rice breeding at international centers (i.e., like IRRI) and national breeding institutions (i.e., such as PhilRice in the Philippines and BRRI in Bangladesh) if rice yield growth is expected to continue in the future and meet the food demand of a population getting close to 10 billion by 2050. Specific focus on funding research projects to develop "climate-change-tolerant" rice varieties should be one of the priorities of funding agencies and donor institutions interested in global food security and poverty alleviation in developing countries (e.g., Bill and Melinda Gates Foundation, USAID, etc.).

For rice farmers, our results indicate that rice variety selection is an important adaptation strategy to climate change. However, the adoption of new rice varieties often demands more knowledge, better management, and higher cost. Therefore, policies and programs that provide more education and outreach programs are needed to help producers understand the relationships between climate (as well as other production environment conditions) and the yield and quality impacts of planting different rice varieties. Providing small initial subsidies for rice farmers to try out new climate-change-tolerant varieties may be one policy option that developing country governments can explore (i.e. if they want to encourage adoption of these varieties). Lastly, providing extension support to provide information about complementary climate change adaptation strategies (other than simply adopting more tolerant varieties) would also better arm producers with tools to face a production environment with higher temperatures and more frequent extreme weather events.

Even though the present study provides important inferences about the likely heterogeneous effects of warming across different rice varietal groups, it is important to recognize some limitations in the study. First, the sample size of our survey data is still relatively small and this constrained us to only focus on climate change effects for irrigated rice farmers in the WS. It may not be appropriate to extrapolate our data to rainfed rice farmers planting in the dry season. Nevertheless, since climate change is likely to cause more damage to rice grown in the dry season, it is reasonable to say that our estimated results can be considered as a lower bound of the warming impacts across rice varietal groups. Second, the relatively small survey sample also made us focus on developing more parsimonious models, rather than developing more flexible models that are less parsimonious. We leave these kinds of efforts for future work. Third, the weather data used in the study was only at the municipal level (rather than at the farmer level or lower levels of aggregation). Future studies may consider collecting individual farm-level weather data to improve inferences going forward. In addition, collecting individual information about other weather variables like radiation and vapor pressure deficit (VPD) may also be important in better understanding rice yield effects under climate change in the future ([Kri05], [Wel10], [Gou13]). Lastly, conducting the analysis in this study for other countries with more variable weather may also be beneficial in the future.

Table 2.1 Descriptive statistics for the economic variables

Variable & Units/Definition	Units/Definition	Mean	St Dev	Min	Max
Yield	kg/ha	3890.09	1555.77	306.67	11250.00
Land Tenure	1=owner; 0=other	0.42	0.49	0.00	1.00
Farm size	ha	1.32	0.97	0.03	9.00
Age of Head	no. of yrs.	52.63	13.65	22.00	94.00
Educ. of Head	no. of yrs.	7.25	3.34	0.00	16.00
Primary farming	no. of family members	1.09	0.38	1.00	5.00
Secondary farming	no. of family members	0.08	0.28	0.00	2.00
Labor	man-days/ha	70.14	28.70	0.00	257.75
Nitrogen Fert.	kg/ha	81.93	50.51	0.00	483.91
Potassium Fert.	kg/ha	11.04	13.50	0.00	127.80
Phosphorus Fert.	kg/ha	9.21	8.28	0.00	67.10
Insecticide	kg/ha	1.50	2.64	0.00	70.27
Molluscicide	kg/ha	0.25	0.97	0.00	10.00
Herbicide	kg/ha	0.90	2.42	0.00	32.00
Rodenticide	kg/ha	0.01	0.16	0.00	5.00

Table 2.2 Descriptive statistics for the weather variables in Central Luzon area

Variable	Unit	Mean	St Dev	Min	Max
vtmin	Deg. C	22.85	0.61	19.91	24.05
vtmax	Deg. C	30.50	0.83	27.56	32.00
vtavg	Deg. C	26.66	0.67	24.16	28.00
vdt	Deg. C	7.65	0.74	5.14	9.45
retmin	Deg. C	22.63	0.74	20.15	24.31
retmax	Deg. C	30.40	0.79	27.78	32.45
retavg	Deg. C	26.48	0.68	24.03	28.07
redt	Deg. C	7.76	0.75	5.00	9.50
ritmin	Deg. C	22.48	0.81	19.83	24.34
ritmax	Deg. C	30.55	0.83	27.62	32.57
ritavg	Deg. C	26.43	0.72	24.02	28.13
ridt	Deg. C	8.07	0.87	6.00	10.51
Cum. Precip.	mm	1386.36	357.47	692.84	3038.72

Notes: The table above displays the descriptive statistics of weather variables used in the regressions. The first four rows are the growing season averages of the daily minimum, maximum, and mean temperatures, as well as the diurnal temperature range for the vegetative phase. The second four rows are the weather variables for the reproductive phase and the third four rows show the weather variables for the ripening phase. The last row is cumulative precipitation for the entire growing season.

Table 2.3 Average maturity of six provinces in Central Luzon area

	Maturity		**Approximate phase durations in days**		
	In days	**In months**	**Vegetative**	**Ripening**	**Reproductive**
La Union	123	4	60	30	30
Pangasinan	123	4	60	30	30
Bulacan	112	4	50	30	30
Nueva Ecija	96	3	35	30	30
Pampanga	123	4	60	30	30
Tarlac	92	3	35	30	30

Table 2.4 Marginal percentage yield impact of weather variables for different warming scenarios and varietal groups

Variables	Model 1 vtmin*V, ritmax*V		Model 2 3 tmin*V, 3tmax*V		Model 3 add prec, precsq		Model 4 add prec*V, precsq*V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tmin&tmax: tv	-0.195	0.130	-0.169	0.202	-0.275	0.025	-0.266	0.028	-0.240	0.122
tmin&tmax: early mv	-0.084	0.116	-0.115	0.049	-0.220	0.000	-0.232	0.000	-0.197	0.024
tmin&tmax: recent mv	-0.066	0.201	-0.110	0.060	-0.199	0.006	-0.187	0.008	-0.124	0.198
1°C increase in tmin:										
tmin: tv	-0.191	0.276	-0.379	0.094	-0.534	0.015	-0.679	0.004	-0.670	0.007
tmin: early mv	-0.111	0.043	-0.100	0.066	-0.229	0.001	-0.239	0.000	-0.236	0.001
tmin: recent mv	-0.065	0.363	-0.196	0.110	-0.344	0.031	-0.315	0.020	-0.215	0.109
1°C increase in tmax:										
tmax: tv	-0.004	0.978	0.210	0.419	0.260	0.306	0.414	0.121	0.430	0.143
tmax: early mv	0.027	0.562	-0.015	0.774	0.009	0.868	0.007	0.889	0.039	0.560
tmax: recent mv	-0.001	0.988	0.087	0.312	0.146	0.169	0.128	0.131	0.091	0.275
1 standard deviation increase in cumulative precipitation:										
prec: tv							-0.213	0.181	-0.285	0.097
prec: early mv							-0.168	0.000	-0.152	0.000
prec: recent mv							-0.084	0.207	0.009	0.891

Notes: (1) The table displays coefficients and p-values of marginal yield effect of 1°C warming scenarios and 1 standard deviation of increase in $prec$ from 5 farm fixed-effect models. Standard errors for each regression are clustered at the village level. (2) The different models are as follows. Model 1 is the "baseline" model where $tmin$ and $tmax$ of each growing phase and the interactions between $tmin$ in the vegetative phase ($vtmin$) and $tmax$ in the ripening phase ($ritmax$) and dummies for rice varietal groups are included in the specification. Model 2 includes the $tmin$ and $tmax$ variables in all the growing phases(e.g., the vegetative($vtmin$ and $vtmax$), reproductive($retmin$ and $retmax$), and the ripening phase ($ritmin$ and $ritmax$)) and their interactions with dummies for rice varietal groups. Model 3 adds on cumulative precipitation in the growing season ($prec$) and its quadratic term ($prec^2$) to Model 2. Model 4 adds on the interactions of $prec$ and squared $prec$ with varietal grouping dummy variables to Model 3. Model 5 is the specification including all the "economic variables" described by Table 2.1 in addition to the variables in Model 4. (3) The first column indicates what weather variables the marginal effects are based on, and which varietal group it pertains to. The three rows of the first panel indicate the marginal effect of a 1°C increase in both $tmin$ and $tmax$ for the TV, early MVs, and recent MVs varietal groups separately. The rows of panel 2 refer to the marginal effect of a 1°C increase in $tmin$ for the TV, early MVs, and recent MVs. The rows of the third panel refer to the marginal effect of a 1°C increase in $tmax$ for the TV, early MVs and recent MVs. Lastly, the rows of the fourth panel indicate the marginal effect of a 1 standard deviation of increase in $prec$ for the TV, early MVs, and recent MVs.

Table 2.5 Marginal percentage yield impact of weather variables: Alternative specification using mean temperatures & DTR

Variables	Model 1 vtmin*V, ritmax*V		Model 2 3 tmin*V, 3tmax*V		Model 3 add prec, precsq		Model 4 add prec*V, precsq*V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tavg: tv	-0.126	0.307	-0.055	0.670	-0.149	0.233	-0.158	0.198	-0.103	0.468
tavg: early mv	-0.073	0.100	-0.066	0.165	-0.142	0.004	-0.162	0.001	-0.116	0.075
tavg: recent mv	-0.052	0.148	-0.048	0.258	-0.126	0.018	-0.116	0.025	-0.031	0.648
1°C decrease in diurnal temperature variation:										
dtr: tv	-0.234	0.256	-0.224	0.382	-0.325	0.190	-0.465	0.047	-0.507	0.034
dtr: early mv	-0.018	0.663	-0.017	0.729	-0.087	0.126	-0.085	0.134	-0.100	0.081
dtr: recent mv	-0.112	0.048	-0.074	0.369	-0.191	0.066	-0.145	0.116	-0.118	0.225
1 standard deviation increase in cumulative precipitation:										
prec: tv							-0.246	0.017	-0.281	0.015
prec: early mv							-0.156	0.000	-0.142	0.000
prec: recent mv							-0.040	0.500	0.015	0.789

Notes: (1) The table displays coefficients and p-values of the marginal yield effect of 1°C increase in $tavg$ and 1°C decrease dtr for all phases in the growing season and 1 standard deviation increase in $prec$, based on the 5 farm fixed-effect models estimated. Standard errors for each regression are clustered at the village level. (2) The different models are as follows. Model 1 is the "baseline" model where $tavg$ and dtr for the three growing phases and the interactions between $tavg$ in the reproductive phase ($retavg$) and dtr in the ripening phase ($ridtr$) and dummies for rice varietal groups are included in the specification. Model 2 includes the $tavg$ and dtr variables in all the growing phases(e.g., the vegetative($vtavg$ and $vdtr$), reproductive($retavg$ and $redtr$), and the ripening phase ($ritavg$ and $ridtr$)) and their interactions with the rice varietal group dummies. Model 3 adds on cumulative precipitation for the growing season ($prec$) and its quadratic term ($prec^2$) to Model 2. Model 4 adds on the interactions of $prec$ and squared $prec$ with the varietal grouping dummy variables to Model 3. Model 5 is the full specification including all the "economic variables" described by Table 2.1 in addition to the variables in Model 4. (3) The first column indicates what weather variables the marginal effects are based on, and which varietal group it pertains to. The three rows of the first panel indicate the marginal effect of a 1°C increase in $tavg$ for the TV, early MVs and recent MVs varietal groups separately. The rows of panel 2 refer to the marginal effect of a 1°C increase in dtr for the TV, early MVs and recent MVs. Lastly, the rows of the third panel indicate the marginal effect of a 1 standard deviation of increase in $prec$ for the TV, early MVs, and recent MVs.

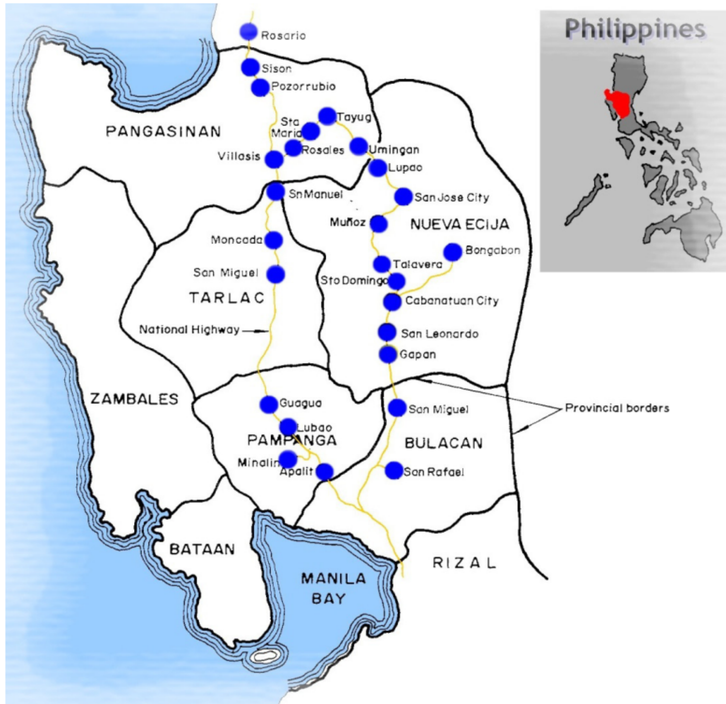

Figure 2.1 The Study Area: Central Luzon Loop Survey

Source: "Changes in rice farming in the Philippines: Insights from five decades of a household-level survey" (http://irri.org/resources/publications/books/changes-in-rice-farming-in-the-philippines-insights-from-five-decades-of-a-household-level-survey)

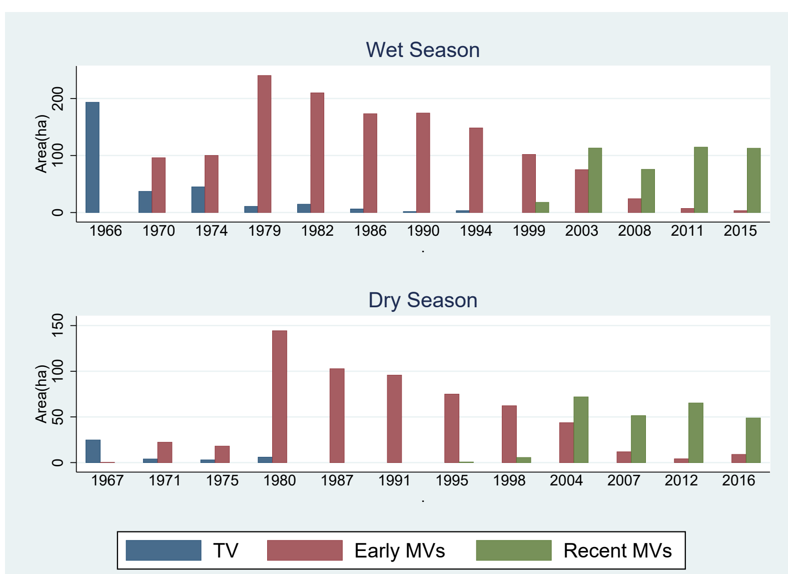

Figure 2.2 Adoption area of rice varietal group by survey year

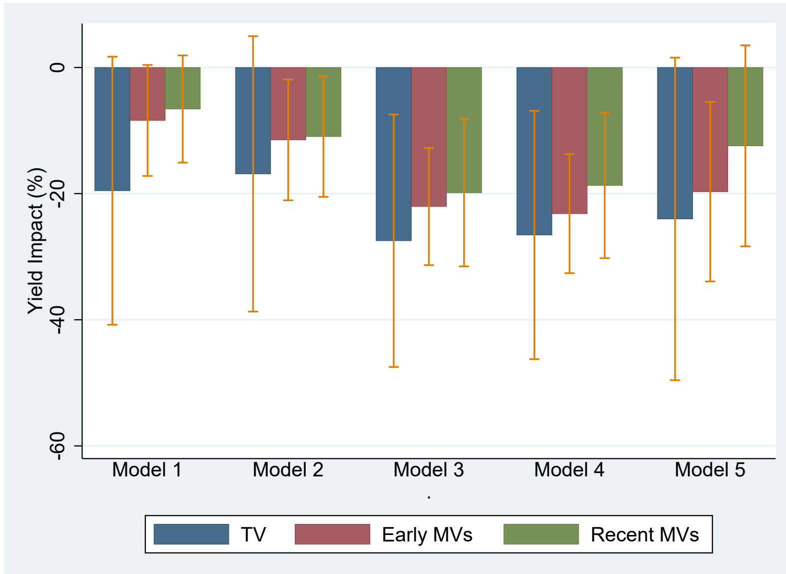

Figure 2.3 Predicted impacts of the 1°C warming scenario on three rice varietal groups for five model specifications described by Table 2.4. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

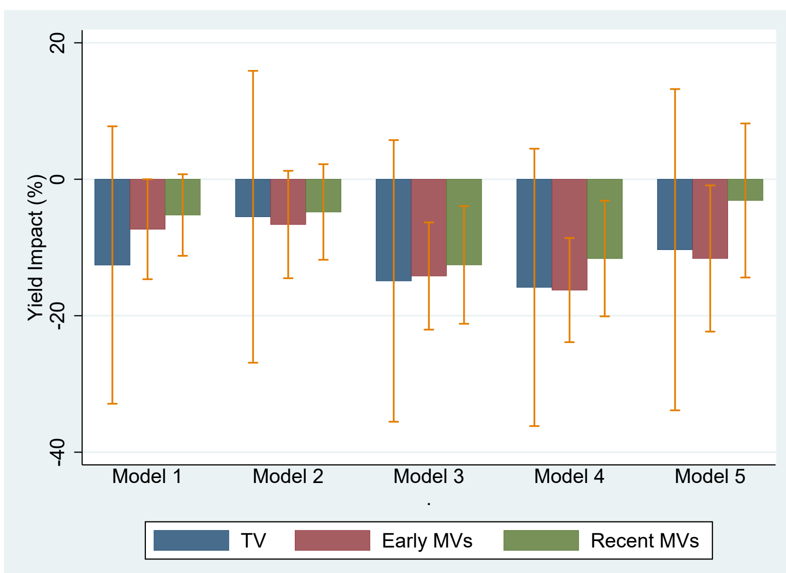

Figure 2.4 Predicted impacts of a 1°C increase in $tavg$ on three rice varietal groups for five model specifications described by Table 2.5. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

CHAPTER

3

DO WARMING TEMPERATURES INFLUENCE YIELD RESPONSE TO HIGHER PLANTING DENSITY?

This chapter explores how warming temperatures influence corn yield response to planting density. Using 1990-2010 field trial data from Wisconsin and econometric models with a variety of specifications, we find that warming temperatures reduce the yield benefits of increasing planting density. However, these adverse warming effects are smaller for genetically-modified (GM) corn varieties with rootworm (RW) resistant traits. Consistent with previous studies, these results support the notion that varietal improvements through genetic modification may have paved the way for higher planting densities in US corn production. Moreover, our results imply that expected in-season temperatures are important considerations when making planting density decisions.

3.1 Introduction

Since the development and diffusion of corn hybrids in the 1930s, commercial corn yields in the United States (US) have increased dramatically over the last 80 years. Data from the US Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) indicate that US corn yields have increased eight-fold from roughly 20 bu/acre in the mid-1930s to about 175 bu/acre in 2016. This tremendous growth implies a yield increase at a rate of about 1.8 bu/acre/year.

Previous literature has posited that a variety of factors, such as varietal improvement (i.e., through traditional plant breeding or genetic modification) and better agronomic practices, have contributed to this observed yield growth ([Duv05]; [Ass18]). However, a number of studies argue that the impressive yield increases seen in US corn can be mainly attributed to increases in planting density or plant population (i.e., the number of plants per acre), rather than to increases in per-plant yields (i.e., mainly through technological advances) ([Tol02]; [Tok04]; [Duv05]).

Growth in corn plant populations in the U.S. has roughly tracked the growth in corn yields from 1964-2016. In this period, yields have more than doubled, from approximately 60 bu/acre to 175 bu/acre, and at the same time plant population has also more than doubled, from about 14,000 plants/acre to close to 30,000 plants/acre. These figures suggest that yield per plant is only slightly higher in 2016 as compared to 50 years ago, and therefore support the notion that corn yield growth may be largely attributed to planting density increases. However, it is likely that the link between improved corn yields and higher plant densities over time is directly influenced by warming temperatures due to climate change, as well as varietal improvement and better agronomic practices ([Lob14]; [Ass18]).

The objective of this study is to determine how the yield response of corn to increasing planting density is affected by warming temperatures. We are also interested in the role of genetically-modified (GM) corn varieties with regards to the impact of warming on the “yield-planting-density” relationship. To accomplish these objectives, we utilize plot-level field trial data collected by the University of Wisconsin over the period 1990-2010 (See [Shi13]; [Cha15]), which is then merged with publicly available weather data. Yield regression models with a variety of specifications (and interaction terms) are then estimated to understand if and how warming temperatures impact corn yield response to increasing planting density.

There is now a robust literature about corn yield response to increasing planting density, and how varietal traits and agronomic practices influence this response (See [Ass16]; [Sta06]; [Car87]; [San01]; [Lin16]; [VR11]; [Fro19]; [Por97]). For example, previous research such as [Cou10], [Bro70], [Bee75], [Cox96], [Wid02], [Naf94], [Nie88], [Var04] have examined the likely impacts of hybrids on a variety of corn agronomic responses to plant density. However, there have only been a handful of studies that specifically explored how the contribution of planting density to improved corn yields are affected by environmental factors and growing conditions. For example, papers such as [San04], [Abb12], [Bro86], [VA92], and [Muc90]) have examined the impact of soil characteristics (such as soil water availability and/or soil fertility) on the relationship between corn yields and planting density. [Ass16] and [Ass18] grouped observations into four hypothetical growth environments based on yield levels (e.g., low yield, medium yield, high yield, and very high yield environments), then estimated the corn-yield-planting-density relationship for each subgroup by utilizing maximum likelihood and least squares based statistical approaches. These studies found that increasing planting density has a larger positive effect on yield under a high yield environment than a low yield environment. Similarly, [Cha14] and [Cha15] investigated the effect of planting density on corn yields for different yield levels. But note that these latter two studies utilized quantile regression techniques to estimate the “yield-planting-density” function (i.e., rather than defining specific yield level subgroups and using maximum likelihood or least squares to estimate the function for each subgroup). In addition, [Cha14] and [Cha15] also explored how GM traits influence corn yield response to increases in planting density. They found that the yield benefits of increasing planting density would be further strengthened when GM varieties are used. We have not found any study that looked at how temperature changes may affect corn yield response to higher planting density using econometric methods and long-run field trial data.

Our main contribution is that we examine the role of a specific environmental factor — temperature changes — with respect to how planting density affects corn yields. This has important implications for corn farmers especially in a world with an increasingly warming climate and the need for climate change adaptation strategies. Although previous studies have explored how a "low-yield" environment generally influence corn yield response to planting density, none of these past studies have particularly investigated how increasing temperatures affect corn yield response to planting density. A better understanding of the effect of temperature on the "yield-planting-density" relationship would allow farmers to make better decisions at the start of the season (e.g., planting density and varietal choices) based on expected in-season temperatures during the growing period ([Sol17]).

The second contribution is the exploration of whether GM traits would cause heterogeneity in the effect of warming on the "yield-planting-density" relationship. Specific interest is in the GM corn varieties with rootworm (RW) resistant traits since it is widely believed that below-ground rootworm protection allows for larger and healthier corn root balls ([Goo19]). These larger and healthier roots then allow these RW resistant varieties to be more resilient to heat stress and higher temperatures. Even though there have been previous studies that examined the "triple" inter-relationship among corn yields, planting density, and GM traits ([Cha14]; [Cha15]), to the best of our knowledge, there has been no study that examined the "quadruple" inter-relationship among corn yields, planting density, GM traits, and warming temperatures. Hence, the present study contributes to further understanding of the so-called genotype (G), environment (E), and management (M) interactions (G × E × M) that determine crop yield outcomes (i.e., in our case, G is the GM trait, E is the warming temperatures, and M is the planting density choice).

Results from our study indicate that corn yield response to planting density varies with temperature, and the degree of variation with temperature is influenced by the GM traits. In general, the yield benefits of increasing planting density diminish as temperature increases. But note that the diminishing yield benefits of higher planting density (in the presence of warming) are mitigated by the use of GM crop varieties, especially those with RW resistance traits.

Chapter 3 proceeds as follows. First, we provide a detailed description of the data sources and our empirical approach that allows us to examine how corn yield responds to changes in plant density under different temperatures and/or GM traits in Section 3.2. This is followed by a thorough discussion of estimation results (Section 3.3) and various robustness checks (Section 3.4). Lastly, conclusions, important implications, and potential avenues for future research are presented in Section 3.5.

3.2 Data Sources and Empirical Approach

In this study, we use data from three sources: (1) annual corn field trial data collected by University of Wisconsin researchers over the period 1990-2010; (2) weather data drawn from the work of [Sch09], which includes interpolated daily minimum and maximum temperature information for 4 kilometer (km) grid cells within the United States from 1950 to 2017; and (3) county-level Palmer Drought Severity Index (PDSI) data from the Centers for Disease Control and Prevention(CDC).[1]

The University of Wisconsin field trial data includes information about plot-level yields (measured in bushels per acre) and farming inputs applied (e.g., fertilizer and insecticides). Input use and management practices (e.g., tillage, rotation) utilized in the trial plots are similar to neighboring commercial fields and are consistent with normal agronomic recommendations ([Cha15]). The management practices employed are typical of those used on corn farms practicing rainfed agriculture in the US corn belt. Fertilizer applications are based on soil type, soil moisture and soil pH provided by a series of soil tests. Insecticide is only applied when the insect infestation level is above an action threshold (The pest density or damage level as which insecticide application is needed to prevent or reduce economic loss). Herbicide is used when it is necessary to control weed growth. The experimental design for these field trials was a randomized complete block design in which each corn hybrid variety was grown in at least three separate plots (replicates) at each site (i.e., to account for field variability). These trials were conducted over the years for the purpose of evaluating the yield performance of different corn hybrids (e.g., conventional hybrids versus various GM hybrids). Hence, these trials were not explicitly designed to assess planting density. As such, management practices are typically the same for plots in each site-year (i.e., which has implications for our empirical specifications as discussed further below). Further note that this is the same data set used in [Shi13] and [Cha15] to mainly evaluate the production risk effects of various GM traits.

For the field trial data that spans crop years 1990-2010, a total of 4,748 hybrids were tested in which 2,653 were conventional hybrids and 2,095 were GM hybrids. Some hybrids were tested in multiple locations and/or for multiple years. The data includes 31,799 usable yield observations. However, for the present study, only 28,521 rainfed observations are utilized given the central role of warming in our analysis. Summary statistics and descriptions of the field-trial variables utilized in this study are provided in Table 3.1.

The corn field trials were conducted in 12 experimental sites (11 for rainfed corn), which are located in four production zones in the state of Wisconsin: South, South Central, North, and North Central (See Figure 3.1). All of the field trial sites are in what is commonly called the Northern Corn Belt. The South production zone includes three sites in the following cities/villages: Arlington, Janesville, and Lancaster. The South Central production zone includes sites in Fond Du Lac, Galesville, and Hancock. The Chippewa Falls, Marshfield, Seymour, and Valders filed trial sites are located in the North Central production zone. Lastly, the North production zone includes exper-

[1] The PDSI data is from Centers for Disease Control and Prevention. National Environmental Public Health Tracking Network. https://data.cdc.gov/Environmental-Health-Toxicology/Palmer-Drought-Severity-Index-1895-2016/en5r-5ds4/data. Accessed: 4/7/2019.

imental sites in Spooner and Coleman. In general, the climatic conditions for the field trial sites within a particular production zone are similar. However, it should be noted that the sites in the Southern production zone tend to have a more favorable climate as compared to the sites located in the other zones. The field trial sites in the South Central, North Central and North production zones typically have a colder climate and a shorter growing season. Figure S3.1 and Figure S3.2 shows box-and-whisker plots of yield and plant density, respectively, for each of the four production zones. Notice that corn yields generally decrease as one goes further north, which is consistent with the observation that climate conditions of more southern sites are more favorable for corn. The temporal pattern of average yield and average planting density for all trial sites are presented in Figures S3.3 and Figure S3.4. The temporal yield and planting density patterns in the data are consistent with the national trend where corn plant population growth roughly track the growth in corn yield.[2]

The grid-level weather data drawn from the work of [Sch09] were aggregated up to the city (or village) where the field trial sites are located. After this aggregation, the monthly average daily minimum ($tmin$) and maximum ($tmax$) temperature data are then calculated. The monthly county-level PDSI data is also matched to the city (or village) where the field trial sites are located. For field trial sites wholly located in a single county, we use the PDSI value for the specific county where the trial site is located. However, for field trial sites that are in the border of two or more counties, we use a county-level average PDSI value for the corresponding counties near these trial sites. Given the nature of the weather data described above, it is important to note that all field trial plots within each site-year are assumed to have the same weather given that the $tmin$, $tmax$, and PDSI data are aggregated at the city (or village) where each field trial site is located. All weather variables are then merged with the plot-level field trial data. The summary statistics for relevant monthly minimum temperature, maximum temperature, and monthly PDSI are reported in Table 3.2. Moreover, the yearly changes in minimum temperatures, maximum temperatures, and PDSI for the period 1990-2010 are presented in Figures S3.9 and S3.10 for each production zone.

3.2.1 Empirical Specification and Estimation Strategies

The main empirical specification to determine how warming temperatures affect corn yield response to planting density is defined as follows:

$$\ln(y_{ilzt}) = \alpha_z + f(\mathbf{tmin}_{lzmt}, \mathbf{tmax}_{lzmt}, \mathbf{PDSI}^{w}_{lzmt}, \mathbf{PDSI}^{d}_{lzmt}, \mathbf{D}_{lzt}) + \gamma \mathbf{X}_{ilzt} + \eta t + \varepsilon_{ilzt} \tag{3.1}$$

where $\ln(y_{ilzt})$ is the natural log of corn yield in bushels per acre (bu/acre) for plot i, field trial location l, production zone z, and year t. We estimate equation (3.1) using ordinary least squares (OLS) regression that includes a production zone fixed effect α_z to eliminate any concerns about

[2] In addition, temporal patterns of the number of plots in the filed trial data that planted conventional corn, GM hybrids with the RW resistance trait, and GM hybrids without the RW resistance trait are presented in Figures S3.6, S3.7, and S3.8, respectively.

time-invariant unobservables at the production zone level.[3] We also include a linear time trend ηt to account for the technological improvement over time. Control variables that represent input use (or practices) are included in the vector $\mathbf{X}_{ilzt}$ (e.g., fertilizer, tillage, and other variables in Table 3.1).

We call $f(\cdot)$ in equation (3.1) the "weather-plant-density" function, which includes as arguments the following weather-related variables: **tmin**, **tmax**, $\mathbf{PDSI}^w$ and $\mathbf{PDSI}^d$ for field trial location l, production zone z, month m, and year t. Note that $\mathbf{PDSI}^w$ refers to positive PDSI values that measures the degree of wetness (w), while $\mathbf{PDSI}^d$ refers to the absolute value of negative PDSI values that reflects the degree of dryness (d). Large $\mathbf{PDSI}^d$ values usually reflects drought conditions, and large $\mathbf{PDSI}^w$ typically reflects extremely wet conditions (i.e., flooding).[4] The planting density variable (in '000s of plants per acre) is also included in $f(\cdot)$ and is represented by $\mathbf{D}_{lzt}$.

In particular, the "weather-plant-density" function is defined as follows:

$$\begin{aligned}
\delta\mathbf{D}_{lzt} + \sum_{m=1}^{5}\beta_{1m}\mathbf{tmin}_{lzmt} + + \sum_{m=1}^{5}\beta_{2m}\mathbf{tmax}_{lzmt} + \sum_{m=1}^{5}\psi_{1m}(\mathbf{tmin}_{lzmt}\times\mathbf{D}_{lzt}) + \\
\sum_{m=1}^{5}\psi_{2m}(\mathbf{tmax}_{lzmt}\times\mathbf{D}_{lzt}) + \sum_{m=1}^{5}\beta_{31m}\mathbf{PDSI}^{w}_{lzmt} + \sum_{m=1}^{5}\psi_{31m}(\mathbf{PDSI}^{w}_{lzmt}\times\mathbf{D}_{lzt}) + \\
\sum_{m=1}^{5}\beta_{32m}\mathbf{PDSI}^{d}_{lzmt} + \sum_{m=1}^{5}\psi_{32m}(\mathbf{PDSI}^{d}_{lzmt}\times\mathbf{D}_{lzt}).
\end{aligned} \tag{3.2}$$

The growing season is specified as spanning 5-months ($m = 1, 2, ..., 5$) from May to September. The ψ parameters associated with the interaction terms in equation (3.2) give us insight into how weather variables affect corn yield response to planting densities.

The specification in equations (3.1) and (3.2) are consistent with previous studies that examined crop yield effects of weather variables (See [Sch10a]; [Lob11]; [Lob07]; [Wel10]; [Tac15a]; [Pen04]). These studies typically use the following variables in their specifications: $tmin$, $tmax$, and a weather variable that reflects water-availability (e.g., typically quadratic functions of precipitation or rainfall). However, in contrast with these aforementioned studies, our specification above utilizes a drought index, specifically the PDSI, as a measure of water-availability rather than quadratic functions of precipitation or rainfall levels.[5] A drought index like PDSI is appropriate as a measure of water/moisture availability because its values are referenced to local climate, which allows one to calculate dryness or wetness relative to local norms ([Xu13]; [Kol14]). In addition, local soil attributes are partly accounted for when calculating drought indices, which is an important factor in a crop's ability to handle extreme dryness or wetness. Using both the positive and negative PDSI values in our specification also adequately account for nonlinearities in the effects of water availability (i.e.,

[3] As mentioned above, plant density and other production inputs are the same for all plots for each site-year combination. Therefore, there is no variation in plant density for each field trial location and year. Therefore, we use production zone fixed effects rather than plot or field trial site fixed effect in our empirical specifications. This means that identification mainly comes from across production zone variation and variation across years.

[4] PDSI values range from -10 to +10. As alluded to above, negative PDSI values reflect dryness, while positive PDSI values reflect wetness. Typically, PDSI values of -4 or below represents extreme drought, while PDSI values of 4 or above reflects an extremely wet environment (i.e., flood conditions).

[5] Although we use PDSI in our main specification, we also conduct robustness checks below where we utilize a quadratic precipitation specification.

typically reflected by having a quadratic precipitation term in previous studies).

Another feature of the specification in equation (3.2) is the linear relationship between planting density (**D**) and crop yields. Previous studies have typically assumed a quadratic specification for planting density (See [Ass18] for example). However, a linear specification is appropriate in our case given that the range of our planting density data do not usually reach the reported "optimal" planting density levels recommended for Wisconsin (i.e., the yield-maximizing planting density level where corn yields plateau (the "turning point") and consequently decreases in a quadratic specification). For example, [Sta06] suggests that the optimal planting densities for Wisconsin are approximately 39,984 plants per acre for non-GM corn and 42,290 plants per acre for GM corn with the Bt trait (for the period between 2002 and 2004). Based on field trial data locations across the corn belt, [Ass18] indicates that optimal planting density ranges from 30,500 plants per acre (in 1987) to about 37,900 plants per acre in the 2007-2016 period. In our field trial data from 1990-2010, the range of planting density values is from about 18,250 plants per acre to around 33,409 plants per acre. This data range is more consistent with the upward sloping (and close to linear) part of the corn yield response function to planting density, which again supports our linear specification. Furthermore, a straightforward regression of the natural log of corn yield on planting density using our data set indicates a relationship that is very close to linear and without a turning point (See Figure S3.5).

3.2.2 Marginal Effects

To achieve the study objective of assessing how the yield impact of planting density changes with temperature, we calculate the marginal effect of planting density on corn yields under different temperature scenarios based on the empirical model specified in equations (3.1) and (3.2). The marginal percentage effect of increasing plant density is the percentage change in corn yields as a result of a 1 unit (in this case, 1000 plants per acre) increase in planting density. This marginal effect calculation can be expressed as follows:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \sum_{m=1}^{5} \psi_{1m} \mathbf{tmin}_{mt} + \sum_{m=1}^{5} \psi_{2m} \mathbf{tmax}_{mt} + \sum_{m=1}^{5} \psi_{31m} \mathbf{PDSI}^{w}_{mt} \tag{3.3}$$

if PDSI in each month is positive, and:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \sum_{m=1}^{5} \psi_{1m} \mathbf{tmin}_{mt} + \sum_{m=1}^{5} \psi_{2m} \mathbf{tmax}_{mt} + \sum_{m=1}^{5} \psi_{32m} \mathbf{PDSI}^{d}_{mt} \tag{3.4}$$

if all monthly PDSI's are negative.

In order to examine how temperature changes influence the yield response to planting density, we calculate marginal effects under two warming scenarios: (1) a warming scenario where both **tmin** and **tmax** change by 1°C increments, and (2) a warming scenario where **tmin** and **tmax** changes separately by 1°C increments. To calculate the marginal effects of planting density under the first warming scenario, we first assume that both the monthly **tmin** and **tmax** variables deviate from their means by the following amounts: −1°C, −2°C, −3°C, −4°C, +1°C, +2°C, +3°C, +4°C. This calculation structure allows us to see how corn yield response to planting density changes as both the minimum and maximum temperatures change (holding PDSI constant at its mean).[6] The marginal effect of planting density under the first warming scenario can then be expressed as follows:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \sum_{m=1}^{5} \psi_{1m}(\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \psi_{2m}(\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \psi_{31m}\overline{\mathbf{PDSI}}_{mt} \tag{3.5}$$

where $\overline{\mathbf{tmin}}_{mt}$, $\overline{\mathbf{tmax}}_{mt}$, and $\overline{\mathbf{PDSI}}_{mt}$ are set at the means in month m and year t, and the nine assumed temperature deviations are where $k = -4, -3, .., 0, .., +3, +4$.[7]

Under the second warming scenario, the marginal effects of planting density are calculated assuming that **tmin** and **tmax** separately changes in 1°C increments (where $k = -4, -3, .., 0, .., +3, +4$). The marginal effect of planting density when only **tmin** changes can be calculated as follows:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \sum_{m=1}^{5} \psi_{1m}(\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \psi_{2m}\overline{\mathbf{tmax}}_{mt} + \sum_{m=1}^{5} \psi_{31m}\overline{\mathbf{PDSI}}_{mt}, \tag{3.6}$$

where **tmax** and the PDSI's are held at their mean values. On the other hand, the marginal effect of planting density when only **tmax** changes can be expressed as follows:

$$\frac{\partial ln(y_t)}{\partial \mathbf{D}_t} = \delta + \sum_{m=1}^{5} \psi_{1m}\overline{\mathbf{tmin}}_{mt} + \sum_{m=1}^{5} \psi_{2m}(\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \psi_{31m}\overline{\mathbf{PDSI}}_{mt} \tag{3.7}$$

where **tmin** and the PDSI's are held at their mean values.

The marginal effect calculations above assume that changes in temperature occur in all months of the season. However, previous literature has argued that the June to August months are the critical months for corn growth. During this period, crop growth is frequently affected by environmental stresses such as high temperatures ([McW99]). Since silking occurs in the summer time, stress conditions that happen two weeks before or after silking typically lead to substantial reductions in yield (see [McW99]). Therefore, we also calculate the marginal effects of increasing planting density under both the warming scenarios described above, but only imposing changes in the temperatures for the June to August months (i.e., and where temperatures in the other months are set at their means).

Another issue of interest in this study is to determine the role of GM corn varieties, especially those that have RW resistant traits, with regards to how corn yield responds to planting density under different warming scenarios (i.e., the "quadruple" inter-relationship among corn yields, planting density, GM traits, and warming temperatures). Given this interest, we modify the "weather-planting-density" function in (3.2) to allow for "triple" interaction terms among the planting density variable, the weather variables, and GM corn varietal dummy variables. In this case, the corn varieties in the field trial data set are categorized into three groups: conventional varieties, GM-RW hybrids, and

[6] We understand that changes in temperatures also likely affects PDSI (i.e., increasing temperature may result in more drier conditions (and lower PDSI's)). Hence, the marginal effect calculation where we hold PDSI's constant at the mean can be considered a lower bound for the effect of warming temperatures on the corn yield response to planting density.

[7] For the purpose of calculating the marginal effect in equation (3.5), as well as in equations (3.6), (3.7), (3.9), (3.10), and (3.11), the term $\overline{\mathbf{PDSI}}_{mt}$ is calculated by taking the average over all PDSI's of each month in the data (i.e., both negative and positive) and the mean PDSI values provided by Table 3.2. Thus, the superscript for the PDSI variable (e.g., w or d) has been omitted in these marginal effect expressions.

other GM hybrids. Note that GM-RW hybrids are those varieties that have RW resistance, either as a single-trait GM crop with only RW resistance, or a "multi-stack" variety with RW resistance combined with other traits (i.e., such as a double-stack GM with combined above-ground corn borer resistance together with below-ground RW resistance). The "other GM hybrids" category includes those GM varieties with GM traits, but specifically without the RW resistance trait (e.g., single-trait Bt corn with resistance only to European corn borers).

With the GM variety categorization above, the "weather-planting-density" specification in (3.2) is modified as follows (to include the GM variety dummies and triple interaction terms):

$$\begin{aligned}
&\delta \mathbf{D}_{lzt} + \sum_{r=1}^{2} \zeta_r \mathbf{V}^r_{ilzt} + \sum_{r=1}^{2} \eta_r (\mathbf{D}_{lzt} \times \mathbf{V}^r_{ilzt}) + \sum_{m=1}^{5} \beta_{1m} \mathbf{tmin}_{lzmt} + \sum_{m=1}^{5} \beta_{2m} \mathbf{tmax}_{lzmt} + \\
&\sum_{m=1}^{5} \beta_{31m} \mathbf{PDSI}^w_{lzmt} + \sum_{m=1}^{5} \beta_{32m} \mathbf{PDSI}^d_{lzmt} + \sum_{r=1}^{2}\sum_{m=1}^{5} \theta_{1rm} (\mathbf{tmin}_{lzmt} \times \mathbf{V}^r_{ilzt}) + \\
&\sum_{r=1}^{2}\sum_{m=1}^{5} \theta_{2rm} (\mathbf{tmax}_{lzmt} \times \mathbf{V}^r_{ilzt}) + \sum_{r=1}^{2}\sum_{m=1}^{5} \theta_{31rm} (\mathbf{PDSI}^w_{lzmt} \times \mathbf{V}^r_{ilzt}) + \\
&\sum_{r=1}^{2}\sum_{m=1}^{5} \theta_{32rm} (\mathbf{PDSI}^d_{lzmt} \times \mathbf{V}^r_{ilzt}) + \sum_{m=1}^{5} \psi_{1m} (\mathbf{tmin}_{lzmt} \times \mathbf{D}_{lzt}) + \\
&\sum_{m=1}^{5} \psi_{2m} (\mathbf{tmax}_{lzmt} \times \mathbf{D}_{lzt}) + \sum_{m=1}^{5} \psi_{31m} (\mathbf{PDSI}^w_{lzmt} \times \mathbf{D}_{lzt}) + \sum_{m=1}^{5} \psi_{32m} (\mathbf{PDSI}^d_{lzmt} \times \mathbf{D}_{lzt}) + \\
&\sum_{r=1}^{2}\sum_{m=1}^{5} \kappa_{1rm} (\mathbf{tmin}_{lzmt} \times \mathbf{D}_{lzt} \times \mathbf{V}^r_{ilzt}) + \sum_{r=1}^{2}\sum_{m=1}^{5} \kappa_{2rm} (\mathbf{tmax}_{lzmt} \times \mathbf{D}_{lzt} \times \mathbf{V}^r_{ilzt}) + \\
&\sum_{r=1}^{2}\sum_{m=1}^{5} \kappa_{31rm} (\mathbf{PDSI}^w_{lzmt} \times \mathbf{D}_{lzt} \times \mathbf{V}^r_{ilzt}) + \sum_{r=1}^{2}\sum_{m=1}^{5} \kappa_{32rm} (\mathbf{PDSI}^d_{lzmt} \times \mathbf{D}_{lzt} \times \mathbf{V}^r_{ilzt}) \qquad (3.8)
\end{aligned}$$

where V^r_{ilzt} represents the GM variety dummy variables for plot i, field trial location l, production zone z, and year t. In the specification above, conventional corn hybrids are designated as the base group (e.g., the omitted category) and V^r are dummy variables that represent the two GM varietal groups, where $r = 1$ corresponds the GM-RW hybrids, and $r = 2$ refers to the other GM hybrids. Among the 28,521 plots in the field trial data, there are 17,680 with conventional corn, 4,044 with GM-RW hybrids, and 6,797 with the other GM hybrids. The change in varietal adoption rate over time for the four production zones are shown in Figure S3.6, Figure S3.7 and Figure S3.8.

Given the "weather-planting-density" specification in equation (3.8), the marginal yield effect of increasing planting density for conventional corn under the first warming scenario (for $k = -4, -3, .., 0, .., +3, +4$) can then be calculated as follows:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \sum_{m=1}^{5} \psi_{1m} (\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \psi_{2m} (\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \psi_{31m} \overline{\mathbf{PDSI}}_{mt} \qquad (3.9)$$

where the weather variables are set at their mean values in all 5 months of the growing season. On the other hand, the marginal effect of increasing planting density for the GM-RW hybrids can be written as:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \eta_1 + \sum_{m=1}^{5} \psi_{1m}(\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \psi_{2m}(\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \kappa_{11m}(\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \kappa_{21m}(\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \psi_{31m}\overline{\mathbf{PDSI}}_{mt} + \sum_{m=1}^{5} \kappa_{311m}\overline{\mathbf{PDSI}}_{mt} \quad (3.10)$$

where the weather variables are again set at their mean values in all 5 months of the growing season. Similarly, the marginal effect of increasing planting density for the other GM hybrids can be calculated as follows:

$$\frac{\partial \ln(y_t)}{\partial \mathbf{D}_t} = \delta + \eta_2 + \sum_{m=1}^{5} \psi_{1m}(\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \psi_{2m}(\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \kappa_{12m}(\overline{\mathbf{tmin}}_{mt} + k) + \sum_{m=1}^{5} \kappa_{22m}(\overline{\mathbf{tmax}}_{mt} + k) + \sum_{m=1}^{5} \psi_{31m}\overline{\mathbf{PDSI}}_{mt} + \sum_{m=1}^{5} \kappa_{312m}\overline{\mathbf{PDSI}}_{mt} \quad (3.11)$$

where the weather variables are again set at their mean values in all 5 months of the growing season. Although not shown here, similar marginal effect calculations can also be computed for the second warming scenario, and for the case where we only consider temperature changes in the June to August months.

3.3 Estimation Results and Marginal Effects

The main empirical model as specified in equations (3.1) and (3.2) are estimated by OLS and, in the spirit of conciseness, the parameter estimates are presented in Appendix B (See Table S3.1).[8]

3.3.1 Warming Effects

To determine the influence of warming on the yield effects of planting density, we calculate the marginal effects of increasing planting density under the two warming scenarios described in the previous section and present results in Table 3.3. For the first warming scenario, where both **tmin** and **tmax** are assumed to change by 1°C increments, we find that the yield benefit of increasing planting density is reduced by 1.86% for every 1°C increase in the minimum and maximum temperatures in each month of the cropping season. This result suggests that the yield benefits of increasing planting density diminish in the presence of warming.

As described in the previous section, we also calculate the marginal effect of increasing planting

[8]Consistent with equation (3.1), results presented here is for the case where $\ln(y_{ilzt})$ is the dependent variable. We also ran all the models where the dependent variable is the actual yield in bu/acre (i.e., not taking the natural logarithms). Results for those runs are consistent with what is presented here and is available from the authors upon request.

density as temperature deviates from the mean by 1°C increments (see equation (3.5)). The results of these marginal effect calculations are graphically presented in Figure 3.2. The mean temperature result in Figure 3.2 indicates that, for average weather conditions in the study area (e.g., average minimum and maximum temperatures, as well as average PDSI), increasing planting density would negatively affect corn yields (albeit by a relatively small percentage amount). Moreover, as the minimum and maximum temperatures increase relative to the mean, increasing planting density becomes more detrimental to corn yields (e.g., a 1000 plants per acre increase in planting density results in more than 5% yield reduction when minimum and maximum temperatures increase by more than 3°C from the mean). On the other hand, note that increasing planting density has a positive marginal effect on yield when temperatures are lower than the mean. The diminishing marginal effect of increasing planting density in a warming environment is consistent with the idea that inter-plant competition for nutrients and resources (i.e., water) intensifies as planting density increases, and this competition escalates further when temperatures increase.

Results from the second warming scenario, where we assume that **tmin** and **tmax** increases separately in 1°C increments in all months, are fairly consistent with the marginal effect estimates calculated in the first warming scenario described above (See Table 3.3). But we note that increases in **tmax** tend to have a larger negative impact on the yield effects of increasing planting density (as compared to the impact of increases in **tmin**). Previous study has also claimed that **tmax** plays a stronger role that **tmin** in creating variability for Wisconsin corn (see [Kuc08]). This suggests that increases in daytime temperatures are more likely to negatively influence yield response to increasing planting density.

For the case where the two warming scenarios are applied only to the critical growth months of June to August, the marginal effect estimates are still largely consistent with the results from the earlier results where warming affects all growing season months (See Table 3.3 and Figure 3.3). The general pattern of results in Figure 3.3 is almost the same as in Figure 3.2. However, the magnitudes of the warming effects are relatively smaller for the case where warming is only felt in the June to August months.

3.3.2 GM traits and Warming Effects

The role of GM traits is examined based on the empirical specification in equations (3.1) and (3.8). Parameter estimates for the specification that includes the GM dummy variables (and the corresponding interactions) are presented in Table S3.2. Similar to the results in Table S3.1, the planting density effect on corn yields is positive if GM traits and weather variables are not taken into account.

The marginal effects of increasing planting density that considers GM traits under our two warming scenarios are presented in Table 3.4. Results from these marginal effect calculations generally suggest that the negative effect of warming is more strongly felt for conventional corn varieties, as compared to the GM-RW hybrids and other GM hybrids. That is, the marginal yield effect of increasing planting density is more negatively affected by warming when conventional varieties are used.

To better visualize the role of GM traits, we also graph the marginal effects of increasing planting density under the first warming scenario (i.e., increasing both **tmin** and **tmax** in all months), but separating it out by the hybrid type – conventional, GM-RW, and other GM (See Figure 3.4). First, at the mean temperature levels, it is important to note that increasing planting density results in a negative yield impact for conventional corn yields. In contrast, for GM-RW hybrids and other GM hybrids, the marginal yield effect of increasing planting density is positive at mean temperature levels. Second, the positive marginal effect of increasing planting density is higher for GM-RW hybrids as compared to the other GM hybrids. Moreover, even at temperatures above or below the mean level, the positive marginal effect of planting density for GM-RW hybrids is still consistently larger than the other GM hybrids. Lastly, the slope of the marginal effect line for the conventional hybrids is steeper than those of the GM-RW and other GM hybrids, suggesting that the marginal effect of increasing planting density diminishes more rapidly (as temperature rises) for conventional corn, relative to the GM-RW and other GM hybrids. Overall, these results provide some evidence that the typical yield benefits of increasing planting density can be more easily maintained under warming conditions if corn varieties with GM traits are used. This outcome suggests that corn varieties with GM traits (especially GM-RW hybrids) may be more efficient in utilizing nutrients and moisture even under intensified inter-plant competition due to increasing planting density and higher temperatures. Moreover, the GM trait results here support the idea that the use of GM varieties may have facilitated the increases in planting density over time.

3.4 Robustness Checks

To verify the strength and stability of our results, we conduct several robustness checks that consider the following alternatives to our main empirical specification (as described in equations (3.1) and (3.2)): (a) the main specification without including the managerial inputs and practices ($\mathbf{X}_{ilzt}$) as control variables, (b) the main empirical specification that includes interaction term between the time trend and the plant density, and (c) the main specification but using a quadratic form of precipitation of the May-September growing season as a measure of water availability (instead of PDSI).

We conduct the first robustness check, which excludes the managerial inputs, to account for concerns that input choices in the production process may be endogenous. However, note that this endogeneity concern may be largely mitigated by the fact the data set used in this study is based on field trial data rather than actual farm-level production data collected through a survey. Estimation results for the first robustness check are presented in Table S3.3, and the corresponding marginal effects of increasing planting density for our two warming scenarios are reported in Table 3.5. Figure 3.5 shows the marginal percentage impact of increasing planting density for the warming scenario where both **tmin** and **tmax** of each month change by 1°C increments when managerial inputs are not considered in the specification. Results from this first robustness check are largely consistent with our main warming results reported in the previous section. The magnitudes of the warming effects on the corn yield response to increasing planting density are very similar to the original results above. Overall, the first robustness check still strongly supports the notion that yield effects of increasing planting density diminish as temperature levels increase.

The second robustness check aims to show whether our results still hold when one assumes that the marginal effect of increasing planting density is not constant through time. Parameter estimates for the second robustness check that include interaction terms between the time trend and planting density are presented in Table S3.4, and the corresponding marginal effects are presented in Table 3.6. Moreover, Figure 3.6 graphically shows the marginal impacts of increasing planting density under the first warming scenario in five-year increments (from 1990-2010). Again, the second robustness check validates our results from the main specification in the previous section. The patterns of results in Figure 3.6 (for all years) are consistent with our main specification result in Figure 3.2. An interesting pattern to note in Figure 3.6 is that the marginal yield impact of increasing planting density (for all temperature levels) shifted upward through time. This is consistent with the observation that GM adoption has increased through time, which in turn may have brought about better yield response to increasing planting density even in warming temperatures (see section 3.2 above).

Then, we conduct a third robustness check where we replace PDSI as a measure of water availability with a quadratic function of precipitation (e.g., we added $prec$ and $prec^2$, instead of the PDSI variables in equations (3.1) and (3.2)).[9]. For this last robustness check, the parameter estimates are reported in Table S3.5 for the case where GM traits are not yet considered, and the corresponding marginal effects of increasing planting density for this specification are presented in Table 3.7. The visual representation of the marginal planting density effects for this last robustness check (under the first warming scenario) is presented in Figure 3.7. All of the results for this last robustness check are fairly consistent with the direction and magnitudes of the marginal impacts of increasing planting density using the main specification. Even when we use precipitation as a measure of water availability, the marginal yield response to increasing planting density deteriorates when temperature levels increase.

In consideration the possibility that the year effect changes over the experimental period, we run a regression controlling year fixed effects rather than linear time trend in our major models. Besides, to consider the potential nonlinear plant density effect, we also run a regression adding quadratic term of plant density into the main model.The changes in the marginal impact of plant density as a result of 1°C warming are presented in Table 3.9 and Table 3.10 and the density impacts at different temperatures estimated by these two alternative models are visually presented by Figure 3.9 and Figure 3.10 .The results from these two models are consistent with our major analysis.

Parameter estimates for the specification where a quadratic form of precipitation is used and GM traits are considered can be seen in Table S3.6. Moreover, the marginal effects associated with

[9]For this robustness check, we use the mean of monthly cumulative precipitation for the whole growing season. But further note that we also ran an additional specification that uses monthly cumulative precipitation. The results are similar to what is presented here. Results for the specification that uses monthly precipitation are available from the authors upon request

this specification is presented in Table 3.8. A corresponding graphical representation of the marginal effects of increasing planting density under the first warming scenario, and separated out by GM type, are shown in Figure 3.8. These robustness check results with precipitation used as a measure of water availability are still consistent with the results from the main specification above. At mean temperatures, the marginal effect of increasing planting density is still the strongest for GM-RW hybrids and is higher than both the conventional and other GM hybrids. At larger positive deviations from mean temperatures, this pattern still holds (as before). But note that, for mean temperatures, the marginal effect of increasing planting density for conventional corn is still positive (as compared to it being negative in the main specification). Lastly, note that the slope of the marginal effect line for conventional corn is still the steepest among the three hybrid groups. However, in contrast to the main specification results (with PDSI), the slope of the marginal effect line for GM-RW is flatter than the other GM hybrids. Nonetheless, even when precipitation is used as a measure of water availability, these robustness check results still support the notion that yield benefits of increasing planting density are better maintained under warming conditions when corn varieties with GM traits are utilized.

3.5 Conclusions

This study aims to explore how yield response to planting density is influenced by warming temperature and to understand the role of GM traits in this situation. Plot-level field trial data from Wisconsin over the period 1990-2010, as well as the corresponding weather data for these field trial locations, are used to fulfill the study objectives. Yield regression models are then developed with interaction terms among planting density, weather variables, and GM hybrid dummy variables to ascertain the impact of warming and GM traits on the corn yield response to increasing planting density. Results from these models suggest that the yield benefits of increasing planting density largely diminish as temperature levels increase, and the rate of deterioration is larger for conventional corn hybrids without GM traits. Corn varieties with RW resistance GM traits generally are better able to maintain the yield benefits of increasing planting density under warming conditions. These results indicate that inter-plant competition for resources (e.g., nutrients and moisture) is further intensified as planting density increases and when temperatures rise, which the results in diminishing benefits. But corn hybrids with GM traits may be more efficient in utilizing these resources such that they perform better than conventional varieties even in situations with increasing planting density and warming temperatures.

Findings from the present study point to a couple of important implications. First, results from the study highlight the important role that expected growing season temperatures should play when farmers make planting density decisions and varietal choices at the start of the season. Increasing planting density does not necessarily result in yield benefits even at mean temperatures when conventional corn hybrids are used. And yield increases from higher planting density still diminish under warming temperatures. Hence, growers would likely benefit from optimizing planting density and variety choices by partly conditioning these decisions on temperature forecasts for the growing season ([Sol17]). For example, if forecasted summer season temperature is higher than normal, then based on our results it may be prudent to not increase planting density for conventional corn production (or only increase it slightly for GM varieties). Second, the study findings also imply that further research investments in developing corn varieties that are more tolerant to higher temperatures would likely facilitate higher optimal planting densities going forward. Not only will more heat-tolerant varieties directly reduce heat-related losses, but these types of varieties may also indirectly provide planting density induced yield benefits. Therefore, public and private research investments for developing heat-tolerant corn varieties (i.e., either through genetic modification or traditional plant breeding) would be important to continue the trend of increasing planting density and yields into the future, especially if climate change continues to result in warmer temperatures.

Although the present study provides important insights regarding the role of warming and GM traits on the yield response to increasing planting density, there are study limitations that need to be acknowledged. First, the geographical scope of the current study is limited to the Northern corn belt and the data is from experimental field trial data rather than actual farmer data from commercial corn production. Future studies may consider using actual farm production data (i.e., data collected through farm surveys or through precision agriculture technologies) and expanding the geographical scope to more areas in the corn belt (or other locations and other corn-producing countries). Exploring the "yield-planting density" relationship in warmer climates (e.g., tropical locations) may also be beneficial. Second, the empirical analysis here would also be further improved if we had a true panel data set at the plot (or trial location) level. This would allow for using plot (or location) fixed effects and better identification of the planting density and warming effects on yields. In addition, a long-term field trial data explicitly aimed to examine how planting density influence yields (e.g., field trials designed specifically to explore planting density effects (instead of variety effects) on yields) would also help in more precisely teasing out the warming and GM trait effects. Lastly, having data for a longer period (i.e., more than 30 years) would also allow one to more accurately estimate the long-run effects of warming on the yield response to increasing planting density. We leave all these potential extensions for future work.

Table 3.1 Descriptive statistics of variables for Wisconsin data

Variable	Unit	Mean	SD	Median	Min	Max
Yield	bu/acre	176.46	40.26	178.53	21	289.81
plant density	1000 plants per acre	28.44	1.95	28.18	18.25	33.41
pcorn	1 if previous crop is corn	0.29	0.46	0	0	1
psoy	1 if previous crop is soybean	0.61	0.49	1	0	1
palf	1 if previous crop is alfalfa/hay	0.07	0.26	0	0	1
pwhe	1 if previous crop is wheat	0.02	0.13	0	0	1
plup	1 if previous crop is lupine	0	0.06	0	0	1
ft	Fall tillage, 1 if yes, 0 if no	0.51	0.5	1	0	1
st	spring tillage, 1 if yes, 0 if no	0.92	0.27	1	0	1
ic	apply insecticide, 1 if yes, 0 if no	0.38	0.49	0	0	1
fertilizer N	lbs acre^{-1}	122.86	41.76	130	0.5	201.5
conventional	1 if conventional corn is planted	0.62	0.49	1	0	1
RW	1 if expressing Bt trait for corn rootworm	0.14	0.35	0	0	1
other GM	1 if without Bt trait for corn rootworm	0.24	0.43	0	0	1

Table 3.2 Summary statistics of weather variables

Month	Variable	Mean	SD	Median	Min	Max
May.	tmin(°C)	7.03	2.153	7.01	1.58	12.26
	tmax(°C)	19.60	2.092	19.60	13.76	24.74
	PDSI	0.78	1.676	0.96	-4.11	5.53
	prec(mm)	98.65	47.23	90.43	23.73	310.79
Jun.	tmin(°C)	12.82	1.748	13.08	7.95	16.47
	tmax(°C)	24.96	1.732	24.93	20.36	29.46
	PDSI	0.95	2.060	1.09	-4.72	7.06
	prec(mm)	122.89	58.20	117.34	20.42	355.04
Jul.	tmin(°C)	14.97	1.754	15.10	9.88	19.07
	tmax(°C)	26.98	1.778	26.98	22.07	31.20
	PDSI	0.98	2.246	1.03	-4.95	6.99
	prec(mm)	102.46	49.64	94.27	18.28	268.96
Aug.	tmin(°C)	14.23	1.891	14.28	9.45	19.74
	tmax(°C)	26.08	1.629	26.34	21.56	29.96
	PDSI	0.81	2.127	0.73	-5.05	7.17
	prec(mm)	105.92	58.41	92.95	20.86	367.83
Sep.	tmin(°C)	9.54	1.634	9.57	4.47	12.87
	tmax(°C)	21.85	1.981	21.81	16.39	26.75
	PDSI	0.52	2.147	0.31	-3.74	6.59
	prec(mm)	83.50	44.75	75.75	8.17	235.18

Table 3.3 Estimated changes in the effects of plant density on yield as a result of 1°C warming

	All Months		Jun-Aug	
	Estimates	P-value	Estimates	P-value
tmin & tmax	-0.0186	0.000	-0.0055	0.000
tmin	-0.0066	0.000	0.0116	0.000
tmax	-0.0121	0.000	-0.0170	0.000

Notes: (1) The results here are estimated through our main specification in equations (3.1) and (3.2). (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row indicates a 1°C increase in both **tmin** and **tmax**. The second row refers to a warming scenario where only **tmin** increases by 1°C. The third row refers to a 1°C increase in **tmax**. (3) The second and the third column report coefficients and p-values of the changes in the marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in the marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.4 Estimated changes in the effects of plant density on yield as a result of 1°C warming

		All months		Jun-Aug	
		Estimates	P-value	Estimates	P-value
tmin & tmax	Conventional	-0.0279	0.000	-0.0069	0.000
	GM-RW	-0.0127	0.227	0.0123	0.388
	Other GM	-0.0019	0.490	-0.0002	0.960
tmin	Conventional	-0.0194	0.000	0.0118	0.000
	GM-RW	-0.1480	0.000	0.0458	0.000
	Other GM	-0.0016	0.620	-0.0240	0.000
tmax	Conventional	-0.0085	0.000	-0.0186	0.000
	GM-RW	0.1353	0.000	-0.0334	0.030
	Other GM	-0.0004	0.908	0.0238	0.000

Notes: (1) The table displays coefficients and p-values of the changes in the marginal effects of plant density as a result of 1° warming. The results are calculated from the estimated results of the model specification in equations (3.1) and (3.8) (the specifications including interactions among the weather, plant density, and GM varietal dummy variables). (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row of the first panel indicates a 1°C increase in both **tmin** and **tmax**. The first row of the second panel refers to a scenario where only **tmin** increases by 1°C. The first row of the third panel refers to a situation where only **tmax** increases by 1°C. (3) The second column indicates the hybrid groups: "RW" is GM hybrids expressing Bt trait for corn rootworm. "other GM" refer to GM hybrids without Bt trait for corn rootworm. (4)The third and fourth column report coefficients and p-values of the changes in marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where the temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.5 Estimated changes in the effects of plant density on yield as a result of 1°C warming

	All Months		Jun-Aug	
	Estimates	P-value	Estimates	P-value
tmin & tmax	-0.0195	0.000	-0.0056	0.000
tmin	-0.0042	0.000	0.0154	0.000
tmax	-0.0153	0.000	-0.0209	0.000

Notes: (1) The table shows the results of the first robustness check (the main specification without including managerial inputs and practices as control variables). (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row indicates a 1°C increase in both **tmin** and **tmax**. The second row refers to a warming scenario where only **tmin** increases by 1°C. The third row refers to a 1°C increase in **tmax**. (3) The second and the third column report coefficients and p-values of the changes in the marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where the temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in the marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.6 Estimated changes in the effects of plant density on yield as a result of 1°C warming

	All Months		Jun-Aug	
	Estimates	P-value	Estimates	P-value
tmin & tmax	-0.0191	0.000	-0.0053	0.000
tmin	-0.0069	0.000	0.0110	0.000
tmax	-0.0122	0.000	-0.0163	0.000

Notes: (1) The table shows the results of the second robustness check (the model specification includes the interaction term between plant density and the time trend in addition to the independent variables of the main specification). (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row indicates a 1°C increase in both **tmin** and **tmax**. The second row refers to a warming scenario where only **tmin** increases by 1°C. The third row refers to a 1°C increase in **tmax**. (3) The second and the third column report coefficients and p-values of the changes in the marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where the temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in the marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.7 Estimated changes in the effects of plant density on yield as a result of 1°C warming

	All Months		Jun-Aug	
	Estimates	P-value	Estimates	P-value
tmin & tmax	-0.0161	0.000	-0.0030	0.000
tmin	-0.0049	0.000	0.0190	0.000
tmax	-0.0112	0.000	-0.0220	0.000

Notes: (1) The table shows the results of the third robustness check which replaces PDSI as a measure of water availability with a quadratic form of the mean of monthly cumulative precipitation for the whole growing season. (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row indicates a 1°C increase in both **tmin** and **tmax**. The second row refers to a warming scenario where only **tmin** increases by 1°C. The third row refers to a 1°C increase in **tmax**. (3) The second and the third column report coefficients and p-values of the changes in the marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where the temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in the marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.8 Estimated changes in the effects of plant density on yield as a result of 1°C warming

		All months		Jun-Aug	
		Estimates	P-value	Estimates	P-value
tmin & tmax	Conventional	-0.0104	0.000	0.0084	0.000
	GM-RW	0.0018	0.547	0.0051	0.331
	other GM	-0.0053	0.030	-0.0151	0.000
tmin	Conventional	0.0086	0.000	0.0280	0.000
	GM-RW	-0.0282	0.000	-0.0222	0.001
	other GM	-0.0176	0.000	-0.0456	0.000
tmax	Conventional	-0.0190	0.000	-0.0197	0.000
	GM-RW	0.0300	0.000	0.0272	0.000
	other GM	0.0123	0.000	0.0305	0.000

Notes: (1) The table displays coefficients and p-values of the change in the marginal effect of plant density as a result of 1° warming. The results are calculated from the estimated results of the model specification in equations (3.1) and (3.8) that replaces monthly PDSI as a measure of water availability with a quadratic form of the mean of monthly cumulative precipitation for the whole growing season. (2) The first column indicates what weather variables are the marginal effects of plant density based on. The first row of the first panel indicates a 1°C increase in both **tmin** and **tmax**. The first row of the second panel refers to a scenario where only **tmin** increases by 1°C. The first row of the third panel refers to a situation where only **tmax** increases by 1°C. (3) The second column indicates the hybrid groups: "RW" is GM hybrids expressing Bt trait for corn rootworm. "other GM" refer to GM hybrids without Bt trait for corn rootworm. (4)The third and fourth column report coefficients and p-values of the change in marginal effect of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the change in the marginal effect of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.9 Estimated changes in the effects of plant density on yield as a result of 1°C warming

	All Months		Jun-Aug	
	Estimates	P-value	Estimates	P-value
tmin & tmax	-0.012	0.000	-0.002	0.052
tmin	-0.010	0.000	0.018	0.000
tmax	-0.002	0.084	-0.020	0.000

Notes: (1) The results here are estimated through our main specification in equations (3.1) and (3.2) but replacing linear time trend with year fixed effects. (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row indicates a 1°C increase in both **tmin** and **tmax**. The second row refers to a warming scenario where only **tmin** increases by 1°C. The third row refers to a 1°C increase in **tmax**. (3) The second and the third column report coefficients and p-values of the changes in the marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in the marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

Table 3.10 Estimated changes in the effects of plant density on yield as a result of 1°C warming

	All Months		Jun-Aug	
	Estimates	P-value	Estimates	P-value
tmin & tmax	-0.021	0.000	-0.008	0.000
tmin	-0.010	0.000	0.003	0.087
tmax	-0.011	0.000	-0.011	0.000

Notes: (1) The results here are estimated through our main specification in equations (3.1) and (3.2) but adding quadratic term of plant density. (2) The first column indicates what weather variables the marginal effects of plant density are based on. The first row indicates a 1°C increase in both **tmin** and **tmax**. The second row refers to a warming scenario where only **tmin** increases by 1°C. The third row refers to a 1°C increase in **tmax**. (3) The second and the third column report coefficients and p-values of the changes in the marginal effects of plant density as a result of warming scenarios (both **tmin** and **tmax**, and **tmin** and **tmax** separately) where temperature of each month of the May-September growing season increases by 1°C. The last two columns provide coefficients and p-values of the changes in the marginal effects of warming scenarios where the temperature of each month from June to August increases by 1°C.

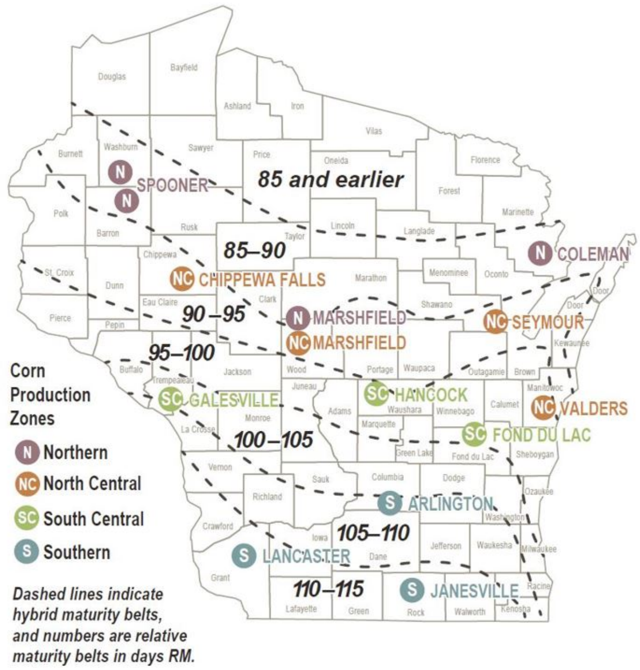

Figure 3.1 Map of research locations of Wisconsin field experimental data Web: http://corn.agronomy.wisc.edu/ HT/images/Map.jpg. Accessed: 4/7/2019

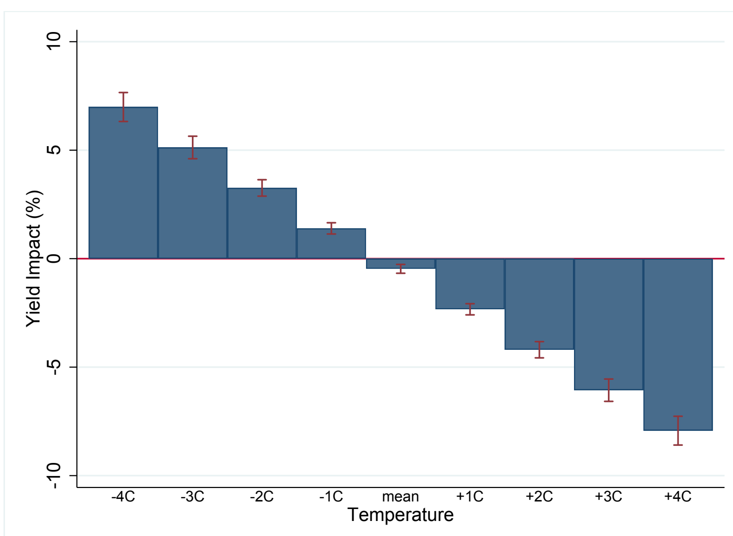

Figure 3.2 Marginal percentage effect of plant densities as $tmin$ and $tmax$ of each month deviate from the mean by 1°C increments

Notes: The main specification in equations (3.1) and (3.2) is implemented. The Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence interval.

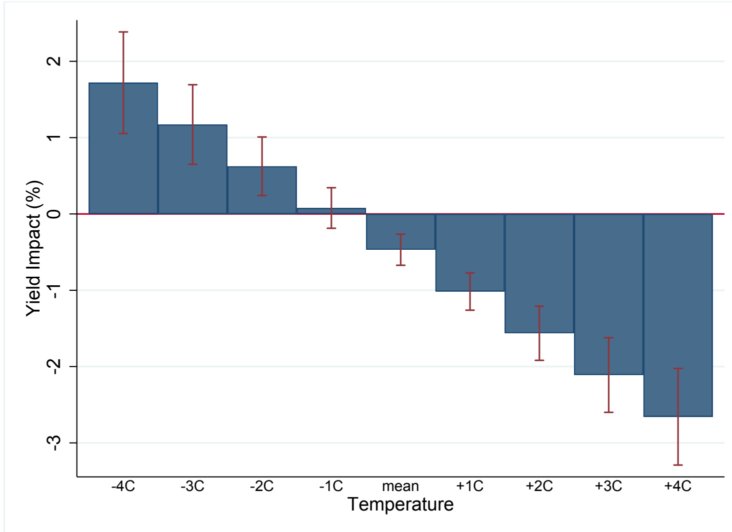

Figure 3.3 Marginal percentage effect of plant densities as $tmin$ and $tmax$ of each month from June to August deviate from the mean by 1°C increments

Notes: The main specification in equations (3.1) and (3.2) is implemented. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

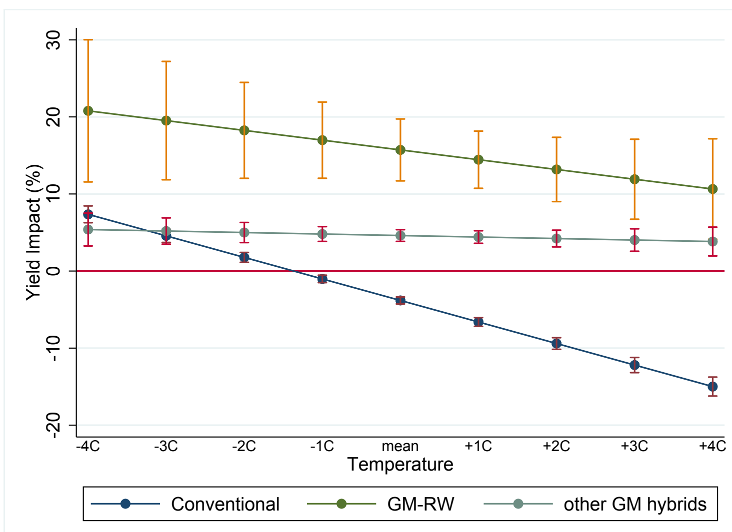

Figure 3.4 Marginal impacts of plant density for the three varietal groups

(3.1) and (3.8)

Notes: The figure shows the results of the model specification in equations (models including interaction terms among weather, planting density and GM varietal group dummy variable). Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

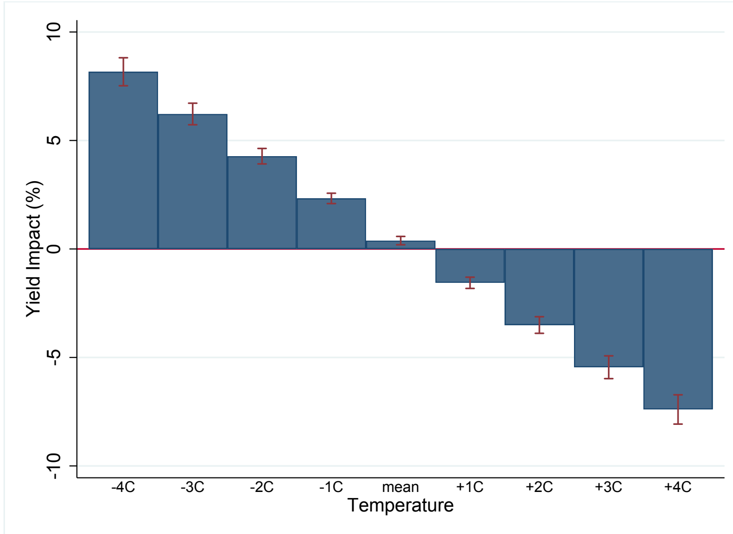

Figure 3.5 Marginal percentage effect of plant density as $tmin$ and $tmax$ of each month deviate from the mean by 1°C increments

Notes: The figure shows the results of the model with all variables of the main specification except the managerial inputs and practices. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

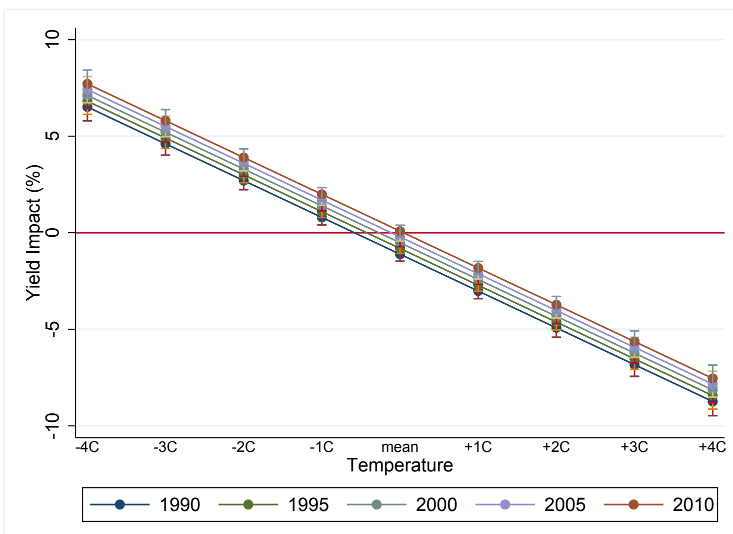

Figure 3.6 Marginal impact of plant density across years estimated by the model including the interaction term between time trend and plant density

Notes: The figure shows the results of the model with all variables of the main specification and the interaction term between time trend and plant density. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

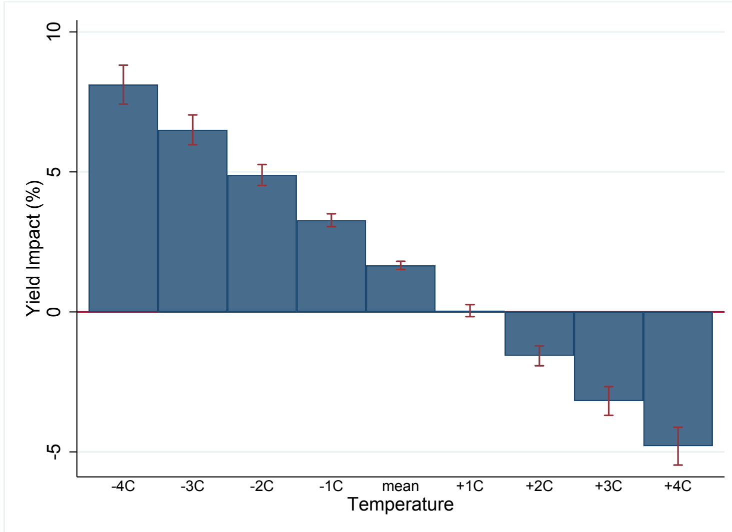

Figure 3.7 Marginal percentage effect of plant densities as $tmin$ and $tmax$ of each month deviate from the mean by 1°C increments

Notes: The figure shows the results of the model with the main specification that replaces PDSI as a measure of water availability with a quadratic function of precipitation.

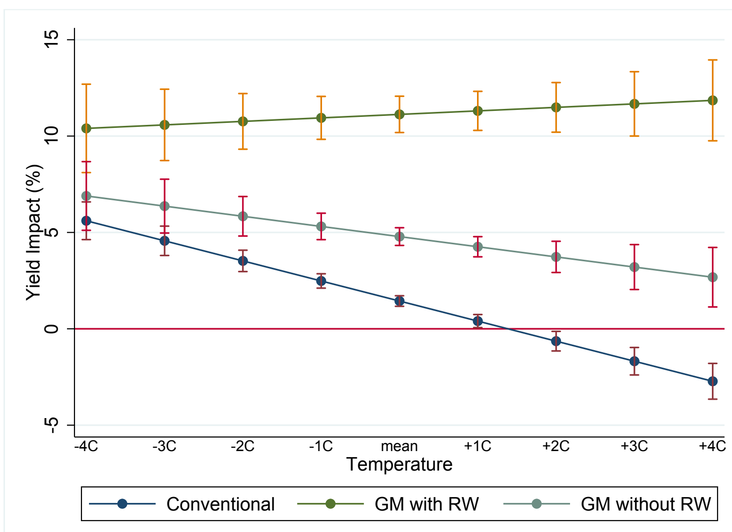

Figure 3.8 Marginal impacts of plant density for the three varietal groups

Notes: The figure shows the results of the model specification in equations (3.1) and (3.8) replacing PDSI as a measure of water availability with a quadratic function of precipitation. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

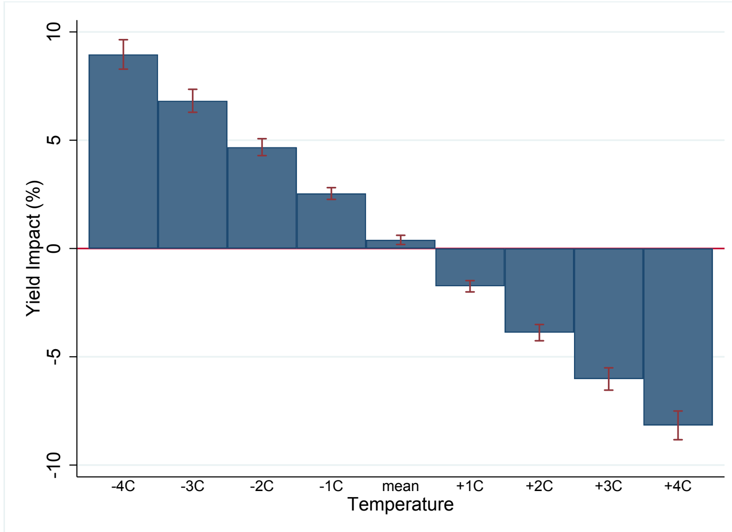

Figure 3.9 Marginal percentage effect of plant densities as $tmin$ and $tmax$ of each month deviate from the mean by 1°C increments

Notes: The difference between this model and the main specification (the specification in equations (3.1) and (3.2)) is that this model controls for year fixed effects rather than linear time trend. The Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

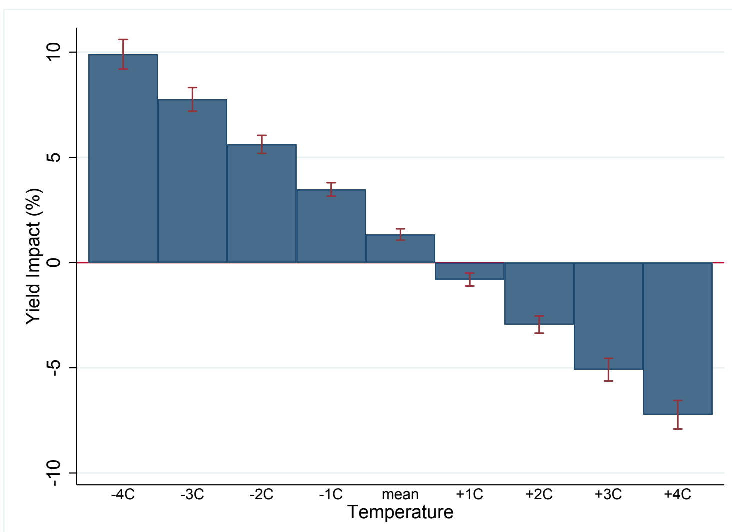

Figure 3.10 Marginal percentage effect of plant densities as $tmin$ and $tmax$ of each month deviate from the mean by 1°C increments

Notes: This model includes a quadratic term of plant density in addition to the explanatory variables adopted in the main specification. The Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

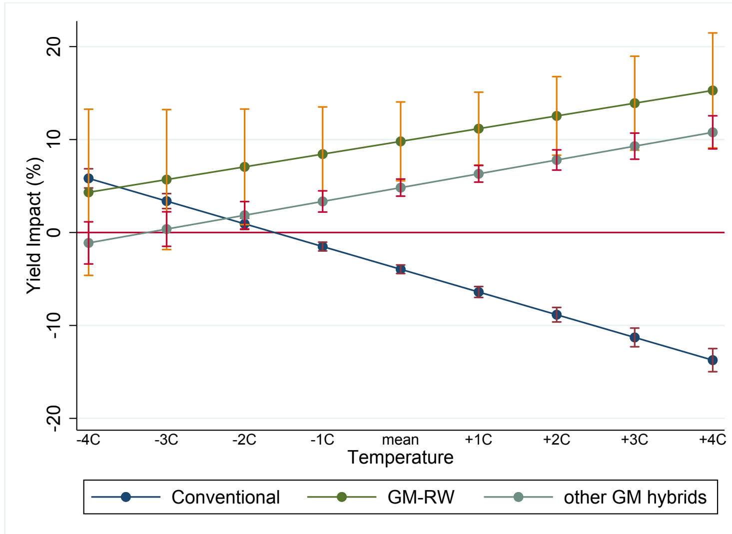

Figure 3.11 Marginal impacts of plant density for the three varietal groups

Notes: The model specification is the same as the model specification in equations (3.1) and (3.8) except it controls for year fixed effect rather than linear time trend. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

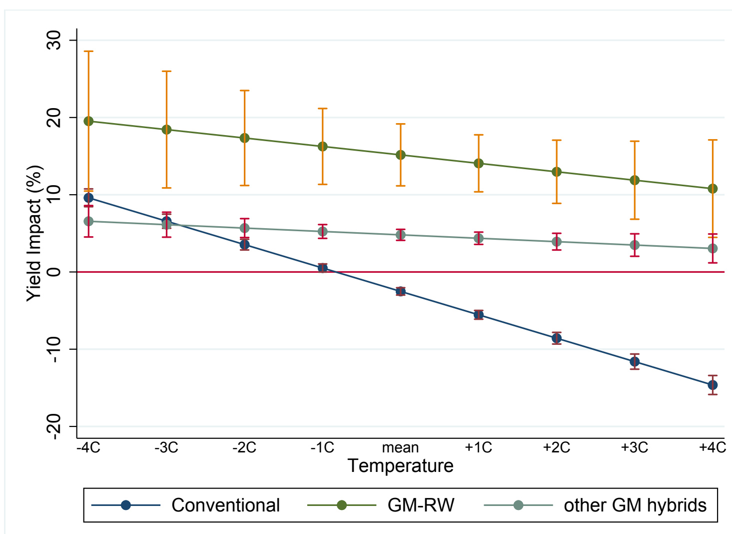

Figure 3.12 Marginal impacts of plant density for the three varietal groups

Notes: The model adds a quadratic term of plant density into the specification in (3.1) and (3.8) except it controls for year fixed effect rather than linear time trend. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

CHAPTER

4 WARMING TEMPERATURES, YIELD RISK, AND CROP INSURANCE PARTICIPATION

In this chapter, we examine how crop insurance participation rate influences the impact of extreme heat on mean yield and yield risk (i.e., yield variance, skewness, and kurtosis) of corn and soybeans in the US. We utilize county-level panel data and parametric moment-based method to evaluate how crop insurance participation affects the relationship between warming temperatures and the moments of crop yield distributions. Our results indicate that the yield risk increasing effect of warming is further increased by high-level insurance participation.

4.1 Introduction

Agriculture is one sector in the economy that is considered to be most vulnerable to climate change because it relies heavily on favorable weather conditions to achieve good crop yield outcomes. A large and growing literature has documented that the likely impacts of climate change and warming temperatures on agricultural crop production (See [D'A16]; [Wel10]; [Ros14]; [Tac15a]; [Sch09], among others). In general, this literature provides evidence that climate change has strong negative impacts on mean yields for a variety of crops, locations, modeling approaches, and climate predictions. For example, [Ske08] have shown that approximately 31% of historical crop yield losses in the United States (US) can be attributed to droughts and extreme heat (i.e., with remaining losses associated with excess moisture (e.g., floods), extreme cold (e.g., freeze), hail, and other weather-related causes).

Aside from climate change impacts on mean yields, there is also a number of previous studies that have examined the effects of climate change and/or weather variables on yield risk (or yield variability) ([Che04]; [Che05]; [Isi06]; [McC08]; [Kim09]; [Bar10]; [Bou10]; [Tac12]; [Att14]; [Ray15]; [Urb12]; [Urb15]; [Tol17]; [Tac18]; [Con20]). Most of these papers indicate that climate change and warming temperatures increases yield risk (and also simultaneously decrease mean yields). Given that most farmers are risk-averse ([Cha96]), farmers typically view the climate change impacts on inter-annual yield variability and/or yield risk – particularly, downside risk – as at least as important as the direct effect of climate change on mean yields.

With the importance of managing yield risk in agriculture, governments all over the world have supported programs and policies that help farmers mitigate the adverse effects of low yield (or revenue) outcomes. One such program that is becoming more ubiquitous in agriculture globally is crop insurance. In the US, for example, crop insurance is now considered the centerpiece risk management program in agriculture, and the federal government has provided over $70 million in crop insurance subsidies to farmers since 2004 ([Tol17]). Given the widespread use of crop insurance in the US, it is likely that adoption of this risk management tool influence farm management behavior (e.g, input use), and these changes in behavior consequently affect eventual yield outcomes (e.g., mean yield and yield risk) ([Ann15]). Therefore, further understanding of the inter-relationships among mean yields, yield risk, climate change, and crop insurance is critical for continued improvements in US agricultural productivity.

This chapter addresses the question of whether crop insurance adoption influences the effect of warming temperatures on yield risk. In particular, we are interested in exploring if increasing crop insurance participation would result in larger increases in the yield risk response to extreme heat. A county-level panel data set that includes rich information on yields, weather variables, and crop insurance participation is constructed to help accomplish the goals of the study. Stochastic production functions are estimated using parametric moment-based estimation procedures (See [Ant83], [Ant84], and [Cha04]) to determine whether the relationship between extreme heat and all four moments of the yield distribution (e.g, mean, variance, skewness, kurtosis) is affected by crop insurance use.

As already mentioned above, a number of studies have already explored the impact of climate change on mean yields and yield risk. The study of [Ann15] is the closest to the present study in spirit because they investigate how crop insurance influence the mean yield response to extreme heat using county-level corn and soybean data in the US. Based on fixed effects regression models, [Ann15] find that subsidized crop insurance tends to further increase the direct negative impact of extreme heat on mean yields. This result implies that subsidized crop insurance encourages moral hazard behavior, where farmers have lower incentives to use climate adaptation strategies (i.e., discourages adoption of practices that would makes their operations more resilient to extreme heat) ([Dol01]; [Sch10b]; [Ske01]; [Ske08]; [DF14]; [O'C13]).[1] Note that [Ann15] examine how extreme

[1] Even though several past studies have indicated that the main mechanism by which subsidized crop insurance exacerbates the negative mean yield effect of climate change is likely through this moral hazard effect (i.e., crop insurance reduce incentives to adopt climate-change-mitigation practices), it is also possible that the so-called "extensive margin effect" of crop insurance (i.e., where marginal lands are brought into production) can be another mechanism for which crop insurance amplify the yield risk response to extreme heat ([Wu99]; [Goo04]; [Yu17]). However, it is important to note that [Sch10b] also argue that well-designed, unsubsidized crop insurance may encourage (rather than discourage) use of

heat affects *mean yield* (rather than *yield risk*), and the role that crop insurance plays in shaping the relationship between extreme heat and mean yields. Our study contributes to the literature by specifically exploring the role of crop insurance in shaping the relationship between extreme heat and yield risk.[2] If subsidized crop insurance products indeed encourage moral hazard behavior and discourage the use of climate adaptation practices, then it is important to empirically examine whether crop insurance also strongly influence the effect of extreme heat on the higher moments of the yield distribution (i.e., not just influencing the direct effect of extreme heat on mean yields). Does crop insurance participation further exacerbate the yield-risk-increasing effect of climate change?

This chapter proceeds as follows. Section 4.2 describes the county-level panel data utilized in the study. Section 4.3 describes the parametric moment-based estimation procedures and the empirical specification . Section 4.4 discusses estimation results. Section 4.5 provides several robustness checks, instrumental variable method and the cost of risk calculated based on estimates of the main model. Section 4.6 concludes.

4.2 Data

The county-level panel data set constructed for this study is based on information from publicly available sources. The county-level corn and soybean data on yields and acreage planted for the period 1989-2017 were drawn from the National Agricultural Statistics Service (NASS) database. County-level data on farmers' expenditures on seed, fuel, fertilizer, and other chemicals, and total production costs were collected from the Bureau of Economic Analysis (BEA). Crop insurance data from 1989-2017 were gathered from the Summary of Business database of the Risk Management Agency (RMA), which includes county-level data on liabilities, insurance plan used, coverage levels, and insured acreage.[3] The weather data used in the analysis is from the data made available by [Sch09]. This weather database includes interpolated daily minimum and maximum temperatures for 4 km grid cells within the US from 1950 to 2017. We aggregated this to the county-level by taking the area-weighted average of recorded weather for all grids in each county. Note that the county-level panel data developed for this study starts from 1989 since the RMA data on insurance coverage

climate-mitigation-strategies and serve as a complement (rather than a substitute) to crop insurance. They argue that "*Accurately priced uncertainties that reflect climate risk can act to incentivize risk reduction through price signals and risk management stipulations. When the probability of an increased climate risk is perceived, this possibility is reflected in insurance prices, leading to a more expensive contract. Such a signal can act as a warning to the client and provide an incentive to use other forms of adaptation.*" Note, however, that crop insurance in the US (and in most other countries) are subsidized and the argument of [Sch10b] may not apply in this case.

[2] Note that a related paper by [Con20] examine how crop insurance participation influence the effect of droughts on the upper and lower partial variance of yields. Our study builds on [Con20] since we investigate how crop insurance affects the magnitude of the warming impact (not just the effect magnitude of specific drought events) on the variance, skewness, and kurtosis of the yield distributions. Admittedly, we do not separately examine the upper and lower variance effect as in [Con20], but we explore the effects on skewness and kurtosis which this previous study did not.

[3] The insurance data used for this study only considers individual-level yield and revenue policies (e.g., Yield Protection (YP) and Revenue Protection (RP)), and excluded area-triggered policies (e.g., county-level policies like Area Risk Protection Insurance (ARPI)). Majority of insured corn and soybean producers utilize RP or YP, and only a small proportion use area-triggered products.

levels are available only from 1989 forward.

We build the county-level panel data for this study by first merging the NASS data with both the BEA and RMA datasets. This allows us to calculate a "liability ratio" as our measure of crop insurance participation at the county-level ([Goo04]). The liability ratio of crop insurance participation is the ratio of total *actual* liability in the county (for each year) over a measure of total *possible* liability. Total actual liability for each county-year is reported in the RMA Summary of Business database. On the other hand, total possible liability (for each county-year) is calculated by taking the product of the following: the Chicago Board of Trade (CBOT) futures market price for the crop, total planted acres for the crop,[4] the average crop yield for the preceding ten years, and the maximum coverage level available ([Goo04]). Appropriate CBOT prices from the Bridge® database were used to be consistent with how RMA calculates the projected price used in their yield and revenue policies.[5] We chose the aforementioned "liability ratio" as our measure of crop insurance participation (i.e., in contrast to the ratio of insured to planted acres in [Ann15]) because this measure accounts for increasing "effective" crop insurance participation through increases in coverage level. Note that the liability ratio can increase with a higher coverage level, even when insured acreage does not change.

Consistent with [Ann15] and [Bur16] the weather variables of interest in this study are: degree days for moderate heat, degree days for extreme heat, and precipitation. The degree day measures provide information about the number of days a crop is exposed to certain temperature ranges. For corn, we use degree days between 10-29°C as the measure of moderate heat, and degree days above 29°C as the measure for extreme heat. For soybeans, we use 10-30°C as the measure for moderate heat, and degree days above 30°C as the measure for extreme heat.[6] The advantage of representing warming in this way is that it allows for capturing the nonlinear relationship between temperatures and yield. The degree day measures are the sums of daily exposures over the April-September growing season. The precipitation variable represents the cumulative sum of precipitation received (in m) over the April-September growing season. The county-level aggregates of these weather variables are then merged together with the NASS, BEA, and RMA datasets to produce the final data set used in this study.

Lastly, we limit the geographical coverage of our analysis to only those counties east of the

[4] As noted in [Ann15], it is possible that there are cases where the reported NASS planted acres value in their database is lower than the true planted acres (or the insured acres reported by RMA). This is because NASS values are only based on a sub-sample of larger farms in a county (e.g., it is not based on a complete enumeration of all farms, as in the agricultural census). Hence, when the aforementioned situation happens, the liability ratio measure (and even the ratio of insured acres to planted acres) becomes greater than one. Consistent with the approach of [Ann15], we use the "maximum" planted acres value for each county-year to avoid having situations where the liability ratio is greater than one.

[5] The data about state-level projected price discovery periods and contract months can be found on USDA website at: https://www.rma.usda.gov/en/Policy-and-Procedure/Insurance-Plans/Commodity-Exchange-Price-Provisions-CEPP.

[6] We use the method in [Sch09] to calculate DD^M and DD^H. For example, suppose DD^H is to measure the degree days above 29°C and DD^M is degree days between 10-29°C, if the maximum temperature of that day is lower than 29°C, the DD^H of that day is 0; if the minimum temperature of that day is above 29°C, the DD^H of that day is equal to the difference between the average temperature and 29°C ($tAvg-29$; $tAvg=(tMin+tMax)/2$); if 29°C is between the maximum and minimum temperature of that day, DD^H of that day is $((tAvg-29)\times acos((2\times 29-tMax-tMin)/(tMax-tMin))+(tMax-tMin)\times sin(acos((2\times 29-tMax-tMin)/(tMax-tMin)))/2)/\pi$. The DD^H of the entire growing season is the sum of daily degree days above 29°C from April 1^{st} to September 30^{nd}. The DD^M is the difference between degree days above 29°C and degree days above 10°C.

100-degree meridian but not including Florida (as is done in [Ann15]) (See Figure S4.1 for the states included in the data set). This allows us to focus more on counties with primarily rainfed (rather than irrigated) corn and soybean operations, and to examine the interactions among yield risk, extreme heat, and crop insurance for this farm type. Descriptive statistics for the yield, weather, and input expenditure variables used in the study are presented in Table 4.1, and the summary statistics for the various crop insurance participation measures are in Table 4.2.

4.3 Empirical Strategy

4.3.1 Parametric Moment-based Estimation Method

To examine the inter-relationships among yield risk, extreme heat, and crop insurance adoption, we use the parametric moment-based framework of [Ant83] and [Ant84] for estimating stochastic production functions. Let the crop production process be represented by the stochastic production function:

$$y = \mu(\mathbf{x}) + \varepsilon, \tag{4.1}$$

where y is crop yield; $\mathbf{x}$ is a vector that includes weather variables, a crop insurance participation measure, and relevant interaction terms; and ε is an error term where $E(\varepsilon|\mathbf{x}) = 0$ and is assumed to be independently distributed.

Evaluating the risk implications of any element in $\mathbf{x}$ can be done through the evaluation of the moments of the production function – mean, variance, skewness, and kurtosis. The first moment (i.e., the mean yield) can be represented as follows: $M_1(\mathbf{x}) = E[\mu(\mathbf{x})]$. The higher moments of the production function represents risk exposure and can be expressed as follows:

$$\hat{\varepsilon}^i = [y - \mu(\mathbf{x})]^i = M_i(\mathbf{x}) + v_i, \quad \forall i = 2, 3, 4 \tag{4.2}$$

where $\hat{\varepsilon}^i$ is the i^{th} power of the predicted residuals from regression specified in equation (4.1), $M_i(\mathbf{x})$ is the i^{th} moment function, and v_i is the error term. Equation (4.2) represents variance when $i = 2$, skewness when $i = 3$, and kurtosis when $i = 3$.

In general, the variance, skewness, and kurtosis of yield vary with vector $\mathbf{x}$. For example, x_1 can be variance increasing, variance neutral, or variance decreasing. Similarly, a specific $\mathbf{x}$ variable can be skewness increasing, skewness neutral, or skewness decreasing. The same pattern can be observed with kurtosis. Note that equation (4.2) above goes beyond the typical mean-variance approach that has been commonly used in the past (as in [Jus78]). This is relevant in situations where exposure to downside risk (i.e., asymmetric risk effects) is a concern and skewness (kurtosis) effects are important.

To estimate equations (4.1) and (4.2), we utilize the linear moment method (LMM) put forward by [Ant83]. With this method, the moments of the yield distribution are assumed to be parametric linear functions of independent variables such that:

$$y = \mathbf{x}\beta_1 + \varepsilon \tag{4.3}$$

$$\hat{\varepsilon}^i = \mathbf{x}\beta_i + v_i, \quad \forall i = 2, 3, 4. \tag{4.4}$$

Note that equations (4.3) and (4.4) exhibit heteroscedasticity, which implies that heteroscedasticity robust standard errors need to be used in the estimation. If endogeneity is not a concern (e.g., more on this below), equations (4.3) and (4.4) can simply be parametrically estimated by ordinary least squares (OLS) with heteroscedasticity robust standard errors.

4.3.2 Empirical Specification

To achieve the objectives of this study, we implement the parametric moment based estimation method above using the following empirical specification:

$$\begin{aligned} y_{jt} = \alpha_{1j} + \beta_{11} Ins_{jt} + \beta_{12} DD^M_{jt} + \beta_{13} DD^H_{jt} + \beta_{14} Prec_{jt} + \beta_{15} Prec^2_{jt} + \\ \beta_{16}(Ins_{jt} \times DD^M_{jt}) + \beta_{17}(Ins_{jt} \times DD^H_{jt}) + \beta_{18}(Ins_{jt} \times Prec_{jt}) + \\ \beta_{19}(Ins_{jt} \times Prec^2_{jt}) + \beta_{110s} t + \beta_{111s} t^2 + \gamma_{1t} + \varepsilon_{jt} \end{aligned} \tag{4.5}$$

where y_{jt} is corn or soybean yield (in bu/ac) for county j in period t (for $t = 1, 2, 3, \ldots$ denoting years from 1989 to 2017); Ins_{jt} is the liability ratio measure of insurance participation ([Goo04]); DD^M_{jt} is the degree day measure for moderate heat (in thousand of Celsius); DD^H_{jt} is the degree day measure for extreme heat (in hunred of Celsius); $Prec_{jt}$ is cumulative precipitation during the growing season (in m); the α, β, and γ coefficients are parameters to be estimated (where α_{1j} are county fixed-effects, γ_{1t} are year fixed effect); and ε_{jt} is the error term. The $\beta_{110s} t$ and $\beta_{111s} t^2$ are included in the specification to control for state-specific time trends (i.e., quadratic time trends).

Following equation (4.5), the higher moment functions can then be represented as:

$$\begin{aligned} \hat{\varepsilon}^i_{jt} = \alpha_{ij} + \beta_{i1} Ins_{jt} + \beta_{i2} DD^M_{jt} + \beta_{i3} DD^H_{jt} + \beta_{i4} Prec_{jt} + \beta_{i5} Prec^2_{jt} + \\ \beta_{i6}(Ins_{jt} \times DD^M_{jt}) + \beta_{i7}(Ins_{jt} \times DD^H_{jt}) + \beta_{i8}(Ins_{jt} \times Prec_{jt}) + \\ \beta_{i9}(Ins_{jt} \times Prec^2_{jt}) + \beta_{i10s} t + \beta_{i11s} t^2 + \gamma_{it} + \varepsilon_{jt} \end{aligned} \tag{4.6}$$

where, $i = 2, 3, 4$ refers to the i^{th} power of the error term ε and represents the variance, skewness and kurtosis of the yield distribution. For the variance of yield ($i = 2$), a positive (negative) parameter estimate indicates that the corresponding variable increases (decreases) yield variability. For skewness of yield ($i = 3$), a positive (negative) parameter estimate indicates that the corresponding variable decreases (increases) the exposure to downside risks. For kurtosis of yield ($i = 4$), a positive (negative) parameter estimate indicates that the corresponding variable increases (decreases) production risk.

Since the aim of this chapter is to examine how crop insurance participation affects the impact of extreme heat on yield risk, the parameter of interest is: β_{i7}. After estimating the parameters in equations (4.5) and (4.6), we can make inferences on how crop insurance participation influence the impact of extreme heat on the moments of the yield distribution. For example, if the parameter β_{23} is positive and significant (i.e., extreme heat increases yield variance), then a positive and significant β_{27} parameter suggests that having insurance coverage would further magnify the impact of extreme heat on yield variability. This result implies that farmers with higher crop insurance coverage tend to experience larger yield variability due to extreme heat (relative to farmers without (or with lower) insurance coverage).

We also utilize the parameter estimates from equations (4.5) and (4.6) to calculate the marginal impacts of a specific warming scenario where daily minimum and maximum temperatures increase by 1°C.[7] This analysis allows us to see how the specific warming event defined above affects the mean, variance, skewness, and kurtosis of yields, at different levels of insurance participation. For example, one would be able to compare the mean yield impact of the warming scenario for the case when there is no insurance coverage in the county ($Ins_{jt} = 0$), versus the situation when there is a 70% participation rate ($Ins_{jt} = 0.7$).

4.4 Estimation Results

Tables 4.3 and 4.4 show the parameter estimates from the corn and soybean models that account for county-level fixed effect, year fixed effect, state-specific linear and quadratic time trend, and the crop insurance participation rate measured using the liability ratio (see equations (4.5) and (4.6)). For uninsured counties, the effect of weather variables on the moments of the yield distribution is represented by the coefficients associated with the weather variable by itself (i.e., without considering the interactions). On the other hand, for insured counties, the effect of weather events is the sum of the single weather variable coefficient plus the coefficient associated with the (weather × insurance participation) interaction terms.

In both Table 4.3 and 4.4, the interaction terms between DD^H and insurance participation for the mean, variance, and kurtosis functions are statistically significant (at the 10% significance level). However, this interaction term is statistically insignificant in the skewness function. These results suggest that, for both corn and soybeans, crop insurance program participation significantly affects the impact of extreme heat on the mean, variance, and kurtosis of yield. Hence, the yield risk profile resulting from an extreme heat event is largely affected by the extent of insurance coverage.

In terms of mean yield, the detrimental effect of extreme heat is significantly higher for insured counties than uninsured counties. As insurance participation increases, the magnitude of the impact also increases. For corn, relative to an uninsured county, the negative mean yield impact of a unit increase in DD^H further increases by 47.34 bushels per acre with insurance participation. For soybeans, the increase is 17.98 bushels per acre. This result implies that participating in insurance programs likely induces farmers to not adopt climate change adaptation practices, such that the impact of higher temperatures on mean yields worsens in the presence of insurance coverage (e.g., this result is consistent with the moral hazard story in [Ann15]).

Insurance participation also significantly affects the impact of extreme heat on the variance and kurtosis of corn and soybean yields. For both corn and soybeans, the variance and kurtosis of yields increase as DD^H increases (i.e., see parameter estimates for the single DD^H variable in Tables 4.3 and 4.4). Moreover, parameter estimates associated with the interaction terms of DD^H

[7] Since we use degree day measures (DD^M and DD^H) in our empirical specification (i.e., not daily minimum and maximum temperatures directly), we examined the impact of degree day changes that is equivalent to the warming scenario described above. For example, a daily minimum and maximum temperature increase of 1°C would be equivalent to an increase in DD^H by 0.24 and an increase in DD^M by 0.14 for area planting corn and an increase in DD^H by 0.18 and an increase in DD^M by 0.15 in area planting soybeans(in the degree day units we utilize).

and insurance participation indicate that the magnitude of the DD^H effect on yield variance and kurtosis becomes larger as insurance participation in the county increases. This implies that the detrimental effect of extreme heat on production risk is higher for counties with higher levels of crop insurance participation, and this added effect is mainly through the statistically significant increases in yield variance and kurtosis.

To better visualize the warming response of the mean, variance, skewness, and kurtosis yields under varying levels of crop insurance participation, we present estimated marginal effects for a particular warming scenario where daily minimum and maximum temperatures increase by 1° (See Table 4.5). Parameter estimates from Tables 4.3 and 4.4 are used to calculate the marginal effects for this particular warming scenario. The results from this analysis suggest that higher levels of crop insurance participation further exacerbate the detrimental mean and risk effects of warming in corn and soybeans.

In the empirical analysis conducted so far, we only consider a single insurance participation variable that lumps participation in yield protection (YP) based plans and revenue protection (RP) based plans together. To take into account the potential difference between the effects of these two types of insurance programs, we also ran another specification where we separate participation in YP and RP insurance plans (See Table 4.6 and Table 4.7). Participation in these two types of insurance plans still intensify the effects of DD^H on the mean, variance, and kurtosis of yields. We also notice that the magnitude of the additional RP participation effect on yield seems to larger than the additional YP participation effect. For higher moments, RP participation significantly increases the sensitivity of variance and kurtosis to DD^H (except the kurtosis of corn), while the impacts of YP participation on them are statistically insignificant and seem to smaller. Given that RP covers both yield and price losses (and YP only coves yield losses), it seems reasonable to expect that RP plans may induce greater moral hazard effects than YP plans. The YP and RP marginal effects for the warming scenario where daily minimum and maximum temperatures increase by 1° are presented in Table 4.8 and Table 4.9. The results here are still largely consistent with our discussion above.

4.5 Robustness Checks

4.5.1 Alternative Fixed Effect Models

We conduct robustness checks to investigate whether the estimation results remain "robust" under alternative specifications described in the following paragraphs. The first robustness check is where we estimate similar models to the ones in Tables 4.3 and 4.4, but where we control for county-specific time trends (See Appendix Tables S4.3 and S4.4). These regression runs still generate results that are comparable to those discussed in the previous section (e.g., same significance and signs, plus roughly the same coefficient magnitudes).

The second robustness check is where we include managerial input expenditures as additional control variables (e.g., fertilizer expenditures, fuel expenditures, labor expenditures, etc.). Regression run results are presented in Appendix Tables S4.5 and S4.6). The estimation results here still support our findings in the previous section, though much of the input variable coefficients are largely insignificant.

To better compare our results with the previous literature (for example, [Ann15]), we also conduct a third robustness check that uses an "area ratio" measure of crop insurance participation (i.e., the ratio of planted acres to the maximum total planted acres) rather than a liability ratio measure (See Appendix Tables S4.7 and S4.8). The sign and significance of the main interaction terms of interest ($DD^H \times$ Ins) are still consistent with the model runs in the previous section using a liability-based insurance participation measure. However, we note that the magnitudes of the coefficients on the relevant interaction terms are smaller here compared to the estimates from the model using the liability ratio insurance measure. This is expected given that the area ratio measure only captures changes in the area insured (e.g., the "extensive margin" effects) and not the changes in insurance protection levels through increases in coverage choices (even with no change in area insured).

4.5.2 Potential Endogeneity and Instrumental Variables

Based on the empirical specification in equations (4.5) and (4.6), there are potential endogeneity concerns with regards to the insurance participation variable since there may be unobservables that simultaneously influence the outcome variable y and the aforementioned explanatory variables (e.g., unobserved management ability, for example). We partly control for this potential endogeneity issue by including county fixed effects (α_{1j}) that controls for time-invariant unobservables. The time trends also control for time-varying unobservables that affect the full sample. However, there may still be other time-varying unobservables at the county-level that can cause endogeneity issues (e.g., time-varying soil quality for example). Therefore, we also use an instrumental variable (IV) estimation procedure (e.g., two-stage least squares (2SLS)) within the moment-based framework to address further concerns about potential endogeneity. (See [DF14] for an application of this type of approach).[8]

An appropriate instrument should be correlated with the potentially endogenous variable, but have no independent direct effects on the dependent variable. In our specification, the dependent variables of interest are the mean yield, and the higher moments of the yield distribution. Hence, legitimate instrumental variables should be uncorrelated with the yield and yield risk, but correlated with insurance participation rates. The previous literature provides several sources of exogenous variation that can be utilized to instrument for insurance participation. The first set of instrumental variables we use in this study are important national insurance policy changes. For example, [Sch14] employed indicators of the years when essential policy changes occurred as instruments for insurance participation. An indicator variable for the year after 1994 was shown to be an essential instrument. This can be explained by the fact that the multiple policy changes caused by the passage of 1994 Farm Bill (such as the introduction of CAT, elimination of annual disaster relief programs and short period mandatory insurance participation) had shifted the trend

[8] In the IV approach used here, we implement the IV approach in the mean and higher moment functions and assume that it is adequate to control for endogeneity in all of the moments of the yield distribution.

in the insurance participation. The second set of possible instruments we utilize is based on the policy changes related to subsidy rates. [Yu17] use the national subsidy rates for yield protection (YP) and revenue protection (RP) policies at the 65% and 75% coverage levels as their instrumental variables for crop insurance adoption (See Figure S4.4).

We made use of the instrumental variables described above to check the robustness of our results. The estimated IV results are shown in Appendix Table S4.9 and Table S4.10. The sign of the interactions between DD^H and insurance participation rate are the same with the major model.

4.5.3 Evaluating the Cost of Risk

To further understand how extreme heat and crop insurance influence farmers' responses to changes in risk exposure, we calculate the "cost of risk" (also called the risk premium) based on the parameters estimated in equations (4.5) and (4.6). When a decision-maker is risk averse, he/she is willing to give up an amount of money to replace risky wealth with the expected value of this wealth. For example, assume the wealth received by an individual is $y = \mu + u$ where u is a random variable, if the individual is a risk averse decision-maker, he/she would be willing to pay R to eliminate u such that $(EU(y+u) = U(y+E(u)-R))$, where R is the "cost of risk" (or risk premium) for this person. In our case, the cost of risk can be defined as the amount of yield that a farmer is willing give up in order to replace random yield with the mean yield.

First, assume that the utility of the representative farmer exhibits constant relative risk aversion (CRRA), which is a behavioral assumption supported by previous empirical studies (See, [Cha96] for example). The utility function of yield under CRRA can then be defined as follows:

$$U(y) = \begin{cases} \frac{1}{1-\theta} y^{1-\theta}, & \text{if } \theta > 0, \theta \neq 1 \\ \ln y, & \text{if } \theta = 1 \end{cases} \tag{4.7}$$

where θ is the Arrow-Pratt relative risk aversion coefficient, which measures the degree of relative risk aversion. Based on the utility function in equation (4.7), the cost of risk can be defined as a function of the mean, variance, skewness and kurtosis of yield (See [Cha04]):

$$R(\mathbf{x}) \approx \sum_{i=2}^{4} -[1/(i!)](U^i/U^1)M_i(\mathbf{x}) \tag{4.8}$$

where $U^i \equiv \partial^i U/\partial y^i$ is the i^{th} derivative of the utility function with respect to y, evaluated at $y = \mu(\mathbf{x})$. With the risk coefficient θ, the cost of risk is given by:

$$R_3(\mathbf{x}) \approx \frac{\theta}{2}\frac{M_2(\mathbf{x})}{\mu(\mathbf{x})} - \frac{\theta(\theta+1)}{6}\frac{M_3(\mathbf{x})}{\mu(\mathbf{x})^2} + \frac{\theta(\theta+1)(\theta+2)}{24}\frac{M_4(\mathbf{x})}{\mu(\mathbf{x})^3} \tag{4.9}$$

From equation (4.9), we evaluate how the cost of risk responds to changes in the weather variables (e.g., increasing days of extreme heat) for different levels of insurance participation. We first fix the other variables at their means, and then see how the cost of risk will change as the DD^H and/or DD^M values increase (or decrease) (due, for instance, to a 1°C and 2°C in daily minimum and maximum temperatures). This step allows us to observe how the cost of risk is affected by extreme heat, and then compare the contribution of each higher moment (e.g., the variance, skewness, and kurtosis) to the change in the cost of risk. Note that a higher (lower) cost of risk indicates an increase (a reduction) in the farmers' exposure to risk. We then repeat this first step, but now utilizing different levels of insurance participation rate from 0 and 1 (e.g., increasing in 0.1 increments). This will allow us to observe how the response of the cost of risk to extreme heat is influenced by insurance participation rates. For example, we can observe whether a high crop insurance participation rate will result in a larger yield risk response to extreme heat. Based on previous literature ([Shi13]; [Gan15]), the most commonly used relative risk aversion parameter is between 1 and 3. In this research, we evaluate the cost of risk at $\theta = 3$.

Table 4.10 provides information on the estimated total cost of risk and the decomposition of this cost of risk (i.e., the contribution of variance, skewness, and kurtosis are separately presented). Cost of risk is evaluated under three temperature scenarios (i.e., at the mean temperature, and when there is a 1°C and a 2°C increase in daily minimum and maximum temperatures) and different levels of insurance participation. Under the average temperature of our data set, the cost of risk constitutes about 0.7% to 2.6% of the mean yield. Most of the cost of risk can be attributed to the variance.

For corn, as temperature increases in our 1°C warming scenario, the cost of risk increases at all insurance participation rates and the impact of the warming temperature on the cost of risk increases as crop insurance participation rate increases (see top panel of the last two columns in Table 4.10). Without insurance coverage the 1°C warming scenario only increases the cost of risk by 0.3 bushels per are. However, as insurance participation increases the marginal impact of the warming scenario increases to 0.83 bushel per acre. A similar result is observed for a more serious warming scenario (where both daily minimum and maximum temperature experience a 2°C increase), though the magnitudes of warming effects are of course higher. The pattern of results for soybeans is similar to that of corn (see bottom panel of the last two columns in Table 4.10), with the exception that higher temperatures seem to reduce the cost risk at lower levels of insurance participation (which is somewhat counterintuitive).

4.6 Conclusions

The main objective of this study is to determine whether crop insurance participation influences the effect of warming temperatures on the mean, variance, skewness, and kurtosis of corn and soybean yields. To the best of our knowledge, this study is one of the first to carefully explore how the adverse production risk impacts of extreme heat is affected by the level of crop insurance coverage. County-level data from 1989-2017 and a parametric moment-based empirical approach were utilized to achieve the study objective. Results from our empirical analysis suggest that higher levels of crop insurance participation statistically worsen the adverse risk impacts of extreme heat. The detrimental effect of extreme heat on production risk is manifested in the statistically larger variance and kurtosis observed at higher insurance participation rates. Moreover, we also validate findings in previous literature (see [Ann15]) where the negative mean yield effect of warming intensifies under higher levels of insurance participation.

These findings are consistent with the argument that crop insurance promotes moral hazard behavior such that insured farmers are less likely to adopt practices that help mitigate the adverse mean yield and production risk effects of climate-change-induced warming. Hence, the new insight here is that the disincentive effect of crop insurance seems to not only affect mean yields but also the variability of yields (e.g., production risk). This is further evidence of the “unintended consequence” of subsidizing crop insurance and encouraging higher participation levels. Crop insurance tends to discourage the adoption of climate change adaptation practices, and consequently intensifies the negative effect of warming on yield variability.

Even though the empirical results from our study contributes to further understanding of the effect of crop insurance on warming-related risk increases, it is important to recognize the limitations of the study and mention promising opportunities for future research. First, the empirical approach used here is primarily based on a more traditional parametric moment-based approach. Although this traditional approach has a long track record of use in various agricultural economics studies (such as [Shi13]), there have also been recent studies that utilized more flexible econometric approaches for investigating higher moment yield effects (See, for example, [Tac12] for an entropy-based approach and [Li18] for a non-parametric approach). The use of these more recent approaches may provide more insights as to the risk effects of warming under crop insurance. Second, although we attempt to control for all sources of endogeneity, further investigation of this issue using alternative instruments and IV approaches may also be useful here. We leave this for future research.

Third, the main behavioral mechanism we posit as the source of the negative crop insurance effect is moral hazard. However, theoretically, it can also possibly be adverse selection. Nonetheless, in our context, we believe that is likely moral hazard rather than adverse selection given that the level of participation in the crop insurance program is already fairly high (i.e., it includes most of the high and low-risk producers). Future studies that can separate out the moral hazard and adverse selection effect would be important. Fourth, the particular insurance plans considered in this study are individual YP and RP products in the US. We did not include other types of insurance plans (e.g., area-based plans, weather index-based plans, etc.) in the analysis. Hence, it may be important to also extend the research to other plans of insurance in other countries. For example, considering the effects of weather index insurance, which is more ubiquitous in developing countries. Lastly, the empirics in this study was based on a county-level data set rather than a farmer-level data set. Future research using individual farm-level survey data might yield richer insights as to how crop insurance coverage affects the risk impacts of warming.

Table 4.1 Descriptive statistics for the economic variables

Variable	Units	N	Mean	St.Dev	Min	Max
Corn yield	bu/acre	38,101	124.039	37.169	0.000	246.700
Soybeans yield	bu/acre	36,095	37.709	10.673	0.700	73.100
DD^H	Celsius and days in handred	74,196	0.435	0.494	0.000	5.377
DD^M	Celsius and days in thousand	74,196	1.858	0.422	0.739	3.161
$Prec$	m	74,196	0.623	0.154	0.121	1.705
Fertilizer and lime	dollars per acre	72,653	152.119	229.052	2.916	12750.000
production	dollars per acre	72,653	1798.826	4366.109	34.092	274560.000
petroleum	dollars per acre	72,653	74.220	151.274	1.817	5815.000
hired labor	dollars per acre	72,653	177.183	564.713	1.549	33117.660
seed	dollars per acre	72,653	69.514	125.134	0.648	8480.770

Table 4.2 Descriptive statistics for crop insurance participation rate

Variable	Mean	St.Dev	Min	Max
Liability Ratio	0.341	0.233	0.000	2.124
Area Ratio	0.461	0.252	0.000	2.439
Liability Ratio_Yield Protection	0.108	0.108	0.000	1.488
Liability Ratio_Revenue Protection	0.233	0.252	0.000	2.108
Area Ratio_Yield Protection	0.192	0.172	0.000	1.351
Area Ratio_Revenue Protection	0.269	0.277	0.000	2.411

Table 4.3 Estimated response of the mean, variance, skewness, and kurtosis of corn yield to weather variables, insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	13.46	-100.9	4796.7	-502838.3
	(1.21)	(-0.45)	(0.36)	(-1.03)
DD^H	-26.26***	195.7***	4094.7	703296.1***
	(-6.33)	(4.07)	(0.84)	(5.00)
$Prec$	71.46**	323.4	-38060.3	-347392.5
	(2.55)	(0.64)	(-1.23)	(-0.30)
$Prec^2$	-49.86**	-242.5	31606.0	292430.5
	(-2.66)	(-0.66)	(1.56)	(0.35)
Ins	-45.75	762.6*	742.5	992410.6
	(-1.66)	(1.92)	(0.02)	(0.76)
DD^M*Ins	39.39***	-254.6	-11227.5	-1126785.0
	(3.13)	(-1.27)	(-0.46)	(-1.38)
DD^H*Ins	-47.34***	366.7**	9113.2	1337087.3**
	(-3.08)	(2.59)	(0.34)	(2.13)
$Prec$*Ins	25.07	-2126.8	52043.1	-374344.6
	(0.32)	(-1.57)	(0.45)	(-0.09)
$Prec^2$*Ins	-30.81	1759.6*	-39767.7	1089532.0
	(-0.53)	(1.82)	(-0.47)	(0.34)
Observations	38101	38101	38101	38101
R squared	0.606	0.0779	0.0101	0.0410
Time Controls	State	State	State	State
Crop	Corn	Corn	Corn	Corn
Ins Measure	LR	LR	LR	LR
Model	FE	FE	FE	FE
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table 4.4 Estimated response of the mean, variance, skewness, and kurtosis of soybean yield to weather variables, insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	10.49***	-32.72***	78.08	-7826.0**
	(3.88)	(-2.78)	(0.24)	(-2.52)
DD^H	-11.78***	9.537*	152.0	2456.6
	(-7.94)	(1.77)	(1.11)	(1.38)
$Prec$	40.52***	-37.50	-809.0	-9882.3
	(5.75)	(-1.14)	(-0.98)	(-1.09)
$Prec^2$	-24.68***	20.33	694.5	5463.8
	(-5.04)	(0.85)	(1.19)	(0.79)
Ins	-15.47***	33.21	-494.6	8466.3
	(-2.89)	(0.95)	(-1.01)	(1.06)
DD^M*Ins	12.63***	-28.29*	-47.70	-8457.5*
	(5.05)	(-1.82)	(-0.16)	(-1.83)
DD^H*Ins	-17.98***	49.46**	306.1	15465.7**
	(-5.93)	(2.42)	(0.67)	(2.35)
$Prec$*Ins	4.058	-10.95	1952.8	-194.4
	(0.31)	(-0.11)	(1.24)	(-0.01)
$Prec^2$*Ins	-8.256	17.30	-1508.2	5899.9
	(-0.93)	(0.26)	(-1.42)	(0.35)
Observations	36095	36095	36095	36095
R squared	0.575	0.0522	0.0104	0.0316
Time Controls	State	State	State	State
Crop	Soybeans	Soybeans	Soybeans	Soybeans
Ins Measure	LR	LR	LR	LR
Model	FE	FE	FE	FE
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table 4.5 The marginal impact of 1°C warming scenario on the mean and higher moments of yield for different insurance participation rates

	Corn				Soybean			
Ins Ptc	mean	variance	skewness	kurtosis	mean	variance	skewness	kurtosis
0	-4.41	32.78	1651.49	98182.36	-0.55	-3.10	38.36	-709.39
0.1	-4.99	38.00	1712.84	114460.70	-0.69	-2.63	43.09	-558.98
0.2	-5.58	43.23	1774.20	130739.04	-0.82	-2.17	47.82	-408.57
0.3	-6.16	48.45	1835.55	147017.38	-0.96	-1.71	52.55	-258.16
0.4	-6.74	53.68	1896.90	163295.72	-1.09	-1.24	57.27	-107.76
0.5	-7.33	58.90	1958.25	179574.06	-1.22	-0.78	62.00	42.65
0.6	-7.91	64.13	2019.60	195852.40	-1.36	-0.32	66.73	193.06
0.7	-8.49	69.35	2080.96	212130.75	-1.49	0.14	71.46	343.47
0.8	-9.08	74.58	2142.31	228409.09	-1.62	0.61	76.19	493.88
0.9	-9.66	79.80	2203.66	244687.43	-1.76	1.07	80.91	644.29
1	-10.24	85.03	2265.01	260965.77	-1.89	1.53	85.64	794.69

Notes: The table displays the estimated marginal impacts of 1°C warming scenario where daily minimum and maximum temperature increase by 1°C on mean and higher moments of yield for different levels of insurance participation. The results are calculated based on the estimates from our major model (model in Table 4.3 and Table 4.4).

Table 4.6 Estimated response of the mean, variance, skewness, and kurtosis of corn yield to weather variables, insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	16.67	-156.2	4430.6	-573490.5
	(1.42)	(-0.73)	(0.31)	(-1.27)
DD^H	-26.84***	257.1***	5822.7	883515.1***
	(-5.72)	(5.02)	(0.79)	(4.18)
$Prec$	81.02***	-56.81	-23371.5	41056.3
	(3.08)	(-0.12)	(-0.91)	(0.04)
$Prec^2$	-52.24***	49.87	21690.9	120464.2
	(-2.94)	(0.14)	(1.28)	(0.15)
YP Ins	5.963	-1550.1**	55226.0	-1229006.3
	(0.17)	(-2.47)	(1.26)	(-0.70)
RP Ins	-46.92	935.1**	-11177.8	870364.2
	(-1.68)	(2.22)	(-0.31)	(0.70)
DD^M*YP Ins	25.70	574.2*	-17523.5	1045157.7
	(1.69)	(1.96)	(-1.08)	(1.00)
DD^H*YP Ins	-24.00**	-224.7	10523.7	-490843.6
	(-2.30)	(-1.09)	(1.02)	(-0.68)
$Prec$*YP Ins	-52.27	1584.7	-93442.1	-1145316.0
	(-0.58)	(1.13)	(-0.95)	(-0.24)
$Prec^2$*YP Ins	-15.19	-1146.5	65786.4	568399.4
	(-0.22)	(-1.12)	(0.94)	(0.18)
DD^M*RP Ins	43.25***	-260.5	-3915.7	-531518.0
	(3.78)	(-1.32)	(-0.21)	(-0.84)
DD^H*RP Ins	-59.42***	343.7**	-1021.7	654197.8
	(-4.36)	(2.14)	(-0.05)	(1.20)
$Prec$*RP Ins	24.55	-2561.1	71221.4	-2278628.1
	(0.30)	(-1.68)	(0.55)	(-0.47)
$Prec^2$*RP Ins	-32.38	2077.9*	-59266.3	2341435.3
	(-0.54)	(1.90)	(-0.62)	(0.65)
Observations	38101	38101	38101	38101
R squared	0.610	0.0726	0.0103	0.0376
Time Controls	State	State	State	State
Crop	Corn	Corn	Corn	Corn
Ins Measure	LR	LR	LR	LR
Model	FE	FE	FE	FE
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table 4.7 Estimated response of the mean, variance, skewness, and kurtosis of soybean yield to weather variables, insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	10.67***	-31.37***	-75.26	-7446.1***
	(4.00)	(-3.00)	(-0.24)	(-3.23)
DD^H	-12.19***	12.19**	259.6*	3507.6*
	(-7.96)	(2.26)	(1.77)	(1.87)
$Prec$	46.10***	-60.32*	-1077.5	-16964.6**
	(6.29)	(-1.84)	(-1.22)	(-2.05)
$Prec^2$	-27.51***	29.45	956.8	8873.1
	(-5.31)	(1.21)	(1.51)	(1.34)
YP Ins	23.55**	-7.445	-1925.8*	-3989.1
	(2.43)	(-0.11)	(-1.74)	(-0.29)
RP Ins	-25.42***	1.630	-478.2	255.4
	(-4.91)	(0.05)	(-1.18)	(0.04)
DD^M*YP Ins	4.533	-47.14*	867.6	-13587.8
	(1.00)	(-1.76)	(1.54)	(-1.50)
DD^H*YP Ins	-11.28**	7.322	-804.9	2248.2
	(-2.05)	(0.27)	(-1.32)	(0.24)
$Prec$*YP Ins	-63.87**	171.3	3115.8	54889.3
	(-2.51)	(0.92)	(1.17)	(1.39)
$Prec^2$*YP Ins	27.41	-42.20	-3225.0	-16295.9
	(1.30)	(-0.31)	(-1.59)	(-0.54)
DD^M*RP Ins	15.79***	-13.57	-216.1	-5061.0
	(6.34)	(-0.82)	(-0.83)	(-1.00)
DD^H*RP Ins	-19.82***	55.72**	583.1	19286.8**
	(-7.24)	(2.44)	(1.24)	(2.13)
$Prec$*RP Ins	17.31	-2.399	2513.3	5675.5
	(1.29)	(-0.03)	(1.67)	(0.30)
$Prec^2$*RP Ins	-16.81*	7.574	-1744.8	623.2
	(-1.82)	(0.14)	(-1.68)	(0.04)
Observations	36095	36095	36095	36095
R squared	0.579	0.0547	0.0123	0.0361
Time Controls	State	State	State	State
Crop	Soybeans	Soybeans	Soybeans	Soybeans
Ins Measure	LR	LR	LR	LR
Model	FE	FE	FE	FE
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table 4.8 The marginal impact of 1°C warming scenario on the mean and higher moments of yield for different YP insurance participation rates

	Corn				Soybeans			
Ins Ptc	mean	variance	skewness	kurtosis	mean	variance	skewness	kurtosis
0	-4.10	39.75	2014.26	131477.81	-0.59982	-2.42826	35.00451	-467.527
0.1	-4.31	42.40	2021.39	134330.64	-0.73344	-2.98806	33.42933	-626.445
0.2	-4.53	45.04	2028.51	137183.47	-0.86707	-3.54787	31.85416	-785.364
0.3	-4.75	47.69	2035.63	140036.29	-1.00069	-4.10767	30.27899	-944.283
0.4	-4.96	50.33	2042.76	142889.12	-1.13432	-4.66747	28.70382	-1103.2
0.5	-5.18	52.98	2049.88	145741.95	-1.26795	-5.22727	27.12865	-1262.12
0.6	-5.39	55.62	2057.00	148594.78	-1.40157	-5.78707	25.55347	-1421.04
0.7	-5.61	58.26	2064.13	151447.60	-1.5352	-6.34687	23.9783	-1579.96
0.8	-5.82	60.91	2071.25	154300.43	-1.66883	-6.90667	22.40313	-1738.88
0.9	-6.04	63.55	2078.38	157153.26	-1.80245	-7.46647	20.82796	-1897.79
1	-6.26	66.20	2085.50	160006.08	-1.93608	-8.02627	19.25278	-2056.71

Notes: The table displays the estimated marginal impacts of 1°C warming scenario where daily minimum and maximum temperature increase by 1°C on mean and higher moments of yield for different yield protection insurance participation rates. The results are calculated based on the estimates from our major model (model in Table 4.6 and Table 4.7).

Table 4.9 The marginal impact of 1°C warming scenario on the mean and higher moments of yield for different RP insurance participation rates

	Corn				Soybeans			
Ins Ptc	mean	variance	skewness	kurtosis	mean	variance	skewness	kurtosis
0	-4.10	39.75	2014.26	131477.81	-0.59982	-2.42826	35.00451	-467.527
0.1	-4.92	44.34	1935.05	139718.93	-0.72014	-1.63914	42.1787	-199.704
0.2	-5.74	48.94	1855.83	147960.04	-0.84047	-0.85002	49.35289	68.11784
0.3	-6.56	53.53	1776.61	156201.15	-0.96079	-0.06089	56.52708	335.9401
0.4	-7.37	58.12	1697.40	164442.26	-1.08112	0.728232	63.70127	603.7624
0.5	-8.19	62.71	1618.18	172683.37	-1.20144	1.517356	70.87547	871.5846
0.6	-9.01	67.30	1538.96	180924.48	-1.32177	2.30648	78.04966	1139.407
0.7	-9.83	71.90	1459.74	189165.60	-1.44209	3.095605	85.22385	1407.229
0.8	-10.65	76.49	1380.53	197406.71	-1.56242	3.884729	92.39804	1675.051
0.9	-11.47	81.08	1301.31	205647.82	-1.68274	4.673853	99.57223	1942.874
1	-12.29	85.67	1222.09	213888.93	-1.80307	5.462977	106.7464	2210.696

Notes: The table displays the estimated marginal impacts of 1°C warming scenario where daily minimum and maximum temperature increase by 1°C on mean and higher moments of yield for different revenue protection insurance participation rates. The results are calculated based on the estimates from our major model (model in Table 4.6 and Table 4.7).

Table 4.10 Estimated cost of risk for corn and soybeans

	COR due to variance			COR to skewness			COR due to kertosis			Total COR			Change in COR	
	mean	+1°C	+2°C	mean	+1°C	+2°C	mean	+1°C	+2°C	mean	+1°C	+2°C	+1°C	+2°C
Ins	Corn													
0	1.97	2.33	2.87	0.11	-0.01	-0.17	0.06	0.12	0.23	2.14	2.44	2.94	0.30	0.80
0.1	1.87	2.28	2.91	0.10	-0.02	-0.19	0.05	0.12	0.25	2.02	2.38	2.97	0.36	0.95
0.2	1.76	2.22	2.94	0.10	-0.03	-0.22	0.04	0.12	0.28	1.89	2.31	3.00	0.42	1.11
0.3	1.65	2.17	2.98	0.09	-0.04	-0.25	0.03	0.12	0.30	1.77	2.24	3.03	0.47	1.26
0.4	1.54	2.11	3.01	0.08	-0.06	-0.27	0.02	0.12	0.33	1.65	2.17	3.07	0.53	1.42
0.5	1.44	2.05	3.05	0.08	-0.07	-0.30	0.01	0.12	0.35	1.53	2.11	3.10	0.58	1.57
0.6	1.33	2.00	3.09	0.07	-0.08	-0.33	0.00	0.12	0.38	1.41	2.04	3.13	0.63	1.73
0.7	1.23	1.94	3.12	0.06	-0.09	-0.36	-0.01	0.12	0.40	1.29	1.97	3.17	0.68	1.88
0.8	1.12	1.88	3.16	0.06	-0.10	-0.39	-0.02	0.12	0.43	1.17	1.90	3.20	0.74	2.04
0.9	1.02	1.83	3.20	0.05	-0.11	-0.42	-0.02	0.12	0.46	1.05	1.83	3.24	0.79	2.19
1	0.92	1.77	3.24	0.05	-0.12	-0.45	-0.03	0.12	0.49	0.93	1.77	3.28	0.83	2.35
	Soybeans													
0	0.49	0.40	0.32	0.05	0.02	-0.03	0.01	-0.01	-0.03	0.55	0.40	0.26	-0.15	-0.29
0.1	0.48	0.40	0.36	0.04	0.00	-0.05	0.01	-0.01	-0.02	0.53	0.39	0.29	-0.14	-0.24
0.2	0.47	0.41	0.39	0.03	-0.01	-0.08	0.01	0.00	-0.01	0.51	0.39	0.31	-0.12	-0.20
0.3	0.46	0.41	0.43	0.02	-0.03	-0.10	0.01	0.00	0.01	0.49	0.38	0.33	-0.10	-0.16
0.4	0.45	0.42	0.46	0.01	-0.05	-0.13	0.01	0.01	0.02	0.47	0.38	0.35	-0.09	-0.11
0.5	0.44	0.43	0.50	0.00	-0.06	-0.16	0.01	0.01	0.03	0.45	0.37	0.38	-0.07	-0.07
0.6	0.43	0.43	0.53	-0.01	-0.08	-0.18	0.01	0.01	0.05	0.43	0.37	0.40	-0.06	-0.03
0.7	0.42	0.44	0.57	-0.02	-0.09	-0.21	0.01	0.02	0.06	0.41	0.36	0.42	-0.04	0.02
0.8	0.41	0.44	0.61	-0.03	-0.11	-0.24	0.01	0.02	0.08	0.39	0.36	0.45	-0.03	0.06
0.9	0.40	0.45	0.65	-0.04	-0.12	-0.27	0.01	0.03	0.09	0.37	0.35	0.47	-0.01	0.10
1	0.39	0.46	0.68	-0.05	-0.14	-0.30	0.01	0.03	0.11	0.35	0.35	0.49	0.00	0.15

Notes: (1)The table displays the cost of risk (COR) calculated based on the major model under three temperature scenarios and different insurance participation rate. (2) The first column shows the insurance participation rate. (3) The table shows the cost of risk under three temperature scenarios: 1) the average temperature of the dataset used; 2) both $tmin$ and $tmax$ increase by 1°C; 3) both $tmin$ and $tmax$ increase by 2°C.

CHAPTER

5 CONCLUSION

The research goal of Chapter 2 is to investigate whether modern rice varieties (MVs) mitigate the adverse yield impacts of climate change, especially the more recent varieties (MV4 and MV5) specifically bred to be more tolerant to abiotic stresses. To acheive this goal, we estimate fixed effect econometric models with "weather-varietal group" interactions and assess whether there is heterogeneity in the warming effects across different rice varietal groups. Results suggest that compared to traditional varieties (TV) and earlier rice MVs, the recent MVs tend to be more resilient to a warming climate relative to the earlier rice MVs. The stronger warming mitigation effects for recent MVs provides evidence that there are indeed direct yield benefits from rice-breeding efforts to improve tolerance to abiotic stresses. Although early modern varieties were not specifically developed to address climate change and abiotic stresses, we find that they in fact partially mitigate the negative yield effects of warming compared to TVs. The presence of some climate change mitigation effects for these early modern rice varieties can be considered a "spillover" benefit from rice breeding efforts that were not specifically targeted to improve resilience to climate change.

Chapter 3 aims to explore how yield response to planting density is influenced by warming temperature and to understand the role of GM traits in this situation. To fulfill the study objectives, we develop and estimate models with interaction terms among planting density, weather variables, and GM hybrid dummy variables to ascertain the impact of warming and GM traits on the corn yield response to increasing planting density. Results from the analysis show that the yield benefits of increasing planting density largely diminish as temperature levels increase, and the rate of deterioration is larger for conventional corn hybrids without GM traits. Corn varieties with RW resistance GM traits generally are better able to maintain the yield benefits of increasing planting density under warming conditions. These results suggest that inter-plant competition for resources (e.g., nutrients and moisture) tends to be further intensified as planting density increases and heating temperature.Therefore, as warming occurs, the yield benefits of plant density decreases. However, corn hybrids with GM traits may be more efficient in utilizing natural resources such that they perform better than conventional varieties even in situations with increasing planting density and warming temperatures.

In Chapter 4, we explore whether crop insurance participation influences the effect of warming temperatures on the mean, variance, skewness, and kurtosis of corn and soybean yields. Through estimating a parametric moment-based empirical model, we found that higher levels of crop insurance participation statistically worsens the adverse risk impacts of extreme heat. The detrimental effect of extreme heat on production risk is manifested in the statistically larger variance and kurtosis observed at higher insurance participation rates. Moreover, we also validate findings in previous literature (see [Ann15]) where the negative mean yield effect of warming intensifies under higher levels of insurance participation. These findings are consistent with the argument that crop insurance promote moral hazard behavior such that insured farmers are less likely to adopt practices that help mitigate the adverse mean yield and production risk effects of climate-change induced warming. Hence, the new insight here is that the disincentive effect of crop insurance seems to not only affect mean yields, but also the variability of yields (e.g., production risk). This is further evidence of the "unintended consequence" of subsidizing crop insurance and encouraging higher participation levels. Crop insurance tend to discourage adoption of climate change adaptation practices, and consequently intensifies the negative effect of warming on yield variability.

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APPENDICES

APPENDIX

A

SUPPLEMENTAL MATERIAL FOR CHAPTER 2

Table S2.1 Regression results for the five main model specifications in Table 2.4

	Model 1 vtmin*V,ritmax*V	Model 2 add 3 tmin*V,3 tmax*V	Model 3 add prec,precsq	Model 4 add prec*V,precsq*V	Model 5 add econ var
year	-0.000	-0.000	0.001	0.002	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
vtmin	-0.186	-0.048	-0.207	-0.203	-0.258
	(0.168)	(0.313)	(0.300)	(0.378)	(0.426)
retmin	-0.084**	-0.599*	-0.583*	-0.548	-0.309
	(0.038)	(0.325)	(0.322)	(0.362)	(0.398)
ritmin	0.079	0.269	0.255	0.072	-0.103
	(0.055)	(0.222)	(0.235)	(0.318)	(0.332)
vtmax	0.009	0.076	0.260	0.337*	0.439**
	(0.021)	(0.168)	(0.166)	(0.176)	(0.193)
retmax	-0.079	0.159	0.108	0.146	0.046
	(0.052)	(0.251)	(0.249)	(0.250)	(0.241)
ritmax	0.066	-0.025	-0.108	-0.070	-0.055
	(0.132)	(0.105)	(0.099)	(0.137)	(0.140)
prec			-0.001***	-0.004	-0.004
			(0.000)	(0.003)	(0.003)
prec × prec			0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)
early MVs	-2.391	0.923	1.148	0.925	-0.166
	(2.999)	(3.654)	(3.459)	(4.478)	(5.030)
recent MVs	-2.530	0.143	-0.303	-1.110	-2.823
	(3.574)	(4.279)	(4.121)	(5.217)	(5.524)
early MVs × vtmin	0.081	-0.023	-0.023	-0.024	0.047
	(0.179)	(0.347)	(0.318)	(0.385)	(0.435)
early MVs × retmin		0.530	0.469	0.433	0.208
		(0.336)	(0.338)	(0.378)	(0.414)
early MVs × ritmin		-0.228	-0.141	0.030	0.180
		(0.231)	(0.240)	(0.321)	(0.342)
early MVs × vtmax		-0.094	-0.188	-0.266	-0.357*
		(0.170)	(0.164)	(0.173)	(0.191)
early MVs × retmax		-0.258	-0.246	-0.282	-0.170
		(0.242)	(0.241)	(0.242)	(0.232)
early MVs × ritmax	0.031	0.127	0.184*	0.141	0.136
	(0.127)	(0.108)	(0.107)	(0.141)	(0.144)
recent MVs × vtmin	0.126	-0.231	-0.097	-0.111	0.024
	(0.183)	(0.367)	(0.367)	(0.398)	(0.462)
recent MVs × retmin		0.608*	0.528	0.480	0.164
		(0.346)	(0.347)	(0.380)	(0.418)
recent MVs × ritmin		-0.194	-0.241	-0.004	0.267
		(0.233)	(0.248)	(0.333)	(0.362)
recent MVs × vtmax		-0.005	-0.135	-0.237	-0.408**
		(0.172)	(0.172)	(0.179)	(0.203)
recent MVs × retmax		-0.146	-0.070	-0.092	0.073
		(0.264)	(0.275)	(0.270)	(0.266)
recent MVs × ritmax	0.003	0.027	0.091	0.043	-0.004
	(0.153)	(0.113)	(0.107)	(0.145)	(0.156)

Table S2.1 Continued

	Model 1 vtmin*V,ritmax*V	Model 2 add 3 tmin*V,3 tmax*V	Model 3 add prec,precsq	Model 4 add prec*V,precsq*V	Model 5 add econ var
early MVs × prec				0.003	0.004
				(0.003)	(0.003)
early MVs × prec × prec				-0.000	-0.000
				(0.000)	(0.000)
recent MVs × prec				0.003	0.004
				(0.003)	(0.003)
recent MVs × prec × prec				-0.000	-0.000
				(0.000)	(0.000)
Land Tenure					-0.019
					(0.043)
Farm size					-0.055***
					(0.019)
Age of Head					-0.001
					(0.002)
Educ. of Head					0.009
					(0.010)
Primary farming					-0.002
					(0.026)
Secondary farming					0.066
					(0.109)
Labor					0.002**
					(0.001)
Nitrogen Fert.					0.002***
					(0.001)
Potassium Fert.					0.003***
					(0.001)
Phosphorus Fert.					-0.001
					(0.003)
Insecticide					0.004
					(0.004)
Molluscicide					-0.023
					(0.014)
Herbicide					0.005
					(0.005)
Rodenticide					0.074
					(0.065)
Constant	13.152**	10.217	10.858*	9.209	12.854*
	(6.257)	(6.394)	(6.494)	(6.988)	(7.607)
Observations	1150	1150	1150	1150	1069
Adj R-squared	0.299	0.302	0.332	0.335	0.392
Number of Farmers	180	180	180	180	180

Notes: (1) The dependent variable of each regression is the natural log of rice yield. (2) $vtmin$, $retmin$, and $ritmin$, respectively, are the average of the monthly minimum temperatures for the vegetative, reproductive and ripening phase; $vtmax$, $retmax$, and $ritmax$, respectively, are the average of monthly maximum temperatures for the vegetative, reproductive and ripening phase. The variable $prec$ is the cumulative precipitation for the entire growing season. (3) Units for $tmin$ and $tmax$ is °C and for prec it is in mm.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S2.2 Marginal percentage yield impacts of 1 standard deviation warming scenarios

Variables	Model 1 vtmin*V, ritmax*V		Model 2 3 tmin*V, 3tmax*V		Model 3 add prec, precsq		Model 4 add prec*V, precsq*V		Model 5 add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1 standard deviation increase in tmin and tmax:										
tmin&tmax: tv	-0.112	0.218	-0.090	0.410	-0.144	0.174	-0.140	0.237	-0.120	0.434
tmin&tmax: early mv	-0.037	0.373	-0.070	0.128	-0.119	0.004	-0.129	0.002	-0.105	0.121
tmin&tmax: recent mv	-0.032	0.400	-0.034	0.346	-0.098	0.018	-0.086	0.060	-0.049	0.456
1 standard deviation increase in tmin:										
tmin: tv	-0.113	0.313	-0.256	0.075	-0.353	0.012	-0.475	0.002	-0.474	0.003
tmin: early mv	-0.063	0.078	-0.062	0.076	-0.133	0.001	-0.142	0.001	-0.143	0.001
tmin: recent mv	-0.035	0.452	-0.105	0.165	-0.216	0.030	-0.189	0.037	-0.118	0.199
1 standard deviation increase in tmax:										
tmax: tv	0.001	0.996	0.166	0.422	0.209	0.299	0.335	0.118	0.353	0.135
tmax: early mv	0.026	0.481	-0.008	0.859	0.014	0.746	0.013	0.769	0.038	0.481
tmax: recent mv	0.003	0.937	0.071	0.300	0.119	0.159	0.103	0.129	0.070	0.303

Notes: (1) The table displays coefficients and p-values of marginal yield effect of warming scenarios where both $tmin$ and $tmax$ in each growing phase increases by 1 standard deviation. The results are estimated based on 5 farm fixed-effect models. Standard errors for each regression are clustered at the village level. (2) The different models are as follows. Model 1 is the "baseline" model where $tmin$ and $tmax$ of each growing phase and the interactions between $tmin$ in the vegetative phase ($vtmin$) and $tmax$ in the ripening phase ($ritmax$) and dummies for rice varietal groups are included in the specification. Model 2 includes the $tmin$ and $tmax$ variables in all the growing phases(e.g., the vegetative($vtmin$ and $vtmax$), reproductive($retmin$ and $retmax$), and the ripening phase($ritmin$ and $ritmax$)) and their interactions with dummies for each rice varietal group. Model 3 adds on the cumulative precipitation for the growing season ($prec$) and its quadratic term ($prec^2$) to Model 2. Model 4 adds on the interactions of $prec$ and squared $prec$ with the varietal grouping dummy variables to Model 3. Model 5 is the specification including all the "economic variables" in addition to the variables in Model 4. (3) The first column indicates what weather variables are the marginal effects based on, and which varietal group it pertains to. The three rows of the first panel indicate the marginal effect of a 1 standard deviation increase in both $tmin$ and $tmax$ in each growing phase for the TV, early MVs, and recent MVs varietal groups separately. The rows of panel 2 refer to the marginal effect of a 1 standard deviation increase in $tmin$ in each growing phase for TV, early MVs, and recent MVs. Lastly, the rows of the third panel refer to the marginal effect of a 1 standard deviation increase in $tmax$ in each growing phase for the TV, early MVs, and recent MVs.

Table S2.3 Correlations between maximum and minimum temperatures by growing phase

Phase	Variable	tmin
Vegetative	tmax	0.5060(0.0000)
Reproductive	tmax	0.5207(0.0000)
Ripening	tmax	0.4404(0.0000)

Note: The table displays correlations between the minimum and maximum temperature for 32 municipalities (34 municipalities in 2015) across 13 survey years. Number of observations = 418. P-values are in parentheses.

Table S2.4 Predicted change in $tmin$ between 1971-2000 and 2011-2041 for six provinces, by quarter of the year

	BCM2(2011-2040)				CNCM3(2011-2040)				MPEH5(2011-2040)			
Provinces	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
A1B												
La Union	0.5	0.5	0.3	0.4	0.9	0.9	0.5	0.7	0.7	0.9	0.3	0.4
Pangasinan	0.5	0.4	0.2	0.4	0.7	0.5	0.3	0.6	0.4	0.6	0.3	0.4
Nueva Ecija	0.5	0.3	0.3	0.4	0.7	0.5	0.3	0.7	0.5	0.6	0.3	0.4
Pampanga	0.5	0.4	0.2	0.4	0.7	0.4	0.2	0.6	0.5	0.6	0.4	0.4
Bulacan	0.6	0.4	0.3	0.4	0.8	0.6	0.4	0.7	0.6	0.7	0.4	0.5
Tarlac	0.5	0.3	0.2	0.3	0.6	0.4	0.3	0.5	0.4	0.5	0.4	0.3
A2												
La Union	0.6	0.7	0.3	0.4	0.6	0.7	0.3	0.5	0.7	0.7	0.3	0.5
Pangasinan	0.5	0.5	0.2	0.4	0.5	0.4	0.2	0.5	0.6	0.5	0.3	0.4
Nueva Ecija	0.5	0.5	0.3	0.4	0.5	0.4	0.3	0.5	0.6	0.6	0.3	0.5
Pampanga	0.5	0.5	0.2	0.3	0.6	0.4	0.2	0.4	0.6	0.5	0.3	0.4
Bulacan	0.6	0.6	0.3	0.4	0.6	0.5	0.3	0.5	0.7	0.7	0.4	0.5
Tarlac	0.4	0.4	0.2	0.3	0.5	0.3	0.2	0.3	0.5	0.5	0.3	0.3

Notes: The climate projection dataset was generated and completed under a cooperation project between the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA-DOST), the Food and Agriculture Organization of the United Nations (FAO) and FAO-AMICAF Philippines. Climate projections are based on the statistical downscaling of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B(business-as-usual scenario) and A2(differentiated world scenario)). DJF, December to February; MAM, March to May; JJA, June to August; SON, September to November. Unit for temperature change is Celsius.

Table S2.5 Predicted change in $tmax$ between 1971-2000 and 2011-2041 for six provinces, by quarter of the year

	BCM2(∘C)				CNCM3(∘C)				MPEH5(∘C)			
Provinces	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
A1B												
La Union	0.2	0.5	0.5	0.6	0.5	0.4	0.1	0.7	0.1	0.4	0.2	0.4
Pangasinan	0.4	0.5	0.3	0.5	0.6	0.5	0.1	0.8	0.2	0.4	0.3	0.4
Nueva Ecija	0.4	0.6	0.4	0.5	0.6	0.6	0.1	0.7	0.2	0.4	0.3	0.3
Pampanga	0.5	0.6	0.3	0.4	0.7	0.6	0.2	0.8	0.3	0.5	0.3	0.4
Bulacan	0.4	0.5	0.4	0.4	0.5	0.5	0.1	0.6	0.2	0.3	0.3	0.3
Tarlac	0.4	0.7	0.3	0.5	0.8	0.7	0.1	1	0.2	0.6	0.4	0.4
A2												
La Union	0.4	0.7	0.4	0.2	0.3	0.5	0	0.6	0.6	0.4	0.1	0.3
Pangasinan	0.5	0.7	0.2	0.3	0.4	0.5	0.1	0.6	0.5	0.4	0.3	0.4
Nueva Ecija	0.5	0.8	0.3	0.3	0.4	0.5	0.1	0.5	0.4	0.4	0.4	0.3
Pampanga	0.5	0.8	0.2	0.3	0.5	0.5	0.1	0.5	0.6	0.4	0.4	0.4
Bulacan	0.4	0.7	0.3	0.3	0.3	0.5	0.1	0.5	0.5	0.3	0.3	0.3
Tarlac	0.6	0.9	0.2	0.4	0.6	0.6	0.2	0.6	0.6	0.4	0.5	0.5

Table S2.6 Predicted change in cumulative precipitation ($prec$) between 1971-2000 and 2011-2041 for six provinces, by quarter of the year

	BCM2(∘C)				CNCM3(∘C)				MPEH5(∘C)			
Provinces	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
A1B												
La Union	-20.7%	-23.6%	0.2%	10.5%	8.2%	10.5%	9.3%	35.5%	27.1%	24.8%	12.2%	17.6%
Pangasinan	8.4%	-4.2%	-1.5%	4.3%	39.1%	22.9%	20.0%	30.0%	36.0%	57.9%	15.4%	22.1%
Nueva Ecija	8.0%	-1.4%	-2.2%	10.1%	24.6%	32.0%	11.4%	19.7%	26.0%	58.5%	13.0%	14.2%
Pampanga	24.5%	3.1%	-0.2%	8.4%	59.0%	20.4%	22.3%	17.7%	46.0%	60.7%	14.9%	12.9%
Bulacan	-1.7%	-6.5%	-4.0%	8.3%	17.6%	10.2%	12.4%	16.2%	20.2%	35.6%	13.9%	18.6%
Tarlac	27.5%	3.3%	-2.1%	14.7%	49.1%	19.7%	21.1%	20.9%	51.1%	64.8%	15.9%	17.0%
A2												
La Union	-7.2%	-17.6%	-4.3%	28.2%	9.1%	5.3%	5.6%	8.1%	30.7%	41.4%	10.3%	28.6%
Pangasinan	19.6%	-11.2%	-2.8%	11.7%	29.4%	2.6%	11.4%	10.9%	24.3%	35.4%	9.4%	28.1%
Nueva Ecija	17.9%	-8.0%	-4.6%	14.2%	13.9%	12.8%	9.2%	6.0%	19.2%	36.7%	8.2%	24.3%
Pampanga	26.4%	-12.6%	2.0%	11.8%	37.7%	9.1%	11.3%	6.0%	33.1%	32.9%	3.9%	24.5%
Bulacan	2.8%	-12.8%	-3.4%	12.6%	14.8%	6.1%	7.1%	1.2%	13.0%	31.6%	9.2%	28.0%
Tarlac	32.9%	-12.3%	-2.0%	15.5%	32.9%	6.0%	10.6%	11.8%	41.7%	33.2%	4.8%	26.5%

Table S2.7 Predicted change in $tmin$ and $tmax$ between 1971-2000 and 2011-2041 averaged over all provinces, by WS growing-phase

		Vegetative		Reproductive		Ripening	
		mean	sd	mean	sd	mean	sd
tmin (in Celsius)							
A1B	bcm2	0.28	0.030	0.33	0.054	0.39	0.028
	cncm3	0.34	0.056	0.43	0.158	0.66	0.065
	mpeh5	0.33	0.040	0.35	0.065	0.40	0.042
A2	bcm2	0.28	0.032	0.33	0.052	0.39	0.034
	cncm3	0.29	0.030	0.37	0.097	0.48	0.059
	mpeh5	0.32	0.031	0.35	0.069	0.46	0.065
tmax (in Celsius)							
A1B	bcm2	0.38	0.037	0.43	0.048	0.49	0.038
	cncm3	0.17	0.111	0.38	0.313	0.74	0.097
	mpeh5	0.32	0.030	0.34	0.048	0.34	0.048
A2	bcm2	0.27	0.038	0.30	0.014	0.31	0.032
	cncm3	0.15	0.072	0.30	0.222	0.53	0.047
	mpeh5	0.38	0.059	0.40	0.045	0.34	0.065

Table S2.8 Predictions of log rice yield (kg/ha) change for TVs, Early MVs and Recent MVs across CGM-estimation scenario combinations

	Model 1		Model 2		Model 3		Model 4		Model 5	
	vtmin*V, vtmax*V		3 tmin*V, 3tmax*V		add prec, precsq		add prec*V, precsq*V		add econ var	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
tv_a1b_bcm2	-0.048	0.334	-0.024	0.713	-0.060	0.342	-0.055	0.455	-0.055	0.536
tv_a2_bcm2	-0.050	0.186	-0.046	0.253	-0.081	0.041	-0.095	0.047	-0.097	0.109
tv_a1b_cncm3	-0.027	0.704	-0.044	0.608	-0.150	0.097	-0.198	0.143	-0.238	0.118
tv_a2_cncm3	-0.035	0.505	-0.059	0.302	-0.137	0.019	-0.167	0.047	-0.186	0.055
tv_a1b_mpeh5	-0.061	0.159	-0.050	0.270	-0.089	0.040	-0.098	0.040	-0.099	0.103
tv_a2_mpeh5	-0.058	0.185	-0.019	0.754	-0.049	0.408	-0.061	0.364	-0.071	0.389
earlymv_a1b_bcm2	-0.010	0.637	-0.002	0.950	-0.038	0.250	-0.061	0.135	-0.065	0.194
earlymv_a2_bcm2	-0.018	0.283	-0.006	0.821	-0.042	0.162	-0.064	0.087	-0.072	0.105
earlymv_a1b_cncm3	0.023	0.478	0.080	0.292	0.008	0.921	-0.056	0.599	-0.096	0.410
earlymv_a2_cncm3	0.005	0.818	0.038	0.419	-0.018	0.713	-0.057	0.376	-0.077	0.281
earlymv_a1b_mpeh5	-0.024	0.190	-0.020	0.392	-0.059	0.018	-0.075	0.010	-0.076	0.044
earlymv_a2_mpeh5	-0.022	0.278	-0.008	0.814	-0.044	0.238	-0.072	0.127	-0.083	0.134
recentmv_a1b_bcm2	-0.011	0.591	0.008	0.786	-0.017	0.579	-0.036	0.312	-0.046	0.345
recentmv_a2_bcm2	-0.014	0.411	-0.002	0.931	-0.032	0.295	-0.049	0.180	-0.052	0.248
recentmv_a1b_cncm3	0.018	0.603	0.039	0.621	-0.017	0.839	-0.072	0.501	-0.113	0.372
recentmv_a2_cncm3	0.004	0.871	0.010	0.839	-0.035	0.516	-0.066	0.314	-0.084	0.288
recentmv_a1b_mpeh5	-0.018	0.319	-0.018	0.458	-0.051	0.074	-0.060	0.048	-0.051	0.201
recentmv_a2_mpeh5	-0.017	0.399	0.007	0.829	-0.020	0.577	-0.042	0.336	-0.048	0.370

Notes: The table shows the predicted changes in the natural log of the yield of three varietal groups under various global climate models and emission scenarios between 1971-2000 and 2011-2041. Projections on seasonal temperature increase and rainfall change are provided by PAGASA. The first panel shows the predicted changes in the average yield of TV under 6 combinations of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2). The second panel shows the predicted changes in the average yield of MV1-MV3 under 6 combinations of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2). The third panel shows the predicted changes in the average yield of recent MVs under 6 combinations of three global climate models (BCM2, CNCM3, and MPEH5) and two emission scenarios (A1B and A2).

Table S2.9 Regression results for the alternative model specifications in Table 2.5

	Model 1 retavg*V, vdtr*V	Model 2 add 3 tavg*V,3 dtr*V	Model 3 add prec,precsq	Model 4 add prec*V,precsq*V	Model 5 add econ var
year	0.001	0.001	0.003	0.004	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
vtavg	-0.021	0.277	0.254	0.342	0.385
	(0.058)	(0.237)	(0.252)	(0.274)	(0.277)
retavg	-0.210	-0.220	-0.268	-0.204	-0.019
	(0.140)	(0.402)	(0.384)	(0.414)	(0.395)
ritavg	0.106	-0.112	-0.135	-0.296	-0.470
	(0.073)	(0.366)	(0.385)	(0.429)	(0.449)
vdtr	0.215	-0.030	0.149	0.194	0.279
	(0.204)	(0.283)	(0.274)	(0.247)	(0.234)
redtr	-0.011	0.309	0.248	0.205	0.057
	(0.030)	(0.371)	(0.371)	(0.352)	(0.327)
ridtr	0.030	-0.056	-0.072	0.067	0.170
	(0.034)	(0.178)	(0.181)	(0.211)	(0.217)
prec			-0.001***	-0.004**	-0.005**
			(0.000)	(0.002)	(0.002)
prec × prec			0.000*	0.000**	0.000**
			(0.000)	(0.000)	(0.000)
early MVs	0.692	2.438	2.170	1.117	1.193
	(3.323)	(3.819)	(3.640)	(4.015)	(4.169)
recent MVs	-0.534	1.591	0.990	-1.000	-1.747
	(3.799)	(4.308)	(4.214)	(4.827)	(4.969)
early MVs × vtavg		-0.264	-0.273	-0.338	-0.343
		(0.256)	(0.270)	(0.294)	(0.299)
early MVs × retavg	0.052	0.032	0.013	-0.079	-0.251
	(0.114)	(0.440)	(0.416)	(0.447)	(0.420)
early MVs × ritavg		0.220	0.268	0.413	0.581
		(0.386)	(0.399)	(0.441)	(0.459)
early MVs × vdtr	-0.215	0.010	-0.069	-0.129	-0.221
	(0.199)	(0.285)	(0.276)	(0.252)	(0.241)
early MVs × redtr		-0.326	-0.262	-0.218	-0.065
		(0.369)	(0.369)	(0.350)	(0.329)
early MVs × ridtr		0.109	0.093	-0.033	-0.121
		(0.181)	(0.182)	(0.212)	(0.224)
recent MVs × vtavg		-0.361	-0.354	-0.453	-0.463
		(0.244)	(0.264)	(0.274)	(0.288)
recent MVs × retavg	0.073	0.079	0.108	0.045	-0.140
	(0.132)	(0.413)	(0.398)	(0.418)	(0.405)
recent MVs × ritavg		0.289	0.269	0.450	0.675
		(0.370)	(0.391)	(0.433)	(0.455)
recent MVs × vdtr	-0.121	0.147	0.034	-0.048	-0.216
	(0.198)	(0.287)	(0.284)	(0.249)	(0.249)
recent MVs × redtr		-0.319	-0.231	-0.164	0.076
		(0.367)	(0.369)	(0.352)	(0.337)
recent MVs × ridtr		0.022	0.062	-0.109	-0.249
		(0.184)	(0.187)	(0.220)	(0.240)

Table S2.9 Continued

	Model 1 retavg*V, vdtr*V	Model 2 add 3 tavg*V,3 dtr*V	Model 3 add prec,precsq	Model 4 add prec*V,precsq*V	Model 5 add econ var
early MVs × prec				0.004*	0.004**
				(0.002)	(0.002)
early MVs × prec × prec				-0.000*	-0.000**
				(0.000)	(0.000)
recent MVs × prec				0.004**	0.004**
				(0.002)	(0.002)
recent MVs × prec × prec				-0.000**	-0.000**
				(0.000)	(0.000)
Land Tenure					-0.018
					(0.041)
Farm size					-0.053***
					(0.018)
Age of Head					-0.001
					(0.002)
Educ. of Head					0.010
					(0.010)
Primary farming					0.020
					(0.029)
Secondary farming					0.039
					(0.097)
Labor					0.002**
					(0.001)
Nitrogen Fert.					0.002***
					(0.000)
Potassium Fert.					0.003***
					(0.001)
Phosphorus Fert.					-0.002
					(0.003)
Insecticide					0.003
					(0.005)
Molluscicide					-0.026*
					(0.015)
Herbicide					0.006
					(0.005)
Rodenticide					0.098
					(0.071)
Constant	6.540	5.096	4.405	3.558	6.300
	(6.269)	(5.843)	(5.796)	(5.150)	(5.846)
Observations	1150	1150	1150	1150	1069
Adj R-squared	0.299	0.298	0.322	0.329	0.393
Number of Farmers	180	180	180	180	180

Notes: (1) All regressions use the natural log of yield as the dependent variable. (2) $vtavg$, $retavg$, and $ritavg$ respectively are the average of daily mean temperature in the vegetative, reproductive and ripening phase; $vdtr$, $redtr$, and $ridtr$ respectively are the average of daily diurnal temperature ranges for the vegetative, reproductive and ripening phase. The variable $prec$ is cumulative precipitation for the entire growing season. (3) Unit for $tavg$ and dtr is °C. Unit for $prec$ is mm.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S2.10 Marginal yield impacts from the separate regressions by varietal group

	TV		Early MVs		Recent MVs	
Method	Estimates	P-value	Estimates	P-value	Estimates	P-value
tmin(+1 °C)	-1.04	0.551	-0.30	0.000	-0.16	0.323
tmax(+1 °C)	0.42	0.819	0.03	0.970	0.09	0.358
prec(1 sd)	-0.52	0.295	-0.15	0.000	0.02	0.913
tmin+tmax(+1 °C warming scenario)	-0.62	0.824	-0.30	0.001	-0.06	0.513

Notes: The table displays estimated change in the natural log of rice yields caused by 1 °C increase in $tmin$, $tmax$, both $tmin$ and $tmax$ and 1 standard deviation of increase in $prec$, by running regressions for varietal groups separately. Columns 2 and 3 are the marginal effects and P-value for the TV subsample, respectively. Columns 4 and 5 are the marginal effects and P-value for the MV1-MV3 subsample, respectively. Columns 6 and 7 are the marginal effects and P-value for the recent MVs subsample, respectively.

Table S2.11 Regression results from the separate regressions by varietal groups

	TV	Early MVs	Recent MVs
	lnyield	lnyield	lnyield
year	-0.034	0.004	0.011
	(0.059)	(0.004)	(0.008)
vtmin	0.054	-0.233**	-0.378***
	(2.275)	(0.099)	(0.109)
retmin	-0.687	-0.108**	0.019
	(2.018)	(0.052)	(0.132)
ritmin	-0.403	0.040	0.202***
	(1.444)	(0.073)	(0.066)
vtmax	0.160	0.053	0.122
	(1.026)	(0.038)	(0.078)
retmax	0.804	-0.103	-0.083
	(1.278)	(0.072)	(0.086)
ritmax	-0.547	0.053	0.055
	(0.725)	(0.048)	(0.077)
prec	-0.006	-0.001***	-0.000
	(0.008)	(0.000)	(0.001)
prec × prec	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	90.536	7.962	-12.832
	(157.576)	(7.482)	(15.530)
Observations	97	762	291
Adj R-squared	-0.110	0.319	0.398
Number of Farmers	69	154	97

Notes: (1) All regressions use the natural log of yield as the dependent variable. As explanatory variables, we use linear terms for $tmin$ and $tmax$ for each growing phase, and linear and quadratic terms for $prec$. (2) The first column indicates the weather variables the marginal effects are based on. Note that $vtmin$,$retmin$, and $ritmin$, respectively, are the average of daily maximum temperature in the vegetative, reproductive and ripening phase; $vtmax$, $retmax$, and $ritmax$, respectively, are the average of daily maximum temperature in the vegetative, reproductive and ripening phase. Note that $prec$ is cumulative precipitation for the entire growing season.(3) Column 2 is on the subsample for TV, column 3 is on the subsample for MV1-MV3 and column 4 is the results for the recent MVs. (4) Unit for $tmin$ and $tmax$ is °C. Unit for $prec$ is mm.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S2.12 Regression results for the model specifications without interactions between rice varietal grouping dummies and weather variables

	Model 1	Model 2	Model 3	Model 4
year	0.001	-0.001	-.128	-.179*
	(0.003)	(0.003)	(.081)	(.069)
early MVs	0.351***	0.272**	0.404***	0.329**
	(0.100)	(0.107)	(0.124)	(0.130)
recent MVs	0.379***	0.339***	0.480***	0.440***
	(0.113)	(0.118)	(0.133)	(0.135)
vtmin	-0.225***	-0.200***	28.166***	33.948***
	(0.080)	(0.066)	(10.038)	(12.346)
retmin	-0.106***	-0.104***	-10.203	-5.944
	(0.036)	(0.035)	(6.419)	(7.319)
ritmin	0.108**	0.098**	-3.034	-10.890
	(0.050)	(0.042)	(6.958)	(6.719)
vtmax	0.082***	0.091***	-6.765	-6.594
	(0.025)	(0.028)	(5.578)	(6.097)
retmax	-0.085	-0.094	-19.884***	-24.842***
	(0.061)	(0.065)	(7.324)	(7.046)
ritmax	0.073**	0.094**	7.439*	8.855*
	(0.036)	(0.042)	(4.426)	(4.717)
prec	-0.001**	-0.001***	-0.005	-0.059
	(0.000)	(0.000)	(0.050)	(0.054)
prec × prec	0.000	0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
year × vtmin			-0.014***	-0.017***
			(0.005)	(0.006)
year × retmin			0.005	0.003
			(0.003)	(0.004)
year × ritmin			0.002	0.006
			(0.003)	(0.003)
year × vtmax			0.003	0.003
			(0.003)	(0.003)
year × retmax			0.010***	0.012***
			(0.004)	(0.004)
year × ritmax			-0.004*	-0.004*
			(0.002)	(0.002)
year × prec			0.000	0.000
			(0.000)	(0.000)
year × prec × prec			0.000	-0.000
			(0.000)	(0.000)

Table S2.12 Continued

	Model 1	Model 2	Model 3	Model 4
Land Tenure		-0.026		-0.026
		(0.045)		(0.040)
Farm size		-0.042**		-0.028
		(0.019)		(0.018)
Age of Head		-0.001		-0.001
		(0.002)		(0.002)
Educ. of Head		0.008		0.007
		(0.009)		(0.009)
Primary farming		-0.015		0.016
		(0.029)		(0.029)
Secondary farming		0.094		0.078
		(0.136)		(0.106)
Labor		0.002**		0.003***
		(0.001)		(0.001)
Nitrogen Fert.		0.002***		0.002***
		(0.001)		(0.001)
Potassium Fert.		0.003***		0.003***
		(0.001)		(0.001)
Phosphorus Fert.		-0.001		-0.001
		(0.003)		(0.002)
Insecticide		0.005		0.004
		(0.004)		(0.005)
Molluscicide		-0.026**		-0.027**
		(0.013)		(0.012)
Herbicide		0.007		0.006
		(0.005)		(0.005)
Rodenticide		0.031		0.019
		(0.037)		(0.039)
Constant	8.627	12.575**	268.518	369.735***
	(5.725)	(5.735)	(162.685)	(139.922)
Observations	1150	1069	1150	1069
Adj R-squared	0.328	0.381	0.348	0.407
Number of Farmers	180	180	180	180
Other Factors Included	N	Y	Y	Y

Notes: The dependent variable is the natural log of rice yield. The independent variables of Model 1 include the maximum and minimum temperature for each growing phase, growing season cumulative precipitation, linear time trend, and varietal grouping dummies. Model 2 includes the independent variables of Model 1 and the economic variables described by Table 2.1. Model 3 includes the interactions between time trend and weather variables in addition to the variables of Model 1. Model 4 includes the independent variables of Model 3 and the economic variables described by Table 2.1.
***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S2.13 Regression results for the model specifications with both varietal group interactions with weather and time trend interactions with the weather

	inter weather and time trend	add input
year	-0.090	0.160
	(0.105)	(0.097)
early MVs	2.128	1.930
	(4.662)	(5.353)
recent MVs	1.061	1.466
	(5.531)	(5.833)
vtmin	57.055***	60.98287***
	(15.532)	(15.783)
retmin	-13.240	-11.419
	(9.836)	((10.809))
ritmin	-12.577	-16.707
	(11.254)	(10.517)
vtmax	-7.264	-9.243
	(8.624)	(10.334)
retmax	-36.945***	-37.789***
	(12.122)	((13.578))
ritmax	16.745**	14.141*
	(7.511)	(7.267)
prec	-0.053	-0.061
	(0.069)	(0.074)
prec × prec	0.000	0.000
	(0.000)	(0.000)
year × vtmin	-0.029***	-0.031***
	(0.008)	(0.008)
year × retmin	0.007	0.006
	(0.005)	(0.005)
year × ritmin	0.006	0.008
	(0.006)	(0.005)
year × vtmax	0.004	0.005
	(0.004)	(0.005)
year × retmax	0.019***	0.019***
	(0.006)	(0.007)
year × ritmax	-0.008**	-0.007*
	(0.004)	(0.004)
year × prec	0.000	0.000
	(0.000)	(0.000)
year × prec × prec	0.000	-0.000
	(0.000)	(0.000)
early MVs × vtmin	0.468	0.562
	(0.401)	(0.456)
early MVs × retmin	0.184	-0.018
	(0.366)	(0.407)
early MVs × ritmin	0.029	0.133
	(0.303)	(0.319)
early MVs × vtmax	-0.154	-0.244
	(0.159)	(0.180)
early MVs × retmax	-0.608**	-0.498*
	(0.275)	(0.297)
early MVs × ritmax	0.160	0.129
	(0.172)	(0.183)
recent MVs × vtmin	0.944*	1.087*
	(0.495)	(0.556)

Table S2.13 Continued

	inter weather and time trend	add input
recent MVs × retmin	0.054	-0.204
	(0.402)	(0.443)
recent MVs × ritmin	-0.129	0.038
	(0.341)	(0.344)
recent MVs × vtmax	-0.183	-0.336
	(0.201)	(0.231)
recent MVs × retmax	-0.831**	-0.675*
	(0.346)	(0.379)
recent MVs × ritmax	0.329	0.243
	(0.209)	(0.212)
early MVs × prec	0.002	0.003
	(0.003)	(0.003)
early MVs × prec × prec	-0.000	-0.000
	(0.000)	(0.000)
recent MVs × prec	0.001	0.002
	(0.003)	(0.003)
recent MVs × prec × prec	-0.000	-0.000
	(0.000)	(0.000)
Land Tenure		-0.017
		(0.040)
Farm size		-0.038**
		(0.019)
Age of Head		-0.001
		(0.002)
Educ. of Head		0.008
		(0.010)
Primary farming		0.024
		(0.027)
Secondary farming		0.064
		(0.097)
Labor		0.002***
		(0.001)
Nitrogen Fert.		0.002***
		(0.001)
Potassium Fert.		0.003***
		(0.001)
Phosphorus Fert.		-0.000
		(0.003)
Insecticide		0.004
		(0.004)
Molluscicide		-0.027**
		(0.012)
Herbicide		0.005
		(0.005)
Rodenticide		0.066
		(0.061)
Constant	192.672	330.580*
	(209.098)	(192.177)
Observations	1150	1069
Adj R-squared	0.360	0.418
Number of Farmers	180	180

Notes: The dependent variable is the natural log of rice yield. Independent variables include both varietal group interactions with weather and time trend interactions with the weather. Model 2 includes the independent variables of Model 1 and the economic variables described by Table 2.1.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S2.14 Marginal percentage yield impact of weather variables on early MVs and recent MVs for different warming scenarios (results from Alternative Model 1-5

Variables	Alternative Mode 1 cubic year trends		Alternative Model 2 year fixed effect		Alternative Model 3 province-specific trend		Alternative Model 4 prec of 3 phases		Alternative Model 5 2 months phases	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tmin&tmax: tv	-0.250	0.101	-0.327	0.078	-0.237	0.138	-0.156	0.460	-0.143	0.483
tmin&tmax: early mv	-0.206	0.017	-0.280	0.042	-0.191	0.027	-0.051	0.635	-0.039	0.775
tmin&tmax: recent mv	-0.133	0.159	-0.277	0.057	-0.137	0.086	0.019	0.884	0.007	0.964
1°C increase in tmin:										
tmin: tv	-0.676	0.006	-0.583	0.006	-0.765	0.004	0.019	0.911	-0.488	0.073
tmin: early mv	-0.241	0.000	-0.133	0.152	-0.254	0.001	-0.027	0.706	-0.183	0.068
tmin: recent mv	-0.225	0.103	0.111	0.402	-0.247	0.024	0.066	0.742	-0.213	0.224
1°C increase in tmax:										
tmax: tv	0.425	0.144	0.256	0.300	0.528	0.097	-0.175	0.561	0.345	0.217
tmax: early mv	0.035	0.599	-0.147	0.158	0.063	0.387	-0.024	0.740	0.144	0.173
tmax: recent mv	0.092	0.279	-0.388	0.001	0.110	0.158	-0.047	0.724	0.220	0.030
1 standard deviation increase in cumulative precipitation:										
prec: tv	-0.287	0.096	-0.409	0.121	-0.278	0.124	-0.680	0.016	-0.142	0.225
prec: early mv	-0.153	0.000	-0.053	0.234	-0.162	0.000	-0.173	0.000	-0.097	0.000
prec: recent mv	0.015	0.817	-0.008	0.914	-0.020	0.803	-0.128	0.461	-0.095	0.339

Notes: (1) The table displays coefficients and p-values of marginal yield effect of 1°C warming scenarios and 1 standard deviation of increase in $prec$ from five alternative farm fixed-effect models. Standard errors for each regression are clustered at the village level. (2) The models are constructed based on the major model (Model 5 described in Table 2.4. The difference between the alternative models in the table above and the major model are: Alternative Model 1 adds a cubic time trend (the quadratic time trend is omitted). Alternative Model 2 controls for year fixed effect rather than linear time trend. Alternative Model 3 includes province-specific time trends. Alternative model 4 estimates the coefficients of precipitation of each of the three growing phases rather than the entire growing season. In Alternative Model 5, we assume that the length of each growing phase is 2 months (June and July are vegetative growing phase, August and September are reproductive season, and October and November are ripening phase).

Table S2.15 Marginal percentage yield impact of weather variables on early MVs and recent MVs for different warming scenarios (results from Aternative Model 6 - 10)

Variables	Alternative Model 6 interact V and input		Alternative Model 7 interact ritmax, prec & V		Alternative Model 8 interact tmax, prec and V		Alternative Model 9 drop TV		Alternative Model 10 drop TV, year fixed effect	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tmin&tmax: tv	-0.240	0.122	-0.383	0.012	-0.551	0.009				
tmin&tmax: early mv	-0.197	0.024	-0.141	0.014	-0.178	0.065	-0.157	0.076	-0.242	0.123
tmin&tmax: recent mv	-0.124	0.198	-0.068	0.443	-0.076	0.443	-0.065	0.526	-0.203	0.218
1°C increase in tmin:										
tmin: tv	-0.670	0.007	-0.131	0.351	0.233	0.508				
tmin: early mv	-0.236	0.001	-0.220	0.001	-0.212	0.003	-0.207	0.004	-0.085	0.396
tmin: recent mv	-0.215	0.109	-0.166	0.073	-0.272	0.014	-0.153	0.269	0.215	0.112
1°C increase in tmax:										
tmax: tv	0.430	0.143	-0.252	0.169	-0.784	0.088				
tmax: early mv	0.039	0.560	0.079	0.179	0.034	0.708	0.050	0.440	-0.157	0.160
tmax: recent mv	0.091	0.275	0.098	0.288	0.196	0.010	0.087	0.350	-0.418	0.001
1 standard deviation increase in cumulative precipitation:										
prec: tv	-0.285	0.097	-0.291	0.047	-0.869	0.007				
prec: early mv	-0.152	0.000	-0.155	0.000	-0.138	0.004	-0.137	0.000	-0.016	0.694
prec: recent mv	0.009	0.891	-0.064	0.253	0.038	0.662	0.024	0.734	0.035	0.690

Notes: (1) The table displays coefficients and p-values of marginal yield effect of 1°C warming scenarios and 1 standard deviation of increase in $prec$ from five alternative farm fixed-effect models. Standard errors for each regression are clustered at the village level. (2) The models are constructed based on the major model (Model 5 described in Table 2.4. The difference between the alternative models here and the major model are: Alternative Model 6 adds the interactions between input variables (quantity of insecticide, herbicide, rodenticide, molluscicide, labor and fertilizer per hectare into the specification of Model 5 described in Table 2.4). Alternative Model 7 adds the interaction between $ritmax$, linear and quadratic $prec$ and varietal grouping dummies into the Model 1 described in Table 2.4. Alternative Model 8 adds the interactions between $tmax$ of three rice growing phases, linear and quadratic $prec$ and varietal grouping dummies into our major model (Model 5 described in Table 2.4). Model 9 and 10 drop the observations for traditional varieties to compare the estimated the warming impacts on the early MVs and recent MVs. Model 10 controls for year-fixed effects rather than linear time trend.

Table S2.16 Regression results for Alternative Model 1 - 5 described in Table S2.14

	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
year	-0.137		-0.003	0.000	0.007**
	(0.419)		(0.005)	(0.004)	(0.004)
year × year					
year × year × year	0.000				
	(0.000)				
vtmin	-0.264	-0.696	-0.418	0.197	-0.191
	(0.424)	(0.424)	(0.458)	(0.391)	(0.276)
retmin	-0.300	0.265	-0.231	-0.452	-0.253
	(0.398)	(0.476)	(0.418)	(0.393)	(0.305)
ritmin	-0.111	-0.151	-0.115	0.274	-0.044
	(0.335)	(0.316)	(0.353)	(0.291)	(0.297)
vtmax	0.422**	0.130	0.486**	-0.243	0.369**
	(0.197)	(0.183)	(0.213)	(0.287)	(0.158)
retmax	0.067	0.553*	0.052	-0.051	0.036
	(0.254)	(0.311)	(0.247)	(0.221)	(0.189)
ritmax	-0.064	-0.427**	-0.009	0.119	-0.060
	(0.142)	(0.206)	(0.150)	(0.177)	(0.145)
prec	-0.004	-0.007*	-0.005*		-0.001
	(0.003)	(0.004)	(0.003)		(0.003)
prec × prec	0.000	0.000*	0.000*		0.000
	(0.000)	(0.000)	(0.000)		(0.000)
early MVs	-0.206	-2.470	0.130	-2.989	-1.321
	(5.017)	(6.288)	(5.332)	(6.484)	(4.291)
recent MVs	-2.945	-1.453	-1.964	-5.356	-2.160
	(5.521)	(5.938)	(5.814)	(6.705)	(4.291)
early MVs × vtmin	0.053	0.511	0.191	-0.370	0.161
	(0.433)	(0.440)	(0.457)	(0.438)	(0.288)
early MVs × retmin	0.202	-0.227	0.127	0.505	0.237
	(0.414)	(0.476)	(0.434)	(0.415)	(0.310)
early MVs × ritmin	0.181	0.165	0.193	-0.181	-0.093
	(0.342)	(0.314)	(0.360)	(0.298)	(0.311)
early MVs × vtmax	-0.343*	-0.103	-0.395*	0.277	-0.200
	(0.194)	(0.173)	(0.207)	(0.292)	(0.150)
early MVs × retmax	-0.193	-0.680**	-0.168	-0.114	-0.133
	(0.248)	(0.319)	(0.237)	(0.219)	(0.198)
early MVs × ritmax	0.146	0.380*	0.098	-0.012	0.132
	(0.147)	(0.204)	(0.149)	(0.178)	(0.147)
recent MVs × vtmin	0.023	0.930*	0.136	-0.162	0.154
	(0.462)	(0.502)	(0.488)	(0.450)	(0.425)
recent MVs × retmin	0.152	-0.481	0.121	0.299	0.222
	(0.419)	(0.498)	(0.436)	(0.410)	(0.306)
recent MVs × ritmin	0.275	0.245	0.260	-0.091	-0.102
	(0.365)	(0.331)	(0.383)	(0.325)	(0.352)

Table S2.16 Continued

	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
recent MVs × vtmax	-0.388*	-0.329*	-0.421*	0.258	-0.297
	(0.212)	(0.188)	(0.221)	(0.296)	(0.185)
recent MVs × retmax	0.051	-0.666*	0.052	0.010	-0.008
	(0.276)	(0.348)	(0.269)	(0.247)	(0.240)
recent MVs × ritmax	0.003	0.351	-0.049	-0.141	0.180
	(0.156)	(0.226)	(0.166)	(0.206)	(0.174)
early MVs × prec	0.004	0.006	0.004		0.001
	(0.003)	(0.004)	(0.003)		(0.003)
early MVs × prec × prec	-0.000	-0.000*	-0.000		-0.000
	(0.000)	(0.000)	(0.000)		(0.000)
recent MVs × prec	0.004	0.007*	0.005		0.000
	(0.003)	(0.004)	(0.003)		(0.003)
recent MVs × prec × prec	-0.000	-0.000**	-0.000		0.000
	(0.000)	(0.000)	(0.000)		(0.000)
Land Tenure	-0.017	-0.016	-0.014	0.004	-0.012
	(0.042)	(0.038)	(0.043)	(0.040)	(0.042)
Farm size	-0.056***	-0.041*	-0.057***	-0.062***	-0.041**
	(0.020)	(0.022)	(0.019)	(0.020)	(0.021)
Age of Head	-0.001	-0.000	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Educ. of Head	0.009	0.009	0.006	0.006	0.009
	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)
Primary farming	-0.001	0.047	-0.004	0.012	0.023
	(0.026)	(0.030)	(0.027)	(0.027)	(0.027)
Secondary farming	0.062	-0.026	0.067	0.079	-0.005
	(0.110)	(0.072)	(0.109)	(0.106)	(0.104)
Labor	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nitrogen Fert.	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potassium Fert.	0.003***	0.003***	0.003***	0.003**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Phosphorus Fert.	-0.001	0.001	-0.001	-0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Insecticide	0.004	0.001	0.001	0.004	0.003
	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)
Molluscicide	-0.023*	-0.029**	-0.022	-0.025*	-0.029**
	(0.014)	(0.012)	(0.015)	(0.014)	(0.013)
Herbicide	0.005	0.006	0.005	0.006	0.005
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Rodenticide	0.073	0.115**	0.073	0.004	0.078
	(0.066)	(0.055)	(0.066)	(0.037)	(0.070)
vprec				0.009	
				(0.008)	
vprec × vprec				-0.000*	
				(0.000)	

Table S2.16 Continued

	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
reprec				-0.013*	
				(0.007)	
reprec × reprec				0.000*	
				(0.000)	
riprec				0.004	
				(0.004)	
riprec × riprec				-0.000	
				(0.000)	
early MVs × vprec				-0.009	
				(0.008)	
early MVs × vprec × vprec				0.000*	
				(0.000)	
early MVs × reprec				0.010	
				(0.008)	
early MVs × reprec × reprec				-0.000	
				(0.000)	
early MVs × riprec				-0.005	
				(0.004)	
early MVs × riprec × riprec				0.000	
				(0.000)	
recent MVs × vprec				-0.006	
				(0.008)	
recent MVs × vprec × vprec				0.000	
				(0.000)	
recent MVs × reprec				0.013*	
				(0.007)	
recent MVs × reprec × reprec				-0.000*	
				(0.000)	
recent MVs × riprec				-0.005	
				(0.004)	
recent MVs × riprec × riprec				0.000	
				(0.000)	
year=1970		-0.759*			
		(0.445)			
year=1974		-1.017**			
		(0.403)			
year=1979		-0.489			
		(0.422)			
year=1982		-0.448			
		(0.446)			
year=1986		-0.697			
		(0.435)			
year=1990		-0.612			
		(0.458)			
year=1994		-0.508			
		(0.479)			

Table S2.16 Continued

	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
year=1999		-0.844*			
		(0.439)			
year=2003		-0.488			
		(0.429)			
year=2008		-0.330			
		(0.437)			
year=2011		-0.841*			
		(0.491)			
year=2015		0.046			
		(0.440)			
La Union			0.000		
			(.)		
Nueva Ecija			-5.170		
			(10.944)		
Pampanga			-50.860**		
			(20.305)		
Pangasinan			0.000		
			(.)		
Tarlac			0.000		
			(.)		
La Union × year			0.010**		
			(0.004)		
Nueva Ecija × year			0.003		
			(0.006)		
Pampanga × year			0.025**		
			(0.010)		
Pangasinan × year			0.005		
			(0.006)		
Tarlac × year			0.007		
			(0.007)		
Constant	195.632	18.664**	15.412	12.134	-5.313
	(556.175)	(7.157)	(9.653)	(9.794)	(9.844)
Observations	1069	1069	1069	1069	1069
Adj R-squared	0.392	0.433	0.392	0.394	0.389
Number of Farmers	180	180	180	180	180

Table S2.17 Regression results for Alternative Model 6 - 10 described in Table S2.15

	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
year	-0.002	0.001	0.001	0.001	
	(0.003)	(0.003)	(0.003)	(0.004)	
vtmin	-0.161	-0.111	0.208	-0.197**	-0.138
	(0.433)	(0.154)	(0.536)	(0.076)	(0.094)
retmin	-0.065	-0.114***	0.305	-0.082*	0.082
	(0.417)	(0.040)	(0.407)	(0.044)	(0.062)
ritmin	-0.276	0.094*	-0.280	0.072	-0.029
	(0.337)	(0.055)	(0.254)	(0.058)	(0.078)
vtmax	0.157	0.079***	-2.749	0.079**	0.007
	(0.197)	(0.029)	(5.023)	(0.036)	(0.060)
retmax	0.263	-0.100*	3.258	-0.100*	-0.089
	(0.255)	(0.058)	(6.830)	(0.060)	(0.055)
ritmax	-0.168	5.505***	7.170	0.071*	-0.075
	(0.162)	(1.805)	(5.131)	(0.042)	(0.079)
prec	-0.004	0.214***		-0.001***	-0.000
	(0.003)	(0.068)		(0.000)	(0.000)
prec × prec	0.000	-0.000***	-0.000**	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
early MVs	-1.442	180.866***	243.318***		
	(5.521)	(53.886)	(91.765)		
recent MVs	-4.226	172.062***	225.542**	-3.011*	0.329
	(5.815)	(55.682)	(97.657)	(1.803)	(1.335)
early MVs × vtmin	-0.050	-0.089	-0.394		
	(0.448)	(0.134)	(0.543)		
early MVs × retmin	-0.030		-0.387		
	(0.429)		(0.415)		
early MVs × ritmin	0.357		0.335		
	(0.346)		(0.265)		
early MVs × vtmax	-0.078		2.840		
	(0.195)		(4.915)		
early MVs × retmax	-0.394		-2.840		
	(0.260)		(7.062)		
early MVs × ritmax	0.243	-5.910***	-7.823		
	(0.167)	(1.806)	(5.197)		
recent MVs × vtmin	-0.058	-0.034	-0.528	-0.005	0.410**
	(0.473)	(0.142)	(0.555)	(0.138)	(0.166)
recent MVs × retmin	-0.061		-0.354	-0.031	-0.252***
	(0.437)		(0.422)	(0.083)	(0.080)
recent MVs × ritmin	0.408		0.376	0.090	0.142
	(0.364)		(0.287)	(0.083)	(0.091)
recent MVs × vtmax	-0.117		2.695	-0.047	-0.241***
	(0.212)		(5.357)	(0.060)	(0.056)
recent MVs × retmax	-0.197		-5.699	0.207**	-0.015
	(0.277)		(7.535)	(0.091)	(0.114)
recent MVs × ritmax	0.169	-5.671***	-4.197	-0.123	-0.005
	(0.168)	(1.861)	(5.793)	(0.079)	(0.100)
early MVs × prec	0.003	-0.233***	-0.329***		
	(0.003)	(0.068)	(0.123)		
early MVs × prec × prec	-0.000	0.000***	0.000***		
	(0.000)	(0.000)	(0.000)		
recent MVs × prec	0.003	-0.223***	-0.304**	0.001	0.001
	(0.003)	(0.072)	(0.130)	(0.001)	(0.001)
recent MVs × prec × prec	-0.000	0.000***	0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land Tenure	-0.015		-0.017	-0.031	-0.028
	(0.043)		(0.041)	(0.041)	(0.036)
Farm size	-0.056***		-0.038*	-0.050**	-0.032
	(0.020)		(0.021)	(0.021)	(0.024)

Table S2.17 Continued

	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
Age of Head	-0.001		-0.001	-0.002	-0.002
	(0.002)		(0.002)	(0.002)	(0.002)
Educ. of Head	0.006		0.006	0.007	0.005
	(0.010)		(0.010)	(0.010)	(0.010)
Primary farming	0.003		0.006	-0.001	0.051
	(0.027)		(0.028)	(0.028)	(0.033)
Secondary farming	0.085		0.039	0.050	-0.034
	(0.097)		(0.095)	(0.106)	(0.069)
Labor	0.000		0.002**	0.002**	0.003**
	(0.003)		(0.001)	(0.001)	(0.001)
Nitrogen Fert.	-0.002		0.002***	0.002***	0.002***
	(0.003)		(0.001)	(0.001)	(0.001)
Potassium Fert.	0.011		0.004***	0.003***	0.003**
	(0.009)		(0.001)	(0.001)	(0.001)
Phosphorus Fert.	-0.007		-0.001	-0.002	0.000
	(0.009)		(0.003)	(0.003)	(0.002)
Insecticide	-0.077**		0.004	0.005	0.002
	(0.032)		(0.005)	(0.005)	(0.004)
Molluscicide	-0.025		-0.023	-0.019	-0.026*
	(0.017)		(0.014)	(0.016)	(0.014)
Herbicide	0.127		0.008	0.006	0.006
	(0.157)		(0.005)	(0.005)	(0.004)
Rodenticide	0.133**		-0.003	-0.080	-0.012
	(0.061)		(0.039)	(0.056)	(0.064)
early MVs × Insecticide	0.082**				
	(0.031)				
recent MVs × Insecticide	0.084*				
	(0.037)				
early MVs × Molluscicide	0.063*				
	(0.029)				
recent MVs × Molluscicide	0.000				
	(.)				
early MVs × Herbicide	-0.122				
	(0.156)				
recent MVs × Herbicide	-0.124				
	(0.157)				
early MVs × Rodenticide	0.460*				
	(0.206)				
recent MVs × Rodenticide	-0.203**				
	(0.071)				
early MVs × Labor	0.002				
	(0.003)				
recent MVs × Labor	0.001				
	(0.004)				
early MVs × Nitrogen Fert.	0.005				
	(0.003)				
recent MVs × Nitrogen Fert.	0.003				
	(0.003)				
early MVs × Phosphorus Fert.	0.007				
	(0.010)				
recent MVs × Phosphorus Fert.	0.004				
	(0.010)				
early MVs × Potassium Fert.	-0.007				
	(0.010)				
recent MVs × Potassium Fert.	-0.009				
	(0.009)				
prec × vtmax			0.002		
			(0.007)		
prec × prec × vtmax			0.000		
			(0.000)		

Table S2.17 Continued

	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
early MVs × prec × vtmax			-0.002		
			(0.007)		
recent MVs × prec × vtmax			-0.002		
			(0.007)		
early MVs × prec × prec × vtmax			-0.000		
			(0.000)		
recent MVs × prec × prec × vtmax			-0.000		
			(0.000)		
prec × retmax			-0.003		
			(0.008)		
prec × prec × retmax			0.000		
			(0.000)		
early MVs × prec × retmax			0.003		
			(0.009)		
recent MVs × prec × retmax			0.006		
			(0.009)		
early MVs × prec × prec × retmax			-0.000		
			(0.000)		
recent MVs × prec × prec × retmax			-0.000		
			(0.000)		
ritmax × prec		-0.007**	-0.010		
		(0.002)	(0.006)		
ritmax × prec × prec		0.000**	0.000		
		(0.000)	(0.000)		
early MVs × ritmax × prec		0.008***	0.010		
		(0.002)	(0.006)		
recent MVs × ritmax × prec		0.007**	0.006		
		(0.002)	(0.007)		
early MVs × ritmax × prec × prec		-0.000***	-0.000		
		(0.000)	(0.000)		
recent MVs × ritmax × prec × prec		-0.000**	-0.000		
		(0.000)	(0.000)		
year=1970					0.000
					(.)
year=1974					-0.314
					(0.213)
year=1979					0.265
					(0.154)
year=1982					0.341*
					(0.162)
year=1986					0.070
					(0.171)
year=1990					0.161
					(0.155)
year=1994					0.297
					(0.202)
year=1999					-0.085
					(0.188)
year=2003					0.360*
					(0.176)
year=2008					0.473**
					(0.161)
year=2011					-0.024
					(0.199)
year=2015					0.836***
					(0.238)
Constant	19.402*	-156.727**	-226.807*	9.608	14.473**
	(7.935)	(54.463)	(96.142)	(6.535)	(4.319)
Observations	1069	1150	1069	973	973
Adj R-squared	0.401	0.336	0.412	0.353	0.399
Number of Farmers	180	180	180	180	180

Table S2.18 Marginal percentage yield impact of weather variables on early MVs and recent MVs for different warming scenarios

Variables	Main Model 4 varietal group		Alternative Model 1 cubic year trends		Alternative Model 2 year fixed effect		Alternative Model 3 province-specific trend		Alternative Model 4 prec of 3 phases		Alternative Model 5 2 months phases	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:												
tmin&tmax: tv	-0.253	0.112	-0.266	0.095	-0.308	0.074	-0.252	0.124	-0.162	0.459	-0.149	0.476
tmin&tmax: early mv	-0.204	0.024	-0.214	0.019	-0.257	0.051	-0.199	0.027	-0.055	0.642	-0.043	0.767
tmin&tmax: mv4	-0.117	0.356	-0.129	0.300	-0.258	0.107	-0.144	0.199	0.030	0.856	0.043	0.803
tmin&tmax: mv5	-0.092	0.381	-0.104	0.300	-0.211	0.152	-0.085	0.368	-0.014	0.928	0.012	0.934
1°C increase in tmin:												
tmin: tv	-0.683	0.006	-0.690	0.005	-0.578	0.005	-0.779	0.004	0.013	0.942	-0.481	0.076
tmin: early mv	-0.238	0.001	-0.244	0.000	-0.128	0.213	-0.256	0.001	-0.028	0.711	-0.177	0.078
tmin: mv4	-0.148	0.302	-0.156	0.281	0.117	0.445	-0.205	0.084	0.137	0.512	-0.076	0.662
tmin: mv5	-0.287	0.185	-0.306	0.169	0.185	0.336	-0.274	0.215	-0.110	0.624	-0.206	0.437
1°C increase in tmax:												
tmax: tv	0.430	0.141	0.424	0.144	0.270	0.200	0.527	0.097	-0.175	0.561	0.333	0.233
tmax: early mv	0.035	0.623	0.030	0.674	-0.130	0.200	0.057	0.449	-0.027	0.724	0.134	0.234
tmax: mv4	0.031	0.770	0.027	0.799	-0.375	0.002	0.062	0.553	-0.107	0.443	0.119	0.360
tmax: mv5	0.195	0.263	0.202	0.259	-0.396	0.009	0.189	0.302	0.096	0.518	0.218	0.274
1 standard deviation increase in cumulative precipitation:												
prec: tv	-0.291	0.092	-0.293	0.090	-0.415	0.115	-0.283	0.118	-0.675	0.018	-0.146	0.216
prec: early mv	-0.154	0.000	-0.156	0.000	-0.050	0.271	-0.165	0.000	-0.173	0.000	-0.098	0.000
prec: mv4	-0.039	0.674	-0.033	0.714	-0.045	0.653	-0.065	0.524	-0.148	0.592	-0.124	0.508
prec: mv5	0.114	0.309	0.116	0.306	0.039	0.720	0.096	0.434	-0.043	0.851	-0.042	0.627

Notes: (1) The table displays coefficients and p-values of marginal yield effect of 1°C warming scenarios and 1 standard deviation of increase in $prec$ from five alternative farm fixed-effect models. Standard errors for each regression are clustered at the village level.(2) Main model in this table have the same setup with our main model (Model 5 described in Table 2.4) but but separate recent MVs into MV4 and MV5. The Alternative Mode 1-5 have the similar setup with Alternative Model 1-5 described by Table S2.14, but separate recent MVs into MV4 and MV5.

Table S2.19 Marginal percentage yield impact of weather variables on early MVs and recent MVs for different warming scenarios

Variables	Alternative Model 6 interact V and input		Alternative Model 7 interact ritmax, prec & V		Alternative Model 8 interact tmax, prec & V		Alternative Model 9 drop TV		Alternative Model 10 drop TV, year effect	
	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:										
tmin&tmax: tv	-0.262	0.128	-0.408	0.006	-0.578	0.009				
tmin&tmax: early mv	-0.207	0.025	-0.152	0.005	-0.208	0.037	-0.164	0.070	-0.230	0.151
tmin&tmax: mv4	-0.090	0.420	-0.113	0.284	-0.146	0.246	-0.054	0.669	-0.197	0.291
tmin&tmax: mv5	-0.036	0.724	-0.131	0.277	0.120	0.436	-0.057	0.583	-0.180	0.310
1°C increase in tmin:										
tmin: tv	-0.507	0.029	-0.155	0.264	0.188	0.603				
tmin: early mv	-0.227	0.001	-0.240	0.000	-0.219	0.002	-0.210	0.003	-0.075	0.451
tmin: mv4	-0.140	0.345	-0.203	0.030	-0.366	0.002	-0.068	0.610	0.256	0.058
tmin: mv5	-0.200	0.372	-0.218	0.072	0.278	0.412	-0.263	0.266	0.191	0.426
1°C increase in tmax:										
tmax: tv	0.245	0.344	-0.253	0.171	-0.765	0.102				
tmax: early mv	0.020	0.769	0.087	0.127	0.011	0.909	0.046	0.491	-0.154	0.192
tmax: mv4	0.050	0.712	0.090	0.316	0.220	0.019	0.015	0.882	-0.453	0.001
tmax: mv5	0.164	0.376	0.087	0.433	-0.158	0.522	0.206	0.300	-0.370	0.037
1 standard deviation increase in cumulative precipitation:										
prec: tv	-0.227	0.227	-0.305	0.038	-0.856	0.009				
prec: early mv	-0.151	0.000	-0.160	0.000	-0.139	0.000	-0.139	0.000	-0.012	0.785
prec: mv4	-0.111	0.229	-0.139	0.004	-0.022	0.832	-0.010	0.912	0.011	0.915
prec: mv5	0.076	0.523	-0.056	0.389	0.829	0.011	0.102	0.418	0.048	0.703

Notes: (1) The table displays coefficients and p-values of marginal yield effect of 1°C warming scenarios and 1 standard deviation of increase in $prec$ from five alternative farm fixed-effect models. Standard errors for each regression are clustered at the village level.(2) Alternative Mode 6-10 have the similar setup with alternative models in Table S2.15 but separate recent MVs into MV4 and MV5.

Table S2.20 Regression results for models described in Table S2.18

	Main Model 4 varietal groups	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
year	0.000	-0.176		-0.002	0.001	0.008**
	(0.003)	(0.477)		(0.005)	(0.004)	(0.004)
year × year		0.000				
		(.)				
year × year × year		0.000				
		(0.000)				
vtmin	-0.257	-0.265	-0.688	-0.417	0.193	-0.191
	(0.427)	(0.425)	(0.422)	(0.461)	(0.402)	(0.282)
retmin	-0.323	-0.311	0.257	-0.244	-0.459	-0.246
	(0.405)	(0.406)	(0.480)	(0.428)	(0.417)	(0.308)
ritmin	-0.103	-0.113	-0.148	-0.118	0.279	-0.044
	(0.333)	(0.337)	(0.319)	(0.354)	(0.301)	(0.300)
vtmax	0.436**	0.414**	0.137	0.479**	-0.245	0.372**
	(0.193)	(0.194)	(0.189)	(0.212)	(0.287)	(0.157)
retmax	0.054	0.081	0.560*	0.063	-0.049	0.019
	(0.244)	(0.253)	(0.312)	(0.252)	(0.224)	(0.188)
ritmax	-0.060	-0.072	-0.427**	-0.015	0.120	-0.058
	(0.142)	(0.145)	(0.209)	(0.152)	(0.178)	(0.145)
prec	-0.004	-0.004	-0.007*	-0.005*		-0.001
	(0.003)	(0.003)	(0.004)	(0.003)		(0.003)
prec × prec	0.000	0.000	0.000*	0.000*		0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
early MVs	-0.303	-0.359	-2.686	-0.038	-3.029	-1.353
	(5.063)	(5.053)	(6.269)	(5.347)	(6.510)	(4.296)
MV4	-2.644	-2.740	-1.258	-1.627	-4.952	-2.311
	(5.815)	(5.805)	(6.261)	(6.101)	(7.329)	(5.266)
MV5	-5.073	-5.198	-2.688	-4.411	-5.770	-2.395
	(5.440)	(5.474)	(5.895)	(5.773)	(6.987)	(4.819)
early MVs × vtmin	0.042	0.050	0.502	0.185	-0.369	0.164
	(0.438)	(0.436)	(0.441)	(0.462)	(0.451)	(0.293)
early MVs × retmin	0.222	0.215	-0.220	0.141	0.513	0.239
	(0.421)	(0.421)	(0.478)	(0.444)	(0.444)	(0.314)
early MVs × ritmin	0.180	0.181	0.168	0.197	-0.185	-0.098
	(0.342)	(0.342)	(0.313)	(0.360)	(0.305)	(0.314)
early MVs × vtmax	-0.355*	-0.338*	-0.101	-0.390*	0.276	-0.201
	(0.190)	(0.191)	(0.173)	(0.206)	(0.293)	(0.148)
early MVs × retmax	-0.178	-0.207	-0.684**	-0.180	-0.115	-0.128
	(0.234)	(0.246)	(0.320)	(0.240)	(0.219)	(0.196)
early MVs × ritmax	0.138	0.150	0.385*	0.100	-0.014	0.129
	(0.145)	(0.148)	(0.203)	(0.150)	(0.178)	(0.148)
MV4 × vtmin	0.122	0.131	0.959*	0.200	-0.069	0.259
	(0.469)	(0.470)	(0.503)	(0.493)	(0.492)	(0.474)
MV4 × retmin	0.119	0.104	-0.502	0.079	0.275	0.274
	(0.417)	(0.422)	(0.493)	(0.432)	(0.433)	(0.338)
MV4 × ritmin	0.294	0.298	0.238	0.295	-0.082	-0.129
	(0.342)	(0.342)	(0.314)	(0.360)	(0.323)	(0.377)
MV4 × vtmax	-0.441**	-0.419*	-0.336*	-0.442*	0.224	-0.455*
	(0.217)	(0.219)	(0.192)	(0.233)	(0.327)	(0.245)
MV4 × retmax	-0.059	-0.083	-0.725*	-0.061	-0.073	-0.045
	(0.294)	(0.301)	(0.373)	(0.294)	(0.283)	(0.242)
MV4 × ritmax	0.100	0.105	0.416	0.037	-0.083	0.287
	(0.190)	(0.188)	(0.251)	(0.189)	(0.269)	(0.208)

Table S2.20 Continued

	Main Model 4 varietal groups	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
MV5 × vtmin	0.501	0.490	0.949	0.705	-0.462	-0.749
	(0.599)	(0.598)	(0.646)	(0.616)	(0.572)	(0.777)
MV5 × retmin	-0.130	-0.141	-0.435	-0.232	0.542	0.379
	(0.484)	(0.494)	(0.572)	(0.502)	(0.545)	(0.344)
MV5 × ritmin	0.025	0.035	0.249	0.032	-0.203	0.645
	(0.454)	(0.454)	(0.417)	(0.473)	(0.524)	(0.529)
MV5 × vtmax	-0.149	-0.120	-0.287	-0.167	0.276	-0.031
	(0.262)	(0.282)	(0.237)	(0.275)	(0.286)	(0.218)
MV5 × retmax	0.096	0.065	-0.602	0.060	0.174	0.157
	(0.270)	(0.282)	(0.365)	(0.276)	(0.404)	(0.289)
MV5 × ritmax	-0.182	-0.167	0.223	-0.231	-0.180	-0.241
	(0.241)	(0.241)	(0.303)	(0.270)	(0.374)	(0.292)
early MVs × prec	0.004	0.004	0.006*	0.004		0.001
	(0.003)	(0.003)	(0.004)	(0.003)		(0.003)
early MVs × prec × prec	-0.000	-0.000	-0.000*	-0.000		-0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
MV4 × prec	0.004	0.004	0.007*	0.004		0.000
	(0.003)	(0.003)	(0.004)	(0.003)		(0.004)
MV4 × prec × prec	-0.000	-0.000	-0.000*	-0.000		-0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
MV5 × prec	0.005*	0.005*	0.008*	0.005*		0.000
	(0.003)	(0.003)	(0.004)	(0.003)		(0.004)
MV5 × prec × prec	-0.000	-0.000	-0.000*	-0.000		0.000
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
Land Tenure	-0.016	-0.013	-0.015	-0.011	0.005	-0.010
	(0.041)	(0.040)	(0.037)	(0.042)	(0.040)	(0.040)
Farm size	-0.054***	-0.056***	-0.041*	-0.056***	-0.061***	-0.041**
	(0.019)	(0.020)	(0.022)	(0.019)	(0.020)	(0.021)
Age of Head	-0.001	-0.001	-0.000	-0.002	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Educ. of Head	0.008	0.008	0.008	0.005	0.006	0.009
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.009)
Primary farming	0.003	0.005	0.046	0.001	0.014	0.019
	(0.026)	(0.027)	(0.029)	(0.027)	(0.028)	(0.028)
Secondary farming	0.049	0.045	-0.028	0.047	0.074	-0.022
	(0.102)	(0.102)	(0.071)	(0.102)	(0.104)	(0.091)
Labor	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Nitrogen Fert.	0.002***	0.002***	0.002***	0.002***	0.002***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Potassium Fert.	0.003***	0.003***	0.003**	0.003***	0.003**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Phosphorus Fert.	-0.001	-0.001	0.001	-0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Insecticide	0.004	0.004	0.001	0.001	0.004	0.003
	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)
Molluscicide	-0.025	-0.025*	-0.031**	-0.024	-0.026*	-0.030**
	(0.015)	(0.015)	(0.013)	(0.016)	(0.015)	(0.014)
Herbicide	0.005	0.005	0.006	0.005	0.006	0.005
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Rodenticide	0.094*	0.093*	0.123**	0.096*	0.010	0.092
	(0.048)	(0.049)	(0.048)	(0.050)	(0.043)	(0.063)

Table S2.20 Continued

	Main Model 4 varietal groups	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
vprec					0.009	
					(0.008)	
vprec × vprec					-0.000	
					(0.000)	
reprec					-0.013*	
					(0.007)	
reprec × reprec					0.000*	
					(0.000)	
riprec					0.004	
					(0.004)	
riprec × riprec					-0.000	
					(0.000)	
early MVs × vprec					-0.009	
					(0.008)	
early MVs × vprec × vprec					0.000	
					(0.000)	
early MVs × reprec					0.010	
					(0.008)	
early MVs × reprec × reprec					-0.000	
					(0.000)	
early MVs × riprec					-0.005	
					(0.004)	
early MVs × riprec × riprec					0.000	
					(0.000)	
MV4 × vprec					-0.007	
					(0.010)	
MV4 × vprec × vprec					0.000	
					(0.000)	
MV4 × reprec					0.013	
					(0.009)	
MV4 × reprec × reprec					-0.000	
					(0.000)	
MV4 × riprec					-0.006	
					(0.005)	
MV4 × riprec × riprec					0.000	
					(0.000)	
MV5 × vprec					-0.004	
					(0.009)	
MV5 × vprec × vprec					0.000	
					(0.000)	
MV5 × reprec					0.009	
					(0.012)	
MV5 × reprec × reprec					-0.000	
					(0.000)	
MV5 × riprec					-0.005	
					(0.007)	
MV5 × riprec × riprec					0.000	
					(0.000)	
year=1970			-0.765*			
			(0.446)			
year=1974			-1.015**			
			(0.408)			
year=1979			-0.482			
			(0.427)			

Table S2.20 Continued

	Main Model 4 varietal groups	Alternative Model 1 cubic trend	Alternative Model 2 year fixed effect	Alternative Model 3 province-specific trend	Alternative Model 4 prec of 3 phases	Alternative Model 5 2 months phases
year=1982			-0.439			
			(0.450)			
year=1986			-0.693			
			(0.437)			
year=1990			-0.610			
			(0.460)			
year=1994			-0.491			
			(0.488)			
year=1999			-0.828*			
			(0.447)			
year=2003			-0.493			
			(0.428)			
year=2008			-0.331			
			(0.437)			
year=2011			-0.801			
			(0.492)			
year=2015			0.056			
			(0.435)			
La Union				0.000		
				(.)		
Nueva Ecija				-3.261		
				(11.644)		
Pampanga				-49.164**		
				(20.725)		
Pangasinan				0.000		
				(.)		
Tarlac				0.000		
				(.)		
La Union × year				0.009*		
				(0.005)		
Nueva Ecija × year				0.002		
				(0.006)		
Pampanga × year				0.025**		
				(0.010)		
Pangasinan × year				0.004		
				(0.006)		
Tarlac × year				0.006		
				(0.007)		
Constant	12.918*	247.694	18.211**	14.683	11.966	-5.953
	(7.622)	(633.656)	(7.389)	(9.738)	(9.971)	(9.812)
Observations	1069	1069	1069	1069	1069	1069
Adj R-squared	0.390	0.389	0.428	0.389	0.387	0.389
Number of Farmers	180	180	180	180	180	180

Table S2.21 Regression results for models described in Table S2.19

	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
year	-0.002	0.002	0.000	0.001	
	(0.003)	(0.003)	(0.003)	(0.004)	
vtmin	-0.146	-0.110	0.158	-0.200**	-0.129
	(0.439)	(0.156)	(0.553)	(0.077)	(0.096)
retmin	-0.092	-0.122***	0.305	-0.081*	0.089
	(0.428)	(0.041)	(0.421)	(0.045)	(0.063)
ritmin	-0.269	0.076	-0.275	0.071	-0.034
	(0.338)	(0.058)	(0.261)	(0.060)	(0.082)
vtmax	0.144	0.087***	-2.812	0.077**	0.006
	(0.195)	(0.030)	(5.106)	(0.037)	(0.068)
retmax	0.272	-0.105*	3.226	-0.099	-0.081
	(0.262)	(0.061)	(6.940)	(0.063)	(0.058)
ritmax	-0.171	5.548***	6.946	0.068	-0.080
	(0.165)	(1.798)	(5.228)	(0.044)	(0.083)
prec	-0.004	0.215***	0.308**	-0.001***	-0.000
	(0.003)	(0.068)	(0.130)	(0.000)	(0.000)
prec × prec	0.000	-0.000***	-0.000**	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
early MVs	-1.676	181.926***	234.291**		
	(5.560)	(53.769)	(94.069)		
MV4	-3.962	140.162**	154.291	-2.826	0.899
	(6.030)	(57.487)	(113.810)	(2.368)	(1.881)
MV5	-7.305	199.208***	127.225	-4.530*	-0.426
	(6.120)	(72.991)	(147.601)	(2.507)	(2.080)
early MVs × vtmin	-0.069	-0.084	-0.354		
	(0.455)	(0.134)	(0.559)		
early MVs × retmin	-0.002		-0.388		
	(0.439)		(0.429)		
early MVs × ritmin	0.350		0.335		
	(0.347)		(0.272)		
early MVs × vtmax	-0.067		2.864		
	(0.193)		(5.004)		
early MVs × retmax	-0.401		-2.800		
	(0.265)		(7.185)		
early MVs × ritmax	0.244	-5.953***	-7.617		
	(0.168)	(1.801)	(5.295)		
MV4 × vtmin	0.057	-0.047	-0.546	0.102	0.467**
	(0.482)	(0.137)	(0.590)	(0.173)	(0.199)
MV4 × retmin	-0.094		-0.294	-0.085	-0.272***
	(0.435)		(0.440)	(0.089)	(0.093)
MV4 × ritmin	0.404		0.286	0.125	0.136
	(0.351)		(0.298)	(0.112)	(0.099)
MV4 × vtmax	-0.131		4.844	-0.083	-0.260***
	(0.238)		(5.764)	(0.072)	(0.059)
MV4 × retmax	-0.377		-7.505	0.081	-0.070
	(0.307)		(8.228)	(0.134)	(0.179)
MV4 × ritmax	0.313	-4.562**	-2.116	-0.029	0.032
	(0.202)	(1.927)	(6.611)	(0.121)	(0.154)
MV5 × vtmin	0.383	-0.063	0.203	0.394	0.288
	(0.652)	(0.162)	(0.790)	(0.457)	(0.461)
MV5 × retmin	-0.268		-1.021*	-0.311	-0.180
	(0.456)		(0.570)	(0.294)	(0.261)
MV5 × ritmin	0.192		0.907*	-0.136	0.158
	(0.483)		(0.471)	(0.231)	(0.210)

Table S2.21 Continued

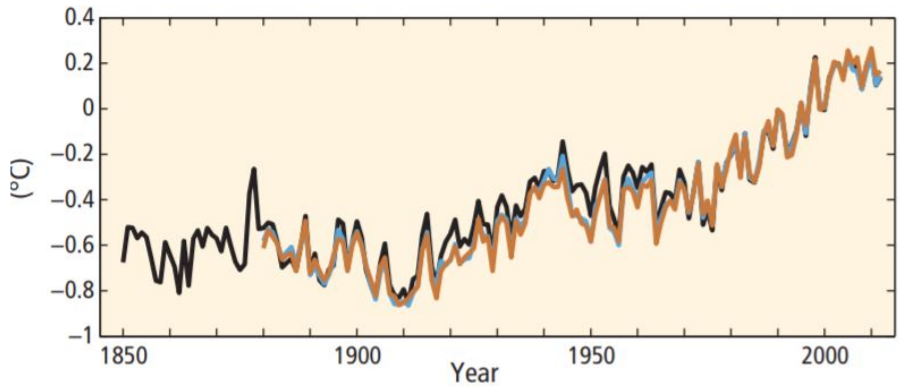
	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
MV5 × vtmax	0.139		-5.596	0.184	-0.189
	(0.293)		(6.644)	(0.211)	(0.184)
MV5 × retmax	-0.173		9.882	0.247	0.041
	(0.290)		(8.460)	(0.153)	(0.150)
MV5 × ritmax	-0.047	-6.596***	-8.651	-0.271	-0.068
	(0.259)	(2.425)	(7.734)	(0.227)	(0.222)
early MVs × prec	0.003	-0.235***	-0.317**		
	(0.003)	(0.068)	(0.126)		
early MVs × prec × prec	-0.000	0.000***	0.000**		
	(0.000)	(0.000)	(0.000)		
MV4 × prec	0.003	-0.180**	-0.215	0.001	0.001
	(0.003)	(0.075)	(0.148)	(0.001)	(0.001)
MV4 × prec × prec	-0.000	0.000**	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MV5 × prec	0.004	-0.270**	-0.107	0.001	0.001
	(0.003)	(0.104)	(0.225)	(0.002)	(0.002)
MV5 × prec × prec	-0.000	0.000**	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land Tenure	-0.013		-0.012	-0.028	-0.027
	(0.041)		(0.039)	(0.040)	(0.035)
Farm size	-0.055***		-0.035	-0.050**	-0.032
	(0.019)		(0.021)	(0.020)	(0.024)
Age of Head	-0.001		-0.002	-0.002	-0.002
	(0.002)		(0.002)	(0.002)	(0.002)
Educ. of Head	0.005		0.006	0.006	0.005
	(0.010)		(0.010)	(0.011)	(0.010)
Primary farming	0.007		0.008	0.004	0.048
	(0.027)		(0.028)	(0.028)	(0.032)
Secondary farming	0.069		0.008	0.036	-0.035
	(0.096)		(0.094)	(0.099)	(0.067)
Labor	0.000		0.002**	0.002**	0.003**
	(0.003)		(0.001)	(0.001)	(0.001)
Nitrogen Fert.	-0.003		0.002***	0.002***	0.002***
	(0.003)		(0.001)	(0.001)	(0.001)
Potassium Fert.	0.010		0.004***	0.003***	0.002**
	(0.009)		(0.001)	(0.001)	(0.001)
Phosphorus Fert.	-0.006		-0.001	-0.001	0.000
	(0.009)		(0.003)	(0.002)	(0.002)
Insecticide	-0.077**		0.003	0.005	0.002
	(0.032)		(0.005)	(0.005)	(0.004)
Molluscicide	-0.038		-0.025	-0.021	-0.027*
	(0.037)		(0.015)	(0.016)	(0.015)
Herbicide	0.130		0.008	0.005	0.006
	(0.157)		(0.006)	(0.005)	(0.004)
Rodenticide	0.137**		0.020	-0.011	0.001
	(0.061)		(0.041)	(0.077)	(0.098)
early MVs × Insecticide	0.083***				
	(0.031)				
MV4 × Insecticide	0.084**				
	(0.041)				
MV5 × Insecticide	0.067				
	(0.051)				

Table S2.21 Continued

	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
early MVs × Molluscicide	0.075				
	(0.047)				
MV4 × Molluscicide	0.015				
	(0.054)				
MV5 × Molluscicide	0.000				
	(.)				
early MVs × Herbicide	-0.124				
	(0.155)				
MV4 × Herbicide	-0.129				
	(0.158)				
MV5 × Herbicide	-0.084				
	(0.158)				
early MVs × Rodenticide	0.467**				
	(0.211)				
MV4 × Rodenticide	-0.253				
	(0.226)				
MV5 × Rodenticide	-0.004				
	(0.175)				
early MVs × Labor	0.002				
	(0.003)				
MV4 × Labor	-0.000				
	(0.004)				
MV5 × Labor	0.002				
	(0.004)				
early MVs × Nitrogen Fert.	0.005				
	(0.003)				
MV4 × Nitrogen Fert.	0.003				
	(0.003)				
MV5 × Nitrogen Fert.	0.003				
	(0.003)				
early MVs × Phosphorus Fert.	0.007				
	(0.010)				
MV4 × Phosphorus Fert.	0.008				
	(0.009)				
MV5 × Phosphorus Fert.	-0.000				
	(0.011)				
early MVs × Potassium Fert.	-0.006				
	(0.010)				
MV4 × Potassium Fert.	-0.010				
	(0.009)				
MV5 × Potassium Fert.	-0.006				
	(0.010)				
prec × vtmax			0.002		
			(0.007)		
prec × prec × vtmax			-0.000		
			(0.000)		
early MVs × prec × vtmax			-0.002		
			(0.007)		
MV4 × prec × vtmax			-0.004		
			(0.008)		
MV5 × prec × vtmax			0.009		
			(0.009)		
early MVs × prec × prec × vtmax			-0.000		
			(0.000)		
MV4 × prec × prec × vtmax			0.000		
			(0.000)		
MV5 × prec × prec × vtmax			-0.000		
			(0.000)		

Table S2.21 Continued

	Alternative Model 6 interact MV and input	Alternative Model 7 interact ritmax, prec and MV	Alternative Model 8 tmax, prec and MV	Alternative Model 9 drop TV	Alternative Model 10 no TV, year effect
prec × retmax			-0.003		
			(0.009)		
prec × prec × retmax			0.000		
			(0.000)		
early MVs × prec × retmax			0.003		
			(0.009)		
MV4 × prec × retmax			0.009		
			(0.010)		
MV5 × prec × retmax			-0.016		
			(0.011)		
early MVs × prec × prec × retmax			-0.000		
			(0.000)		
MV4 × prec × prec × retmax			-0.000		
			(0.000)		
MV5 × prec × prec × retmax			0.000*		
			(0.000)		
ritmax × prec		-0.007***	-0.009		
		(0.002)	(0.006)		
ritmax × prec × prec		0.000***	0.000		
		(0.000)	(0.000)		
early MVs × ritmax × prec		0.008***	0.010		
		(0.002)	(0.006)		
MV4 × ritmax × prec		0.006**	0.003		
		(0.003)	(0.008)		
MV5 × ritmax × prec		0.009**	0.011		
		(0.003)	(0.011)		
early MVs × ritmax × prec × prec		-0.000***	-0.000		
		(0.000)	(0.000)		
MV4 × ritmax × prec × prec		-0.000**	-0.000		
		(0.000)	(0.000)		
MV5 × ritmax × prec × prec		-0.000**	-0.000		
		(0.000)	(0.000)		
year=1970					0.000
					(.)
year=1974					-0.326
					(0.218)
year=1979					0.266
					(0.162)
year=1982					0.352**
					(0.168)
year=1986					0.078
					(0.173)
year=1990					0.165
					(0.156)
year=1994					0.307
					(0.217)
year=1999					-0.084
					(0.190)
year=2003					0.373**
					(0.180)
year=2008					0.482***
					(0.162)
year=2011					0.037
					(0.204)
year=2015					0.871***
					(0.222)
Constant	19.446**	-158.360***	-214.984**	9.478	14.158***
	(7.974)	(54.448)	(98.765)	(6.577)	(4.461)
Observations	1069	1150	1069	973	973
Adj R-squared	0.394	0.336	0.409	0.350	0.394
Number of Farmers	180	180	180	180	180



IPCC AR5

Figure S2.1 Annually and globally averaged combined land and ocean surface temperature anomalies relative to the average over the period 1986 to 2005. Colors indicate different data sets

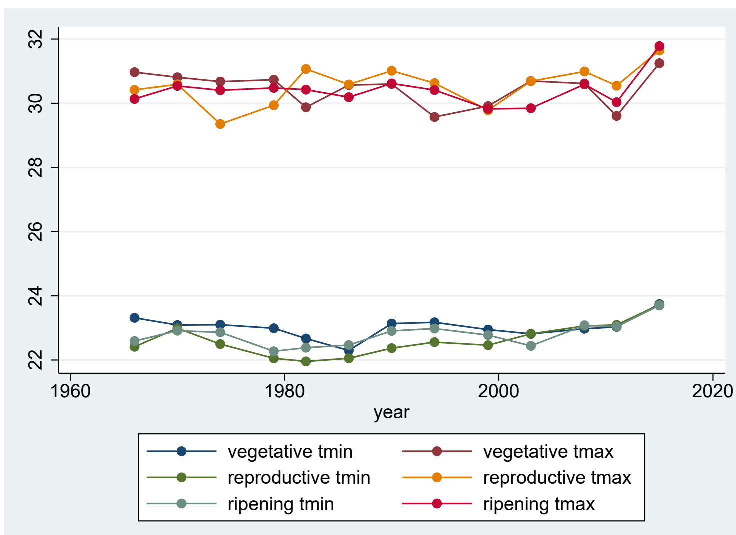


Figure S2.2 Average minimum temperature and maximum temperature trends across survey years for the study area

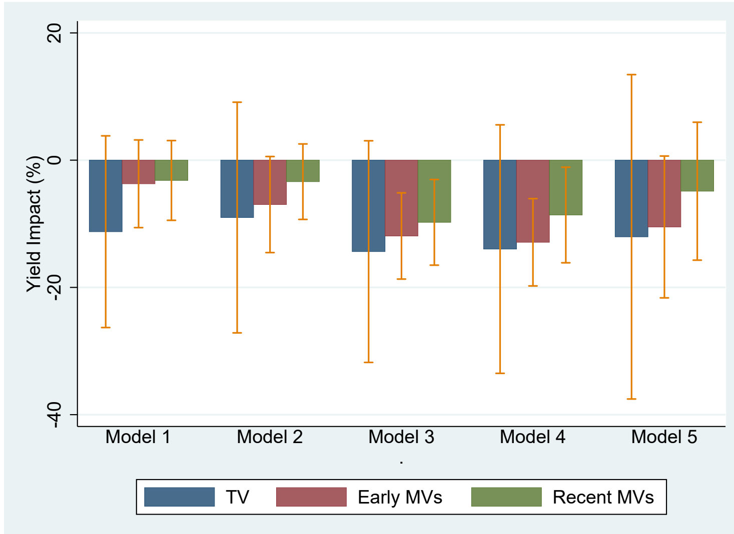


Figure S2.3 The 1 standard deviation warming impact on three rice varietal groups estimated by the 5 models based on Equation 2.1 and Equation 2.2 (specifications described by Table 2.4). Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

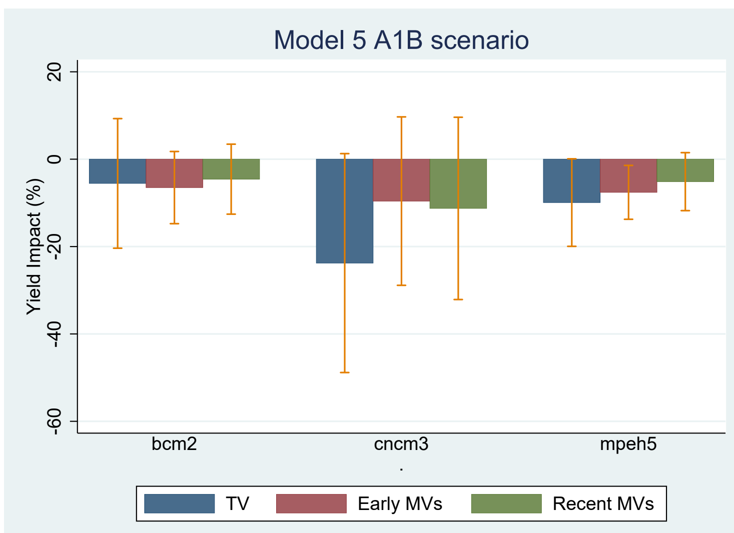


Figure S2.4 Predicted warming impacts under the A1B scenario and Model 5 described by Table 2.4. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

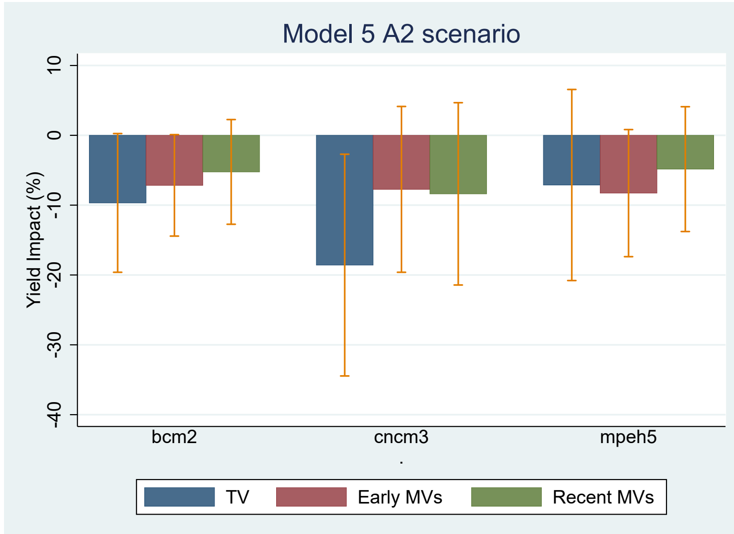


Figure S2.5 Predicted warming impacts under the Scenario A2 and Model 5 described by Table 2.4. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

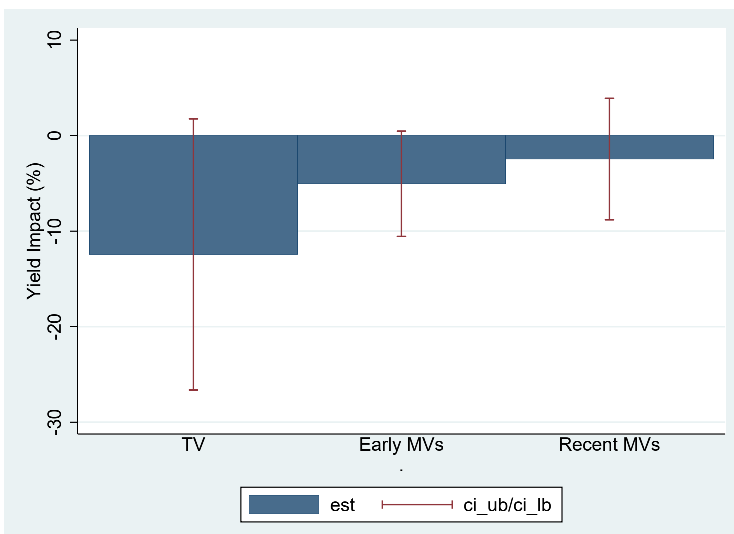


Figure S2.6 Predicted changes in yields of three varietal groups at the average of predicted temperature changes of the six GCM-emission-scenarios. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

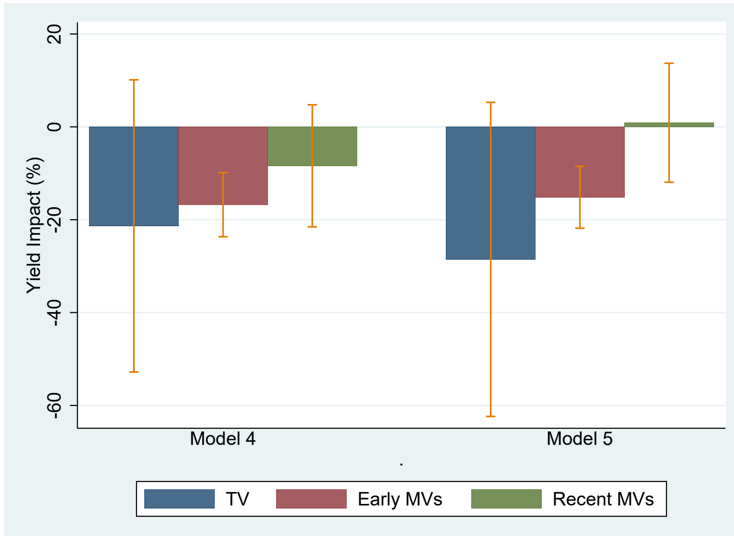


Figure S2.7 Marginal effects of a 1 standard deviation increase in $prec$ for Model 4 and Model 5 described by Table 2.4. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

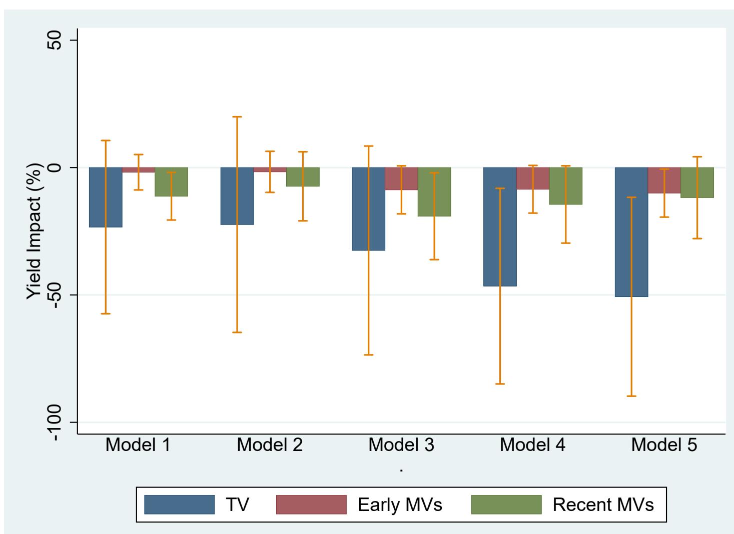


Figure S2.8 Predicted impacts of 1°C decrease in dtr on three rice varietal groups for 5 model specifications described by Table 2.5. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

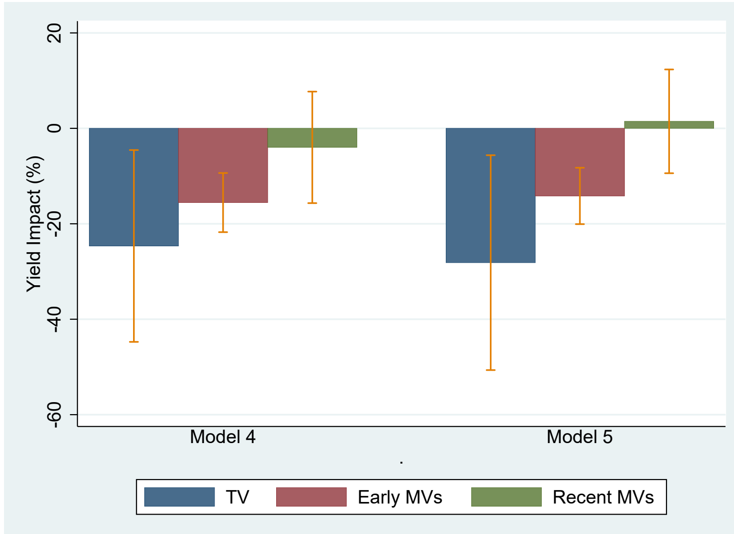


Figure S2.9 Marginal effects of a 1 standard deviation increase in $prec$ for Model 4 and Model 5 described by Table 2.5. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

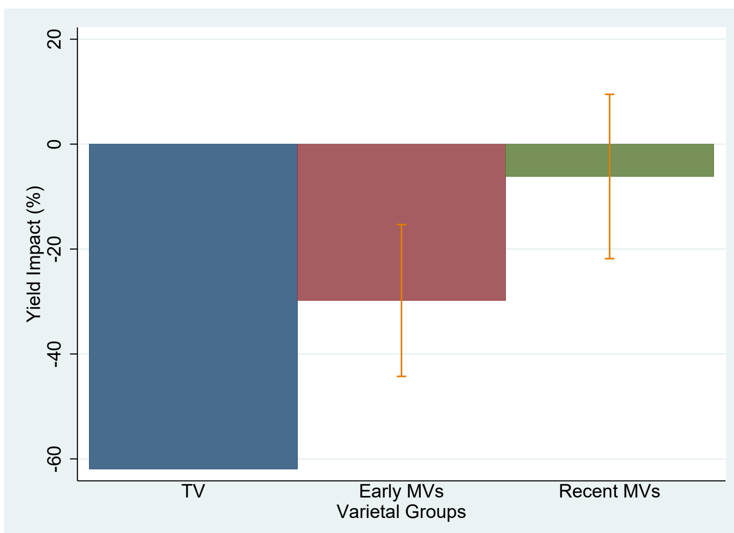


Figure S2.10 The 1°C warming impacts on three rice varietal groups estimated by running separate regressions by varietal groups (Models are described in Table S2.11). Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

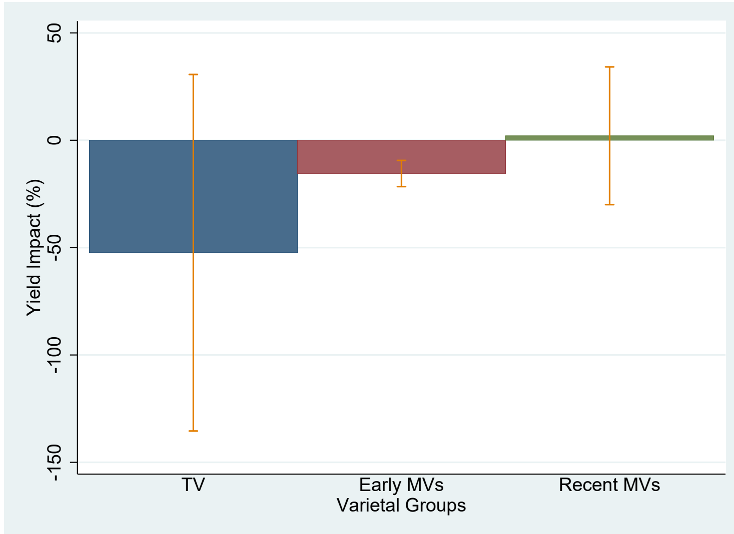


Figure S2.11 The marginal impact of a 1 standard deviation increase in $prec$ on three rice varietal groups estimated by running separate regressions by varietal groups (Models are described in Table S2.11). Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

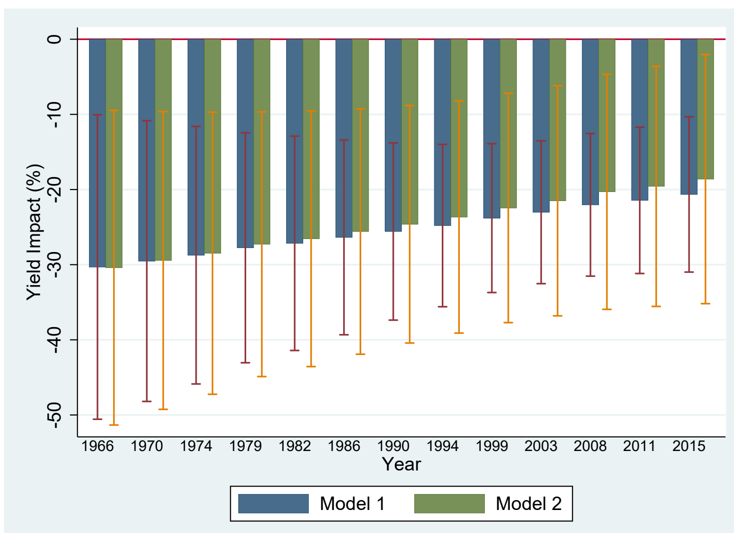


Figure S2.12 The marginal impact of 1°C warming scenario across years estimated from 2 specifications described by Table S2.12 (Model 1 here is Model 3 in Table S2.12 and Model 2 here is Model 4 in Table S2.12). Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

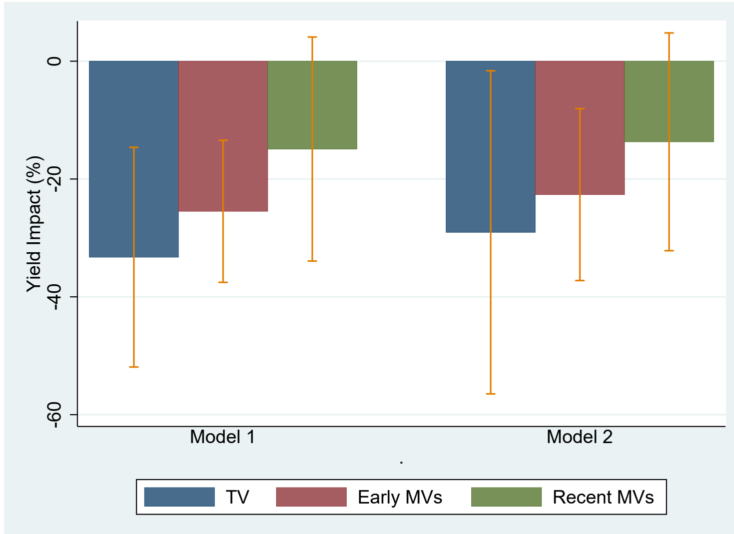


Figure S2.13 The average marginal impact of 1°C warming scenario across years estimated from the models by Table S2.13 (Models include interaction terms between varietal group dummies and weather variables and interaction terms between time trend and weather). Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

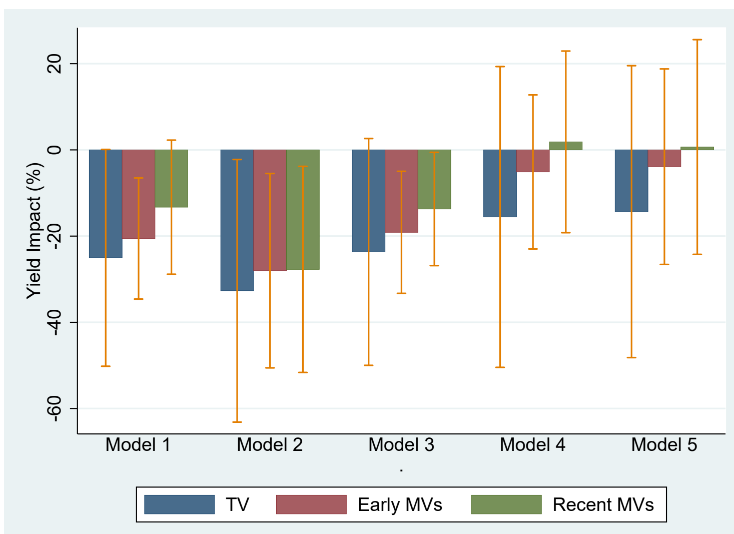


Figure S2.14 Predicted impacts of 1°C warming scenario on different rice varietal groups estimated from Alternative Model 1 to Alternative Model 5 described by Table S2.14. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

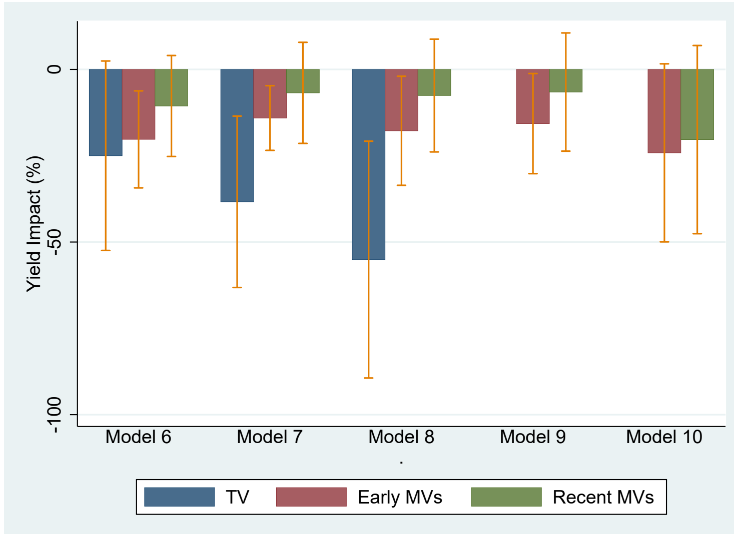


Figure S2.15 Predicted impacts of 1°C warming scenario on different rice varietal groups estimated from Alternative Model 5 to Alternative Model 10 described by Table S2.15. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

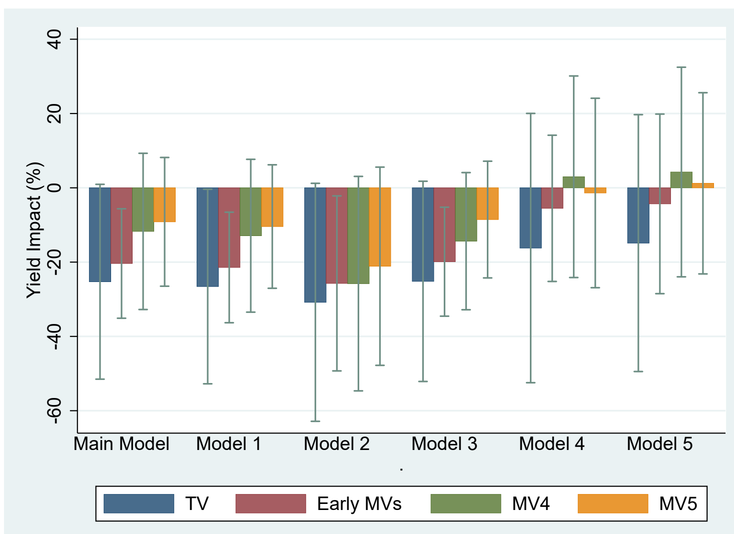


Figure S2.16 Predicted impacts of 1°C warming scenario on different rice varietal groups estimated from main model and Alternative Model 1 to Alternative Model 5 described by Table S2.18. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

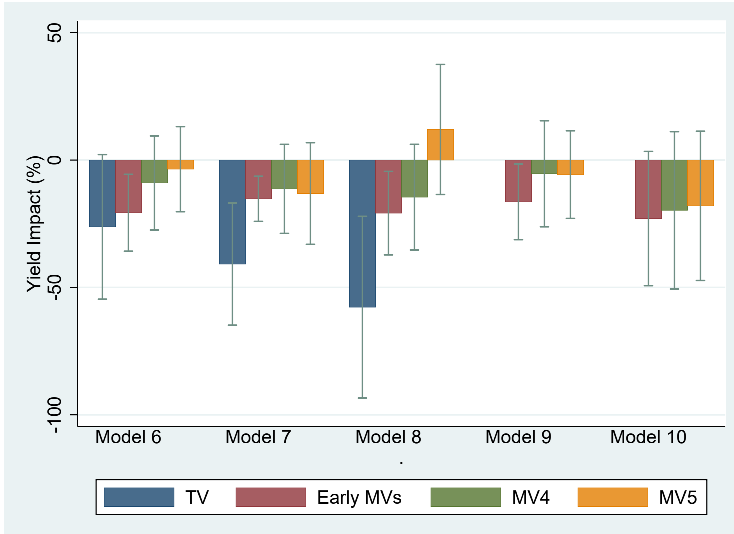


Figure S2.17 Predicted impacts of 1°C warming scenario on different rice varietal groups estimated from Alternative Model 6 to Alternative Model 10 described by Table S2.19. Impacts are reported as the percentage change in yield. The vertical solid lines show 90% confidence intervals.

APPENDIX

B

SUPPLEMENTAL MATERIAL FOR CHAPTER 3

Table S3.1 Regression results of the main model specification

	lnyield
plant density	0.329***
	(0.019)
tmin5	0.168***
	(0.031)
tmin6	-0.153***
	(0.042)
tmin7	0.211***
	(0.038)
tmin8	-0.446***
	(0.033)
tmin9	0.451***
	(0.029)
tmax5	-0.031
	(0.026)
tmax6	0.071*
	(0.038)
tmax7	0.170***
	(0.031)
tmax8	0.306***
	(0.031)
tmax9	-0.135***
	(0.027)
tmin5 × plant density	-0.004***
	(0.001)
tmin6 × plant density	0.003**
	(0.001)
tmin7 × plant density	-0.007***
	(0.001)
tmin8 × plant density	0.015***
	(0.001)
tmin9 × plant density	-0.014***
	(0.001)
tmax5 × plant density	0.000
	(0.001)
tmax6 × plant density	-0.001
	(0.001)
tmax7 × plant density	-0.005***
	(0.001)
tmax8 × plant density	-0.011***
	(0.001)

Table S3.1 Continued

tmax9 × plant density	0.005***
	(0.001)
PDSI5(wet)	-0.077**
	(0.033)
PDSI6(wet)	-0.148***
	(0.039)
PDSI7(wet)	0.146***
	(0.029)
PDSI8(wet)	-0.466***
	(0.037)
PDSI9(wet)	0.021
	(0.035)
PDSI5(dry)	-1.479***
	(0.067)
PDSI6(dry)	1.885***
	(0.121)
PDSI7(dry)	0.000
	(0.087)
PDSI8(dry)	-1.363***
	(0.088)
PDSI9(dry)	-0.652***
	(0.077)
PDSI5(wet) × plant density	0.001
	(0.001)
PDSI6(wet) × plant density	0.006***
	(0.001)
PDSI7(wet) × plant density	-0.005***
	(0.001)
PDSI8(wet) × plant density	0.016***
	(0.001)
PDSI9(wet) × plant density	-0.000
	(0.001)
PDSI5(dry) × plant density	0.051***
	(0.002)
PDSI6(dry) × plant density	-0.065***
	(0.004)
PDSI7(dry) × plant density	-0.003
	(0.003)
PDSI8(dry) × plant density	0.046***
	(0.003)
PDSI9(dry) × plant density	0.023***
	(0.003)

Table S3.1 Continued

year	0.009***
	(0.000)
RW	0.039***
	(0.005)
other GM	0.040***
	(0.003)
1 if previous crop is corn	0.080***
	(0.027)
1 if previous crop is wheat	0.120***
	(0.027)
1 if previous crop is alfalfa or alfalfa/hay	0.185***
	(0.026)
1 if previous crop is soybean	0.095***
	(0.026)
1 if previous crop is lupine	-0.175***
	(0.035)
fall tillage, 1 if yes, 0 if no	0.000
	(0.002)
spring tillage, 1 if yes, 0 if no	-0.037***
	(0.004)
apply insecticide, 1 if yes, 0 if no	-0.062***
	(0.004)
fertilizer N	0.000***
	(0.000)
Observations	28521
R-squared	0.662

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and monthly PDSI from May to September), the interactions between plant density and weather variables, and the managerial inputs and practices described in Table 3.1. The model also includes linear time trend and production zone fixed effect model. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.2 Regression results of the model specification in equations (3.1) and (3.8)

	lnyield
planting density	0.267***
	(0.045)
RW × planting density	-2.025***
	(0.132)
other GM × planting density	-0.126*
	(0.072)
tmin5	0.282***
	(0.056)
tmin6	0.504***
	(0.087)
tmin7	-0.244***
	(0.077)
tmin8	-0.650***
	(0.059)
tmin9	0.702***
	(0.054)
tmax5	0.068
	(0.044)
tmax6	-0.155**
	(0.071)
tmax7	0.380***
	(0.048)
tmax8	0.364***
	(0.056)
tmax9	-0.372***
	(0.047)
tmin5 × planting density	-0.008***
	(0.002)
tmin6 × planting density	-0.020***
	(0.003)
tmin7 × planting density	0.009***
	(0.003)
tmin8 × planting density	0.022***
	(0.002)
tmin9 × planting density	-0.023***
	(0.002)
tmax5 × planting density	-0.003*
	(0.002)
tmax6 × planting density	0.007***
	(0.003)
tmax7 × planting density	-0.012***
	(0.002)
tmax8 × planting density	-0.013***
	(0.002)
tmax9 × planting density	0.013***
	(0.002)

Table S3.2 Continued

RW × tmin5	3.550***
	(0.559)
RW × tmin6	4.771***
	(0.556)
RW × tmin7	-4.341***
	(0.617)
RW × tmin8	-1.386***
	(0.374)
RW × tmin9	1.354***
	(0.342)
other GM × tmin5	-0.389***
	(0.140)
other GM × tmin6	-0.646***
	(0.144)
other GM × tmin7	0.546***
	(0.141)
other GM × tmin8	1.269***
	(0.157)
other GM × tmin9	-1.293***
	(0.127)
RW × tmax5	-2.967***
	(0.395)
RW × tmax6	-2.851***
	(0.558)
RW × tmax7	1.108***
	(0.373)
RW × tmax8	2.100***
	(0.535)
RW × tmax9	-1.829***
	(0.414)
other GM × tmax5	-0.004
	(0.114)
other GM × tmax6	-0.544***
	(0.138)
other GM × tmax7	-0.091
	(0.108)
other GM × tmax8	-0.705***
	(0.125)
other GM × tmax9	1.038***
	(0.108)
PDSI5(wet)	-0.594***
	(0.070)
PDSI6(wet)	0.149
	(0.091)

Table S3.2 Continued

PDSI7(wet)	-0.397***
	(0.064)
PDSI8(wet)	-0.583***
	(0.070)
PDSI9(wet)	-0.166***
	(0.063)
PDSI5(dry)	-4.155***
	(0.462)
PDSI6(dry)	2.785***
	(0.294)
PDSI7(dry)	0.386*
	(0.210)
PDSI8(dry)	-2.973***
	(0.251)
PDSI9(dry)	-0.447**
	(0.183)
PDSI5(wet) × planting density	0.020***
	(0.002)
PDSI6(wet) × planting density	-0.005
	(0.003)
PDSI7(wet) × planting density	0.014***
	(0.002)
PDSI8(wet) × planting density	0.021***
	(0.003)
PDSI9(wet) × planting density	0.006***
	(0.002)
PDSI5(dry) × planting density	0.147***
	(0.017)
PDSI6(dry) × planting density	-0.097***
	(0.011)
PDSI7(dry) × planting density	-0.018**
	(0.008)
PDSI8(dry) × planting density	0.103***
	(0.009)
PDSI9(dry) × planting density	0.016**
	(0.007)
RW × PDSI5(wet)	2.185***
	(0.381)
RW × PDSI6(wet)	-2.111***
	(0.438)
RW × PDSI7(wet)	0.998***
	(0.236)
RW × PDSI8(wet)	-0.148
	(0.479)
RW × PDSI9(wet)	1.175***
	(0.295)

Table S3.2 Continued

other GM × PDSI5(wet)	0.609***
	(0.115)
other GM × PDSI6(wet)	-0.156
	(0.128)
other GM × PDSI7(wet)	0.681***
	(0.089)
other GM × PDSI8(wet)	0.904***
	(0.132)
other GM × PDSI9(wet)	-0.364***
	(0.133)
RW × PDSI5(dry)	5.027***
	(0.618)
RW × PDSI6(dry)	3.669***
	(1.292)
RW × PDSI7(dry)	-3.996***
	(0.473)
RW × PDSI8(dry)	2.584**
	(1.062)
RW × PDSI9(dry)	-0.459
	(0.881)
other GM × PDSI5(dry)	3.768***
	(0.503)
other GM × PDSI6(dry)	-3.970***
	(0.433)
other GM × PDSI7(dry)	0.189
	(0.272)
other GM × PDSI8(dry)	4.147***
	(0.386)
other GM × PDSI9(dry)	-0.420
	(0.275)
RW × tmin5 × planting density	-0.116***
	(0.018)
RW × tmin6 × planting density	-0.162***
	(0.018)
RW × tmin7 × planting density	0.145***
	(0.021)
RW × tmin8 × planting density	0.051***
	(0.012)
RW × tmin9 × planting density	-0.046***
	(0.011)
RW × tmax5 × planting density	0.095***
	(0.013)
RW × tmax6 × planting density	0.096***
	(0.018)
RW × tmax7 × planting density	-0.039***
	(0.012)

Table S3.2 Continued

RW × tmax8 × planting density	-0.071***
	(0.018)
RW × tmax9 × planting density	0.064***
	(0.014)
other GM × tmin5 × planting density	0.012**
	(0.005)
other GM × tmin6 × planting density	0.023***
	(0.005)
other GM × tmin7 × planting density	-0.018***
	(0.005)
other GM × tmin8 × planting density	-0.040***
	(0.005)
other GM × tmin9 × planting density	0.042***
	(0.004)
other GM × tmax5 × planting density	0.000
	(0.004)
other GM × tmax6 × planting density	0.017***
	(0.005)
other GM × tmax7 × planting density	0.003
	(0.004)
other GM × tmax8 × planting density	0.022***
	(0.004)
other GM × tmax9 × planting density	-0.034***
	(0.004)
RW × PDSI5(wet) × planting density	-0.073***
	(0.012)
RW × PDSI6(wet) × planting density	0.072***
	(0.015)
RW × PDSI7(wet) × planting density	-0.035***
	(0.008)
RW × PDSI8(wet) × planting density	0.003
	(0.016)
RW × PDSI9(wet) × planting density	-0.038***
	(0.010)
RW × PDSI5(dry) × planting density	-0.172***
	(0.022)
RW × PDSI6(dry) × planting density	-0.129***
	(0.044)
RW × PDSI7(dry) × planting density	0.146***
	(0.017)
RW × PDSI8(dry) × planting density	-0.089**
	(0.035)
RW × PDSI9(dry) × planting density	0.012
	(0.029)

Table S3.2 Continued

other GM × PDSI5(wet) × planting density	-0.020***
	(0.004)
other GM × PDSI6(wet) × planting density	0.005
	(0.004)
other GM × PDSI7(wet) × planting density	-0.024***
	(0.003)
other GM × PDSI8(wet) × planting density	-0.030***
	(0.005)
other GM × PDSI9(wet) × planting density	0.012***
	(0.005)
other GM × PDSI5(dry) × planting density	-0.133***
	(0.018)
other GM × PDSI6(dry) × planting density	0.142***
	(0.015)
other GM × PDSI7(dry) × planting density	-0.008
	(0.010)
other GM × PDSI8(dry) × planting density	-0.142***
	(0.013)
other GM × PDSI9(dry) × planting density	0.013
	(0.009)
1 if previous crop is corn	-0.006
	(0.032)
1 if previous crop is wheat	0.038
	(0.032)
1 if previous crop is alfalfa or alfalfa/hay	0.090***
	(0.031)
1 if previous crop is soybean	0.001
	(0.031)
1 if previous crop is lupine	-0.092***
	(0.033)
fall tillage, 1 if yes, 0 if no	-0.001
	(0.003)
spring tillage, 1 if yes, 0 if no	-0.048***
	(0.005)
apply insecticide, 1 if yes, 0 if no	-0.076***
	(0.005)
fertilizer N	0.000***
	(0.000)
Observations	28521
R-squared	0.705

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and monthly PDSI from May to September), GM variety dummies, and managerial inputs and practices. The specification also includes linear time trend, production fixed effect and the interactions among plant density, weather variables, and GM variety dummies. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.3 Regression results of the main model specification without including the managerial inputs and practices as control variables

	lnyield
planting density	0.396***
	(0.020)
year	0.012***
	(0.000)
tmin5	0.142***
	(0.029)
tmin6	-0.310***
	(0.041)
tmin7	0.061
	(0.042)
tmin8	-0.237***
	(0.033)
tmin9	0.498***
	(0.033)
tmax5	-0.070***
	(0.025)
tmax6	0.195***
	(0.037)
tmax7	0.237***
	(0.034)
tmax8	0.210***
	(0.031)
tmax9	-0.100***
	(0.027)
tmin5 × planting density	-0.003***
	(0.001)
tmin6 × planting density	0.009***
	(0.001)
tmin7 × planting density	-0.001
	(0.002)
tmin8 × planting density	0.007***
	(0.001)
tmin9 × planting density	-0.016***
	(0.001)
tmax5 × planting density	0.002*
	(0.001)
tmax6 × planting density	-0.006***
	(0.001)
tmax7 × planting density	-0.008***
	(0.001)
tmax8 × planting density	-0.008***
	(0.001)
tmax9 × planting density	0.004***
	(0.001)

Table S3.3 Continued

PDSI5(wet)	-0.046
	(0.033)
PDSI6(wet)	-0.168***
	(0.042)
PDSI7(wet)	0.212***
	(0.029)
PDSI8(wet)	-0.363***
	(0.038)
PDSI9(wet)	0.011
	(0.037)
PDSI5(dry)	-1.738***
	(0.068)
PDSI6(dry)	1.443***
	(0.110)
PDSI7(dry)	0.220***
	(0.074)
PDSI8(dry)	-1.538***
	(0.096)
PDSI9(dry)	-0.134
	(0.082)
PDSI5(wet) × planting density	0.001
	(0.001)
PDSI6(wet) × planting density	0.006***
	(0.001)
PDSI7(wet) × planting density	-0.007***
	(0.001)
PDSI8(wet) × planting density	0.013***
	(0.001)
PDSI9(wet) × planting density	-0.000
	(0.001)
PDSI5(dry) × planting density	0.060***
	(0.002)
PDSI6(dry) × planting density	-0.048***
	(0.004)
PDSI7(dry) × planting density	-0.010***
	(0.003)
PDSI8(dry) × planting density	0.052***
	(0.003)
PDSI9(dry) × planting density	0.004
	(0.003)
Observations	28521
R-squared	0.641

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and monthly PDSI from May to September), and the interactions between plant density and weather variables. The model also includes linear time trend and production zone fixed effect model. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.4 Regression results of the second robustness check

	lnyield
plant density	0.328***
	(0.019)
t	-0.007
	(0.005)
t × plant density	0.001***
	(0.000)
tmin5	0.173***
	(0.031)
tmin6	-0.112**
	(0.044)
tmin7	0.200***
	(0.039)
tmin8	-0.462***
	(0.033)
tmin9	0.441***
	(0.029)
tmax5	-0.025
	(0.026)
tmax6	0.018
	(0.042)
tmax7	0.194***
	(0.032)
tmax8	0.315***
	(0.031)
tmax9	-0.118***
	(0.028)
tmin5 × plant density	-0.004***
	(0.001)
tmin6 × plant density	0.002
	(0.002)
tmin7 × plant density	-0.007***
	(0.001)
tmin8 × plant density	0.016***
	(0.001)
tmin9 × plant density	-0.014***
	(0.001)
tmax5 × plant density	-0.000
	(0.001)
tmax6 × plant density	0.001
	(0.001)
tmax7 × plant density	-0.006***
	(0.001)
	(0.001)

Table S3.4 Continued

tmax8 × plant density	-0.012***
	(0.001)
tmax9 × plant density	0.004***
	(0.001)
PDSI5(wet)	-0.030
	(0.036)
PDSI6(wet)	-0.199***
	(0.042)
PDSI7(wet)	0.170***
	(0.030)
PDSI8(wet)	-0.467***
	(0.037)
PDSI9(wet)	0.014
	(0.036)
PDSI5(dry)	-1.475***
	(0.067)
PDSI6(dry)	1.946***
	(0.120)
PDSI7(dry)	-0.005
	(0.086)
PDSI8(dry)	-1.414***
	(0.086)
PDSI9(dry)	-0.624***
	(0.076)
PDSI5(wet) × plant density	-0.000
	(0.001)
PDSI6(wet) × plant density	0.007***
	(0.001)
PDSI7(wet) × plant density	-0.006***
	(0.001)
PDSI8(wet) × plant density	0.016***
	(0.001)
PDSI9(wet) × plant density	-0.000
	(0.001)
PDSI5(dry) × plant density	0.051***
	(0.002)
PDSI6(dry) × plant density	-0.067***
	(0.004)
PDSI7(dry) × plant density	-0.003
	(0.003)
PDSI8(dry) × plant density	0.048***
	(0.003)
PDSI9(dry) × plant density	0.022***
	(0.003)

Table S3.4 Continued

1 if previous crop is corn	0.089***
	(0.026)
RW	0.036***
	(0.004)
other GM	0.039***
	(0.003)
1 if previous crop is wheat	0.128***
	(0.027)
1 if previous crop is alfalfa or alfalfa/hay	0.193***
	(0.026)
1 if previous crop is soybean	0.102***
	(0.026)
1 if previous crop is lupine	-0.175***
	(0.035)
fall tillage, 1 if yes, 0 if no	0.000
	(0.002)
spring tillage, 1 if yes, 0 if no	-0.038***
	(0.004)
apply insecticide, 1 if yes, 0 if no	-0.063***
	(0.004)
fertilizer N	0.000***
	(0.000)
Observations	28521
R-squared	0.662

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and monthly PDSI from May to September), the interactions between plant density and weather variables, and the managerial inputs and practices described in Table 3.1. The model also includes linear time trend, and production zone fixed effect model. The density effect is allowed to vary across years by including the interaction between plant density and time trend. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.5 Regression results of the model using a quadratic form of precipitation as measure of water availability

	lnyield
plant density	0.352***
	(0.020)
tmin5	0.135***
	(0.031)
tmin6	-0.501***
	(0.042)
tmin7	0.055
	(0.034)
tmin8	-0.133***
	(0.030)
tmin9	0.615***
	(0.034)
tmax5	-0.043*
	(0.023)
tmax6	0.405***
	(0.029)
tmax7	0.210***
	(0.032)
tmax8	0.058**
	(0.028)
tmax9	-0.272***
	(0.026)
tmin5 × plant density	-0.003***
	(0.001)
tmin6 × plant density	0.016***
	(0.001)
tmin7 × plant density	-0.001
	(0.001)
tmin8 × plant density	0.004***
	(0.001)
tmin9 × plant density	-0.021***
	(0.001)
tmax5 × plant density	0.001
	(0.001)
tmax6 × plant density	-0.012***
	(0.001)
tmax7 × plant density	-0.008***
	(0.001)
tmax8 × plant density	-0.002**
	(0.001)
tmax9 × plant density	0.010***
	(0.001)

Table S3.5 Continued

prec	0.030***
	(0.007)
prec × plant density	-0.001***
	(0.000)
prec × prec × plant density	0.000***
	(0.000)
year	0.011***
	(0.000)
RW	0.034***
	(0.005)
other GM	0.026***
	(0.003)
1 if previous crop is corn	0.023
	(0.025)
1 if previous crop is wheat	0.094***
	(0.025)
1 if previous crop is alfalfa or alfalfa/hay	0.125***
	(0.024)
1 if previous crop is soybean	0.004
	(0.024)
1 if previous crop is lupine	-0.177***
	(0.040)
fall tillage, 1 if yes, 0 if no	-0.027***
	(0.003)
spring tillage, 1 if yes, 0 if no	-0.005
	(0.003)
apply insecticide, 1 if yes, 0 if no	-0.057***
	(0.003)
fertilizer N	0.000***
	(0.000)
Observations	28521
R-squared	0.627

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and a quadratic form of the mean of monthly cumulative precipitation for the whole growing season, the interactions between plant density and weather variables, and the managerial inputs and practices described in Table 3.1. The model also includes linear time trend and production zone fixed effect model. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.6 Regression results of the model specification measuring water availability with a quadratic form of precipitation

	lnyield
planting density	0.516***
	(0.047)
RW × planting density	-1.617***
	(0.091)
other GM × planting density	-0.322***
	(0.070)
tmin5	0.255***
	(0.057)
tmin6	-0.575***
	(0.091)
tmin7	-0.610***
	(0.061)
tmin8	0.359***
	(0.049)
tmin9	0.362***
	(0.042)
tmax5	-0.180***
	(0.048)
tmax6	0.493***
	(0.070)
tmax7	0.448***
	(0.043)
tmax8	-0.339***
	(0.048)
tmax9	0.161***
	(0.036)
tmin5 × planting density	-0.008***
	(0.002)
tmin6 × planting density	0.019***
	(0.003)
tmin7 × planting density	0.023***
	(0.002)
tmin8 × planting density	-0.014***
	(0.002)
tmin9 × planting density	-0.012***
	(0.002)
tmax5 × planting density	0.006***
	(0.002)
tmax6 × planting density	-0.016***
	(0.002)
tmax7 × planting density	-0.016***
	(0.002)

Table S3.6 Continued

tmax8 × planting density	0.013***
	(0.002)
tmax9 × planting density	-0.005***
	(0.001)
RW × tmin5	-0.524***
	(0.141)
RW × tmin6	1.353***
	(0.182)
RW × tmin7	-0.146
	(0.236)
RW × tmin8	0.277
	(0.208)
RW × tmin9	0.057
	(0.210)
other GM × tmin5	-0.567***
	(0.108)
other GM × tmin6	0.629***
	(0.128)
other GM × tmin7	1.385***
	(0.096)
other GM × tmin8	0.214**
	(0.103)
other GM × tmin9	-0.920***
	(0.111)
RW × tmax5	0.586***
	(0.147)
RW × tmax6	-0.430**
	(0.184)
RW × tmax7	0.155
	(0.153)
RW × tmax8	-1.131***
	(0.185)
RW × tmax9	-0.667***
	(0.171)
other GM × tmax5	0.397***
	(0.088)
other GM × tmax6	-1.274***
	(0.119)
other GM × tmax7	-0.464***
	(0.077)
other GM × tmax8	0.216**
	(0.089)
other GM × tmax9	0.171*
	(0.089)
RW × tmin5 × planting density	0.018***
	(0.005)

Table S3.6 Continued

RW × tmin6 × planting density	-0.050***
	(0.006)
RW × tmin7 × planting density	0.002
	(0.008)
RW × tmin8 × planting density	-0.002
	(0.007)
RW × tmin9 × planting density	-0.004
	(0.007)
RW × tmax5 × planting density	-0.023***
	(0.005)
RW × tmax6 × planting density	0.015**
	(0.006)
RW × tmax7 × planting density	-0.004
	(0.005)
RW × tmax8 × planting density	0.036***
	(0.006)
RW × tmax9 × planting density	0.025***
	(0.006)
other GM × tmin5 × planting density	0.018***
	(0.004)
other GM × tmin6 × planting density	-0.023***
	(0.004)
other GM × tmin7 × planting density	-0.049***
	(0.003)
other GM × tmin8 × planting density	-0.002
	(0.004)
other GM × tmin9 × planting density	0.029***
	(0.004)
other GM × tmax5 × planting density	-0.014***
	(0.003)
other GM × tmax6 × planting density	0.043***
	(0.004)
other GM × tmax7 × planting density	0.017***
	(0.003)
other GM × tmax8 × planting density	-0.010***
	(0.003)
other GM × tmax9 × planting density	-0.004
	(0.003)
prec	0.124***
	(0.017)
prec × prec	-0.001***
	(0.000)
prec × planting density	-0.004***
	(0.001)
prec × prec × planting density	0.000***
	(0.000)

Table S3.6 Continued

RW × prec	-0.517***
	(0.029)
other GM × prec	-0.042*
	(0.023)
RW × prec × prec	0.002***
	(0.000)
other GM × prec × prec	0.000*
	(0.000)
RW × prec × prec × planting density	-0.000***
	(0.000)
other GM × prec × prec × planting density	-0.000**
	(0.000)
pcorn	0.047*
	(0.027)
1 if previous crop is wheat	0.113***
	(0.027)
1 if previous crop is alfalfa or alfalfa/hay	0.166***
	(0.026)
1 if previous crop is soybean	0.044*
	(0.026)
1 if previous crop is lupine	-0.067*
	(0.038)
fall tillage, 1 if yes, 0 if no	-0.037***
	(0.003)
spring tillage, 1 if yes, 0 if no	0.006
	(0.003)
apply insecticide, 1 if yes, 0 if no	-0.055***
	(0.004)
fertilizern N	0.000***
	(0.000)
Observations	28521
R-squared	0.665

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and a quadratic form of the mean of monthly cumulative precipitation for the whole growing season), GM variety dummies, and managerial inputs and practices. The specification also includes linear time trend, production fixed effect and the interactions among plant density, weather variables, and GM variety dummies. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.
***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.7 Regression results of the model controlling for year fixed effects

	lnyield
plant density	0.083***
	(0.022)
tmin5	0.457***
	(0.043)
tmin6	0.055
	(0.055)
tmin7	-0.105**
	(0.049)
tmin8	-0.470***
	(0.038)
tmin9	0.354***
	(0.033)
tmax5	-0.316***
	(0.033)
tmax6	0.315***
	(0.044)
tmax7	0.153***
	(0.037)
tmax8	0.168***
	(0.037)
tmax9	-0.229***
	(0.032)
tmin5 × plant density	-0.016***
	(0.001)
tmin6 × plant density	-0.003
	(0.002)
tmin7 × plant density	0.003*
	(0.002)
tmin8 × plant density	0.017***
	(0.001)
tmin9 × plant density	-0.012***
	(0.001)
tmax5 × plant density	0.010***
	(0.001)
tmax6 × plant density	-0.010***
	(0.002)
tmax7 × plant density	-0.003**
	(0.001)
tmax8 × plant density	-0.008***
	(0.001)
tmax9 × plant density	0.008***
	(0.001)

Table S3.7 Continued

PDSI5(wet)	0.011
	(0.039)
PDSI6(wet)	-0.146***
	(0.048)
PDSI7(wet)	0.243***
	(0.034)
PDSI8(wet)	-0.695***
	(0.043)
PDSI9(wet)	0.132***
	(0.039)
PDSI5(dry)	-1.180***
	(0.071)
PDSI6(dry)	1.252***
	(0.140)
PDSI7(dry)	0.669***
	(0.105)
PDSI8(dry)	-0.773***
	(0.099)
PDSI9(dry)	-0.965***
	(0.087)
PDSI5(wet) × plant density	-0.000
	(0.001)
PDSI6(wet) × plant density	0.005***
	(0.002)
PDSI7(wet) × plant density	-0.009***
	(0.001)
PDSI8(wet) × plant density	0.025***
	(0.001)
PDSI9(wet) × plant density	-0.004***
	(0.001)
PDSI5(dry) × plant density	0.041***
	(0.002)
PDSI6(dry) × plant density	-0.038***
	(0.005)
PDSI7(dry) × plant density	-0.029***
	(0.004)
PDSI8(dry) × plant density	0.025***
	(0.003)
PDSI9(dry) × plant density	0.034***
	(0.003)

Table S3.7 Continued

RW	0.047***
	(0.005)
other GM	0.046***
	(0.003)
1 if previous crop is corn	0.159***
	(0.028)
1 if previous crop is wheat	0.148***
	(0.028)
1 if previous crop is alfalfa or alfalfa/hay	0.261***
	(0.027)
1 if previous crop is soybean	0.165***
	(0.027)
1 if previous crop is lupine	-0.223***
	(0.036)
fall tillage, 1 if yes, 0 if no	-0.006**
	(0.003)
spring tillage, 1 if yes, 0 if no	-0.020***
	(0.004)
apply insecticide, 1 if yes, 0 if no	-0.059***
	(0.004)
fertilizer N	0.000***
	(0.000)
Observations	28521
R-squared	0.689

Notes: Table regresses plot-level log of yield on plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and monthly PDSI from May to September), the interactions between plant density and weather variables, and the managerial inputs and practices described in Table 3.1. The model also includes year fixed effects and production zone fixed effect model. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S3.8 Regression results of the model including quadratic term of plant density

	lnyield
plant density	0.123***
	(0.025)
plant density × plant density	0.004***
	(0.000)
tmin5	0.051
	(0.034)
tmin6	0.259***
	(0.055)
tmin7	0.151***
	(0.039)
tmin8	-0.553***
	(0.033)
tmin9	0.424***
	(0.029)
tmax5	0.134***
	(0.030)
tmax6	-0.193***
	(0.046)
tmax7	0.232***
	(0.031)
tmax8	0.333***
	(0.030)
tmax9	-0.151***
	(0.027)
tmin5 × plant density	0.000
	(0.001)
tmin6 × plant density	-0.011***
	(0.002)
tmin7 × plant density	-0.005***
	(0.001)
tmin8 × plant density	0.019***
	(0.001)
tmin9 × plant density	-0.013***
	(0.001)
tmax5 × plant density	-0.006***
	(0.001)
tmax6 × plant density	0.009***
	(0.002)
tmax7 × plant density	-0.007***
	(0.001)
tmax8 × plant density	-0.012***
	(0.001)
tmax9 × plant density	0.006***
	(0.001)

Table S3.8 Continued

PDSI5(wet)	0.255***
	(0.041)
PDSI6(wet)	-0.485***
	(0.048)
PDSI7(wet)	0.244***
	(0.030)
PDSI8(wet)	-0.441***
	(0.038)
PDSI9(wet)	-0.031
	(0.037)
PDSI5(dry)	-1.558***
	(0.067)
PDSI6(dry)	2.179***
	(0.120)
PDSI7(dry)	-0.031
	(0.084)
PDSI8(dry)	-1.659***
	(0.087)
PDSI9(dry)	-0.387***
	(0.078)
PDSI5(wet) × plant density	-0.010***
	(0.001)
PDSI6(wet) × plant density	0.017***
	(0.002)
PDSI7(wet) × plant density	-0.009***
	(0.001)
PDSI8(wet) × plant density	0.016***
	(0.001)
PDSI9(wet) × plant density	0.001
	(0.001)
PDSI5(dry) × plant density	0.054***
	(0.002)
PDSI6(dry) × plant density	-0.075***
	(0.004)
PDSI7(dry) × plant density	-0.002
	(0.003)
PDSI8(dry) × plant density	0.057***
	(0.003)
PDSI9(dry) × plant density	0.014***
	(0.003)

Table S3.8 Continued

RW	0.037***
	(0.004)
other GM	0.042***
	(0.003)
year	0.008***
	(0.000)
1 if previous crop is corn	0.064**
	(0.026)
1 if previous crop is wheat	0.103***
	(0.027)
1 if previous crop is alfalfa or alfalfa/hay	0.165***
	(0.026)
1 if previous crop is soybean	0.072***
	(0.026)
1 if previous crop is lupine	-0.173***
	(0.032)
fall tillage, 1 if yes, 0 if no	-0.002
	(0.002)
spring tillage, 1 if yes, 0 if no	-0.043***
	(0.004)
apply insecticide, 1 if yes, 0 if no	-0.060***
	(0.004)
fertilizer N	0.000***
	(0.000)
Observations	28521
R-squared	0.665

Notes: Table regresses plot-level log of yield on linear and quadratic plant density, weather variables(monthly average of daily minimum and maximum temperature(**tmin** and **tmax**), and monthly PDSI from May to September), the interactions between plant density and weather variables, and the managerial inputs and practices described in Table 3.1. The model also includes linear time trend and production zone fixed effect model. Units for **tmin** and **tmax** are °C. Unit for plant density is 1000 acre^{-1}. In consideration of the possible heteroskedasticity, Huber-White's robust standard errors are calculated and shown in parentheses.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

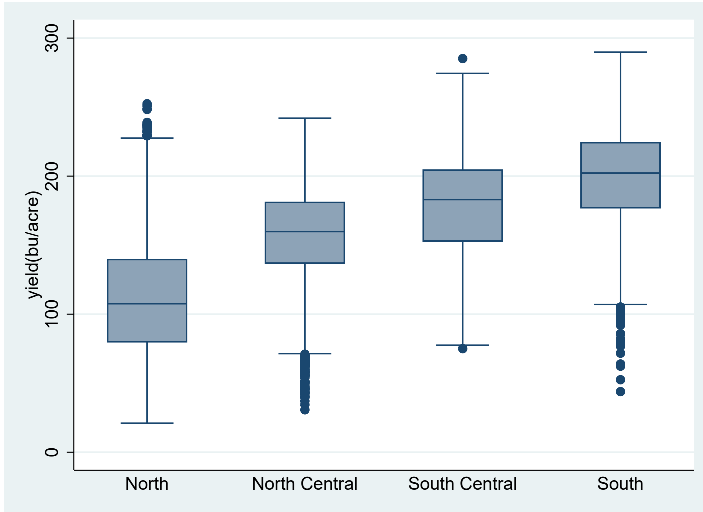


Figure S3.1 Distribution of yield for four production zones

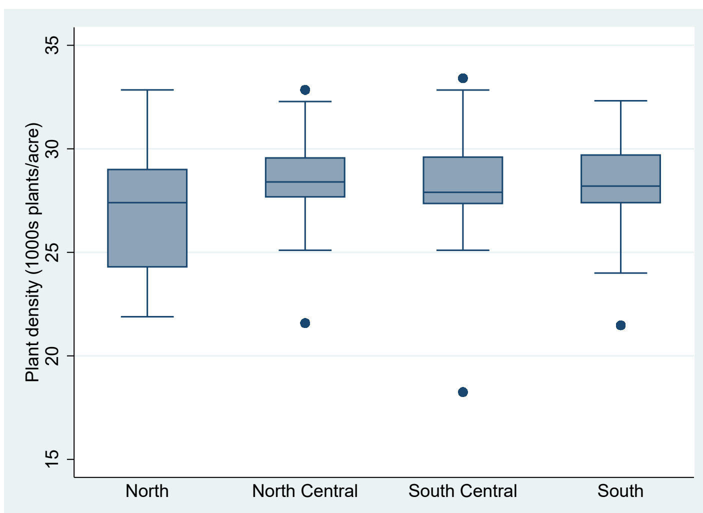


Figure S3.2 Distribution of plant density for four production zones

Notes: In the two figures above, each box plot corresponds to the plant density of plots in a production zone. The solid line in each distribution is the median. The upper hinge and the lower hinge are the 75^{th} and the $25th$ percentile values of plant density separately. The upper adjacent line represents 75^{th} $percentile\ value + 1.5 \times interquantile\ range$ and the lower adjacent line represents 25^{th} $percentile\ value - 1.5 \times interquantile\ range$.

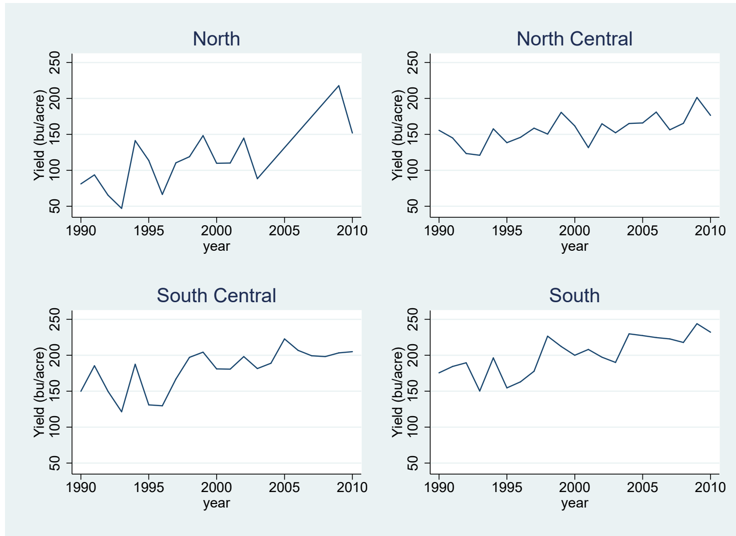


Figure S3.3 The change in the average corn yields in four production zones over years

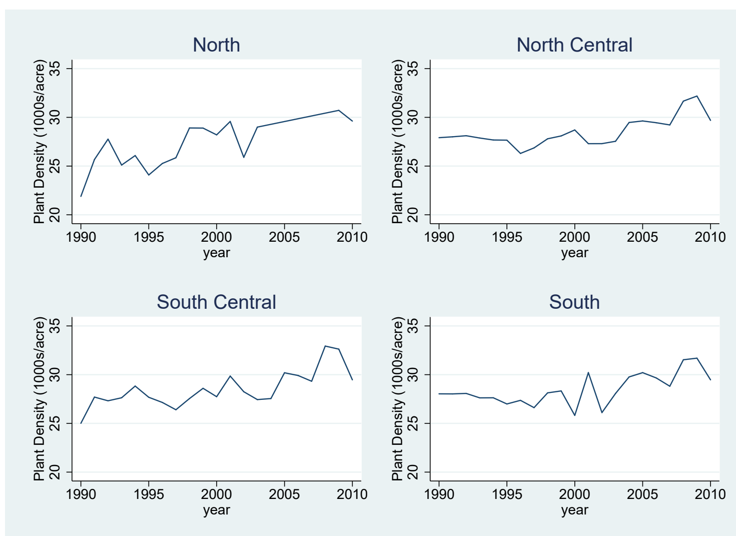


Figure S3.4 The change in the average of plant density in four production zones over years

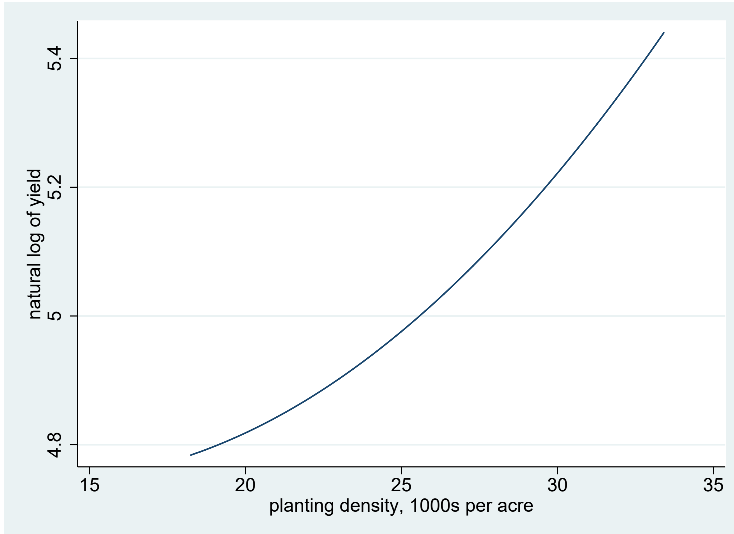


Figure S3.5 Regression of the natural log of yield on a quadratic form of plant density

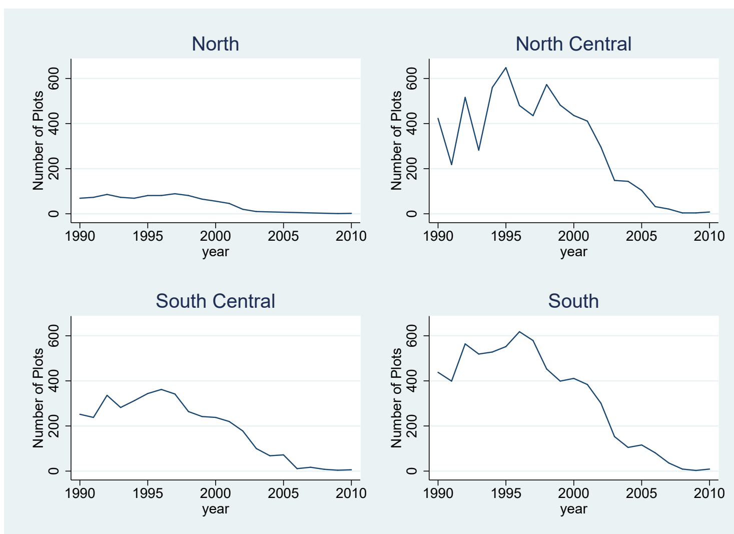


Figure S3.6 The change in number of plots planting conventional corn over years

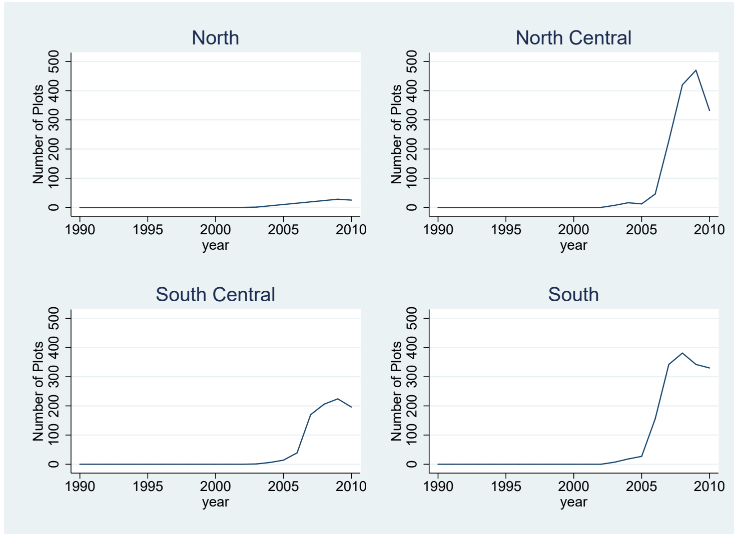


Figure S3.7 The change in number of plots planting GM corn with Bt trait for corn rootworm

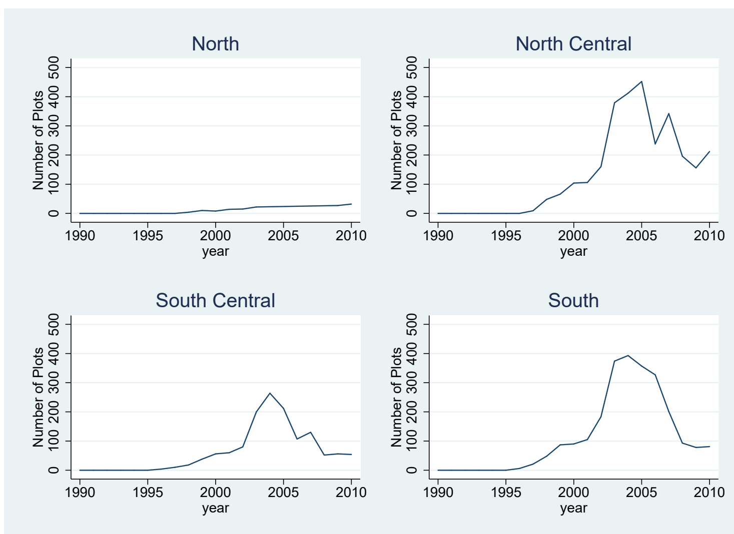


Figure S3.8 The change in number of plots planting GM corn without Bt trait for corn rootworm

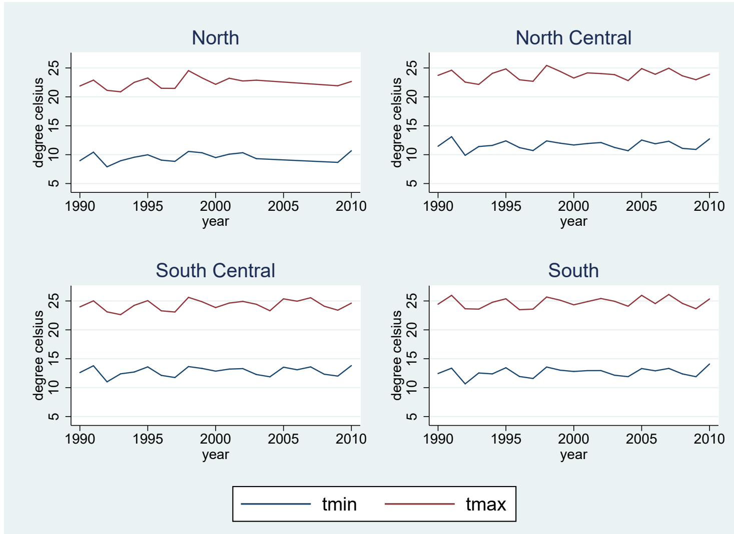


Figure S3.9 The change in **tmin** and **tmax** across years

Notes: **tmin** and **tmax** are the average of monthly minimum and maximum temperature during the May-September growing season.

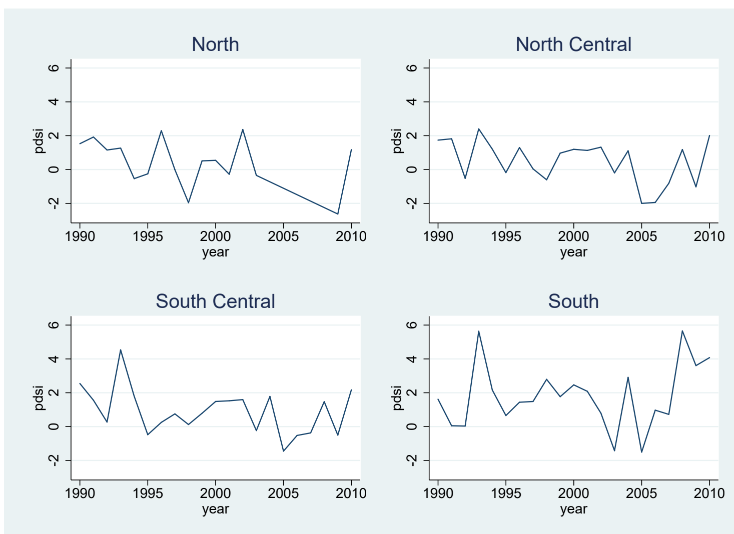


Figure S3.10 The change in PDSI across years

Notes: PDSI here are the average of monthly PDSI during the May-September growing season.

APPENDIX

C

SUPPLEMENTAL MATERIAL FOR CHAPTER 4

Table S4.1 The difference in the responses of the mean and higher central moments of corn and soybean yields to extreme heat between uninsured and insured field

Crop	Approach	Time Trend	Ins Ptc	Mean	Variance	Skewness	Kurtosis
corn	FE	state	LR	-47.34***	366.7**	9113.2	1337087.3**
corn	FE	county	LR	-55.57***	418.8**	18761.5	2465340.9*
soybeans	FE	state	LR	-17.98***	49.46**	306.1	15465.7**
soybeans	FE	county	LR	-18.52***	49.30***	326.5	14051.3***

Notes: (1) The table displays the marginal impact of insurance participation on the sensitivity of the mean and higher central moments of corn and soybeans yield to extreme heat (degree days above 29º C for corn and 30º C for soybeans, measured in hundreds, for the months April-September). (2) All models control for county-level fixed effect and use liability ratio to measure insurance participation rate. The model for the first row and the third row accounts for year fixed effect and state-specific linear and quadratic time trend. The model that corresponds the second and the fourth row accounts for year fixed effect, and county-specific linear and quadratic time trend.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S4.2 The difference in the responses of the mean and higher central moments of corn and soybean yields to extreme heat between uninsured and insured field

Crop	Approach	Time Trend	Ins	Mean yield		Variance of yield		Skewness of yield		Kurtosis of yield	
				YP	RP	YP	RP	YP	RP	YP	RP
corn	FE	state	LR	-24.00**	-59.42***	-224.7	343.7**	10523.7	-1021.7	-490843.6	654197.8
corn	FE	county	LR	-20.27	-68.86***	-317.6*	367.7*	12959.4	2319.8	-749463.2*	1018961.5
soybeans	FE	state	LR	-11.28**	-19.82***	7.322	55.72**	-804.9	583.1	2248.2	19286.8**
soybeans	FE	county	LR	-9.137	-21.30***	5.881	53.66***	-535.0	639.1	585.0	18688.4**

Notes: (1) The table displays the marginal impact of yield and revenue protection program participation on the sensitivity of the mean and higher central moments of corn and soybeans yield to extreme heat (degree days above 29º C for corn and 30º C for soybeans, measured in hundreds, for the months April-September). (2) All models control for county-level fixed effect and use liability ratio to measure insurance participation rate. The model for the first and third row accounts for year fixed effect and state-specific linear and quadratic time trend. The model that corresponds to the second and fourth row accounts for year fixed effect and county-specific linear and quadratic time trend.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table S4.3 Estimated response of the mean, variance, skewness, and kurtosis of yield to weather variables, insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	14.39	-53.06	4867.2	-28037.3
	(1.19)	(-0.24)	(0.45)	(-0.05)
DD^H	-24.49***	141.6***	-84.51	143611.3
	(-5.36)	(3.03)	(-0.02)	(0.66)
$Prec$	76.97**	322.0	-35910.7	-135032.2
	(2.57)	(0.65)	(-1.09)	(-0.14)
$Prec^2$	-52.26**	-257.6	27908.1	-23725.5
	(-2.58)	(-0.70)	(1.27)	(-0.03)
Ins Ptc	-24.84	524.7	11344.7	1269840.6
	(-0.86)	(1.55)	(0.29)	(0.83)
DD^M *Ins Ptc	37.11**	-173.4	-18231.3	-1669024.7
	(2.31)	(-0.72)	(-0.55)	(-1.16)
DD^H *Ins Ptc	-55.57***	418.8**	18761.5	2465340.9*
	(-3.14)	(2.43)	(0.54)	(1.95)
$Prec$*Ins Ptc	1.168	-2226.3	45395.3	-256776.2
	(0.01)	(-1.62)	(0.39)	(-0.06)
$Prec^2$ *Ins Ptc	-18.27	1944.9**	-31340.0	1617158.4
	(-0.30)	(2.07)	(-0.37)	(0.56)
Observations	38101	38101	38101	38101
R squared	0.651	0.160	0.0381	0.113
Time Controls	County	County	County	County
Crop	Corn	Corn	Corn	Corn
Ins Ptc Measure	Lb Ratio	Lb Ratio	Lb Ratio	Lb Ratio
Model	FE	FE	FE	FE
Input Expenditure	No	No	No	No

t statistics in parentheses

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

Table S4.4 Estimated response of the mean, variance, skewness, and kurtosis of yield to weather variables, insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	12.36***	-26.61**	26.48	-5697.0**
	(4.17)	(-2.56)	(0.09)	(-2.23)
DD^H	-11.93***	6.645	118.3	1860.3
	(-7.68)	(1.34)	(1.03)	(0.98)
$Prec$	41.89***	-35.66	-521.6	-10755.2*
	(6.13)	(-1.15)	(-0.77)	(-1.86)
$Prec^2$	-25.10***	19.51	491.7	6692.1
	(-5.49)	(0.91)	(1.07)	(1.56)
Ins Ptc	-4.345	33.42	-243.4	5140.8
	(-0.51)	(0.83)	(-0.38)	(0.61)
DD^M *Ins Ptc	9.240**	-33.51**	-108.4	-7757.6
	(2.72)	(-2.10)	(-0.36)	(-1.70)
DD^H *Ins Ptc	-18.52***	49.30***	326.5	14051.3***
	(-5.09)	(2.88)	(0.75)	(3.02)
$Prec$*Ins Ptc	-1.227	-11.64	1623.5	3783.8
	(-0.09)	(-0.14)	(1.23)	(0.23)
$Prec^2$ *Ins Ptc	-5.392	23.20	-1232.4	2750.8
	(-0.58)	(0.42)	(-1.46)	(0.25)
Observations	36095	36095	36095	36095
R squared	0.627	0.132	0.0376	0.100
Time Controls	County	County	County	County
Crop	Soybeans	Soybeans	Soybeans	Soybeans
Ins Ptc Measure	Lb Ratio	Lb Ratio	Lb Ratio	Lb Ratio
Model	FE	FE	FE	FE
Input Expenditure	No	No	No	No

t statistics in parentheses

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

Table S4.5 Estimated response of the mean, variance, skewness, and kurtosis of corn yield to weather variables, insurance participation, interaction terms, and input expenditures.

	Mean	Variance	Skewness	Kurtosis
DD^M	14.78	-116.3	7142.8	-516567.8
	(1.34)	(-0.49)	(0.56)	(-1.02)
DD^H	-26.43***	199.2***	3300.2	678180.1***
	(-6.41)	(3.86)	(0.69)	(4.79)
$Prec$	72.88**	349.6	-36452.6	-307836.3
	(2.57)	(0.68)	(-1.19)	(-0.26)
$Prec^2$	-51.54**	-265.4	30776.0	254127.2
	(-2.70)	(-0.71)	(1.52)	(0.30)
Ins	-43.68	725.7*	8541.9	1067033.0
	(-1.56)	(1.76)	(0.24)	(0.75)
DD^M*Ins	38.59***	-204.4	-16133.1	-1124627.9
	(3.14)	(-0.92)	(-0.66)	(-1.25)
DD^H*Ins	-47.81***	350.1**	12955.4	1418539.9**
	(-3.14)	(2.31)	(0.48)	(2.06)
$Prec$*Ins	23.94	-2303.6	50271.6	-950746.4
	(0.30)	(-1.65)	(0.42)	(-0.22)
$Prec^2$*Ins	-28.64	1895.8*	-37996.6	1567360.8
	(-0.48)	(1.91)	(-0.44)	(0.48)
Fertilizer and lime	-0.00371**	0.0379	-1.144	268.4
	(-2.51)	(0.58)	(-0.57)	(0.85)
production	-0.000122	-0.000838	-0.0457	-10.84
	(-0.71)	(-0.26)	(-0.18)	(-0.89)
petroleum	0.000473	-0.00428	-0.672	-103.4
	(0.11)	(-0.04)	(-0.08)	(-0.17)
hired labor	0.000368	0.0103	0.567	101.1
	(0.39)	(0.40)	(0.33)	(1.34)
seed	0.00472*	-0.0511	3.342	-317.7
	(1.88)	(-0.69)	(1.23)	(-1.08)
Observations	37302	37302	37302	37302
R squared	0.596	0.0767	0.0109	0.0403
Time Controls	State	State	State	State
Crop	Corn	Corn	Corn	Corn
Ins Measure	LR	LR	LR	LR
Model	FE	FE	FE	FE
Input Expenditure	Yes	Yes	Yes	Yes

t statistics in parentheses

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

Table S4.6 Estimated response of the mean, variance, skewness, and kurtosis of soybean yield to weather variables, insurance participation, interaction terms, and input expenditures

	Mean	Variance	Skewness	Kurtosis
DD^M	10.81***	-32.41**	88.59	-7607.5**
	(3.91)	(-2.72)	(0.26)	(-2.46)
DD^H	-11.92***	10.23*	147.0	2507.7
	(-8.03)	(1.91)	(1.04)	(1.36)
$Prec$	41.77***	-23.03	-591.2	-4871.5
	(5.89)	(-0.85)	(-0.80)	(-0.81)
$Prec^2$	-25.90***	9.811	539.0	1637.4
	(-5.25)	(0.52)	(1.05)	(0.37)
Ins	-15.06**	42.74	-319.1	12216.2
	(-2.63)	(1.22)	(-0.61)	(1.57)
DD^M*Ins	12.64***	-28.38*	-72.89	-9063.6*
	(5.05)	(-1.73)	(-0.24)	(-1.80)
DD^H*Ins	-18.00***	48.18**	342.5	15831.3**
	(-6.16)	(2.36)	(0.73)	(2.31)
$Prec$*Ins	1.350	-40.82	1503.2	-10101.3
	(0.10)	(-0.44)	(1.03)	(-0.54)
$Prec^2$*Ins	-5.438	40.37	-1182.3	14006.8
	(-0.58)	(0.67)	(-1.20)	(1.08)
Fertilizer and lime	-0.00188**	-0.00517	-0.0152	-1.479
	(-2.71)	(-1.12)	(-0.22)	(-1.02)
production	-0.0000252	0.00000978	0.00133	-0.0514
	(-0.65)	(0.04)	(0.22)	(-0.61)
petroleum	0.000544	0.00933	0.0240	3.012
	(0.33)	(0.96)	(0.12)	(1.27)
hired labor	0.000279*	-0.000412	-0.0249	0.249
	(1.77)	(-0.17)	(-0.75)	(0.34)
seed	0.00258***	0.00191	0.0324	0.632
	(3.05)	(0.31)	(0.40)	(0.34)
Observations	35351	35351	35351	35351
R squared	0.565	0.0535	0.0109	0.0330
Time Controls	State	State	State	State
Crop	Soybeans	Soybeans	Soybeans	Soybeans
Ins Measure	LR	LR	LR	LR
Model	FE	FE	FE	FE
Input Expenditure	Yes	Yes	Yes	Yes

t statistics in parentheses

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

Table S4.7 Estimated response of the mean, variance, skewness, and kurtosis of corn yield to weather variables, “area-ratio” insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	12.40	-181.0	9941.4	-479942.7
	(1.01)	(-0.73)	(0.65)	(-0.80)
DD^H	-26.40***	217.3***	1397.4	568915.6***
	(-6.38)	(4.02)	(0.31)	(4.00)
$Prec$	87.61***	434.8	-33036.1	117655.3
	(2.90)	(0.79)	(-0.82)	(0.08)
$Prec^2$	-59.01***	-374.0	27780.5	-254989.1
	(-2.94)	(-0.95)	(1.06)	(-0.23)
Ins	-29.67	347.1	16772.1	1213635.6
	(-1.24)	(0.95)	(0.46)	(0.75)
DD^M*Ins	28.64***	-32.16	-18639.5	-1103011.3
	(2.95)	(-0.17)	(-0.93)	(-1.19)
DD^H*Ins	-30.20***	215.3*	13415.5	1498706.9**
	(-3.01)	(1.88)	(0.71)	(2.44)
$Prec$*Ins	-12.54	-1916.4	26335.5	-2096022.7
	(-0.18)	(-1.39)	(0.23)	(-0.45)
$Prec^2$*Ins	-5.242	1660.6	-20365.3	2613128.4
	(-0.10)	(1.64)	(-0.24)	(0.75)
Observations	38101	38101	38101	38101
R squared	0.602	0.0837	0.0110	0.0445
Time Controls	State	State	State	State
Crop	Corn	Corn	Corn	Corn
Ins Measure	AR	AR	AR	AR
Model	FE	FE	FE	FE
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table S4.8 Estimated response of the mean, variance, skewness, and kurtosis of soybean yield to weather variables, "area-ratio" insurance participation, and the interactions between them

	Mean	Variance	Skewness	Kurtosis
DD^M	11.16***	-34.38**	91.97	-8058.4**
	(3.84)	(-2.56)	(0.26)	(-2.26)
DD^H	-12.74***	12.29**	177.5	2801.9*
	(-7.44)	(2.28)	(1.17)	(1.91)
$Prec$	39.79***	-25.34	-1041.9	-9301.0
	(5.62)	(-0.75)	(-1.15)	(-0.86)
$Prec^2$	-24.62***	11.62	869.6	4988.2
	(-4.80)	(0.47)	(1.34)	(0.62)
Ins	-11.60**	39.76	-530.6	8301.5
	(-2.61)	(1.58)	(-1.33)	(1.52)
DD^M*Ins	6.793***	-19.47	-34.68	-6710.6
	(3.38)	(-1.49)	(-0.14)	(-1.62)
DD^H*Ins	-9.033***	27.62*	142.7	10086.8**
	(-3.32)	(1.95)	(0.39)	(2.24)
$Prec$*Ins	6.155	-47.28	1952.0	-3251.9
	(0.62)	(-0.63)	(1.50)	(-0.17)
$Prec^2$*Ins	-6.913	41.33	-1501.9*	6797.4
	(-1.03)	(0.83)	(-1.75)	(0.51)
Observations	36095	36095	36095	36095
R squared	0.571	0.0518	0.0103	0.0308
Time Controls	State	State	State	State
Crop	Soybeans	Soybeans	Soybeans	Soybeans
Ins Measure	AR	AR	AR	AR
Model	FE	FE	FE	FE
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table S4.9 Estimated response of the mean, variance, skewness, and kurtosis of corn yield to weather variables, insurance participation, and the interactions between them (mean IV approach)

	Mean	Variance	Skewness	Kurtosis
DD^M	-33.46	-1021.8***	51847.9	-10700718.6
	(-0.98)	(-2.72)	(0.56)	(-0.74)
DD^H	-5.011	-167.0	54649.4	-3808578.3
	(-0.19)	(-0.52)	(0.89)	(-0.20)
$Prec$	-155.2	1326.0	772407.8***	50266617.9
	(-1.14)	(0.68)	(2.58)	(0.94)
$Prec^2$	103.0	-1212.5	-425712.0**	-24858083.4
	(1.17)	(-0.91)	(-2.36)	(-0.66)
Ins	-604.9*	-463.2	2592681.4**	224647714.4
	(-1.66)	(-0.12)	(2.46)	(1.32)
DD^M*Ins	203.9**	1160.1	-235993.7	10203545.9
	(2.23)	(1.27)	(-0.91)	(0.22)
DD^H*Ins	-121.3	2014.4**	-190594.5	8999423.0
	(-1.62)	(2.13)	(-0.92)	(0.14)
$Prec$*Ins	718.7	-10547.6*	-2642400.7**	-205182971.3
	(1.63)	(-1.79)	(-2.50)	(-1.15)
$Prec^2$*Ins	-511.0*	8485.1**	1590617.6**	119931815.5
	(-1.76)	(2.06)	(2.38)	(0.93)
Observations	38098	38098	38098	38098
R squared	0.511	0.0723	-1.011	-1.182
Time Controls	State	State	State	State
Crop	Corn	Corn	Corn	Corn
Ins Measure	LR	LR	LR	LR
Model	IV	IV	IV	IV
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

Table S4.10 Estimated response of the mean, variance, skewness, and kurtosis of soybean yield to weather variables, insurance participation, and the interactions between them (mean IV approach)

	Mean	Variance	Skewness	Kurtosis
DD^M	0.293	-145.2**	5288.9**	-47641.7*
	(0.02)	(-2.00)	(2.32)	(-1.76)
DD^H	-16.10***	-23.94	588.0	-697.2
	(-4.70)	(-1.07)	(1.54)	(-0.09)
$Prec$	-83.30	-155.1	14024.9***	149508.0*
	(-1.58)	(-0.93)	(2.71)	(1.69)
$Prec^2$	54.77	76.80	-8878.0**	-108902.9*
	(1.56)	(0.65)	(-2.38)	(-1.65)
Ins	-230.5**	487.5*	27522.1***	464469.3***
	(-2.49)	(1.72)	(2.58)	(3.25)
DD^M*Ins	40.71	105.1	-12661.1***	12583.2
	(1.34)	(0.85)	(-2.71)	(0.26)
DD^H*Ins	-0.787	114.5	-556.0	25187.2
	(-0.08)	(1.39)	(-0.31)	(0.94)
$Prec$*Ins	389.8**	-1093.2	-42770.6*	-1234539.5***
	(2.41)	(-1.62)	(-1.91)	(-2.80)
$Prec^2$*Ins	-260.2**	863.4*	27089.5	889527.3***
	(-2.38)	(1.66)	(1.64)	(2.64)
Observations	36088	36088	36088	36088
R squared	0.370	-0.190	-0.507	0.0320
Time Controls	State	State	State	State
Crop	Soybeans	Soybeans	Soybeans	Soybeans
Ins Measure	LR	LR	LR	LR
Model	IV	IV	IV	IV
Input Expenditure	NO	NO	NO	NO

t statistics in parentheses

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

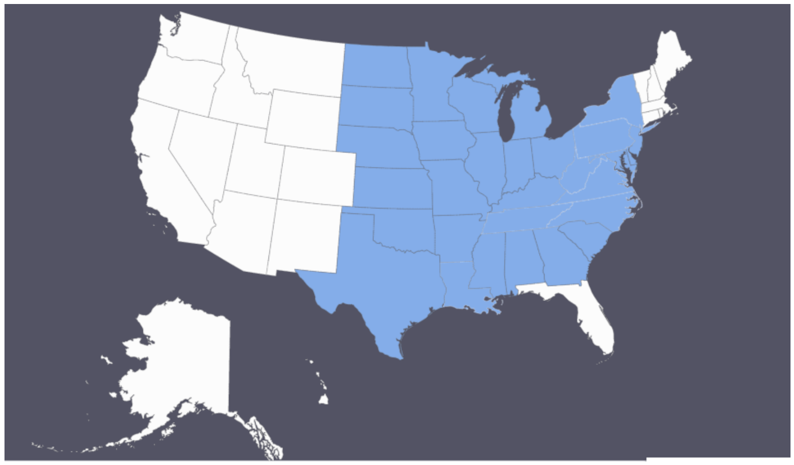


Figure S4.1 The states included in the analysis
Notes: The blued states in the figure above are the states included.

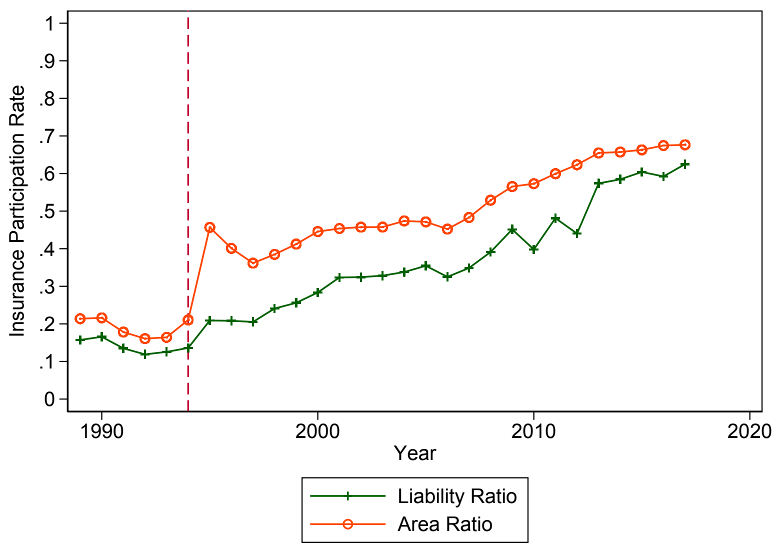


Figure S4.2 Annually averaged insurance participation rate over the period 1989-2017

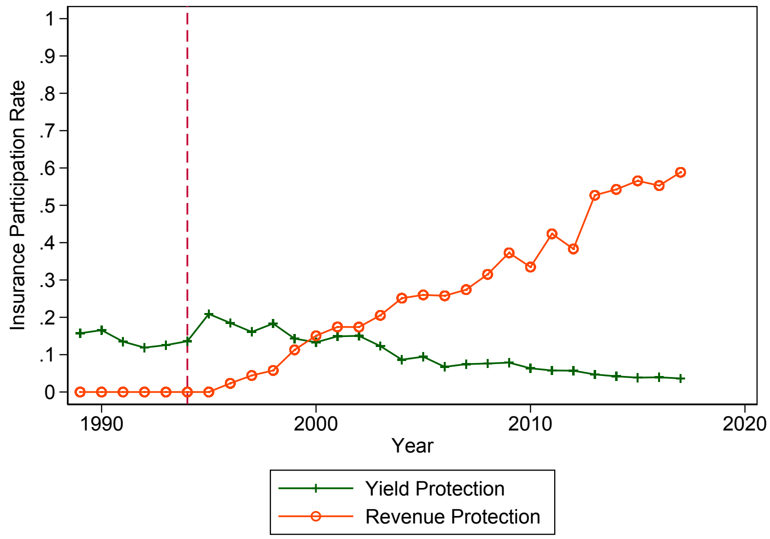


Figure S4.3 Annually averaged yield protection and revenue protection insurance product participation rate over the period 1989-2017

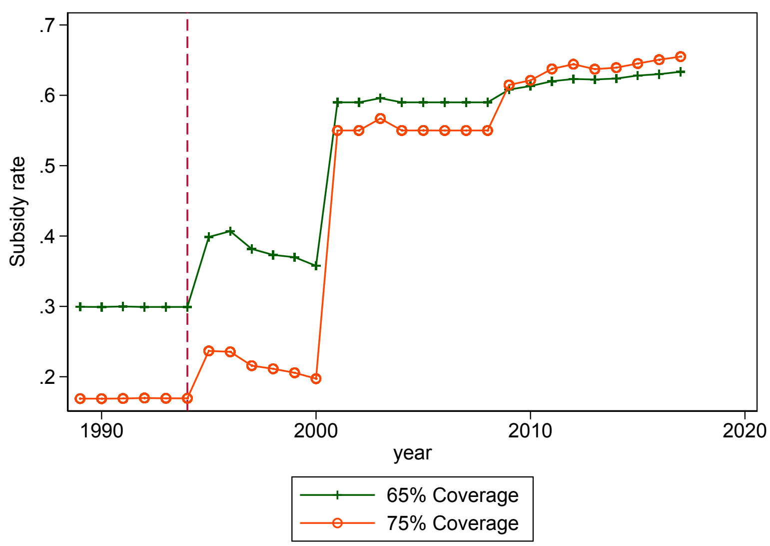


Figure S4.4 Annually averaged subsidy rate for insurance with 65% and 75% coverage level over the period 1989-2017