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

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This study examines the relationship between yields of modern rice varieties and warming temperatures. Data from a long-running farm-level survey in the Philippines, with rich information on planted rice varieties, allow us to estimate fixed effect econometric models of rice yields. We find that increases in temperature, especially minimum temperatures, have statistically significant negative impacts on rice yields. Point estimates of the marginal effect of higher temperatures on rice yields indicate that early modern varieties bred primarily for higher yields, pest resistance, and/or grain quality traits (i.e., not necessarily abiotic stress tolerance) tend to be more resilient to heat events than traditional rice varieties. Moreover, the marginal effect point estimates also suggest that more recent rice varieties bred for better tolerance to abiotic stresses are likely more resilient to warming than both traditional varieties and early modern varieties. Notwithstanding the heat resilience pattern suggested by these point estimates, we are unable to find statistically significant differences in the marginal yield response to warming across these three rice varietal groups. These results provide suggestive evidence that rice breeding efforts have improved resilience to warming temperatures and point to several interesting future research directions.

Key words: Central Luzon, climate change, rice yield, rice varieties.

JEL codes: Q12, Q16, Q18.

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 in Latin America (Nigatu et al. 2017; USDA-ERS 2020). Over 144 million farms cultivate rice across an area of about 167 million hectares (ha) in more than 100 countries (FAOSTAT 2019). 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 (Fan et al. 2005).

Given the importance of rice as a major food staple and a source of income for farmers worldwide, a key challenge is to find strategies that would maintain or improve rice productivity in the presence of climate change. Based on the recent climate assessment reports of the Intergovernmental Panel on Climate Change

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(IPCC), global warming has intensified over the last fifty years, and this warming trend is predicted to persist in the future (see figure S1 in the online supplementary appendix). A warming climate has the potential to adversely affect rice yields and rice quality (Peng et al. 2004; Iizumi et al. 2006; Lyman et al. 2013; Kawasaki and Uchida 2016)[1]. For example, extremely high temperatures can lead to spikelet sterility and reduce rice yields (Wassmann et al. 2009; Nguyen et al. 2014; Bheemanahalli et al. 2016). These adverse warming effects then have the potential to compromise food security in countries that rely on it as a food staple or a source of income.

One strategy that may help address the climate change challenge in rice production is the development and use of 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 (Barker, Herdt, and Rose 1985; Hayami and Otsuka 1994; Otsuka, Gascon, and Asano 1994; Estudillo and Otsuka 2006), especially as compared to the traditional rice varieties (TVs) available prior to the Green Revolution.

With this history of rice varietal development over time, it is important to examine whether 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. Findings from this study have important implications with regards to whether past rice breeding investments, especially recent efforts aimed at developing climate-tolerant traits, have led to modern varieties that are more resilient to warming in farmer fields. 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 (Moya et al. 2015; Laborte et al. 2015). Examining the Philippine case is especially relevant because it is one of the top ten rice-producing countries in the world (FAOSTAT 2019), and the evolution of major varietal group releases in this country is representative of other major rice-producing countries like India, Indonesia, Bangladesh, and Vietnam (Brennan and Malabayabas 2011; Pandey et al. 2012). Because farmers are tracked over time in the data set utilized, we are able to develop fixed effects econometric models, which then allow us to identify "varietal-group-specific" yield response to several weather variables (e.g., minimum temperature, maximum temperature, and precipitation).[2] Therefore, the study results provide insights on the effectiveness of prior breeding investments and rice varietal development efforts, specifically in terms of mitigating adverse impacts of climate change.

Due to concerns about the effect of climate change on agriculture, there is now a large literature that uses econometric methods to examine how weather variables influence crop yield outcomes (see, for example, Auffhammer, Ramanathan, and Vincent 2006; Welch et al. 2010; Sarker, Alam, and Gow 2012; Lyman et al. 2013; and Kawasaki and Uchida 2016 for rice; Schlenker and Roberts 2009 for corn; Tack, Barkley, and Nalley 2015 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 Chen, Wang, and Huang 2014; Wang et al. 2010; Deressa et al. 2009; Di Falco, Veronesi, and Yesuf 2011; Butler and Huybers 2013; Huang, Wang, and Wang 2015). Despite this rich literature on climate change adaptation and climate change effects on yields, to the best of our knowledge, there are a limited number of studies that investigate how the yield impact of weather

[1]The effects of high temperatures on rice quality include increased broken (or cracked) grain percentage and chalkiness. The quality effects of warming can substantially influence the eventual revenues received by rice farmers (as mentioned in the studies above). However, quality information is not available for the farm level data utilized in this study. As such, estimating the effects of high temperatures on rice quality (based on farm-level data) is left for future research.

[2]As noted in Launio et al. (2008) and Laborte et al. (2015) 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 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.

variables may vary depending on the rice variety, or the rice varietal group, used by farmers. Tack et al. (2016), 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. Hasan, Sarker, and Gow (2016) 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 utilizes 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 impact of warming on rice yields by allowing for and econometrically identifying varietal-group-specific effects. This is important because it will allow us to know which rice varietal group is most effective in attenuating the adverse effects of warming temperatures and whether the older MVs had some climate change adaptation features (Wassmann et al. (2009)). Although not all previously released rice MVs are widely used anymore (Laborte et al. 2015), it is still important to determine whether these older varietal groups have historically been effective climate change adaptation tools, especially because they were not specifically bred for this purpose (see more discussion on this issue below). If climate change attenuation 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 attenuation effects of these newer varieties on farmers' fields allows one to see whether there has been "on-the-ground" progress from breeding efforts to produce climate-change-tolerant varieties.

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 have 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 the paper is organized as follows. Section 2 discusses the empirical setting, evolution of rice varieties in the Philippines, and data sources. The modeling framework is described in Section 3. Section 4 presents the estimation results. Section 5 provides various robustness checks, and Section 6 discusses the conclusions.

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 Laborte et al. 2015), 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 (82%) of the area under irrigation (i.e., which is slightly higher than the ~70% of rice area irrigated nationally). The study area is considered as one of the major rice producing regions in the Philippines, where average rice yield was 4.7 tons per ha, per cropping season in 2013, which is slightly higher than the national average. The average farm size in the study area is around 1 ha (Moya et al. 2015) and is consistent with the national average. The sociodemographic profile of farmers in the study area is also roughly in line with the national average (i.e., age in the mid-50s, with about nine years of education). Rice is planted twice a year in the study area: (*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 (Moya et al. 2015).[3] 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, the evolution of Philippine rice varietal group development roughly follows the pattern for other major rice-producing countries in Asia (Brennan and Malabayabas 2011; Pandey et al. 2012). 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 taller TVs, the semi-dwarf MV1s 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 (Launio et al. 2008). 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 (Launio et al. 2008). Last, 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 (Laborte et al. 2015).[4]

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 1). Face-to-face interviews were conducted to collect various socio-demographic, input use, and rice production information from the sample respondents (See Moya et al. 2015 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; whereas DS information was available for 1967, 1971, 1975, 1980, 1987, 1991, 1995, 1998, 2004, 2007, 2012, and 2016[5].

Note that the Loop Survey collected production and input use data for each parcel (or field) the farmer uses (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 because 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.

[3]The seasonal production ranges coincide with the climate regime in the study area—one with a distinct wet monsoon season and a distinct dry season. Note that the Philippines is a spatially heterogeneous country with four major climate regimes: (*a*) distinct wet monsoon season and dry season; (*b*) no distinct dry season but a strong wet monsoon season; (*c*) intermediate between type 1 and 2, where there is a short wet monsoon and short dry season; and (*d*) an even distribution of rainfall throughout the year (Stuecker, Tigchelaar, and Kantar (2018)).

[4]As noted in Laborte et al. (2015), 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 a same varietal group—we call them "Recent MVs" in this study. Further, note that hybrid rice varieties are excluded from the analysis given that only a small proportion of this variety is adopted in the study area, especially in the wet season (Moya et al. 2015).

[5]Not all households have a complete set of data for all years (i.e., attrition). This is common for studies based on repeated surveys. However, further analysis on this issue suggest that attrition is likely random in our case, though one cannot completely rule it out.

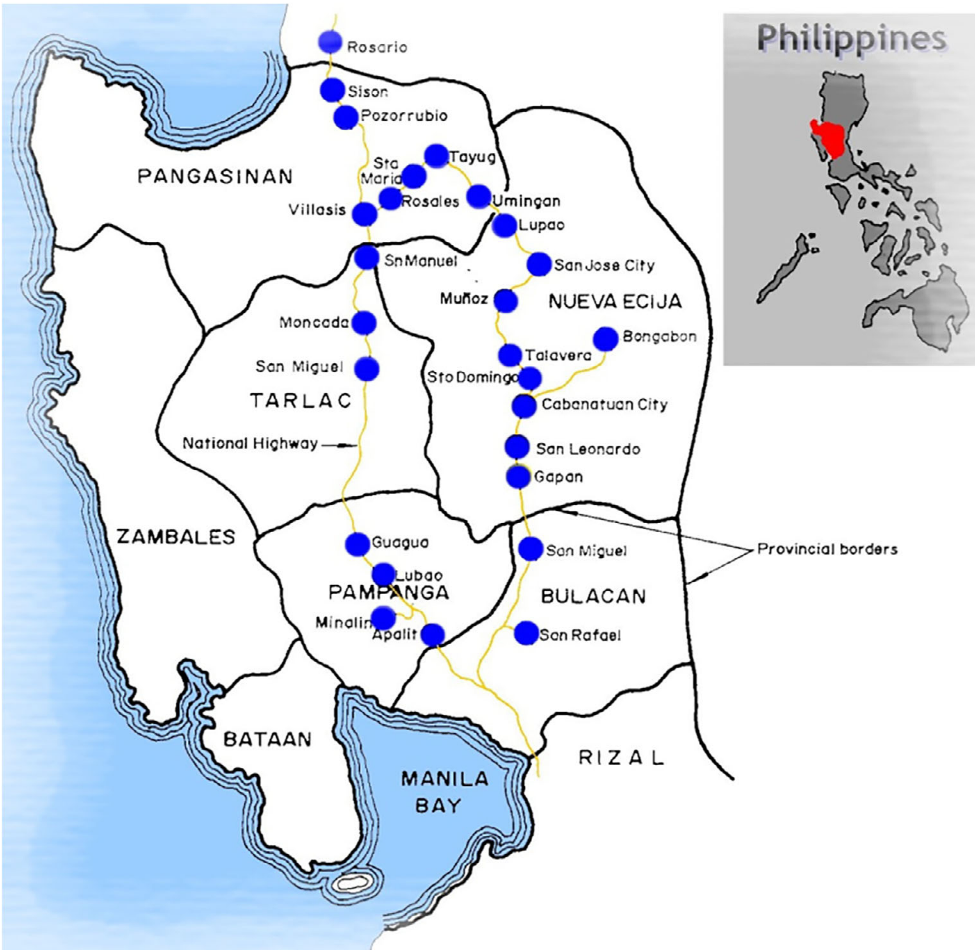

Figure 1. The study area: Central Luzon loop survey.

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)

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 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 are inappropriate. With the construction and operation of large scale irrigation systems and wide use of small pumps used 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.[6]

[6]Limiting the sample to irrigated WS rice production produces a more homogeneous sample that allows us to better tease out the effect of warming on yields for different varietal groups. In addition, focusing on irrigated production in the WS makes it possible to have a more parsimonious empirical specification. Including DS and non-irrigated observations would require at least a doubling of the already sizable number of parameters to be estimated (see equations 1 and 2 below). The number of parameters need to at

Aside from the loop survey data, we also utilized data on the monthly average of daily values for minimum temperature (in °C) and maximum temperature (in °C), and monthly total precipitation (in mm/month) in our analysis. The two main sources of raw climate data used are: (*a*) the University of East Anglia's Climatic Research Unit (CRU) time-series (TS) data (version 4.01), and (*b*) the WorldClim data (version 2).[7] The CRU-TS data, which is a gridded, historic, monthly climate data set at 0.5 degrees resolution (Harris et al. 2018, were downscaled to a 30 arc-second (approx 1 km) resolution by using the delta method and the high-spatial resolution reference climatology data from WorldClim (Fick and Hijmans 2018). In particular, the GlobalClimateData.org Downscaling Package (used with the MATLAB software) is used to produce the 30 arc-second monthly downscaled climate data (Mosier, Hill, and Sharp 2014, 2018).[8] For each municipality covered by the loop survey, we then overlay the municipal boundaries from the Global Administrative Areas (GADM) database (version 3.6) on the downscaled climate data to calculate the mean monthly climate data values used in the study.[9] Therefore, the climate data in this study 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.

least double because of the additional interaction terms (e.g., double and triple interactions) needed to differentiate the warming effects for wet versus dry season and for irrigated versus non-irrigated environments (for proper interpretation). Parsimony of the specification is compromised in this case, with likely smaller gains in the accuracy of the estimates, given the sample size of the survey.

[7]See http://wwww.worldclim.org 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 Harris et al. (2018) and Hijmans et al. (2005), respectively.

[8]The resulting downscaled, monthly climate data were compared against the Global Historical Climatology Network (GHCN) station data (see Lawrimore et al. 2011) to assess the reliability and accuracy of the downscaled data. We find that the mean absolute errors (MAE) and mean weighted absolute percentage errors (MWAPE) between downscaled and observed station data are reasonable for the purposes of this study (given the variation in the observed data).

[9]The Global Administrative Areas (GADM) database is located at http://www.gadm.org (see GADM 2018 for more information). Calculation of the climate data per municipality was done in the software **R** version 3.5.1 using the raster package v2.6–7 (Hijmans 2015).

Modeling Framework

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

$$\ln\left(y_{ijmt}\right) = \alpha_j + f\left(\mathbf{tmin}_{kmt}, \mathbf{tmax}_{kmt}, \mathbf{prec}_{mt}, \mathbf{V}_{ijmt}; \delta, \beta, \psi\right) + \gamma \mathbf{X}_{ijmt} + \eta t + \varepsilon_{ijmt} \tag{1}$$

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 (1) are defined 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 (i.e., see the subsection below describing the climate function specification for more details); and (*b*) a vector of parcel-level rice varietal group dummy variables $\mathbf{V}_{ijmt}$.

For parsimony and ease of interpretation, 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.[10] 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 includes parcel-level input applications

[10]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 Launio et al. 2008 and Laborte et al. 2015).

(e.g., fertilizer use, pesticide applications, and labor), as well as other farmer/farm sociodemographic 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 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.

Climate Function Specification

To estimate Equation (1), the function f ($\mathbf{tmin}_{kmt}$, $\mathbf{tmax}_{kmt}$, $\mathbf{prec}_{mt}$, $\mathbf{V}_{ijmt}$; δ, β, ψ) 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 (Welch et al. 2010; Hasan, Sarker, and Gow 2016).[11] 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 Welch et al. (2010).

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. Because 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 climate data set only contains 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 harvesting) for each growing season in the data are required. For this purpose, we utilized the RiceAtlas (Laborte et al. 2017), which contains the planting and harvesting dates for all of the provinces covered by the Central Luzon Loop Survey.[12] However, the RiceAtlas mainly focused on the "growing windows" from 1979 onwards, whereas 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 five to six months, and the wet season starts around June and ends in November. The vegetative phase usually lasts seventy five–ninety five days (i.e., three months), with the duration of both the reproductive and ripening phases around one month (see http://

[11]Minimum temperature is normally associated with nighttime temperatures and maximum temperature is associated with daytime temperatures. Welch et al. (2010) have shown that these two variables may have differing effects on rice yield and can enter linearly in the specification. For the temperature range of our data, the linear relationship between rice yields and temperature is supported by previous agronomic studies (Peng et al. 2004, Nagarajan et al. 2010) and other past rice yield and temperature studies (Sarker, Alam, and Gow 2012, Pattanayak and Kumar 2014).

[12]See Table S20 in the online supplementary appendix for information on the average maturity lengths and growing phase lengths for each province.

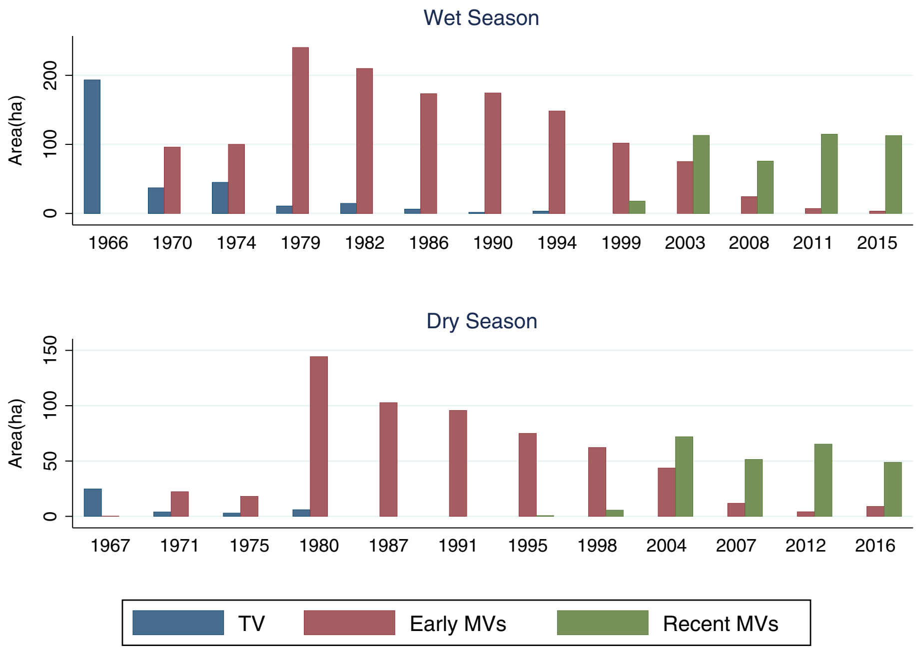

Figure 2. Adoption area of rice varietal group by survey year

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 (Moya et al. 2015). 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 two 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.

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

$$(2)\quad \sum_{r=1}^{2}\beta^r\mathbf{V}_{ijmt}^r + \sum_{k=1}^{3}\delta_{1k}\mathbf{tmin}_{kmt} + \sum_{k=1}^{3}\delta_{2k}\mathbf{tmax}_{kmt} + \delta_3\mathbf{prec}_{mt} + \delta_4\left(\mathbf{prec}_{mt}\right)^2 + \sum_{k=1}^{3}\sum_{r=1}^{2}\psi_{1k}^r\left(\mathbf{tmin}_{kmt}\times\mathbf{V}_{ijmt}^r\right) + \sum_{k=1}^{3}\sum_{r=1}^{2}\psi_{2k}^r\left(\mathbf{tmax}_{kmt}\times\mathbf{V}_{ijmt}^r\right) + \sum_{r=1}^{2}\psi_3^r\left(\mathbf{prec}_{mt}\times\mathbf{V}_{ijmt}^r\right) + \sum_{r=1}^{2}\psi_4^r\left(\left(\mathbf{prec}_{mt}\right)^2\times\mathbf{V}_{ijmt}^r\right)$$

Table 1. Descriptive Statistics for the Economic Variables

Variable	Units/definition	Obs	Mean	St dev	Min	Max
Yield	kg/ha	1,151	3889.51	1555.22	306.67	11250.00
Land tenure	1 = owner; 0 = other	1,151	0.42	0.49	0.00	1.00
Farm size	ha	1,151	1.32	0.97	0.03	9.00
Age of head	No. of years	1,149	52.63	13.64	22.00	94.00
Educ. of head	No. of years	1,151	7.25	3.34	0.00	16.00
Labor	man-days/ha	1,151	70.13	28.70	0.00	257.75
Nitrogen fert.	kg/ha	1,151	81.89	50.50	0.00	483.91
Potassium fert.	kg/ha	1,151	11.03	13.50	0.00	127.80
Phosphorus fert.	kg/ha	1,151	9.20	8.28	0.00	67.10
Insecticide	kg/ha	1,151	1.50	2.64	0.00	70.27
Herbicide	kg/ha	1,151	0.89	2.42	0.00	32.00

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 (Tack, Barkley, and Nalley 2015, Lobell, Schlenker, and Costa-Roberts 2011, Schlenker and Lobell 2010).[13] The climate–MV interaction terms make it possible to examine whether there is heterogeneity in each varietal groups' response to weather variables.

Specification of Control Variables

The next component of Equation (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 sociodemographic farm characteristics. Including these variables in the specification allows us to control for observable factors (i.e., varying over time and space) that can influence rice yields, thereby improving the accuracy and efficiency of our estimations.

The input application variables included in the specification are fertilizer (e.g., nitrogen, phosphorus, and potassium applications in kg/ha), insecticide use (in kg/ha), herbicide use (in kg/ha), and labor (in man-days/ha). These are considered major inputs in Philippine rice production (Moya et al. 2015). Sociodemographic and farm characteristics included in the specification are: land tenure status, age, and education of household head (in no. of years), and farm size (ha). 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 1 provides descriptive statistics for the "economic variables" included in the empirical model,[14] and table 2 presents the summary statistics for the weather variables.

Marginal Effects

One of the main goals of this study 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), the marginal effect of minimum and maximum temperatures can be calculated using the following:

$$(3)\qquad \frac{\partial y}{\partial \mathbf{tmin}_k} = \delta_{1k} + \left(\psi_{1k}^{r} \times \mathbf{V}_{ijmt}^{r}\right),$$

$$(4)\qquad \frac{\partial y}{\partial \mathbf{tmax}_k} = \delta_{2k} + \left(\psi_{2k}^{r} \times \mathbf{V}_{ijmt}^{r}\right)$$

[13]Although it would have been ideal to include quadratic temperature terms in the climate function (i.e., to capture non-linear temperature effects), an out-of-sample forecasting analysis in the spirit of Schlenker and Roberts (2009) indicate that adding these quadratic terms in equation (2) actually decrease model performance. This suggests that the inherent variation in the weather data, and perhaps the thinness of the temperature data at the tails (as in Welch et al. 2010), precludes improvement in model performance even if one adds more quadratic terms. Overfitting becomes an important concern. For these reasons, only linear temperature terms are used in the climate function specification.

[14]See table S22 in the online supplementary appendix for more details about how the sample statistics have evolved over time for the irrigated WS observations. In addition, we point the interested reader to Moya et al. (2015) for a description about the full survey sample and the evolution of the pertinent survey statistics over the 1966–2012 period. Note that the sample size in our study does not exactly match the ones in Moya et al. (2015) because we drop observations with missing data, unrealistic values, and hybrid varieties (see footnote 4).

Table 2. Descriptive Statistics for the Weather Variables

Variable	Unit	Obs	Mean	St dev	Min	Max
vtmin	Deg. C	1,151	22.85	0.62	19.91	24.05
vtmax	Deg. C	1,151	30.50	0.83	27.56	32.00
vtavg	Deg. C	1,151	26.66	0.67	24.16	28.00
vdt	Deg. C	1,151	7.65	0.74	5.14	9.45
retmin	Deg. C	1,151	22.63	0.74	20.15	24.31
retmax	Deg. C	1,151	30.40	0.78	27.78	32.45
retavg	Deg. C	1,151	26.47	0.68	24.03	28.07
redt	Deg. C	1,151	7.76	0.74	5.00	9.50
ritmin	Deg. C	1,151	22.48	0.81	19.83	24.34
ritmax	Deg. C	1,151	30.55	0.83	27.62	32.57
ritavg	Deg. C	1,151	26.43	0.72	24.02	28.13
ridt	Deg. C	1,151	8.07	0.87	6.00	10.51
precip	mm	1,151	1386.85	357.70	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.

where $\mathbf{V}_{ijmt}^{r}$ is the parcel-level rice varietal group dummy variables. For example, suppose the rice variety adopted belongs to the "Early MVs" group, then $\mathbf{V}_{ijmt}^{1} = 1$. In this case, the marginal yield effect of a one-unit change in the minimum (maximum) temperature for the kth phase is $\delta_{1k} + \psi_{1k}^{r}$ $(\delta_{2k} + \psi_{2k}^{r})$ (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:

$$(5) \qquad \frac{\partial y}{\partial \mathbf{prec}} = \delta_3 + (2 \times \delta_4 \times \mathbf{prec}) + \left(\psi_3^r \times \mathbf{V}_{ijmt}^r\right) + \left(2 \times \psi_4^r \times \mathbf{prec} \times \mathbf{V}_{ijmt}^r\right)$$

The simple marginal effect expressions in Equations (3) and (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, 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 (3) and (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).[15] The marginal effect of this specific "warming scenario" can then be calculated respectively for the TVs, Early MVs, and Recent MVs as follows:

$$(6) \qquad \sum_{k=1}^{3} \frac{\partial y \mid V = \mathrm{TV}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \mathrm{TV}}{\partial \mathbf{tmax}_k} = \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k}$$

$$(7) \qquad \sum_{k=1}^{3} \frac{\partial y \mid V = \mathrm{Early\,MVs}}{\partial \mathbf{tmin}_k} + \sum_{k=1}^{3} \frac{\partial y \mid V = \mathrm{Early\,MVs}}{\partial \mathbf{tmax}_k} = \sum_{k=1}^{3} \delta_{1k} + \sum_{k=1}^{3} \delta_{2k} + \sum_{k=1}^{3} \psi_{1k1} + \sum_{k=1}^{3} \psi_{2k1}$$

[15] 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 Welch et al. 2010; Peng et al. 2004). Our data also support this behavior (see figure S2 and table S3 in the online supplementary appendix). Therefore, the base "warming scenario" examined here is still 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 4 below).

$$(8)\quad \sum_{k=1}^{3}\frac{\partial y \mid V=\text{RecentMVs}}{\partial \mathbf{tmin}_k}+\sum_{k=1}^{3}\frac{\partial y \mid V=\text{RecentMVs}}{\partial \mathbf{tmax}_k}=\sum_{k=1}^{3}\delta_{1k}+\sum_{k=1}^{3}\delta_{2k}+\sum_{k=1}^{3}\psi_{1k2}+\sum_{k=1}^{3}\psi_{2k2}$$

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.

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 1 mm increase in the cumulative precipitation for the TVs, Early MVs and Recent MVs can be calculated as follows:

$$(9)\quad \frac{\partial y \mid V=\text{TV}}{\partial \mathbf{prec}}=\delta_3+2\times\delta_4\times\mathbf{prec}$$

$$(10)\quad \frac{\partial y \mid V=\text{EarlyMVs}}{\partial \mathbf{prec}}=\delta_3+2\times\delta_4\times\mathbf{prec}+\psi_{31}+2\times\psi_{41}\times\mathbf{prec}$$

$$(11)\quad \frac{\partial y \mid V=\text{RecentMVs}}{\partial \mathbf{prec}}=\delta_3+2\times\delta_4\times\mathbf{prec}+\psi_{32}+2\times\psi_{42}\times\mathbf{prec}$$

Given that a squared precipitation term and its interaction with the varietal group dummy are included in Equation (2), the marginal impacts of precipitation in Equations (9) to (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 one standard deviation increase in precipitation (at the mean of *prec*).

Estimation Results

The fully specified empirical model for this study is primarily based on Equations (1) and (2) above. However, in this section, we also present estimation results from two more parsimonious models, which then build towards the full specification results from Equations (1) and (2). The first parsimonious model (Model 1) is our baseline where we do not include any of the control variables $\mathbf{X}_{ijmt}$ in the specification and only include weather variables, varietal group dummies, and relevant interactions. The second parsimonious model (Model 2) adds in the sociodemographic and farm characteristics variables: land tenure, age, education and farm size. The fully specified empirical model (Model 3) includes everything in Model 2 plus the input application variables. The pertinent marginal effects for Models 1 to 3 under a variety of warming scenarios are presented in table 3.[16] 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.

For all model specifications, a warming scenario that increases both *tmin* and *tmax* by 1°C in all growing phases substantially reduces rice yields, and these estimated warming effects are statistically significant at the usual levels of significance (i.e., see warming scenario in the top panel of table 3). The magnitudes of our marginal effects range from −13% (for Recent MVs in Model 3) to −27.6% (for the TVs under Model 1). Results presented in the other two warming scenarios, where only *tmin* or *tmax* are increased separately by 1°C (see middle panels of table 3), indicate that *tmin* is the likely source of the observed negative yield impact of warming (given the strong statistically significant negative effect of *tmin* and the largely statistically insignificant effect of *tmax*). This result is consistent with results from Welch et al. (2010) 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 1 became smaller as socio-demographic and input variables were added to the specification (Models 2 and 3). This suggests that controlling for farm-level time-varying confounding factors (like input use and sociodemographic

[16]The main warming scenario considered in table 3 is a 1°C increase in *tmin* and/or *tmax*. We also provide the marginal effects for a warming scenario that increases *tmin* and *tmax* by 1 standard deviation in table S2 and figure S3 in the online supplementary appendix. The pattern of results in both cases are similar.

Table 3. Marginal Percentage Yield Impact of Weather Variables for Different Warming Scenarios and Varietal Groups

	Model 1		Model 2		Model 3	
	No economic variables		With farm characteristics		With farm char. & inputs	
Variables	Estimates	P-value	Estimates	P-value	Estimates	P-value
		1°C warming scenario:				
tmin&tmax: TV	−0.276	0.021	−0.270	0.031	−0.214	0.086
tmin&tmax: Early MVs	−0.235	0.000	−0.219	0.001	−0.167	0.007
tmin&tmax: Recent MVs	−0.190	0.007	−0.161	0.021	−0.134	0.070
		1°C increase in tmin:				
tmin: TV	−0.668	0.006	−0.717	0.003	−0.624	0.014
tmin: Early MVs	−0.242	0.000	−0.218	0.001	−0.196	0.002
tmin: Recent MVs	−0.318	0.019	−0.263	0.048	−0.266	0.046
		1°C increase in tmax:				
tmax: TV	0.392	0.167	0.447	0.135	0.410	0.183
tmax: Early MVs	0.007	0.892	−0.001	0.978	0.029	0.593
tmax: Recent MVs	0.128	0.132	0.102	0.223	0.131	0.114
		One standard deviation increase in cumulative precipitation:				
prec: TV	−0.200	0.191	−0.194	0.247	−0.236	0.145
prec: Early MVs	−0.168	0.000	−0.154	0.000	−0.147	0.000
prec: Recent MVs	−0.084	0.211	−0.081	0.234	−0.036	0.589

Notes: (*a*) The table displays coefficients and P-values of marginal yield effect of 1°C warming scenarios and one standard deviation of increase in *prec* from three farm fixed-effect models. Standard errors for each regression are clustered at the village level. (*b*) The different models are as follows. Model 1 includes *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*]), linear and quadratic cumulative precipitation in the growing season (*prec* and $prec^2$) and their interactions with dummies for rice varietal groups. Model 2 adds farm characteristics (age and education of household head, land tenure and farm size) to Model 1. Model 3 adds input variables (labor, fertilizer [n, p, k], insecticide and herbicide) to Model 2. (*c*) The first column indicates what weather variables on which the marginal effects are based and to which varietal group it pertains. 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. Last, 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.

characteristics) may be important in our empirical context.[17]

Another important result from table 3 is the apparent heterogeneity in the warming impacts across the three varietal groups based solely on the magnitudes of the marginal effect point estimates. In figure 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 three model specifications, the warming impact point estimate is smallest for the Recent MVs varietal group. In addition, we observe that point estimates of the negative warming effect on yields is smaller for the Early MVs as compared to the TVs (across all model specifications). These point estimate results are suggestive of improved heat resilience for Early MVs and Recent MVs relative to the TVs.

The point estimate result indicating improved heat tolerance of Early MVs relative to TVs is particularly interesting given that Early MVs were not primarily bred to have enhanced tolerance to abiotic stresses. Though it should be noted that there are previous studies that point out the agronomic and physiological basis for why post-green-revolution Early MVs may have better heat

[17]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 correlated with input use and yield outcomes that are not adequately controlled for by the farm-level-fixed effects, time trends, and other control variables. Nonetheless, this concern is mitigated by the result that the magnitudes and statistical significance of the estimated effects in Models 1 and 2 (without the input use variables) are roughly similar to the one in Model 3 (when input use variables are included). Results from a battery of robustness checks (see next sub-section) also supports the main findings here. Last, there may also be concerns about endogeneity of the varietal group dummies per se. However, Moya et al. (2015, p. 59) point out that seed cost is a small proportion of total costs for the loop survey farmers (<5%) and real seed prices have been relatively stable over time. Hence, it is likely that agronomic, soil, and climate factors are the main drivers of varietal decisions (not unobserved economic-related factors) and these factors are already sufficiently controlled for through farm fixed effects, farm/farmer characteristics, time trends, and weather variables. Hence, endogeneity associated with varietal group dummies is not a major issue.

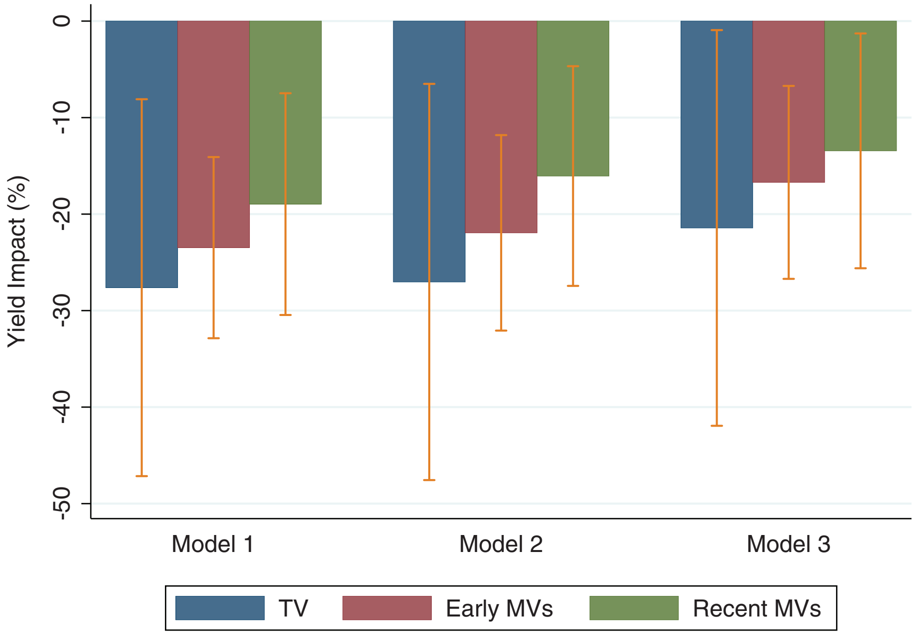

Figure 3. Predicted impacts of the 1˚C warming scenario on three rice varietal groups for three model specifications described by table 3.

Notes: Impacts are reported as the percentage change in yield. Whiskers show 90% confidence interval

tolerance than TVs (Wassmann et al. (2009)). For example, Wassmann et al. (2009) explains that the semi-dwarf plant architecture of these Early MVs, as compared to the taller TVs, makes it sturdier and more tolerant to heat events. Specifically, the semi-dwarf architecture of the Early MVs allows them to have panicles that are surrounded by canopy, which makes it possible for these Early MVs to have more efficient transpiration cooling during the heat sensitive flowering period and, consequently, better heat resilience. In addition, the shorter growing season of Early MVs, as compared to TVs, allows for reduced exposure to heat events during critical growth stages (i.e, "heat avoidance" concept), which may then lead to smaller heat-induced yield damages. For the more Recent MVs, the point estimate results suggesting better heat tolerance of this varietal group relative to the Early MVs and TVs, is in line with rice variety releases in the Philippines with abiotic stress tolerance traits. For example, drought-tolerant varieties have been released in the Philippines since the mid- to late-2000s, and arguably these drought tolerant varieties have some abilities to better withstand heat given that drought events are usually associated with lack of moisture and above-average temperatures.

Notwithstanding the pattern of results for the marginal effect point estimates in table 3 and figure 3, the confidence bands in figure 3 indicate that the marginal yield response to warming do not differ statistically across varietal groups (i.e., confidence interval "whiskers" across varietal group vertically overlap with each other). Formal statistical tests of equality (e.g., F-tests) among the coefficients used for calculating the marginal effect point estimate for each varietal group also suggest that there are no statistically significant differences among these coefficients (and the marginal effects themselves). Thus, even with the apparent varietal group heterogeneity in the point estimates of the marginal yield response to warming, the lack of statistical difference among the marginal effects across varietal groups highlights the need for further rice breeding, agronomic, and economic research on this topic (i.e., more on this in the conclusions).

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.[18] 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 seasonal 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): (*a*) the BCM2, (*b*) the CNCM3, and (*c*) MPEH5; and two plausible emissions scenarios: (*a*) the A1B emission scenario, and (*b*) the A2 emission scenario.[19]

The projected changes in *tmin* and *tmax* and *prec* for each of the six provinces in this study are presented in tables S5–S7 of the online supplementary appendix. In addition, the summary statistics for the average across the six Loop Survey provinces by growing phase (in the WS) are provided in table S4 of the online supplementary appendix. Note that table S4 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 the online supplementary appendix figures S4 and S5 for Model 2 (i.e, specification with farm characteristics, but without input variables). The detailed yield effect point estimates for all models are presented in supplementary table S8. In general, our yield prediction point estimates suggest that the Recent MVs 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). Point estimate 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 marginal effect point estimates from the earlier analysis (table 3), as well as the statistically insignificant yield response differences across varietal groups.

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 S7 in the online supplementary appendix, we also show the marginal rice yield response due to a one 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 point estimates indicate that the Recent MVs is the rice varietal group that tend to be more tolerant to increases in cumulative precipitation. Although, it should be noted that the Early MVs also exhibit resilience to increases in cumulative precipitation (as compared to the TVs). However, similar to the findings on yield effects of higher temperatures, we do not find statistically significant differences in the varietal-group-specific yield response to increases in cumulative precipitation (even though there is apparent heterogeneity in the marginal effect point estimates).

Robustness Checks

As a robustness check, we also estimate similar models as described in Equations (1) and (2),

[18]Simulating the effect of projected future climate on rice yields also provides additional insights relative to the 1°C warming scenario examined in table 3 because 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).

[19]Note that GCMs are powerful computer programs that use physical processes to replicate, as accurately as possible, the functioning of the global climate system (Comer, Fenech, and Gough 2007). 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). Last, 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 (Tolentino et al. 2016).

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.

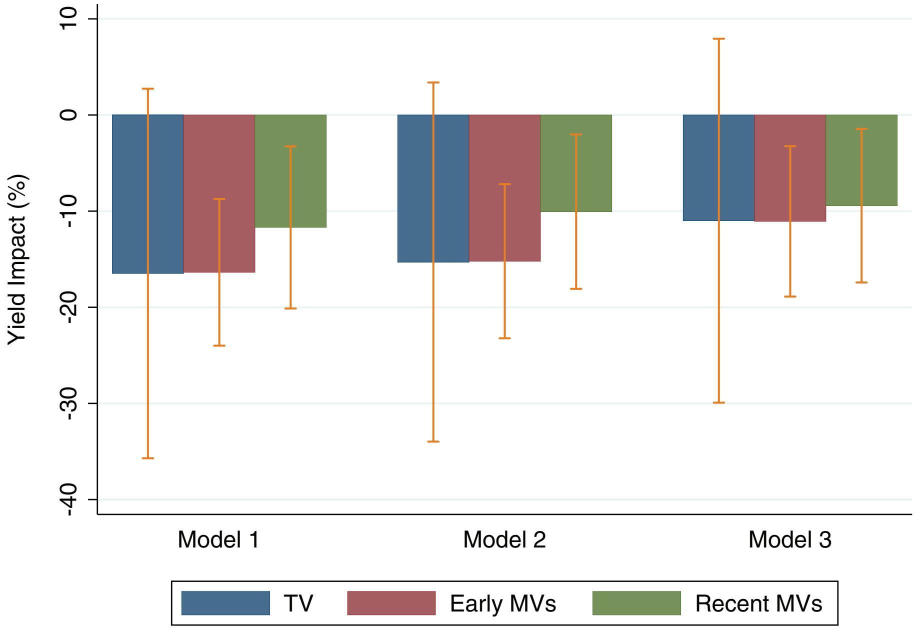

Figure 4. Predicted impacts of a +1˚C increase in *tavg* on three rice varietal groups for three model specifications described by table 4.

Notes: Impacts are reported as the percentage change in yield. Whiskers show 90% confidence interval

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 three model specifications (Models 1–3).

The estimated marginal yield effects of *tavg* and *dtr* for various warming scenarios and model specifications are presented in table 4 (and regression results for the specifications are in table S9 in the online supplementary appendix). In addition, the marginal effects of a 1˚C increase in *tavg* are graphically shown in figure 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*, with the TV marginal effects being largely statistically insignificant (consistent with previous studies like Welch et al. 2010). This may be because *tmin* and *tmax* have opposing rice yield impacts for most varietal groups in nearly all specifications in table 4. Thus, the opposing temperature impacts may partly cancel each other out when using *tavg*. On the other hand, the marginal effect of a decrease in *dtr* (i.e., *tmin* increasing more than *tmax*) is generally negative (as expected), though these estimates are largely statistically insignificant (see table 5 [middle panel] and figure S8 in the online supplementary appendix).

Under all three model specifications, the point estimate for the percentage negative yield impact of *tavg* is highest for TVs and lowest for the Recent MVs. This is consistent with the point estimate patterns observed in the previous section. However, as seen in figure 4, the confidence intervals for each varietal group still largely overlaps, suggesting that there are no statistically significant differences in the marginal yield response to *tavg* across varietal groups. In addition, figure S9 in the online supplementary appendix shows the marginal yield impacts of *prec* at the mean for the model using *tavg* and *dtr*, and this figure supports the robustness of the precipitation effects from the regression runs in the previous section.

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

Table 4. Marginal Percentage Yield Impact of Weather Variables: Alternative Specification Using Mean Temperatures & DTR

	Model 1		Model 2		Model 3	
	No economic variables		With farm characteristics		With farm char. & inputs	
Variables	Estimates	P-value	Estimates	P-value	Estimates	P-value
1°C warming scenario:						
tavg: TV	–0.165	0.157	–0.153	0.177	–0.110	0.337
tavg: Early MVs	–0.164	0.001	–0.152	0.002	–0.111	0.021
tavg: Recent MVs	–0.117	0.024	–0.101	0.040	–0.094	0.053
1°C decrease in diurnal temperature variation:						
dtr: TV	–0.447	0.064	–0.512	0.030	–0.465	0.063
dtr: Early MVs	–0.086	0.128	–0.070	0.202	–0.078	0.192
dtr: Recent MVs	–0.145	0.116	–0.118	0.199	–0.148	0.108
one standard deviation increase in cumulative precipitation:						
prec: TV	–0.236	0.021	–0.210	0.050	–0.241	0.031
prec: Early MVs	–0.156	0.000	–0.141	0.000	–0.135	0.000
prec: Recent MVs	–0.039	0.512	–0.039	0.527	0.000	0.994

Notes: (*a*) 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 three farm fixed-effect models estimated. Standard errors for each regression are clustered at the village level. (*b*) The different models are as follows. Model 1 includes *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*]), linear and quadratic cumulative precipitation in the growing season (*prec* and $prec^2$) and their interactions with dummies for rice varietal groups. Model 2 adds farm characteristics (age and education of household head, land tenure, and farm size) to Model 1. Model 3 adds input variables (labor, fertilizer [n, p, k], insecticide and herbicide) to Model 2. (*c*) The first column indicates what weather variables on which the marginal effects are based and to which varietal group it pertains. 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 decrease in *dtr* for the TV, Early MVs, and Recent MVs. Last, the rows of the third panel indicate the marginal effect of a one standard deviation of increase in *prec* for the TV, Early MVs, and Recent MVs.

group subsample (i.e., due to the smaller sample size for each varietal group, we did not include the control variables for farmer/farm characteristics and input use). The estimated impacts of a +1°C warming scenario and a one standard deviation increase in *prec* for each varietal group subsample are seen in table S10 and the parameter estimates are reported in table S11 (see the online supplementary appendix). In addition, we graphically show the impact of a +1°C warming scenario based on the separate regression runs in figure S10 in the online supplementary appendix, whereas the impact of a one standard deviation increase in *prec* is provided graphically in figure S11. Note that in figure S10, 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. Overall, results from this robustness check is still consistent with the previous analysis—point estimates of the marginal effect of our 1°C warming scenario follow the pattern where the highest negative warming impact is observed for TVs and the lowest is obseved for Recent MVs. Confidence bands also indicate that there are no statistical differences among all the marginal yield response estimates to warming.

Since the rollout 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 with no 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 table S12 in the online supplementary appendix. 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 point estimate 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 point estimates of the negative warming effects than earlier years given the release of recent MVs. This pattern is indeed verified and shown in figure S12, which supports the robustness of our earlier point estimate 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 table S13 in the online supplementary appendix, and the pertinent marginal effects are presented in figure S13. Marginal effect point estimates 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 the TV varietal group is relatively small and available only at the beginning of the study period (see figure 2). For this reason, estimates related to TV generally have large standard errors, though in our main warming scenario in table 4 the marginal effects for TVs are still statistically different from zero. Due to the difficulty of getting efficient estimators for TV, we conduct another robustness check where we run our models using data that do not include observations for TV (i.e., only the Early MV and Recent MV observations are included in the data). Appendix Table S18 shows the warming impacts on early MVs and recent MVs when TV observations are dropped from the data. For our main 1°C warming scenario, the point estimates of the marginal effects indicate a larger reduction in yields for Early MVs as compared to Recent MVs.

Even though the classification of MV5 is mainly based on the year of release rather than the difference in its characteristics relative to the previous generation of modern varieties (Laborte et al. 2015), it is still interesting to determine whether resistance to warming is different between MV4 and MV5. For this reason, we also conduct a robustness check where we separate recent MVs into MV4 and MV5 and estimate the coefficients for them separately. The marginal impact of warming estimated from these models are provided in table S14 in the online supplementary appendix. The marginal effect point estimates indicate that MV4 tend to be more resilient to heat relative to early MVs and TVs, and early MVs tend to be more resilient relative to the TVs. However, we find that MV5 tend to be affected more by heat as compared to MV4. Hence, it seems like MV4 is the main varietal group driving the resilience of the Recent MVs varietal group in our main analysis. But note that this may also be due to MV5 being adopted only for a shorter period in the data. In addition, consistent with results from the main model (table 3), there are no statistically significant different marginal effects across the four varietal groups (i.e, confidence intervals overlap) in the robustness check separating out MV5.

Last, we conduct three other robustness checks: (*a*) a specification that includes three growing phase precipitation variables and their respective quadratic terms (i.e., rather than using a cumulative season-long precipitation variable and its quadratic term; table S15), (*b*) a specification with precipitation only for the reproductive phase (i.e, because precipitation has been shown in previous agronomic studies to be critical for this phase; table S16), and (*c*) a specification with fixed two-month growing phase windows, rather than growing phases primarily based on the Philippine RiceAtlas estimates (table S17). Results from these alternative models also generally support the findings from our main analysis in the previous section, especially the magnitude pattern of the marginal effect point estimates.

Conclusions

The main objective of this study is to investigate whether modern rice varieties (MVs) reduce the adverse yield impacts of warming temperatures, especially the more recent varieties bred to be more tolerant to abiotic stresses (i.e., those in the MV4 and MV5 varietal groups). We provide unique empirical evidence on whether investments in breeding programs have led to farmer-planted rice varieties that are more resilient to warming. By merging Philippine farm-level survey data (from 1966 to 2016) with monthly, municipality-level climate data, we are able to estimate fixed effect econometric models of rice yields with "weather-varietal group" interactions and assess whether there is heterogeneity in the warming effects across different rice varietal groups. Our regression models suggest that increases in temperature, especially minimum temperatures, have substantial negative impacts on rice yields, regardless of varietal group. Point estimates of the marginal yield effects of warming suggest that early MVs bred primarily for higher yields, pest resistance, and/or grain quality traits, as well as recent modern rice varieties bred for better abiotic stress tolerance, are more resilient to heat events than traditional rice varieties. However, our estimates of marginal yield responses to higher temperatures are not statistically different across the three modern varietal groups. Taken together, these results do not provide strong statistical evidence that recent MVs are more resilient to heat than TVs and Early MVs, even though the marginal effect point estimates provide suggestive evidence of this. This is especially important given that yields of abiotic stress tolerant varieties (e.g., drought- and/or heat-tolerant varieties) have been shown to outperform non-tolerant "check" varieties in stress conditions, specifically when rice breeders evaluated these tolerant varieties in the laboratory and/or field trials prior to release (Dixit, Singh, and Kumar 2014, Basu, Jongerden, and Ruivenkamp 2017, Dar et al. 2020).

Our findings are consistent with multiple alternative explanations (or implications) and lay the groundwork for future research directions. First, the limited statistical evidence on the resilience of modern rice varieties to warming (relative to traditional varieties) may indicate that there could be other factors constraining the effectiveness of these varieties with regard to reducing the adverse yield effects of warming. It is possible that farmers adopting the abiotic stress tolerant varieties did not properly utilize complementary agronomic management practices appropriate for these new varieties. For example, it could be that farmers did not adopt the fertilizer application rates, planting dates, and irrigation schedules appropriate for the new stress-tolerant varieties (Dixit, Singh, and Kumar 2014; Haefele, Kato, and Singh 2016; Yamano et al. 2018). Farmers may have simply used past "rule of thumb" agronomic practices that are more consistent with non-tolerant varieties. It is also possible that extension and outreach efforts were insufficient such that information about proper management practices that accompany the recent MVs were not properly disseminated. There may have been shortcomings in the seed sector and national extension systems in terms of making these abiotic stress tolerant varieties more accessible to farmers in areas vulnerable to warming. The discussion above points to the potential importance of funding: (*a*) research that develops holistic management packages appropriate for abiotic stress tolerant varieties, and (*b*) outreach and extension efforts that more effectively disseminate information and improve uptake of the new varieties together with complementary inputs. Further economic research identifying potential bottlenecks to adoption and to improved performance of climate change resilient varieties is an important future research direction.

Second, our main empirical results could also imply that public rice breeding efforts have not yet reached their full potential such that the released varieties with "high-temperature tolerance traits" can still be improved.[20] For example, molecular breeding efforts that can more precisely improve heat tolerance in the sensitive stages of rice production is seen as a potential area for future breeding advancement, as well as incorporating abiotic stress tolerance traits to several other widely grown "mega-varieties" that already have favorable characteristics demanded by farmers: high-yielding with good grain quality (Wassmann et al. (2009), Dixit, Singh, and Kumar 2014). In this case, continued public investments in rice breeding programs at international centers (i.e., like IRRI) and national breeding institutions (i.e., such as PhilRice in the Philippines and BRRI in Bangladesh) could increase the likelihood of developing and releasing new rice MVs that can further decrease the adverse yield effects of high temperatures. In studying and developing these new abiotic stress tolerant varieties, it is important to also assess how the warming response of these varieties in experimental trials differ from the warming response observed in farmer fields. An in-depth evaluation of so-called "yield gaps" can help identify new bottlenecks that may preclude realizing the full benefit of these new MVs in farmer fields (as alluded to in the previous paragraph) and can further guide rice breeders and agronomists on how to enhance the impact of abiotic stress tolerant varieties. If the identified bottlenecks in farmer fields cannot be overcome, then pivoting funding to developing climate-change-resilient

[20]Note that breeding institutions like IRRI already have existing programs that specifically aims to develop rice varieties with tolerance to high temperatures (See Jagadish, Craufurd, and Wheeler 2007; Wassmann et al. 2009; Hirabayashi et al. 2015; IRRI 2020). For example, IRRI breeding programs screen improved and traditional varieties (as well as wild rice species) with heat tolerance traits to see if they can serve as donors in crossing programs.

agronomic management practices for non-heat tolerant varieties may be warranted.

Last, our inability to find statistically significant differences in heat tolerance across MVs may also be the result of limitations in our data and study design, which eventually did not allow us to more precisely distinguish the effects. For instance, the sample size of our survey data is modest and may have not allowed us to find strong statistical differences across varietal groups. The modest sample size also constrained us to only focus on warming effects for irrigated rice farmers in the wet season. Hence, it should be noted that extrapolating our inferences to rainfed rice farmers planting in the dry season may not be appropriate. Nevertheless, because climate change is likely to cause more damage to rice grown in the dry season, we interpret our estimated results as a lower bound of the warming impacts across rice varietal groups. In addition, the relatively modest survey sample restricted our analysis to more parsimonious models rather than developing more flexible models. Future work may consider these kinds of extensions.

Furthermore, the weather data used in the study were 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. Collecting individual information on 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 (Krishnan and Rao 2005, Welch et al. 2010, Gourdji et al. 2013). Moreover, conducting the analysis in this study for other countries with more variability in weather patterns may also be a potential fruitful avenue for future research.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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