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Distributional heterogeneity in climate change impacts and adaptation: Evidence from Indian agriculture

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Distributional heterogeneity in climate change impacts and adaptation: Evidence from Indian agriculture

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Abstract: This study estimates the distributional heterogeneity in the effects of climate change on yields of three major cereal crops: rice, maize, and wheat in India using district-level information for the period 1966-2015. We distinguish between the effects of changes in growing season weather from those due to changes in long-term climate trends and the heterogeneity in these effects across the distribution of crop yields by estimating naïve and climate penalty inclusive models using fixed-effect quantile panel models. We observe an absence of adaptation against rising temperatures for rice and wheat. However, we find a statistically significant presence of adaptation for wheat and maize for changes in precipitation, though the magnitude is small. Moreover, we find that the effects are asymmetric, and are larger at the lower tail of productivity distribution and smaller at the upper tail of the distribution. A 1 C increase in temperature lowers rice and wheat productivity by 23% and 9%, respectively at the first quantile, but the damage is only 6% and 5% at the ninth quantile. Heterogeneity in impacts and adaptation estimates over the yield distribution curve and across crops suggests the importance of customizing strategies for adaptation to changing weather and climate conditions across regions, crops, and current productivity levels.

JEL Classification: Q54, C23, Q16

Key Words: climate change, climate adaptation, quantile regressions, panel data, crop yields

1. Introduction

Changes in the climate and the growing frequency of extreme weather events are leading farmers to take adaptive measures to limit damage to their crops. However, the effects of long-term climate changes are not uniform across regions, productivity zones, and crops. The deleterious effects depend on climate, level of development, and adaptive capacity of farmers (Field, 2014; Mendelsohn and Dinar, 2006; Tol et al., 2004; Rosenzweig and Parry, 1994).

A large number of statistical studies have investigated the responsiveness of crop yields to weather changes (e.g., Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Yu et al., 2010; Chen et al, 2016; Miao et al., 2016; Zhang et al., 2017; Malikov et al., 2020; among others). These studies use panel data fixed effect models to identify the effects of year-to-year changes in weather variables on economic outcomes and do not consider the potential for climate-specific adaptation for mitigating its impacts. Some recent studies have tried to measure the adaptation potential using reduced form panel data models or long difference models (e.g., Burke and Emerick, 2016; Hendricks, 2018; Scott and Lindsey, 2018; Cui et al., 2020; Mérel and Gammans, 2021). A common concern with these studies is that they may be overstating the climate damage. Panel fixed-effect models rely on weather fluctuations rather than climatic variations and are unable to account for long-run adaptation to climate change. The long difference approach can address this concern to some extent (Yu et al., 2021). Moreover, some of these studies use non-linear panel data models for estimating the climate-economy relationship raising the question of whether these studies are identifying effects through cross-sectional variations in weather or temporal changes in climate because cross-sectional weather variation enters into model identification. The estimates obtained using panel data models are a weighted average of short-run and long-run response functions to climate and weather depending on the ratio of the within time-series variation to cross-sectional variation in weather variables. A higher degree of cross-sectional variation relative to within dimension in weather variables is supposed to represent a long-run response.

We estimate short-run and long-run climate change impacts for Indian agriculture using Cui et al. (2020) and Mérel and Gammans (2021) behavioral models. These studies assume a behavioral framework whereby economic agents maximize expected outcomes using a long-run choice of inputs. The agents choose inputs considering climate rather than the weather; for example, the construction of irrigation channels is worth creating in an arid climate rather than as a response to a one-year drought (Schlenker, 2017). These studies identify adaptation through the exploitation of variation in the interaction of weather and climate variables and by considering the deviation between observed weather and its long-term average that represents normalized climate. They estimate the impact of weather variables with and without a climate penalty term when the weather and climate variables are used in a quadratic specification. However, Cui et al. (2020) and Mérel and Gammans (2021), like earlier studies, also measure the average relationship between crop yields and climatic factors and ignore potential heterogeneity in the effects.

Unlike these studies, we use the panel fixed effect quantile regression approach for estimating the response function to account for heterogeneity in the potential distribution of yields. The quantile regression approach allows the coefficients of weather variables to systematically vary by the distribution of crop yield. By using quantile regression, we control for the effect of interactions in location-specific time-invariant variables and the weather variables. Our approach is, therefore, different from Cui et al. (2020) because they allow only the coefficients of weather variables to vary by location whereas we allow all the coefficients of the estimated function to vary over the distribution of yield function. Moreover, we use the rolling average of climate variables instead of their stationary values, which has the advantage of exploiting both cross-sectional and temporal variation in climate variables in estimating the effect of climate on crop yields.

Quantile regressions provide a complete description of the association between the distribution of crop yields and their determinants, unlike the conventional regressions that examine the relationship via conditional-mean models. These models examine the relationship using conditional quantiles of the yield distribution. For the estimation of the climate–yield relationship, we use the recently developed fixed effect quantile panel regression approach by Machado and Santos Silva (2019). We apply this approach to examining the effects of climate change on crop yields in India and the heterogeneity in these effects across the yield distribution for a crop. Indian agriculture is a suitable case for applying quantile panel regression models since climate and weather conditions and crop yields are not uniform across the county. More than half of the net sown area is not irrigated. There is a huge variation in farm household monthly income and the size of the landholdings and thus in the potential for adaptation.[1] This paper intends to estimate distributional heterogeneity in climate change impacts and adaptation in Indian agriculture using district-level information on crop yields and weather and climate variables for the period 1966-2015. We estimate the effect of weather and climate variables on the yields of three crops, namely rice, maize, and wheat. Two of the crops (rice and maize) are grown during the Kharif season (May-June through October-November) and wheat is a Rabi crop (November to April).[2] These three crops are major food grains in India and the adverse effects of climate change on their yields can have significant implications for food security in the country.

The study is first on many counts. It provides the first estimates of the long-run and short-run impacts of climate change on crop yields and thus identifies adaptations for Indian agriculture using a framework where long-run effects envelop the short-run impacts. Earlier work on adaptation in Indian agriculture is mainly confined to the impact of changes in rainfall patterns in the country (e.g.,

[1] Households in the states of Punjab and Haryana earn about four times relative to the household in the states of Jharkhand and Uttar Pradesh. Only 13 percent of households own more than two hectares of land and about 30 percent of land holdings are of the size of less than 0.4 hectares of land. https://www.newindianexpress.com/nation/2020/dec/28/farmers-income-rose-only-by-rs-2505-between-2012-13-and-2016-17-data-2242031.html as accessed on June 23, 2021

[2] In India, the period of May to December is defined as the Kharif season and the Rabi season takes place during the period of November to April. Exact sown and harvest months vary from state to state.

Fishman 2018 and Taraz, 2017). In a recent study, Taraz (2018) observes that damages due to high temperature are lower in heat-prone districts in comparison to low-temperature zones using standard panel data regression models. Our study is also first in the sense that it measures heterogeneity in the estimates using quantile regressions over the distribution of crop yield curve. Earlier studies using quantile regressions are either limited to a cross-sectional framework (e.g., Barnwal and Kotani, 2013) or panel data studies, identifying distributional heterogeneity in the impacts of climate change on crop yields, are not distinguishing between long-run and short-run impacts, i.e., we are measuring adaptation in climate-crop yield relationship. Lastly, except a few studies (e.g., Lobell, 2007; Schlenker and Roberts, 2006), most of the studies measure the impact of growing season average temperature and cumulative precipitation on crop yields, we measure the impact of growing season T_{max} and cumulative precipitation. In the water stress areas, it is the T_{max} that is expected to impact crop yields.

From the fixed effect quantile models, we find that increasing T_{max} and reducing precipitations not only reduce crop yields but also increase dispersions of the observed yields. The study finds that the impacts are asymmetric over the crop productivity distribution curve. We find that the impacts are higher at the lower tail of the distribution but are higher at the upper tail of the distribution. It is observed that the adaptation measures are taken at the lower tail of the yield distribution curve. We also observe that the impacts of climate change and adaptation are not uniform across crops. There is adaptation to increase in T_{max} for rice and maize but not in the case of wheat; the difference in the long-term and short-term impact of increase in T_{max} on wheat yield is not statistically significant. Increasing precipitation enhances rice productivity and adversely affects maize and wheat productivity. We do not find adaptation to changing patterns of precipitation.

The paper is organized as follows: Section 2 describes the estimation strategy followed in the study. Data and empirical results are presented and discussed in Sections 3 and 4, respectively. The paper closes in Section 5 with some concluding remarks.

2. Empirical Strategy

Economic agents choose long-run inputs to maximize long-run expected outcomes, i.e., the choice of long-run inputs is conditional on climate rather than the weather. For example, farmers are observed to make an investment in irrigation channels to combat heat stress in an arid climate region but not in response to occasional droughts (Lobell & Gourdji, 2012; Auffhammer and Schlenker, 2014; Tack et al., 2017; Taraz, 2017). Farmers are expected to make inter-and intra-crop changes in response to changing climate rather than changes in weather conditions. Exposure to climatic conditions works as a determinant of long-run outcomes subject to short-run weather conditions. The difference in the long-run and short-run outcomes depends on the distance between climate and weather conditions, which is termed as climate penalty (Cui et al. (2020); Mérel and Gammans (2021)). They identify adaptation as a difference between long-run and short-run outcomes.[3] These papers build upon the existing non-linear panel regression models and show that the response of weather variables to yield is a weighted average of the long-run and short-run responses; weights depend on the nature of variation in weather variables.[4] Short-run responses are supposed to depend on this difference. Conditional on weather, the locations that have weather realizations similar to long run climate conditions, are expected to fare better than locations where the realized weather conditions are far different than long run climate conditions, *ceteris paribus*. Therefore, the climate-yield relationship is assumed as:

$$y_{it} = \alpha_i + \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 (x_{it} - \mu_{it})^2 + f_i(t) + \varepsilon_{it} \qquad (1)$$

where y_{it} is the logarithm of crop yield, x_{it} is the weather variables (seasonal T_{max} and seasonal cumulative precipitation) and μ_{it} is the climate variable at location i and time t; μ_{it} is the 20-year moving average of x_{it}. and $f_i(t)$ captures secular changes at location i including secular changes in climatic conditions and is a polynomial function. The presence of a smooth trend variable ensures that the identification of β_3 is not confounded from trend in climate variable and the interaction of weather with climate trend. Modeling location-specific secular trends in the form of $f_i(t)$ also captures technological changes that are unrelated to climate. It is expected that $\beta_3 \leq 0$. Moreover, we are using quantile regressions for estimation; therefore, our approach will be immune to the effect of interactions of variables such as soil-weather, which are potential concerns in studies that consider stationary climate during the period of observations (Mérel and Gammans, 2021).

Modeling the climate-economy relationship and identifying adaptation implied by equation (1) is consistent with the basic theory of production. Some actions of the economic agent are variable in the long run but fixed in the short-run and the outcome (e.g., yield) values are optimized. As the long-run average cost curve is the envelope of short-run average cost curves, the long-run climate change response function envelopes the collection of short-run response functions. Mendelsohn et al, (1994) define the long-run response function as an envelope of short-run possibilities to motivate the Ricardian framework to climate change impact assessment.

In response to change in climate, all factor inputs can be varied in the long run, and consequently, the penalty term can vanish from equation (1). The expected long-run response function at location i is:

$$y_i^{LR}(x) = \alpha_i + \beta_1 x_i + \beta_2 x_i^2 \qquad (2)$$

[3] Burke and Emrick (2016) identify adaptation as the difference in outcomes obtained using panel data and long difference estimates.

[4] Mérel and Gammans (2021) also measure climate in a year as a moving average of weather conditions in the preceding 20 years. The climate penalty term is defined as the square of the difference between contemporaneous weather realization and normal climate. The normal climate is defined as the moving average of weather variables computed over the preceding 20 years

and short-run response to weather and climate at location i would be:

$$y_i^{SR}(x) = \alpha_i + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 (x_i - \mu_i)^2 \quad (3)$$

Equation (3) reveals that the short-run response depends on both realized weather and expected climate. Note that climate affects farmers committed actions such as inter- and intra-cropping changes or other adaptation measures, and observed outcomes are affected through these behavior channels conditional on realized weather. That is, in the short run all the factors of production are not variable but in the long run all the factors are variable, therefore, the short run outcomes depend on both realized weather and climate and the choice of long run inputs respond only to climate. Thus, β_3 is expected to be negative in the situation when weather realization differs from the expected climate and if β_3 is equal to zero, it indicates absence of climate adaptation. Also note that at the point where $x_i = \mu_i$, the short-run response function would be tangent to the long-run response function. It implies that the response function represented by equation (1) is a parsimonious function that allows for non-monotonicity and non-linearity in both short-run and long-run response functions and yields a long-run response function that envelopes short-run response functions. In the literature, there are some studies (e.g., Deschenes and Kolstad, 2011; Dell et al., 2014; Moore and Lobell, 2015) that use the quadratic response function in weather variables to assess climate change damages, but in these studies, short-run response functions intersect the long-run response function rather than being tangent to it. Moreover, the interpretation of the more commonly used quadratic response function only in weather variables (without climate penalty term) is far from trivial (Mérel and Gammans, 2021).

We use quantile regressions for estimating the climate-economy relationship. A similar approach has been applied by a few other studies (e.g., Barnwal and Kotani, 2013; Van Passel et al., 2016; DePaula, 2018; Malikov et al., 2020). Barnwal and Kotani use quantile regression to disentangle the heterogeneous impacts of weather conditions across different quantiles on rice yield in the state of Andhra Pradesh for the period 1971-2004 for 13 districts.[5] DePaula applies quintile and interquartile regressions to understand the impact of climatic factors on land values using Brazilian Census data for about a half-million commercial farms. Van Passel et al. use quantile regression and the Ricardian framework to uncover the impacts of climate variables on Western European countries. These studies use cross-sectional quantile regressions that outperform OLS regressions; however, these studies may be suffering from omitted variable bias in the estimates. Malikov et al. (2020) use a fixed effect panel model with time-varying coefficients to measure the effects of climate on crop yields for US agriculture. The limitation of using fixed effect panel data approach to control for unobserved time-invariant cross-district heterogeneity or unobservable confounders such as soil quality is that these unobservables may be correlated with weather variables. Unlike these studies, we use the fixed effect quantile panel regression approach to identify adaptation to climatic changes in agricultural crop yields. Like Machado and

[5] Barnwal and Kotani (2013), though, have panel data but use a cross-sectional (pooled) quantile regression approach to identify the climate effect on rice yield.

Santos Silva, we use moments for indirect estimation of quantile parameters and this approach is more suitable for non-linear specifications.

The quantile regression approach explicitly allows distributional heterogeneity in the effects of climatic variables on crop yields in low-, average- and highly-productive areas. It gives a complete account of the relationship between the distribution of the dependent variable and its determinants, whereas the traditional regression models focus on the first moment. Moreover, the quantile regression is robust to error distributions even in the presence of outliers in the data and reveals a useful property of equivalence. It avoids biases in predictions of the outcome variable. This framework also controls for locational time-invariant unobservable confounders via fixed effects, thereby providing with-in estimates of the response function. Given the non-linearity in the quantile operator, the direct estimation of fixed effect quantile regressions using a routine estimator is cumbersome (e.g., see Koenker, 2004; Galvao & Kato, 2018). Machado and Santos Silva (2019) propose indirect estimation of the parameters via moments, which is easy to implement and is more suitable for non-linear specifications.

Equation (1), using Koenker and Bassett (1982) location-scale quantile regression model with fixed effect, is rewritten as:

$$y_{it} = \alpha_i + \beta_0 + \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 (x_{it} - \mu_{it})^2 + f_i(t) + \varepsilon_{it}$$

where

$$\varepsilon_{it} = [\gamma_0 + \gamma_1 x_{it} + \gamma_2 x_{it}^2 + \gamma_3 (x_{it} - \mu_{it})^2] u_{it} \quad (5)$$

Following Machado and Santos Silva (2019), it is assumed that (i) u_{it} is i.i.d. across locations with some cdf F_u; (ii) $\mathbb{E}[u_{it}] = 0$ and $\mathbb{E}[|u_{it}|] = 1$; and (iii) $Pr[\gamma_0 + \gamma_1 x_{it} + \gamma_2 x_{it}^2 + \gamma_3 (x_{it} - \mu_{it})^2 > 0] = 1$. In such a model the distributions of the coefficients are assumed to differ only in their location and scale, but the unobserved heterogeneity comes from the random variation of the parameters. The τth conditional quantile of the crop yield is:

$$\mathbb{Q}_\tau(y_{it}|x_{it}) = \alpha_i + [\beta_0 + \gamma_0 q_\tau] + [\beta_1 + \gamma_1 q_\tau] x_{it} + [\beta_2 + \gamma_2 q_\tau] x_{it}^2 + [\beta_3 + \gamma_3 q_\tau] (x_{it} - \mu_{it})^2 \quad (6)$$

where $\tau \in (0,1)$; both intercept and slope coefficients vary with the quantile of crop yield and q_τ is an unknown τth quantile of u_{it}. Due to the presence of fixed effects in the model we use the location-scale model to estimate the conditional quantile function of interest represented by equation (6). Though equation (6) can be estimated in a single step via non-linear moments, we follow Machado and Santos Silva and opt for a multistep procedure to obtain the parameter estimates, as it is easier to implement.[6]

[6] For details on the estimation of the fixed-effect quantile panel model via moments, please refer to Machado and Santos Silva (2019).

Our study differs in the measurement of annual weather effects. Most of the earlier studies have used a growing season or annual average temperature changes or growing degree days (GDD)[7] to measure the impact of weather variables on crop yields. However, changes in daily minimum and maximum temperatures may have more significant effects on crops' growth and phenology than average temperature (Hatfield et al., 2011). The growth of crops is likely to be affected by the range between minimum and maximum temperature. Temperatures above or below or above a threshold at critical times of plant development adversely affect crop yields.[8] Moreover, it should be noted that the minimum air temperature is governed by mesoscale variables such as atmospheric water vapor contents, whereas the maximum temperature is determined by local conditions, especially soil water content and evaporative heat loss as soil water evaporates (Alfaro et al., 2006). This implies that changes in minimum temperatures are more suitable in irrigated areas whereas in water stress areas it is the changes in maximum temperatures that affect the crop yields; hence we estimate the impact of maximum temperature (T_{max}) on crop yields.[9] We use the growing season T_{max} which is the average of growth season's monthly T_{max}. Growing season cumulative precipitation is the sum of precipitation in the crop specific season's months.

Higher T_{max} increases vapor water demand leading to water stress quickly; therefore, the effect of T_{max} on crop yields is a combined effect of warm air temperature and the increasing atmospheric demand.[10] A country-level study, including India, finds that higher daytime temperature is more harmful than night temperatures for crop yields (Lobell, 2007). Guntukula and Goyari (2020) find that T_{max} adversely affects rice, cotton, and groundnut yields in Telangana state. An experimental study finds that there is a positive association between sterility of rice and average T_{max} during the 20 days before and after the flowering period in China (Tao et al., 2006). Similarly, Schlenker and Roberts (2006) using minimum and maximum temperature data observe that US maize yield reduces non-linearly with a temperature above 25.8 C. Following these studies, we consider T_{max} rather than average temperature as a determinant of crop yields.

3. Data

The objective of the study is to identify adaptation realized in Indian agriculture. We measure adaptation as a difference between the long-run and short-run

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[7] GDD is the sum of the difference between the observed average temperature and the base temperature, if observed is greater than the base, on a daily basis. Generally observed average is the mean of daily observed T_{min} and T_{max} temperatures. This is different from our approach which relies only on T_{max}.

[8] During the pollination stage of the initial grain, exposure to extremely high temperatures reduce yield potentials (Hatfiled and Prueger, 2015). For example, rice pollen viability and production reduce as the daytime maximum temperature exceeds 33 C (Kim et al., 1996). Similarly, maize yield reduces as the exposure to daytime temperature exceeds 30 C; higher maximum temperature damages cell division and amyloplast replication in maize kernels (Commuri and Jones, 2001).

[9] Since we are considering only the impacts of growing season maximum temperature on crop yields, please read temperature and maximum temperature interchangeably throughout the paper.

[10] For details on the relationship of these parameters, please see Hatfield et al. (2011)

response of crop yields to climatic changes. We need information on crop yields and climatic variables along with some control variables for attaining the objective.

We consider agricultural crop yields as key outcome variables, which are measured as output per hectare. We focus on three key cereals crops namely, rice, maize, and wheat that constitute a large proportion of food-grain production and are the basis of food security in the country. Note that the ICRISAT-TCI dataset does not provide information on the weather variables for the apportioned districts.[11] Therefore, we use data for the unapportioned districts for apportioned districts, assuming that the weather in the base districts and the geographic areas of these districts after carving out new districts is the same. The dataset provides information of monthly average T_{max} and average minimum temperature (T_{min}) and total monthly precipitation for each of the districts from which we construct growing season average T_{max} and total precipitation figures for the three crops under consideration for all the districts for which information is available. The required information is obtained from the ICRISAT-TCI, which provides district-level data on Indian agriculture and allied sectors for the period 1966-2015.[12] The data is available for 313 districts across 20 states.[13] We estimate two naïve models; from 1966 to 2015 for which the complete data is available and for the period for which we have the climate penalty term data, i.e., 1986-2015 (since we consider a moving average of last twenty years of the weather variables as indicators of climate) (Models R1, R2, M1, M2, W1, and W2). The third estimated model is inclusive of the climate penalty term for the period of 1986-2015 (Models R2P, M2P, and W2P).

Though India is a tropical country, the climate in the country is very diverse. The southern peninsula region is warmer than the northern part of the country. Most of the rainfall takes place in the monsoon season (June to September). Some the states such as Rajasthan observe very small rainfall. Most of the crops are grown during the two seasons: Kharif and Rabi. Kharif season generally runs from May-June to November-December. Rice and maize among others are the main Kharif crops. Rabi season commonly runs from November to April and wheat is a major rabi crop. There is some variation of crops sowing and harvesting seasons among the states given the diversity in the climate. The government of India (2019) provides a state-wise crop calendar of major crops that we follow for creating weather variables of interest for the growing season for each of the states for the three crops. We consider two Kharif crops (rice and maize) and one Rabi crop (wheat) for estimating the climate effect. For rice and maize, we have information for 293 and 286 districts respectively. There is information on 275 districts for the wheat crop. The descriptive statistics of the variables used in the study are given in Table 1. The table reveals distributional heterogeneity not only in crop yields

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[11] The ICRISAT-TCI database is divided into two datasets: apportioned and unapportioned; we use the first dataset. The advantage of this dataset is that it provides a consistent and comparable time series for the districts that are constant over time

[12] http://data.icrisat.org/dld/ as accessed in April 2021

[13] Andhra Pradesh, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, Bihar, West Bengal, Odisha, Assam, Himachal Pradesh, Kerala, Chhattisgarh, Jharkhand, Uttarakhand, and Telangana

but also in weather and climate variables. There is an increase in growing season quinquennial average of T_{max} for rice and maize of the magnitude of 0.16 and 0.15 C during 2011-2015 over 1966-1970, but, there is a decline of about 0.7 C in T_{max} for the wheat growing season during the same period. It is also observed that the quinquennial (5-year) average of Tmax has changed only 0.07, 0.06, and -0.03 C for rice, maize and wheat during 2011-2015 over 1986-1990. Average growing season cumulative precipitation has increased by 167 and 179 mm for the crops of rice and maize but there is a decline in the growing season precipitation for wheat by 120 mm in 2011-2015 over 1966-1970. Figure A1 presents the trend in average crop yields across districts during the study period.

Changes in weather and yield in the 2011-15 period over 1966-1970 reveal that T_{max} change is higher at the lower tail of its distribution for rice and maize but the increase in T_{max} is higher at the upper tail of its distribution for wheat. Precipitation increase is higher at the lower tail of its distribution for rice and maize during this period but there is a decline in precipitation is higher at the upper tail of its distribution for wheat. Change in crop yields is not uniform over the distribution.

4. Empirical Results

We estimate the extent of climate change adaptation in Indian agriculture by estimating a quadratic equation in weather variables with and without climate penalty terms using fixed-effect panel quantile regression models. For the sake of comparison, we also estimate the effects using conventional fixed effect panel models (Table A1). District-specific unobserved heterogeneity is controlled for via fixed effects, which engrosses time-invariant confounding variation. We control for time effect with state-specific quadratic time trends. We report standard errors clustered at the state level.

Table A1 presents the regression results obtained using conventional fixed-effect models and Tables A3 through A11 display the estimates acquired from the fixed effect quantile regression for quantiles 0.1 through 0.9 for rice, maize, and wheat. Table A2 presents the location-scale parameters of the quantile regressions. We find that temperature and precipitation parameters in their linear and quadratic terms have effects on agricultural yields with opposite signs on the location and scale. These results suggest that increasing temperatures and declining precipitations reduce crop yields, but also increase dispersions of the observed yields. The location effects suggest that marginal effects of temperature increase damage more at the lower tail of the unconditional distribution of crop yields. The scale effects suggest the opposite, i.e., reducing the overall dispersion of the temperature would increase the lower quantile yields but reduces the upper ones.

Effects on Average Crop Yields

Estimates of fixed effect panel models presented in Table A1 reveal the presence of adaptation to rising temperature for maize yields, which is statistically significant. The short-run effect of an increase in T_{max} by 1 C reduces maize yields by about 9% and by 1% in the long term. The naïve models (Models M1 and M2) estimate that the long-term decline in maize yield is about 10% and 6% for the periods of 1986-2015 and 1966-2015 respectively at the overall mean level of T_{max} across districts over the sample period. This implies that the penalty-inclusive models identify the presence of adaptation. We find insignificant adaptation to the rising T_{max} by rice and wheat as the coefficient of climate penalty term is not statistically different from zero. Concerning precipitation, the results reveal that the adaptation is statistically significant for maize and wheat, but the difference in long-term and short-term impacts is very small in magnitude. We also find that the yields of rice and precipitation are positively associated, but wheat yields and precipitation are inversely related. A 100-mm increase in precipitation enhances rice yields by 2.4%, however, it reduces the wheat yields by 3% at the overall mean level of the precipitation. Moreover, it is observed that the naïve models overestimate the negative effects of weather change and underestimate the positive effects. However, these average effects of climate change on agriculture inhibit our understanding of potential differential impacts on the lower and upper tails of the distribution of agricultural yields.

Distributional Heterogeneity in the Effects of Climate Change on Crop Yields

We estimate the naïve and climate penalty inclusive models using fixed-effect quantile panel models to get an understanding of potential distributional heterogeneity in the effects of climate change on agricultural yields and compare the estimated results with the conventional results obtained using fixed-effect panel models. Figures 1 to 3 display the effects of temperature and precipitation changes on the crop yield of rice, maize, and wheat respectively for all the three models and compare them with the results obtained from fixed effect panel models.

Figure 1 (upper left panel) shows the effect of an increase in T_{max} by 1 C at the overall mean level for rice yields for quantile 0.1 to quantile 0.9 for the naïve models estimated for the periods 1966-2015 and 1986-2015. We find that the effects are not uniform across the quantiles. The negative effects of T_{max} increase are higher at the lower tail of the distribution and lower at the upper tail of the distribution. For example, a 1 C increase in T_{max} at the mean level of the sample reduces rice productivity by 23% at the first quantile and the reduction in yield is only 6% at the 9th quantile for the estimates obtained using the sample for the whole period of 50 years. We observe a similar trend in the effects of T_{max} rise on rice yields across quantile for the sample 1986-2015. However, it should be noted that the magnitude of the effects is lower, suggesting that some adaptation is taking place to rise T_{max} in rice production. Moreover, at the median level, the magnitude of the effects is almost equal whether it is estimated using conventional fixed-effect models or fixed-effect quantile regression models. Similarly, the right panel of Figure 1 (upper right panel) reports the effects of change in precipitation, which are heterogeneous across the quantiles. Low productive regions or the observations at the lower tail of the distribution of the yield curve benefit more from the increase in precipitations relative to the observations at the upper tail of the distribution. It should be noted that for the 9th quantile the benefits of the increase in precipitation are almost equal for both datasets, i.e., at 100-mm increase in precipitation leads to about a 2% increase in rice productivity. This observation is consistent with the fact that highly productive regions have better irrigation facilities. The regions are less dependent on monsoons.

Figure 1 (lower left panel) display the estimates obtained for climate response function inclusive of penalty term. We observe that at the lower tail of the distribution, there is a significant difference between the long-term and short-term impacts of T_{max} changes on rice yield (Table A5), but at the upper tail of productivity distribution the impacts are lower and the long-term and short-term impact curves coincide in each other. Alternatively, it can be said that at the lower tails of the productivity curve the impacts of T_{max} increase by 1 C at the overall sample mean (31 C) on rice yields are higher and some adaptation occurs but at the upper tail of productivity distribution the impacts are lower and there is no significant adaptation measures are taken by the farmers. Moreover, we find that increase in precipitation enhances rice productivity; a 100-mm increase in rainfall gains rice productivity by 3.5% at the lowest tail of the productivity curve, but the increase in productivity for the top 10% producers is only about 1% (Figure 1, lower right panel). It is also observed that there is no difference in the long-term and short-term impacts of precipitation changes on rice productivity in India.

Figures 2 (and Appendix Tables A6 to A8) demonstrate the effects of changes in temperature and precipitations on the distribution of maize productivity. The pattern of T_{max} change impacts on maize yield is similar to the pattern observed for the effects on rice productivity. At the lower tail of productivity distribution, the impacts are higher but at the upper tail of the distribution the impacts are lower and of low magnitude for the naïve models. Contrary to rice yields, we find higher impacts at the lower tail of the productivity curve for the estimates obtained using the sample of 1986-2015 in comparison to the estimates obtained for the sample 1966-2015, but the impacts obtained from both the sample coincide at the higher tail of productivity distribution and are not statistically significant (Appendix Table A6 and Table A7). For example, for the first quantile, the marginal effect of a 1 C increase in T_{max} on maize productivity is about 16% for the sample period 1986-2015 and the impacts are about half of it for the sample period 1966-2015. The marginal impacts of precipitation changes on maize yields are negligible in magnitude for both sets of samples; the impacts are statistically significant for the first three quantiles for the 1966-2015 sample but they are not significant for any of the quantiles for the sample of 1986-2015.

Figure 2 (lower panel) shows the marginal effects of T_{max} and precipitation changes for the short-term and long-term for the sample period of 1986-2015 on maize yield. Appendix Table A8 reveals that only the coefficients of climate penalty term for temperature are statistically significant for the quantiles 0.3 onwards and these impacts are higher at the lower tail of the productivity curve in comparison at the higher tail of the curve. These results suggest that rising T_{max} only affects short-run maize productivity and maize yields are insensitive to precipitation changes in India.

Wheat is a rabi crop and its calendar runs from November-December to April-May, whereas the crops of rice and maize are grown during the monsoon season. It should be noted that most of the rainfall takes place during the monsoon season. The marginal impacts of weather changes on wheat yield are shown in Figure 3. Figure 3 (upper panel) shows that the effects for the conventional fixed-effect models, though homogenous over the productivity curve, are much lower for the sample of 1986-2015 in comparison to the sample of 1966-2015. The quantile regression results reflect that the effects are of the same magnitude across sample periods but are heterogeneously distributed across quantiles. The negative effects are larger at the lower quantiles; at the 0.1 quantile, a 1 C increase in T_{max} lowers wheat productivity by 9% but the decline in the yield is about 5% at the 0.9 quantile. The marginal effects of precipitation increase for wheat yield are negative, and they are more negative at the lower tail of the productivity distribution. Moreover, the magnitude of the precipitation effect is larger for the sample period of 1966-2015 relative to the sample period of 1986-2015. We fail to observe any significant difference between long-term and short-term impacts of T_{max} and rainfall on wheat productivity, though the negative marginal impacts are higher at the lower tail of the productivity curve; at the higher tail of productivity, the marginal effects are negligible, and statistically insignificant (Figure 3, lower panel). These results reveal an absence of any adaptation to changes in T_{max} and rainfall in wheat production in India.

The previous discussion reveals that at the overall mean of weather variables, the impact of these variables on crop yields is heterogeneous. The magnitude of productivity damages due to T_{max} increases varies both across crops and quantiles of productivity curves. At the lower tail of the productivity curve, adaptation to T_{max} increase is relatively higher and the impacts, both short term, and long term are substantial. Adaptation to precipitation changes is almost absent for all three crops.

In figures 1 through 3, it is observed that, at the median quantile level, the estimates of marginal impacts obtained from conventional fixed effect panel models and fixed effect panel quantile models almost coincide. Therefore, figures 5 to 10 provide a graphical representation of long-run and short-run response functions estimated for the naïve and climate penalty inclusive regressions for both the weather variables at the median quantile and compare them with the estimates obtained from the fixed effect panel regressions.[14]

Figure 4 (left panel) and Appendix Figure A2 show the marginal effects of T_{max} on rice yield estimated from quantile regressions and fixed effect regressions, respectively. The pattern of short- and long-term impacts depicted in the figures is similar. The estimates obtained from the inclusive model show that the short-term marginal impact of T_{max} rise is higher than the long-term impacts (6% versus 4%) but the difference is not statistically significant at the T_{max} level of about 33 C; the level of T_{max} around which most of the districts are located. It should also be noted that the marginal impacts of T_{max} rise are not uniform across its levels, i.e., the marginal yield response to T_{max} increase is asymmetric, especially in the short run. The long- and short-run response functions are tangent at a T_{max} level of about

[14] Appendix figures A1 to A6 provide a graphical representation of yield response functions for both the weather variables and three crops.

22 C. Long-run marginal impact function estimated using the naïve model intersects the long-run and short-run response functions at 28 C and 31 C levels of T_{max} respectively. Figure 4 (right panel) (and Figure A2) depicts the response function of rice yield concerning changes in precipitation. We find that the long-run impact of change in precipitation at different precipitation levels is almost constant, but the short-run impacts of precipitation rise follow a 'U' shaped pattern, an increase in precipitation beyond 1500-mm level increases rice productivity significantly. In most of the districts, the precipitation level lies between 500-mm to 1000-mm and marginal changes in precipitation at this level do not much affect median rice productivity either in the short- or long run.

Figure 5 displays the response functions of maize productivity concerning T_{max} and precipitation. Maize is generally produced in hot regions in the monsoon season. Most of the sample observations observe an average of T_{max} 32 to 35 C. At this level, a one-degree increase in T_{max} reduces median maize yield by about 10% in the short run but the long-run impact of T_{max} increase on the maize productivity is negligible, suggesting a significant adaptation to T_{max} increase takes place in Indian agriculture. This observation is consistent with the fact that maize is a heat-tolerant and less water-consuming crop. This is grown mostly in drought-prone areas. In the short run, the marginal impacts of an increase in precipitation on median maize productivity are negative but are asymmetric. An increase in precipitations at the initial levels reduces the magnitude of negative effects. However, beyond the level of about 2700-mm level, a further increase in precipitation augments the negative effects on crop productivity.

The impacts of changes in weather variables on median wheat productivity are depicted in Figure 6. Wheat is grown throughout the country even in hilly cold regions such as the states of Himachal Pradesh and Uttarakhand. From Figure 6 (left panel) it is evident that the ideal range for T_{max} lies somewhere 10 to 12 C and beyond that level, a further increase in T_{max} negatively affects wheat productivity in the country. Most of the wheat-growing regions observe a T_{max} in the range of 27 – 32 C, the marginal impact of T_{max} rise on median wheat productivity is statistically significant and reduces median wheat yields by about 3%. We also observe that there is no significant difference in the short- and long-run impacts of T_{max} rise on wheat productivity suggesting the absence of any adaptation measures taken in wheat production against T_{max} rise. It should also be noted that most wheat-growing regions observe rainfall below 100-mm during the growing season (Figure 6, right panel). The short-run and long-run response functions of median wheat yield concerning precipitation follow a similar pattern and there is no significant difference in the magnitude of the response functions. A further increase in precipitation by 100-mm negatively affects the median wheat productivity in the growing regions by 2.5%. Here, it should be noted that the long-run response function obtained from the naïve model reveals that there is no significant marginal effect of change in precipitation on median wheat productivity.

To summarize, we find the effects of weather and climate changes are asymmetric: the effects are small at the upper tail of yields distribution while these variables have larger impacts at the lower tail of the distribution if the impacts are negative.

The opposite is true if the impacts are positive. Largely, farmers take some adaptation measures at the lower tail of the yield distribution to counter the negative effects of T_{max} increase, however, we find insignificant adaptation at the upper tail of the distribution. At the upper tail of the distribution, the impacts of T_{max} increase are relatively small. Moreover, it should be noted that the presence of adaptation to changing temperatures in Indian agriculture is not uniform across crops. We observe there is an adaptation to T_{max} increase for the crops of rice and maize but the difference in the long-term and short-term impacts of T_{max} rise on wheat yield are not statistically significant. Increasing precipitations enhance rice productivity and adversely affect maize and wheat productivities and generally, adaptation is absent to changing patterns of precipitation, suggesting that weather and climate effects can vary substantially across crops.

5. Conclusions

This study estimates adaptation to changing weather and climate in Indian agriculture using district-level information for the period 1966-2015 for the three major cereal crops: rice, maize, and wheat. The identification strategy is based on the idea that the heat-prone districts fare better to higher temperatures relative to the districts that are located in colder regions. Most of the existing studies estimate quadratic equations in weather variables and focus on measuring the average relationship between crop yields and climatic factors. These studies ignore potential heterogeneity in the effects. We estimate the naïve and climate penalty inclusive models using fixed-effect quantile panel models to get an understanding of potential distributional heterogeneity in the effects of climate change on agricultural yields and compare the estimated results with the results obtained using fixed-effect panel models.

The difference in the estimates of quadratic equation with and without penalty term depends not only on the magnitude of the coefficient of climate penalty term but also on the cross-sectional variation relative to with-in variation in weather variables. The naïve models estimate the long-term effects of climate change and are nested within the penalty inclusive models, the coefficient of the penalty term is indicative of the magnitude of the adaptation.

The boundary of minimum and maximum temperature defines the growth of crops; temperatures beyond certain thresholds from below or above can adversely affect crop yields. Changes in minimum temperatures are more suitable in irrigated areas whereas in water stress regions it is the changes in maximum temperatures that affect the crop yields; hence the study considers estimating the impact of T_{max} on crop yields.

Conventional fixed-effect models inhibit our understanding of potential differential impacts on lower and upper tails of the distribution of agricultural yields. Quantile regression models identify the effects on the probability distribution of crop yields. This is important as the effects are complex and vary depending on the timing of occurrence, duration, and spatial distribution. Moreover, the fixed effect quantile regression models capture unobserved effects of variables that may be associated with the weather variables. The results of quantile regressions suggest that increasing T_{max} and declining precipitation reduce crop yields, but also increase the dispersions on observed yields. It is found that the naïve models overestimate the negative effects of weather change.

The estimated results reveal that the effects of weather and climate changes are asymmetric; the effects are larger at the lower tail of productivity distribution and are smaller at the upper tail of the distribution. It is also observed that significant adaptation measures are taken at the lower tail of the yield distribution curve to counter the negative effects of the T_{max} increase. Moreover, it should be noted that the presence of adaptation to changing T_{max} in Indian agriculture is not uniform across crops. We observe there is adaptation to the increase in T_{max} for rice and maize. Increasing precipitations enhances rice productivity but adversely affects maize and wheat productivity. Heterogeneity in impacts and adaptation estimates over the yields distribution curves and across crops suggests that farm management decisions can help farmers to adapt to changing weather and climate conditions.

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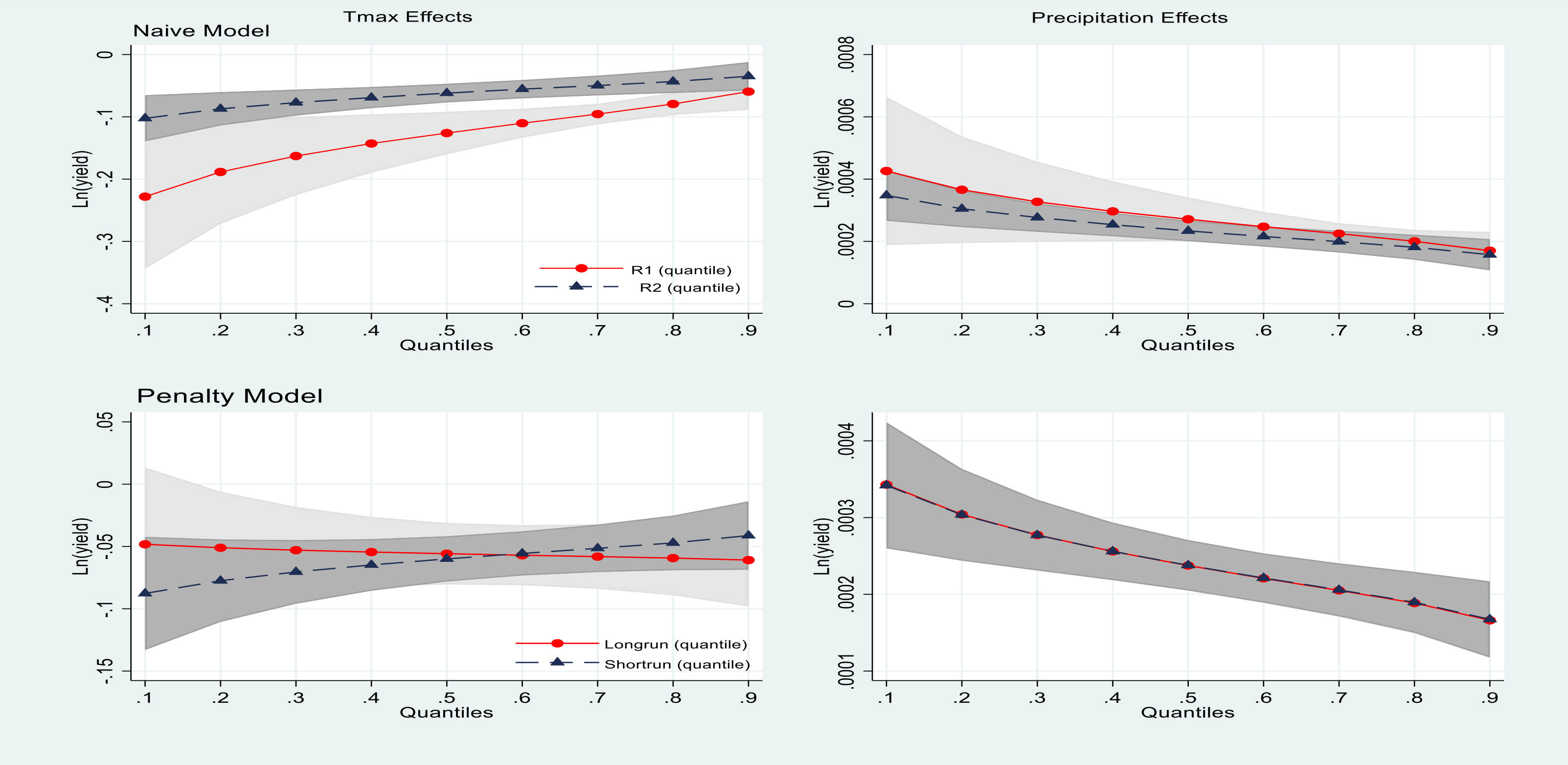
Table 1: Descriptive Statistics 1966-2015

Variable	Mean	Min	1st Qu	Median	3rd Qu	Max	S.D.	Obs
1966-2015								
Rice Yield (kg)	1571.08	9.12	900.69	1382.11	2128.19	5653.83	883.51	13763
Rice T_{max} (C)	31.65	7.90	30.80	32.36	33.49	39.32	3.52	14836
Rice Prec (mm)	1003.81	0.85	625.26	889.17	1188.35	5914.72	635.74	14836
Maize Yield (kg)	1541.44	3.35	888.05	1253.26	1904.76	11120.22	1064.78	13022
Maize T_{max} (C)	31.71	7.90	30.85	32.40	33.77	40.46	3.72	14836
Maize Prec (mm)	969.06	0.71	603.22	870.65	1159.35	5741.40	604.20	14836
Wheat Yield (kg)	1722.72	46.11	1019.12	1517.13	2256.72	5541.52	933.33	12645
Wheat T_{max} (C)	28.87	-9.39	28.26	29.99	31.26	35.02	5.07	14836
Wheat Prec (mm)	152.44	0.00	34.60	75.25	197.63	1934.17	194.26	14836
1986-2015								
Rice Yield (kg)	1832.77	55.74	1099.08	1754.25	2425.60	5653.83	925	8252
Rice T_{max} (C)	31.73	8.01	30.92	32.46	33.55	39.32	4	8900
Rice T_{max} Clim (C)	31.59	8.44	30.80	32.33	33.38	37.53	3	8801
Rice Prec (mm)	1028.35	23.05	645.06	890.50	1199.53	5914.72	645	8900
Rice Prec Clim (mm)	1015.68	111.38	687.53	892.69	1158.22	4077.63	592	8801
Maize Yield (kg)	1801.05	6.06	1033.39	1500.00	2162.24	11120.22	1170	7939
Maize T_{max} (C)	31.78	8.01	30.98	32.52	33.83	40.46	4	8900
Maize T_{max} Clim (C)	31.68	8.44	30.85	32.37	33.69	38.69	4	8801
Maize T_{max} (mm)	997.20	16.16	624.69	880.66	1175.16	5610.31	612	8900
Maize Prec Clim (mm)	981.46	108.95	662.26	882.41	1121.57	3916.63	557	8801
Wheat Yield (kg)	2037.72	74.32	1291.42	1882.35	2640.88	5541.52	974	7597
Wheat T_{max} (C)	29.00	-9.20	28.34	30.17	31.46	35.02	5	8900
Wheat T_{max} Clim (C)	28.79	-8.35	28.27	29.95	31.18	34.05	5.08	8801
Wheat Prec (mm)	119.89	0	29.24	65.55	152.08	956.4	140.21	8900

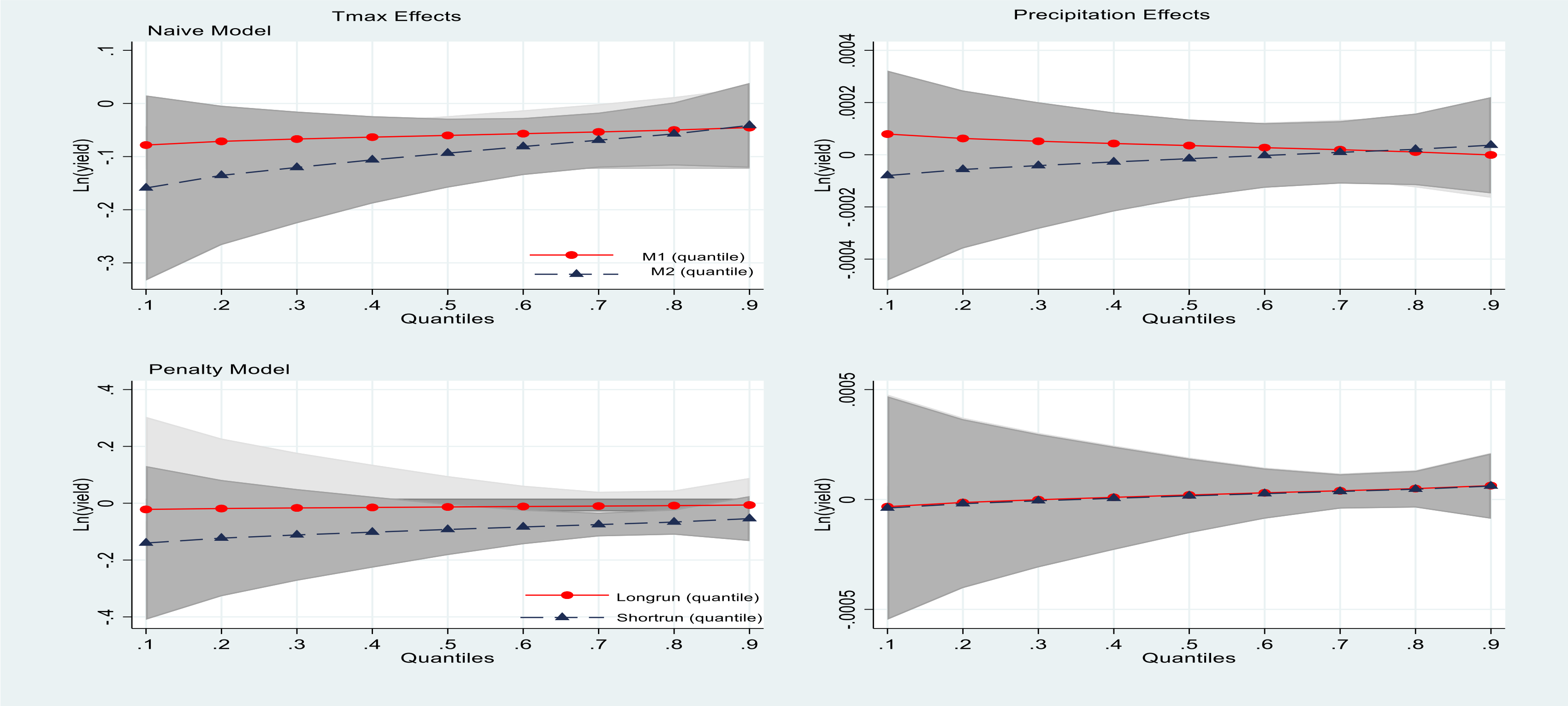
Wheat Prec Clim (mm)	135.63	1.96	45.41	75.13	190.35	754.58	135.99	8801

Figure 1: Estimated climate change impacts over quantiles for rice crop at mean T_{max} and precipitation for naïve models (R1 and R2) and penalty inclusive model (R2P)



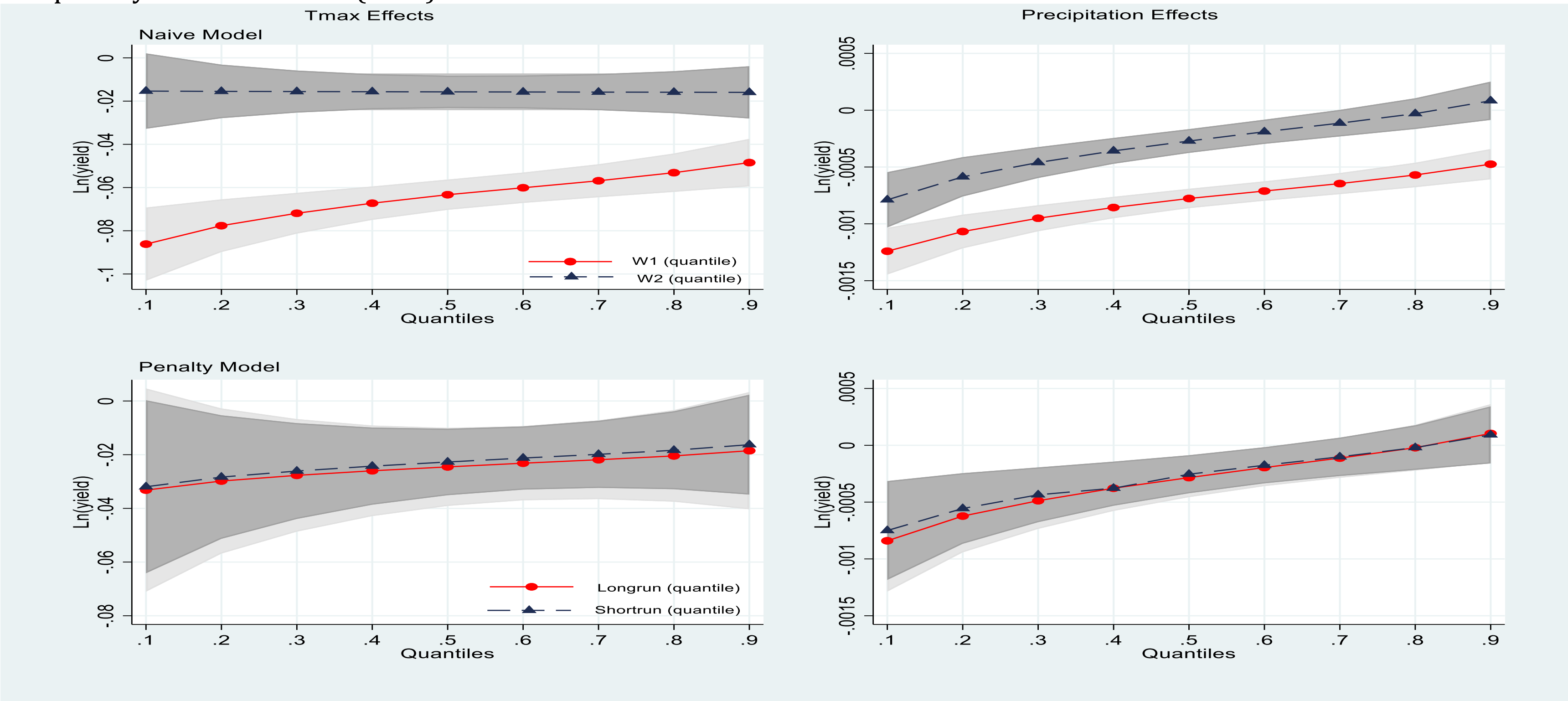
Note: R1 is the naïve model using the data for the period of 1966-2015 and R2 is the naïve model using data for the period of 1986-2015. Quantile and fixed effect in parentheses indicate that the models are estimated using quantile and fixed effect regression models. Shaded area indicates confidence interval. Longrun and Shortrun indicate long-run and short-run impacts; and quantile and fixed effect in parenthesis denote that the models are estimated using quantile and fixed effect regressions. Shaded area is an indicator of confidence intervals.

Figure 2: Estimated climate change impacts over quantiles for maize crop at mean T_{max} and precipitation for naïve models (M1 and M2) and penalty inclusive model (M2P)



Note: M1 is the naïve model using the data for the period of 1966-2015 and M2 is the naïve model using data for the period of 1986-2015. Quantile and fixed effect in parentheses indicate that the models are estimated using quantile and fixed effect regression models. Shaded area is an indicator of confidence intervals. Longrun and Shortrun indicate long-run and short-run impacts; and quantile and fixed effect in parenthesis denote that the models are estimated using quantile and fixed effect regressions. Shaded area is an indicator of confidence intervals.

Figure 3: Estimated climate change impacts over quantiles for wheat crop at mean T_{max} and precipitation for naïve models (W1 and W2) and penalty inclusive model (W2P)



Note: W1 is the naïve model using the data for the period of 1966-2015 and W2 is the naïve model using data for the period of 1986-2015. Quantile and fixed effect in parentheses indicate that the models are estimated using quantile and fixed effect regression models. Shaded area is an indicator of confidence intervals. Longrun and Shortrun indicate long-run and short-run impacts; and quantile and fixed effect in parenthesis denote that the models are estimated using quantile and fixed effect regressions. Shaded area is an indicator of confidence intervals.

Figure 4: Rice yield responses to T_{Max} and precipitation (fixed effect quantile panel model)

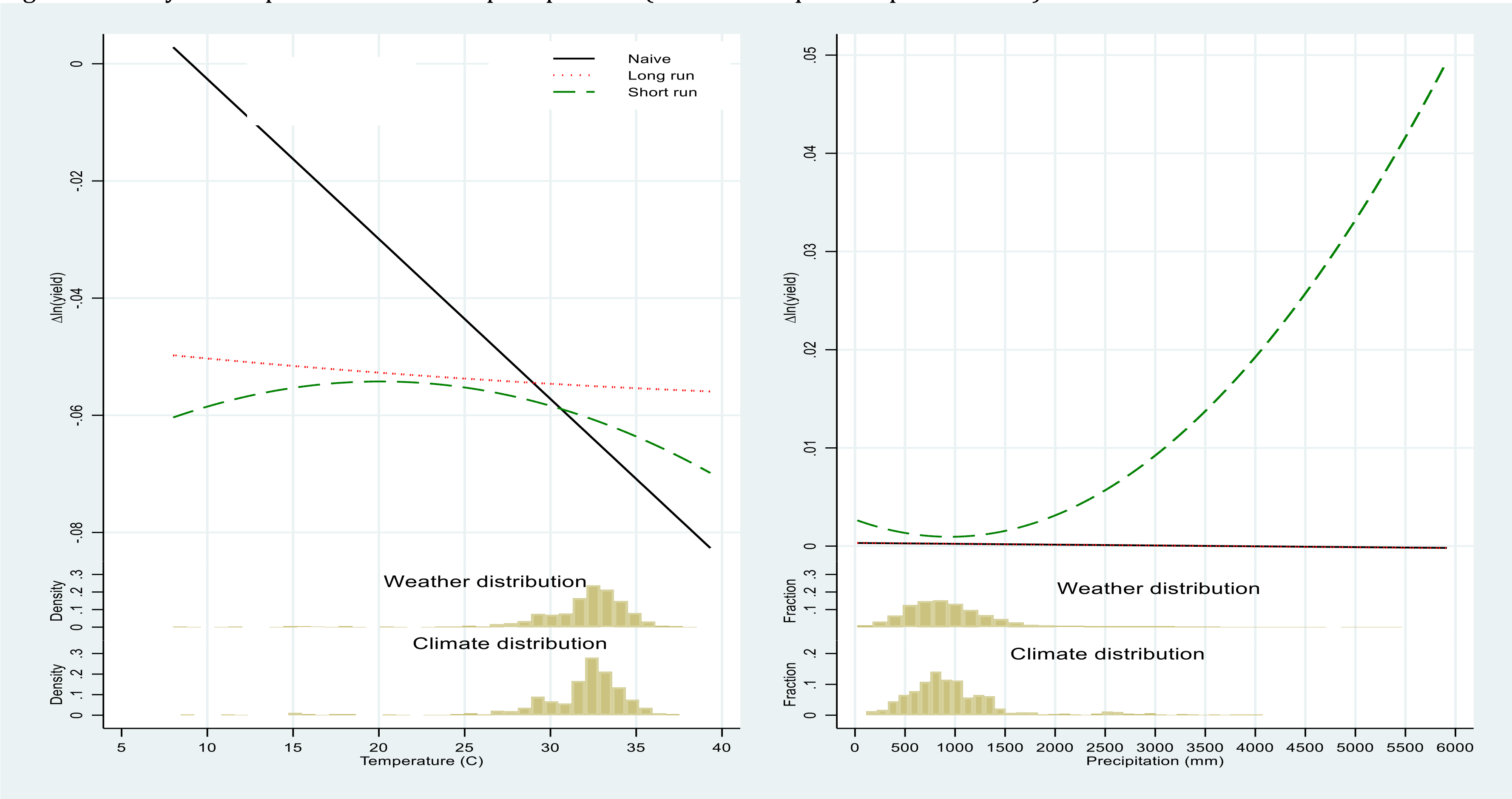


Figure 5: Maize yield responses to T_{Max} and precipitation (fixed effect quantile panel model)

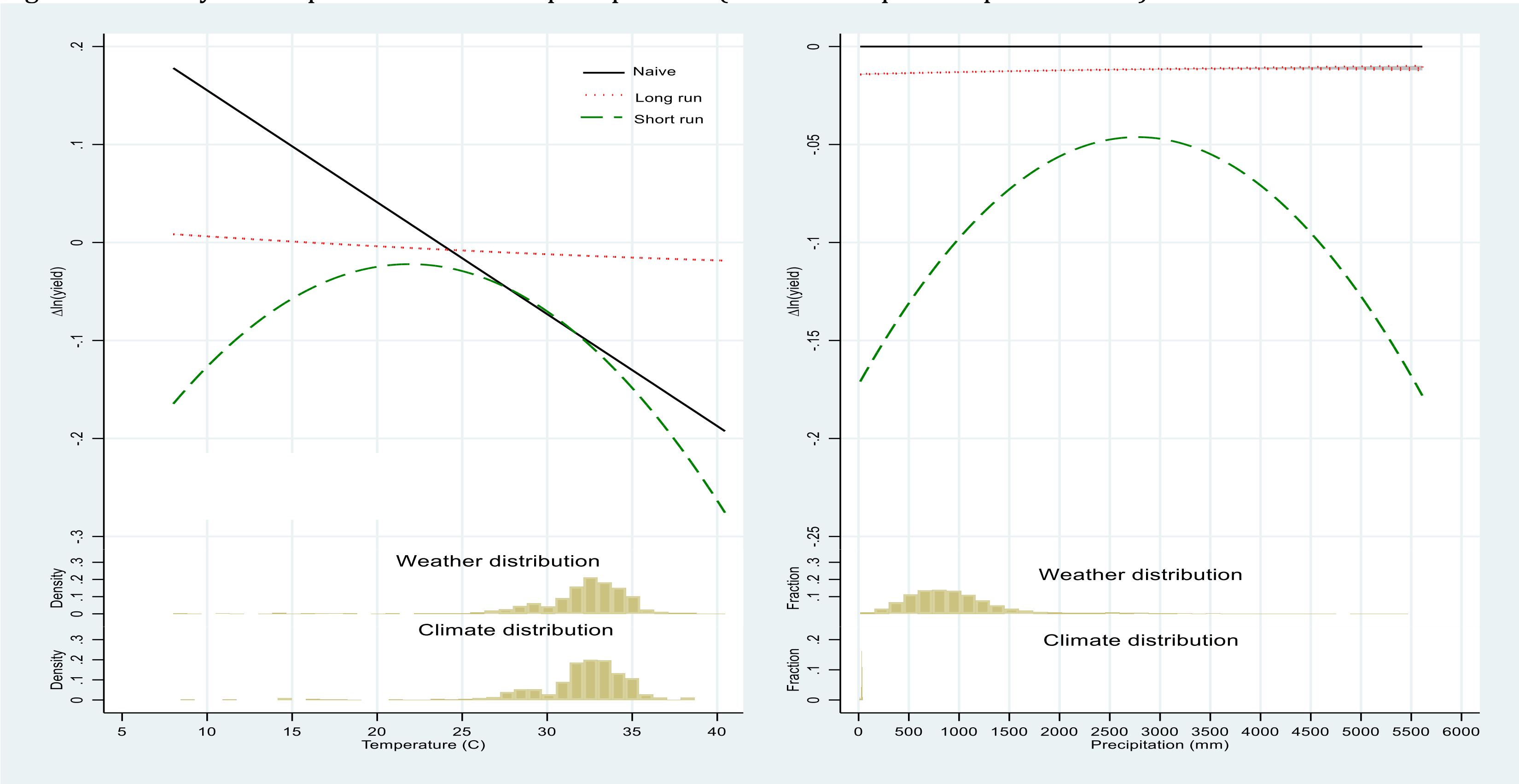
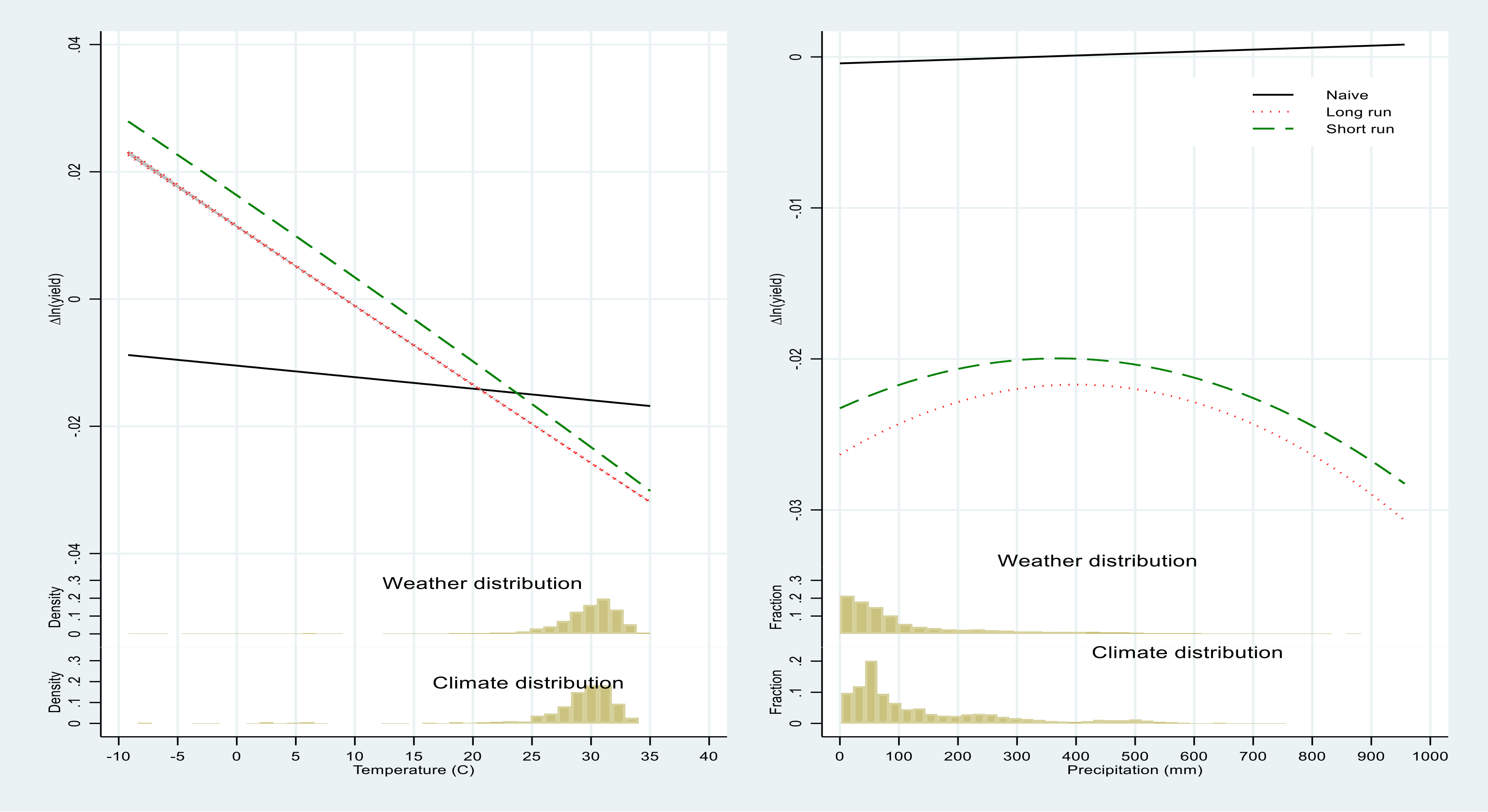


Figure 6: Wheat yield responses to T_{Max} and precipitation (fixed effect quantile panel model)



Appendix

Table A1: fixed effect panel data model estimates

	Rice			Maize			Wheat		
	50-year naïve model (R1)	30-year naïve model (R2)	Penalty inclusive model (R2P)	50-year naïve model (M1)	30-year naïve model (M2)	Penalty inclusive model (M2P)	50-year naïve model (W1)	30-year naïve model (W2)	Penalty inclusive model (W2P)
T_{max}	0.1844**	0.0276	-0.0560***	0.1599*	0.2730**	0.1598*	-0.0387*	-0.0091	0.0075
	(0.081)	(0.063)	(0.018)	(0.090)	(0.121)	(0.096)	(0.022)	(0.020)	(0.011)
T_{max} 2	-0.0050***	-0.0015	0.00001	-0.0035**	-0.0058***	-0.0026*	-0.0005	-0.0001	-0.0007**
	(0.001)	(0.001)	(0.000)	(0.0014)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Prec	0.0004***	0.0003***	0.0003***	0.0001	-0.00002	-0.00001	-0.0011***	-0.0005***	-0.0006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prec2	-0.0000***	-0.0000***	-0.0000***	-0.0000	-0.0000	0.0000	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Penalty_{Tmax}$			-0.0194			-0.2420***			0.0042
			(0.018)			(0.025)			(0.008)
$Penalty_{prec}$			0.0000			-0.0000***			-0.0000**
			(0.000)			(0.000)			(0.000)
Constant	5.8280***	7.4120***	8.5759***	5.2748***	4.2148**	4.5616***	8.6262***	7.6459***	7.4377***
	(1.268)	(0.991)	(0.335)	(1.397)	(1.872)	(1.519)	(0.314)	(0.273)	(0.180)
LT_{max}	-0.1342***	-0.0651***	-0.0553***	-0.0612***	-0.0979***	-0.0063	-0.0656***	-0.0157***	-0.0253***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.012)	(0.011)	(0.004)	(0.004)	(0.008)
ST_{max}			-0.0621***			-0.0874***			-0.0235***
			(0.008)			(0.012)			(0.007)
LPrec	0.0003***	0.0002***	0.00024***	0.00003*	-0.0000***	0.00002	-0.0008***	-0.0003***	-0.0003***

	(0.00002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
SPrec			0.00025***			0.00001			-0.0003***
			(0.0000)			(0.0000)			(0.0001)
R2	0.411	0.251	0.246	0.213	0.305	0.329	0.490	0.244	0.247
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,763	8,252	8,158	13,022	7,939	7,844	12,645	7,597	7,512
Districts	293	291	291	287	286	286	275	272	272
Sample	1966-2015	1986-2015	1986-2015	1966-2015	1986-2015	1986-2015	1966-2015	1986-2015	1986-2015

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

LT_{max}: Long term marginal temperature effect at overall mean of observed temperature; ST_{max}: Short term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; SPrec: Short term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A2: Location and scale parameters of quintile regressions models

	Rice				Maize				Wheat			
	Location		scale		Location		Scale		location		scale	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std. Err.
Sample 1966-2015												
T_{max}	1.8E-01	8.1E-02	-1.2E-01	5.0E-02	1.6E-01	9.0E-02	1.1E-01	7.0E-02	-3.9E-02	2.2E-02	5.4E-03	1.3E-02
$T_{max}{}^2$	-5.0E-03	1.3E-03	2.8E-03	8.2E-04	-3.5E-03	1.5E-03	-1.5E-03	1.1E-03	-4.7E-04	4.0E-04	1.1E-04	2.4E-04
Prec	4.1E-04	3.9E-05	-1.2E-04	1.9E-05	6.5E-05	4.1E-05	-5.0E-05	2.1E-05	-1.1E-03	9.5E-05	3.3E-04	5.8E-05
$Prec^2$	-6.1E-08	9.1E-09	2.2E-08	3.6E-09	-1.4E-08	1.3E-08	1.3E-08	6.3E-09	7.7E-07	1.3E-07	-3.0E-07	7.6E-08
Sample 1986-2015												
T_{max}	2.8E-02	6.3E-02	-1.9E-02	4.0E-02	2.7E-01	1.2E-01	-3.0E-02	7.9E-02	-9.1E-03	2.0E-02	-8.1E-03	2.0E-02
$T_{max}{}^2$	-1.5E-03	1.0E-03	6.4E-04	6.5E-04	-5.8E-03	2.0E-03	1.1E-03	1.3E-03	-1.1E-04	3.6E-04	1.4E-04	3.5E-04
Prec	3.3E-04	3.5E-05	-8.3E-05	1.8E-05	-1.8E-05	5.0E-05	4.2E-05	2.4E-05	-4.9E-04	1.2E-04	3.8E-04	8.0E-05
$Prec^2$	-4.4E-08	6.6E-09	1.1E-08	3.2E-09	-6.5E-10	1.7E-08	-2.3E-09	5.2E-09	7.3E-07	1.6E-07	-4.6E-07	1.2E-07
Sample 1986-2015												
T_{max}	-5.6E-02	1.8E-02	4.5E-02	1.1E-02	5.7E-03	2.4E-02	4.3E-02	1.4E-02	7.5E-03	1.1E-02	-1.4E-02	8.7E-03
$T_{max}{}^2$	1.3E-05	3.8E-04	-7.8E-04	2.3E-04	-3.5E-04	5.2E-04	-6.8E-04	2.9E-04	-7.4E-04	3.6E-04	4.2E-04	2.8E-04
Prec	3.4E-04	3.6E-05	-7.0E-05	1.9E-05	-6.0E-06	4.8E-05	3.9E-05	2.2E-05	-5.5E-04	1.3E-04	4.4E-04	7.9E-05
$Prec^2$	-4.6E-08	6.6E-09	7.0E-09	3.5E-09	1.2E-08	1.5E-08	-4.3E-09	5.2E-09	9.1E-07	1.9E-07	-6.2E-07	1.2E-07
$Penalty_{temp}$	-1.9E-02	1.8E-02	3.3E-02	1.2E-02	-2.4E-01	2.6E-02	6.7E-02	2.1E-02	4.2E-03	7.7E-03	7.3E-04	4.9E-03
$Penalty_{Prec}$	8.2E-09	1.6E-08	2.8E-08	9.7E-09	-1.4E-07	5.1E-08	4.3E-08	2.0E-08	-1.2E-06	4.7E-07	1.1E-06	2.5E-07

Table A3: Fixed effect quantile regression naïve model for rice crop (1966-2015) (R1)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	0.40158***	0.30971***	0.25080***	0.20421***	0.16540***	0.12897***	0.09496***	0.05756***	0.01161***
	(0.013)	(0.010)	(0.007)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
$T_{max}{}^2$	-0.00995***	-0.00787***	-0.00654***	-0.00548***	-0.00460***	-0.00378***	-0.00301***	-0.00216***	-0.00112***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prec	0.00063***	0.00053***	0.00047***	0.00043***	0.00039***	0.00035***	0.00031***	0.00028***	0.00023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	-0.00000	-0.00000*	-0.00000**	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LT_{max}	-0.228***	-0.188***	-0.162***	-0.143***	-0.126***	-0.110***	-0.096***	-0.079***	-0.059***
	(0.058)	(0.042)	(0.031)	(0.023)	(0.017)	(0.011)	(0.008)	(0.009)	(0.014)
LT_{max}	0.0004***	0.0003***	0.0003***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0001)	(0.0001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,763	13,763	13,763	13,763	13,763	13,763	13,763	13,763	13,763
Districts	293	293	293	293	293	293	293	293	293

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

LT_{max}: Long term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A4: Fixed effect quantile regression naïve model for rice crop (1986-2015) (R2)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	0.06146***	0.04762***	0.03855***	0.03121***	0.02470***	0.01892***	0.01359***	0.00776***	0.00006
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
T_{max} 2	-0.00258***	-0.00212***	-0.00182***	-0.00158***	-0.00137***	-0.00117***	-0.00100***	-0.00080***	-0.00055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
prec	0.00048***	0.00042***	0.00038***	0.00035***	0.00032***	0.00030***	0.00027***	0.00025***	0.00021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
prec2	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTemp	-0.102***	-0.087***	-0.077***	-0.069***	-0.061***	-0.056***	-0.050***	-0.043***	-0.035***
	(0.019)	(0.013)	(0.011)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)
LPrec	0.0003***	0.0003***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,252	8,252	8,252	8,252	8,252	8,252	8,252	8,252	8,252
Districts	291	291	291	291	291	291	291	291	291

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
LTmax: Long term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation, QTime: Quadratic state time trend

Table A5: Fixed effect quantile regression inclusive of penalty term model for rice crop (1986-2015) (R2P)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	-0.13607***	-0.10410***	-0.08202***	-0.06446***	-0.04933***	-0.03554**	-0.02269	-0.00915	0.00933
	(0.041)	(0.030)	(0.023)	(0.019)	(0.016)	(0.016)	(0.017)	(0.020)	(0.025)
$T_{max}{}^{2}$	0.00138	0.00084	0.00046	0.00016	-0.00010	-0.00034	-0.00056	-0.00079*	-0.00111**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Prec	0.00046***	0.00041***	0.00038***	0.00035***	0.00033***	0.00031***	0.00029***	0.00027***	0.00024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Penalty_{Tmax}$	-0.07668*	-0.05380*	-0.03800	-0.02544	-0.01462	-0.00475	0.00444	0.01413	0.02735
	(0.043)	(0.032)	(0.024)	(0.020)	(0.017)	(0.017)	(0.018)	(0.021)	(0.026)
$Penalty_{prec}$	-0.00000	-0.00000	-0.00000	0.00000	0.00000	0.00000	0.00000	0.00000*	0.00000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTemp	-0.048*	-0.051***	-0.052***	-0.054***	-0.056***	-0.057***	-0.058***	-0.059***	-0.061***
	(0.026)	(0.022)	(0.017)	(0.014)	(0.012)	(0.012)	(0.013)	(0.015)	(0.019)
STemp	-0.088***	-0.077***	-0.070***	-0.065***	-0.059***	-0.055***	-0.051***	-0.047***	-0.041***
	(0.023)	(0.016)	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.011)	(0.014)
LPrec	0.0003***	0.0003***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SPrec	0.0003***	0.0003***	0.0003***	0.0003***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTime	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,252	8,252	8,252	8,252	8,252	8,252	8,252	8,252	8,252
Districts	291	291	291	291	291	291	291	291	291

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

LTmax: Long term marginal temperature effect at overall mean of observed temperature; STmax: Short term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; SPrec: Short term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A6: Fixed effect quantile regression naïve model for maize crop (1966-2015) (M1)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	-0.0087***	0.0601***	0.1039***	0.1396***	0.1717***	0.2045***	0.2368***	0.2726***	0.3191***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
T_{max}^{2}	-0.0011***	-0.0021***	-0.0027***	-0.0032***	-0.004***	-0.0041***	-0.0046***	-0.0051***	-0.0058***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Prec	0.00015***	0.00011***	0.0001***	0.00007***	0.0001***	0.00004***	0.00003***	0.00001***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	-0.0000	-0.0000*	-0.000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTmax	-0.078***	-0.071***	-0.067***	-0.063***	-0.060***	-0.0568**	-0.0536**	-0.0499*	-0.0453
	(0.019)	(0.013)	(0.013)	(0.015)	(0.018)	(0.022)	(0.0266)	(0.0316)	(0.038)
LPrec	0.0000*	0.0000**	0.0000*	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,022	13,022	13,022	13,022	13,022	13,022	13,022	13,022	13,022
Districts	287	287	287	287	287	287	287	287	287

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

LTmax: Long term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A7: Fixed effect quantile regression naïve model for rice crop (1986-2015) (M2)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	0.32105***	0.30244***	0.29069***	0.27946***	0.26954***	0.25978***	0.25036***	0.24115***	0.22849***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
$T_{max}{}^2$	-0.00755***	-0.00689***	-0.00647***	-0.00607***	-0.00571***	-0.00536***	-0.00502***	-0.00470***	-0.00424***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Prec	-0.00009***	-0.00006***	-0.00004***	-0.00003***	-0.00001***	0.00000	0.00001***	0.00003***	0.00004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	0.00000	0.00000	0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTmax	-0.159*	-0.135**	-0.120**	-0.106**	-0.093***	-0.081***	-0.069***	-0.057*	-0.0412
	(0.089)	(0.067)	(0.054)	(0.042)	(0.033)	(0.027)	(0.026)	(0.030)	(0.041)
LPrec	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	0.0000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,939	7,939	7,939	7,939	7,939	7,939	7,939	7,939	7,939
Districts	286	286	286	286	286	286	286	286	286

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

LTmax: Long term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A8: Fixed effect quantile regression inclusive of penalty term model for maize crop (1986-2015) (M2P)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	-0.06325	-0.03684	-0.01933	-0.00436	0.01041	0.02414	0.03705	0.05072	0.06962
	(0.247)	(0.187)	(0.148)	(0.114)	(0.083)	(0.056)	(0.038)	(0.041)	(0.072)
$T_{max}{}^2$	0.00075	0.00033	0.00005	-0.00019	-0.00043	-0.00065	-0.00085	-0.00107	-0.00138
	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Prec	-0.00007	-0.00005	-0.00003	-0.00002	-0.00000	0.00001	0.00002	0.00004	0.00005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Penalty_{tmax}$	-0.35271	-0.31101	-0.28336*	-0.25971**	-0.23640***	-0.21471***	-0.19433***	-0.17273***	-0.14290*
	(0.251)	(0.190)	(0.150)	(0.116)	(0.084)	(0.056)	(0.039)	(0.041)	(0.073)
$Penalty_{prec}$	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTemp	-0.022	-0.0185	-0.0166	-.0148	-0.013	-0.011	-0.010	-0.008	-0.006
	(0.166)	(0.125)	(0.099)	(0.076)	(0.055)	(0.037)	(0.025)	(0.027)	(0.048)
STemp	-0.139	-0.123	-0.111	-0.102*	-0.092*	-0.083***	-0.075***	-0.066***	-0.054
	(0.138)	(0.104)	(0.082)	(0.064)	(0.046)	(0.031)	(0.021)	(0.022)	(0.040)
LPrec	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SPrec	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,844	7,844	7,844	7,844	7,844	7,844	7,844	7,844	7,844
Districts	286	286	286	286	286	286	286	286	286

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

LTmax: Long term marginal temperature effect at overall mean of observed temperature; STmax: Short term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; SPrec: Short term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A9: Fixed effect quantile regression naïve model for wheat crop (1966-2015) (W1)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	-0.04801***	-0.04416***	-0.04156***	-0.03946***	-0.03769***	-0.03624***	-0.03478***	-0.03309***	-0.03098***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{max}{}^2$	-0.00066***	-0.00058***	-0.00053***	-0.00048***	-0.00044***	-0.00041***	-0.00038***	-0.00035***	-0.00030***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prec	-0.00164***	-0.00140***	-0.00124***	-0.00110***	-0.00099***	-0.00090***	-0.00081***	-0.00071***	-0.00058***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000**	0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTmax	-0.086***	-0.078***	-0.072***	-0.067***	-0.063***	-0.060***	-0.057***	-0.053***	-0.048***
	(0.008)	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
LPrec	-0.001***	-0.001***	-0.001***	-0.0009***	-0.0008***	-0.0007***	-0.0006***	-0.0005***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,645	12,645	12,645	12,645	12,645	12,645	12,645	12,645	12,645
Districts	275	275	275	275	275	275	275	275	275

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
LTmax: Long term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A10: Fixed effect quantile regression naïve model for wheat crop (1986-2015) (W2)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	0.00488***	-0.00112***	-0.00485***	-0.00790***	-0.01046***	-0.01287***	-0.01512***	-0.01760***	-0.02096***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{max}{}^2$	-0.00035**	-0.00025**	-0.00019**	-0.00013*	-0.00009	-0.00005	-0.00001	0.00003	0.00009
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prec	-0.00115***	-0.00087***	-0.00069***	-0.00055***	-0.00043***	-0.00031***	-0.00021***	-0.00009***	0.00007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000**	0.00000	0.00000	0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTmax	-0.015*	-0.016**	-0.016***	-0.0158***	-0.0157***	-0.0157***	-0.0158***	-0.0158***	-0.0159***
	(0.008)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
LPrec	-0.0008***	-0.0006***	-0.0005***	-0.0004***	-0.0003***	-0.0002***	-0.0001***	-0.00003***	0.00008
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,597	7,597	7,597	7,597	7,597	7,597	7,597	7,597	7,597
Districts	272	272	272	272	272	272	272	272	272

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

LTmax: Long term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Table A11: Fixed effect quantile regression inclusive of penalty term model for wheat crop (1986-2015) (W2P)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_{max}	0.03121	0.02106	0.01476	0.00963	0.00527	0.00114	-0.00274	-0.00701	-0.01285
	(0.028)	(0.020)	(0.015)	(0.012)	(0.011)	(0.010)	(0.011)	(0.012)	(0.016)
$T_{max}{}^2$	-0.00146*	-0.00115*	-0.00096**	-0.00081**	-0.00068**	-0.00055*	-0.00043	-0.00030	-0.00013
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Prec	-0.00131***	-0.00099***	-0.00078***	-0.00062***	-0.00048***	-0.00034***	-0.00022*	-0.00008	0.00011
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Prec^2$	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000***	0.00000**	0.00000	-0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Penalty_{Tmax}$	0.00292	0.00345	0.00379	0.00406	0.00429	0.00451	0.00471	0.00494	0.00525
	(0.022)	(0.015)	(0.012)	(0.010)	(0.008)	(0.008)	(0.008)	(0.010)	(0.012)
$Penalty_{prec}$	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000**	-0.00000	-0.00000	-0.00000	0.00000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LTmax	-0.033*	-0.0298**	-0.0277**	-0.0259***	-0.0245***	-0.0232***	-0.0219***	-0.020**	-0.0185*
	(0.019)	(0.013)	(0.010)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)
STmax	-0.0319*	-0.0283**	-0.026***	-0.0243***	-0.0227***	-0.0212***	-0.0199***	-0.0183**	-0.0162*
	(0.016)	(0.011)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.009)
LPrec	-0.0008***	-0.0006***	-0.0005***	-0.0004***	-0.0003***	-0.0002**	-0.0001	-0.0000	0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
SPrec	-0.0007***	-0.00056***	-0.0004***	-0.0003***	-0.0002***	-0.0002***	-0.0001	-0.0000	0.0001
	(0.0002)	(0.0001)	(0.0001)	(.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State QTrend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,512	7,512	7,512	7,512	7,512	7,512	7,512	7,512	7,512
Districts	272	272	272	272	272	272	272	272	272

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
LTmax: Long term marginal temperature effect at overall mean of observed temperature; STmax: Short term marginal temperature effect at overall mean of observed temperature; LPrec: Long term marginal precipitation effect at overall mean of observed precipitation; SPrec: Short term marginal precipitation effect at overall mean of observed precipitation; QTrend: Quadratic state time trend

Figure A1: Trend in crop yields

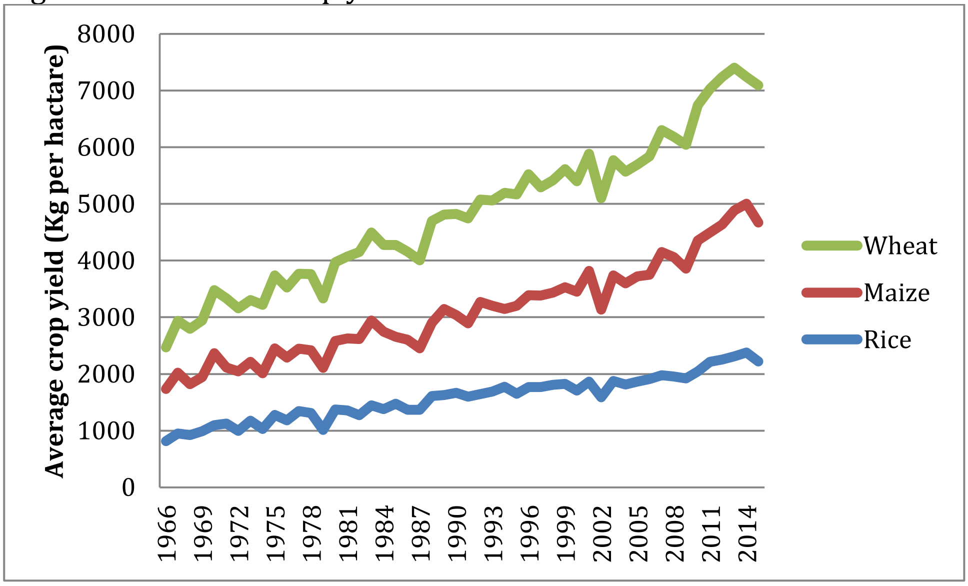


Figure A2: Rice yield responses to T_{max} and precipitation (fixed effect panel model)

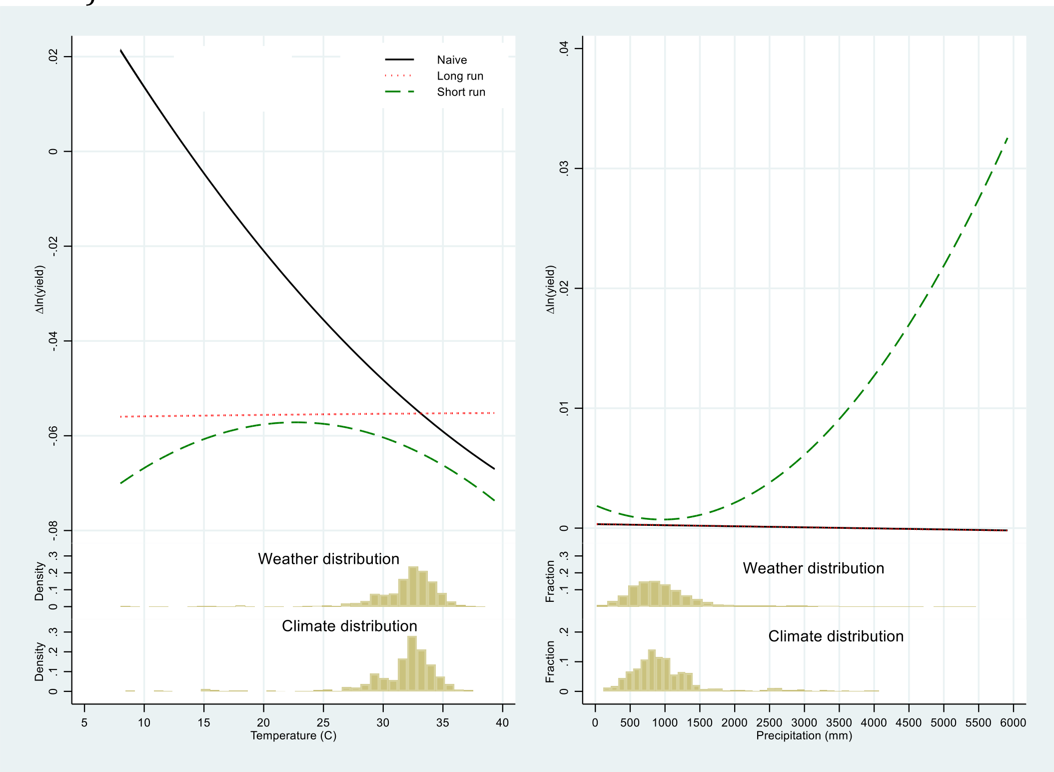


Figure A3: Maize yield responses to T_{max} and precipitation (fixed effect panel model)

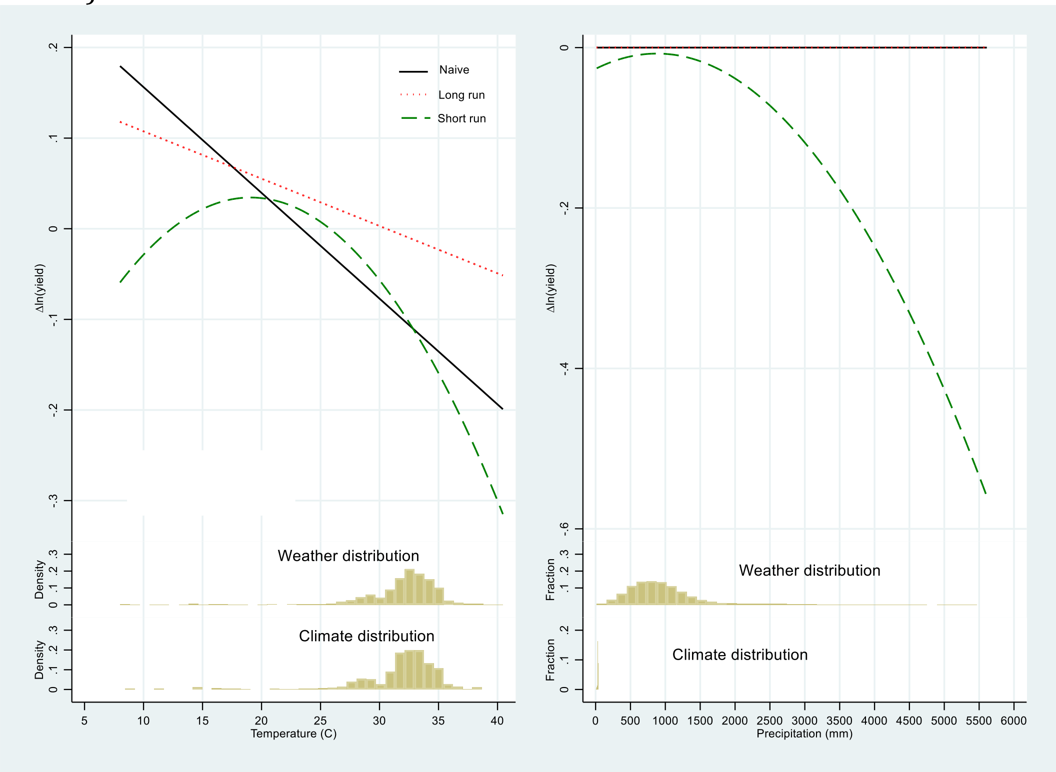


Figure A4: Wheat yield responses to T_{max} and precipitation (fixed effect panel model)