Adaptation to Temperature Extreme in Chinese Agriculture, 1981 to 2010 *

Di Wang† Shuai Chen‡ Peng Zhang †§

November 20, 2020

Abstract

Temporal Evolution of extreme temperature effects on agriculture is important for understanding adaptation to climate change but has been insufficiently studied. This study examines the time-varying impacts of extreme temperatures on Chinese agriculture over 1981 to 2010. We estimate a period-specific panel regression model using nationwide county-level agriculture production data combined with fine-scale meteorological data. There are three primary findings. First, crop yields have become more heat-resilient over time. The impact of a daily exposure to extreme temperatures on corn and soybean yields in the post-1996 period is 40% to 50% less than that in the pre-1996 period. Second, irrigation is the most effective adaptive input among the four examined. Third, the decline in the temperature sensitivity of crop yields over time has mainly occurred in counties with irrigation expansion. The estimates of the marginal adaptation effect of irrigation and average irrigation expansion suggest that expanding irrigation coverage over time accounts for 25% to 30% of the decline in the impacts of extreme temperatures.

Keywords: Climate Change, Ex Post Adaptation, Chinese Agriculture

JEL Classification: Q54 Q56 O13 C23

*Di Wang is grateful to his advisors Olivier Deschenes, Kelsey Jack and Kyle Meng for their continuous guidance and support on this project. We also appreciate comments from Tamma Carleton, Clement de Chaisemartin, Christopher Costello, Tatyana Deryugina, Ignacio Esponda, Frances Moore, Andrew Plantinga, Douglas Staigerwald, Dick Startz and all the participants of Econometrics Reading Group and Environmental Economics Reading Group at UCSB and from Ariel Ortiz-Bobea and Jeffery Shrader at the OSWEET Seminar. We are responsible for all the errors.

†Department of Economics, University of California, Santa Barbara, USA; email: dwang01@ucsb.edu

‡China Academy for Rural Development(CARD), Zhejiang University, China; email: shuaichen@zju.edu.cn

§Corresponding author: School of Management and Economics, The Chinese University of Hong Kong, Shenzhen, China; email: zhangpeng@cuhk.edu.cn

1 Introduction

Agriculture is one of the most vulnerable sectors to climate change. The impacts of climate change on agriculture have important implications for food security and relevant well-beings, especially in developing countries in which agriculture is a fundamental source of income. Although literature accumulates on the link between weather and agricultural outcomes, studies of the evolution of agricultural sensitivity to temperature extremes remain limited (Mendelsohn et al., 1994; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Welch et al., 2010; Fisher et al., 2012; Roberts et al., 2012; Lobell et al., 2013; Chen et al., 2016; Burke and Emerick, 2016; Zhang et al., 2017; Chen and Gong, 2020). Understanding the temporal evolution of relationship between temperature and agricultural outcomes helps develop reliable estimates of the costs of climate change and identify solutions that moderate the risks imposed by such change.

Crop yield–the amount of crop production per unit of land area–determines grain supply in the long run, given we can only claim a limited amount of farmland from nature. This study examines the temporal evolution of the temperature-yield relationship in the world's most populous country and provides evidence of a significant decline in extreme temperature impacts on yields that is larger than the those in the literature (Schlenker and Roberts, 2009; Roberts and Schlenker, 2010; Bleakley and Hong, 2017; Ortiz-Bobea et al., 2018). The decline in extreme temperature impacts on yields implies the effect of adaptation to extreme weather conditions. According to the Intergovernmental Panel on Climate Change (IPCC,2007), adaptation generally refers to adjustments by economic agents in response to actual or expected change of weather conditions, which moderates harm or exploits beneficial opportunities.[1] The essence of adaptation is adjustment of inputs.

Since 1980s, as part of the modernization campaign initiated by China's central government, farming methods in Chinese agriculture have been improved through mechanization, irrigation expansion and fertilizer use (OECD, 2012). Especially after 1996, a number of agricultural policies are collectively designed to achieve a food self-sufficiency objective set in 1996 (The State Council of P.R. China, 1996). Agricultural subsidy aim to provide farmers with an incentive to replace traditional labor-intensive and low-productivity methods of farming with modern mechanized production systems, which will increase productivity and reduce production vulnerability to extreme heat (Huang et al., 2013). We empirically find that the decline in extreme temperature impacts is significantly associated with the expansion of irrigation coverage since 1996, suggesting that input-driven decline in temperature sensitivity across time periods can be used to infer the effect of adaptation to extreme temperatures.

[1] The formal definition of adaptation by the Intergovernmental Panel on Climate Change is adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (2007,6). However, this paper focuses on adaptation to temperature extremes. To reconcile the difference in the subject matter, we define adaptation as adjustment to a change of weather conditions including a new long-lasting climate normal and a new temporary weather condition. Extreme temperatures are predicted to be more frequent under climate change. This study, by focusing on adaptation to temperature extremes, can also shed light on the potential adaptive capacity for long-lasting climate change.

When the timing of input adjustment is taken into consideration, adaptation can be classified as *ex ante* adaptation that is taken before weather realizes and *ex post* adaptation that is taken after weather realizes (Shrader,2018). This paper focuses on the effect of an extreme temperature shock that realizes within growing seasons of crops. Given *ex ante* inputs such as seed variety and irrigation infrastructure that are determined before the growing season, farmers can adjust inputs in response to the actual weather shock such as spraying water on crops to cool the canopy temperature. Therefore, weather realization identifies a combination of the direct impact of extreme temperatures without adaptation and *ex post* adaptation effect conditioning on *ex ante* adaptation, which decreases the estimated size of the direct effect.

This research is one of the most comprehensive studies of the temporal evolution of temperature-yield relationship in China using thirty-year (1981-2010) county-level agriculture production data combined with fine-scale meteorological data. We focus on the yields of corn and soybean, two major grain crops accounting for more than 20% of cropland in China that are important raw materials for edible oil making and livestock feed. Over 1981 to 2010, China experienced noticeable climate change. Annual average temperature increased by 0.02-0.03 °C annually in these three decades based on a calculation using our meteorological data. As China has the world's largest agricultural economy and is a major importer of feed grains (FAO, 2012), adaptation effect implied by the decline in temperature sensitivity is crucial for evaluating the risks imposed to domestic food security and the global grain market by climate change.

The empirical analysis is divided into three parts. The first part documents the decline in the extreme temperature impacts on crop yields by estimating a period-specific panel fixed effect model. We estimate the period-specific extreme temperature effects on crop yields and conduct an F test to examine whether the estimated extreme temperature effects are significantly different across periods in a nested model. We primarily find the impact of daily exposure to extreme temperature (measured by degree days above an endogenously-selected temperature threshold) for corn and soybean production in 1996 to 2010 is 40-50% less than that in the period of 1981 to 1995. This results in a loss reduction of national aggregate corn production by about 155,000 tons and of soybean production by about 11,000 tons compared to the scenario in which pre-1996 extreme temperature impacts on crop yields prevailed.[2] A secondary result shows that yield loss of the two crops due to temperature extremes in the southern regions has declined by a larger percentage than that of the northern regions, which is consistent with the idea that hotter places adapt to temperature extremes better than cooler ones. The estimation of extreme temperature effects relies on controlling for a full set of fixed effects and county-specific time trends, which are added to account for confounding adaptation mechanisms other than *ex post* adjustment of input quantities.

[2] In Section 6.1.1, we provide detailed numerical derivation of the yield loss reduction.

The second part of the analysis aims to examine potential adaptation mechanisms that may mute the relationship between crop yields and high temperatures by estimating marginal adaptation effects of each input. We focus on four inputs–irrigation, fertilizer, agricultural machinery and electricity. We estimate an augmented panel model with temperature-input interactions where the temporal change in inputs is interacted with all the temperature variables. The empirical results point to irrigation as the only effective adaptive input. Irrigation expansion is associated with a significant reduction in yield losses due to extremely high temperatures. By contrast, we find that the use of fertilizer, agricultural machinery and electricity are not statistically related to reductions in heat-related yield losses. Due to data limitation, instead of observing water used for irrigation, we observe irrigation coverage or the proportion of arable land effectively irrigated, which serves as a measure about irrigation capital stock that is determined by farmers *ex ante*. Based on the reasonable assumption that irrigation capital (e.g. pipelines, drainage ditches, wells and dams) facilitates the *ex post* use of irrigation water, we use irrigation coverage as a proxy for the quantity of irrigation water.

Quasi-experimental variation in irrigation is not available, imposing an upward bias on the estimation of the irrigation effect if irrigation co-varies with other temperature-directed adaptation measures (e.g. heat-resilient seed varieties). Three additional results lend credibility to the findings on the adaptation effects of irrigation. First, the temporal change in irrigation is negatively correlated with the change in extreme temperature variables, suggesting that the estimation of the irrigation effect may be downward biased, which is a less severe problem than the effect being upward biased. Second, irrigation does not affect the yield consequences of exposure to low temperatures below a threshold, suggesting that irrigation expansion is not coincident with factors that determine the overall yields. Third, the estimation of irrigation effect is robust to a model including parametric proxies for confounding factors. Temperature-by-year trends which are generated by the interactions of the year with all the temperature variables, allows for the possibility that the effects of temperature extremes on crop yields change over time for reasons co-varying with irrigation. The interactions between temperature change and the change of economic development indicators such as GDP and cargo quantities by road (a proxy for road kilometers) control for other time-varying observables in parallel with input adoption. But we cannot rule out all sources of bias. Therefore, we only claim the association between irrigation expansion and temperature sensitivity reduction as suggestive evidence for the adaptation effect of irrigation.

Following the second part pointing to irrigation as the central adaptive input, the third part of the empirical analysis provides evidence of the mechanisms for adaptation through the change of irrigation. The role of irrigation in attenuation of temperature sensitivity can be quantified by the heterogeneous adaptation effect by the extent of temporal change in irrigation coverage.[3] We create

[3] As 1996 serves as the dividing year of the whole period (1981 to 2010), the irrigation variation over time periods is calculated by the difference between the 1981-1995 average of irrigation and 1996-2010 average.

a category variable specifying whether a county has experienced increases or decreases in irrigation coverage and interact the category variable with the temperature and precipitation variables in the baseline period-specific panel model. Only counties with an increase in irrigation coverage experienced a significant decline in agricultural sensitivity to extreme temperatures, implying that irrigation may be one of the mechanisms for the evolving effects of temperature extremes on yields. The estimated marginal adaptation effect of irrigation and average size of irrigation expansion suggests that expansion of irrigation coverage over time accounts for 25% to 30% of the decline in extreme temperature impacts. We also find that only yields in counties with an increase in irrigation coverage above 9.5 percentage points which is the 75th percentile of the distribution of the change in irrigation coverage, became less sensitive to excessive precipitation (measured by precipitation above a threshold) over the two periods suggesting irrigation also affects adaptation to a precipitation shock.

This study contributes to three threads of literature. First, it is the first comprehensive study of the temperature-yield relationship over a period of unprecedented economic structural change in the world's most populous country. Our finding shows a decline in the impacts of extreme temperatures on crop yields over time that is larger than that in the previous literature (Schlenker and Roberts, 2009; Roberts and Schlenker, 2011; Bleakley and Hong, 2017 and Ortiz-Bobea et al., 2018). Three of the four papers on temporal evolution of temperature-yield relationship in the US find no evolution of temperature sensitivity or increasing temperature sensitivity in the most recent decades of the 20th century. The only exception is Bleakley and Hong (2017), which find the temperature sensitivity of farm value in the US of the 20th century was significantly lower than that in the 19th century but they do not show how the farm value had evolved within the 20th century. The findings of this study suggest that estimates of temperature sensitivity from an earlier period may not be a good guide to predicting climate-change impacts in the future.

Second, this paper provides new evidence on the importance of irrigation for adaptation to temperature extremes(Taraz, 2017; Tack et al., 2017; Fishman, 2018; Zaveri and Lobell, 2019). Taraz (2017) and Fishman (2018) focus on the use irrigation to adapt to precipitation shocks and find no adaptation effects of irrigation to precipitation change. Tack et al. (2017) and Zeveri and Lobell (2019) find that temperature sensitivity of yields in irrigated farming areas is lower than that in the pure rain-fed farming areas. The major difference between this study and those by Tack et al., Zeveri and Lobell is that they focus on a cross-sectional comparison of temperature sensitivity across areas grouped by the extent of irrigation coverage while we provide a longitudinal comparison of temperature sensitivity over time that varies by irrigation coverage. The variation in irrigation coverage over time allows us to restrict the correlation between irrigation adoption and unobserved confounding factors such as crop varieties already adaptive to local climates.

Third, this studies shows the complementarity between *ex ante* and *ex post* adaptation: the expansion of irrigation coverage is associated with a stronger *ex post* adaptation effect. The literature assumes that all adaptive adjustments are made ex ante (Dell et al., 2009, 2012; Burke and Emerick, 2016; Lemoine, 2017; Shrader, 2018, Chen and Gong, 2020). This is how researchers argue that weather realizations cannot identify adaptation effect. But this paper shows theoretically and empirically that weather realizations identify a combination of without-adaptation effect of extreme temperatures and *ex post* adaptation effect, similar to adaptation in the aspect of heat-related mortality (Barreca et al., 2016) and amelioration behavior after the state realizes (Graff Zivin and Neidall, 2013). However, the *ex post* adaptation effect cannot be overstated because the effectiveness of *ex post* adaptation relies on *ex ante* adaptation inputs.

Weather realizations, with a panel fixed effect model conditional on *ex ante* adaptation, bound the direct effect without adaptation from above. The estimated adaptation effect may be downward biased estimated when the without-adaptation effect identified by weather fluctuations is compared to the with-adaptation effect identified by the variation in subsample weather averages (See Dell et al., 2014 for a review). The downward bias may be exacerbated by the complementarity between *ex ante* adaptation and *ex post* adaptation. A stronger *ex ante* adaptation effect is associated with stronger *ex post* adaptation effect due to complementarity. Thus, the direct effect estimated by weather realization is more attenuated upward by the stronger *ex post* adaptation effect and the downward bias is more salient as a result.

Finally, this studies contributes to the literature on the overall effects of adaptation in developing countries. Earlier literature about adaptation in developing countries have been focused on effects of explicitly observed adaptative measures (Kurukulasuriya and Mendelsohn, 2008; Wang et al., 2010; Huang et al., 2015) and determinants of farmers' adaptation decisions (Deressa et al., 2009; Di Falco et al., 2011 a and b). A few more recent studies focus on farmers' *ex post* adjustments of agricultural inputs in response to short-run extreme temperature shock (Aragon, et al., 2019; Jagnani, et al., 2020) but do not evaluate how these adjustments moderate the extreme temperature impacts on agricultural outcomes. The main difference between this study and those above is that this study estimates the overall *ex post* adaptation effects with the approach of examining the temporal evolution of the extreme temperature effects driven by the temporal change in irrigation, a mechanism that is not formally investigated in those studies.

The remainder of the paper is organized as follows. Section 2 introduces the background of agricultural policies after 1996. Section 3 introduces a conceptual framework that explains how the link between temperature and crop yields can be used to identify adaptation effects as well as the mechanisms through which agricultural inputs may mute the temperature-yield relationship. Section 4 describes the data sources and reports the summary statistics. Section 5 presents the econometric models used to examine the temporal evolution of the temperature-yield relationship and the potential explanations of its change over the past 30 years. Section 6 reports the results from fitting the models in Section 5. Section 7 concludes.

2 Background

This section introduces several policies launched after 1996 to encourage investments on agriculture and may improve agricultural adaptation (i.e., 1996 marks the starting year of the change in the temperature–yield relationship). In 1996, the Chinese government set an objective for grain self-sufficiency, aiming to satisfy a minimum of 95% of domestic consumption of rice, wheat, corn, coarse grains, soybeans and potatoes through domestic production(The State Council of P.R. China, 1996; Hyde and Syed, 2014). This state objective stems from the Chinese government's view that China's food security is best maintained by meeting its domestic food demand with domestically produced food, thereby minimizing its reliance on international markets. While the target explicitly focuses on these crops, the production of other food is generally supported by a range of other policies (Hyde and Syed, 2014; Simon et al. 2014).

The self-sufficiency objective is one of the main reasons why the Chinese government intervenes in China's agricultural market. Self-sufficiency is supported by market price support and agricultural subsidies that encourage agricultural production. Price support refers to a minimum purchase price set by the Chinese government for each targeted crop(OECD, 2005, 2013), which is shown to increase monthly average prices and reduce the price volatility (Li and Chavas, 2018). Therefore, price support may increase farmers' income and stimulate investment on agriculture through the income effect. Agricultural subsidies for private farmers are designed to improve uptake of modern agricultural practices, thereby providing farmers with an incentive to adopt capital-intensive inputs that may include adaptive inputs(OECD, 2013).[4] Other subsidies known as awards are paid directly to county governments in areas that have high grain production. These subsidies are aimed to encourage public investment in both infrastructure and research to support production (Gale, 2013).

Although the policies supporting the national objective of food self-sufficiency are designed to ensure food security and increase farmers' income, rather than targeting climate change, they may improve adaptation to extreme weather condition because they encourage the adoption of more efficient agricultural inputs such as fertilizer, irrigation and agricultural machinery. Understanding how input utilization driven by these agricultural policies moderates extreme temperature impacts is thus important for developing effective adaptive strategies.

[4] An example is the "One Exemption and Three" policy. "One Exemption" refers to the exemption of agricultural taxes. "Three Subsidies" refers to subsidies to farmers based on individual's total planted area to increase their income, subsidies for high-quality seed varieties and subsidies for the purchase of mechanized agricultural inputs. The adaptation effect of adopting heat-resilient seed varieties cannot be explicitly investigated because of data limitations. Hence, we use county-specific time trends in the panel model to account for the smooth change in crop yields that may be driven by technology advancement including high-quality seeds.

3 Conceptual Framework

3.1 Identifying Ex post Adaptation

In this section, we present the theoretical framework used to formalize how temporal evolution of extreme temperature impacts implies effect of adaptation to temperature extremes and the relationship between *ex ante* adaptation and *ex post* adaptation, which helps us understand the identification strategy for the *ex post* adaptation effect and the linkage between theory-predicted input adjustment and the real input adjustment that can be observed in the data. The key factor to understanding the relationship between *ex ante* adaptation and *ex post* adaptation is the timing of adaptive inputs. For extreme temperature shocks that occur after the start of the growing season, farmers can adjust inputs in response to realization of extreme temperatures (e.g. using irrigation water). *Ex ante* adaptive inputs can facilitate the use of *ex post* adaptive inputs. For example, it is very costly to extract irrigation water after extreme temperature realizes unless irrigation system (e.g. drainage ditches, wells, dams, canals) has been built up ex ante.

Consider a farmer producing a single type of crop on a unit parcel of land in year t. Conditioning on the capital stock K^* for adaptation, which is determined before weather realizes, the farmer chooses input x_t after weather realizes to maximize the profits in equality (1). The yield is a function of realized weather w_t during the growing season of year t, adaptive capital stock K and an adaptive flow input x_t determined after weather w_t realizes.[5] The adaptive capital stock K_t^* (e.g. irrigation infrastructure) is *ex ante* adaptation input that is determined before weather realizes while the flow input x_t is *ex post* adaptive input that is determined after weather realizes. Therefore, the farmer's problem can be written as

$$\max_{x_t} \pi_t(K_t^*, w_t) = P_t \cdot F(x_t, K_t^*(\mathbb{E}_{t-1}(w_t)), w_t) - P_{x,t} \cdot x_t - P_{K,t} \cdot K_t^*(\mathbb{E}_{t-1}(w_t)) \tag{1}$$

The farmer chooses K_t^* in year $t-1$ based on $\mathbb{E}_{t-1}(w_t)$ which is farmer's expected weather of year t conditional on information about the weather in all years up to and including the most recent year $t-1$.[6] $P_t, P_{x,t}$ and $P_{K,t}$ denote the crop price and input prices. Assume that production function $F(x, K, w)$ is continuous, twice differentiable and concave. The marginal productivity of the two inputs is assumed to be strictly decreasing. *Ex ante* adaptive capital K_t is assumed to be complementary to *ex post* adaptive input x_t such that $F'_w < 0, F''_{wx} > 0, F''_{wK} > 0, F''_{xK} > 0$.[7] Conditioning on a fixed K^* and a realization of weather w_t, the first order condition is

[5] As we aim to estimate effects of realized extreme temperatures during the growing season, seed variety and cropping area are determined prior to weather realizations and therefore are not arguments of the realized production function.
[6] For a derivation of *ex ante* investment as a decision in anticipation of future weather conditions, see Lemoine (2019).
[7] $F'_w = \frac{\partial F}{\partial w}, F''_{wx} = \frac{\partial^2 F}{\partial w \partial x}, F''_{wK} = \frac{\partial^2 F}{\partial w \partial K}, F''_{xK} = \frac{\partial^2 F}{\partial x \partial K}$.

$$P_t \cdot F_x'(x_t, K_t^*(\mathbb{E}_{t-1}(w_t)), w_t) = P_{x,t}$$

The first-order condition clarifies that optimal x_t^* is a function of realized weather w_t and *ex ante* input K^*. Differentiating the first order condition with respect to K_t^* and w_t, we can show that $\partial x_t^* / \partial w_t > 0$ given the *ex ante* adaptive input K_t^* and $dx_t^*/dK_t^* > 0$ conditioning on weather realization w_t. The former implies that *ex post* adaptation is positively responsive to rising temperatures and the latter suggests *ex ante* adaptation facilitates use of *ex post* adaptation. The complementary relationship between *ex ante* and *ex post* adaptive inputs provides a basis for using the change in the *ex ante* input as a proxy for the change in the *ex post* input. This is applicable to estimating the adaptation effect of irrigation. In the data, we can only observe irrigation coverage (i.e. the fraction of arable land that is irrigated) which is a measure more about *ex ante* adaptation. The complementary relationship between irrigation capital and irrigation water use allows us to use the change in irrigation coverage as a proxy for *ex post* use of irrigation water.

Denote $y_t = F(x_t^*(K_t^*, w_t), K_t^*, w_t)$ as realized crop yield at the optimal input level. The aggregate effect of a temperature shock on crop yields can be expressed as

$$\frac{\partial y_t}{\partial w_t} = \frac{\partial F}{\partial w_t} + \frac{\partial F}{\partial x_t^*} \frac{\partial x_t^*}{\partial w_t} \tag{2}$$

The first term is the direct effect of an extreme temperature shock without adaptation and the second term is the *ex post* adaptation effect. The effect of weather realization is a combination of the direct effect of realized weather without an adaptation effect and *ex post* adaptation effect. This implies that the effect of weather realization on economic outcomes estimated through a panel fixed effect model conditional on *ex ante* adaptation bounds the direct effect without adaptation from above. Therefore, the adaptation effect may be downward biased when estimated by comparing the without-adaptation effect identified by weather fluctuations with the with-adaptation effect identified by the variation in subsample weather averages (See Dell et al., 2014 for a review). The downward bias may be exacerbated by the complementarity between *ex ante* adaptation and *ex post* adaptation. A stronger *ex ante* adaptation effect is associated with a stronger *ex post* adaptation effect due to complementarity. Thus, the direct effect estimated by weather realization will be more attenuated upwards by the stronger *ex post* adaptation effect and the downward bias will be more salient as a result.

The adaptation effect consists of marginal adaptation effect of the *ex post* input ($\partial F / \partial x^*$) and responsiveness of the *ex post* input to weather realization ($\partial x^* / \partial w$). Hence, mechanisms for *ex post* adaptation are either a quantity change in inputs in response to weather realizations or a efficiency change in inputs in terms of adapting to temperature extremes, which may be related to technological innovation (e.g. drip irrigation is more efficient than sprinkler irrigation which is more efficient than surface irrigation). Because we only observe agricultural inputs rather than technological innovation in the data, this study aims to estimate the *ex post* adaptation effect through the mechanism of quantity change in inputs. Our approach is to compare extreme temperature impacts on crop yields ($\partial y/\partial w$) over time periods based on the assumption that the direct effect ($\partial F/\partial w$) remains constant over time periods. We use a model specification of province-by-year fixed effects and local time trends to account for the temporal change in input efficiency in terms of moderating extreme temperature impacts on yields. In this way, we can disentangle the adaptation mechanism of change in input benefits from the mechanism of change in inputs quantity to quantify the share of decline in temperature sensitivity that is explained by temporal change in inputs.

Figure 1 illustrates the empirical strategy by depicting the evolution of temperature-yield relationship over time periods. This relationship is modeled as an inverted U shaped parabola because the literature has documented the nonlinear effects of temperature on crop yields (Schlenker and Roberts, 2009 and Lobell et al, 2011). The steeper parabola denotes the temperature-yield relation in Period 1 and the flatter one denotes the relation in Period 2. In Period 1, an unanticipated increase of temperature from the yield-maximizing T_0 to T_1 generates yield loss measured by $AB = Y_0 - Y_1$. If farmers have more access to adaptive inputs in Period 2, the yield loss caused by the same temperature increase reduces to $AC = Y_0 - Y_2$. The adaptation benefit is $BC = Y_2 - Y_1$, which represents the reduction in temperature-related yield loss due to increased use of adaptive inputs. The evolutionary effects of extreme temperatures on crop yields can be estimated by a period-specific panel fixed effect model following the empirical strategy by Barreca et al. (2016). Instead of estimating AB and AC directly, we can only estimate marginal effects of temperature rise. The coefficients for the high temperature variable provide the estimate of $\frac{|AB|}{|T_1-T_0|}$ and $\frac{|AC|}{|T_1-T_0|}$.

3.2 The Ideal Econometric Model and A Practical Substitute

The temperature-yield relationship derived above suggests that contemporaneous crop yield is a function of both realized weather and expectation of current weather conditions from the previous standing point. Therefore, the ideal econometric model on this relationship would be

$$y_{it} = b_0 + b_1 \cdot w_{it} + b_2 \cdot \mathbb{E}_{i,t-1}(w_{it}) + \nu_{it} \tag{3}$$

where i denotes the cross-sectional unit (e.g. counties). w_{it} is the current local realization of weather. $\mathbb{E}_{i,t-1}(w_{it})$ is individual i's expectation about the future weather based on previous realized weather up to and including year $t-1$, as described in equality (1). The term of weather realization is to estimate the marginal effect of a temperature shock including the direct effect and the *ex post* adaptation benefit. The term of weather expectation is to estimate the *ex ante* adaptation benefit.

However, observing private expectation is impossible in this study and finding good proxies for farmers' beliefs is challenging in general. Leaving the expected weather term into the error term would threaten the identification assumption for weather realization (i.e. $\mathbb{E}(w_{it}\nu_{it}) = 0$) because weather expectation as a function of previous weather may be correlated with the current weather under climate change wherein temperatures at locals have been stably increasing over time. A panel model with two-way fixed effects is thus the preferred substitute for the ideal model.

By conditioning on county and province by year fixed effects, the weather variation comes from county-specific deviations in weather around the county averages after controlling for shocks common to all counties in a province (Deschenes and Greenstone, 2007) which is less likely to suffer from the serial correlation problem. In addition, we estimate spatial heteroskedasticity- and autocorrelated-consistent (HAC) standard errors to allow for county-specific serial correlation (Hsiang, 2010). Therefore the practical model for estimation is

$$y_{it} = \alpha_i + b_0 + b_1 \cdot w_{it} + \eta_{pt} + \nu_{it} \tag{4}$$

where α_i are the county fixed effects and η_{pt} is province-by-year fixed effect. We extend equation (4) to a period-specific panel fixed effect regression model in Section 4.

4 Data Sources and Summary Statistics

4.1 Data Sources

Agricultural production data. We collect a county-level agricultural dataset on China from 1981 to 2010. The county-level agriculture data comes from the Chinese Academy of Agricultural Sciences, which collected this data jointly with the Ministry of Agriculture. The Chinese Academy of Agricultural Sciences sent agricultural survey teams to villages where surveyors interviewed farmers. The data were then aggregated to the county level. Agricultural data on the Xizang Autonomous Region (Tibet) and Qinghai Province are limited. These two provinces are located on the Qinghai–Tibet Plateau with an average elevation of over 4000 m; hence, agricultural activities involving the three major crops are scarce. Thus, the impact of these missing data on our analysis should be limited.

The variables in the agricultural data relevant to this research include the county-level production and planted area for the two investigated crops, corn and soybean, as well as agricultural inputs that may alleviate extreme temperature effects. These inputs include the irrigated sown area (in hectares), agricultural machinery power (in kilowatts), aggregate labor inputs (labor employed in the crop farming, forestry, husbandry, and fishery sector as a whole), fertilizer use, and electricity use (in kilowatt hours) in each county's rural area. In the analysis of agricultural inputs as adaptation measures, we use irrigation coverage (i.e., proportion of farmland irrigated; calculated as the ratio of the irrigated area to the arable area), per hectare agricultural machinery power (kilowatt/ha), per hectare fertilizer use (ton/ha), and per capita electricity use (kilowatt hour per capita). However, we cannot observe agricultural inputs for a single crop, preventing us from accurately estimating the role of agricultural inputs for each crop in mitigating the heat-related yield loss.

Crop region division and growing season. Corn and soybean are planted across China but they differ in variety and growing season by region because of spatially varying climatic conditions. The Chinese Cropping System (2005) and Liu (1993) provide us with the division of the corn and soybean regions and corresponding growing seasons, as illustrated in Figures A.1 and A.2, respectively. Corn and soybean in China can be categorized by season (Chen et al., 2016). Spring corn and soybean, typically planted in April and harvested in late September, are concentrated in the northeast, northwest inland areas, and southwest mountainous areas. Summer corn and soybean are grown in June and have a slightly shorter growing season than spring corn does and are primarily produced in the Huang-Huai-Hai (HHH) Plain area. Autumn corn and soybean are mainly planted in the mountainous areas of the south and southwest regions. A small amount of winter corn and soybean is planted in the tropical areas of the south and southwest regions, accounting for less than 5% of national production (Zhang et al., 2017). Figure A.2 shows that the growing seasons of the two crops are concentrated around April to September (i.e., spring and summer) when the country is experiencing frequent heat shocks. This provides us more data variation for estimating the heat-related yield loss.

Weather. The weather data are from the National Meteorological Information Center of China, which is the official institute of weather data gathering and publishing. We collected station-day data for 824 stations across China from 1981 to 2010 (see Figure A.3). To transform the weather data from the station level to the county level, we use the inverse distance weighting method, a standard method commonly used in the literature (Mendelsohn et al., 1994; Deschenes and Greenstone, 2007, 2011; Zhang et al., 2017). First, we choose a circle with a 200 km radius for each county's centroid. We then take the weighted average of the weather data for all the stations within the circle, where the weights are the inverse of the distance between each station and the county's centroid. Finally, we assign the weighted average to each county.[8]

4.2 Summary Statistics

Weather Statistics. Table 1 summarizes the corn and soybean productivity and climate conditions within the growing season of each crop. The mean value of each variable is the national mean of county's average within each time period (1981-1995 and 1996-2010) weighted by county's planted area

[8] Auffhammer et al. (2013) suggest using a relatively continuous weather record for weather stations when averaging daily station-level data across space. This is to avoid the large pseudo-variation generated by missing station-level data, which is crucial for estimating standard errors because the weather variation should be small in the panel setting relative to the cross-sectional setting. This is a minor issue, as the proportion of missing values in all the observations is less than 0.01% for all the climate variables except evaporation (Zhang et al., 2017). The share of missing values for evaporation is about 25% and the stations with a large amount of missing observations for evaporation are all located in the Tibet–Qinghai Plateau, which is dropped from the analysis.

for each crop. To highlight differences over time, Table 1 reports summary statistics separately for the 1981-1995 and 1996-2010 periods. From the pre-1996 period to the post-1996 period, the average annual corn(soybean) yield increased from 4262 kg/ha (1361 kg/ha) to 5698 kg/ha (1819 kg/ha). Climate conditions are described by two parts: regular climate variables including temperature and precipitation and additional climate variables including relative humidity, sunshine duration, wind speed, evaporation and ground surface temperature. Evolution of these climate conditions over the two time periods suggests that the climate has become hotter, drier, less humid and exposed to less sunshine in the historical long run.

Figure 2 presents the spatial distribution of the change in temperature and precipitation change in the corn and soybean area over time. The climate has changed largely and the extent of change vary substantially over space. As shown in Figure 2, China has experienced a nationwide temperature rise from 1981 to 2010, with the annual average temperature increase varies from less than 0.2 °C to more than 1 °C. Only a few counties in the south and southwest of the corn and soybean area experienced a decreasing temperature. Counties in the north experienced a more rapid temperature increase. At the same time, annual average of precipitation decreased in the north or increased in the south as much as 10 mm (1 cm). The spatial difference and changing climate provide large variation for reliably estimating the temperature-yield relationship.

Agricultural production statistics. Figure 3 depicts spatial distribution of annual average of crop yields over 1981-2010 and of percentage change of annual average of 1981-1995 relative to 1996-2010. The majority of counties had increasing yields of the two crops (See Figure 3, Panel b and d) but counties experiencing larger temperature increase in Figure 2 tend to have a lower increasing rate of crop yields, implying that high temperature deteriorate crop productivity.

The agricultural data set provides data on irrigation coverage, fertilizer use, agricultural machinery and electricity. These four inputs are the potential measures that can effectively mitigate the extreme temperature effect on crop yields.[9] Irrigation coverage is measured by the fraction of arable land that is effectively irrigated i.e. the ratio of irrigated land area over arable land area; agricultural machinery is measured by agricultural machinery power used for each hectare of total planted area; fertilizer is measured by fertilizer inputs used for each hectare of total planted area; electricity is measured by electricity consumption per capita of rural population. The total planted area is the aggregate planted area for all crops. We cannot observe separate inputs for each crop in the data.

We are more interested in the change in the four inputs over time than the level because we aim

[9] The four inputs may help farmers mitigate extreme temperature effects in different ways based on agronomic theory. Irrigation may reduce heat stress by offsetting the additional evapotranspiration demand due to higher temperatures (Lobell et al., 2013) and cooling the canopy temperature (Siebert et al., 2014). Fertilizer use enhances plant growth by providing the nutrients essential to leaf growth (nitrogen) as well as the development of roots, flowers, seeds, and fruit (phosphorus) and strong stem growth, moving water in plants, and promoting flowering and fruiting (potassium). Apart from at the start of the growing season for sowing, agricultural machinery also plays an important role in plant protection (mobile sprayers) and harvesting (Edwards and Hanna, 2020), the timing of which is sensitive to daily weather conditions. Electricity, as a necessary fuel to power agricultural activities, should be regarded as a potential mechanism for mitigating extreme temperature effects.

to estimate the extent to which the change in potential adaptive inputs accounts for the change in temperature sensitivity. Figure 4 depicts the distribution of the change between the pre-1996 and post-1996 periods for each adaptive input. The change in input variables is calculated by the difference between the 1981–1995 average and 1996–2010 average. The mean value of each input change, as depicted by the dashed line in each histogram, is positive, implying that agricultural inputs have increasingly been used in China over time, which is consistent with the rapid growth in the Chinese economy in the past three decades. There is large variation in the change in each input across counties, allowing us to accurately estimate the effects of inputs in mitigating extreme heat impacts. In contrast to those inputs increasingly used in most counties, almost as many counties show irrigation expansion as irrigation contraction, generating a close-to-zero mean value of irrigation change. Considering the distributional characteristics for irrigation coverage, we compare the temperature sensitivity of crop yields in counties with irrigation expansion to that in counties with irrigation contraction to explain the change in temperature sensitivity.

5 Empirical Strategy

This section describes the models estimated to infer the relationship between crop yields and weather shocks over time periods as well as factors that modify the relationship over time.

5.1 The Econometric Model for Temperature-Yield Relationship

We first describe the regression model used to estimate the temperature-yield relationship. Since we use a panel setting with county and province-by-year fixed effects, the responses of crop yields to weather shocks are identified through the plausibly exogenous variation in weather over time at the county level after adjusting for common shocks to all counties within a province in a year. We interact all the weather variables with a dummy variable of period indicator to capture the evolution of temperature-yield relationship due to adaptation. The baseline regression model we estimate is as follows:

$$
\begin{aligned}
y_{it} = &\sum_{d=1}^{D} GDD_{it,l_0:l_1} \cdot \mathbf{1}\{period = d\} \cdot \beta_{1,d} + \sum_{d=1}^{D} GDD_{it,l_1:\infty} \cdot \mathbf{1}\{period = d\} \cdot \beta_{2,d} \\
&+ \sum_{d=1}^{D} Prec_{it,p<p_0} \cdot \mathbf{1}\{period = d\} \cdot \beta_{3,d} + \sum_{d=1}^{D} Prec_{it,p>p_0} \cdot \mathbf{1}\{period = d\} \cdot \beta_{4,d} \\
&+ \sum_{d=1}^{D} \mathbf{w}_{it} \cdot \mathbf{1}\{period = d\} \cdot \boldsymbol{\beta_{5,d}} + \sum_{d=1}^{D} \mathbf{w'}_{it} \cdot \mathbf{w}_{it} \cdot \mathbf{1}\{period = d\} \cdot \boldsymbol{\beta_{6,d}} \\
&+ \alpha_i + \eta_{pt} + \lambda_{i,1} t + \lambda_{i,2} t^2 + \epsilon_{it}
\end{aligned} \tag{5}
$$

where y_{it} is the log of annual crop yields in county i and year t. D denotes the number of periods in the panel. The baseline period is 15 years i.e. the first period is 1981 to 1995 and the second period is 1996 to 2010. The motivation for the 15-year division is based on a series of agriculture policies formulated in the post-1996 period, as introduced in the background section. In addition, the 15-year division allows us to construct two balanced time periods as there are 30 years of data in total.

GDD_{it} and $Prec_{it}$ denote growing degree days and precipitation, respectively; the measurement of these two variables is introduced in the following paragraph. The vector $\mathbf{w}_{it}$ denotes the additional climate variables other than temperature and precipitation including relative humidity, sunshine duration, wind speed, evaporation and ground surface temperature as mentioned in Section 4.2 and their quadratic forms captured by the inner product of vector $\mathbf{w}_{it}$. Additional climate variables are controlled for because the full set of climate variables are correlated (Lawrence, 2005; Wooten, 2011; Zhang et al, 2017) and omitting climate variables other than temperature and precipitation can overestimate the extreme temperature effects on crop yields (Zhang et al, 2017). The indicator variable $\mathbf{1}\{period = d\}$ specifies the time period denoted by d and this interacts with all climate variables.

The specification includes a full set of fixed effects. α_i are the county fixed effects to account for county-specific time-invariant determinants of crop yields such as soil quality; η_{pt} denotes province-by-year fixed effects to account for province-level shocks. For example, agricultural subsidies provided by provincial-level governments can affect agricultural productivity, while province-level price shocks especially government-procuring crop prices provide incentives of adjusting inputs such as cropland and labor and therefore affect crop productivity. Omitting policy-wise distinctions across provinces may lead to comparison of counties in different policy regimes, which may bias the estimation of temperature-yield relationship if climate conditions are inputs for agricultural-policy making.

Along with the province-by-year fixed effects, county-specific time trends account for province-level differences and county-specific heterogeneity in adaptation mechanisms other than *ex post* adjustment of input quantities. We adopt two potential confounding adaptation mechanisms for the *ex post* adaptation. The first case is *ex ante* adjustment of inputs in anticipation of local climate trends. For example, farmers adopt more heat-resilient seed varieties before the start of growing season in anticipation of evolution of local climate. The second case is increasing marginal adaptation effect of inputs over time that may moderate extreme temperature impacts without adjusting input quantities. For example, water-saving irrigation technologies allow farmers to irrigate more extensively with the same amount water as used under old technologies.

The variable of central interest is extreme temperatures. The literature has demonstrated strong nonlinearities in the relationship between temperature and agricultural outcomes (Schlenker and Roberts, 2009). Nonlinearities are generally captured using the concept of growing degree days (GDD), which measure the amount of time a crop is exposed to temperatures between a given lower and upper bound. Following Schlenker and Roberts (2009) and Burke and Emerick (2016), we use the within-day distribution of temperatures to calculate the percentage of each day that each county is exposed to temperatures between given lower and upper bounds , and then sum these daily exposures over a fixed growing season (e.g. April 10 to October 20 for corn in North region) to get a measure of annual growing degree days for those bounds.[10] The lower temperature piece $GDD_{it,l_0:l_1}$ is the sum of GDD between bounds l_0 and l_1 and the upper temperature piece $GDD_{it,l_1:\infty}$ has a lower bound l_1 and is unbounded at the upper end.

Similarly, we measure precipitation in a county as a piece-wise linear function with a kink at p_0. The variable $Prec_{it,p<p_0}$ is the difference between precipitation and p_0 interacted with an indicator variable for precipitation being below the threshold p_0.[11] $Prec_{it,p>p_0}$ is similarly defined for precipitation above the threshold. In the estimation, we set $l_0 = 8$ since 8 °C is considered as the minimum temperature for crop growth (Chen et al, 2016) and allow the data to determine l_1 and p_0 by looping over all possible thresholds and selecting the model that best fit the data based on the Bayesian Information Criterion. This selection process is applied to both the full sample (nationwide) and each single region described in Figure A.1 (in Appendix A). The selected thresholds for growing degree days and precipitation by region are presented in Table 2.[12] The Choice of period length, either 10 or 15 years as a period does not make a big difference to the selected thresholds both for the nationwide sample and regional samples, implying the thresholds of GDD and precipitation have remained stable over time and verifying that evolution of temperature-yield relationship is mainly reflected by flattening the temperature response function instead of shifting temperature thresholds over time, as illustrated by Figure 1. We also conduct robustness checks with multiple thresholds other than the selected ones in Table 2 to avoid threshold misspecificiation. The results of robustness analysis on threshold selection will be presented in Figure 8.

The key coefficient of the model in equation (5) is the β_2 in each period, which measures how crop yields are impacted by exposure to extreme heat in each time period. If economic agents adapt significantly to extreme temperatures, we would expect $\beta_{2,d=1} < \beta_{2,d=2} < 0$; in other words, the estimated marginal effect of a daily exposure to temperature above the threshold in the later period should be significantly lower than that in the earlier period. The value $(\beta_{2,d=1} - \beta_{2,d=2})/\beta_{2,d=1}$ provides the percentage of the short-run impacts of extreme heat offset in the long run and is our measure of the effect of *ex post* adaptation to extreme heat.

[10] We use trigonometric sine curve to approximate the within-day distribution following Snyder (1985). But in the following simple example, we assume instantaneous temperature within a day is identical. If $l_0 = 0$ and $l_1 = 30$, a set of daily average temperature of -1, 0, 5, 10, 29, 31 and 35 would generate $GDD_{it,l_0:l_1}$ equal to 0,0,5,10,29,30 and 30 and $GDD_{it,l_1:\infty}$ equal to 0,0,0,0,0,1 and 5. This example is the same as the one in Burke and Emerick (2016).

[11] We use a simple example to illustrate the idea of piece-specific linear measurement of precipitation. Suppose a county with precipitation of 60 cm this year and the kink point is 48cm, then $Prec_{it,p<p_0} = 0$ and $Prec_{it,p>p_0} = 12$.

[12] We do not estimate a separate temperature–yield relationship for the Loess Plateau region of soybean. Both the northeast region and the Loess Plateau are subregions of the north region in the primary classification of soybean production according to the Chinese cropping system (Liu, 1993). Although they share a common growing season (see Figure A.2), the two subregions have different planted areas. The county-level average soybean planted area of the northeast region (14,502 ha) is 6.7 times as large as that of the Loess region (2162 ha). Restricting the analysis to the northeast subregion only does not make a difference to our conclusion of the adaptation effects in the north of China.

5.2 The Econometric Model for Quantifying the Marginal Adaptation Effects of Inputs

This part of empirical analysis aims to figure out inputs that may have muted the temperature-yield relationship overtime. As shown in Section 3.2, the temporal evolution evolution of temperature sensitivity is driven by changes in the quantities of adaptive inputs over time periods given the assumption that the direct effect of an extreme temperature shock and the marginal adaptation effects of inputs remain stable over time. In the augmented panel model described in equation (6), the interactions of temperature variables and inter-temporal change of adaptive inputs are added to estimate the marginal adaptation effect of inputs.

$$\begin{aligned} y_{it} =& GDD_{it,l_0:l_1} \cdot \beta_1 + GDD_{it,l_0:l_1} \cdot \Delta\overline{\mathbf{Inputs}}_i \cdot \theta_1 + GDD_{it,l_1:\infty} \cdot \beta_2 + GDD_{it,l_1:\infty} \cdot \Delta\overline{\mathbf{Inputs}}_i \cdot \theta_2 \\ &+ \Delta\overline{\mathbf{Inputs}}_i \cdot \phi + Prec_{it,p<p_0} \cdot \beta_3 + Prec_{it,p>p_0} \cdot \beta_4 + \mathbf{w}_{it} \cdot \boldsymbol{\beta_5} + \mathbf{w'}_{it} \cdot \mathbf{w}_{it}\boldsymbol{\beta_6} \\ &+ \alpha_i + \eta_{pt} + \lambda_{i,1}t + \lambda_{i,2}t^2 + \epsilon_{it} \end{aligned} \tag{6}$$

where $\mathbf{Inputs}_{it}$ is a vector of four inputs including irrigation, machinery, fertilizer and $\Delta\overline{\mathbf{Inputs}}_i = \frac{1}{15}\sum_{t=1996}^{2010} \mathbf{Inputs}_{it} - \frac{1}{15}\sum_{t=1981}^{1995} \mathbf{Inputs}_{it}$. Equation (6) is different from equation (5) in two ways. First, equation (6) includes the main effects for the inputs (denoted by $\mathbf{Inputs}_{it} \cdot \phi$) and their interactions with the temperature variables (GDD low piece and high piece). Second, equation (6) is estimated using the entire 30-year data without specifying the period-specific effects, which echoes the stability assumption of the direct weather effect (without-adaptation effect) and marginal adaptation effects of inputs. In this specification, the evolution of temperature effects on yields is captured by the change in inputs across the pre-1996 and post-1996 period so that we can quantify the role of each input in reducing the temperature sensitivity. The adaptation effect through each input is estimated by comparing the temperature sensitivity of yields in counties with a larger increase of input adoption to that in counties with a smaller increase or even decrease (e.g. irrigation as shown in Figure 4).

The interaction term estimates the extent to which the effect of a daily exposure to temperatures above the threshold l_1 can be altered by the adaptive inputs. Our hypothesis is that the coefficient on the interaction term (θ_2) is positive. A positive coefficient would be interpreted as evidence that the diffusion of a particular input reduces a crop's vulnerability to temperature extremes. The province-by-year fixed effects along with county-specific time trend account for the same type of confounding factors that may threat the stability assumption, the same as we stated in Section 5.1. For example, adoption of new irrigation technologies such as switching from surface irrigation to sprinkling irrigation may improve the marginal adaptation effect of irrigation even without change in water use. The interaction between inputs and the low temperature category (e.g. $GDD_{l_0:l_1}$) serves as a placebo check because adaptive inputs will not directly protect crops from low temperatures.

A traditional challenge to identification of the inputs' adaptation effects is that the variation in inputs is not experimental, so the estimated θ_2 coefficient is likely to be biased. One type of bias is caused by the correlation between inputs and temperature. If the investigated four inputs co-vary with other temperature-directed adaptation measures that are unobserved, the estimates of the marginal adaptation effects of inputs may be upward biased. Figure 5 shows the extent to which the estimates of the input effects are upward-biased, demonstrating the correlation between the change in an input and change in exposure to extreme temperatures. Extreme temperature exposure is measured by degree days for temperature above the selected threshold presented in Table 2 and the unit of the extreme temperature variable is 100 degree days. The positive correlations for fertilizer use and electricity use with extreme temperature exposure become insignificant after province fixed are controlled for, suggesting that province-level differences are the common driver for the temporal change in irrigation and extreme temperature exposure. Thus, controlling for province fixed effects is necessary for eliminating confounding effects. The correlation between irrigation coverage change and temperature change remains significantly negative even after province fixed effects are controlled for, implying that the estimation of irrigation effect in equation (6) may be downward biased. If the downward-biased estimate is still significantly positive, the endogeneity problem for irrigation may be a less severe problem.

Although we cannot rule out all sources of bias, we adopt the following strategies to minimize the confounding effects generated by factors move in parallel with the four inputs. First, when using province-by-year fixed effects and county-specific time trends, the bias generated by confounding factors cannot occur through province-by-year differences (e.g. Province A expanded irrigation coverage this year relative to Province B as A encountered a growing season with abnormally high temperature) or county-specific gradual changes in crop yields (e.g. investment in irrigation is increased in anticipation of temperature rise and exacerbating temperature sensitivity of crop yields).

Second, we add a temperature-by-year trend to equation (6) as a robustness check. The local temperature trend consists of the interaction between all the temperature variables and a linear year trend. This specification allows for the possibility that the effects of temperature extremes on crop yields change over time for reasons co-varying with any of the four inputs. Third, in addition to local temperature trend, we further control for time-varying observables moving in parallel with the four inputs. For example, irrigation expansion is supported by local economic prosperity and road building is complementary to the use of agricultural machinery. In light of this, interactions of temperature variables with temporal change of local GDP and change in cargo quantities by road are added to equation (6) as another robustness check. The results for these two robustness checks are provided in Section 6.2.

5.3 The Econometric Model for Mechanisms Explaining the Decline in Temperature Sensitivity

The result for estimating equation (6) presented in Section 6.2 will point to irrigation as the central adaptive input that effectively mitigate extreme temperature impacts. This suggests that the decline in temperature sensitivity of yields may be explained by the change in irrigation coverage across the pre-1996 and post-1996 period to some extent. To quantify the extent of this explanation, we estimate equation (7)

$$
\begin{aligned}
y_{it} =& \sum_{j=1}^{4} \sum_{d=1981}^{1996} GDD_{it,l_0:l_1} \cdot \mathbf{1}\{\Delta\overline{\mathbf{Irrigation}}_i \in \mathbf{I}_j\} \cdot \mathbf{1}\{period = d\} \cdot \beta_{j,d}^{T<l_1} \\
&+ \sum_{j=1}^{4} \sum_{d=1981}^{1996} GDD_{it,l_1:\infty} \cdot \mathbf{1}\{\Delta\overline{\mathbf{Irrigation}}_i \in \mathbf{I}_j\} \cdot \mathbf{1}\{period = d\} \cdot \beta_{j,d}^{T>l_1} \\
&+ \sum_{j=1}^{4} \sum_{d=1981}^{1996} Prec_{it,p<p_0} \cdot \mathbf{1}\{\Delta\overline{\mathbf{Irrigation}}_i \in \mathbf{I}_j\} \cdot \mathbf{1}\{period = d\} \cdot \beta_{j,d}^{P<p_0} \\
&+ \sum_{j=1}^{4} \sum_{d=1981}^{1996} Prec_{it,p>p_0} \cdot \mathbf{1}\{\Delta\overline{\mathbf{Irrigation}}_i \in \mathbf{I}_j\} \cdot \mathbf{1}\{period = d\} \cdot \beta_{j,d}^{P>p_0} \\
&+ \sum_{d=1981}^{1996} \mathbf{w}_{it}\gamma_{1,d} \cdot \mathbf{1}\{period = d\} + \sum_{d=1981}^{1996} \mathbf{w'}_{it} \cdot \mathbf{w}_{it}\gamma_{2,d} \cdot \mathbf{1}\{period = d\} \\
&+ \alpha_i + \eta_{pt} + \lambda_{i,1}t + \lambda_{i,2}t^2 + \epsilon_{it}
\end{aligned} \tag{7}
$$

where $\mathbf{1}\{\Delta\overline{\mathbf{Irrigation}}_i \in \mathbf{I}_j\}$ is an indicator variable specifying whether each county's variation in irrigation coverage $\Delta\overline{\mathbf{Irrigation}}_i$ belongs to a specific category of the national distribution of irrigation variation denoted by $\mathbf{I}_j$. The inter-temporal variation $\Delta\overline{\mathbf{Irrigation}}_i$ is calculated by the difference in the average of irrigation coverage between the pre-1996 and post-1996 period. We classify all the counties into four categories based on the distribution of irrigation variation: strictly below the 25th percentile (denoted by $\mathbf{I}_1$), above the 25th percentile but strictly below the 50th percentile (denoted by $\mathbf{I}_2$), above the 50th percentile but strictly below the 75th percentile (denoted by $\mathbf{I}_3$) and above the 75th percentile (denoted by $\mathbf{I}_4$). We also interact irrigation with precipitation which affects water resources for irrigation. All other model specifications remain the same as equation (5).

According the distribution of irrigation variation depicted in Figure 4 (a), the 25th, 50th, and 75th percentile are -0.022, 0.029, and 0.095, respectively. With the triple interaction of extreme temperature variable, irrigation category and period indicator, we estimate the heterogeneous evolution of yield sensitivity to temperature extremes by category which indicates the extent to which irrigation has changed over time. Our hypothesis for the extreme temperature effect on yields is that for $j \geq 3, \beta_{j,1996}^{T>l_1} > \beta_{j,1981}^{T>l_1}$ significantly while for $j \leq 2, \beta_{j,1996}^{T>l_1} = \beta_{j,1981}^{T>l_1}$. If irrigation is one of the main mechanisms driving the reduction in temperature sensitivity over time, we expect that the reduction of temperature sensitivity in counties with irrigation expansion (Category $\mathbf{I}_3$ and $\mathbf{I}_4$) will be significantly larger than that in the counties with irrigation contraction (Category $\mathbf{I}_1$ and $\mathbf{I}_2$).

6 The Evolution of the Temperature-Yield Relationship Over 1981-2010

This section presents the estimates of temperature-yield relationship over time periods. Our primary analysis focuses on the period-specific effects of random year-to-year variation in temperature on the yields of corn and soybean, two important grain crops in China in terms of total area sown and total production. The yield (production per hectare) of these two crops is the basic measure of agricultural productivity. We also estimate the effects of the four agricultural inputs on reducing the heat-related yield loss and examine the extent to which the decline in temperature sensitivity of yields can be explained by the expansion of inputs over time. The unit for the temperature variables in all the tables and figures reporting estimation results hereafter is 100 degree days and the unit for precipitation is 100 cm.

6.1 Temporal Evolution of the Temperature-Yield Relationship

6.1.1 Corn and Soybean Yields

Table 3 provides the results based on equation (5) for corn yields. In our piece-wise linear approach, yield is expected to increase linearly up to an endogenous threshold and then decrease linearly beyond that threshold. The temperature threshold for the whole country is selected at 28 °C and the precipitation threshold is at 51 cm. Columns 1-3 of Table 3 vary on the specification of fixed effects as articulated in the table. Columns 4 and 5 are different from 1-3 on estimation of standard errors. In Columns 1-3, the standard errors are clustered at the county level, whereas we use spatial HAC robust standard error in Columns 4 and 5. Exposure to growing degree days (GDD) below 28 °C in 1981-1995 and 1996-2010 has small and generally insignificant effects on yields but increases in exposure of corn to temperatures above 28 °C result in sharp declines in yields, as shown in the third and fourth row in Table 3. In the period of 1981-1995, the point estimate of yield loss due to additional 100-day exposures to temperature above 28 °C ranges from -37 % to -23 % while the corresponding estimates in the period of 1996-2010 ranges from -11% to -4%, significantly lower than the yield loss estimation of 1981-1995, as shown by the row of p values which are derived from an F test of the null hypothesis $\beta^{1981} = \beta^{1996}$. The comparison among Columns 1 to 3 shows the relatively robust estimates of the temperature-yield relationship in the two periods and that the province-by-year differences and county-specific gradual changes in unobserved determinants of corn yields to some extent affect the yield loss caused by extreme temperatures. As shown in Columns 1 to 3, the relative adaptation effect are 90%, 71% and 50%, respectively; hence, it declines as the model specifications become more restrictive.[13] The province-by-year fixed effects and county-specific trends to some extent account for province-level differences and county-specific heterogeneity in adaptation mechanisms other than the pure change in input quantities, which can be partially verified by the decrease in the estimated adaptation effects under more restrictive specifications. Therefore, the most conservative estimation of the adaptation potential is 50%. Moreover, our estimation of adaptation benefits is robust when using spatial HAC robust standard errors, as reported in Columns 4 and 5.[14]

Precipitation impacts also exhibit a nonlinear pattern. Corn yields significantly increase as annual precipitation increase up to 51 cm, beyond which an additional 100 additional centimeter of rainfall decreases corn yields by about 15% to 30%. However, the yield loss due to excessive precipitation has not significantly decline over time periods. Irrigation may influence how excessive precipitations affects crop yields in a number of ways. For example, surface drainage can solve the waterlogging problem due to excessive rain (Konukcu, et al., 2006). We speculate that yields of counties with irrigation expansion will be less sensitive to extreme amount of precipitation. This speculation is verified in Section 6.3 after we introduce the irrigation effect. Table B.1 in Appendix B.1 presents the effects of additional climate change variables (humidity, sunshine duration, wind speed, evaporation, and ground surface temperature) on corn yields.

Table 4 shows the results for soybean yields in the same format as Table 3. The temperature threshold for the linear piece-wise temperature-yields for soybean is selected at 26 °C and the precipitation threshold is at 44 centimeter (cm). Exposure to GDD below 26 °C in the period of 1981-1995 and 1996-2010 both has small and generally insignificant effects on yields, whereas increases in the exposure of corn to temperatures above 26 °C result in sharp declines in yields, as shown in the third and fourth rows in Table 4. The estimated temperature-yield relationships of soybean using the different specifications exhibit similar pattern with the relationships of corn in Table 3. In the period of 1981-1995, the point estimate of yield loss due to additional 100-day exposures to temperature above 26 °C ranges from -16% to -3% while that in the period of 1996-2010 ranges from -8% to 6%, significantly lower than the yield loss estimation of pre-1996 period, as shown by the row of p values which are derived from an F test of the null hypothesis $\beta^{1981} = \beta^{1996}$. The comparison between Columns 1 and 3 reveals the relatively robust estimates of the temperature–yield relationship in the two periods. As shown in Columns 2 to 5, the relative adaptation effect ranges between 44% and 56%, declining as more

[13] The relative adaptation effects for different model specifications are estimated through the uniform formula shown in the previous section: $(\beta_{2,d=1} - \beta_{2,d=2})/\beta_{2,d=1}$.

[14] We obtain different point estimates when we switch from cluster robust standard errors to spatial HAC robust standard errors (compare Column 2 with Column 4 and Column 3 with Column 5). The difference between the point estimates is the calculation error generated by manually demeaning the variables for the regression in terms of the province-by-year fixed effects and local time trends for the spatial HAC model. The Stata package for calculating spatial HAC standard errors provided by Hsiang (2010) can only be applied to cross-sectional data.

constraints for the models are added.[15] Precipitation impacts exhibit an inverted V-shaped pattern as well. The yield loss due to an additional 100 cm of precipitation above 44 cm is approximately 20% and does not significantly decline over time periods. Results for impacts of additional climate change variables are presented in Table B.2 of Appendix B.1.

As shown in Table 1, the annual average corn yield in the post-1996 period is 4262.52 kg. Therefore, it saves about 4.68 kg (4262.52 $\times$ 0.12%) of corn per hectare if the effect of daily exposure to temperature above 28 °C is reduced from 0.23% to 0.11%. The annual planted area of corn in the post-1996 is 24.8 million hectares. Therefore, the loss reduction of national aggregate corn production is about 155,000 tons per year (0.00468 ton/hectare $\times$ 24.8 million hectares) compared with the scenario in which the pre-1996 extreme temperature impacts prevailed. The loss reduction of aggregate soybean production is about 11,000 tons per year based on the same reasoning. To obtain a sense of the magnitude of the effects of extreme temperatures, it is necessary to compare the temporal evolution of effects on yields to that of aggregate area planted for each crop. Formal estimation of temperature-area relationship requires a different approach than the panel model, which is out of the scope of this study. Figure 6 demonstrates the time trend of the area planted with corn and soybean as well as the proportion of the two crops accounting for the total planted area. In contrast to the rapid expansion of corn production, the scale of soybean production remains stable over the last 30 years suggesting that there have been more of increased planted area that is planted to corn than to soybean. Given the decline in yield sensitivity to extreme temperatures and the evolutionary pattern of planted area, climate change is predicted not to alter the growing trend of corn production nor significantly reduce soybean production of China. The 95% self-sufficiency objective on corn can be maintained. However, the stagnant growth of soybean production has forced China to import about 80% of its domestic soybean consumption. Hence, the growing demand of soybean from China will impose a large impact to the international soybean market.

6.1.2 Heterogeneous Temperature-Yield Relationships by Region

In Tables 5 and 6, we estimate heterogeneous temperature-yield relationship of corn and soybean by region (the regions depicted in Figure A.1) to understand heterogeneity in the response functions across crop regions and to test whether regions that are more accustomed to temperature extremes have adapted better such that they have a more muted temperature-productivity. For example, regions that experience high-temperature days more frequently (i.e. HHH and South versus North and Northeast in Figure 4) may have higher adoption rates of technologies that mitigate the detrimental impacts of extreme heat.

Each column in Table 5 comes from a single regression in which the sample is restricted to the

[15] Column 1, which is the specification only controlling for the county and year fixed effects, provides an estimate of relative adaptation as high as 300%. We do not take this result seriously, as this specification doesn't control province-level differences that can confound the temperature-yield relationship.

corresponding corn regions in Figure A.1. The point estimates of the corn yield loss generated by an additional-day exposure to temperature above the regional threshold vary largely across regions for both of the two periods. Northern regions generally suffer more from extreme temperature than the southern regions (Northwest is an exception among the northern regions but the estimated coefficient of the high temperature category is not significant). All the regions except the inland Northwest experienced a dramatic decline on the extreme temperature impacts over the two periods, indicating prevalent adaptation effects all over the country. For the North, HHH, South and Southwest region, the relative adaptation effects are 60%, 75%, 74% and 76%, respectively. The finding of large cross-sectional and longitudinal variation in temperature-generating yield losses is consistent with the idea that hotter places adapt to higher temperatures better than colder places do.

Table 6 reports the regional differences in the temperature-yield relationships of soybean. Each column presents the same of information as in Table 5. An additional-day exposure to temperatures above the regional threshold generates a significant loss on annual soybean yields for all the regions except the South. The detrimental impacts of extreme temperatures vary largely across regions for both periods. Northern regions suffer more from extreme temperatures than southern regions, which is consistent with the idea that hotter places adapt to high temperature better than the cooler places do. Only the HHH and Northwest region show significant declines in the yield loss due to extreme heat and the adaptation effect is about 80%. the decline in extreme temperature impacts in the Southwest is not significant and high temperatures are not even harmful to soybean yields in the South. The nationwide decline in the heat-related yield loss estimated in Table 4 is thus mostly driven by the HHH and Northwest region.

6.1.3 Robustness Check

The Standard error estimation is changed to a spatial HAC standard error estimation in the robustness check to account for heteroskedasticity, county-specific serial correlation and cross-sectional spatial correlation (Hsiang, 2010). The nonparametric estimation of the variance-covariance matrix for the error term allows for contemporaneous spatial correlations between counties whose centroids lie within d km of one another (Conley, 1999). Following Conley (2008), the weights in the matrix are uniform up to the cutoff distance d. Moreover, nonparametric estimates of county-specific serial correlation are estimated using linear weights that decrease to zero after a lag length of q years (Newey and West, 1987). In our model, the cutoff distance d takes the value from 100 km to 400 km with an increment of 100 km and the length of years q is 3 years and 5 years. The results in Figure 7 show the estimated impacts of an additional 100 days of exposure to extreme temperatures in the pre-1996 period and the difference in the impact estimates between the pre-1996 and the post-1996 periods. We find that the spatial HAC standard errors do not change the estimation of temperature-yield relationships for the two crops compared with clustering-robust standard errors.

Diverse temperature thresholds are applied to check the sensitivity of estimation to variation in temperature thresholds. It is a concern that the selected temperature thresholds are misspecified. Figure 8 reports the estimation of temperature-yield relationships of corn and soybean for the full sample using five temperature thresholds.[16] The significance of the yield loss decline is robust to variation in temperature thresholds. The impacts of extreme temperatures on crop yields in the period of 1981 to 1995 are obviously exacerbated as temperature threshold increases but are relatively stable in the later period of 1996 to 2010. For example, as shown in Panel (a) of Figure 8, the national average yield loss of corn caused by an additional 100 days of exposure to extreme temperatures in the pre-1996 period increases from 22% to 42% as the threshold increases from 28 °C to 32 °C, while the decline in the temperature sensitivity (marked by the triangle) in the post-1996 period rises with an increase in the threshold. As a result, the yield loss due to extreme temperature exposures is stable around 10% in the post-1996 period with respect to the temperature threshold.

The length of time period is varied to test the sensitivity of estimation results to the choice of endpoint years of time periods and the number of years in a time period. In the robustness check, we use 5 years and 10 years as the period lengths and rerun regression in equation (5).[17] The results are shown graphically in Figure 9. We display the point estimates and 95 % confidence intervals of the extreme temperature impacts on crop yields in the first period (1981-1986 is the first period in the 5-year setting and 1981-1990 is the first period in the 10-year setting) and of the change in the extreme temperature impacts in later periods relative to the first period. The extreme temperature variable remains annual growing degree days above the endogenous temperature threshold used before (28 °C for corn and 26 °C for soybean). Temperature thresholds other than 28 °C for corn and 26 °C are applied; see Figures B.3–B.6 of Appendix B.2. For the two period lengths, we obtain significant estimates of the extreme temperature impacts in the initial period when farmers were less prepared for climate change and invested less in adaptive inputs. Compared to the 15-year-period setting in Tables 3 and 4, the heat-related yield losses of the 5-year and 10-year settings are more severe in the initial period. This is reasonable because the yield impacts of extreme heat in the first 15-year period (1981 to 1995) might have already incorporated the effects of adaptation occurring after the first 5-year period or 10-year period. The significantly positive point estimates of the difference between the initial period and later periods show that our conclusion of significant adaptation effects is insensitive to the choice of the number of years in a time period or the ending years of the time periods. Another interesting result is that in the 5-year setting, the improvement of temperature sensitivity to extreme heat for

[16] We use five consecutive temperature thresholds that include the threshold reported in Table 2 but fix the precipitation thresholds at the values in Table 2 for all the regions, as we find that changing the precipitation thresholds does not change the estimation of coefficients of temperature variables. The estimates for the same robustness analysis for crop regions on temperature thresholds are presented in Figure B.1 and Figure B.2 of Appendix B.

[17] An alternative way of checking the robustness of the results to the ending years of the time periods is running panel regressions over rolling time periods such as 1950 to 1965 compared with 1966 to 1980, 1966 to 1980 compared with 1981 to 1995, 1981 to 1995 compared with 1996 to 2010, and so on. However, we only collected 30 years of data from 1981 to 2010. Hence, using rolling time periods is not feasible.

the 1986-1990 period and 1991-1995 period relative to the initial 1981-1995 period is not statistically significant at 5% level and also smaller than the improvement in the post-1996 periods. This echoes our findings on the irrigation mechanism that can explain the drop in the temperature sensitivity of crop yields.

The model specification is changed from a period-specific panel model to a more flexible panel model that allows all the climate variables to interact with polynomials of calendar years such that the impact of extreme temperature can change smoothly and flexibly over time (Roberts and Schlenker, 2011). The polynomial takes linear, quadratic and cubic form in this study. Specifically, the new regression model is

$$
\begin{aligned}
y_{it} =& GDD_{it,l_0:l_1} \cdot \beta_1 + GDD_{it,l_0:l_1} \cdot f_{1,L}(t) + GDD_{it,l_1:\infty} \cdot \beta_2 + GDD_{it,l_1:\infty} \cdot f_{1,H}(t) \\
&+ Prec_{it,p<p_0} \cdot \beta_3 + Prec_{it,p<p_0} \cdot f_{2,L}(t) + Prec_{it,p>p_0} \cdot \beta_4 + Prec_{it,p>p_0} \cdot f_{2,H}(t) \\
&+ \mathbf{w}_{it} \cdot \boldsymbol{\beta_6} + \mathbf{w}_{it} \cdot f_3(t) + \mathbf{w'}_{it} \cdot \mathbf{w}_{it} \cdot \boldsymbol{\beta_6} + \mathbf{w'}_{it} \cdot \mathbf{w}_{it} \cdot f_4(t) + \alpha_i + \eta_{pt} + f_y(t) + \epsilon_{it}
\end{aligned}
$$

where the functions $f(\cdot)$ are the polynomial of years and all the other variables are defined in the same way as in equation (1). We continue to use $l_1 = 28$ for corn and $l_1 = 26$ for soybean. Figure 10 displays the evolution of marginal impacts of extreme temperatures on crop yields, i.e., $\beta_2 + f_{1,H}(t)$. The linear and quadratic form of year trend exhibit a steadily rising tolerance of crop yields to extreme temperatures. In the model of linear and quadratic form, the marginal impacts of extreme temperatures decrease by 40% to 50%. In the linear(quadratic) model, marginal impacts of degree days above 28 °C on corn yields increases from -0.23% (-0.27%) to -0.09% (-0.13%), consistent with the results provided by the period-specific panel model. We have a similar evolutionary pattern on soybean. The model of cubic time trend depicts a more complex evolutionary path but exhibits an improving trend of heat tolerance. Estimation of polynomial-trend model with other temperature thresholds are presented in Figure B.7 and B.8 of Appendix B.2.

6.2 Estimating the Marginal Adaptation Effects of Agricultural Inputs

The analysis in Section 6.1 showed a large decline in the temperature sensitivity of crop yields. The question that arises is why the temperature sensitivity declines over time periods. We address this question in two steps. The first step, presented in this subsection, estimates the marginal adaptation effects of agricultural inputs, which is the parameter of $\partial F/\partial x^*$ in the conceptual framework of Section 3, which serves as the backbone element for quantifying the proportion of the decline in temperature sensitivity explained by some central input. It also helps us determine which inputs contribute to the decline in temperature sensitivity of crop yields. The moderating effects are estimated by the interactions of extreme temperatures with temporal changes in the inputs in equation (6).

We now describe the estimation results of equation (6), the augmented model to quantify how agricultural inputs mitigate the impacts of extreme temperatures on crop yields. The data allows us to examine four inputs. Irrigation is measured by the fraction of arable land that is effectively irrigated i.e. the ratio of irrigated land area over arable land area. Agricultural machinery is measured by the machinery power used for each hectare of total planted area. Fertilizer is measured by fertilizer inputs used for each hectare of total planted area. Electricity is measured by electricity consumption per capita of rural population.[18] The total planted area is the aggregate planted area for all crops.

Due to data limitations, we cannot observe separate inputs for each crop. We use the change in irrigation coverage as a proxy for the change of ex post use of irrigation water based on the relation that ex ante adaptation facilitates ex post adaptation. Using equation (6) we estimate the adaptation effects through the change in inputs by comparing yield sensitivity to extreme temperatures in counties with a higher increase of input adoption with a lower increase (or even decrease as illustrated in Panel (a) of Figure 4). This part of empirical analysis helps us to find which of the four inputs are effective at moderating the extreme temperature impacts and contribute to the decline in the temperature sensitivity of crop yields. Tables 7 and 8 only report the direct impacts of extreme temperatures (growing degree days above the threshold) and interaction effects of the input change with extreme temperatures. We find that none of the agricultural inputs significantly affect the relationship between low temperatures and crop yields (see Table B.3 and B.4 in Appendix B.2). We consider the specification in which each input enters individually (Columns 1–4 in Tables 7 and 8) as well as the one in which all the inputs enter the same specification (Column 5 in Tables 7 and 8).

Columns 1 in Tables 7 and 8 shows that the diffusion of irrigation is associated with a sizable and significant decrease in crop yield loss due to extreme temperatures. Table 7 demonstrates that an expansion of irrigation coverage from 0% to 100% in a county is associated with a reduction in the impact of 100-day exposure to extreme temperatures on corn yields by 23 to 25 percentage points on average. Table 8 demonstrates that the moderating effect for soybean yields is 13 to 15 percentage points. On the contrary, none of the other three inputs generate significant adaptation effects to extreme temperatures. We conduct two robustness analyses on the findings of adaptation effects through temporal changes in inputs. First, we show that none of the modifiers affect yield sensitivity to low temperatures, suggesting that adoption of these modifiers is not coincident with factors that determine the overall crop yields. The results are provided in Table B.3 and B.4 in Appendix B.2. Second, we measure irrigation coverage by the ratio of irrigated area to the total planted area as used by the literature (Chen et al., 2016; Zhang, et al., 2017).

[18] According to *Technical Terminology for Irrigation and Drainage* by Ministry of Water Resources of China (1993), effective irrigation area is defined as the area of arable land that is relatively flat, accompanied by water sources nearby, equipped with irrigation infrastructure and can be irrigated normally in the situation without extreme weather intervention. So effective irrigation area refers to part of arable land. Another measurement for irrigation coverage in the literature is effective irrigation area over total planted area which is different from arable land area in the sense that crops can be planted in arable and non-arable land (Chen et al., 2016 and Zhang et al., 2017).

For a robustness check, we provide estimation of irrigation effects using the ratio of effective irrigation area over total planted area in Table B.5 and B.6. As shown in Table B.5 and B.6, the results of sizable and significant adaptation effects uniquely by irrigation still hold.

Finally, we add a temperature-by-year trend and interactions of temperature with observed factors in parallel with inputs to equation (6) to account for confounding effects that co-vary with the four inputs (Barreca et al., 2016). Table 9 reports the results of this robustness check. Columns 1 and 3 only add temperature-by-year trends (i.e. interactions between calendar year and the two temperature variables) in the baseline specification to control for unobserved factors that may lead to smooth change of temperature sensitivity. Columns 2 and 4 add interactions of temperature with observed confounding factors to the specifications in Column 1 and 3. Table 9 only reports the interaction effects between the change in inputs and temperature variables. The comparison of Table 9 with Tables 7 and 8 suggests that controlling for potential confounding factors through the above specifications does not significantly change the estimates of the adaptation effects of inputs. The robustness analysis thus supports the key finding in Tables 7 and 8 that irrigation is the most effective input among the four examined ones to moderate the extreme temperature impacts on yields. Although the variation in inputs over time have exogenous characteristics (shown in Figure 5) and the estimation is robust to specifications with confounding factors, the evidence on adaptation effects of inputs is only suggestive rather than causal.

6.3 The Mechanism for the Decline in Temperature Sensitivity Through Irrigation

This section examines the mechanism for the decline in temperature sensitivity through the temporal change of the most promising input–irrigation. If the change in irrigation partially explains the decline in extreme temperature impacts, the extent of decline in counties with a larger increase in irrigation coverage should be at least larger than that in the counties with lower increase. Given the distributional characteristics of irrigation change shown in Panel (a) of Figure 4, we classify the distribution of the irrigation coverage change into four categories based on the percentiles of the distribution. Category 1 to 4 cover the counties with irrigation change ranging from the 25th percentiles, the 25th to the 50th percentiles, the 50th to the 75th percentiles, and the 75th percentile to 1, respectively. The 25th percentile, the 50th percentile and the 75th percentile are -0.022, 0.029 and 0.095 respectively, indicating that most of the counties covered in Categories 1 and 2 have experienced irrigation contraction while all the counties in Categories 3 and 4 have experienced irrigation expansion.

We estimate the heterogeneous evolution of temperature sensitivity by these categories of irrigation change in equation (7), a triple-interaction panel model where temperature variables interact with the category and period indicators. Our hypothesis for the effect of extreme temperatures on yields is that for $j \geq 3, \beta^{T>l_1}_{j,1996} > \beta^{T>l_1}_{j,1981}$ significantly, while for $j \leq 2, \beta^{T>l_1}_{j,1996} = \beta^{T>l_1}_{j,1981}$. In other words, the decline in temperature sensitivity in counties with irrigation expansion (Categories $\mathbf{I}_3$ and $\mathbf{I}_4$) will be significantly larger than that in the counties with irrigation contraction (Category $\mathbf{I}_1$ and $\mathbf{I}_2$). Figure 11 presents the estimation of the heterogeneous irrigation effects. There are five pairs of estimates in each panel. The first pair is for the estimate of the temporal evolution of extreme temperature effects for the model in equation (5) without the category interaction. The remaining four pairs are for heterogeneous evolution by the categories of irrigation change. In each pair, the black circle denotes the extreme temperature effects in the first 15-year period and the blue triangle denotes the difference in the extreme temperature effects between the first 15-year and the second 15-year period. Only in counties of category 3 and 4 (counties with irrigation expansion) is there significant attenuation towards zero on the extreme temperature effects from the first period to the second period. The decline in Categories 3 and 4 is approximately 50%, consistent with that in the full sample estimated by the uninteracted model. Thus, the decline in temperature sensitivity mainly occurs in counties with irrigation expansion, suggesting that irrigation is a mechanism for *ex post* adaptation to temperature extremes.

We can derive the share of temperature sensitivity decline explained by irrigation expansion using the estimates of the adaptation effects of irrigation in Section 6.2. Tables 7 and 9 show that an increase in irrigation coverage from 0% to 100% is associated with a decrease in extreme temperature effects on corn yields by 20 to 26 percentage points. The average change in irrigation coverage for counties with irrigation expansion (Categories 3 and 4) is approximately 0.14.[19] An increase in irrigation coverage by 14 percentage points reduces the heat-related yield loss by 2.83 to 3.68 percentage points (0.2×0.14 to 0.26×0.14) accounting for 25.7% to 33.4% of the 11 percentage-point decline in the corn yield loss for the full sample. Similarly, an average increase in irrigation coverage for the counties planting soybean by 13.3 percentage points accounts for 24.8% to 28.6% of the 7 percentage-point decline of soybean yield loss.

There are two caveats about the benefits of irrigation in terms of temperature sensitivity reduction that may improve decision making on irrigation investment. First, the *ex post* adaptation effect of irrigation is conditioned on *ex ante* investment in irrigation systems such as drainage ditches, wells and reservoirs. Ex ante investment in irrigation capital stock is complementary instead of substitutable for the ex post use of irrigation water after weather realizes. Second, irrigation may be a maladaptation to longer-term climate change. Climate change in the long run may alter precipitation distribution

[19] The average change in irrigation coverage is weighted by each county's average of corn planted area, which is consistent with the panel regression weighted by annual planted area of corn. The unweighted average change in irrigation coverage for counties with irrigation expansion is 0.12.

and therefore the availability of irrigating water. investment in irrigation may be less efficient if viewed in relation to the longer-term projections of drying in the region. Economic agents should thus consider the longer-term risk of water shortages when expanding irrigation coverage without technological improvements in irrigation.

Finally, we analyze why there is no adaptation to precipitation shocks. Because some irrigation equipment such as drainage can protect crops from waterlogging due to excessive rainfall, we hypothesize that crop yields in counties with irrigation expansion become less sensitive to an extreme precipitation shock compared with counties with irrigation contraction. Figure 12 verifies this hypothesis by presenting the heterogeneous change in extreme precipitation effects over time by categories of irrigation change. The format of Figure 12 is the same as that of Figure 11 except it reports the results for precipitation. The impacts of excessive precipitation decrease only in Category 4 counties both for corn and soybean. As a result, the decline in extreme precipitation effects across the two periods is not significant for the full sample estimated by the uninteracted model.

7 Conclusion

Using a comprehensive county-level dataset on agricultural production and weather conditions during the period of unprecedented economic growth in China, this study makes three primary findings on the temperature-yield relationship over the past 30 years. First, we find a decline in the effects of extreme temperatures on crop yields: the impact of daily exposure to temperatures above a threshold on corn and soybean yields has declined by 40-50% from 1981-1995 to 1996-2010, saving approximately 155,000 tons of corn and 11,000 tons of soybean per year compared with the scenario in which the pre-1996 extreme temperature impacts prevailed. The decline in temperature sensitivity implies large opportunities of adaptation to climate change and relaxes concerns over food security in the world's most populous country. A full set of fixed effects and local time trends help control for factors that confound the evolutionary temperature-yield relationship through mechanisms other than change in input quantities.

Second, the empirical results indicate that irrigation is the most effective input among the four examined in terms of moderating the production risk associated with extreme temperatures. Specifically, an expansion of irrigation coverage from 0% to 100% in a county is associated with a reduction the impact of 100-day exposure to extreme temperatures on corn (soybean) yields by 23 to 25 (12 to 14) percentage points on average. By contrast, we find that the use of fertilizer, agricultural machinery and electricity is not statistically related to attenuation of temperature sensitivity. Corresponding to the conceptual framework that decomposes the aggregate adaptation effect into the marginal adaptation effect of each input and responsiveness of inputs to temperature rises, this part of empirical analysis estimates the marginal adaptation effects of all the four inputs. The specification with rich fixed effects and local time trends allows us to control for endogenous factors that may generate adaptation effects through mechanisms other than *ex post* adjustments of the four examined inputs. The results of the baseline model with temperature-inputs interactions are robust to specifications controlling for a proxy for overall temperature-related adaptation mechanisms and observable confounders in parallel with the four inputs.

Third, the decline in the temperature sensitivity of crop yields mainly occurs in counties with irrigation expansion, suggesting that irrigation is a mechanism for the *ex post* adaptation effect. Our calculation shows that irrigation coverage has increased by about 14 percentage points in counties with irrigation expansion and can explain about 25% to 30% of the decline in the temperature sensitivity of crop yields. This opens a new avenue for future research to explore additional adaptation mechanisms such as technology innovation. In addition, the decline in the impacts of extreme precipitation only occurs in 25% of all the counties which experience the highest level of increase in irrigation coverage. The majority in the whole sample do not adapt to extreme precipitation shocks.

Adjustment of inputs is generally regarded as adaptation. We define ex ante adaptation as inputs adjusted before weather realizes and ex post adaptation as inputs adjusted after weather realizes. The input-driven decline in the impacts of unanticipated temperature shock across time periods reflects effect of ex post adaptation to experienced weather. This implies that weather realization can identify ex post adaptation effects, which extends the classical panel approach to the area of adaptation estimation. The irrigation coverage used in this paper reflects irrigation capital stock and therefore is a measure of ex ante adaptation. The statistical association of temperature sensitivity reduction with increase in irrigation coverage suggests that ex ante adaptation is complementary to rather than substitute for ex post adaptation, which is a new statement of the relationship between ex ante adaptation and ex post adaptation that has not been stressed in the literature.

As a critical strategy for climate change, adaptation is believed to be taken only ex ante. With strong evidence that *ex ante* adaptation facilitates *ex post* adaptation, this paper demonstrates that *ex ante* investment in inputs benefits both the *ex ante* adaptation effect and *ex post* adaptation effect. Focusing only on *ex ante* adaptation effect may thus underestimate the benefits of *ex ante* adoption of adaptive inputs such as irrigation. There are at least two promising areas for future research in addition to adaptation mechanisms other than irrigation. First, causal evidence on the adaptation effects of agricultural inputs with quasi-experimental variation is highly needed. Second, it is important to understand adaptation costs. We cannot evaluate adaptation against greenhouse gas mitigation for the importance of climate change unless we understand the benefits and costs of adaptation equally well.

Tables

Table 1: Summary Statistics

	1981-1995				1996-2010			
	Mean	Min	Max	Std.Dev.	Mean	Min	Max	Std.Dev.
Corn								
Yields(kg/ha)	4262.52	111.49	14764.87	1772.02	5697.73	100.24	14359.79	1898.82
Temperature (°C)	20.33	6.01	29.65	3.41	20.80	6.18	30.57	3.39
Precipitation (cm)	45.29	0.27	294.01	16.56	43.62	0.31	280.23	17.53
Humidity (%)	73.29	24.88	94.83	8.08	70.41	27.00	93.51	9.29
Sunshine Hours	6.45	0.94	11.34	1.65	6.41	0.32	11.29	1.61
Wind Speed (m/s)	2.20	0.20	7.25	0.79	2.14	0.19	7.00	0.67
Evaporation (mm)	5.44	0.03	17.75	1.40	3.24	0.00	16.46	2.60
Ground Surface Temperature (°C)	23.11	0.20	34.89	3.67	23.80	0.83	36.15	3.39
Observations	29083				31917			
Soybean								
Yields(kg/ha)	1361.23	66.82	7101.01	569.40	1818.71	103.64	7748.96	629.56
Temperature (°C)	20.59	7.13	29.11	3.11	20.37	7.82	28.97	3.18
Precipitation (cm)	57.24	0.45	327.68	27.33	53.96	1.05	339.64	28.63
Humidity (%)	73.53	24.85	90.04	6.40	70.67	27.20	90.99	7.06
Sunshine Hours	6.66	2.37	11.20	1.24	6.77	0.33	10.94	1.51
Wind Speed (m/s)	2.41	0.34	6.27	0.67	2.29	0.33	6.93	0.60
Evaporation (mm)	5.63	0.13	17.53	0.94	3.63	0.00	16.36	2.59
Ground Surface Temperature (°C)	23.57	0.70	34.56	3.16	23.63	0.69	35.04	2.94
Observations	27772				28084			

Notes: The mean value of each variable is weighted by the corn and soybean planted area. Crop yields are defined as products divided by planted area.

Table 2: Thresholds of Temperature (T) and Precipitation (P) for Linear Piecewise Temperature-Yield Relationship: (T,P)

(a) Panel A: Corn

Period Length	Nationwide	North	Northwest	HHH	South	Southwest
10 years	28 °C, 49 cm	30 °C, 51cm	32 °C,26cm	28°C, 55 cm	30 °C, 62 cm	30 °C, 41 cm
15 years	28 °C, 51 cm	30 °C, 51 cm	32 °C,24cm	28 °C, 54 cm	30 °C, 58 cm	30 °C, 41 cm

(b) Panel B: Soybean

Period Length	Nationwide	Northeast	Northwest	HHH	South	Southwest
10 years	26 °C, 48 cm	26 °C, 46 cm	29 °C, 19 cm	27 °C, 56 cm	27 °C, 60 cm	28 °C , 62 cm
15 years	26 °C, 44 cm	26 °C, 45 cm	28 °C, 25 cm	26 °C, 54 cm	27 °C, 60 cm	30 °C , 64 cm

Table 3: Marginal Impacts of Temperature and Precipitation On Corn Yields Over Time Periods

	(1) Log Yields	(2) Log Yields	(3) Log Yields	(4) Log Yields	(5) Log Yields
period=1981 × GDD below T	0.0453***	-0.0081	0.0071	-0.0096	0.0086
	(0.0065)	(0.0097)	(0.0087)	(0.0122)	(0.0115)
period=1996 × GDD below T	0.0065	-0.0059	0.0029	-0.0057	0.0045
	(0.0069)	(0.0100)	(0.0094)	(0.0121)	(0.0110)
period=1981 × GDD above T	-0.3741***	-0.2912***	-0.2316***	-0.2879***	-0.2295***
	(0.0280)	(0.0328)	(0.0306)	(0.0478)	(0.0431)
period=1996 × GDD above T	-0.0375*	-0.0827***	-0.1146***	-0.0834**	-0.1147***
	(0.0204)	(0.0277)	(0.0286)	(0.0364)	(0.0382)
period=1981 × Prec below T	0.1622***	0.1233**	0.1522***	0.1298	0.1781**
	(0.0533)	(0.0542)	(0.0474)	(0.0916)	(0.0700)
period=1996 × Prec below T	0.1916***	0.0795*	0.1085**	0.0936	0.1144**
	(0.0412)	(0.0451)	(0.0440)	(0.0633)	(0.0567)
period=1981 × Prec above T	-0.3824***	-0.1431***	-0.2418***	-0.1548**	-0.2595***
	(0.0395)	(0.0427)	(0.0411)	(0.0647)	(0.0571)
period=1996 × Prec above T	-0.3273***	-0.2876***	-0.1939***	-0.2908***	-0.1892***
	(0.0306)	(0.0356)	(0.0359)	(0.0532)	(0.0418)
p-Value for GDD below T : $\beta^{1981} = \beta^{1996}$	0.0000	0.7332	0.5614	0.5538	0.5976
p-Value for GDD above T : $\beta^{1981} = \beta^{1996}$	0.0000	0.0000	0.0002	0.0000	0.0114
p-Value for Prec. below P : $\beta^{1981} = \beta^{1996}$	0.6577	0.5303	0.4905	0.7207	0.4541
p-Value for Prec. above P : $\beta^{1981} = \beta^{1996}$	0.2424	0.0070	0.3180	0.0494	0.2991
Observations	59269	59269	59269	59274	59274
R squared	0.7525	0.7981	0.8421	0.0338	0.0210
Fixed Effects	Cty,Year	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr
County Quadratic Trend	No	No	Yes	No	Yes
Std. Error	Clustered	Clustered	Clustered	Spatial HAC	Spatial HAC
T threshold	28 $°C$	28 $°C$	28 $°C$	28 $°C$	28 $°C$
P threshold	51 cm	51 cm	51 cm	51 cm	51 cm
Distance	N/A	N/A	N/A	500km	500km
Years of Lag	N/A	N/A	N/A	5 years	5 years

Note: Each column corresponds to a separate regression varying on specification of fixed effects and estimation of standard errors as specified in the table. The dependent variable is log annual corn yields from 1981 to 2010. The regressions are weighted by annual corn hectares. Only coefficients on temperature and precipitation are reported but additional climate variables are also included in the regression. Temperature threshold is 28 °C and precipitation threshold is 51 cm in all specifications. County-specific quadratic trends are controlled and standard errors are clustered at the county level. The p values of testing hypotheses of coefficient estimate distinction are provided immediately below the row of coefficient estimates. * p<0.1, ** p<0.05, *** p<0.01.

Table 4: Marginal Impacts of Temperature and Precipitation On Soybean Yields Over Time Periods

	(1) Log Yields	(2) Log Yields	(3) Log Yields	(4) Log Yields	(5) Log Yields
period=1981 × GDD below T	0.0106	0.0245	0.0436***	0.0257*	0.0457***
	(0.0088)	(0.0159)	(0.0144)	(0.0141)	(0.0119)
period=1996 × GDD below T	0.0001	0.0197	0.0254*	0.0210	0.0272**
	(0.0091)	(0.0161)	(0.0147)	(0.0140)	(0.0110)
period=1981 × GDD above T	-0.0323	-0.1642***	-0.1527***	-0.1621***	-0.1563***
	(0.0218)	(0.0294)	(0.0261)	(0.0273)	(0.0273)
period=1996 × GDD above T	0.0626***	-0.0737**	-0.0882***	-0.0747***	-0.0873***
	(0.0194)	(0.0295)	(0.0266)	(0.0249)	(0.0262)
period=1981 × Prec below T	0.5136***	0.4807***	0.5274***	0.4968***	0.5393***
	(0.1259)	(0.1263)	(0.1196)	(0.1470)	(0.1137)
period=1996 × Prec below T	0.5910***	0.4020***	0.3906***	0.3991***	0.3913***
	(0.1111)	(0.1097)	(0.1140)	(0.1146)	(0.0989)
period=1981 × Prec above T	-0.1885***	-0.2408***	-0.2035***	-0.2455***	-0.2059***
	(0.0477)	(0.0516)	(0.0443)	(0.0404)	(0.0339)
period=1996 × Prec above T	-0.1890***	-0.1610***	-0.1382***	-0.1559***	-0.1366***
	(0.0312)	(0.0349)	(0.0340)	(0.0312)	(0.0258)
p-Value for GDD below T : $\beta^{1981} = \beta^{1996}$	0.0001	0.2019	0.0003	0.1408	0.0036
p-Value for GDD above T : $\beta^{1981} = \beta^{1996}$	0.0000	0.0001	0.0067	0.0000	0.0059
p-Value for Prec. below P : $\beta^{1981} = \beta^{1996}$	0.6573	0.6637	0.4546	0.5936	0.3386
p-Value for Prec. above P : $\beta^{1981} = \beta^{1996}$	0.9921	0.1574	0.1814	0.0646	0.0930
Observations	54327	54322	54322	54323	54323
R squared	0.6819	0.7265	0.7869	0.0238	0.0239
Fixed Effects	Cty,Year	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr
Trend	No	No	Yes	No	Yes
Std. Error	Clustered	Clustered	Clustered	Spatial HAC	Spatial HAC
T threshold	26 $^{\circ}C$	26 $^{\circ}C$	26 $^{\circ}C$	26 $^{\circ}C$	26 $^{\circ}C$
P threshold	44 cm	44 cm	44 cm	44 cm	44 cm
Distance	N/A	N/A	N/A	500 km	500 km
Years of Lag	N/A	N/A	N/A	5	5

Note: Each column corresponds to a separate regression varying on specification of fixed effects and estimation of standard errors as specified at the bottom of the table. The dependent variable is log annual soybean yields from 1981 to 2010. The regressions are weighted by annual soybean hectares. Only coefficients on temperature and precipitation are reported but additional climate variables are also included in the regression. Temperature threshold is 26 °C and precipitation threshold is 44 cm in all specifications. County-specific quadratic trends are controlled and standard errors are clustered at the county level. The p values of testing hypotheses of coefficient estimate distinction are provided immediately below the row of coefficient estimates. * p<0.1, ** p<0.05, *** p<0.01.

Table 5: Marginal Impacts of Temperature and Precipitation On Soybean Yields Over Time Periods

	(1) North	(2) HuangHuaiHai	(3) Northwest	(4) South	(5) Southwest
period=1981 × GDD below T	0.0426**	-0.0172	-0.0300	0.0449**	-0.0158
	(0.0174)	(0.0129)	(0.0195)	(0.0207)	(0.0130)
period=1996 × GDD below T	0.0255	-0.0294**	-0.0296	0.0257	0.0027
	(0.0181)	(0.0134)	(0.0198)	(0.0211)	(0.0133)
period=1981 × GDD above T	-0.9987***	-0.2054***	0.0915	-0.2963***	-0.1509**
	(0.2115)	(0.0501)	(0.1549)	(0.0797)	(0.0706)
period=1996 × GDD above T	-0.4029**	-0.0516	0.0696	-0.0607	-0.0293
	(0.1777)	(0.0360)	(0.1417)	(0.0497)	(0.0502)
period=1981 × Prec below P	0.1068	0.2638***	0.1236	0.0429	-0.1584**
	(0.1458)	(0.0689)	(0.4096)	(0.0942)	(0.0756)
period=1996 × Prec below P	0.3085***	0.0674	0.2998	0.0483	0.0319
	(0.1130)	(0.0444)	(0.2614)	(0.0556)	(0.0526)
period=1981 × Prec above P	-0.4479***	-0.1591*	-0.2592	-0.0543	-0.0554
	(0.0870)	(0.0840)	(0.6325)	(0.0494)	(0.0600)
period=1996 × Prec above P	-0.4036***	-0.1803***	-0.3608	-0.1012***	-0.1703**
	(0.1153)	(0.0430)	(0.3986)	(0.0270)	(0.0702)
p-Value for GDD below T : $\beta^{1981} = \beta^{1996}$	0.3915	0.2936	0.9825	0.1049	0.0869
p-Value for GDD above T : $\beta^{1981} = \beta^{1996}$	0.0256	0.0018	0.9174	0.0115	0.0949
p-Value for Prec. below P : $\beta^{1981} = \beta^{1996}$	0.3041	0.0105	0.7151	0.9563	0.0152
p-Value for Prec. above P : $\beta^{1981} = \beta^{1996}$	0.7298	0.8059	0.8987	0.3748	0.1912
Observations	10532	16852	3031	16513	12341
R squared	0.8288	0.7909	0.9032	0.8912	0.8956
Fixed Effects	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr
County Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	30 $°C$	28 $°C$	32 $°C$	30 $°C$	30 $°C$
P threshold	51 cm	54 cm	24 cm	58 cm	41 cm

Note: This table presents region-heterogeneous impacts of extreme temperatures on corn yields over time periods. Division of corn regions is illustrated in Figure A.1. Each column is from a separate regression corresponding to a particular corn region. The regression model is presented in equation (5) and the rest model specifications are the same as equation (5). The North region includes province-level administrative districts of Heilongjiang, Jilin, Liaoning, Inner Mongolia, Northern Shaanxi, Northern Hebei (north to the Great Wall) and Southern Gansu. The Huanghuaihai (HHH) region includes Beijing, Tianjin, Southern Hebei (south to the Great Wall), Shandong, Henan, Shanxi, Middle Shaanxi, Northern Jiangsu (north to Huai River) and Northern Anhui (north to Huai River). The Northwest region includes Xinjiang, Ningxia and Northern Gansu. The South region includes Southern Jiangsu(south to Huai River), Southern Anhui(south to Huai River), Eastern Hubei, Eastern Hunan, Jiangxi, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi and Hainan. The Southwest region includes Southern Shaanxi, Western Hubei, Western Hunan, Chongqing, Sichuan, Guizhou and Yunnan. The Plateau region includes Qinghai and Tibet (Xizang). * p<0.1, ** p<0.05, *** p<0.01.

Table 6: The Heterogeneous Temperature-Yield Relationships of Soybean By Regions

	(1) Northeast	(2) HHH	(3) Northwest	(4) South	(5) Southwest
period=1981 × GDD below T	0.0609*	0.0075	0.3351***	0.0098	0.0259
	(0.0347)	(0.0306)	(0.1225)	(0.0106)	(0.0247)
period=1996 × GDD below T	0.0562	0.0477	0.3191**	0.0111	-0.0024
	(0.0346)	(0.0312)	(0.1244)	(0.0103)	(0.0277)
period=1981 × GDD above T	-0.5078***	-0.1590***	-1.6760***	0.0200	-0.2450**
	(0.1457)	(0.0597)	(0.5607)	(0.0256)	(0.1032)
period=1996 × GDD above T	-0.5659***	-0.0345	-0.1357	0.0407	-0.1334
	(0.1190)	(0.0547)	(0.3495)	(0.0302)	(0.0865)
period=1981 × Prec below P	0.3211	0.2350**	-3.9404	-0.2040*	0.7679***
	(0.2669)	(0.1106)	(2.4742)	(0.1110)	(0.2470)
period=1996 × Prec below P	0.2609	0.1326	-1.4733	-0.0135	0.4525***
	(0.1938)	(0.1033)	(1.0640)	(0.0576)	(0.1732)
period=1981 × Prec above P	-0.1273	-0.7281***	0.7403	-0.0652***	-0.1034
	(0.1027)	(0.1707)	(0.6737)	(0.0242)	(0.0789)
period=1996 × Prec above P	-0.2637*	-0.1654**	-0.6868**	-0.0846***	0.0243
	(0.1394)	(0.0743)	(0.3144)	(0.0194)	(0.0463)
p-Value for GDD below T : $\beta^{1981} = \beta^{1996}$	0.9110	0.2674	0.9386	0.7258	0.1514
p-Value for GDD above T : $\beta^{1981} = \beta^{1996}$	0.7580	0.0316	0.0230	0.1753	0.1802
p-Value for Prec. below P : $\beta^{1981} = \beta^{1996}$	0.8722	0.4811	0.3353	0.1343	0.2632
p-Value for Prec. above P : $\beta^{1981} = \beta^{1996}$	0.4277	0.0023	0.0390	0.5100	0.1502
Observations	5870	16393	1750	21438	5860
R squared	0.6758	0.7983	0.7998	0.8941	0.8661
Fixed Effects	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr
County Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	26 $°C$	26 $°C$	28 $°C$	27 $°C$	30 $°C$
P threshold	45 cm	54 cm	25 cm	60 cm	64 cm

Note: This table presents region-heterogeneous impacts of high temperature on soybean yields over time periods. Division of corn regions is illustrated in Figure A.1. Each column is from a separate regression corresponding to a particular corn region. The regression model is presented in equation (5) and all the rest model specifications are the same as equation (5). The Northeast region includes province-level administrative districts of Heilongjiang, Jilin, Liaoning, Eastern Inner Mongolia. The Huanghuaihai (HHH) region includes Beijing, Tianjin, Southern Hebei (south to the Great Wall), Shandong, Henan, Southern Shanxi, Middle Shaanxi, Southeastern Gansu, Northern Jiangsu (north to Huai River) and Northern Anhui (north to Huai River). The Northwest region includes Western Inner Mongolia, Xinjiang and Most of Gansu. The South region includes Southern Jiangsu(south to Huai River), Southern Anhui(south to Huai River), Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, Hainan, Hubei, Eastern Hunan, Jiangxi, Chongqing and Eastern Sichuan. The Southwest region includes Western Hunan, Western Sichuan, Guizhou and Yunnan. The Plateau region includes Qinghai and Tibet (Xizang). * p<0.1, ** p<0.05, *** p<0.01.

Table 7: Interaction Effects of Inputs Change with High Temperatures for Corn Counties

	(1)	(2)	(3)	(4)	(5)
GDD above T	-0.3005***	-0.1516***	-0.1387***	-0.1532***	-0.2640***
	(0.0484)	(0.0371)	(0.0406)	(0.0364)	(0.0489)
GDD above T × Δ Irrigation (%)	0.2576***				0.2310***
	(0.0558)				(0.0594)
GDD above T × Δ Machinery (Kw./Ha.)		0.0016			-0.0023
		(0.0050)			(0.0037)
GDD above T × Δ Fertilizer(Tons of Ha.)			-0.0676		-0.0839
			(0.0970)		(0.0878)
GDD above T × Δ Electricity (Kwh. per capita)				0.0015	-0.0024
				(0.0168)	(0.0117)
Observations	59255	53655	53645	58332	53475
R squared	0.8664	0.8444	0.8444	0.8423	0.8727
County FE	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes
Cty-Quadratic Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	28 °C	28 °C	28 °C	28 °C	28 °C
P threshold	51 cm	51 cm	51 cm	51 cm	51 cm

Note: The dependent variable is log corn yields. The change of all the agricultural inputs are calculated with the difference in the mean values between the pre-1996 and post-1996 period. The low temperature variable for interactions is the growing degree days above 28 °C. Precipitation and additional climate variables are included. The standard error is clustered at county level and the regressions are weighted by annual corn planted area. * p<0.1, ** p<0.05, *** p<0.01.

Table 8: Robustness Analysis of the Adaptation Effects of Agricultural Inputs on the Relationship between Extreme High Temperatures and Yields over 1981 to 2010

	(1)	(2)	(3)	(4)	(5)
GDD above T	-0.1881***	-0.1347***	-0.1334***	-0.1294***	-0.2080***
	(0.0376)	(0.0242)	(0.0241)	(0.0228)	(0.0417)
GDD above T × Irrigation (%)	0.1293***				0.1486***
	(0.0478)				(0.0524)
GDD above T × Machinery (Kw./Ha.)		0.0007			-0.0002
		(0.0005)			(0.0035)
GDD above T × Fertilizer (Tons of Ha.)			0.0040*		0.0050
			(0.0024)		(0.0250)
GDD above T × Electricity (Kwh. per capita)				-0.0151	-0.0163
				(0.0272)	(0.0228)
Observations	54263	54287	54287	54252	54174
P1					
R squared	0.8175	0.8201	0.8201	0.8201	0.8211
County FE	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes
Cty-Quadratic Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	26 °C	26 °C	26 °C	26 °C	26 °C
P threshold	44 cm	44 cm	44 cm	44 cm	44 cm

Note: The dependent variable is log corn yields. The change of all the agricultural inputs are calculated with the difference in the mean values between the pre-1996 and post-1996 period. The low temperature variable for interactions is the growing degree days above 28 °C. Precipitation and additional climate variables are included. The standard error is clustered at county level and the regressions are weighted by annual soybean planted area. * p<0.1, ** p<0.05, *** p<0.01.

Table 9: Robustness Analysis of the Adaptation Effects of Agricultural Inputs on the Relationship between Extreme High Temperatures and Yields over 1981 to 2010

	(1) Corn	(2) Corn	(3) Soybean	(4) Soybean
GDD above T × Δ Irrigation (%)	0.2297***	0.2032***	0.1491***	0.1293**
	(0.0472)	(0.0555)	(0.0525)	(0.0644)
GDD above T × Δ Machinery (Kw./Ha.)	-0.0026	-0.0009	-0.0002	0.0013
	(0.0029)	(0.0030)	(0.0035)	(0.0037)
GDD above T × Δ Fertilizer (Tons /Ha.)	-0.0809	-0.0321	0.0056	-0.0055
	(0.0826)	(0.0976)	(0.0250)	(0.0261)
GDD above T × Δ Electricity (Kwh. per capita)	-0.0021	0.0037	-0.0159	-0.0070
	(0.0102)	(0.0155)	(0.0228)	(0.0298)
Δ GDP × Temperature	No	Yes	No	Yes
Δ (Cargo by Road) × Temperature	No	Yes	No	Yes
Temperature × Year	Yes	Yes	Yes	Yes
Observations	53475	37617	54174	40178
R squared	0.8727	0.8601	0.8211	0.8176
County FE	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes
Cty-Quadratic Trend	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered
T threshold	28 °C	28 °C	26 °C	26 °C
P threshold	51 cm	51 cm	44 cm	44 cm

Note: This table presents the adaptation effects of agricultural inputs on the extreme-temperature-yield relationship. Each column is from a separate regression. The dependent variable is log crop yields. All the agricultural inputs, local GDP and cargo amount by road are measured with the difference in the mean values between the pre-1996 and post-1996 period. The GDP and cargo amount are in the prefecture level. The temperature variables used for interactions are the growing degree days above the thresholds. Precipitation and additional climate variables are included. The standard error is clustered at county level and the regressions are weighted by annual soybean planted area. * p<0.1, ** p<0.05, *** p<0.01.

Figures

Figure 1: Crop Productivity of Two Periods As A Function of Temperature

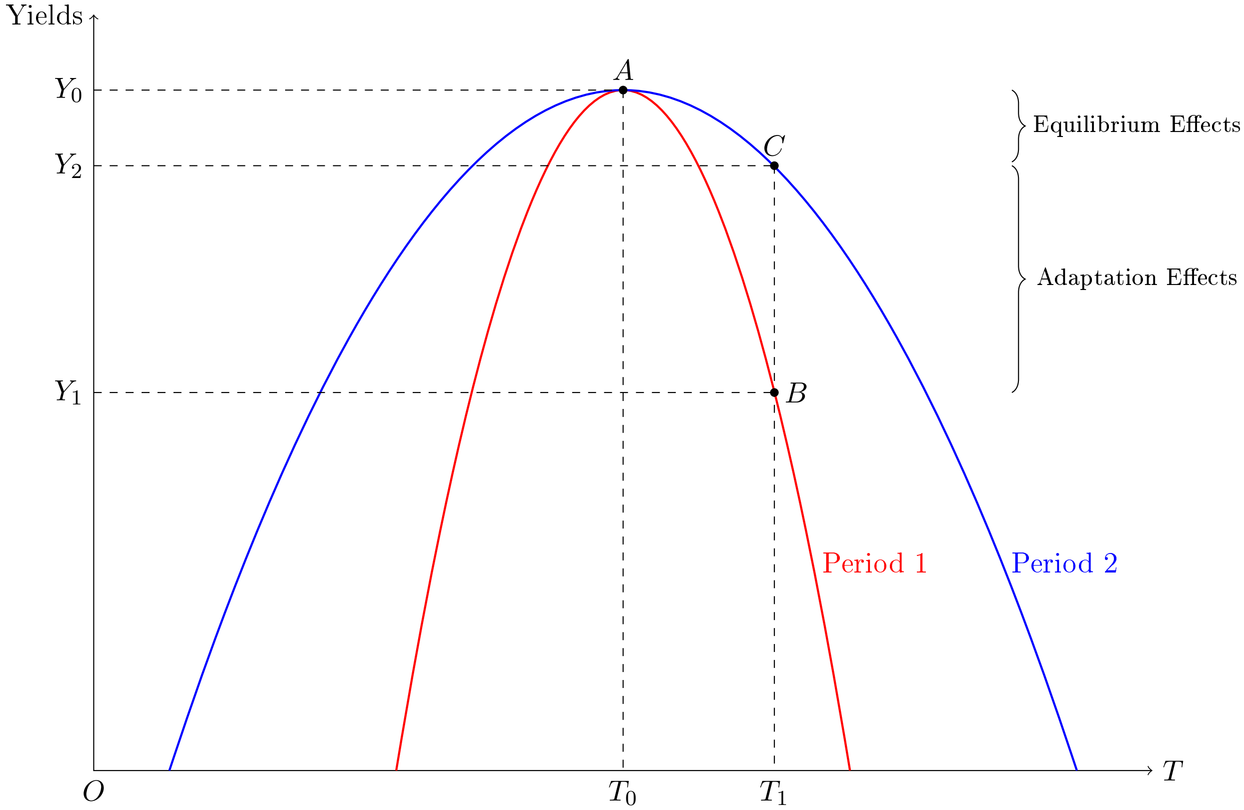
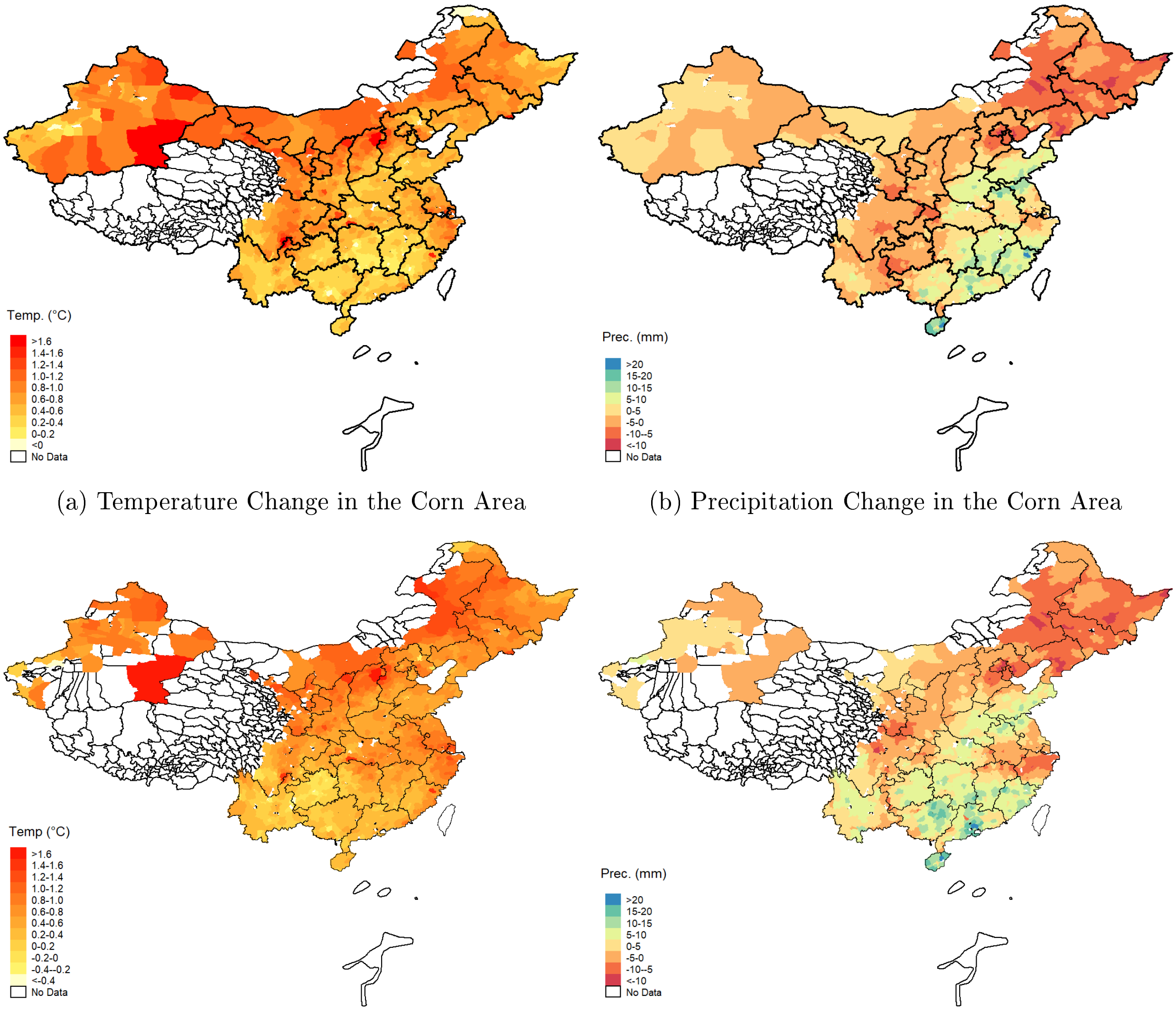


Figure 2: Temperature and Precipitation Change in the Corn and Soybean Area Over Time



(a) Temperature Change in the Corn Area

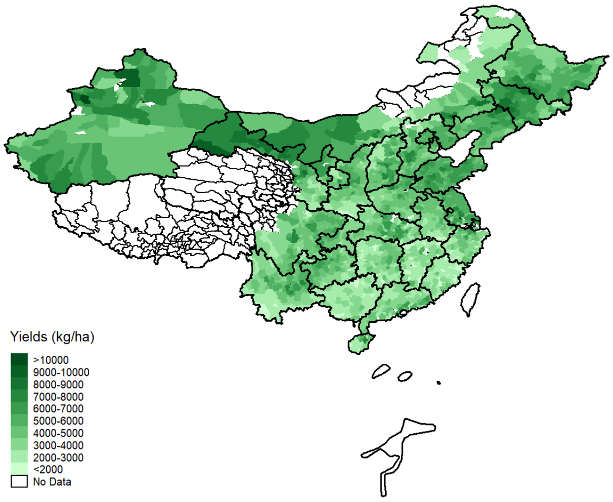
(b) Precipitation Change in the Corn Area

(c) Temperature Change in the Soybean Area

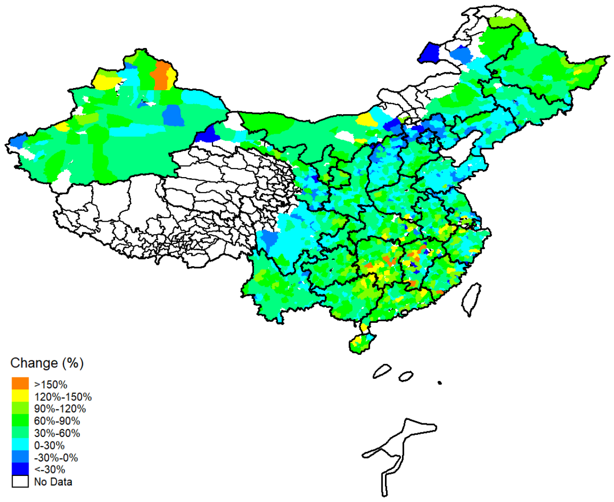
(d) Precipitation Change in the Soybean Area

Notes: Panel (a) and (c) plot county-level average of corn and soybean yields over 1981-2010, respectively. Panel (b) and (d) plot county-level percentage change in the average of corn and soybean yields during 1981-1995 relative to that during 1996-2010, respectively.

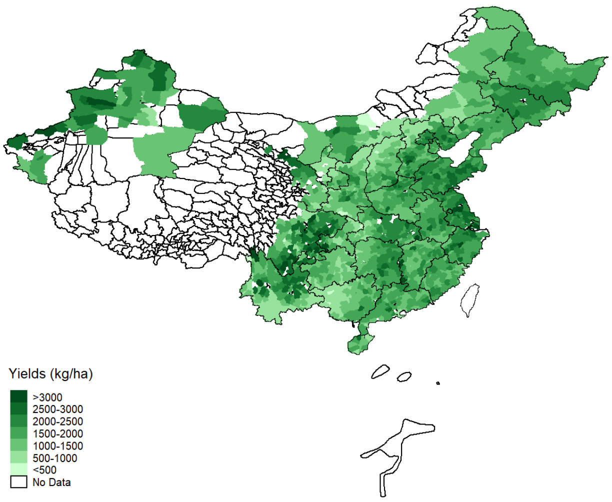
Figure 3: Annual Average of Crop Yields and Crop Yield Change Over Time



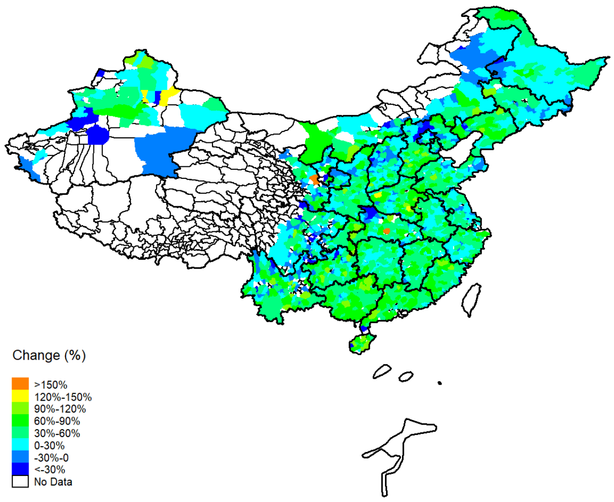
(a) 30-year Average of Corn Yields



(b) Percentage Change of Period-Averaged Corn Yields



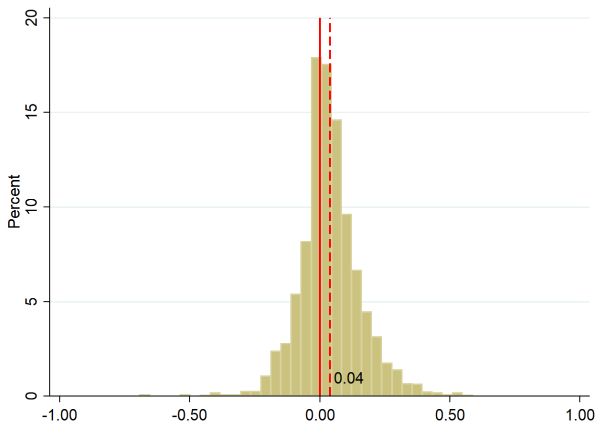
(c) 30-year Average of Soybean Yields



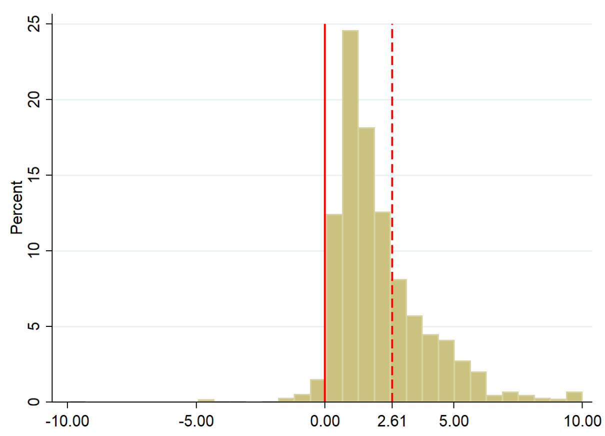
(d) Percentage Change of Period-Averaged Soybean Yields

Notes: Panel (a) and (c) plot county-level annual average of corn and soybean yields over 1981-2010, respectively. Panel (b) and (d) plot county-level percentage change in the average of corn and soybean yields in the pre-1996 period relative to that in the post-1996 period, respectively.

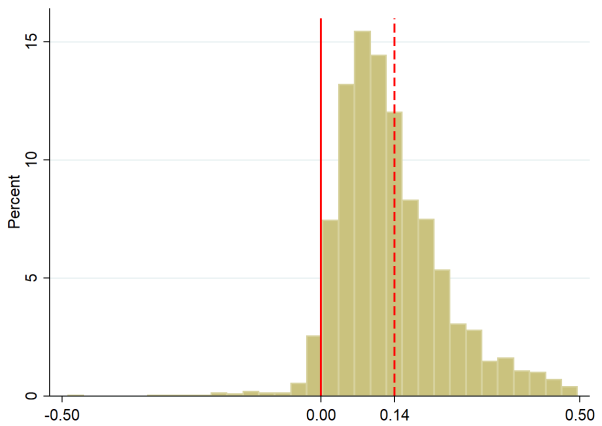
Figure 4: Distribution of Temporal Change of Agricultural Inputs



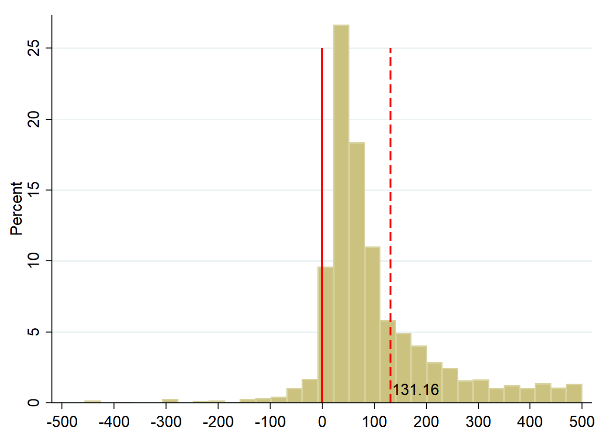
(a) Distribution of Irrigation Coverage Change (%)



(b) Distribution of Machinery Power Change (kilowatt/ha.)



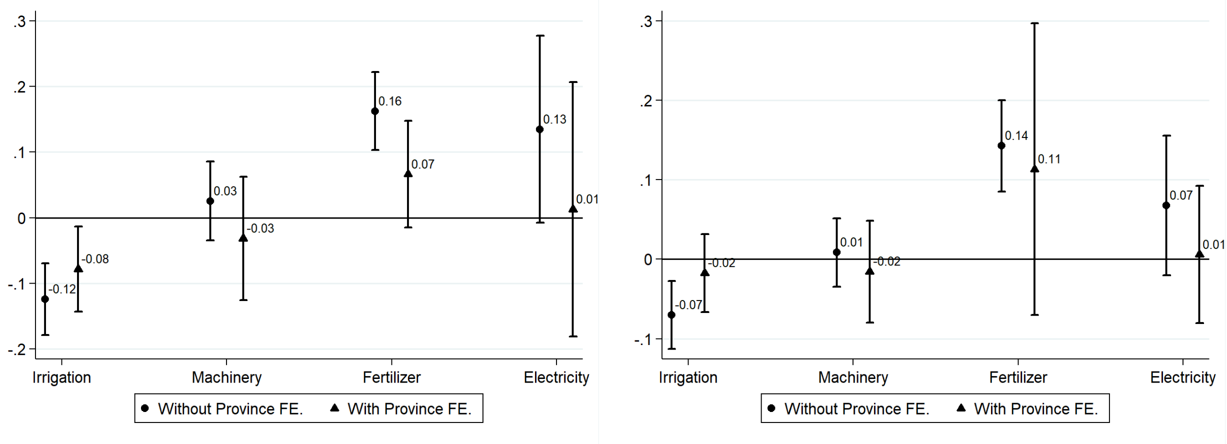
(c) Distribution of Fertilizer Change (ton/ha.)



(d) Distribution of Change (kw · h per capita)

Notes: This figure presents the distribution of input change over 1981 to 2010. The change of the input variables is calculated by the difference between the 1981-1995 average and 1996-2010 average. The solid line depicts zero and the dashed line is the mean of the change. The mean value for the change of each input is presented in the histogram.

Figure 5: Correlation of Inputs Change with Temperature Change

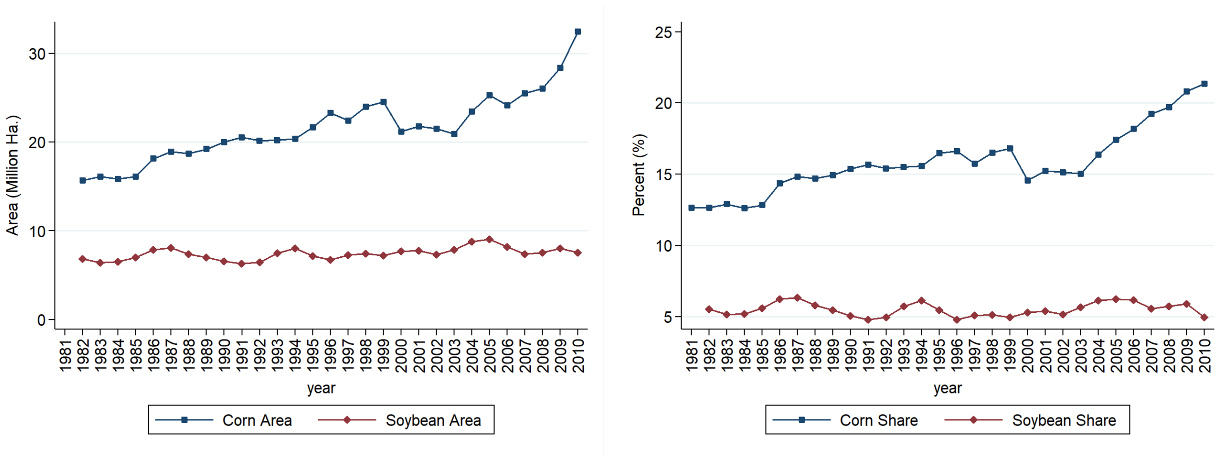


(a) Corn Counties

(b) Soybean Counties

Notes: Figure 5 presents the correlations between the temporal change in the four inputs and that in extreme temperature exposure. The correlation is estimated by regressing input change on temperature change. The change of temperature and inputs is calculated by the difference of the mean values between the pre-1996 period and the post-1996 period. The extreme temperature exposure for corn (soybean) counties is measured by degree days for temperature above 28 (26) °C. The unit of the extreme temperature exposure is 100 degree days. The regressions estimating the correlations denoted by triangles control for the province fixed effect while the regressions for correlations denoted by circles do not. The stand errors for both types of regressions are clustered at the county level.

Figure 6: The Planted Area of Corn and Soybean and the Corresponding Share in the Total Planted Area Over Time

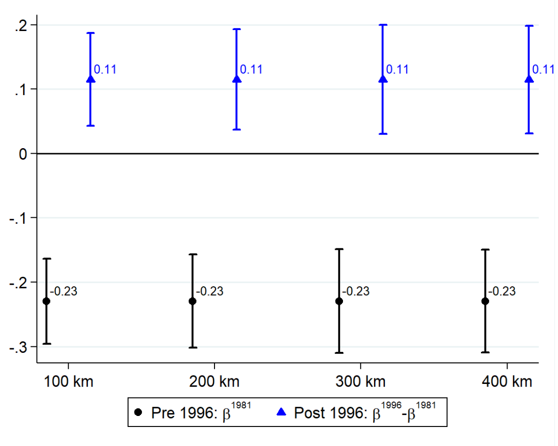


(a) The Planted Area of Corn and Soybean

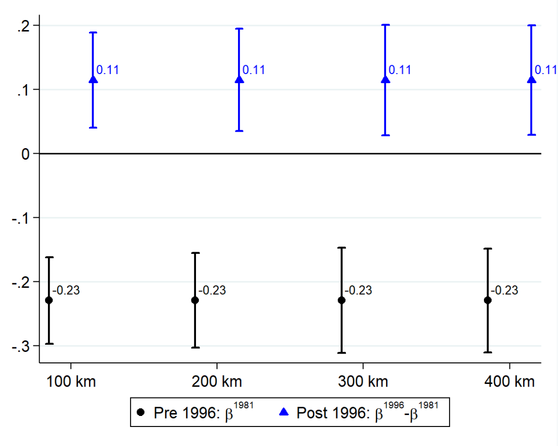
(b) The Percentage of Total Farmland Planted to Corn and Soybean

Notes: The planted area of corn or soybean for each year is calculated by aggregating the corn or soybean planted area of all the counties in each year. The corresponding share is calculated with the percentage of aggregate corn or soybean area accounting for the total planted area for all crops.

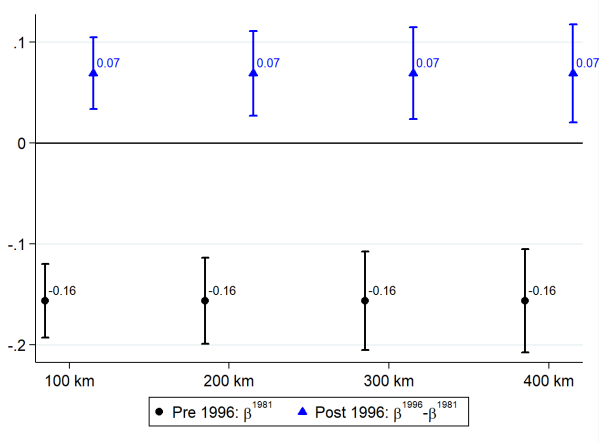
Figure 7: Robustness Analysis of Temperature-Yield Relationship Using Spatial HAC Standard Errors



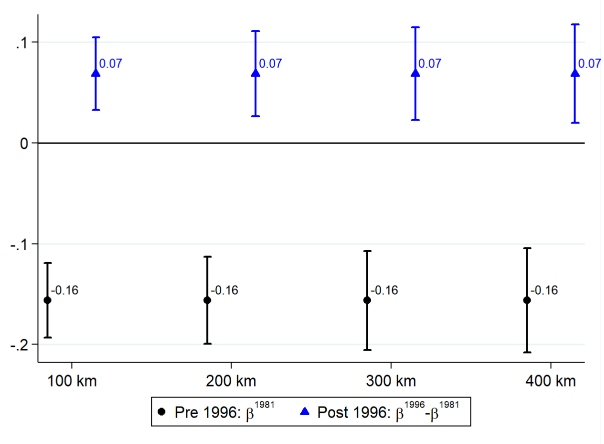
(a) Corn: Lag=3 years



(b) Corn: Lag=5 years



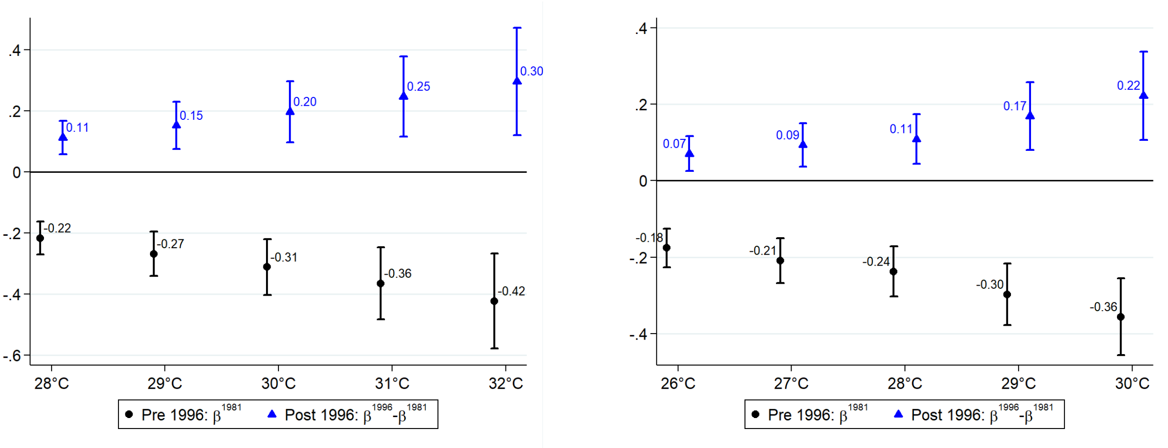
(c) Soybean: Lag=3 years



(d) Soybean: Lag=5 years

Notes: In Figure 7, we estimate the model in equation (5) with spatial heteroskedastic autocorrelated standard error using the stata code provided by Hsiang (2010). The regression is weighted by annual planted area for each crop. In each panel, the cutoff distance is specified at the horizontal axis. For each distance choice, we report the point estimate and the corresponding confidence interval at the 95% significance level for the effects of 100-day exposure to temperature above the threshold in the pre-1996 period (denoted by the circle symbol) and the difference in the effects between the pre-1996 and post-1996 period (denoted by the triangle symbol).

Figure 8: Marginal Impacts of Extreme Temperatures on Corn and Soybean Yields by Temperature Thresholds

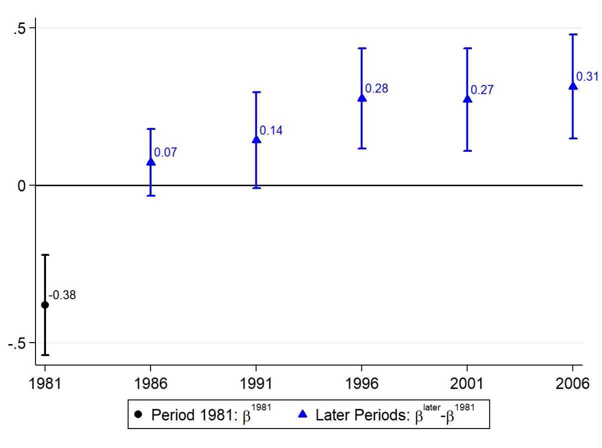


(a) Corn: Nationwide

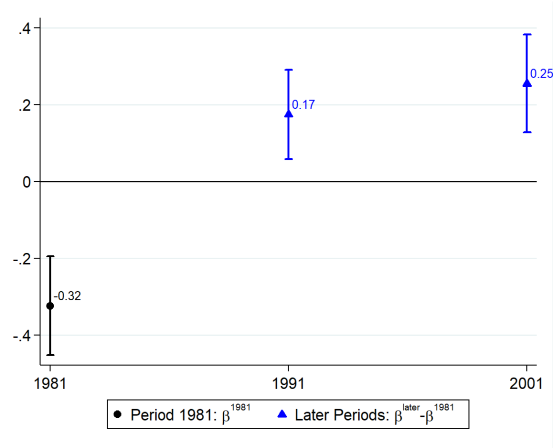
(b) Soybean: Nationwide

Note: Figure 8 presents heterogeneous impacts of extreme temperature on corn and soybean yields by temperature threshold. The alternative thresholds are specified below the horizontal axis. We estimate the model in equation (5) using the specified temperature thresholds. The regressions are weighted by annual planted area for each crop and the standard error is clustered at the county level. For each threshold choice, we report the point estimate and the corresponding confidence interval at the 95% significance level for the effects of 100-day exposure to temperature above the threshold in the pre-1996 period (denoted by the circle symbol) and the difference in the effects between the pre-1996 and post-1996 period (denoted by the triangle symbol). Heterogeneous impacts of extreme temperature by temperature threshold for each region are reported in Figure B.1 and Figure B.2 of Appendix B.

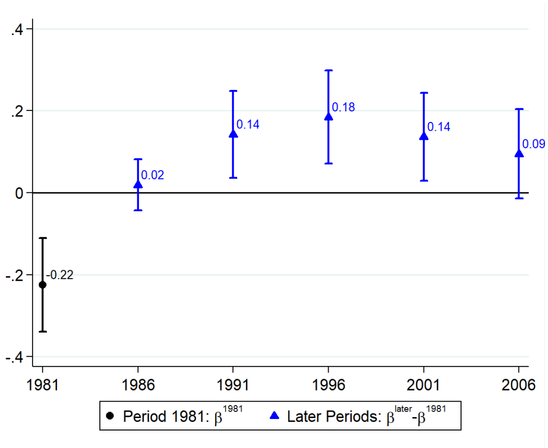
Figure 9: Sensitivity of Results to Starting Year and Length of Time Period
–Using 5 years or 10 years as a Period



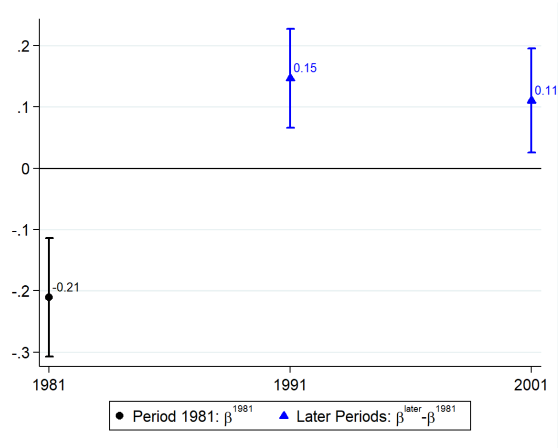
(a) GDD above 28 °C: 5 years



(b) GDD above 28 °C: 10 years



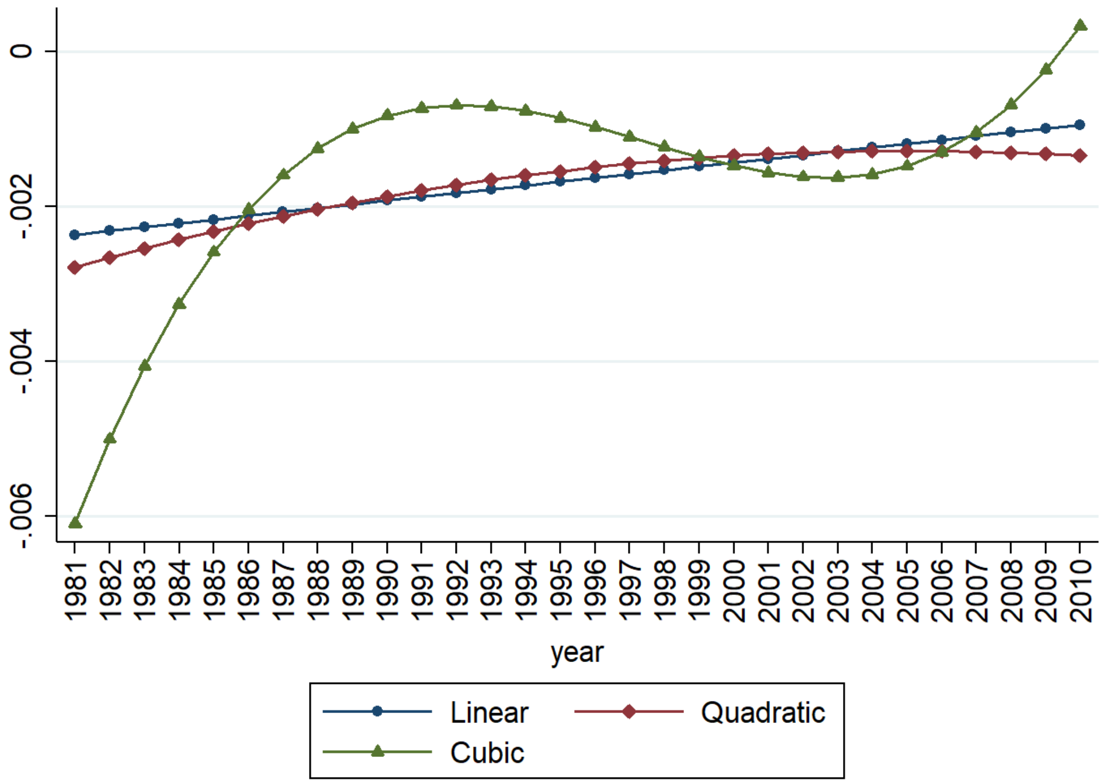
(c) GDD above 26 °C: 5 years



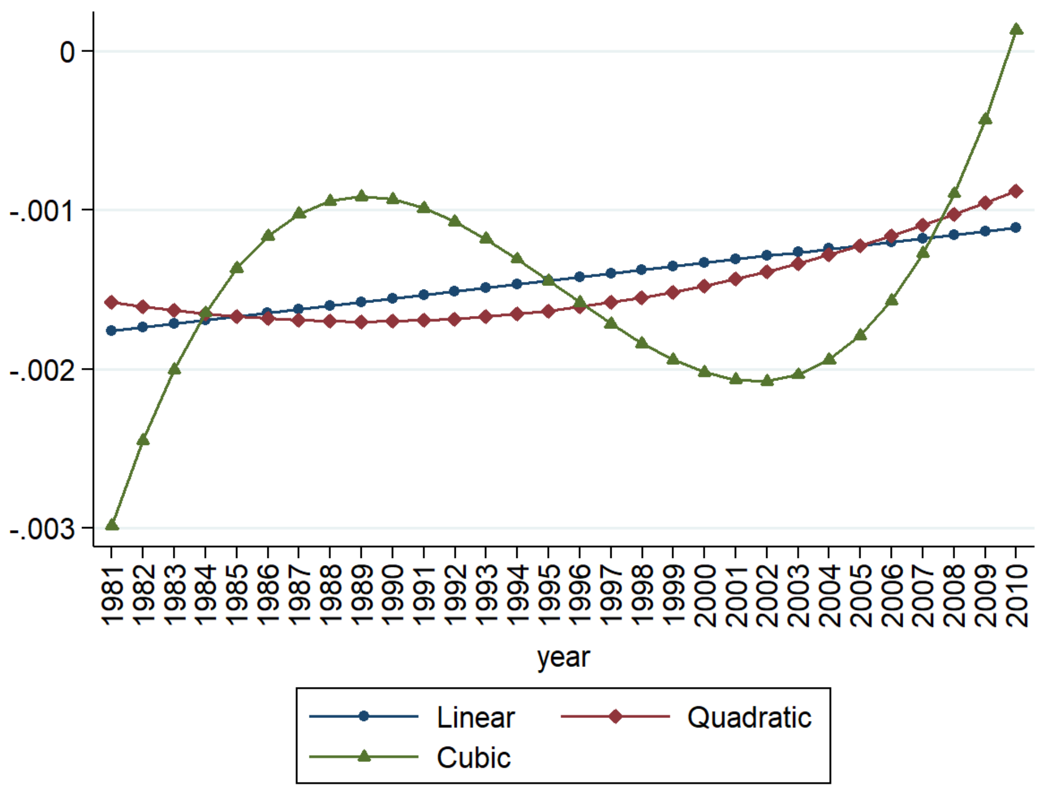
(d) GDD above 26 °C: 10 years

Note: Figure 9 presents the evolution of extreme temperature effect on crop yields estimated with model in equation (5) using 5 years or 10 years as a period. The regressions are weighted by annual planted area for each crop and the standard error is clustered at the county level. In each panel, we report the point estimate and the corresponding confidence interval at the 95% significance level for the effects of 100-day exposure to temperature above the threshold in the first period (period 1981-1985 or period 1981-1990 denoted by the circle symbol) and the difference in the effects between the following period and the first period (denoted by the triangle symbol). The initial year for each period is specified below the horizontal axis. The analysis of sensitivity to period length using alternative temperature thresholds are reported in Figure B.3 to Figure B.6 of Appendix B.

Figure 10: Sensitivity of Results to Model Specification Using Polynomial Time Trend –The Evolution of Marginal Impacts of Extreme Temperatures on Crop Yields

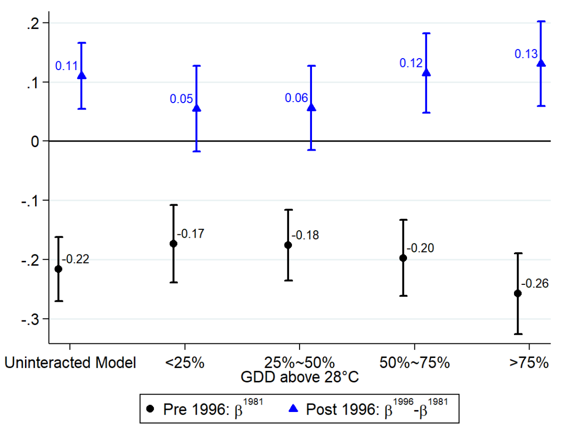


(a) Corn:Evolution of Marginal Impacts of GDD above 28 °C

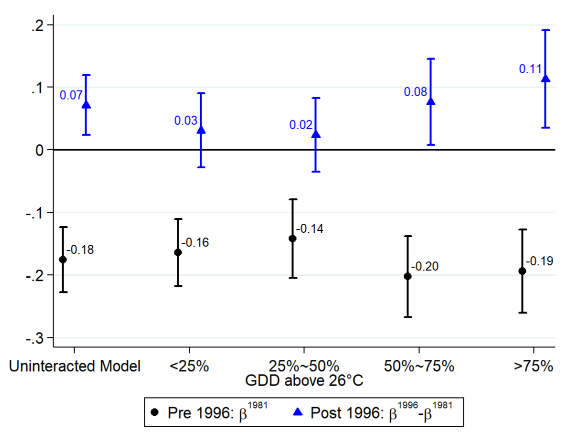


(b) Soybean: Evolution of Marginal Impacts of GDD above 26 °C

Figure 11: The Heterogeneous Evolution of Extreme Temperature Impacts by Categories of Irrigation Coverage Change



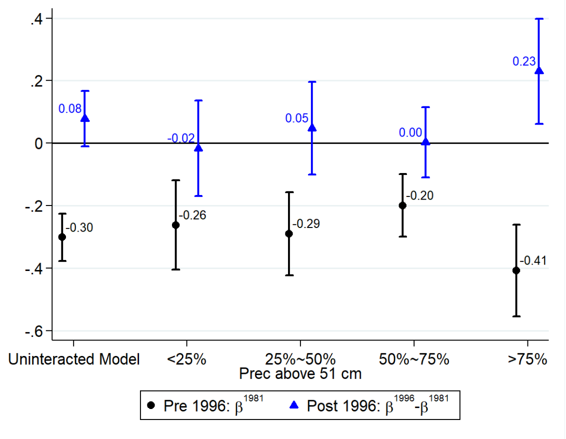
(a) Corn: GDD above 28 °C



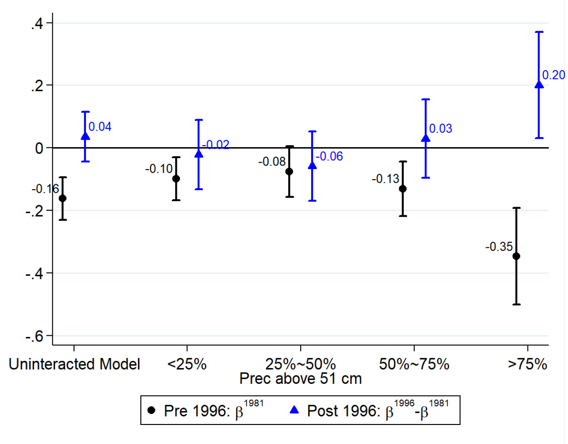
(b) Soybean: GDD above 26 °C

Note: Underneath the horizontal axis in each panel, the uninteracted model is the model in equation (6) and the rest four labels correspond to the evolution of the extreme temperature effects by the category of irrigation coverage change, which is estimated with equation (7). "<25%" denotes the category of counties with irrigation coverage change below the 25th percentile of the nationwide distribution; "25%∼50%" denotes the category of counties with irrigation coverage change above the 25th percentile but below the 50th percentile; "50%∼ 75%" denotes the category of counties with irrigation coverage change above the 50th percentile but below the 75th percentile; ">75%" denotes the category of counties with irrigation coverage change above the 75th percentile. We report the point estimate and the corresponding confidence interval at the 95% significance level for the effects of 100-day exposure to temperature above the threshold in the pre-1996 period (denoted by the circle symbol) and the difference in the effects between the pre-1996 and post-1996 period (denoted by the triangle symbol).

Figure 12: The Temporal Evolution of Excessive Precipitation Impacts by Categories of Irrigation Coverage Change



(a) Corn: Prec above 51 cm



(b) Soybean: Prec above 44 cm

Note: Underneath the horizontal axis in each panel, the uninteracted model is the model in equation (6) and the rest four labels correspond to the evolution of the extreme precipitation effects by the category of irrigation coverage change, which is estimated with equation (7). "<25%" denotes the category of counties with irrigation coverage change below the 25th percentile of the nationwide distribution; "25%∼50%" denotes the category of counties with irrigation coverage change above the 25th percentile but below the 50th percentile; "50%∼ 75%" denotes the category of counties with irrigation coverage change above the 50th percentile but below the 75th percentile; ">75%" denotes the category of counties with irrigation coverage change above the 75th percentile. We report the point estimate and the corresponding confidence interval at the 95% significance level for the effects of 100-day exposure to temperature above the threshold in the pre-1996 period (denoted by the circle symbol) and the difference in the effects between the pre-1996 and post-1996 period (denoted by the triangle symbol).

Reference

Aragon, F.M., Oteiza, F. and Rud, J.P., 2020. Climate Change and Agriculture: Subsistence Farmers' Response to Extreme Heat. American Economic Journal: Economic Policy. Forthcoming.

Auffhammer, M. Hsiang, S.M, Schlenker, W. and Sobel, A. 2013. Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. Review of Environmental Economics and Policy, Vol.7(2): 181-198.

Auffhammer, M. and Schlenker, W. 2014. Empirical Studies on Agricultural Impacts and Adaptation. Energy Economics 46(2014): 555-561.

Barichello, R. 2004. Agricultural Development and Poverty Reduction in East Asia: The Impact of OECD Agricultural Policies. Working Paper: 1-30.

Brown, L. R. 1995. Who Will Feed China? Wake-up Call for A Small Planet? The World Watch Environmental Alert Series. W.W. Norton & Company, New York, USA.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M. and Shapiro, J. 2016. Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. Journal of Political Economy, 2016, Vol.124, No.1,105-159.

Burke, M., Craxton, M., Kolstad, C.D., Onda, C., Allcott, H., Baker, E.,..., Tol, R.S.J. 2016. Opportunities for Advances in Climate Change Economics. Science, 352(6283):292-293.

Blinder, A.S. 1973. Wage Discrimination: Reduced Form and Structural Estimates. Journal of Human Resources, 8(4): 436-455.

De Bruin, KC.2011. Distinguishing Between Proactive (Stock) and Reactive (Flow) Adaptation. CERE Working Paper 2011: 8. Center for Environmental and Resource Economics. Umea University. Burke, M.B. and Emerick,K. 2016. Adaptation to Climate Change: Evidence from US Agriculture. American Economic Journal: Economic Policy, 8(3): 108-140.

Butler, E.E. and Huybers, P. 2012. Adaptation of US Maize to Temperature Variables. Nature Climate Change, 3(1): 68-72.

Carleton, T.A. and Hsiang, S.M. 2016. Social and Economic Impacts of Climate. Science, 353(6304): 1112.

Chen, S., Chen, X. and Xu, J. 2016. Impacts of Climate Change on Agriculture: Evidence from China. Journal of Environmental Economics and Management 76 (2016) 105-124.

Chen,S. and Gong, B. 2020. Response and Adaptation of Agriculture to Climate Change: Evidence from China. Journal of Development Economics. Forthcoming.

Chen, W., Ye, X., Li, J., Fan,X., Liu, Q. and Dong, W. Analyzing Requisition-Compensation Balance of Farmland Policy in China through Telecoupling: A Case Study in the Middle Reaches of Yangtze River Urban Agglomerations. Land Use Policy 83 (2019): 134-146.

Conley, T. 1999. GMM Estimation With Cross Sectional Dependence. Journal of Econometrics 92: 1-45.

Conley, T. 2007. Spatial Economics. New Palgrave Dictionary of Economics, eds Durlauf SN, Blume LE (Palgrave Macmillan, New York), pp 741-747.

Cui, X. 2020. Climate Change and Adaptation in Agriculture: Evidence from US Cropping Patterns. Journal of Environmental Economics and Management 101.

Cui, K. and Shoemaker, S.P. 2018. A Look at Food Security in China. Nature Partner Journal Science of Food (2018) 2-4.

Dell, B.M., Jones, B.F. and Olken, B.A., 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. American Economic Journal: Macroeconomics, 4(3): 66-95.

Dell, B.M., Jones, B.F. and Olken, B.A., 2014. What Do We Learn from the Weather? The New Climate Economy Literature. Journal of Economic Literature Vol.52, No.3, 740-798.

Deschênes, Olivier and Greenstone, Michael, 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. American Economic Review 97(1): 354-385.

Deschênes, Olivier and Greenstone, Michael, 2011. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. American Economic Journal: Applied Economics 3, 152-185.

Deryugina, T. and Hsiang, S.M. 2017. The Marginal Product of Climate. NBER Working Paper, No. 24072.

Di Falco S. 2014. Adaptation to Climate Change in Sub-Saharan Agriculture: Assessing the Evidence And Rethinking the Drivers. European Review of Agricultural Economics 41(3): 405-430.

Di Falco S. and Veronesi, M. 2013. How African Agriculture Can Adapt to Climate Change? A Counterfactual Analysis From Ethiopia. Land Economics 89(4), 743-766.

Di Falco S., Veronesi, M. and Yesuf, M. 2011. Does Adaptation to Climate Change Provide Food Security? A Micro Perspective From Ethiopia. American Journal of Agricultural Economics 93(3): 829-846.

Divanbeigi, R. and Kayumova., M. 2017. The Regulation of Agriculture in Developing East Asia. World Bank Working Paper: 1-10.

Du, L., Xu, L., Li, Y., Liu, C., Li, Z., Wong, J. and Lei, B. 2019. China's Agricultural Irrigation and Water Conservancy Projects: A Policy Synthesis and Discussion of Emerging Issues. Sustainability 2019, 11, 7027, 1-20.

Food and Agricultural Organization of United Nations, Faostat-Agriculture.2012. Food and Agricultural Organizations of the United Nations. Available from http://www.fao.org/statistics/en/.

Edwards,W. and Hanna, M. 2020. Days Suitable for Fieldwork in Iowa. Iowa State University Extension and Outreach Ag Decision Maker. File A3-25. Available from https://www.extension.iastate.edu/agdm/crops/html/a3-25.html

Gorst, A., Dehlavi, A. and Groom, B. 2018. Grop Productivity and Adaptation to Climate Change in Pakistan. Environment and Development Economics 23, 679-701.

Hoffman, G.J. and Jobes, J.A. 1978. Growth and Water Relations of Cereal Crops As Influenced By Salinity and Relative Humidity. Agronomy Journal, 70(5): 765-769.

Hsiang, S.M., 2010. Temperatures and Cyclones Strongly Associated With Economic Production in the Caribbean and Central America. Proceedings of the National Academy of Sciences of the United States of America. 2010 107(35) 15367-15372.

Huang, K., Wang, J., Huang, J. and Findlay, C. 2018. The Potential Benefits of Agricultural Adaptation to Warming in China in the Long Run. Environment and Development Economics 23, 139-160.

Huang, Q., Rozelle, S., Lohmar, B., Huang, J. and Wang, J. 2006. Irrigation, Agricultural Performance and Poverty Reduction in China. Food Policy 31 (2006): 30-52.

Huang, J., Wang, X. and Rozelle, S. 2013. The Subsidization of Farming Households in China's Agriculture. Food Policy 41(2013) 124-132.

Huang, J., Wang, Y. and Wang, J. 2015. Farmers' adaptation to Extreme Weather Events Through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China. American Journal of Agricultural Economics. 97(2): 602-617.

Hyde,M. and Syed, F. 2014. China's Food Self-sufficiency Policy. Agricultural Commodities (2014), 4(4): 22-31.

IPCC (Intergovernmental Panel on Climate Change). 2001. Climate Change 2007: Impacts, Adaptation and Vulnearability. Edited by M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson. Cambridge: Cambridge University Press. IPCC (Intergovernmental Panel on Climate Change). 2007. Climate Change 2007: Impacts, Adaptation and Vulnearability. Edited by M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson. Cambridge: Cambridge University Press.

Kitagawa, E.M. 1955. Components of A Difference Between Two Rates. Journal of the American Statistical Association. 50 (272): 1168-1194.

Jagnani, M., Barrett, C., Liu, Y. and You, L. 2020. Within-season Producer Response to Warmer Temperatures: Defensive Investments by Kenyan Farmers. The Economic Journal, ueaa063.

Konukcu, F., Gowing, J.W. and Rose, D.A. 2006. Dry Drainage: A Sustainable Solution to Waterlogging and Salinity Problems in Irrigation Areas? Agricultural Water Management 83 (2006): 1-12.

Patel., B.R., Shrivastava, R.K. and Raman, S. 2000. Solution of Waterlogging and Salinity Problems Through Subsurface Drainage System-A Case Study. Conference: 8th International Drainage Workshop, Volume I. Available from https://www.researchgate.net/publication/235705844_Solution_of_Waterlogging_and_Salinity_Problems_Through_Subsurface_Drainage_System_-_A_case_Study.

Kolstad, C.D. and Moore, F.C., 2019. Estimating the Economic Impacts of Climate Change Using Weather Observations. NBER Working Paper No. 25537.

Kurukulasuriya, P. and Mendelsohn, R. 2008a. A Ricardian Analysis of the Impact of Climate Change on African Cropland. African Journal Agriculture and Resource Economics, 2, 1-23.

Kurukulasuriya, P. and Mendelsohn, R. 2008b. Crop Switching As An Adaptation Strategy to Climate Change. African Journal Agriculture and Resource Economics, 2, 105-126.

Kurukulasuriya, P. and Mendelsohn, R. 2008c. Modeling Endogenous Irrigation: The Impact of Climate Change on Farmers in Africa. World Bank Policy Research Working Paper 4278 (World Bank: Washington DC).

Laurenceson, J. and Chai, J.C.H. 2003. Financial Reforms and Economic Development in China. Chapter 2. Edward Elgar Publishing, Inc.

Lawrence, M. 2005. The Relationship Between Relative Humidity and the Dewpoint Temperature in Moist Air: A Simple Conversion and Applications. Bullet American Meteorology Society, 86(2): 225-233.

Lawton, H.W., Wike, P.J. (1979). Ancient Agricultural Systems in Dry Regions of the Old World. in Hall, A.E., Cannell, G.H., Lawton, H.W. (eds.). Agriculture in Semi-Arid Environments. Ecological Studies. 34. Berlin: Springer Science & Business Media (published 2012).

Lemoine, D. 2017. Estimating the Consequences of Climate Change from Variation in Weather. NBER

Working Paper No. 25008.

Liu, L., Liu, Z., Gong, J., Wang, L. and Hu, Y. 2019. Quantifying the Amount, Heterogeneity and Pattern of Farmland: Implications for China's Requisition-Compensation Balance of Farmland Policy. Land Use Policy 81 (2019): 256-266.

Liu, Xunhao, 1993. Chinese Cropping System. China Agriculture Press, Beijing.

Lobell, D.B., Hammer, G.L., McLean, G., Messina, C., Roberts, M.J. and Wolfram, S. 2013. The Critical Role of Extreme Heat for Maize Production in the United States. Nature Climate Change 3(5): 497-501.

Maddison, D. 2007. The Perception of and Adaptation to Climate Change. Climatic Change 45, 583-600.

Ministry of Water Resources of China. 1993. Technical Terminology for Irrigation and Drainage. Beijing, China.

Mendelsohn, R., Nordhaus, W. and Shaw, D. 1994. The Impact of Global Warming on Agriculture: A Ricardian Analysis. American Economic Review 89 (4): 753-71.

Mendelsohn, R. 2008. The Impact of Climate Change on Agriculture in Developing Countries. Journal of Natural Resources Policy Research, Vol.1, No.1, 5-19.

Moore,F.C. and Lobell, D.B. 2014. The Adaptation Potential of European Agriculture in Response to Climate Change. Nature Climate Change, 4(7): 610-614.

Newwey, W. and West, K. 1987. A Simply Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55: 703-708.

MWRC (Ministry of Water Resources, P.R. China). 2009. China Water Statistical Yearbook 2009. Beijing: China Water Power Press.

Oaxaca, R. 1973. Male-Female Wage Differentials in Urban Labor Markets. International Economic Review. 14(3): 693-709.

OECD. 2005. Review of Agricultural Policies: China. Available from https://read.oecd-ilibrary.org/agriculture-and-food/oecd-review-of-agricultural-policies-china-2005_9789264012615-en#page1

OECD. 2013. Agricultural Policy Monitoring and Evaluation 2013. Available from https://read.oecd-ilibrary.org/agriculture-and-food/agricultural-policy-monitoring-and-evaluation-2013_agr_pol-2013-en#page1

On-Kit Tam, 1988. Rural Finance in China. The China Quarterly 113, 60-76.

Fishman, R. 2018. Groundwater Depletion Limits the Scope for Adaptation to Increased Rainfall Variability in India. Climate Change 147, 195-209.

Pumin, Y. 2013. Feeding the Future: New Challenges in Ensuring Food Security Require New Solutions. Beijing Review. 2014 (1). Available from https://www.cnki.com.cn/Article/CJFDTotal-BJZB201401005.htm.

Smit, B. ed. 1993. Adaptation to Climatic Variability and Change: Report of the Task Force on Climate Adaptation. 19. Canadian Climate Program, Department of Geography Occasional Paper.

Smit, B.. Burton, I., Klein, R.J.T. and Wandel, J. 2000. An Anatomy of Adaptation to Climate Change and Variability. Climate Change 45, pp. 223-251.

Taraz, V. 2017. Adaptation to Climate Change: Historical Evidence from the Indian Monsoon. Environmental Development Economics 22, 517-545.

Taraz, V. 2018. Can Farmers Adapt to Higher Temperatures? Evidence from India. World Development 112, 205-219.

Rebetez, M. and Beniston, M. 1998. Changes in Sunshine Duration Are Correlated With Changes in Daily Temperature Range This Century: An Analysis of Swiss Climatological Data. Geophysical Research Letters, Vol. 25, No. 19, 3611-3613.

Roberts, M. and Schlenker, W. 2011. The Evolution of Heat Tolerance of Corn. Chapter Eight in NBER Book *The Economics of Climate Change: Adaptations Past and Present*, edited by Gary D. Libecap and Richard H. Steckel, 225-251.

Schlenker, W. and Roberts, M. 2009. Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields Under Climate Change. Proceedings of the National Academy of Sciences 106(37): 15594-98.

Snyder, R.L. 1985. Hand Calculating Degree Days. Agricultural and Forest Meteorology, 35(1985): 353-358.

Stone, B. 1988. Developments in Agricultural Technology. The China Quarterly. 116, 767-822.

Tack, J., Barkley, A. and Hendricks, N. 2017. Irrigation offsets wheat yield reductions from warming temperatures. Environmental Research Letters 12(2017) 114027.

The State Council Information Office of the People's Republic of China. 1996. White Paper-The Grain Issue in China. English Version Available from https://www.iatp.org/sites/default/files/Grain_Issue_in_China_White_Paper_The.htm. Chinese Version Available from http://www.scio.gov.cn/zfbps/ndhf/1996/Document/307978/307978.htm.

Xinhua News Agency. 2008. China Achieved 95% Self-sufficiency in Grain for the Last 10 Years. Available from https://www.chinadaily.com.cn/bizchina/2008-07/04/content_6821000.htm

Wang, J., Zhang, J. and Zhang, P. 2020. Weather, Climate Change and Land Use: A High-Resolution Analysis in China. Working Paper, 1-37.

Wang, J., Mendelsohn, R., Dinar, A., Huang, J. and Rozzelle, S. 2008. Can China Continue Feeding Itself? The Impact of Climate Change on Agriculture. World Bank Policy Research Working Paper 4470 (Workd Bank: Washington DC).

Wang, J., Mendelsohn, R., Dinar, R. and Huang, J. How Chinese Farmers Change Crop Choice to Adapt to Climate Change. Climate Change Economics. Vol. 1, No. 3 (2010): 167-185.

Welch, J., Vincent, J.R., Auffhammer, M., Moya, P.F., Dobermann, A. and Dawe, D. 2010. Rice

Yields in Tropical/Subtropical Asia Exhibit Large but Opposing Sensitivities to Minimum and Maximum Temperatures. Proceedings of the National Academy of Sciences 107 (33): 14562-67.

Wooten, R.D., 2011. Statistical Analysis of the Relationship Between Wind Speed, Pressure and Temperature. Journal of Applied Sciences, 11(15): 2712-2722.

World Bank. 2008. Agriculture for Development. Report. Available from https://openknowledge.worldbank.org/handle/10986/5990

World Bank. 2010. Economics of Adaptation to Climate Change. Washington, DC: World Bank.

World Bank. 2015. Climate Change Threatens to Deepen Poverty in East Asia Pacific by 2030. Available from https://www.worldbank.org/en/news/press-release/2015/11/12/climate-change-threatens-to-deepen-poverty-in-east-asia-pacific-by-2030

World Bank. 2019. Action Plan on Climate Change Adaptation and Resilience. Washington, DC.

Snyder, R.L., Melo-Abreu, J.P. 2005. Frost Protection: Fundamentals, Practice and Economics. Vol.1. Food and Agriculture Organization of the United Nations.

Williams, J.F., Roberts, S.R., Jill, J.E., Scardaci, S.C., Tibbits, G. 2007. Managing Water for Weed Control in Rice. UC Davis, Department of Plant Sciences. Available from https://web.archive.org/web/20070403211941/http://www.plantsciences.ucdavis.edu/uccerice/WATER/water.htm

Snyder, R.L. 1985. Hand Calculating Degree Days. Agricultural and Forest Meteorology, 35(1985): 353-358.

Zaveri, E. and Lobell, D.B. 2019. The Role of Irrigation in Changing Wheat Yields and Heat Sensitivity in India. Nature Communications (2019) 10: 4144.

Zhang, P., Zhang, J. and Chen, M. 2017. Economic Impacts of Climate Change on Agriculture: Importance of Additional Climatic Variables Other Than Temperature and Precipitation. Journal of Environmental Economics and Management 83(2017): 8-31.

Zhu, X., Li, Y., Li, M., Pan, Y. and Shi, P. 2013. Agricultural Irrigation in China. Journal of Soil and Water Conservation, 68(6): 147A-154A.

Neil,A., Arnell, N. and Tompkins, E. 2005. Successful Adaptation to climate change across scales. Global Environmental Change. 15 (2): 77-86.

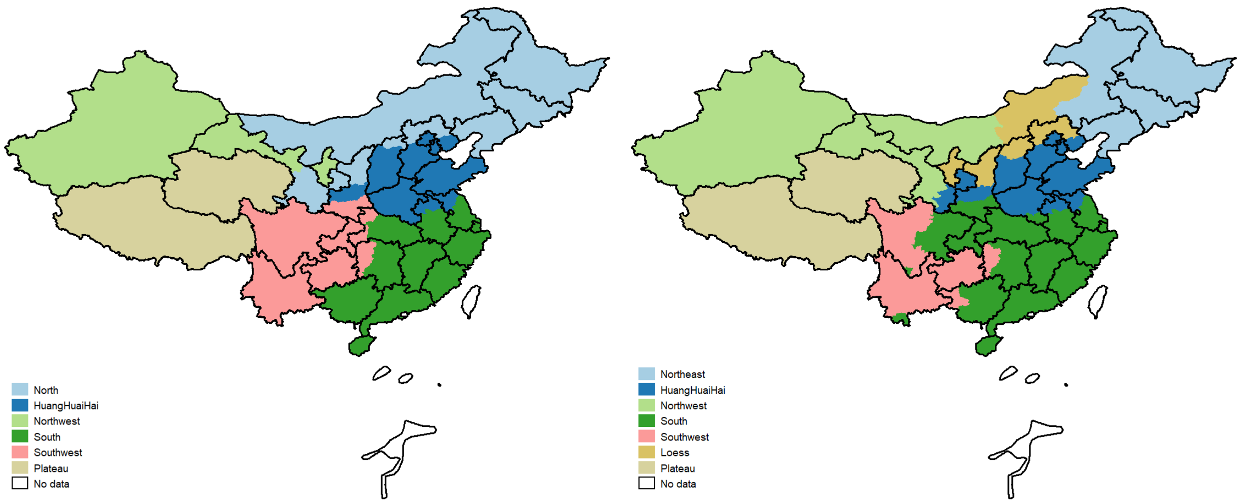
Hatfield, J.L. and Prueger, J.H. 2015. Temperature Extremes: Effect on Plant Growth and Development. Weather and Climate Extremes 10 (2015) 4-10.

Xiao, G., Liu, W., Xu, Q., Sun, Z. and Wang, J. 2005. Effects of Temperature Increase and Elevated CO2 Concentration With Supplemental Irrigation on the Yield of Rain-fed Spring Wheat in a Semiarid Region of China. Agricultural Water Management 75(2005) 243-255.

Appendices

A Figures and Tables on Summary Statistics of Data

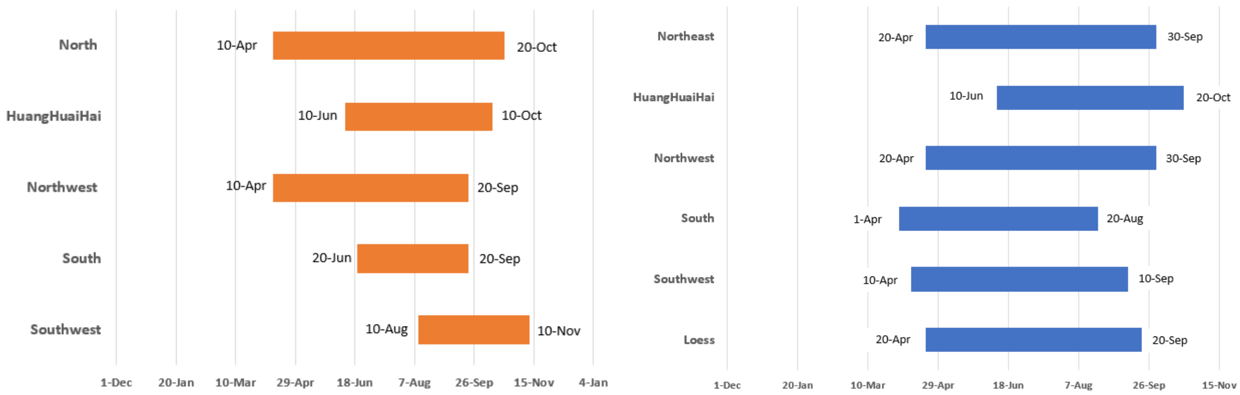
Figure A.1: The Maps of Crop Regions: Corn and Soybean



(a) The Map of Corn Regions (b) The Map of Soybean Regions

Notes: Figure A.1 depicts the growing regions of corn and soybean. Most of the regions are directly named after their geographical locations. The HuangHuaiHai (HHH) region is largely located on the HuangHuaiHai Plain which is a alluvial plain created by the deposition of sediment over a long period of time by Huang (Yellow) River, Huai River and Hai River. Similarly, the Loess region is largely the area of the Loess Plateau which is named for its most distinctive feature, the highly friable loess soil that has been deposited by wind storms over the ages.

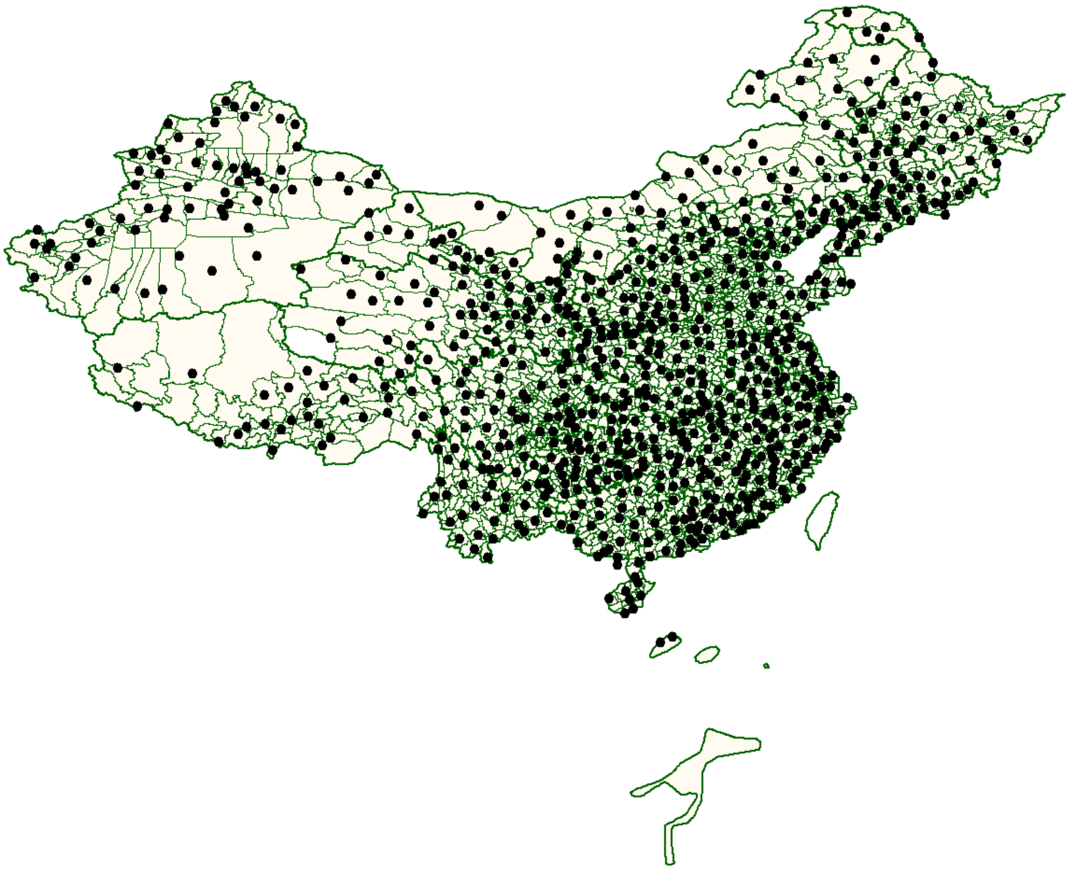
Figure A.2: Growing Seasons of Crops By Region: Corn and Soybean



(a) Growing Seasons of Corn By Region (b) Growing Seasons of Soybean By Region

Notes: This graph exhibits the full growing season of all the main types of crops in terms of planted hectares. For example, the main types of soybean planted in the South are spring, summer and autumn and the consecutive growing seasons of the three types of soybean span over the period from April to August.

Figure A.3: The Locations of Weather Stations from 1981 to 2010



Notes: The black dots in the map denote the locations of all the 824 weather stations. All the 824 stations remained to be active from 1981 to 2010, avoiding selection bias created by opening and closure of weather stations from time to time.

B Temperature-Yield Relationship

B.1 The Role of Additional Climate Variables in the Temperature-Yield Relationship

Table B.1: The Evolution of Temperature-Yield Relationship of Corn: the Impacts of Additional Climate Variables

	(1)	(2)	(3)	(4)	(5)
period=1981 × Humidity	4.8558***	3.5170**	5.4263***	3.4188*	5.2651***
	(1.3424)	(1.4536)	(1.3551)	(1.8339)	(1.6802)
period=1996 × Humidity	3.0706***	1.0243	2.4456**	0.9064	2.5533**
	(0.7100)	(0.9627)	(0.9502)	(1.2051)	(1.0983)
period=1981 × Humidity ^{2}	-2.7303***	-2.5158**	-3.4348***	-2.4548*	-3.3423***
	(0.9218)	(0.9907)	(0.9095)	(1.2996)	(1.1992)
period=1996 × Humidity ^{2}	-2.0531***	-0.5720	-1.4890**	-0.4797	-1.5943**
	(0.5002)	(0.6679)	(0.6532)	(0.8403)	(0.7463)
period=1981 × Sunshine	4.5166*	-1.5612	0.3593	-3.1237	-0.0303
	(2.4985)	(2.6176)	(2.2980)	(3.7980)	(3.2589)
period=1996 × Sunshine	2.7386*	8.7506***	4.9695**	8.6309***	4.4465*
	(1.5250)	(2.3257)	(1.9995)	(3.0080)	(2.6196)
period=1981 × Sunshine ^{2}	1.1678	31.9171	14.2726	40.7551	16.7578
	(18.4792)	(20.4081)	(19.3290)	(29.8051)	(26.1956)
period=1996 × Sunshine ^{2}	0.1462	-53.1059***	-26.4431	-50.6477**	-23.5103
	(14.0209)	(20.0276)	(18.5532)	(24.1883)	(21.8004)
period=1981 × Wind	12.6822***	2.9003	1.7830	3.1931	1.9452
	(4.4450)	(4.3263)	(4.2325)	(4.0846)	(3.8398)
period=1996 × Wind	-2.5224	-4.5894	-1.9539	-4.7509	-2.1635
	(3.9878)	(4.0738)	(4.3082)	(4.0699)	(4.0810)
period=1981 × Wind ^{2}	-284.8097***	16.3355	74.9892	13.8005	70.4159
	(94.9079)	(87.9925)	(93.9014)	(76.2907)	(75.1698)
period=1996 × Wind ^{2}	100.4426	178.5359**	111.2850	181.6654**	115.4660
	(86.8305)	(86.6485)	(98.2608)	(82.4844)	(81.9532)
period=1981 × Evaporation	-12.4397***	-12.8965***	-6.6016***	-11.0622***	-6.8851**
	(3.5828)	(2.7598)	(2.4201)	(3.0015)	(2.8389)
period=1996 × Evaporation	-1.2328*	-0.7532	-0.7776	-0.6220	-0.6315
	(0.6641)	(0.7929)	(1.0957)	(0.7254)	(0.8274)
period=1981 × Evaporation ^{2}	77.3252***	75.6097***	46.8512**	62.5565***	47.4403**
	(26.5534)	(21.5832)	(20.8486)	(19.5488)	(19.8966)
period=1996 × Evaporation ^{2}	2.7237	1.9537	4.0656	0.2661	1.6231
	(6.4317)	(8.8349)	(9.9723)	(8.0898)	(7.7328)
period=1981 × GSTDD below T	0.0052	0.0136***	0.0078*	0.0137***	0.0081**
	(0.0047)	(0.0036)	(0.0041)	(0.0044)	(0.0041)
period=1996 × GSTDD below T	0.0136***	-0.0011	-0.0002	-0.0016	-0.0000
	(0.0041)	(0.0037)	(0.0041)	(0.0046)	(0.0041)
period=1981 × GSTDD above T	-0.0012	-0.0051	-0.0014	-0.0052	-0.0008
	(0.0070)	(0.0060)	(0.0052)	(0.0076)	(0.0071)
period=1996 × GSTDD above T	-0.0187***	-0.0153**	-0.0131*	-0.0149**	-0.0125**
	(0.0068)	(0.0072)	(0.0079)	(0.0061)	(0.0059)
Observations	59269	59269	59269	59274	59274
R squared	0.7525	0.7981	0.8421	0.0338	0.0210
Fixed Effects	Cty,Year	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr
Trend	No	No	Yes	No	Yes
Std. Error	Clustered	Clustered	Clustered	Spatial HAC	Spatial HAC
T threshold	28 $°C$	28 $°C$	28 $°C$	28 $°C$	28 $°C$
P threshold	51 cm	51 cm	51 cm	51 cm	51 cm
Distance	N/A	N/A	N/A	500 km	500 km
Years of Lag	N/A	N/A	N/A	5	5

Note: This table follows Table 3 to present the impacts of additional climate variables on corn yields including humidity, sunshine duration, wind speed, evaporation and ground surface temperature. This table and Table 3 are based on the same regression. Each column corresponds to a separate regression varying on specification of fixed effects and estimation of standard errors as specified in the table. The dependent variable is log annual corn yields from 1981 to 2010. The regressions are weighted by annual corn hectares. Temperature threshold is 28 °C and precipitation threshold is 51 cm in all specifications. County-specific quadratic trends are controlled and standard errors are clustered at the county level.

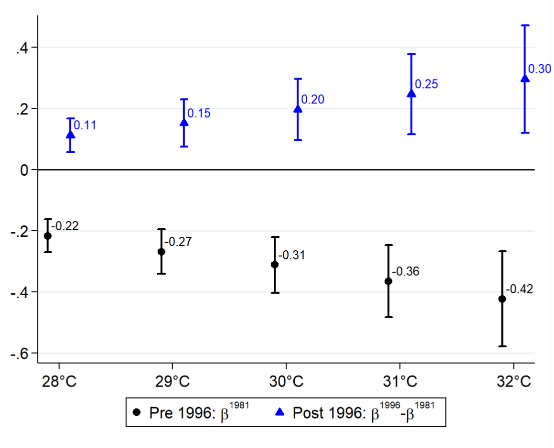
Table B.2: The Evolution of Temperature-Yield Relationship of Soybean: the Impacts of Additional Climate Variables

	(1)	(2)	(3)	(4)	(5)
period=1981 × Humidity	0.4105	3.3967	1.8653	3.3451	2.0624
	(2.4224)	(2.9606)	(3.0894)	(2.8254)	(2.2054)
period=1996 × Humidity	4.9127**	3.0832	2.8996	3.4287	2.7038
	(1.9167)	(2.5472)	(2.3184)	(2.5587)	(1.9574)
period=1981 × Humidity ^{2}	-0.6570	-2.4395	-1.3947	-2.3723	-1.5312
	(1.5859)	(1.9907)	(2.0197)	(1.8879)	(1.5082)
period=1996 × Humidity ^{2}	-3.1913**	-1.5905	-1.9717	-1.8375	-1.8703
	(1.2839)	(1.7860)	(1.6238)	(1.7915)	(1.3251)
period=1981 × Sunshine	11.5723**	3.3262	0.5132	3.2316	-0.0231
	(4.8105)	(6.4674)	(5.7232)	(5.5624)	(4.8487)
period=1996 × Sunshine	-0.1673	3.1777	11.7199**	3.3445	11.5340***
	(3.9256)	(5.1432)	(5.4419)	(5.1919)	(4.3031)
period=1981 × Sunshine ^{2}	-46.3149	9.1336	25.5045	10.7672	29.0898
	(38.8951)	(53.1490)	(48.2396)	(48.5647)	(39.7375)
period=1996 × Sunshine ^{2}	-8.6529	4.2461	-64.2970	2.7104	-64.6412*
	(28.8306)	(40.0742)	(40.2122)	(43.4510)	(36.1032)
period=1981 × Wind	-0.6193	-2.9659	1.5109	-3.3065	1.4699
	(7.0333)	(6.9804)	(7.4539)	(5.9724)	(4.8800)
period=1996 × Wind	-4.7204	0.2266	1.8803	-0.4208	1.2214
	(7.3825)	(7.5822)	(7.6391)	(6.0988)	(4.9070)
period=1981 × Wind ^{2}	63.8687	41.4636	68.0034	47.4491	64.0503
	(124.5652)	(129.5193)	(141.3947)	(146.0938)	(104.6091)
period=1996 × Wind ^{2}	240.8413	79.0646	80.3120	92.1338	89.1135
	(157.8163)	(160.5469)	(167.4935)	(148.4572)	(110.2699)
period=1981 × Evaporation	-1.3909	1.3168	0.4985	-0.1275	-0.4049
	(4.5617)	(4.9764)	(4.6616)	(4.7136)	(3.4755)
period=1996 × Evaporation	0.1464	1.0166	-0.8119	1.0141	-0.6465
	(1.1356)	(1.3028)	(1.5506)	(1.1316)	(1.1587)
period=1981 × Evaporation ^{2}	-60.6455	-45.8914	-18.5320	-32.4938	-9.7248
	(42.6463)	(45.9285)	(42.6171)	(40.9255)	(30.2648)
period=1996 × Evaporation ^{2}	-24.2417*	-21.2860	-13.9129	-21.0577	-16.1461
	(12.7238)	(15.4893)	(16.3715)	(15.6708)	(15.3188)
period=1981 × GSTDD below T	0.0128***	0.0027	0.0008	0.0030	0.0006
	(0.0037)	(0.0042)	(0.0038)	(0.0034)	(0.0030)
period=1996 × GSTDD below T	0.0192***	0.0079*	0.0115**	0.0080***	0.0113***
	(0.0036)	(0.0041)	(0.0051)	(0.0029)	(0.0034)
period=1981 × GSTDD above T	-0.0207***	-0.0050	-0.0062	-0.0051	-0.0062
	(0.0075)	(0.0074)	(0.0070)	(0.0052)	(0.0042)
period=1996 × GSTDD above T	-0.0227***	-0.0133**	-0.0211**	-0.0126***	-0.0211***
	(0.0065)	(0.0065)	(0.0085)	(0.0044)	(0.0046)
Observations	54327	54322	54322	54323	54323
R squared	0.6819	0.7265	0.7869	0.0238	0.0239
Fixed Effects	Cty,Year	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr	Cty,Prov-Yr
Trend	No	No	Yes	No	Yes
Std. Error	Clustered	Clustered	Clustered	Spatial HAC	Spatial HAC
T threshold	26 $°C$	26 $°C$	26 $°C$	26 $°C$	26 $°C$
P threshold	44 cm	44 cm	44 cm	44 cm	44 cm
Distance	N/A	N/A	N/A	500 km	500 km
Years of Lag	N/A	N/A	N/A	5	5

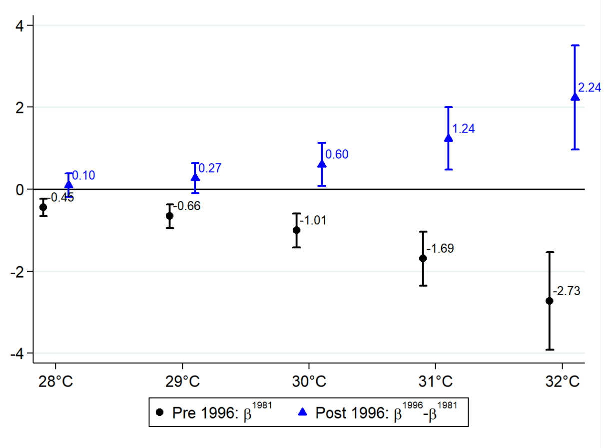
Note: This table follows Table 4 to present the impacts of additional climate variables on soybean yields including humidity, sunshine duration, wind speed, evaporation and ground surface temperature. All the specifications of the regression models are identical to Table 4. Each column corresponds to a separate regression varying on specification of fixed effects and estimation of standard errors as specified in the table. The dependent variable is log annual soybean yields from 1981 to 2010. The regressions are weighted by annual soybean hectares. Temperature threshold is 26 °C and precipitation threshold is 44 cm in all specifications. County-specific quadratic trends are controlled and standard errors are clustered at the county level.

Figure B.1 and B.2 report the estimation of marginal impacts of extreme temperatures on corn and soybean yields using multiple temperature thresholds for the whole nationwide sample and sub-regions based on cropping regions for each crop. The division of cropping regions for corn and soybean are based on Figure A.1. The two figures are the robustness analysis of estimation sensitivity to temperature thresholds. The thresholds are introduced as the labels for x-axis. Figure B.1 is about corn and Figure B.2 is about soybean. All the figures depict the point estimate and the corresponding 95 % confidence interval for the coefficient for GDD above the threshold.

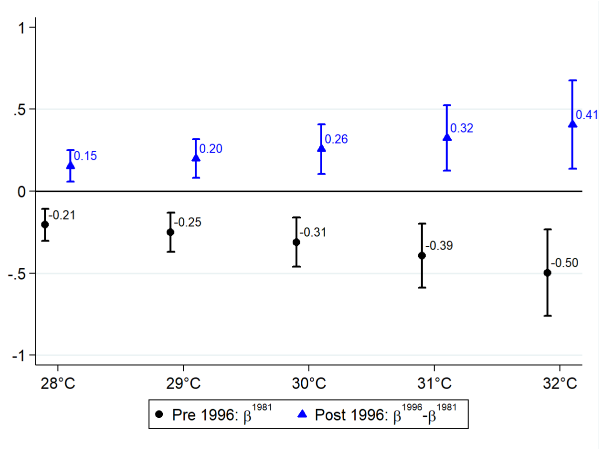
Figure B.1: Marginal Impacts of Extreme Temperatures on Corn Yields by Temperature Thresholds



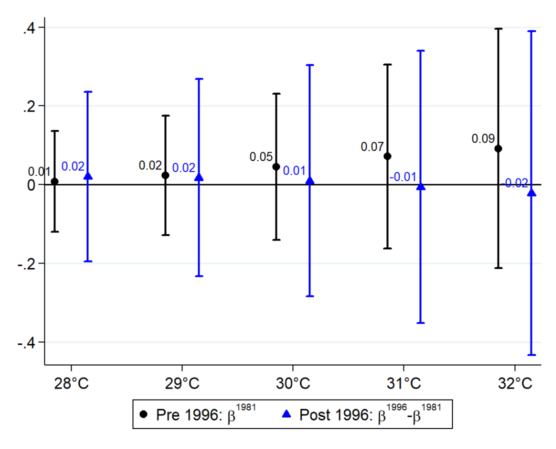
(a) Corn: Nationwide



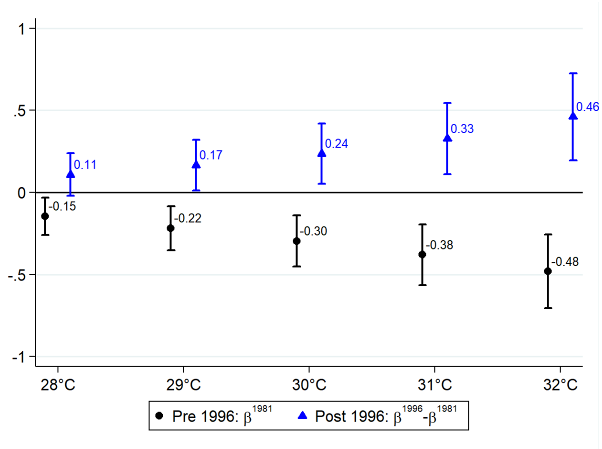
(b) Corn: North



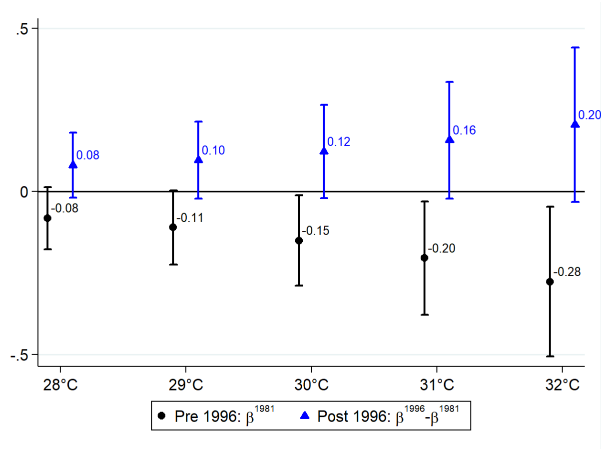
(c) Corn: Huanghuaihai (HHH)



(d) Corn: Northwest

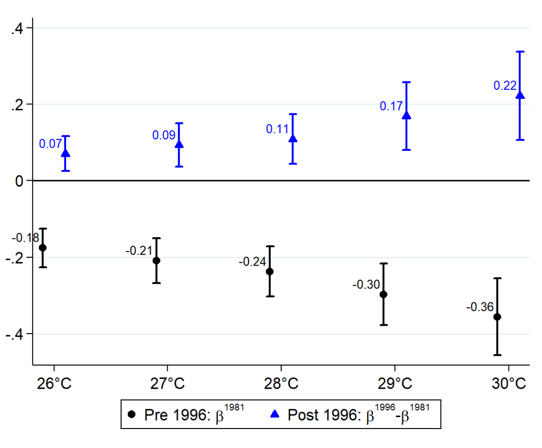


(e) Corn: South

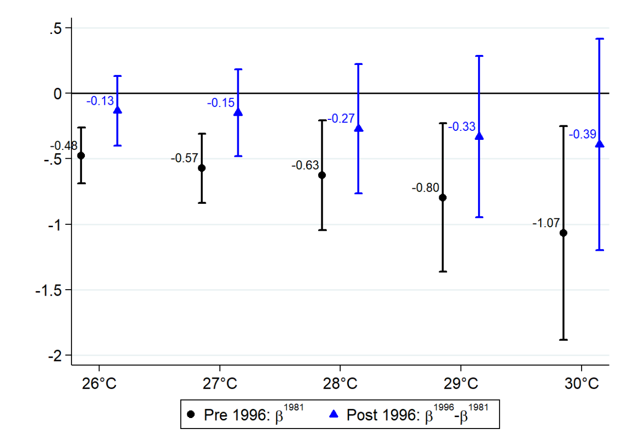


(f) Corn: Southwest

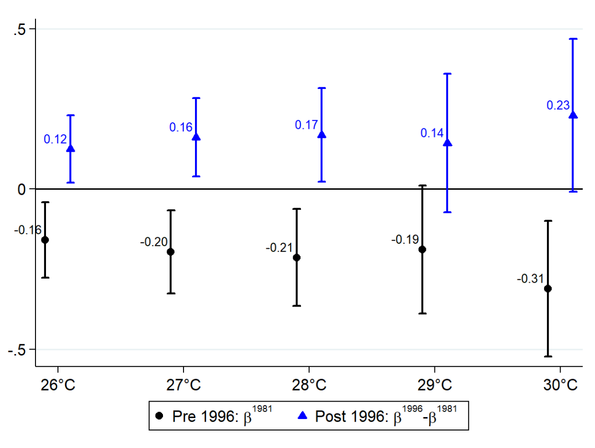
Figure B.2: Marginal Impacts of Extreme Temperatures on Soybean Yields by Temperature Thresholds



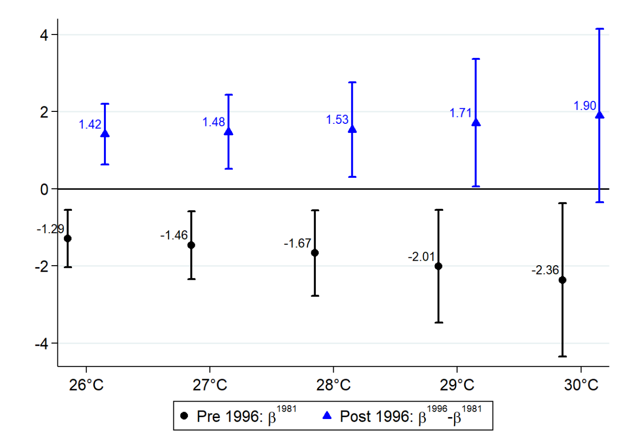
(a) Soybean: Nationwide



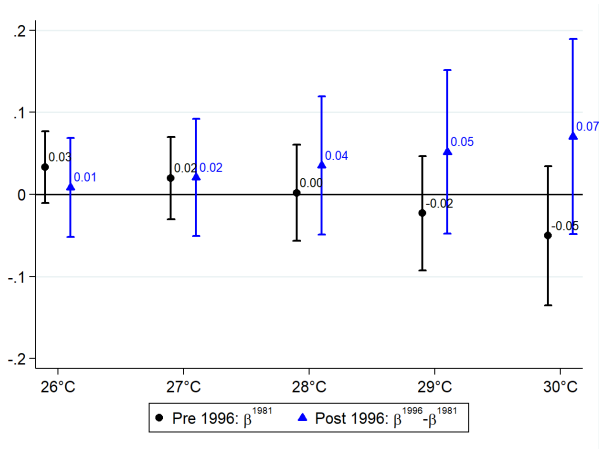
(b) Soybean: North



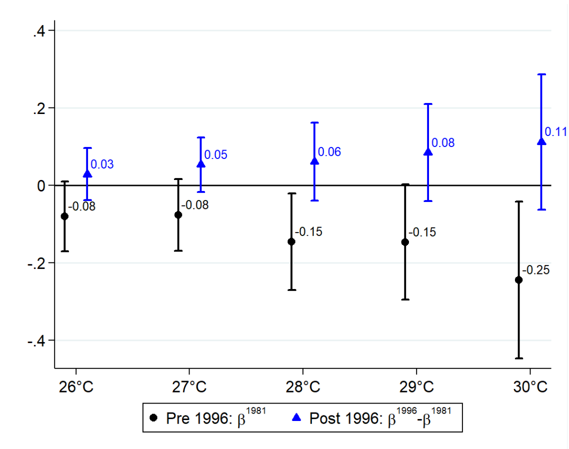
(c) Soybean: Huanghuaihai (HHH)



(d) Soybean: Northwest



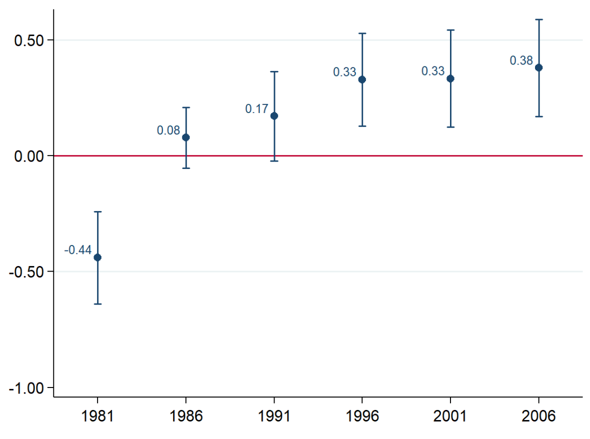
(e) Soybean: South



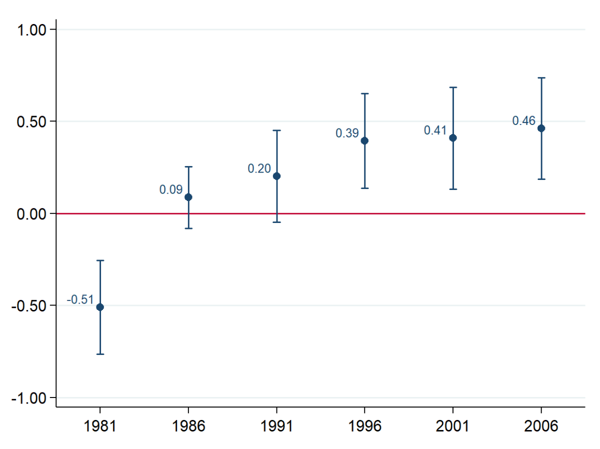
(f) Soybean: Southwest

Figure B.3 to B.6 report the estimation of marginal impacts of extreme temperatures on corn and soybean yields estimated through a period-wise panel model in equation (5) using 5 years or 10 years as a period to test the sensitivity of results to the choice of endpoints and length of time periods. In addition, we try other temperature thresholds apart from 28 °C for the corn and 26 °C for the soybean to avoid misspecification of temperature threshold for the growing degree days (we only control province-by-year fixed effects when we select the thresholds). Figure B.3 and B.4 are about corn yields and Figure B.5 and B.6 are about soybean yields. All the figures depict the point estimate and the corresponding 95 % confidence interval for the coefficient for GDD above the threshold of each period which is denoted by the starting year of the period on the horizontal axis. For example, 1981 denotes the period 1981-1985 if 5-year period is used in the regression. The coefficient of the first period is the marginal impact of extreme high temperature (measured by GDD above the threshold) and the coefficients of all the later periods are the differences of the marginal impacts of extreme temperature in the corresponding period relative to the impact in the first period. The initial year of each period is specified in the label of the horizontal axis.

Figure B.3: Marginal Impacts of Extreme Temperatures on Corn Yields By Temperature Thresholds: 5 Years as a Period



(a) GDD above 29 °C

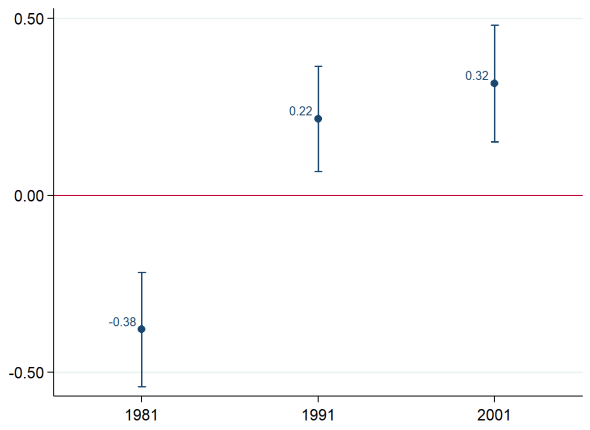


(b) GDD above 30 °C

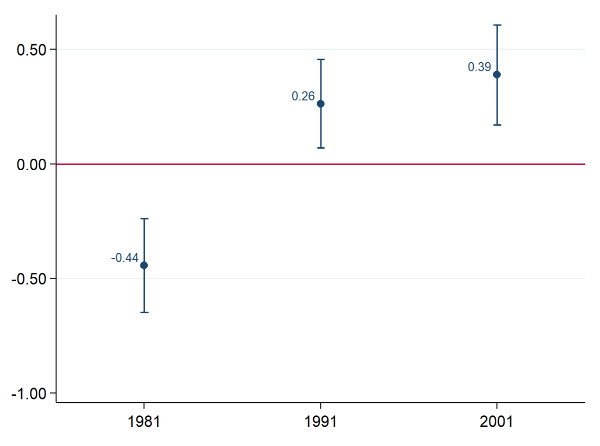
(c) GDD above 31 °C

(d) GDD above 32 °C

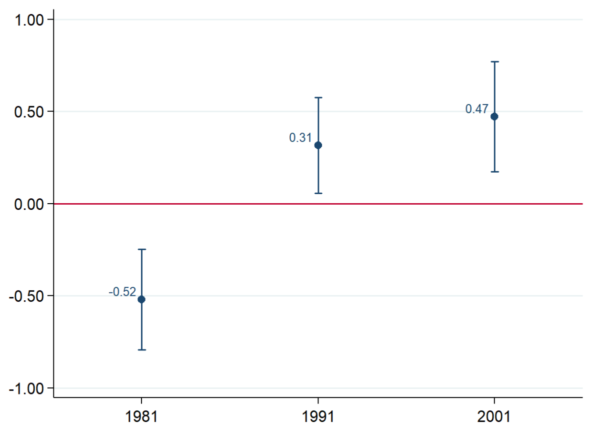
Figure B.4: Marginal Impacts of Extreme Temperatures on Corn Yields By Temperature Thresholds: 10 Years as a Period



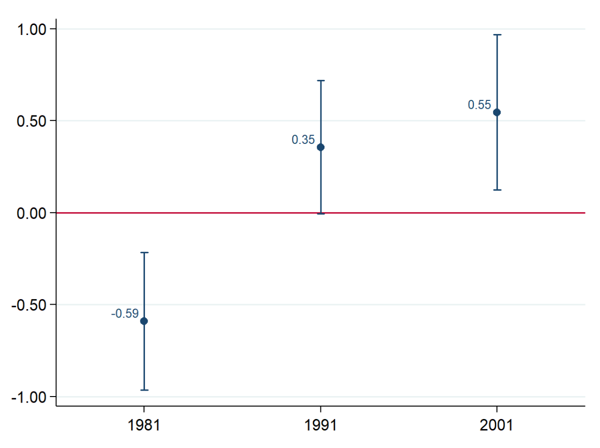
(a) GDD above 29 °C



(b) GDD above 30 °C



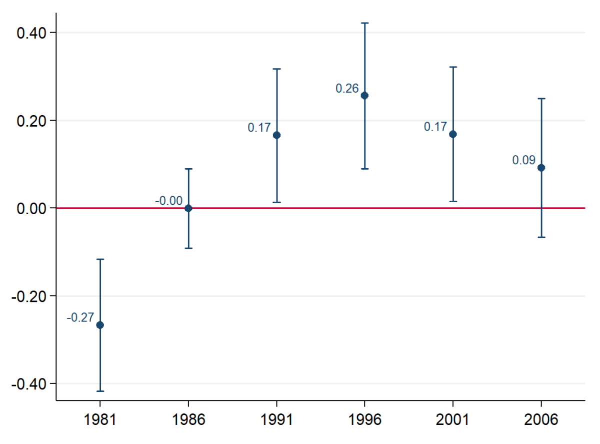
(c) GDD above 31 °C



(d) GDD above 32 °C

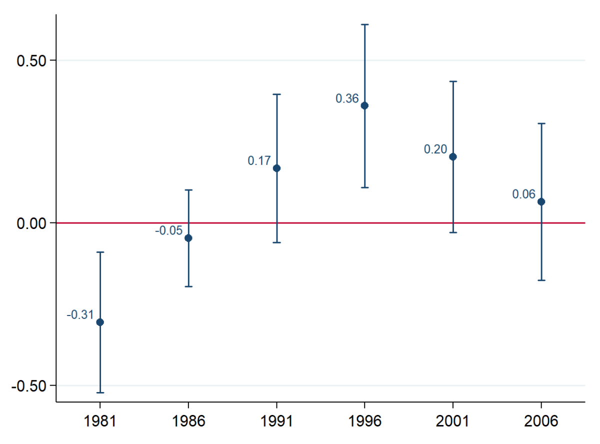
Figure B.5: Marginal Impacts of Extreme Temperatures on Soybean Yields By Temperature Thresholds: 5 Years as a Period

(a) GDD above 29 °C



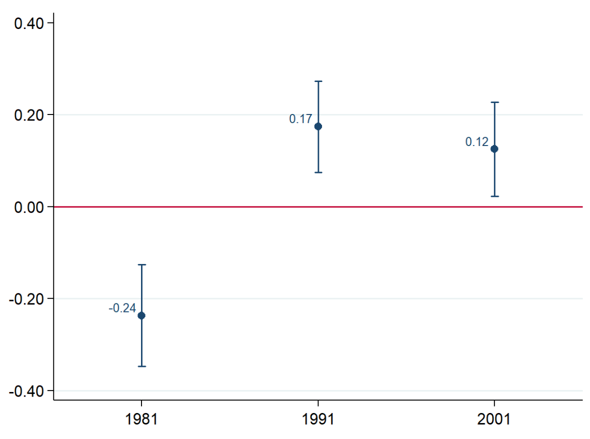
(b) GDD above 28 °C

(c) GDD above 29 °C

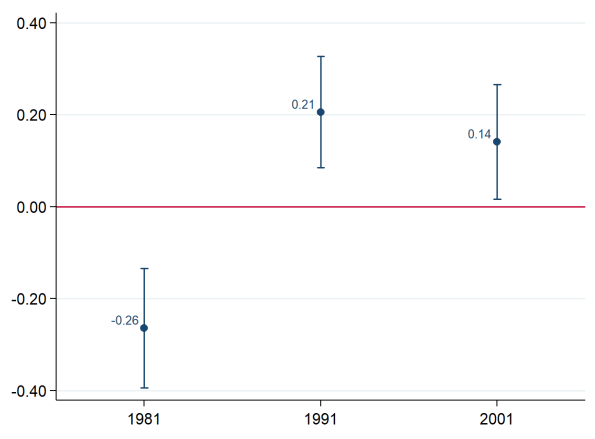


(d) GDD above 30 °C

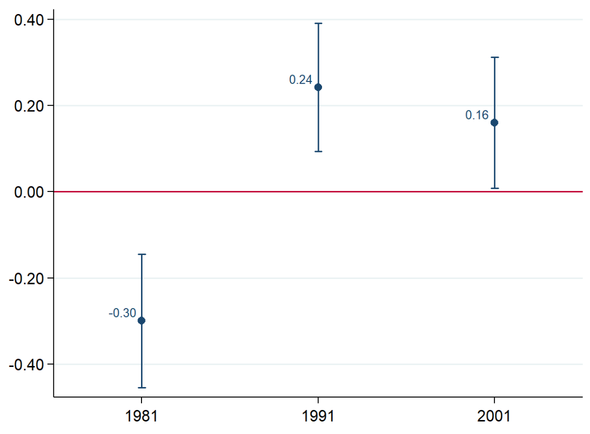
Figure B.6: Marginal Impacts of Extreme Temperatures on Soybean Yields By Temperature Thresholds: 10 Years as a Period



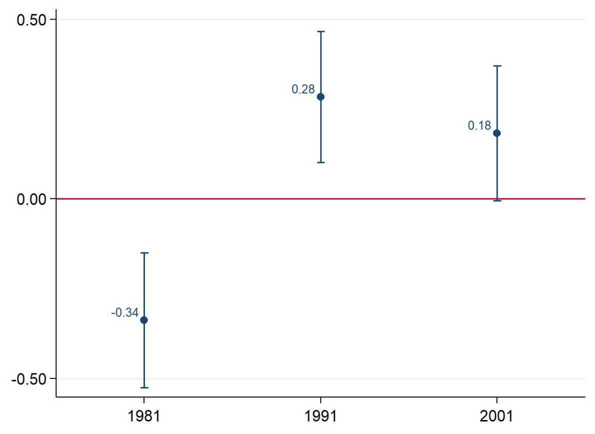
(a) GDD above 29 °C



(b) GDD above 28 °C



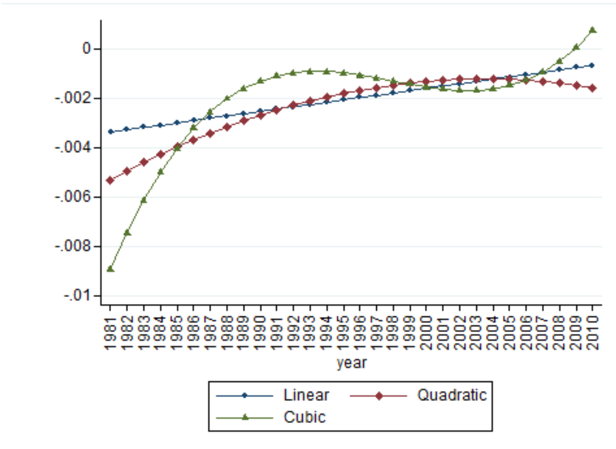
(c) GDD above 29 °C



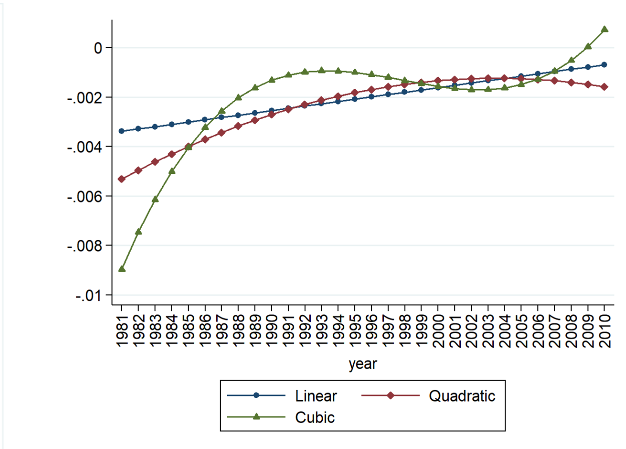
(d) GDD above 30 °C

Figure B.7 and B.8 presents the evolutionary trajectory of marginal impacts of extreme high temperature on crop yields. The extreme high temperature is measured by growing degree days above four temperature thresholds different from the proceeding thresholds. This is to avoid misspecification of the temperature threshold used in the growing degree days since we don't separately select the threshold for the polynomial model introduced in equation (3). Figure B.7 is about corn and Figure B.8 is about soybean.

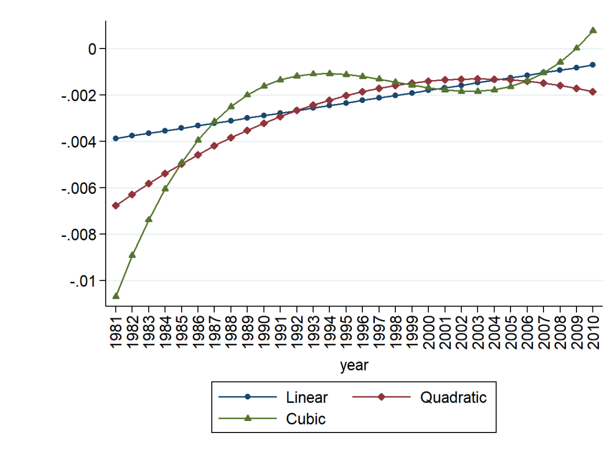
Figure B.7: Marginal Impacts of Extreme Temperatures on Corn Yields By Temperature Thresholds: Using Polynomial Model of Time Trend



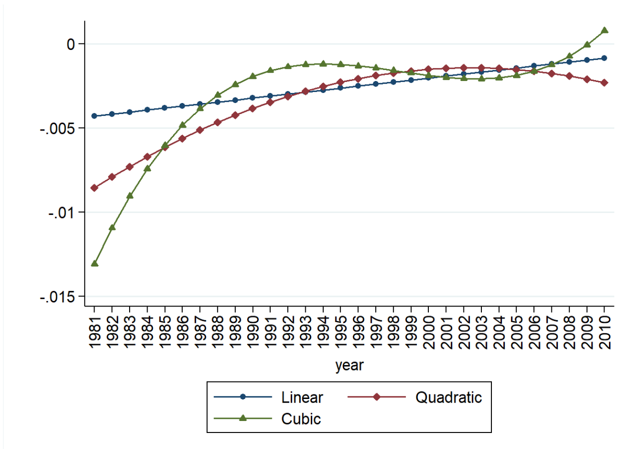
(a) GDD above 29 °C



(b) GDD above 28 °C

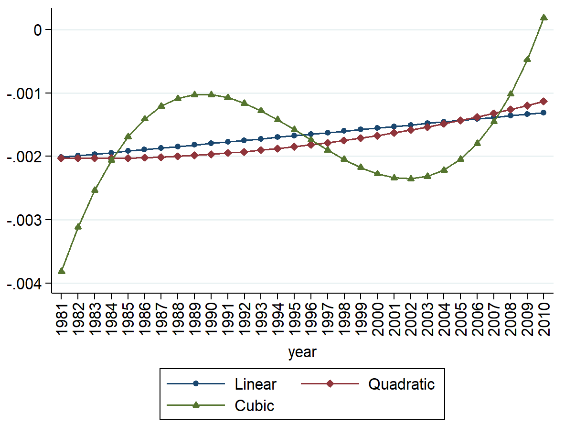


(c) GDD above 29 °C

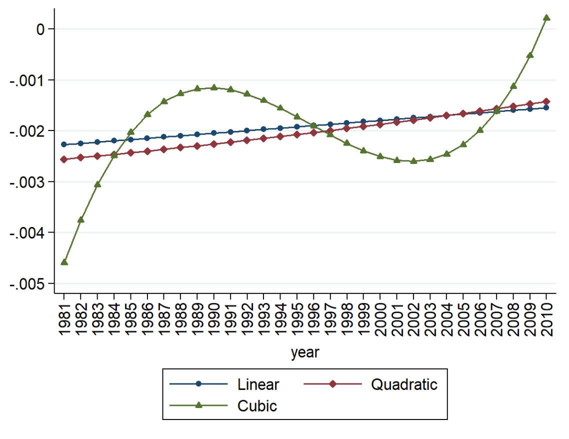


(d) GDD above 30 °C

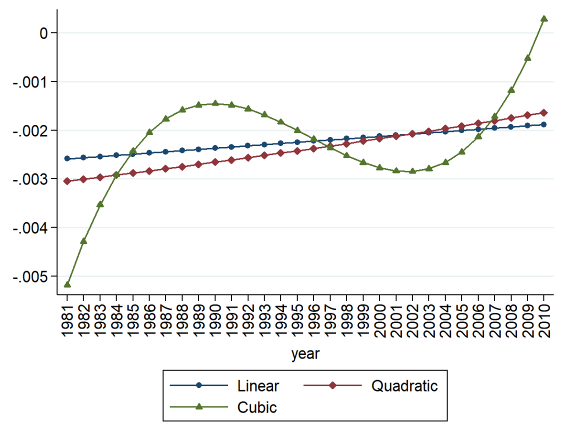
Figure B.8: Marginal Impacts of Extreme Temperatures on Soybean Yields By Temperature Thresholds: Using Polynomial Model of Time Trend



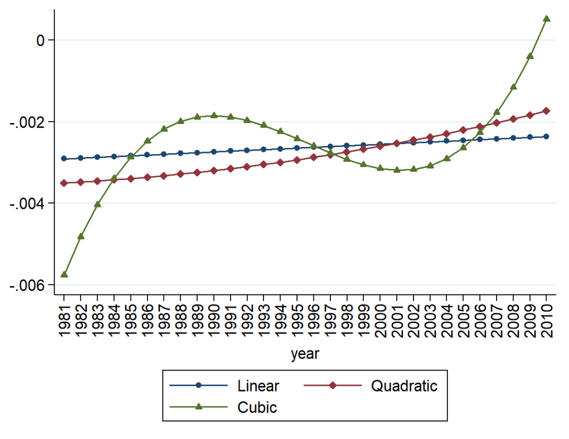
(a) GDD above 27 °C



(b) GDD above 28 °C



(c) GDD above 29 °C



(d) GDD above 30 °C

B.2 The Effects of Agricultural Inputs on the Relationship Between Crop Yields and Low Temperatures

Table B.3 and B.4 reports the effects of agricultural inputs on the relationship between yields and low temperatures, which are measured by the interaction effects between temporal change in inputs and low temperatures (GDD below the threshold) using the model in equation (6). Table B.5 reports the robustness analysis of the interaction effects of inputs with low temperatures by adding the temperature-by-year trend and interactions of economic controls with temperatures. The analysis on the interaction effects of inputs with low temperatures is a placebo test of the moderation effects of inputs on extreme temperature impacts. We do not expect that inputs can protect yields from low temperatures. Insignificant interaction effects of inputs with low temperatures suggest that the adoption of inputs is not coincidental with factors that determine the overall crop yields.

Table B.3: Interaction Effects of Inputs Change with Low Temperatures for Corn Counties

	(1) Irrigation	(2) Machinery	(3) Fertilizer	(4) Electricity	(5) Combined
GDD below T	0.0053	-0.0016	-0.0113	-0.0016	-0.0039
	(0.0095)	(0.0089)	(0.0097)	(0.0082)	(0.0102)
GDD below T × Irrigation (%)	-0.0002				0.0110
	(0.0130)				(0.0132)
GDD below T × Machinery (Kw./Ha.)		-0.0012			-0.0012
		(0.0011)			(0.0012)
GDD below T × Fertilizer (Tons of Ha.)			0.0487		0.0365
			(0.0313)		(0.0278)
GDD below T × Electricity (Kwh. per capita)				-0.0049	-0.0047
				(0.0053)	(0.0050)
Observations	59255	53655	53645	58332	53475
R squared	0.8664	0.8444	0.8444	0.8423	0.8727
County FE	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes
Cty-Quadratic Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	28 °C	28 °C	28 °C	28 °C	28 °C
P threshold	51 cm	51 cm	51 cm	51 cm	51 cm

Note: The dependent variable is log corn yields. The change of all the agricultural inputs are calculated with the difference in the mean values between the pre-1996 and post-1996 period. The low temperature variable for interactions is the growing degree days below 28 °C. Precipitation and additional climate variables are included. The standard error is clustered at county level and the regressions are weighted by annual corn planted area. * p<0.1, ** p<0.05, *** p<0.01.

Table B.4: Interaction Effects of Inputs Change with Low Temperatures for Soybean Counties

	(1) Irrigation	(2) Machinery	(3) Fertilizer	(4) Electricity	(5) Combined
GDD below T	0.0335*	0.0332***	0.0324***	0.0301**	0.0401**
	(0.0175)	(0.0119)	(0.0118)	(0.0119)	(0.0174)
GDD below T × Δ Irrigation (%)	0.0011				-0.0066
	(0.0242)				(0.0241)
GDD below T × Δ Machinery (Kw./Ha.)		-0.0010***			-0.0003
		(0.0003)			(0.0018)
GDD below T × Δ Fertilizer (Tons of Ha.)			-0.0092***		-0.0066
			(0.0024)		(0.0130)
GDD below T × Δ Electricity (Kwh. per capita)				0.0202	0.0195
				(0.0285)	(0.0275)
Observations	54263	54287	54287	54252	54174
R squared	0.8175	0.8201	0.8201	0.8201	0.8211
County FE	Yes	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes	Yes
Cty-Quadratic Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	26 °C	26 °C	26 °C	26 °C	26 °C
P threshold	44 cm	44 cm	44 cm	44 cm	44 cm

Note: The dependent variable is log soybean yields. The change of all the agricultural inputs are calculated with the difference in the mean values between the pre-1996 and post-1996 period. The low temperature variable for interactions is the growing degree days below 26 °C. Precipitation and additional climate variables are included in the regressions. The standard error is clustered at county level and the regressions are weighted by annual corn planted area. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table B.5: Effects of Agricultural Inputs on Mitigating Heat-related Losses of Corn Yields –Using A Different Measurement of Irrigation

	(1) Irrigation	(2) Machinery	(3) Fertilizer	(4) Electricity	(5) Combined
GDD above T	-0.2223***	-0.1564***	-0.1535***	-0.1400***	-0.1952***
	(0.0308)	(0.0280)	(0.0267)	(0.0254)	(0.0324)
GDD above T × Δ Irrigation Coverage (%)	0.2082***				0.1658***
	(0.0435)				(0.0403)
GDD above T × Δ Machinery Power (Kw./Ha.)		0.0021			0.0009
		(0.0017)			(0.0018)
GDD above T × Δ Fertilizer (Tons /Ha.)			0.0455		0.0209
			(0.0431)		(0.0477)
GDD above T × Δ Electricity (Kwh. per capita)				0.0231*	0.0226*
				(0.0135)	(0.0131)
Observations	56054	56124	56269	54167	51587
R squared	0.8437	0.8690	0.8434	0.8395	0.8690
County Fixed Effect	Yes	Yes	Yes	Yes	Yes
Prov-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
County Quadratic Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	28 °C	28 °C	28 °C	28 °C	28 °C
P threshold	51 cm	51 cm	51 cm	51 cm	51 cm

Note: The irrigation coverage is measured by effective irrigated area over total planted area, which is the only difference to Table 7. Each column corresponds to a regression in which an agricultural input is interacted with extreme temperature measured by the annual GDD above the endogenous threshold. The regression equation is specified by equation (5). Only coefficients on *GDD above the threshold* and relevant interactions are reported in the table. All the regressions are weighted by annual planted area of corn. Only coefficients on *GDD above the threshold* and relevant interactions are reported but GDD below the threshold, precipitation and additional climate variables are included in the regressions. * p<0.1, ** p<0.05, *** p<0.01.

Table B.6: Effects of Agricultural Inputs on Mitigating Heat-related Losses of Soybean Yields –Using A Different Measurement of Irrigation

	(1) Irrigation	(2) Machinery	(3) Fertilizer	(4) Electricity	(5) Combined
GDD above T	-0.1752***	-0.1266***	-0.1142***	-0.1181***	-0.1670***
	(0.0351)	(0.0231)	(0.0236)	(0.0233)	(0.0374)
GDD above T × Δ Irrigation Coverage (%)	0.1118**				0.0855**
	(0.0544)				(0.0415)
GDD above T × Δ Machinery Power (Kw./Ha.)		-0.0002***			0.0036
		(0.0001)			(0.0028)
GDD above T × Δ Fertilizer (Tons /Ha.)			-0.0019***		-0.0290*
			(0.0004)		(0.0153)
GDD above T × b57				-0.0035	-0.0036
				(0.0029)	(0.0029)
Observations	51314	51602	51454	49175	46668
R squared	0.8220	0.8181	0.7858	0.8171	0.8217
County Fixed Effect	Yes	Yes	Yes	Yes	Yes
Prov-Year Fixed Effect	Yes	Yes	Yes	Yes	Yes
County Quadratic Trend	Yes	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered	Clustered
T threshold	26 °C	26 °C	26 °C	26 °C	26 °C
P threshold	44 cm	44 cm	44 cm	44 cm	44 cm

Note: The irrigation coverage is measured by effective irrigated area over total planted area, which is the only difference to Table 8. Each column corresponds to a regression in which an agricultural input is interacted with extreme temperature measured by the annual GDD above the endogenous threshold. The regression equation is specified by equation (6). Only coefficients on *GDD above the threshold* and relevant interactions are reported in the table. All the regressions are weighted by annual planted area of soybean. Only coefficients on *GDD above the threshold* and relevant interactions are reported but GDD below the threshold, precipitation and additional climate variables are included in the regressions. * p<0.1, ** p<0.05, *** p<0.01.

Table B.7: Robustness Analysis of the Interaction Effects of Agricultural Inputs with Low Temperatures for Corn and Soybean

	(1) Corn	(2) Corn	(3) Soybean	(4) Soybean
GDD below T × Δ Irrigation	0.0107	0.0074	-0.0073	0.0316
	(0.0135)	(0.0159)	(0.0243)	(0.0269)
GDD below T × Δ Machinery	-0.0011	-0.0013	-0.0003	-0.0009
	(0.0012)	(0.0012)	(0.0018)	(0.0019)
GDD below T × Δ Fertilizer	0.0383	0.0386	-0.0069	-0.0029
	(0.0282)	(0.0346)	(0.0130)	(0.0134)
GDD below T × Δ Electricity	-0.0047	-0.0076	0.0196	0.0283
	(0.0050)	(0.0052)	(0.0275)	(0.0306)
Δ GDP × Temperature	No	Yes	No	Yes
Δ (Cargo by Road) × Temperature	No	Yes	No	Yes
Temperature × Year	Yes	Yes	Yes	Yes
Observations	53475	37617	54174	40178
R squared	0.8727	0.8601	0.8211	0.8176
County FE	Yes	Yes	Yes	Yes
Prov-Year FE	Yes	Yes	Yes	Yes
Cty-Quadratic Trend	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered
T threshold	28 °C	28 °C	26 °C	26 °C
P threshold	51 cm	51 cm	44 cm	44 cm

Note: This table presents the robustness analysis on the interaction effects of agricultural inputs with low temperatures. Each column is from a separate regression using different endogeneous controls. The dependent variable is log crop yields. The agricultural inputs, local GDP and cargo amount by road are measured with the difference in the mean values between the pre-1996 and post-1996 period. The GDP and cargo amount are in the prefecture level. The temperature variables used for interactions are the growing degree days below the thresholds. Precipitation and additional climate variables are included in the regressions. The standard error is clustered at county level and the regressions are weighted by annual corn and soybean planted area. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.