University of California
Santa Barbara

Economic Analyses of Environmental Change in China

A dissertation submitted in partial satisfaction
of the requirements for the degree

Doctor of Philosophy
in
Economics

by

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June 2021

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June 2021

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Dedication

This dedication is wholeheartedly dedicated to my beloved parents *Junwei Wang* and *Xueling Zhang*, who have been my source of inspiration and gave me strength when I though of giving up, who continually provide the moral, spiritual. emotional and financial support.

To my beloved girlfriend *Yubo Han* who shared her experience, words of advice and encouragement to finish this dissertation and my PhD study.

And lastly, I dedicate this work to my dissertation defense committee: *Olivier Deschenes*, *Kelsey Jack* and *Kyle Meng*. Thank you all for the guidance, strength, power of mind, protection, support and skills and for giving me a healthy PhD life. All of these, I credit to you.

Acknowledgements

Throughout the writing of this dissertation I have received a great deal of support and encouragement. Foremost, I would like to express my sincere gratitude to my advisor Professor Olivier Deschênes for the continuous support of my PhD study and research, for his patience, motivation, enthusiasm and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my PhD study.

Besides my advisor, I would like to thank the rest of my dissertation committee: Professor Kelsey Jack and Professor Kyle Meng for their encouragement, insightful comments and enlightening questions.

My sincere thanks also go to Professor Ted Bergstrom, Professor Chengzhong Qin, Professor Marek Kapicka, Professor Xiaoning Li, Professor Danyang Li and Professor Hongbo Jia who opened the gate of modern economics for me and supported me to pursue a PhD degree in economics.

I thank my fellow classmates at UC, Santa Barbara: Ken Bao, Danae Hernandez-Cortes, Samuel Collie, Jeffrey Cross, Yang Gao, Jacob Gellman, Dave Hales, Hongyuan Jin, Xin Jiang, Yongwook Kim, Ziteng Lei, Andrew Liu, Chris Malloy, Alec Mcquilkin, Ganghua Mei, Charlie Nusbaum, Hakan Ozyilmaz, Emily Robertson, Vincent Thivierge, Lawrence Wei, Guangli Zhang and Shuo Zhang, who gave me valuable comments on improving this dissertation.

Last but not the least, I would like to thank my family: my parents Junwei Wang and Xueling Zhang for giving birth to me at the first place and supporting me spiritually throughout my life, my grandma for raizing me for 18 years, my girlfriend Yubo Han for wholeheartedly accompanying me, my cousin Horace Zhang for giving me a hand whenever I need his help.

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Wang, D., Chen, S. and Zhang, P. 2020. Adaptation to Temperature Extremes in Chinese Agriculture, 1981 to 2010.

Wang, D. 2021. The Environmental Consequences of Creating Cities: Evidence from the County-to-City Upgrading Policy in China.

Wang, D. 2021. How Does Temperature Affect the Agricultural Growth in China: 1981 to 2015

Abstract

Economic Analyses of Environmental Change in China

by

Di Wang

China has experienced drastic climate change and severe environmental pollution since the 1980s. This dissertation provides economic analyses of these two types of environmental changes in China by focusing on the temporal evolution of agricultural sensitivity to extreme heat and the political economy explanations for severe air pollution in China. Chapter 1 examines the time-varying impacts of extreme temperatures on Chinese agriculture over 1981 to 2010. By estimating a period-specific panel regression model using nationwide county-level agriculture production data combined with fine-scale meteorological data, I primarily find 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 and the decline in the extreme temperature impacts on crop yields mainly occurs in counties with expanding irrigation coverage.

Chapter 2 explores reasons for severe air pollution from the perspective of political economy by examining the environmental consequences of the county-to-city upgrading policy which delegates the autonomy of building cities to upgraded counties. In a centralized system like China, economic decentralization without changing the promotion metrics centered around economic performance for local government officials would likely lead to worse environmental quality because local officials compete for promotion on economic performance. Using a comprehensive county-level dataset on economic performance indicators and air pollutant concentrations, I primarily find sig-

nificantly positive policy effects on economic growth and air pollutant concentrations, suggesting that the upgraded counties promoted economic performance at the cost of local air quality. I also calculate the total loss due to the increasing air pollution as valued in terms of statistical life to indicate the magnitude of the social cost of the upgrading policy.

Following the finding of decline in agricultural sensitivity to extreme heat in Chapter 1, Chapter 3 quantifies the contribution of the temporal evolution of extreme temperature impacts to the growth of agricultural revenue during 1981-2010 using an Oaxaca-Blinder decomposition which attributes the growth of agricultural revenue to the change in the levels of predictors and to the change in the coefficients for the predictors. I find extreme temperature impacts on agricultural revenues per hectare in the post-1996 period is more than 60% lower than that in the pre-1996 period, contributing 6.1 percentage points of revenue growth over the two periods, which is 5.4% of the overall growth of agricultural revenue. The significant increase in marginal benefit of irrigation in terms of moderating extreme temperature impacts may have contributed about 40% of the decline in the extreme temperature impacts on agricultural revenue per hectare.

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Chapter 1

Adaptation to Temperature Extremes in Chinese Agriculture, 1981 to 2010[1]

1.1 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; Deschênes 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, 2021). Understanding the temporal evolution of relationship

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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 those in the literature (Schlenker and Roberts, 2009; Roberts and Schlenker, 2011; 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.[2] 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, 2013). 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 China, 1996). Agricultural subsidies aim to provide farmers with an incentive to replace traditional labor-intensive and low-

[2] 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.

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.

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., 2020). 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 (Food Agricultural Organization, 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 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.[3] 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 factors that may affect the temperature-yield relationship through mechanisms other than *ex post* adjustment of input quantities.

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,

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

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.[4] We create 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

[4] 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.

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 four 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; 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 Zaveri 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. (2017) and Zaveri and Lobell (2019) 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 adapted 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., 2020; Chen and Gong, 2021). 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 Neidell, 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, 2008a,b,c; Wang et al., 2010; Huang et al., 2018) and determinants of farmers' adaptation decisions (Bryan et al., 2009; Di Falco et al., 2011; Di Falco and Veronesi, 2013; Di Falco, 2014). 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., 2021; 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.

1.2 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 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; Siebert 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).[5] Other sub-

[5] 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

sidies 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 (Gentzkow, 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.

1.3 Conceptual Framework

1.3.1 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

the panel model to account for the smooth change in crop yields that may be driven by technology advancement including high-quality seeds.

(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.[6] 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

$$\max_{x_t} \pi_t(K_t^*, w_t) = P_t \cdot F(x_t, K_t^*(\mathbb{E}_{t-1}(w_t)), w_t) - P_{x,t} \cdot x_t - P_{K,t} \cdot K_t^*(\mathbb{E}_{t-1}(w_t)) \quad (1.1)$$

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 $t-1$.[7] $P_t, P_{x,t}$ 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*

[6] 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.

[7] For a derivation of *ex ante* investment as a decision in anticipation of future weather conditions, see Lemoine (2017).

adaptive input x_t such that $F'_w < 0, F''_{wx} > 0, F''_{wK} > 0, F''_{xK} > 0$.[8] Conditioning on a fixed K^* and a realization of weather w_t, the first order condition is

$$P_t \cdot F'_x(x_t, K^*_t(\mathbb{E}_{t-1}(w_t)), w_t) = P_{x,t}$$

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

$$\frac{\partial y_t}{\partial w_t} = \frac{\partial F}{\partial w_t} + \frac{\partial F}{\partial x^*_t}\frac{\partial x^*_t}{\partial w_t} \tag{1.2}$$

The first term is the direct effect of an extreme temperature shock without adaptation

[8] $F'_w = \frac{\partial F}{\partial w}, F''_{wx} = \frac{\partial^2 F}{\partial w \partial x}, F''_{wK} = \frac{\partial^2 F}{\partial w \partial K}, F''_{xK} = \frac{\partial^2 F}{\partial x \partial K}$.

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 1.1 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; Lobell et al., 2013). 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 $\frac{|AC|}{|T_1 - T_0|}$.

1.3.2 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

$$y_{it} = b_0 + b_1 \cdot w_{it} + b_2 \cdot \mathbb{E}_{i,t-1}(w_{it}) + \nu_{it} \tag{1.3}$$

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 (Deschênes 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

$$y_{it} = \alpha_i + b_0 + b_1 \cdot w_{it} + \eta_{pt} + \nu_{it} \tag{1.4}$$

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.

1.4 Data Sources and Summary Statistics

1.4.1 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. Liu (1993) provide us with the division of the corn and soybean regions and corresponding growing seasons, as illustrated in Figure A.1 and A.2 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; Deschênes 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.[9]

1.4.2 Summary Statistics

Weather Statistics. Table 1.1 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 for each crop. To highlight differences over time, Table 1.1 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 vari-

[9] Auffhammer et al. (2014) 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.

ables 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 1.2 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 1.2, 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 1.3 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 1.3, Panel b and d) but counties experiencing larger temperature increase in Figure 1.2 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.[10] 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 to estimate the extent to which the change in potential adaptive inputs accounts for the change in temperature sensitivity. Figure 1.4 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

[10] 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.

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.

1.5 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.

1.5.1 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.[11] 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.[12] $Prec_{it,p>p_0}$ 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 1.2.[13]

[11] 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).

[12] 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 $Prec_{it,p>p_0} = 12$.

[13] 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

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 1.1. We also conduct robustness checks with multiple thresholds other than the selected ones in Table 1.2 to avoid threshold misspecificiation. The results of robustness analysis on threshold selection will be presented in Figure 1.8.

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.

1.5.2 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

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.

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 1.4).

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 1.5 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 1.2 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.

1.5.3 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 1.4 (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 $j \geq 3, \beta^{T>l_1}_{j,1996} > \beta^{T>l_1}_{j,1981}$ significantly while for $j \leq 2, \beta^{T>l_1}_{j,1996} = \beta^{T>l_1}_{j,1981}$. 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 $\mathbf{I}_2$).

1.6 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.

1.6.1 Temporal Evolution of the Temperature-Yield Relationship

Corn and Soybean Yields

Table 1.4 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 1.4 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 1.4. 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.[14] 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.[15]

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

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

[15] 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.

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 A.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 1.5 shows the results for soybean yields in the same format as Table 1.4. 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 1.5. The estimated temperature-yield relationships of soybean using the different specifications exhibit similar pattern with the relationships of corn in Table 1.4. 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 constraints for the models are added.[16] 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

[16] 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.

not significantly decline over time periods. Results for impacts of additional climate change variables are presented in Table A.2 of Appendix B.1.

As shown in Table 1.1, 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 × 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 1.6 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.

Heterogeneous Temperature-Yield Relationships by Region

In Figure 1.5 and Figure 1.6, 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 1.4) may have higher adoption rates of technologies that mitigate the detrimental impacts of extreme heat.

Each column in Table 1.6 comes from a single regression in which the sample is restricted to the 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 1.7 reports the regional differences in the temperature-yield relationships of soybean. Each column presents the same of information as in Table 1.6. 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 1.5 is thus mostly driven by the HHH and Northwest region.

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 (2007), 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 (Newwey 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 1.7 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.

Varying 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 1.8 reports the estimation of temperature-yield relationships of corn and soybean for the full sample using five temperature thresholds.[17] 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 1.8, 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).[18] The results are shown graphically in Figure

[17] We use five consecutive temperature thresholds that include the threshold reported in Table 1.2 but fix the precipitation thresholds at the values in Table 1.2 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 A.4 and Figure A.5 of Appendix B.

[18] 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.

1.9. 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 Figure 1.6–1.9 in 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 Table 1.4 and Figure 1.5, 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 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 1.10 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.

1.6.2 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.[19] The total planted area is the aggregate planted area for

[19] 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; 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 A.5 and A.6. As shown in Table A.5 and A.6, the results of 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 1.4). 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. Table 1.8 and 1.9 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 A.3, A.4 and A.7 in Appendix B.2). We consider the specification in which each input enters individually (Columns 1—4 in Table 1.8 and Table 1.9) as well as the one in which all the inputs enter the same specification (Column 5 in Table 1.8 and 1.9).

Columns 1 in Table 1.8 and Table 1.9 shows that the diffusion of irrigation is associated with a sizable and significant decrease in crop yield loss due to extreme temperatures. Table 1.8 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 1.9 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

sizable and significant adaptation effects uniquely by irrigation still hold.

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 A.3 and A.4 in Appendix B.2. Second, we measure irrigation coverage by the ratio of irrigated area to the total planted area as used in the previous literature (Chen et al., 2016; Zhang et al., 2017).

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 1.10 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 1.10 only reports the interaction effects between the change in inputs and temperature variables. The comparison of Table 1.10 with Table 1.8 and Table 1.9 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 Table 1.8 and Table 1.9 that irrigation is the most effective input among the four examined ones to moderate the extreme temperature impacts on yields. Although the variations in inputs over time have exogenous characteristics (shown in Figure 1.5) and the estimation is robust to specifications with confounding factors, the evidence on adaptation effects of inputs is only suggestive rather than causal.

1.6.3 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 1.4, 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 1.11 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.[20] 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.

[20] 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.

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 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 1.12 verifies this hypothesis by presenting the heterogeneous change in extreme precipitation effects over time by categories of irrigation change. The format of Figure 1.12 is the same as that of Figure 1.11 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.

1.7 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.

1.8 Tables for Chapter 1

Table 1.1: 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 1.2: Thresholds of Temperature (T) and Precipitation (P) for Linear Piecewise Temperature-Yield Relationship for 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

Table 1.3: Thresholds of Temperature (T) and Precipitation (P) for Linear Piecewise Temperature-Yield Relationship for 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 1.4: 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 specifications of fixed effects and estimation of standard errors. 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. County-specific quadratic trends are controlled and standard errors are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table 1.5: 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 $°C$	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 presents the same content as Table 1.5 except that the dependent variable is log annual soybean yields. The temperature threshold for soybean is 26 °C and precipitation threshold is 44 cm in all specifications. * p<0.1, ** p<0.05, *** p<0.01.

Table 1.6: Marginal Impacts of Temperature and Precipitation On Soybean Yields Over Time Periods

	(1) North	(2) HHH	(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: Each column is from a separate regression corresponding to a particular corn region. The regression model is presented in equation (5). The North region includes 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. * p<0.1, ** p<0.05, *** p<0.01.

Table 1.7: 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: Each column is from a separate regression corresponding to a particular soybean region. The Northeast region includes 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. * p<0.1, ** p<0.05, *** p<0.01.

Table 1.8: 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 ×	0.2576***				0.2310***
Δ Irrigation (%)	(0.0558)				(0.0594)
GDD above T ×		0.0016			-0.0023
Δ Machinery (Kw./Ha.)		(0.0050)			(0.0037)
GDD above T ×			-0.0676		-0.0839
Δ Fertilizer(Tons of Ha.)			(0.0970)		(0.0878)
GDD above T ×				0.0015	-0.0024
Δ Electricity (Kwh. per capita)				(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 1.9: 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 ×	0.1293***				0.1486***
Δ Irrigation (%)	(0.0478)				(0.0524)
GDD above T ×		0.0007			-0.0002
Δ Machinery (Kw./Ha.)		(0.0005)			(0.0035)
GDD above T ×			0.0040*		0.0050
Δ Fertilizer (Tons of Ha.)			(0.0024)		(0.0250)
GDD above T ×				-0.0151	-0.0163
Δ Electricity (Kwh. per capita)				(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 1.10: 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 ×	0.2297***	0.2032***	0.1491***	0.1293**
Δ Irrigation (%)	(0.0472)	(0.0555)	(0.0525)	(0.0644)
GDD above T ×	-0.0026	-0.0009	-0.0002	0.0013
Δ Machinery (Kw./Ha.)	(0.0029)	(0.0030)	(0.0035)	(0.0037)
GDD above T ×	-0.0809	-0.0321	0.0056	-0.0055
Δ Fertilizer (Tons /Ha.)	(0.0826)	(0.0976)	(0.0250)	(0.0261)
GDD above T ×	-0.0021	0.0037	-0.0159	-0.0070
Δ Electricity (Kwh. per capita)	(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.

1.9 Figures for Chapter 1

Figure 1.1: Crop Productivity of Two Periods As A Function of Temperature

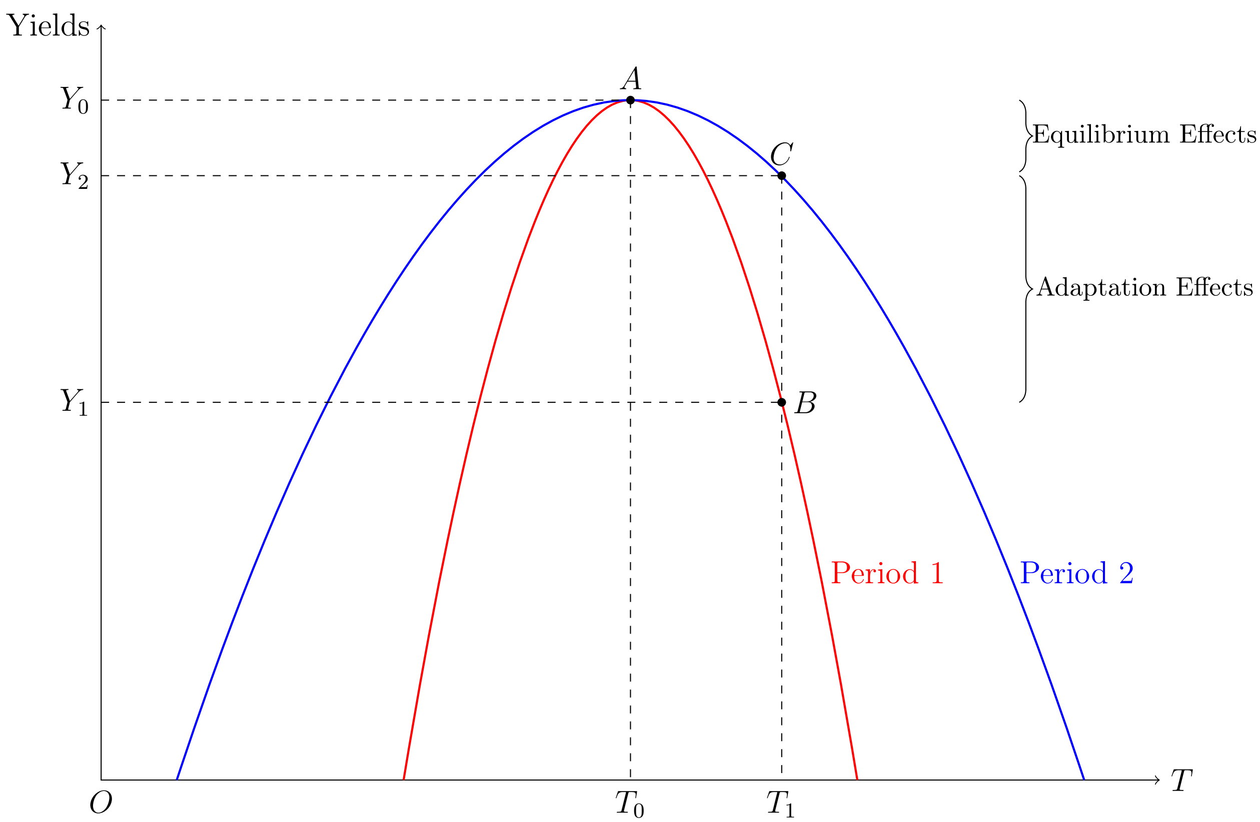
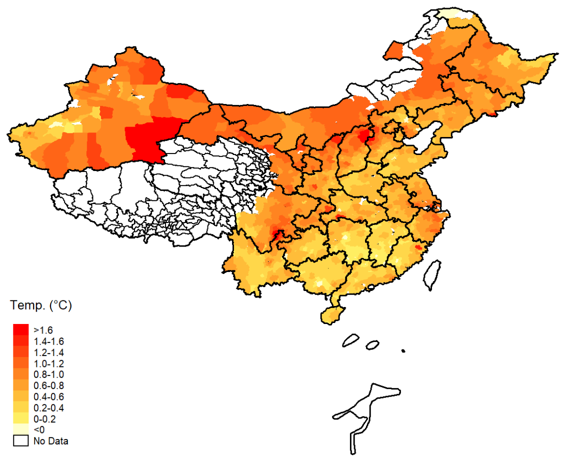
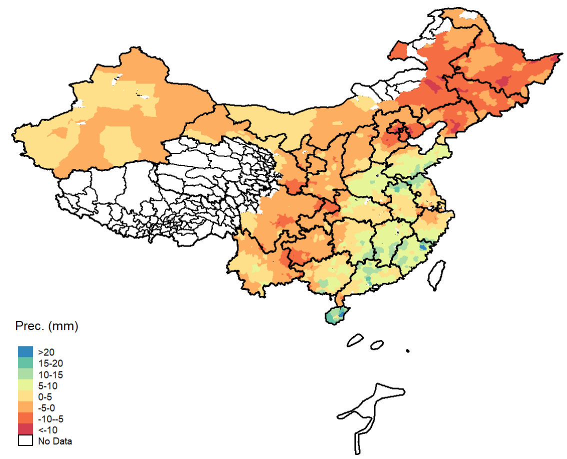


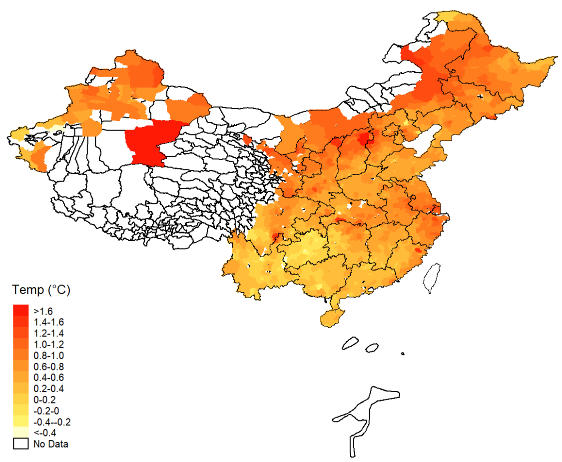
Figure 1.2: Temperature and Precipitation Change in the Corn and Soybean Area Over Time



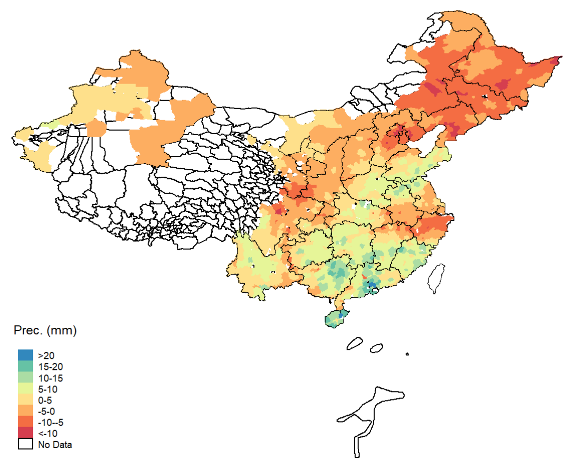
(a) Temperature Change in the Corn Area



(b) Precipitation Change in the Corn Area



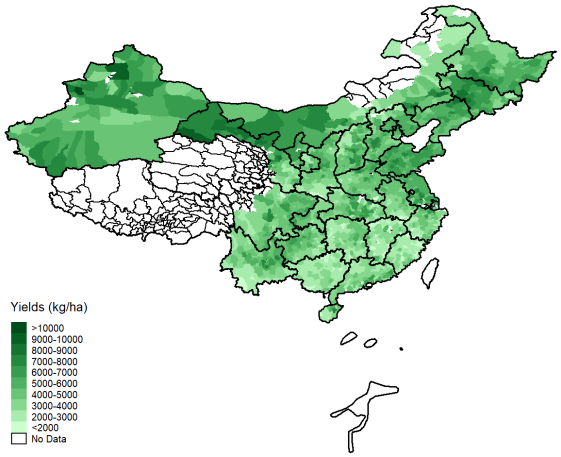
(c) Temperature Change in the Soybean Area



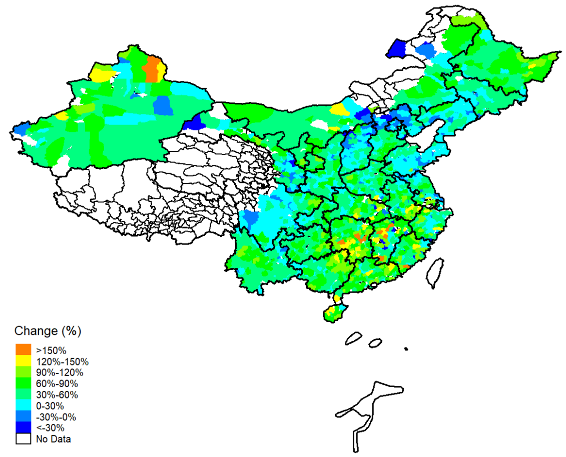
(d) Precipitation Change in the Soybean Area

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.

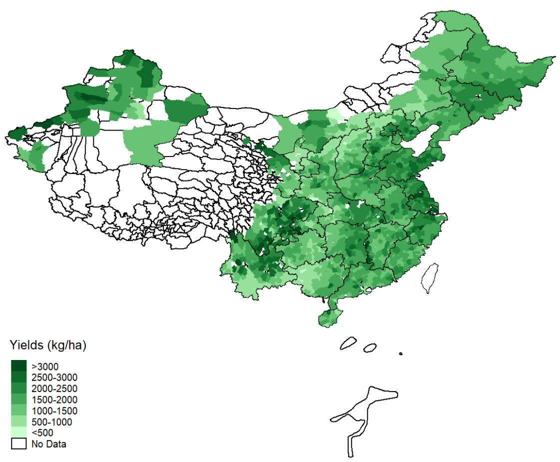
Figure 1.3: Annual Average of Crop Yields and Crop Yield Change Over Time



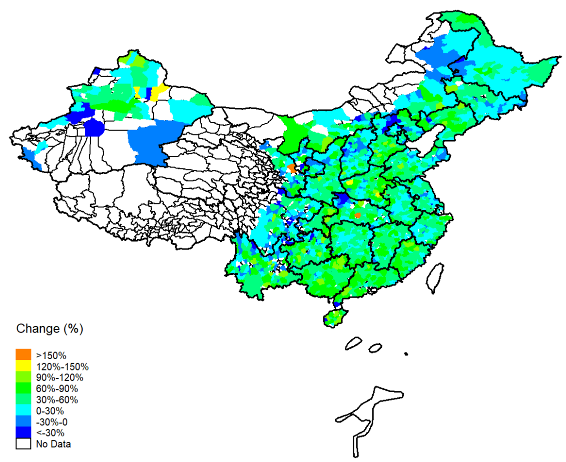
(a) 30-year Average of Corn Yields



(b) Percentage Change of Period-Averaged Corn Yields



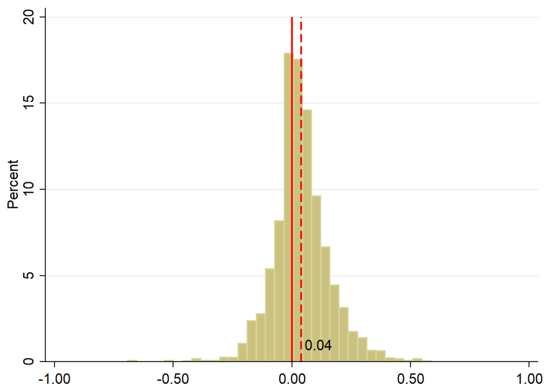
(c) 30-year Average of Soybean Yields



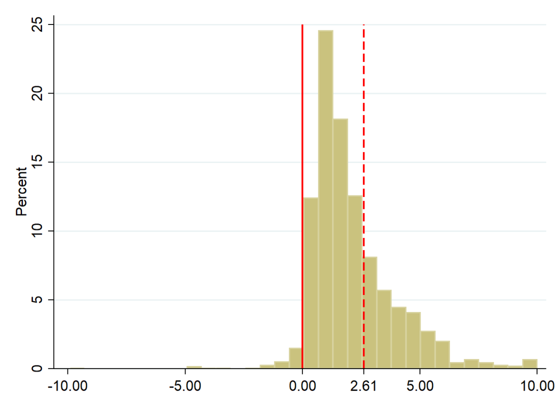
(d) Percentage Change of Period-Averaged Soybean Yields

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.

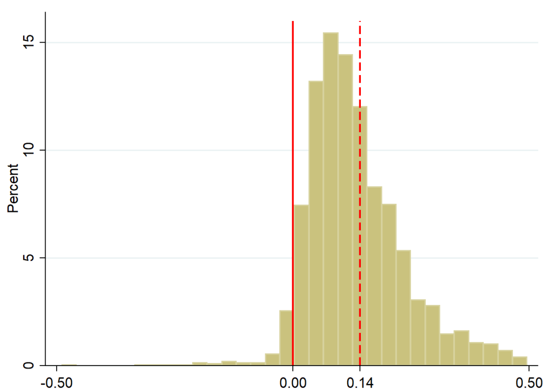
Figure 1.4: Distribution of Temporal Change of Agricultural Inputs



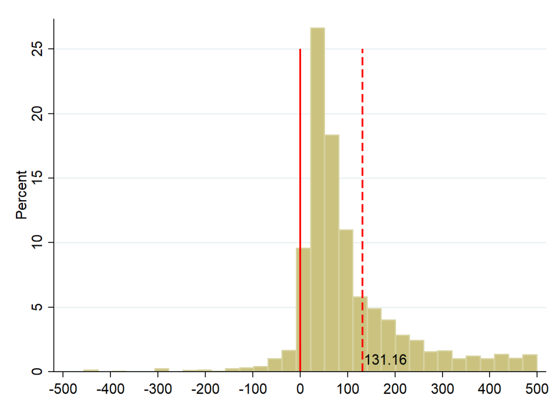
(a) Distribution of Irrigation Coverage Change (%)



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



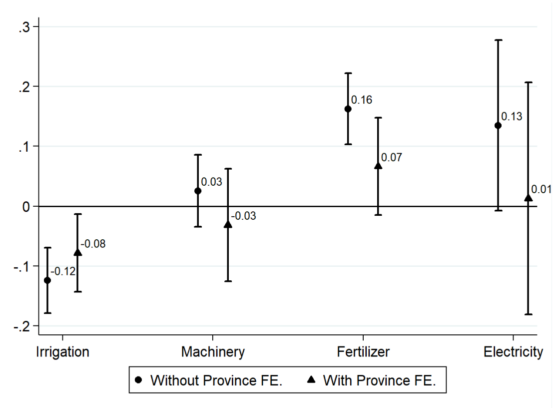
(c) Distribution of Fertilizer Change (ton/ha.)



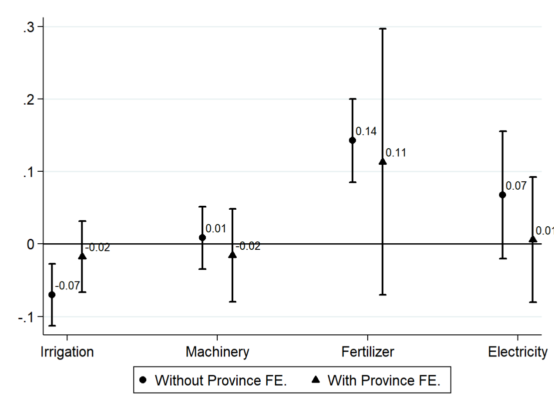
(d) Distribution of Change (kw · h per capita)

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 1.5: Correlation of Inputs Change with Temperature Change



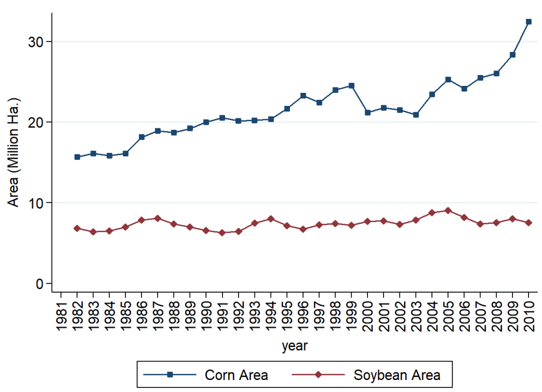
(a) Corn Counties



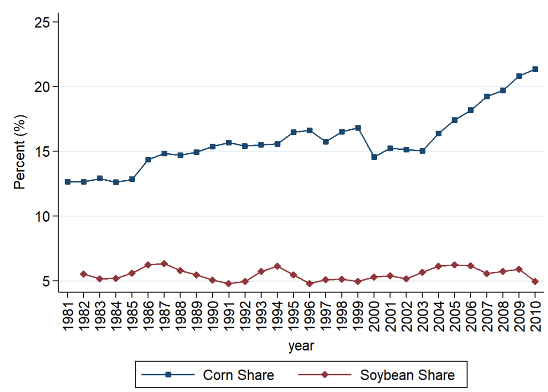
(b) Soybean Counties

Notes: Figure 1.5 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 1.6: The Planted Area of Corn and Soybean and the Corresponding Share in the Total Planted Area Over Time



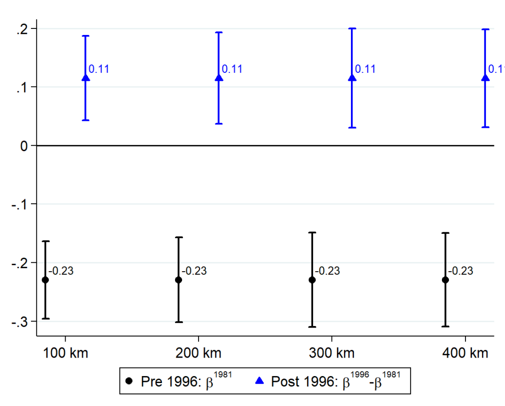
(a) The Planted Area of Corn and Soybean



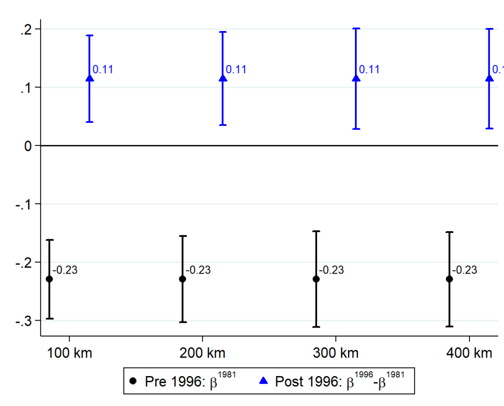
(b) The Percentage of Total Farmland Planted to Corn and Soybean

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.

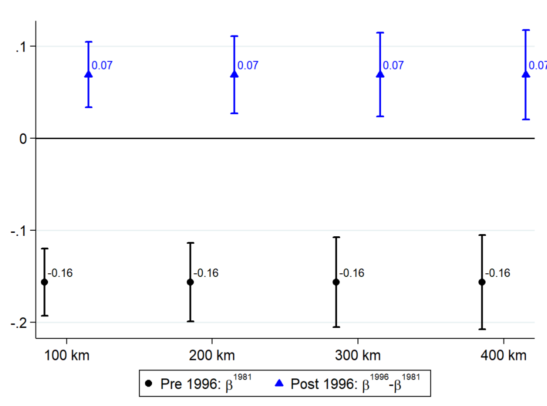
Figure 1.7: Robustness Analysis of Temperature-Yield Relationship Using Spatial HAC Standard Errors



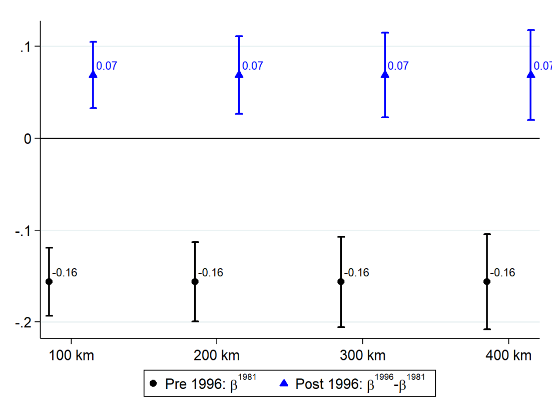
(a) Corn: Lag=3 years



(b) Corn: Lag=5 years



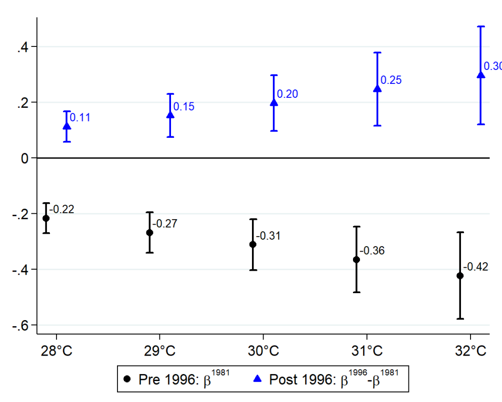
(c) Soybean: Lag=3 years



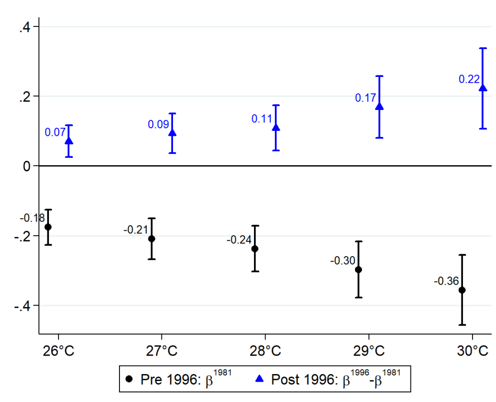
(d) Soybean: Lag=5 years

Notes: In Figure 1.7, 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 1.8: Marginal Impacts of Extreme Temperatures on Corn and Soybean Yields by Temperature Thresholds



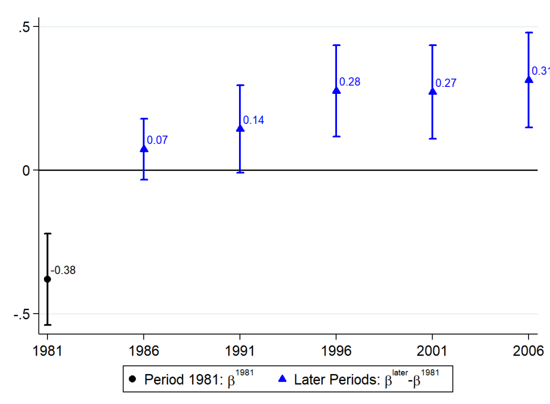
(a) Corn: Nationwide



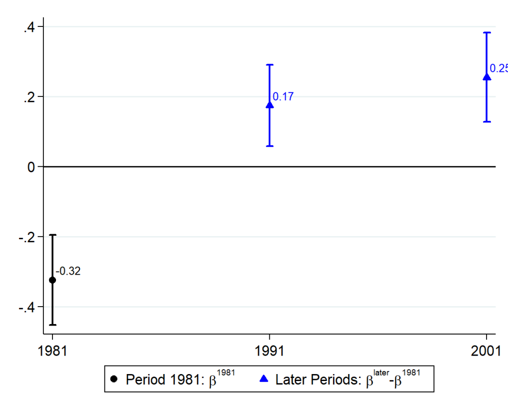
(b) Soybean: Nationwide

Note: Figure 1.8 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 A.4 and Figure A.5 of Appendix B.

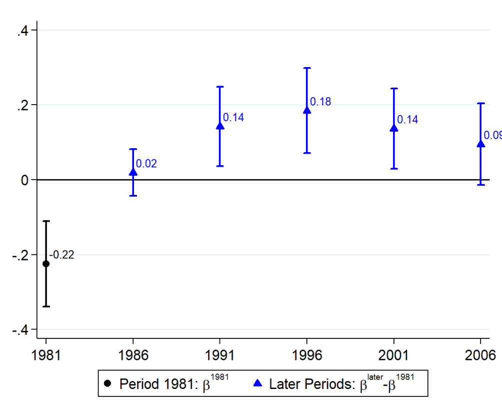
Figure 1.9: Sensitivity of Results to Starting Year and Length of Time Period –Using 5 years or 10 years as a Period



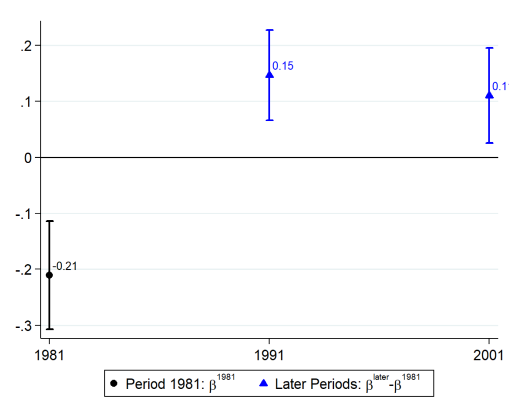
(a) GDD above 28 °C: 5 years



(b) GDD above 28 °C: 10 years



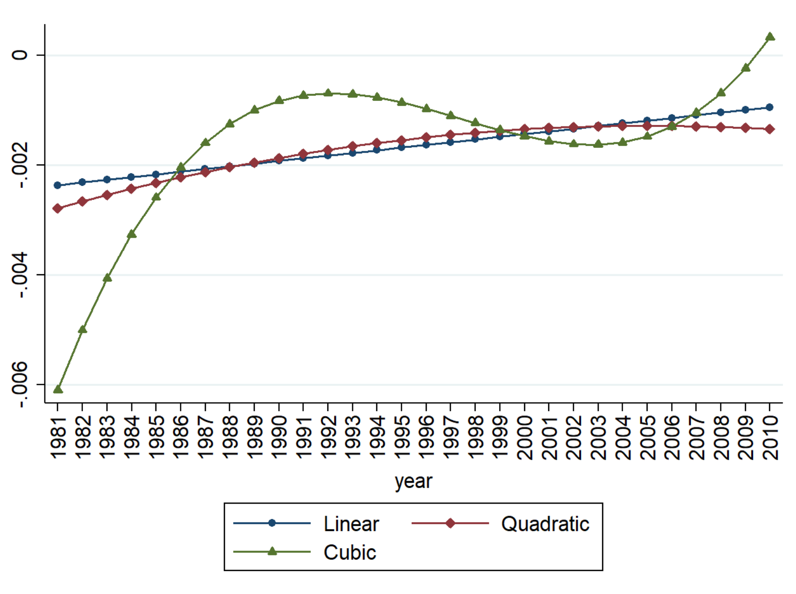
(c) GDD above 26 °C: 5 years



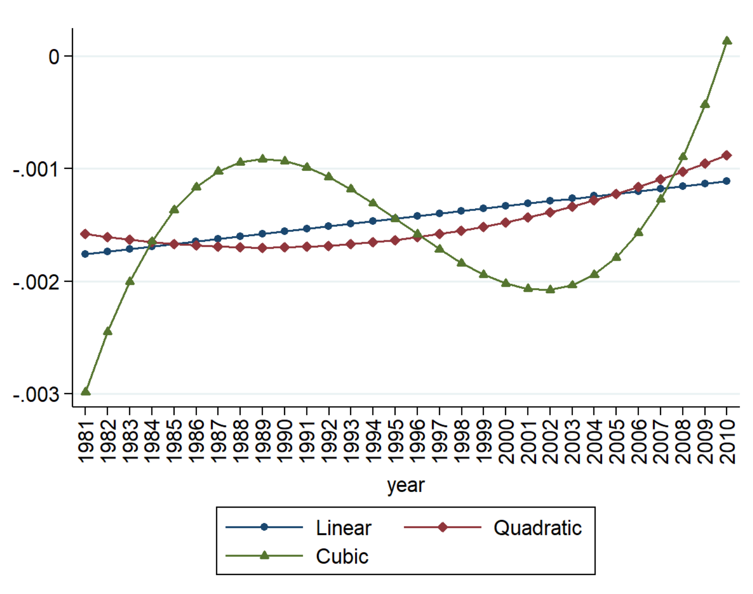
(d) GDD above 26 °C: 10 years

Note: Figure 1.9 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 A.6 to Figure A.9 of Appendix B.

Figure 1.10: Sensitivity of Results to Model Specification Using Polynomial Time Trend –The Evolution of Marginal Impacts of Extreme Temperatures on Crop Yields

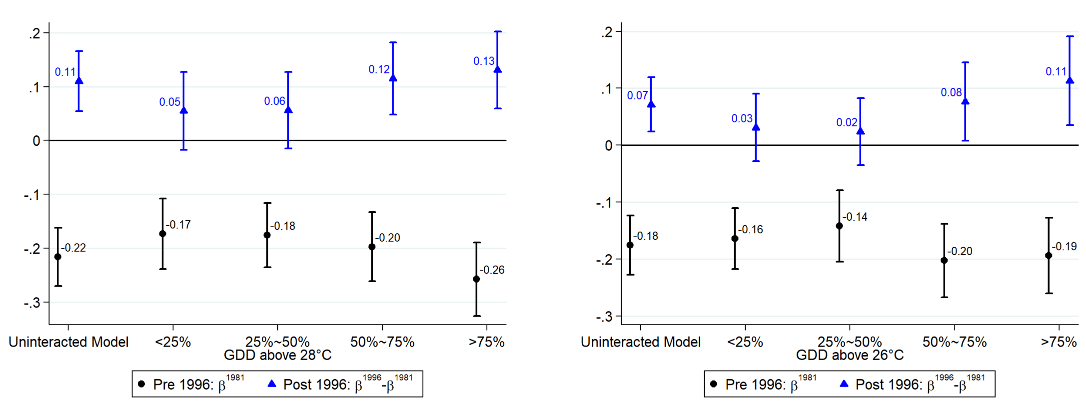


(a) Corn:Evolution of Marginal Impacts of GDD above 28 °C



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

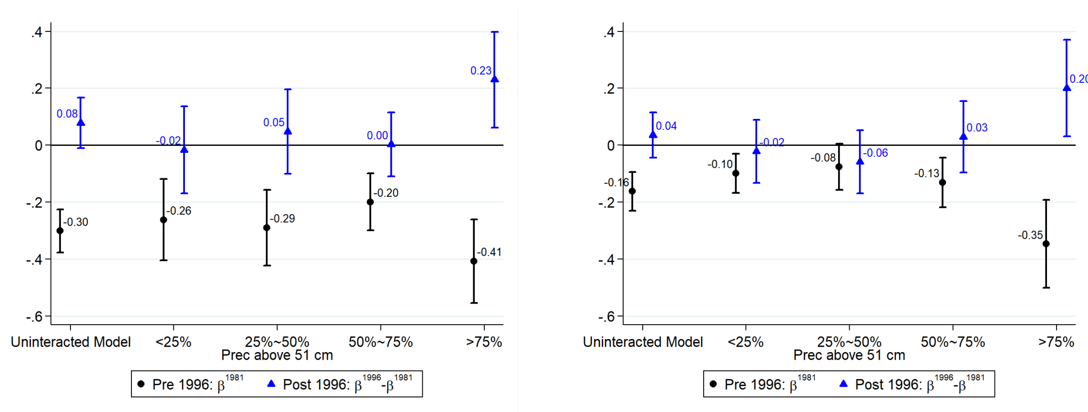
Figure 1.11: The Heterogeneous Evolution of Extreme Temperature Impacts by Categories of Irrigation Coverage Change



(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 1.12: 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).

Chapter 2

The Environmental Consequences of Creating Cities in China [1]

2.1 Introduction

It has been discussed in the literature that China is under-urbanized (World Bank, 2008), (Au and Henderson, 2006a,b).[2] In order to promote urbanization and economic growth, the Chinese government adopted a "county-to-city upgrading" policy from 1993 to 1997, which gave the upgraded counties the autonomy to create new urban administrative units.The upgrading policy is not only about administrative change but also a decentralization reform that delegates higher levels of autonomy to upgraded counties on land use, tax collection, government expansion and administrative power etc. (more details in subsection 2.1). Because China's local entities for environmental regulation

[1] The full title of Chapter 2 is "The Environmental Consequences of Creating Cities: Evidence from the County-to-City Upgrading Policy in China".

[2] Apart from the household registration (*hukou*) system that has constrained migration of population, China has a hierarchical and centralized structure of governance, under which neither the citizens nor the local governments have the discretion to expand the current size of cities or create new ones (Fan et al., 2012).

(Bureau of Environment Protection) are mainly responsible to local governments, local governments have full control over environmental regulation. Decentralization on local governance as a result of the upgrading policy implies decentralization on local environmental regulation (more details in subsection 2.2).

It has been long argued that decentralization of local governance can improve the quality of governance because local governments have better access to information about local constituents' preferences and the competition among local jurisdictions to attract residents and capitals achieves a market-like outcome in the provision of public goods (Tiebout, 1956). Preservation of local environment due to decentralization of environmental regulation in developed countries has been supported by a series of empirical studies (List and Gerking, 2000; Levinson, 2003; Konisky, 2007). But the preservation effect is based on the presumption that local governments are accountable for local constituents who vote for them. In contrast, China's regionally decentralized authoritarian system (RDA) featuring a combination of regional economic decentralization and political centralization makes a regional government only accountable for its upper-level government who will promote the head of the regional government who wins a tournament for economic growth among all the regional governments under the jurisdiction of the upper-level government (Li and Zhou, 2005; Zhou, 2007).

Motivated by the common objective for promotion, local officials are predicted to focus more on economic growth and less on environmental protection. The situation will become worse if economic growth and environmental regulation are conflicting tasks: higher environmental standard implies lower economic growth (He et al., 2020). Officials in the upgraded counties may intentionally deteriorate the environment for a higher economic growth rate and therefore a higher chance of promotion. Formally we ask "does decentralization affect environmental quality when local officials are selected but not democratically elected?"

Previous literature assessing the upgrading policy has focused on the policy effect on economic performance (Li, 2011a,b; Fan et al., 2012; Tang, 2014). But a more comprehensive evaluation calls for estimating the economic costs caused by this nationwide policy that may affect the welfare of more than half of Chinese population. The unprecedented economic growth in China has generated severe environmental pollution, which also substantially undermines people's health. Omission of the environmental consequences and resulting health effect of the economic stimulating policy will overstate the policy benefits and generate misleading policy implications for environment-development balance. The main objective of this paper is to evaluate the upgrading policy from the perspective of environmental consequence by examining the impact of the policy effect on ambient air quality, which affects people's health status substantially.

To empirically investigate environmental consequences of the upgrading policy, we compiled data that covers economic performance indicators, fiscal situation and air pollution from 1980s to the most recent. The empirical analysis has two parts. The first part is about causally estimating the effects of the upgrading policy on economic performance proxied by night light intensity and per capita industrial revenue, which is used as estimation of economic benefits of the policy and a mechanism for the policy effects on air pollution that will be investigated in the second part. The second part is about causally estimating the effects of the upgrading policy on the concentrations of $PM_{2.5}$ and SO_2, two major air pollutants in China. The most widely used empirical methodology in the quasi-experiment setting is the difference-in-difference method (DID) which takes advantage of the rich spatial variations in the timing of upgrading policy adoption. The validity of the DID method and causal inference of the result rely on the assumption that counties remaining the county status and counties that were upgraded later are valid counterfactuals for what would have happened to earlier upgraded ones in absence of the upgrading policy.

There are two challenges to the assumption for identifying the causal effect of the policy. First, the upgraded counties are not randomly selected but selected based on a set of criteria with regard to industrialization, urbanization and fiscal revenue(more details in Table 2.2). We call these official requirements *de jure* criteria. Second, the upgrading decisions did not strictly follow the *de jure* criteria in practice (Li, 2011b; Fan et al., 2012), which implies that unobserved characteristics may affect the chance of obtaining city status. However, previous studies also show that meeting more criteria increases the chance of obtaining the city status and the city status is more likely to awarded to counties with higher economic growth rate, implying that economic growth rate serves as a *de facto* criterion for upgrading selection (Li, 2011a). To address the identification challenges, we control for county specific year trends to account for each county's characteristics that lead to the pre-treatment differences in the trends of the outcome variable between treatment and control. County fixed effects and province-by-year fixed effects are controlled for to account for time invariant characteristics that may affect the chance of obtaining the city status such as special geographic locations (e.g. border counties and counties with seaports) as well as shocks that are common to counties within a province and affect outcome variables.

In addition, we conduct an event study to estimate the year-wise changes in air pollution and economic performance before and after the upgrading policy with a window from 10 years before the policy adoption and 20 years after that. The event study helps us test whether the policy effect has significant pre-trend i.e. pre-treatment outcome variable (economic performance and air pollution) can predict how likely a county can be upgraded to a city. We also conduct a placebo test by randomly assigning the adoption of upgrading policy to counties to check the extent to which the policy results are influenced by any omitted variables. Finally, to select a subset of the control units comparable to the treated units and hence in alleviating the bias due to systematic differences between the treated and control units, we use the propensity score matching method to match each upgraded county with its nearest neighboring non-upgraded county based on their propensity scores which are scalar summaries of pre-treatment characteristics consisting of the de jure and de facto criteria for upgrading selection. After matching, we conduct the DID estimation using the matched sample.

In the first part of the empirical analysis, we investigate the policy effects on local economic performance which is proxied by night light intensity and industrial revenue per capita as an estimation of policy benefits and a mechanism for the policy effects on air pollution that will documented in the second part of the empirical analysis. Previous literature shows that upgraded counties did not perform better than their counterparts remaining the county status in terms of economic growth in the period of 1993 to 2004 (Fan et al., 2012). In contrast, we find that the average treatment effects on economic performance are significant after 2004–10 years after the policy adoption. The night light intensity for the upgraded counties is 2.14 higher than that for the non-upgraded counties. As the average night light intensity for the treatment and control group altogether before 1993 (excluding 1993) is 1.07, the increase in the night light intensity of the treated (upgraded) counties compared with the untreated counties by 2.14 is very substantial. The industrial output measured by the industrial revenue per capita in the price of 2010, is 17419 CNY (2573 USD) higher than that for the non-upgraded counties after 2004 while the average industrial revenue per capita for the treatment and control group is only 1055 CNY (155 USD) before 1993.

Inspired by the benefit that upgraded counties are authorized to build a larger government, we estimate the average treatment effects on the administrative expenditure and construction expenditure of governments as an explanation for the lagging policy effects on economic performance. We find that upgraded counties significantly hire more employees and spend more on administrative expenditure for each employee than the remaining counties on average from 1993 to 2000 but the construction expenditure of the upgraded counties is not significantly higher than the remaining counties in the same period. This evidence suggests that upgraded counties focused on expanding governments rather than boosting the economy at the beginning of the policy adoption, which can provide an explanation for the lagging policy effect on economic performance.

In the second part of the emipirical analysis, we continue to show that the adoption of the county-to-city upgrading policy significantly increases the $PM_{2.5}$ concentration by 0.8 $\mu g/m^3$ and the SO_2 concentration by 0.49 $\mu g/m^3$. The results are robust to the placebo test and estimation using the PSM-DID method. The event study shows that the policy impact on air pollution does not come into effect until 10 years after the policy adoption. $PM_{2.5}$ (SO_2) concentration in the upgraded counties is 1.9 $\mu g/m^3$ (1.23 $\mu g/m^3$) higher than that in the rest counties that remained county status after 2004 but the upgrading policy effect on the pollutant concentration is not significant, which is consistent with the period-specific policy effects on economic performance. Because economic performance proxied by night light intensity and industrial revenue is a good indicator for pollution (Wang et al., 2017; Yue et al., 2019; Ji et al., 2019), the consistent evolutionary pattern of the dynamic policy effects on economic performance and air pollution indicates that economic growth leads to more severe pollution. Our result of environmental degradation due to decentralization is opposite to the findings for the developed countries where decentralization that adjusts the provision of local public goods based on local people's need can preserve the environmental quality(List and Gerking, 2000; Levinson, 2003; Konisky, 2007). This reflects an intrinsic deficiency of China's decentralization reform–failing to respond to residents' preferences for balanced economic prosperity and provision of public services.

After documenting the policy effects on air pollution, we further quantified the social costs of air pollution increase as a result of upgrading policy. The literature points to the impacts of air pollution on health as one of the major sources for the social costs of air pollution (Ebenstein, 2012; Chen et al., 2013; Ebenstein et al., 2015; Deschênes et al., 2020; Qi et al., 2020). Lacking data on health prevents us from directly estimating the impacts of air pollution on health. We conduct a back-of-envelop calculation of the cost by multiplying the marginal effect of pollution on life expectancy obtained from the relevant literature with the estimated policy effect on air pollution. Without policy interventions or avoidance behaviors reducing exposure to air pollution, lifetime additional exposure to pollutant concentration increase of the magnitude caused by the upgrading policy is associated with 4.25 years of life lost, which amounts to 13536 CNY loss in terms of value of statistical years for each person in the upgraded counties or 10 billion CNY in total for an average county-level city (average population of upgraded counties is 740,000). The aggregate value of the years of life lost for an average city is equal to 10 times of an average city's fiscal revenue in 2010. The substantial health cost suggests assessing the upgrading policy only based on the economic performance can generate a biased assessment of the policy.

This paper mainly contributes to three strands of literature. First, this paper complements to the literature of assessing reforms of administrative divisions in China. Earlier studies mainly focused on quantifying the effects of those reforms on economic performance (Li, 2011b; Fan et al., 2012; Li et al., 2016; Bo, 2020; Jia et al., 2020). This paper focuses on county-to-city upgrading policy, a formula-based policy to promote urbanization and economic growth and documents significantly positive policy effects on $PM_{2.5}$ and SO_2 concentration and resulting substantial health costs. The main result of this paper on pollution increase implies that previous literature assessing the reforms of administrative divisions only through the lens of economic efficiency may be biased in the sense that the policy benefits net of social costs may be overstated.

As the county-to-city upgrading policy has been used as an instrument by the central government to promote economic growth and urbanization, this paper contributes to the literature on the environmental consequences and relevant social cost of China's industrialization and urbanization process(Almond et al., 2009; Ebenstein, 2012; Chen et al., 2013; Ebenstein et al., 2015). Ebenstein (2012) estimated that a deterioration of water quality by a single grade (on a six-grade scale) increased the digestive cancer death rate by 9.7% by exploiting variation in pollution across China's river basins with aid of instrument variables of rainfall and distance from a river's headwaters. Using the variation of distance to the North-South boundary that is formed by the Huai River and Qinling Mountain range and determines discontinuous provision of winter heating across the boundary, Almond et al. (2009) and Chen et al. (2013) documented substantial increase in total suspended particulates air pollution and consequent lose of life years in Northern China relative to Southern China.

As a comparison, the DID approach in this paper allows us to estimate the environmental consequence of China's development policy on a nationwide scale as compared to the local scale suggested by the regression discontinuity design. Almond et al. (2009) and Chen et al. (2013) only find significant increase in concentrations of total suspended particulates as a result of the heating policy in Northern China. This paper also finds a significant increase in SO_2 concentration as a result of industrialization and urbanization promoted by the county-to-city upgrading policy, which implies that previous studies may underestimate the air pollution caused by economic activities in China.

Third, this paper contributes to the literature on the strategic interactions among governments within the hierarchy of the governance system, which falls more broadly into the literature on decentralization. Despite decentralization is promoted as a means to improve the quality of governance by scholars, it has been long argued that the lack of coordination among local jurisdictions makes them fail to internalize regional spillovers and spatial externalities, which would lead to Pareto inefficient outcomes (Oates, 1972; Zodro and Mieszkowski, 1986; Wildasin, 1991; Wilson, 1999; Saavedra, 2000). In the literature on decentralization of environmental governance, the phenomenon of "polluting your neighbor" has been documented extensively (Sigman, 2002, 2005; Fredriksson and Millimet, 2002; Gray and Shadbegian, 2004; Fredriksson et al., 2006; Konisky and Woods, 2010; Burgess et al., 2012; Lispcomb and Mobarak, 2017). This paper provides evidence that higher levels of autonomy incentivize government officials to boost the economy at the cost of reduced environmental quality of their own cities. Using the example of the upgrading policy, this paper reveals the possibility that a decentralization reform that features economic decentralization and political centralization may distort the provision of local public goods (environmental protection in this paper) when local governments are only accountable for the upper-level governments who hinge appointment, removal and promotion of officials for the lower-level governments upon the economic performance of the lower-level jurisdictions. Therefore, this paper provides a new possibility of decentralization failure in addition to the fact that decentralized jurisdiction fails to internalize regional spillovers.

The rest of the paper is organized as follows. Section 2 introduces the background of the county-to-city upgrading policy and the decentralized system of environmental regulation in China. The latter can explain why a decentralization reform on economic governance can lead to a decentralized system of environmental regulation. Section 3 provides an analytical framework with elements of local government officials' objectives and constraints for accomplishing their objectives in order to predict how higher levels of autonomy affect officials' constraints and therefore affect the local environmental quality. Section 4 introduces the data source. Section 5 introduces the empirical strategy based on the data variation in policy adoption and how robustness analysis will be conducted. Section 6 presents the empirical results for the policy effects on economic performance based on the empirical strategy in Section 5. Section 7 provides the empirical results for the policy effects on air pollution and quantifies the resulting health effects. Section 8 concludes with policy implications of the main findings.

2.2 Background

2.2.1 County-to-City Upgrading

In the Chinese civil administrative structure, there are four levels of local government: province, prefecture (*diqu*), county and town(See Figure B.1). Cities as an administrative status conferred by the central government to a local government, exists at three levels: provincial-level municipality, prefecture-level cities and county-level cities. Provincial-level municipalities (Beijing, Tianjin, Shanghai and Chongqing) are under the direct jurisdiction of the central government; prefecture-level cities are under the direct jurisdiction of provincial-level governments. There are three types of county-level administrative divisions: counties, county-level cities and urban districts, which are all under the direct jurisdiction of prefecture-level cities.

County-to-city upgrading discussed in this paper refers to the reclassification from a county into a county-level city at the same rank. After such upgrading, an entire county is labeled as a city. From 1983 to 1997 nearly 15% of China's more than 2000 counties obtained city status through upgrading, i.e., reclassifying the whole county. Although achieving county-level city status does not change a county's rank in the administrative hierarchy illustrated by Figure B.1, the autonomy in taxation, finance, trade and transportation for a county-level city is largely expanded, which is why we use the term *upgrading*. Table 2.1 lists the detailed benefits associated with the upgraded counties (county-level cities) that are summarized by a series of studies about the upgrading policy. For example, cities are authorized to raise certain taxes including urban maintenance and construction tax (Chan, 1994). Probably the most important advantage is that cities are entitled wit more land quotas with which more agricultural land can be converted to nonagricultural use. Local governments can obtain a huge amount of revenues from such conversion of land use (Lichtenberg and Ding, 2009).

The policy objective of increasing the number of small cities through upgrading is to speed up local economic growth by shifting surplus labor from rural areas to cities and reducing the rural-urban income gap (Kamal-Chaoui et al., 2015). The upgrading policy was initially designed as a formula-based policy to promote urbanization. Official rules and criteria for the upgrading were issued by the central government of China as early as 1983 when the demand for the city status soared as the the economy grew rapidly. The Ministry of Civil Affairs initiated a set of simple guidelines for county-to-city upgrading and nearly 100 counties obtained the city status between 1983 and 1986. As the number of cities and demand for the city status continued to increase, the central government raised the minimum requirements in 1993. The 1993 criteria classify counties into three groups based on their population density. For each group, there are criteria on urban population, industrialization and fiscal condition. In this paper, we will only investigate the upgrading policy between 1993 and 1997 because (1) the criteria for upgrading before 1993 were very different from those after 1993 and (2) a large amount of upgraded counties that obtained city status before 1993 continued to be upgraded to urban districts which have less autonomy than regular counties and county-level cities and therefore are not not comparable to counties that remaining the county status (Fan et al., 2012; Tang, 2014).

Table 2.2 lists the criteria on industrialization level, population engaged in non-agricultural activities, and fiscal strength. Each criterion has an absolute criterion and a relative criterion (per capita or share as a percentage). These upgrading criteria vary with population densities. However, studies have observed that the official upgrading criteria are not enforced in practice (Chung and Lam, 2004; Li, 2011b). (Li, 2011b) examined the extent to which the de jure criteria were fulfilled for the upgraded counties and non-upgraded counties and found that 6 out of 36 counties that met all the three criteria were upgraded, 39 of 463 counties that met two criteria were upgraded and 30 out of 1313 counties that met only one criterion were upgraded. It is obvious that the probability for upgrading is increased as more official criteria are fulfilled. Li (2011b) further documented economic growth rate measured by growth rate of the gross value of industrial and agricultural outputs was the key factor in determining which counties obtained city status in practice (the de facto criterion). The above finding inspires us to use both the de jure (official) criteria and de facto criteria for the upgrading as the variables for matching. Largely because the de jure criteria were not enforced strictly and the upgraded counties did not perform better than counties that non-upgraded counties in terms of economic growth from 1993 to 1997, the upgrading policy was called off in 1997 by the central government.

2.2.2 Decentralized System of Environmental Regulation in China

Unlike the environmental regulation system in the US, where regional or local environmental enforcement is under the direct control of the federal Environmental Protection Agency (EPA), China's local entities for environmental regulation are mainly responsible to local governments (Zhang et al., 2018). The Ministry of Environmental Protection (MEP), the entity for environmental regulation at the level of central government, only provides guidance to provincial and sub-provincial regulatory administrations (Yang, 2017). Therefore, local governments have considerable discretion over environmental regulations in the local areas. Here is introduced the background of China's local environmental regulation system (Zhang et al., 2018).

China first announced an environmental regulation system at the beginning of the reform era that has converted China to a market-oriented economy (OECD, 2006). In 1978, the National People's Congress (NPC) added Article 11, Section 1 to China's constitution, stating that "the state protects and improves the living environment and the ecological environment and prevents and controls pollution and other public hazards". The Environmental Protection Law (EPL) was passed in the same year and required the central government and regional governments at all levels (provincial, prefectural, county and township) to establish environmental regulatory institutions. According to EPL(1989), "the local people's governments at various levels shall be responsible for the environment quality of areas under their jurisdiction and take measures to improve the environment quality".[3] The environmental legislation thereby provides a

[3] For more details, see Article 16, Chapter 3 of the EPL(1989), which can be reached `http://www.lawinfochina.com/display.aspx?id=1208&lib=law&SearchKeyword=Environmental%20Protection%252%200Law&SearchCKeyword=`.

legal foundation for the decentralized system of environmental regulation in China.

As the environmental challenge has become increasingly severe, Chinese environmental institutions have undergone remarkable expansion. At the central government level, the Environmental Protection Leadership Group (EPLG) of the State Council was upgraded from a department within a ministry to the State Environmental Protection Administration (SEPA) in 1998 and finally to the Ministry of Environmental Protection (MEP) in 2008. At the local level, a system of jurisdictional management was established stipulating that local governments are responsible for environmental regulation within their jurisdictions.

The main principle of this system is to make local governments accountable for the implementation of central environmental policies. As a result, more than 3000 Environmental Protection Bureaus (EPB) have been established and subordinated to local governments. These EPBs are the primary environmental regulators that conduct daily regulatory activities such as monitoring polluting firms, analyzing environmental complaints, suing for environmental damage and enforcing sanctions, all of which determine the stringency of environmental regulations (Zhang et al., 2018). However, in practice, local EPBs are more controlled by the local government through budgetary allocation and personnel appointment than by the upper-level EPBs. Because the local EPBs are not independent of the local governments, local governments have large discretion over the strictness of the environmental regulation which can be tailored to fit the local economic development plan. Lacking independent local entities for environmental regulation creates a decentralized local environmental regulation system. A decentralized reform that gives local governments higher autonomy thereby makes the environmental regulation system decentralized as well in the sense that local governments have more discretion over environmental regulation.

2.3 An Analytical Framework

The county-to-city upgrading policy aims to promote local urbanization and industrialization in China by creating small cities. The enforcement of the upgrading policy is compatible with local bureaucrats' objectives for promotion because of China's regionally decentralized authoritarian (RDA) system featuring a combination of political centralization and regional economic decentralization(Xu, 2011). On the one hand, China's political and personnel governance structure has been highly centralized. The upper-level governments has substantial control over the appointment and promotion of the officials of lower-level governments. And the appointment and promotion serve as powerful instruments for the upper-level governments to induce regional lower-ranking officials to follow the policies made by the upper-level governments especially by the central government in Beijing. On the other hand, the governance of the national economy is delegated to local governments (following the hierarchies of the governance system in China as illustrated in Figure B.1). The local (subnational) governments from the province level to the county level, have responsibilities of initiating economic reforms, providing public services and making and enforcing laws within their jurisdictions. They also have direct control over a substantial amount of resources such as land, energy, minerals and financial resources.This feature of economic decentralization qualitatively distinguishes the Chinese economy from a centrally planned economy.

Under the RDA institution, the central government uses a tournament-style competition among local officials of the same administrative ranking to make the central government's objective compatible with local officials' private incentives based on their career concerns (Li and Zhou, 2005; Zhou, 2007).[4] Regions (provinces, prefectures,

[4] See Maskin et al. (2000) for the relationship between the RDA system and high-powered incentives associated with regional competition which includes tournament-like competition. See Section 3 in Xu (2011) for the necessary conditions for tournament-style competition to function.

counties and townships) compete against those of the same administrative ranking within the jurisdiction of the common upper-level government and regional officials' careers are determined by their performance in the tournaments. During the last four decades, promoting economic growth was the first priority for China's central government. Indexes indicating economic development such as GDP (total and per capita) and GDP growth rate, FDI have been the most important indicators used in evaluating regional officials' performances.[5] If a region (e.g. a county) has a higher economic growth rate than other regions within the jurisdiction of the upper-level government (e.g. a prefecture), the head of the region have a better chance to be promoted. Motivated by their career concerns that are about climbing ladders within the government hierarchy, regional officials will put more efforts on growth-enhancing policies or practices but neglect those that are less valued by the upper-level governments.

It has been widely reported that China's environment has been severely deteriorated as a result of the rapid economic growth(Ebenstein et al., 2015). The environmental deterioration is closely related to a lack of interest from the regional officials who find that enforcing environmental regulations detracted from their ability to promote local economic growth (Li, 2006). This feature of the RDA institution reflects its intrinsic deficiency–failing to respond to residents' preferences for balanced economic prosperity and provision of public services. Though China's RDA institution has the feature of decentralization, it is fundamentally different from the federalism institution where governors or mayors are elected and they are supposed to represent and be accountable to their constituents.

The county-to-city upgrading policy can be regarded as a decentralization policy

[5] Before GDP was introduced and used in China's national economic accounting in 1997, gross value of industrial and agricultural outputs or gross value of industrial outputs is used as an index measuring regional economic performance.

because it delegates more autonomous power on tax collection and allocation of land quota to the upgraded counties. Heads of counties are motivated by the common objective for promotion, the chance of which depends on local economic performance rather than other indicators including environmental protection. The upgrading policy relaxes the constraints for the upgraded counties to develop the economy by delegating higher levels of autonomy to the officials of upgraded counties and therefore incentivizes the upgraded counties to insert more efforts on economic growth compared with non-upgraded counties. Assuming that environmental protection is conflicted with economic growth, upgraded counties are predicted to deteriorate the environment more intensively than the non-upgraded counties. In addition to the traditional point of view that regards environmental degradation as a byproduct of economic growth, this proposed analytical framework elaborates the relationship between economic growth and environmental deterioration from the perspective of political economy featuring China's institutions.

2.4 Data and Summary Statistics

2.4.1 Economic Performance Data: 1980-2017

The data for economic performance comes from two sources. As the primary data source for economic performance, the Public Finance Statistical Materials of Prefectures, Cities and Counties (henceforth, "public finance data") collected the data about the de jure and de facto criteria from 1993 to 2009 (I have complied the public finance data from 1993 to 2000) including industrialization level, population engaged in non-agricultural activities, fiscal revenue and economic growth rate. The Social and Economic Yearbook of Counties and Cities (henceforth, "social and economic yearbook") collecting county-level panel data of economic performance from 1980 to 2017 complements the public finance data by providing the data on the criteria before treatment. Before-treatment data for the criteria will be used in the matching method.

2.4.2 Night Light Data 1992-2013

We adopt the global night light data from 1992 to 2013 that was recorded and issued by the Defense Meteorological Satellite Program (DMSP) in the National Geophysical Data Center(NGDC) now part of National Oceanic and Atmospheric Administration (NOAA). This data records images of the earth captured from 8:30 pm to 10:00 pm at local time. Natural firelight, temporary lights and other background noisy lights are technically excluded such that the recorded data is a good measure of luminosity of artificial light sources. Light intensity is reported as a six-bit digital number for every 30-by-30 arc-second output pixel (approximately 0.86 km^2 at the equator). The values for the light intensity range from 0 to 63 where a higher value reflects a higher intensity of luminosity. The problem that the light intensity is trimmed by the upper bound restriction is not influential to our analysis because there are only 5 urban districts that reach the upper bound but our analysis will only use counties and county-level cities.

We calculate each county's average light intensity in each year using the aggregate light intensity of all the pixels within the county divided by the total number of pixels. Hereafter, the term light intensity specially refers to county's average light intensity unless confusion arises. Night light intensity is believed to serve as an objective proxy for economic prosperity (Chen and Nordhaus, 2011; Henderson et al., 2012; Hodler and Raschky, 2014). Use of night light data can effectively resolve the problems of the official statistics of China's economic performance.

First, local bureaucrats have strong incentives to upward manipulate the statistics of local performance to obtain a higher probability of promotion conditioning on that local economic growth is evaluated as the most important indicator for local bureaucrats' performances. Manipulation of official data calls for a more objective proxy for local economic performance. Second, apart from the issue of data manipulation, the quality of official data is degraded because official datasets cannot provide important economic indicators such as GDP, gross value of industrial outputs for period before 1997 in China. China did not introduce the accounting method of GDP until 1997; the most comprehensive county-level datasets mentioned in Section 4.3 (public finance data and social and economic yearbook) only provide county-level economic indicators in 1989 and 1991, which also has a problem of lacking observations. The night light data is a strong balanced panel from 1992 to 1993 which can make up the drawback of official data.

2.4.3 Air Pollution Data: 1980-2017

The data on air pollution are derived from the satellite-based AOD retrievals. This technique is particularly popular for estimating air pollutants in areas lacking ground-level measurements (Van Donkelaar et al., 2010). AOD essentially measures the amount of sunshine duration that are absorbed, reflected, and scattered by the particulates suspended in the air, and can be used to estimate particular matter concentrations. The AOD-based pollution data closely match the ground-based monitoring station measures (Gupta et al., 2006; Kumar et al., 2011). We obtain the AOD data from the product M2TMNXAER version 5.12.4 from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the National Aeronautics and Space Administration (NASA) of the U.S.. The data are reported at each

0.5degree$\times$0.625degree (around 50km$\times$60km) latitude by longitude grid in each month since 1980. The concentration of SO_2 is reported in the data, while the concentration of $PM_{2.5}$ is calculated following Buchard et al. (2016). The daily pollution data are then aggregated from grid to county. We then average to annual level across all days within a calendar year for each county.

2.4.4 Summary Statistics

In Table 2.2 we present the summary statistics and compare the upgraded counties (*treatment*) to non-upgraded counties (*control*) in both pre- and post-treatment periods. Table 2.2 lists the trends of the upgrading criteria for the upgraded counties and non-upgraded counties from the pre-treatment period (before 1993) to the post-treatment (after 1993). Table 2.2 lists mean values of the de jure and de facto criteria for upgrading and outcomes variables including air pollutant concentration and night light intensity. The time span for each variable covered by the data is also articulated in Table 2.2. The treatment group includes 121 county-level cities that upgraded from counties during 1993 to 1997 and the control group includes 1522 ordinary counties that have never been converted to other types of county-level jurisdictions. It is obvious that the treatment group has both higher levels and growth rate in industrialization, urbanization and fiscal strength as well as air pollution and economic performance proxied by night light intensity. This is also consistent with 2.2 and Figure 2.4 which depict the trend of air pollution and light intensity for the treatment and control group since 1980s.

2.5 Empirical Strategy

2.5.1 Empirical Framework

To identify the effect of county-to-city upgrading policy on outcomes of interest, we use time and geographic variations in the upgrading policy during 1993-1997. Specially, the difference-in-difference estimation involves comparing the outcomes of interest before and after they were upgraded with those of counties which had not been upgraded yet during the same period.

Figure 2.1 and 2.2 illustrate the validity of our identification strategy. They show the time trends of the outcome variables of air pollution and land development of the counties that were upgraded to cities during 1993–1997 and those that were not adopt it during the same period. The treatment and the control group show similar trends before 1993. The baseline DID estimation has the following specification:

$$y_{ipt} = \beta \cdot Upgraded_{ipt} + \alpha_i + \gamma_{pt} + \epsilon_{ipt} \tag{2.1}$$

where i, p and t indicates county, province and year, respectively; y_{ipt} represents an outcome variable measuring economic performance proxied by nightlight intensity and industrial revenue per capita or environmental quality such as $PM_{2.5}$ and $PM_{2.5}$ concentration in the air or indicating economic performance such as local GDP and its growth rate; α_i is the county fixed effect capturing all the time-invariant characteristics of a county, γ_{pt} is the province-by-year fixed effects, controlling province-specific shocks in a particular year affecting all counties in each province and ϵ_{ipt} is the error term. $Upgraded_{ipt}$ is the regressor of interest indicating the county's city status. Specifically, $Upgraded_{ipt} = Treatment_i \cdot Post_{it}$ where $Treatment_i = 1$ if county i adopts a city status during 1993-1997 and 0 otherwise. $Post_{ct}$ is a post-treatment indicator, taking a value of 1 if $t \geq t_{i0}$ where t_{i0} is the year county i received the city status and 0 otherwise. To address the potential serial correlation and heteroskadesticity, we cluster the standard error at the county level.

2.5.2 Identifying Assumptions and Modifications

The identifying assumption underlying the DID estimation is that the upgraded counties would have followed the same time trends as the non-upgraded counties if the treated had not received the city status. A primary threat to this identifying assumption is that the upgraded counties were definitely not randomly selected as discussed in Section 2. The divergence of air pollutant concentration between upgraded counties and non-upgraded ones after the occurrence of the policy, as illustrated by Figure 2.1 and Figure 2.2, may be caused by pre-existing differences between these two groups of counties. To address this concern and improve the identification, we follow an approach used by Gentzkow (2006) and Li et al. (2016) to control for quadratic treatment-specific trends or county-specific trends to account for the differences in the trends of outcomes between the upgraded counties and non-upgraded counties. The two trend specifications allow us to control for the differences in the chronological evolution of the outcome variables whose correlation with the upgrading policy is caused by the endogenous pattern of upgrading selection. The augmented DID equations with the two trend specifications are presented in the following.

$$y_{ipt} = \beta \cdot Upgraded_{ipt} + \alpha_i + \gamma_{pt} + \text{Treatment}_i \cdot t + \text{Treatment}_i \cdot t^2 + \epsilon_{ipt} \tag{2.2}$$

$$y_{ipt} = \beta \cdot Upgraded_{ipt} + \alpha_i + \gamma_{pt} + \lambda_{1,i} \cdot t + \lambda_{2,i} \cdot t^2 + \epsilon_{ipt} \tag{2.3}$$

where $Treatment_i = 1$ if county i adopts a city status during the sample period and 0 otherwise. The treatment-specific trends control for the differences in factors that affect the outcome variable between the treatment and the control group. Equation (3) controls for county-specific time trends to allow the factors that affect the trend of the outcome variable to differ for each specific counties. Equation (3) is a more flexible specification than equation (2) in terms of the time trend specification.

To address concerns about the identifying assumptions and confirm the empirical results estimated via equation (2) and (3), a set of robustness checks will be conducted.

2.5.3 Event Study

An important assumption for the DID method is that the trends of the outcome variable for the treatment group and the control group are parallel before the implementation of the upgrading policy. If the outcome variable for the treatment and control group had the parallel chronological evolution, we could construct the counterfactual evolution of the treatment group using the evolution of the control group when the policy did not take place. The difference in the outcome variable between the treatment and control group after the implementation of the upgrading policy is the treatment effect of interest. An event study is conducted where year-wise changes in the outcome of interest before and after the upgrading are estimated to test the hypothesis of parallel pre-trend. Equation (4) presents the estimated equation for the event study.

$$y_{ipt} = \sum_{k=-10, k\neq -1}^{20} D_{ip,t_{i0}-k} \cdot \beta_k + \alpha_i + \gamma_{pt} + \lambda_{1,i} \cdot t + \lambda_{2,i} \cdot t^2 + \epsilon_{ipt} \tag{2.4}$$

where the dummy variables $D_{ip,t_{i0}-k}$ jointly represent a window of 20 periods around the upgrading policy event and the fixed effect and trend specifications have the same definition with those in Equation (3). In particular, t_{i0} denotes the year when county i received the city status. The omitted time category is $k = -1$ i.e. one year prior to the occurrence of the upgrading policy. All the non-upgraded counties and upgraded counties when upgrading did not happen are regarded as controls.

2.5.4 A Placebo Test

To check the extent to which the results are influenced by any omitted variables, a placebo test will be conducted by randomly assigning the city status to counties (Li et al., 2016). Table B.1 provides the timeline for the county-to-city upgrading policy, which shows that there are five years (1993-1997) that the upgrading policy took place. To preserve this fact (i.e. five years with city status adoption 41,40,15,21,4 shown in Table B.1) while allowing for at least one year before and one year after the upgrading policy adoption as required by the DID method, we select 5 years between 1981 and 2016 (the whole data covers the period 1980-2017) at random and within each year counties are randomly assigned a city status as the treatment group without replacement. For instance, consider that $t_1, ..., t_5$ are first randomly selected from the time set of 1981-2016. Then, for time t_1, 41 counties are selected randomly and assigned the city status. For time t_2, 40 counties are randomly selected from the remaining non-upgraded counties to become upgraded counties since t_2. This random selection process continues until t_5 where the last 4 upgraded counties are selected from the remaining non-upgraded counties by then. With this false city status variable, we conduct a placebo DID estimation using the specification in equation (3). Given the random data generation process, the false upgrading variable should have produced no significant effect of the upgrading policy with a magnitude close to zero; otherwise, it would imply a mis-specification of the DID model in equation (2) and (3). To increase the inference power if the permutation test, it is repeated 500 times. The results will be presented in Section 6 and 7.

2.5.5 PSM-DID strategy

DID estimation is only appropriate when the treatment is randomly assigned. However, practical policies in the real world do not easily meet the requirements of random experiments. In the absence of an experiment, researchers usually alternatively find or construct a comparable control group using matching techniques. Matching on the propensity score–the probability of receiving the treatment conditional on covariates is suggested and proved to succeed in selecting a subset of the control units comparable to the treated units and hence in alleviating the bias due to systematic differences between the treated and control units (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002). Hence, the PSM method is widely used in the field of program evaluation such as the environmental effects of the US Clean Air Act (Greenstone, 2004; Laurenceson and Chai, 2003).

The assignment of the city status in the upgrading policy is not random but relies on de jure and de facto criteria for city upgrading that are listed in Table 2.1. Therefore, we use the PSM approach to construct a comparable control group. A logistic regression is used in the PSM approach in which the dependent variable is equal to 1 for upgraded counties and is equal 0 otherwise and the predictors for the propensity score consist of pretreatment characteristics that may affect the propensity to be an upgraded county. The predictors for the propensity score are the de jure and de facto criteria for the city status as summarized in Table 2.3. The propensity score predicts the probability that a county will be assigned the city status for a set of given observable characteristics ($P(X) = \text{Prob}(D = 1|X)$). We choose industrial revenue per capita, industrialization level, urbanization level, fiscal strength and economic growth rate as the predictors.[6] The predictors are lagged by one year and the post-upgrading observations for the treatment group are not included in the estimation because city status is assigned based on previous performance and post-treatment levels of predictors would be affected by the city status. Counties are matched with their nearest neighbor (NN) based on their propensity scores, which are scalar summaries of pretreatment characteristics from a logistic regression.

The treated counties are also matched with the control counties based on kernel matching method. The basic idea of the nearest neighboring matching method is matching a treated units with one unique or multiple comparison units (ties on the propensity score) in the control group with the closest estimated propensity scores to that of the very treated unit in terms of absolute value. The basic idea of the kernel matching method is matching an existing treated unit and a constructed comparison unit that is generated by an weighted average of all the control units where the weight is determined by the kernel function of the propensity score distance between the very treated unit and all control units.

[6] In our data, industrial revenue is measured by the gross value of industrial outputs, the industrialization level is measured by the share of the gross value of industrial outputs in the gross value of industrial and agricultural outputs. The urbanization level is measured by the size of non-agricultural population and the share of non-agricultural population in the county's whole population. Fiscal strength is measured by fiscal revenue per capita.

2.6 The Policy Effects on Economic Performance

Section 3 elaborates that environmental degradation may be a result of economic growth in the sense that regional officials want to pursue better economic performance and thereafter higher chance of promotion at the cost of air quality and they are able to do so because of higher autonomy on local economic governance and environmental regulation due to the upgrading policy. This section will investigate the policy effects on economic performance as an estimation of the pecuniary benefits of the upgrading policy and a potential mechanism for the policy effects on air pollution which will be studied in the next section.

With data on local fiscal and economic statistics from 1993 to 2004, (Fan et al., 2012) found that the upgraded counties did not perform better than their counterparts that remained county status in terms of economic growth before 2004. It remains an open question how the upgraded counties perform in terms of economic growth as opposed to the non-upgraded counties after 2004. Table 2.4 reports the comparison of the upgrading policy effects on air pollutant concentration and economic performance before 2004 with the counterparts after 2004 (excluding 2004). In Table 2.4, using the DID model in equation (3) controlling for the pre-treatment characteristics that may affect the chance of obtaining the city status, we estimate the average treatment effects on economic performance by period which is divided by 2004 as suggested by the literature (Fan et al., 2012). It is clear that only treatment effects after 2004 are significant for economic performance. As an indicator for urbanization and industrialization (Huang et al., 2012; Ma et al., 2012), the night light intensity for the upgraded counties is 2.14 higher than that for the non-upgraded counties. As the average night light intensity for the treatment and control group altogether before 1993 (excluding 1993) is 1.07, the increase in the night light intensity of the treated (upgraded) counties compared with the untreated counties by 2.14 is very substantial. The industrial output per capita for the upgraded counties, which is measured by the industrial revenue per capita in the price of 2010, is 17419 CNY (2573 USD) higher than that for the non-upgraded counties after 2004 while the average industrial revenue per capita for the treatment and control group is only 1055 CNY (155 USD) before 1993.

Figure 2.3 presents the event study of the upgrading policy on economic performance that is measured by night light intensity (Panel a) and gross value of industrial output per capita (Panel b). After pre-treatment characteristics of each county are controlled for, we do not find significant pre-trend of the policy effects, excluding the possibility of reversal causality that the pre-treatment outcome variable may affect the chance of being upgraded to a city. It is also clear that the policy impact on economic performance does not come into effect until about 10 years after adoption of the upgrading policy. We conduct a placebo test with regard to night light intensity and industrial output by randomly generating fake upgraded counties and estimate the policy effect on these two outcome variables with a PSM-DID approach. The results are presented in Figure B.2, Table B.2 and Table B.3.

Night light intensity and industrial output are good predictors of air pollutant emission. Based on the estimation of the correlation between pollutant concentration and economic performance indicators using our data, one unit increase in the night light intensity is significantly associated with 0.26 $\mu g/m^3$ (0.15 $\mu g/m^3$) increase in the concentration of $PM_{2.5}$ (SO_2) and 10,000 CNY increase in the industrial output is significantly associated with 0.15 $\mu g/m^3$ (0.10 $\mu g/m^3$) increase in the concentration of $PM_{2.5}$ (SO_2). The literature documents similar relationship between air pollutant concentration (or emissions) and economic performance.Wang et al. (2017) show that construction sector, machinery manufacturing sector and power and gas sector which are important contributors to industrial output, dominate other sectors in terms of emissions of SO_2, NOx and dust (an important source of particulate matter). Yue et al. (2019) explored the relationship between spatial temporal variations of industrial SO_2 emissions in China the nighttime brightness and confirmed that there was a positive correlation between these two variables. Because we can only provide evidence or literature support for the correlation between the air pollutant concentration (or emission) and economic performance, the explanation of the dynamic policy effects on pollutant concentration through the lens of economy-environment relationship is only suggestive rather than causal. Ji et al. (2019) analyzed the correlation between the inter-calibrated Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) sensor nighttime stable light (NSL) data and statistical $PM_{2.5}$ emissions at the provincial level from 1992 to 2012, respectively and demonstrated that there was a positive correlation between the inter-calibrated DMSP-OLS NSL data and $PM_{2.5}$ emission.

A following question we ask is why the policy impact on economic performance comes into effect about 10 years after the adoption of the city status. Inspired by the benefit of the upgrading policy that upgraded counties can build more government branches and employ a larger number of public employees (see Table 2.1), we make a conjecture that the governments of the upgraded counties focus on expanding the government size rather than supporting economic development at the beginning of the policy adoption. Our fiscal dataset provides data on number of public employees employed by the government, administrative expenditure and construction expenditure of each county-level government up to 2000 and therefore allows us to test the above conjecture.[7] Table 2.5 reports the results of the average policy treatment effects on the

[7] Administrative expenditure as an item of fiscal expenditure for all-level governments, refers to expenditure for all-level state power organs to exercise their authorities. Based on the purpose of use,

employment of public employees, administrative expenditure and construction expenditure from 1994 to 2000. The counties obtaining the city status in 1993 are excluded from the treatment group to preserve data at least one year before the policy adoption.

Column (1) shows that governments of upgraded counties hired 1732 more employees than counties remaining the county status, suggesting the government size of upgraded counties was expanded as motivated by the policy benefit. Column (2) shows that governments of upgraded counties even hired more employees for every 10,000 citizens than those of the non-upgraded counties do, suggesting that the city governments hire more employees than the need for population management. As a result, administrative expenditure of the upgraded counties was significantly higher than that of the remaining counties on the aggregate level, per capita level and the share in the total fiscal expenditure as shown by Columns (3), (4) and (5). The average higher administrative expenditure per employee implies that the public employees working in the upgraded counties may have more resources as a support including their salaries and benefits and financing for operational activities, which strengthens the demand for higher administrative expenditure. In contrast, upgraded counties didn't spend significantly higher on construction than the remaining counties in terms of the aggregate level and per capita level of construction expenditure as well as its share in total fiscal expenditure. It is possible that expansion of government size and increase in administrative expenditure occupied financial resources that should have been used for economic construction. Because China as a developing country had scare capital in the time period when the upgrading policy was designed to stimulate capital accu-

administrative expenditure can be classified into two categories: (1) personnel expenditure including payments for salaries, stipends and benefits of employees; (2) operational expenditure including construction and maintenance of work places, procurement, maintenance and replacement of office equipment and motor vehicles as well as travel allowance, financing of operational activities for government employees (Wang et al., 1991).

mulation and economic growth, the lack of government support in investment would suppress economic development and the growth of pollution emissions. As economic growth is an important driver of pollution, we expect that air pollution takes on a similar evolutionary pattern as the economic performance.

2.7 The Policy Effects on Air Pollution

This section presents the main results of the impacts of the county-to-city upgrading policy on air quality, robustness checks on the main results, the mechanisms whereby air pollution increased for the upgraded counties.

2.7.1 Effects on the Environment

We first test the effects of county-to-city upgrading policy on air quality. The policy effects are reported in Table 2.6. The outcome variables are $PM_{2.5}$ and SO_2 concentration (μ/m^3). We use the specifications for the fixed effects and treatment-specific trends in equation (2) and (3) . The county-specific fixed effects account for county's time-invariant characteristics that affect the probability of city status and therefore affect the pollution level. For example, counties nearby rivers and coastal lines are usually are more likely to be upgraded to cities as they have more access to trade. Province-by-year fixed effects account for shocks of provincial-level policies that are correlated with the timing of the upgrading policy. Columns (1) and (2) show that upgraded counties are exposed to a significantly 0.8 μ/m^3 higher concentration of $PM_{2.5}$ than non-upgraded counties. Columns (4) and (5) show that the concentration of SO_2 in the upgraded counties has been significantly $0.5\mu/m^3$ higher than counties remaining the county status. In Column (4) and (6), we investigate the policy effect on air pollutant concentration for period before 2004 and after 2004. $PM_{2.5}$ (SO_2) concentration in the upgraded counties is 1.9 $\mu g/m^3$ (1.23 $\mu g/m^3$) higher than that in the rest counties that remained county status after 2004 but the upgrading policy effect on the pollutant concentration is not significant, which is consistent with the period-specific policy effects on economic performance in Table 2.4.

2.7.2 Event Study

In this section, we test the parallel pre-trend hypothesis for the DID estimation in section 5.1. We use the model in equation (4) with pre-treatment characteristics are controlled for. Figure 2.4 depicts the dynamic effects of the upgrading policy on the air quality estimated through the event study approach. None of the pre-treatment indicators for the years to the policy adoption shows any statistical significance, suggesting that upgraded and non-upgraded counties followed similar time trends at least 10 years before the upgrading. However, the policy effect on the pollution concentration does not become significant until 10 years after the upgrading policy adoption. We conduct a robustness analysis to verify the lagging pattern of the policy effect on pollution by rolling the time window for the event study. We restrict the sample to be in 1980-2005, 1985-2010 and 1990-2015 as the alternative time windows for the event study, all covering the full period of policy implementation (1993-1997). The results of the rolling-window event studies for $PM_{2.5}$ and SO_2 are presented in Figure 2.5 and Figure 2.6, respectively. The rolling window analysis demonstrates consistent lagging pattern of the policy effect on air pollutant concentration–the treatment does not come into effect until 8-10 years after the policy adoption.

2.7.3 Randomly Generated City Status

Figure 2.7 shows the distribution of the estimates of the falsified policy effects using randomly generated city status along with the benchmark estimate of the true policy effect on $PM_{2.5}$ (SO_2) concentration from Column (3) (Column (6)) in Table 2.6. To increase the inferential power of the test, we run the simulation that randomly generates city status following the timetable of upgrading policy in Table B.1 for 500 times. The distribution of estimates from the random assignments is clearly centered around zero and the standard deviation is small enough (0.22 for $PM_{2.5}$ and 0.15 for SO_2) such that there is no effect with the randomly constructed upgrading policy. Additionally, the benchmark estimate lies outside the entire distribution. These features of the distribution suggest that the positive and significant effect of the county-to-city upgrading policy on air pollution is not driven by unobserved confounding factors.

2.7.4 PSM-DID Approach

The PSM-DID strategy is suitable for the case that assignment of treatment is determined by pre-treatment characteristics. The pre-treatment characteristics that may affect the city status assignment are industrialization rate, urbanization rate, fiscal strength and economic growth which are listed in Table 2.2 as the de jure criteria. These characteristics are supposedly determinants of city status assignment. Although it has been found that these criteria are not stringently enforced in practice, they might still be predictive of whether a county can be upgraded to a city (Fan et al., 2012). The economic growth rate (measured by the growth rate of the gross value of industrial and agricultural outputs) is included in the logit estimation to attenuate the estimation bias because economic growth is found to be an important determinant for city status (Li, 2011b). These criteria are classified as de jure and de facto criteria. The post-upgrading observations for the treatment group are not included in the estimation because they already obtained city status and the characteristics would have been affected by the city status. All the predictors for the propensity scores are lagged by 1 year because previous economic performance instead of the current performance are more likely to affect the chance of obtaining city status for a county. The logit estimation results are presented in Table 2.7. It is clear that the two types of criteria have a positive and significant effect on the chance of obtaining the city status.

Before introducing the results for the matching estimation, we first check whether the propensity scores are balanced across the treatment and control group. Figure 2.8 demonstrates biases between the treated and control before and after matching. Upgraded counties are one-to-one matched with their nearest neighbors in terms of propensity score distance. We find that the bias for most of the propensity-score predictors between the two groups decreases substantially after matching.

We then use the matching technique to combine counties and cities (upgraded counties) with similar propensity scores. We use two matching techniques–nearest neighboring matching and kernel matching. Using the nearest neighboring matching method, we match 118 pairs of upgraded counties and their counterparts that remain county status. Table 2.8 reports the results of the policy effect estimated with the DID method after matching. The model specification for the fixed effects is the same as the specification in equation (3). Columns (1) and (2) present the estimated policy effect on $PM_{2.5}$ concentration for which the nearest neighboring matching and kernel matching are used,respectively. Columns (3) and (4) do the same for SO_2. We also test the significance of the difference between the DID estimates and PSM estimates. The estimates via the DID model controlling for county-specific year trends are used in the test. The second row in Table 2.8 presents the p value for the test. The standard error for the hypothesis test is simply calculated by the summation of the DID standard error and the PSM standard error because we assume that separate regressions are independent (i.e. the covariance between the DID estimate and PSM estimate is zero).

2.7.5 Interpretation of the Policy Effects on Air Pollution

The main results and the following robustness analyses have verified significant but lagging policy effects on air pollution and the dynamic policy effects on air pollution share the common trend with the policy effects on economic performance–policy effects on the two types of outcomes came into significant effect only 10 years after the policy adoption. As economic outcomes proxied by night light intensity and industrial output are good predictors of air pollutant emission, the common evolutionary trend of the dynamic policy effects on economic performance and air pollution provides suggestive evidence that economic growth leads to more severe pollution using exogenous variation in economic activities.

The policy effects on economic performance and air pollution also lend support to the validity of our analytical framework that leverages decentralization and tournament competition theory to predict the tradeoff between pursuing economic performance and protecting local environment. Decentralized economic governance in the centralized system like China that evaluates local official's qualities for promotion primarily based on the economic performance incentivizes local officials to promote local economic growth at the cost of environmental quality given that pollution is positively associated with economic growth when the upgrading policy lifts the constraints of finance and land for boosting economies. The result of environmental degradation due to decentralization are opposite to the findings for the developed countries where decentralization that adjusts the provision of local public goods based on local people's need can preserve the environmental quality(List and Gerking, 2000; Levinson, 2003; Konisky, 2007). This reflects an intrinsic deficiency of China's decentralization reform–failing to respond to residents' preferences for balanced economic prosperity and provision of public services.

2.7.6 Economic Costs of Air Pollution due to the Upgrading Policy

The above analysis documents a statistically significant and positive effect of an urbanization policy on air pollutant concentration in China. This subsection interprets the economic cost of the increase in the air pollutant concentration as a result of this upgrading policy to help people understand the magnitude of the policy effect. As estimating economic cost of air pollution is out of scope of this paper, we rely on introducing relevant literature that empirically estimates the social cost of air pollution in terms of health impacts of the pollution.

A large body of evidence has linked air pollution with morbidity and mortality (Schwartz, 1994; Stieb et al., 2002; Organization, 2006; Huang et al., 2013; Raaschou-Nielsen and et al, 2013; Kan et al., 2009; Shang and et al., 2013; Li et al., 2013; Lai et al., 2013; He et al., 2016). The majority of previous literature that estimated the effect of air pollution on mortality used daily death counts as the dependent variable in their regression models (He et al., 2016). The approach of daily death counting ignores the difference in ages of dying, implicitly giving equal weights to the deaths occurring at a younger age and those occurring at an older age (Huang et al., 2012). However, from the perspective of public health, deaths at different ages are not equally important because younger people's life expectancy is longer than that of older people, which means dying at a young age leads to more potential years of life lost (Huang et al., 2012). Therefore, years of life lost (YLL) is more accurate than daily death counts to calculate premature deaths and could be an important index to measure mortality (Brustugun et al., 2014; Rabl, 2003) .

More recent studies examine the effect of air pollution on YLL in China in the period with unprecedented economic growth. It is documented that a daily increase of 10 $\mu g/m^3$ in $PM_{2.5}$ concentration is associated with 2.97 increase in YLL and a daily increase of the same magnitude in SO_2 concentration is associated with 29.98 increase in YLL (He et al., 2016; Qi et al., 2020). Because our annual data of the $PM_{2.5}$ and SO_2 concentration is derived from a daily average of the pollutant concentration in a year, the policy effect of a yearly increase of 1.90 $\mu g/m^3$ in $PM_{2.5}$ concentration for the upgraded counties is equivalent to an average increase of 1.90 $\mu g/m^3$ for every day. Similarly, a yearly increase of 1.23 $\mu g/m^3$ in SO_2 is equivalent to an increase of the same magnitude for every day. Therefore, YLL is predicted to increase by 4.25 YLL on average: the portion due to increase in $PM_{2.5}$ concentration is $1.9 \times 2.97/10 = 0.56$ YLL and the portion due to increase in SO_2 concentration is $1.23 \times 29.98/10 = 3.69$ YLL. Using air purifier sales in China, Ito and Zhang (2020) estimated willingness to pay for removing air pollution and inferred the value of a statistical life year was $455 USD or 3185 CNY. The 4.25 years of life lost amounts to 13536 CNY loss in terms of value of statistical years for each person in the upgraded counties or 10 billion CNY in total for an average county-level city. The aggregate value of the years of life lost for an average city is equal to 10 times of an average city's fiscal revenue in 2010. The substantial health cost suggests assessing the upgrading policy only based on the economic performance can generate a biased assessment of the policy.

Note that we do not provide a clear-cut estimation for the net benefits of the upgrading policy because we can only develop a partial estimation of the benefits and costs of the upgrading policy. The DID estimates of air pollutant concentration using the year-to-year variation cannot take people's avoidance behaviors for air pollution (e.g. migration and purchasing of air filter) into consideration so the increase in air pollution due to the upgrading policy may overestimate the people's exposure to pollution. Therefore, the health cost of air pollution caused by the upgrading policy may also be overestimated. In regard of the economic benefits of the upgrading policy, due to data limitation, we are not able to examine the policy effect on local GDP but only the manufacturing sector, which may underestimate the economic benefits of the upgrading policy. The per capita industrial revenue increased by 17,400 CNY, which is larger than the health cost of 13536 CNY. We cannot rule out the possibility that policy benefits might be larger than the policy costs.

2.8 Conclusion

Previous literature on evaluating reforms of administrative divisions in China has focused on effects of relevant reforms on economic performance. This paper complements to the literature on such reform evaluation by providing causal evidence of the environmental consequences of county-to-city upgrading policy which is about delegating upgraded counties based on a set of criteria with higher levels of autonomy in order to promote economic growth, industrialization and urbanization. To get a comprehensive understanding of the impacts, we compile a comprehensive panel dataset consisting of information about the administrative records of the county-to-city transformation, indicators of economic performance and air pollutant concentration ($PM_{2.5}$ and SO_2). With the difference-in-difference method in a quasi-experiment setting, we exploit rich geographic variations in the timing of upgrading policy adoption, which enables us to estimate the environmental consequence of China's industrialization and urbanization process on a nationwide scale as compared to the regression discontinuity design taking advantage of the discontinuous pollution level across China's North-South Boundary before this study.

Our empirical results show that the $PM_{2.5}$ and SO_2 concentrations in the upgraded counties are significantly higher than those in the remaining non-upgraded counties on average but the effect of significant increase in air pollution took place about 10 years after the policy adoption. We also find lagging policy effect on economic performance– the night light intensity and industrial output per capita of the upgraded counties became significantly higher than the non-upgraded counties about 8 years after the policy adoption. Motivated by the policy benefit of supporting a larger government, upgraded counties spent significantly higher fiscal expenditure on hiring more public employees in the first 8 years after the policy was implemented. At the same time, construction expenditure on the aggregate level and per capita level in the upgraded counties was not significant higher than that the non-upgraded counties, which suggests that governments of upgraded counties has focused on activities that benefit themselves most rather than promoting economic growth at the beginning and therefore provides a suggestive mechanism for the lagging policy effects on economic performance and air pollution.

Our back-of-envelop calculation of the consequent health cost shows that the long-term increase in $PM_{2.5}$ and SO_2 concentration as a result of the upgrading policy is associated with 4.25 years of life lost for each person, which amounts to a loss of about 10 billion CNY in total for an average upgraded county in terms of value of statistical life. The aggregate loss in the value of statistical life is equal to 10 times of the fiscal revenue of an average upgraded county in 2010. It is important to note that our findings do not yield a clear-cut estimation for the net benefits imposed by the upgrading policy. Our calculation of the health cost assumes people's exposure to the air pollutants are constant over lifetime, which may be overstated if people's avoidance behaviors such as migration and purchasing of air filter are taken into consideration. Though more research is needed for more accurate estimation of the health cost of air pollution on a nationwide scale in China, the apparent overestimation of the health cost by this paper provides a counterfactual for the health cost of air pollution in the scenario that no actions against pollution are taken. Due to data limitation, we are not able to examine the policy effect on local GDP but only the manufacturing sector, which may underestimate the economic benefits of the upgrading policy. The per capita industrial revenue increased by 17,400 CNY, which is larger than the health cost of 13536 CNY. We cannot rule out the possibility that policy benefits might be larger than the policy costs.

Our findings have important policy implications. The phenomenon of developing economy at the cost of environmental quality is deeply rooted in China's regionally decentralized authoritarian system (RDA) where lower-level governments are incentivized to focus on improving their performance on some single task required by upper-level governments (e.g. economic growth), which cannot match local people's demand for public goods (e.g. environmental protection). There are two ways to handle the mismatch problem without abolishing the RDA system. First, the central government which is hard to be held up by local governments' interests, can compose a more comprehensive set of standards with a higher weight on public services for evaluating local officials' qualifications. Second, monitoring and law enforcement functions including regulation should be separated from regional governments and be carried out by an independent entity such as specialized regulatory bodies or special courts (Xu, 2011). Future research work are needed for evaluating reforms against the inherent deficiencies of the RDA system.

2.9 Tables for Chapter 2

Table 2.1: Benefits of the County-to-City Upgrading Policy

Category	Contents of Benefits	Sources
Tax and fee	(1) Cities are entitled with a higher urban construction tax (7% compared to 5% for counties)	Chan (1994)
	(2) In Liaoning province, cities can get 1-2 million additional subsides annually after being upgraded.	
Land	Cities have higher land quota to convert to construction use and retain a larger share of revenue from land sale.	Zhang and Zhao (1998); Chung and Lam (2004); Ping (2006)
Favorable Policy	(1) Cities can be specially designated in the state plan by the province government such that cities can report directly to the provincial administration to ask for investment projects.	Su (2000)
Administrative Power	(1) Cities have more authority on foreign trade and exchange management;	Zhang and Zhao (1998)
	(2) Cities have authority over police recruitment and vehicle administration;	Chung and Lam (2004)
	(3) Cities can establish the branch of custom and large state-owned banks.	
Government Size	Cities can establish more branches of government and have a larger number of public employees.	Du (1993); Ren and Wang (1999)
Salary	Officials' salaries can be raised after upgrading.	Liu (2005)
Reputation	Cities generally carry greater prestige and are more attractive to investors from outside.	Gu (1997); Wang et al. (1998) Chung and Lam (2004))

Table 2.2: Criteria for Upgrading to City Status

Criteria	Indicators for the Criteria	Counties by Population Density (persons/km^2)		
		>400	100-400	<100
Urbanization	Non-agricultural population (NAP)	≥150K	≥120K	≥100K
	Share of NAP in total population	≥ 30%	≥25%	≥20%
Industrialization	Industrial output value (in billion CNY)	≥1.5	≥1.2	≥0.8
	Share of industrial output value in GVIAO	≥80%	≥70%	≥60%
Fiscal Strength	Fiscal revenue (in million CNY)	≥60	≥50	≥40
	Per capita fiscal revenue (CNY)	≥100	≥80	≥60

Source: Re-examining China's "Urban" Concept and the Level of Urbanization. The China Quarterly: 331-380. (Zhang and Zhao, 1998)

Notes: GVIAO is the abbreviation of the gross value of the industrial and agricultural outputs. CNY stands for the Chinese currency. Non-agricultural population is the population engaged in non-agricultural activities.

Table 2.3: Summary Statistics

	Data Coverage	Upgraded Counties $N = 112$		Non-upgraded Counties $N = 1522$	
		Before 1993	After 1993	Before 1993	After 1993
De jure Upgrading Criteria					
Gross value of industrial and agricultural outputs (GVIAO, billion CNY)	1989, 1991, 1993-2000	31.99	117.19	10.85	28.95
Industrial output value (billion CNY)	1989, 1991, 1993-2016	15.87	94.34	3.34	17.99
Share of industrial output in GVIAO	1993-2000	0.43	0.71	0.25	0.48
Size of nonagricultural population (10,000 people)	1993-2000	N/A	12.19	N/A	4.86
Share of nonagricultural population	1993-2000	N/A	0.20	N/A	0.14
Fiscal revenue (billion CNY)	1992-2000	1.85	9.17	0.66	3.00
Fiscal revenue per ca pita	1992-2000	326.03	933.54	198.33	567.59
De facto Upgrading Criteria					
Annual growth rate of GVIAO	1991-2000	0.08	0.18	0.07	0.09
Annual growth rate of agricultural output	1991, 1993-2000	0.07	0.08	0.06	0.07
Annual growth rate of industrial output	1991, 1993-2000	0.12	0.19	0.11	0.10
Outcome variables					
Concentration of $PM_{2.5}$ ($\mu \cdot m^{-3}$)	1980-2017	39.77	61.41	33.14	49.52
Concentration of SO_2 ($\mu \cdot m^{-3}$)	1980-2017	12.24	20.55	8.13	14.03
Night Light Intensity	1992-2013	3.04	6.56	0.96	2.12

Notes: Table 2.3 presents the mean values of the selection criteria and outcome variables of interest for the treatment and control group in the pre-treatment period (before 1993) and in the post-treatment period (after 1993). All the output and revenue measures have been adjusted to 2010 constant prices using the annual GDP deflator.

Table 2.4: The Upgrading Policy Effects on Economic Performance Before 2004 and After 2004

	(1) Night Light Intensity	(2) Industrial Output Per Capita (10,000 CNY)
Upgraded Before 2004	0.2454*	0.4924
(Including 2004)	(0.1350)	(0.4254)
Upgraded After 2004	2.1461***	1.7419***
(Excluding 2004)	(0.2861)	(0.3523)
Time Coverage	1992-2013	1989, 1991, 1993-2016
Observations	36674	35803
R squared	0.9079	0.5740
County FE	Yes	Yes
Prov. Year FE	Yes	Yes
County Trend	Yes	Yes
Cluster	County	County

Note: *** denotes significance at 1%, ** at 5% and * at 10%. All observations are at the county-year level. The regressions control for county fixed effects, province-by-year fixed effects and county-specific time trends. The time trends are in quadratic forms. The standard errors are reported in parentheses, clustered by counties. The standard robust errors for the coefficients are clustered at the county level.

Table 2.5: The Upgrading Policy Effects on Fiscal Expenditure from 1993 to 2000

	(1) Public Employees	(2) Public Employees per 10000 people	(3) Administrative Expenditure (10,000 CNY)	(4) Administrative Expenditure per Public Employee
Upgrading Before 2000	1732.2030***	11.7963***	394.7947***	10.6565**
(Including 2000)	(658.3302)	(4.0962)	(109.7653)	(5.1933)
Observations	9506	9505	12562	9401
R squared	0.6922	0.6534	0.7710	0.6936
County FE	Yes	Yes	Yes	Yes
Prov. Year FE	Yes	Yes	Yes	Yes
County Trend	Yes	Yes	Yes	Yes
Cluster	County	County	County	County

	(5) Share of Administrative Expenditure	(6) Construction Expenditure (10,000 CNY)	(7) Construction Expenditure per capita (10,000 CNY)	(8) Share of Construction Expenditure
Upgrading Before 2000	0.0445***	2.7746	-0.0700	-0.0012
(Including 2000)	(0.0154)	(3.8821)	(0.0800)	(0.0037)
Observations	11589	6397	2377	6397
R squared	0.8491	0.5524	0.6609	0.5945
County FE	Yes	Yes	Yes	Yes
Prov. Year FE	Yes	Yes	Yes	Yes
County Trend	Yes	Yes	Yes	Yes
Cluster	County	County	County	County

Note: *** denotes significance at 1%, ** at 5% and * at 10%. All observations are at the county-year level. The regressions control for county fixed effects, province-by-year fixed effects and county-specific time trends. The time trends are in quadratic forms. The standard errors are reported in parentheses, clustered by counties. The standard robust errors for the coefficients are clustered at the county level. All the outcome variables with regard to expenditure are in the price level of 2010.

Table 2.6: Effects of County-to-City Upgrading on $PM_{2.5}$ and SO_2 Concentration

	(1) $PM_{2.5}$	(2) $PM_{2.5}$	(3) $PM_{2.5}$	(4) SO_2	(5) SO_2	(6) SO_2
Upgraded	0.7692**	0.8003**		0.4721***	0.4889***	
	(0.3388)	(0.3483)		(0.1525)	(0.1566)	
Upgraded Before 2004			-0.0420			-0.1355
			(0.2161)			(0.1095)
Upgraded After 2004			1.9006***			1.2360***
			(0.5406)			(0.3067)
Observations	63612	63612	63612	63612	63612	63612
R squared	0.9802	0.9952	0.9854	0.9751	0.9751	0.9822
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Treatment Trend	Yes	No	No	Yes	No	No
County Trend	No	Yes	Yes	No	Yes	Yes
Cluster	County	County	County	County	County	County

Note: *** denotes significance at 1%, ** at 5% and * at 10%. All observations are at the county-year level. The regressions control for county fixed effects, province-by-year fixed effects, either treatment-specific time trends or county-specific time trends. The time trends are in quadratic forms. The standard errors are reported in parentheses, clustered by counties.

Table 2.7: Logit Estimation for the Propensity Scores

	Prob(Upgrading = $1\|X$)
Growth Rate of GVIAO	0.0927^{*}
	(0.0536)
Log(Gross Value of Industrial Outputs per capita)	0.0434
	(0.0414)
Share of Industrial Outputs in GVIAO	3.2617^{***}
	(0.5853)
Log(Nonagricultural Population)	2.4422^{***}
	(0.1505)
Share of Nonagricultural Population	2.0723^{***}
	(0.7308)
Population Density	0.0003
	(0.0003)
Log(Fiscal Revenue per capita)	1.6259^{***}
	(0.1636)
Constant	-2.9147^{***}
	(0.6697)
Observations	4563
R squared	0.3935

Note: *** denotes significance at 1%, ** at 5% and * at 10%. GVIAO stands for the gross value of industrial and agricultural outputs, which is the summation of industrial revenue and agricultural revenue. The growth rate is calculated by the change in GVIAO in the last year relative to the year before last year. The standard robust errors for the coefficients are clustered at the county level.

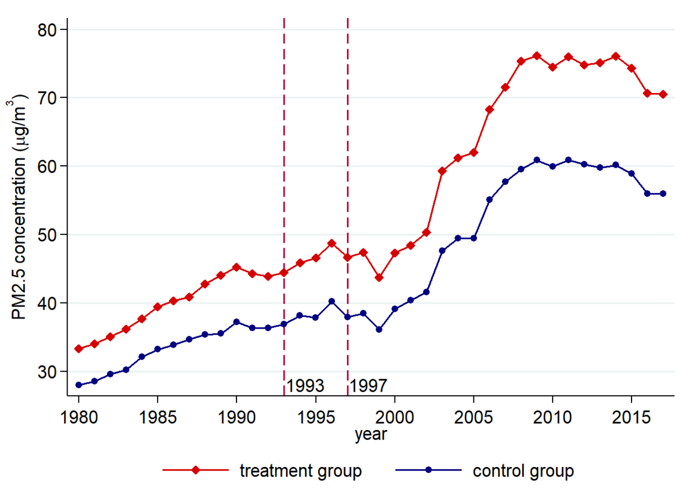
Table 2.8: Estimation of Policy Effects on $PM_{2.5}$ and SO_2 Concentration Using PSM-DID Approach

	(1) PM 2.5 NN	(2) PM 2.5 Kernel	(3) SO_2 NN	(4) SO_2 Kernel
City Upgrading	0.6805**	0.6904**	0.3963**	0.4034**
	(0.3072)	(0.3068)	(0.1640)	(0.1641)
p-Value for test:				
$\beta^{PSM} = \beta^{DID}$	0.8550	0.8666	0.7727	0.7898
Observations	8968	36033	8968	36033
R squared	0.9954	0.9954	0.9959	0.9959
County FE	Yes	Yes	Yes	Yes
Prov.-Year FE	Yes	Yes	Yes	Yes
County Trend	Yes	Yes	Yes	Yes
Cluster	County	County	County	County

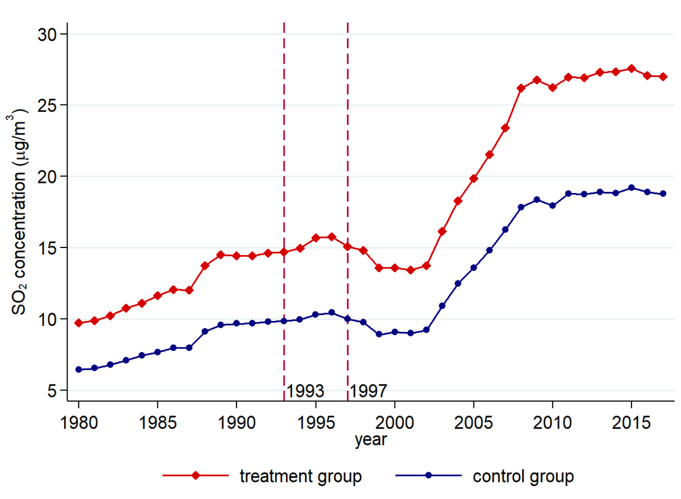
Note: *** denotes significance at 1%, ** at 5% and * at 10%. "NN" stands for the nearest neighboring matching and "Kernel" stands for the kernel matching. The regressions control for county fixed effects, province-by-year fixed effects and county-specific time trends. The time trends are in quadratic forms. The standard errors are reported in parentheses, clustered by counties.

2.10 Figures for Chapter 2

Figure 2.1: Trend of Air Pollutant Concentration: Treatment versus Control



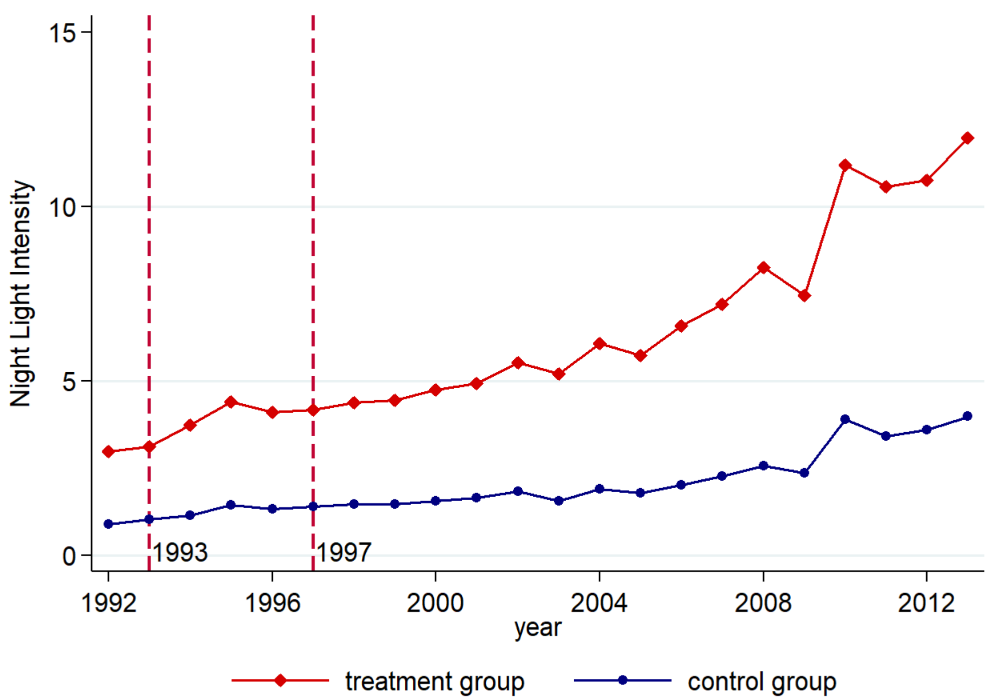
(a) Time Trend of $PM_{2.5}$ Concentration (μ/m^3)



(b) Time Trend of SO_2 Concentration (μ/m^3)

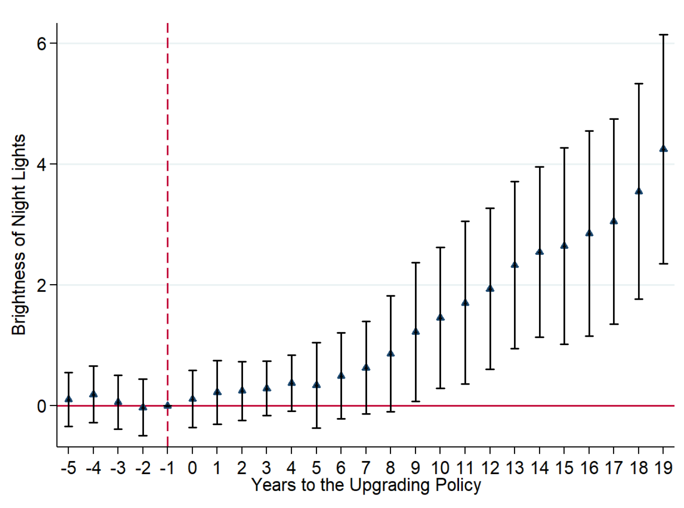
Note: Figure 2.1 presents the trend of air pollutant concentration from 1980 to 2017. The data point of each year in the figure is the average over the treatment group or the control group. The treatment group is the upgraded counties (cities) consisting of 121 counties and the control group is the non-upgraded counties consisting of 1522 counties.

Figure 2.2: Trend of Night Light Intensity: Treatment versus Control

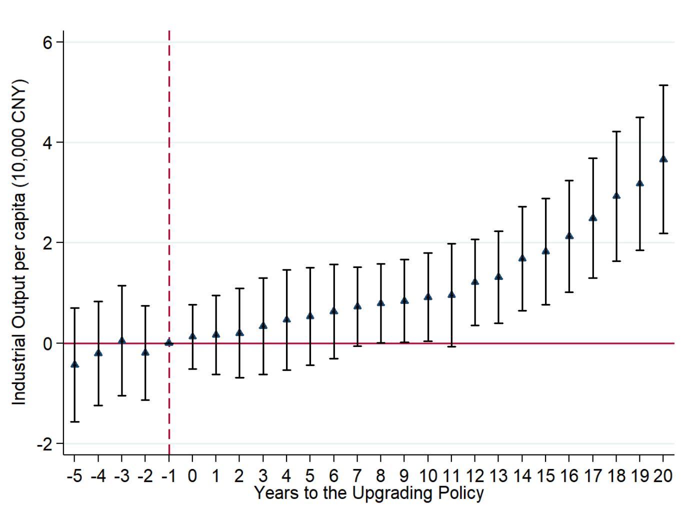


Note: Figure 2.2 presents the trend of night light intensity from 1992 to 2013. The data point of each year in the figure is the average over the treatment group or the control group. The treatment group is the upgraded counties (cities) consisting of 121 counties and the control group is the non-upgraded counties consisting of 1522 counties.

Figure 2.3: Dynamic Effects of the Upgrading Policy on Economic Performance



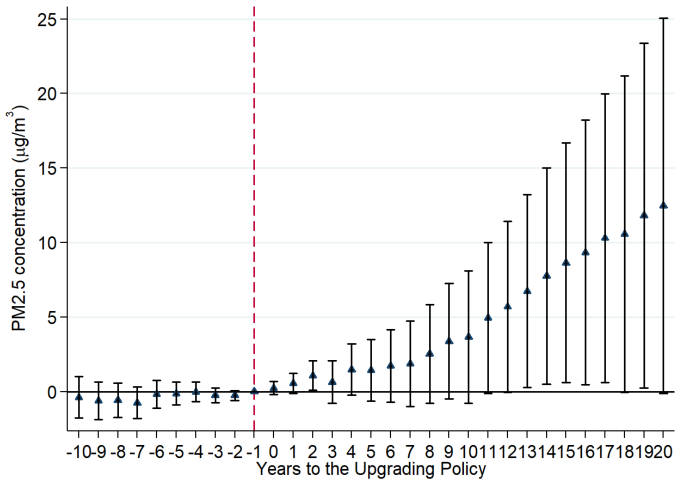
(a) Dynamic Effects on Night Light Intensity



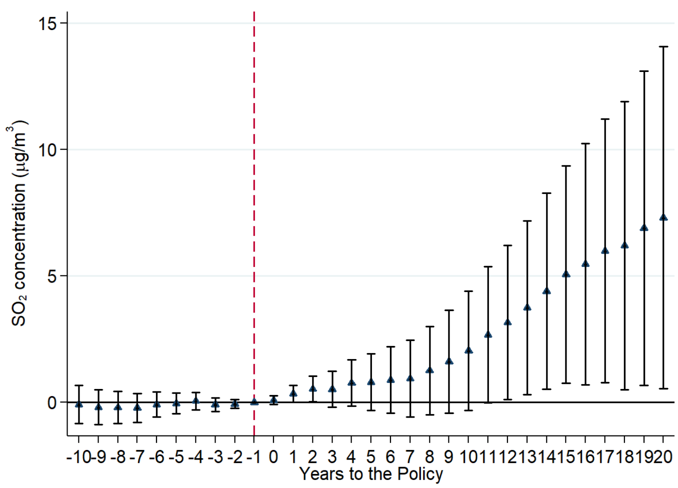
(b) Dynamic Effects on Industrial Output per capita

Notes: Figure 2.3 depicts the point estimates of the policy effects on economic performance for each year before and after the policy adoption relative to the first lagged year to the policy adoption and the corresponding 95 confidence intervals. The omitted time category is the first lagged period to the policy adoption. As the data of night light intensity is from 1992 to 2013, we can only test the pretrend up to 5 years prior to the policy adoption in Panel (a). As the data of industrial output per capita covers 1989, 1991, 1993-2016, we can test the pretrend up to more than 5 years but less than 10 years prior to the policy adoption in Panel (b). So the time indicator "-5" in Panel (a) denotes 5 years prior to the policy adoption while the time indicator "-5" in Panel (b) includes 5 years and more before the policy adoption.

Figure 2.4: Dynamic Effects of the Upgrading Policy on the Air Quality



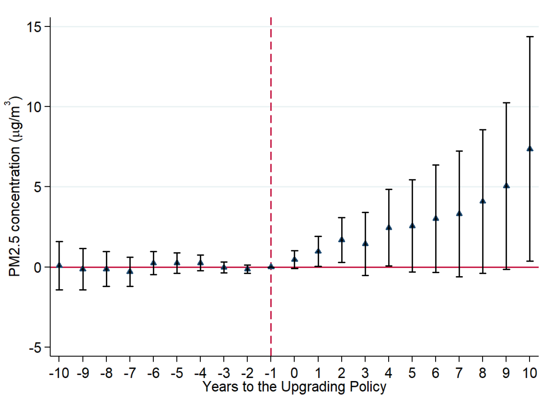
(a) Dynamic Effects on $PM_{2.5}$ Concentration (μ/m^3)



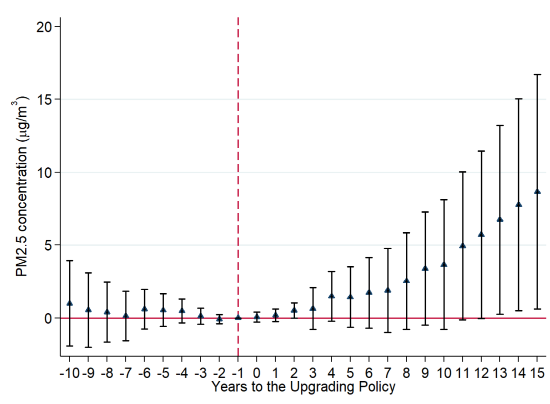
(b) Dynamic Effects on SO_2 Concentration (μ/m^3)

Notes: Figure 2.4 depicts the point estimates of the effects of the upgrading policy for each year before and after counties were upgraded and the corresponding 95 confidence intervals. The omitted time category is the first lagged period to the occurrence of the upgrading. The time indicator denoted as "-10" includes the 10 years and more prior to the policy adoption while the one denoted as 10 includes 10 years and more after the policy implementation. We have similar specification for the time indicator denoted as "20"

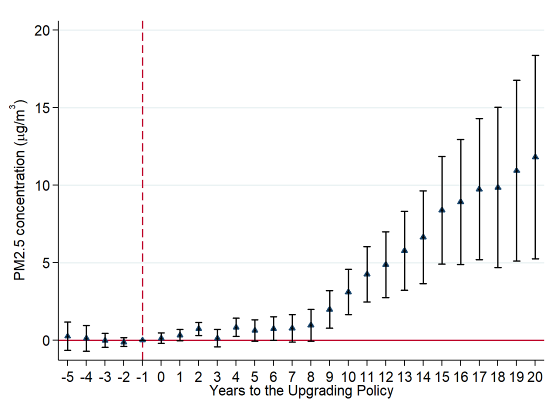
Figure 2.5: Dynamic Effects of the Upgrading Policy on $PM_{2.5}$ Concentration with Rolling Windows



(a) $PM_{2.5}$: 1980-2005



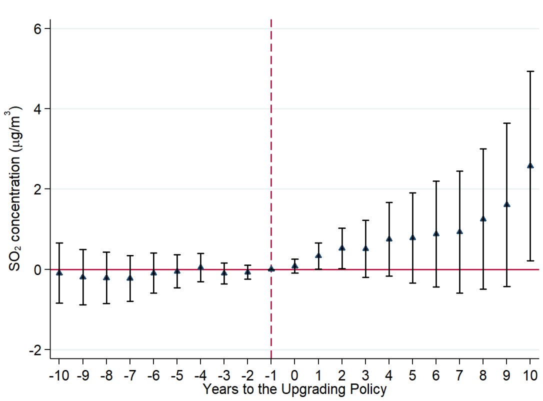
(b) $PM_{2.5}$: 1985-2010



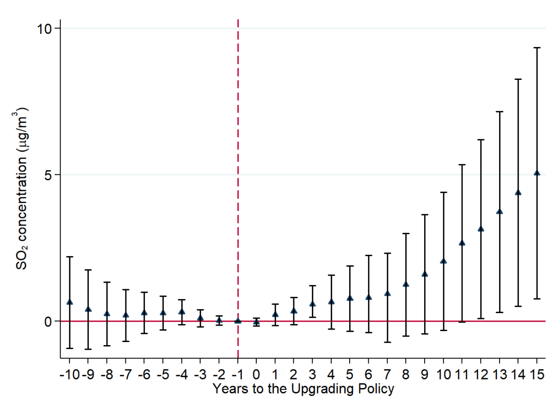
(c) $PM_{2.5}$: 1990-2015

Notes: From (a) to (c), the omitted time category is the first lagged period to the occurrence of the upgrading. The model used for the event study is equation (4). In panel (a), the sample is restricted to be in 1980-2005. The time indicator denoted as "-10" includes the 10 years and more prior to the policy adoption while the one denoted as 10 includes 10 years and more after the policy implementation. We have similar specification for the ending points of the time windows in Panel (b) and (c).

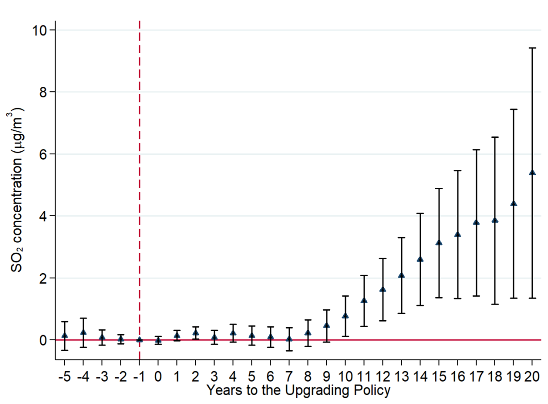
Figure 2.6: Dynamic Effects of the Upgrading Policy on SO_2 Concentration with Rolling Windows



(a) SO_2: 1980-2005



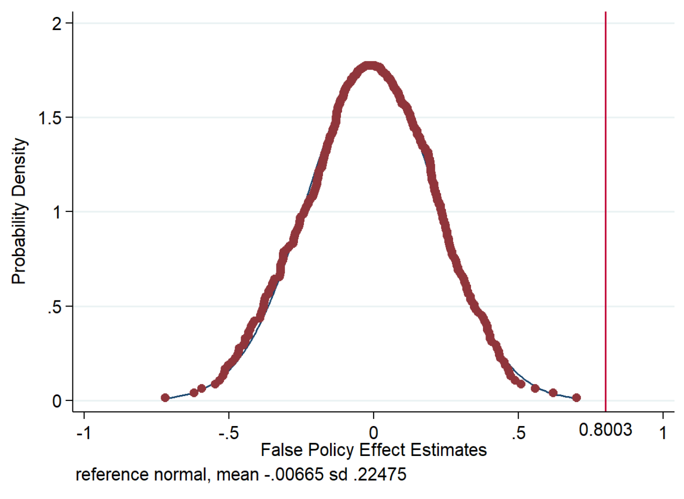
(b) SO_2: 1985-2010



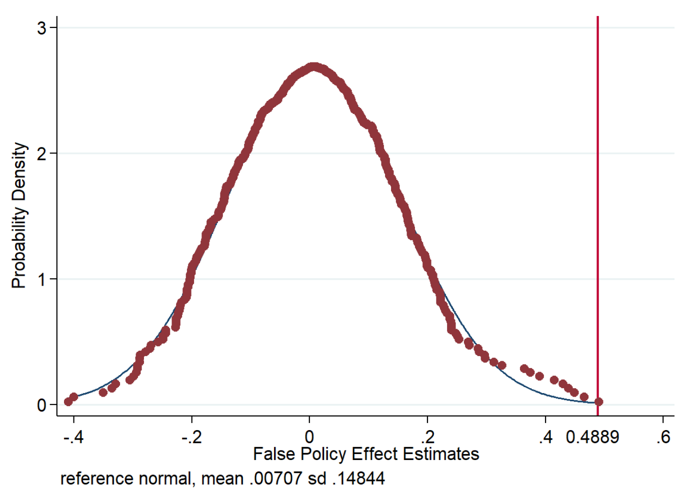
(c) SO_2: 1990-2015

Notes: From (a) to (c), the omitted time category is the first lagged period to the occurrence of the upgrading. The model used for the event study is equation (4). In panel (a), the sample is restricted to be in 1980-2005. The time indicator denoted as "-10" includes the 10 years and more prior to the policy adoption while the one denoted as 10 includes 10 years and more after the policy implementation. We have similar specification for the ending points of the time windows in Panel (b) and (c).

Figure 2.7: Distribution of Estimated Coefficients for Falsification Test



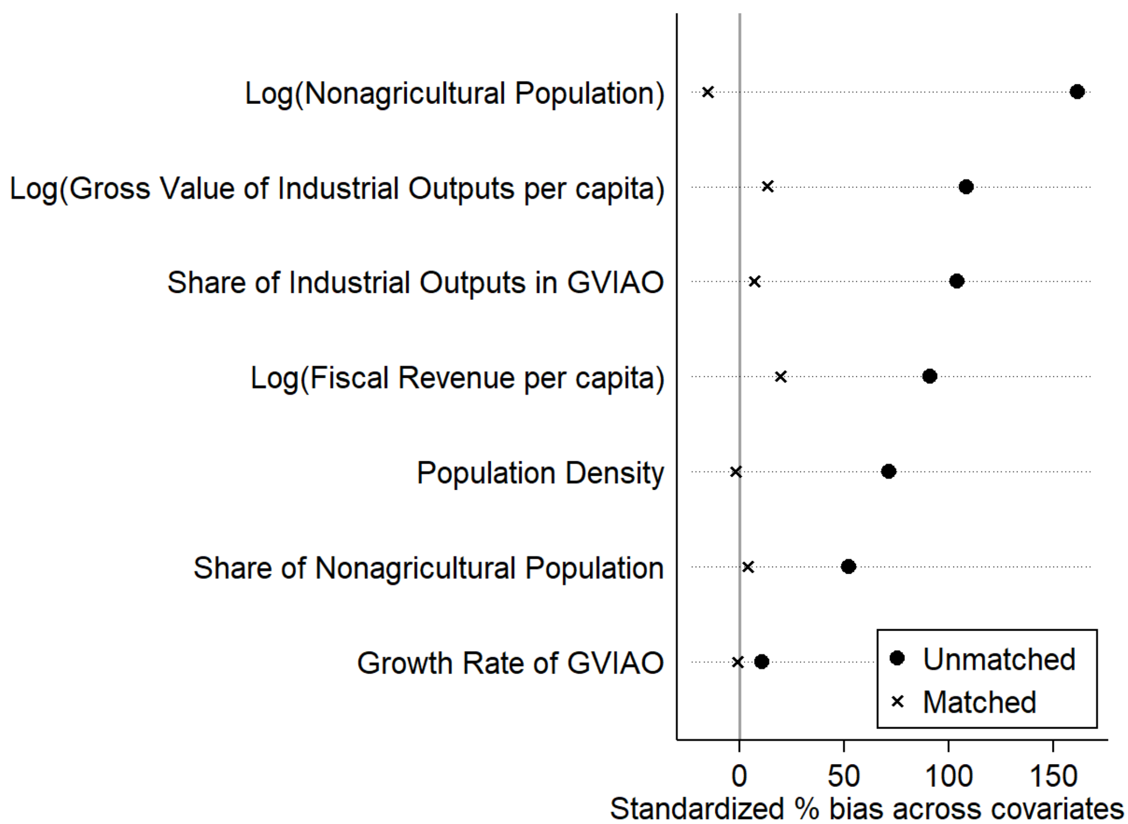
(a) Falsified Effects on $PM_{2.5}$ Concentration



(b) Falsified Effects on SO_2 Concentration

Notes: This figure depicts the probability density distribution of the estimated coefficients from 500 simulations randomly assigning the city status to counties. The vertical line presents the results of Columns 3 and 6 in Table 2.6.

Figure 2.8: Bias of County Characteristics



Notes: This figure depicts the biases of counties' characteristics based on the de jure and de facto criteria for city selection between the treated and control group before and after matching.

Chapter 3

How Does Temperature Affect the Agricultural Growth in China: 1981 to 2010

3.1 Introduction

Understanding the major drivers of Chinese agricultural growth is important for making policies regarding maintaining agricultural growth and food security. Previous literature has analyzed the contribution of inputs change, technical change, institutional change and price effects (McMillan et al., 1989; Fan, 1991; Lin, 1992, 1997; Kalirajan et al., 1996; Gong, 2018). Despite recent work on the climate-agriculture relationship in China (Chen et al., 2016; Zhang et al., 2017; Chen and Gong, 2021; Wang et al., 2020), few studies have analyzed how the impacts of extreme hot temperatures on agricultural outcomes account for the growth of agricultural productivity in China (Zhang and Carter, 1997).

Omission of weather in agricultural growth accounting may overestimate the contributions of inputs and technologies to the growth because farmers may choose levels of inputs and new technologies based on weather conditions (Frisvold and Murugesan, 2013; Haigh et al., 2015). Farmers are more likely to increase inputs under favorable weather conditions (e.g. labor increases in cooler days) while increase of inputs use and favorable weather conditions are both beneficial to agricultural growth. Wang et al. (2020) has documented that the agricultural sensitivity to extreme temperatures (i.e. marginal impact of one daily exposure to temperatures above some threshold on agricultural outcomes) declined over time. If we could quantify the contribution of decline in agricultural sensitivity and document the decline is associated with input adjustments or technology advancement, this paper can help people understand that input increase or technology advancement can promote agricultural growth not only by directly increasing outputs but also by reducing impacts of potential risks.

In this paper, we examine the temporal evolution of the extreme temperature impacts on agricultural revenue per hectare and the contribution of the temporal evolution to the growth of agricultural revenue. Formally, we ask "to what extent the growth rate of agricultural revenue would have decreased if the extreme temperature sensitivity of agricultural revenue did not decline over time". Inspired by the labor economics literature on decomposition methods starting with the seminal papers of Oaxaca (1973) and Blinder (1973), we apply the decomposition method to partition the agricultural growth into the portion attributable to the changes in the predictors and the one attributable to changes in how predictors are associated with the outcome variable and to quantify each portion's contribution to the overall growth of agricultural outcome Percentage. Our main finding is that the sensitivity of agricultural revenue to extreme hot temperatures declined by about 60% from the pre-1996 period to the post-1996 period, which accounts for 5.4% of the overall growth of agricultural revenue per unit of land.

The Oaxaca-Blinder decomposition is a regression-based decomposition method that partitions the gap in the outcome of interest between two groups that are classified based on some time-invariant characteristics (e.g.race) into a portion attributed to change in the predictors and a portion attributed to change in the predictability of the predictors. We extend the traditional decomposition method by dividing the whole sample into two periods: 1981-1995 and 1996-1996. We first estimate a period-specific Cobb-Douglas log linear production function that models county's agricultural revenue as a function of agricultural inputs and weather interacted with period indicators as well as county fixed effects and province-year fixed effects to obtain the marginal effect of each predictor for each period. By conditioning on county and province-year fixed effects, the period-specific impacts of extreme temperatures are identified by county-specific deviations from the county averages after controlling for time-invariant unobservables for each county and time-trending unobservables shocks for all counties in a province. We then conduct the OB decomposition on the period-specific production function by subtracting the sample average of agricultural revenue in the period 1981-1995 from that in the period 1996-2010.

We collect a county-level agricultural data for more than 2400 counties combined with a station-level meteorological data from 1981 to 2010, which allows us to investigate the temporal evolution of elasticity of labor, machinery, fertilizer and irrigation and of marginal impacts of extreme hot temperature and precipitation. The empirical analysis is divided into two parts. The first part is documenting the temporal evolution of the agricultural sensitivity to extreme temperatures and estimating the extent to which the temporal evolution of temperature sensitivity explains the growth of agricultural revenue with the Oaxaca-Blinder decomposition regression. Period 1981-1995 and 1996-2010 are the baseline period specification because a number of agricultural policies have been collectively designed to achieve a food self-sufficiency objective set in 1996 (The State Council of China, 1996). Agricultural subsidies 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.

We find that the extreme temperature impact on agricultural revenue per hectare in the post-1996 period was more than 60% lower than that in the pre-1996 period, contributing 6.1 percentage points growth of the agricultural revenue. If the temperature sensitivity in the post-1996 period remained the one in the pre-1996 period, the growth rate of the agricultural revenue would have reduced by 6.1 percentage points, which is about 5.4% of the overall growth of agricultural revenue. We conduct robustness analysis on the sensitivity of the results to the choices of period length and temperature specification. The result is robust to 10-year period with rolling time windows and binning specification of growing degree days that calculate the accumulation of heat for 3°C and 5°C interval, various thresholds for extreme temperatures as well as model specification without input variables as an investigation of the bad control problem.

The empirical results show that labor elasticity is decreasing while machinery elasticity and fertilizer elasticity are increasing, which is consistent with the trend of input elasticity documented in previous studies (Gong, 2018). The extreme temperature impact on agricultural revenue in the post-1996 period is about 70% lower than that in the pre-1996 period, contributing 6.1 percentage points of growth of agricultural revenue, which is about 5.4% of the overall growth of agricultural revenue. The result is robust to the specification of 10-year period with rolling time window, binning specifications of growing degree days that calculate the accumulation of heat for 3 °C and 5 °C interval as well as model specification without input variables as an investigation of the bad control problem. We provide suggestive evidence that irrigation plays an important role in moderating extreme temperature effects and precipitation effects. Dramatic increase in the marginal benefit of irrigation in terms of moderating extreme temperature effects and precipitation effects dominates increase in the irrigation coverage generates significant in contributing to the agricultural growth. Increase in the coefficient for irrigation's moderation effect (interaction between extreme temperature and irrigation coverage) contributes 2.36 percent of the agricultural growth, which accounts for about 40% of the contribution of the decline in the temperature sensitivity to the overall revenue growth. In addition to moderating extreme temperature effects, irrigation also contributes to the growth of agricultural revenue directly.

The second part of the empirical analysis is estimating moderation effects of agricultural inputs on temperature sensitivity and quantifying the contribution of the moderation effects of inputs to agricultural growth. Wang et al. (2020) investigates effects of input expansion on moderating the extreme temperature impacts but did not evaluate the contribution of agricultural inputs to growth of agricultural outcomes. In this paper, we assess roles of agricultural inputs in the growth of agricultural revenue by incorporating the interactions between the temperature and precipitation variables and inputs into the decomposition regression. The data allows us to examine the moderation effects of four inputs: labor, machinery, fertilizer and irrigation. We find that only irrigation can moderate the effects of extreme temperatures on agricultural revenue with a substantial increase over time in the marginal moderation effects on extreme temperature impacts rather than increase in the irrigation coverage. Expansion of irrigation coverage from 0 to 100% in the post-1996 period is associated with a 12.27

percentage-point decrease in the temperature sensitivity of agricultural revenue while the moderation effect of irrigation in the pre-1996 period is negligible. The increase in the moderation effects of irrigation contributes 2.68 percentage points of the agricultural growth. The decline in the temperature sensitivity through mechanisms other than irrigation contributes about 3.84 percentage points of agricultural growth, implying that irrigation accounts for about 40% of the contribution of the decline in the temperature sensitivity to the overall agricultural growth. Without experimental variation in irrigation, we can only provide suggestive evidence for the irrigation benefits in terms of moderating extreme temperature effects.

This paper contributes to the literature in the following aspects. First, it contributes to the literature that evaluates the agricultural impacts of climate change. Previous literature has focused on identifying the impacts of short-run or long-run climate change on economic outcomes for both developed countries and developing countries using cross-sectional variation or inter-annual variation in weather (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Welch et al., 2010; Lobell et al., 2013; Burke and Emerick, 2016; Chen et al., 2016; Zhang et al., 2017; Chen and Gong, 2021). A more recent development of the literature using the inter-annual variation in weather investigates the temporal evolution of extreme temperature effects on economic outcomes (Schlenker and Roberts, 2009; Roberts and Schlenker, 2011; Barreca et al., 2016; Bleakley and Hong, 2017; Ortiz-Bobea et al., 2018; Wang et al., 2020).

Among the literature on the weather-agriculture relationship, this paper is closest to Wang et al. (2020) which documents a significant decline in the extreme temperature impacts on corn and soybean yields (production per hectare) and attributes part of the decline to expansion of irrigation coverage. This paper not only documents substantial decline in extreme temperature impacts on agricultural revenue but also quantifies the contribution of the decline in temperature sensitivity to the growth of agricultural revenue of unit land, which has not been sufficiently studied in the literature including Wang et al. (2020). Growth of agricultural revenue determines growth of rural population's income and standard of living. As agriculture is one of the most vulnerable sectors to climate change, knowledge about the role of extreme temperature impacts in agricultural growth is important for understanding how economic impacts of climate change evolve over time. Temporal evolution of extreme temperature effects can be regarded as an indicator for adaptive capabilities to climate change (Barreca et al., 2016). By examining temporal evolution of extreme temperature impacts on revenue, this paper can provide a more comprehensive estimation of pecuniary benefits of adaptation to climate change than counterpart estimation of adaptation benefits using crop yields in Wang et al. (2020). In addition, this paper finds that improvement of marginal moderation effects of irrigation over time dominates expansion of irrigation coverage in explaining the decline of the extreme temperature effects, which is not documented in Wang et al. (2020).

Second, this paper contributes to the literature on agricultural growth accounting. 1980s to 1990s witnessed market-oriented reforms in developing countries (transitional countries) that promoted decollectivization in agricultural production. Literature on agricultural growth accounting during 1980s to 1990s focused on estimating the contribution of inputs change, technical change, institutional change and price effects to the agricultural production growth in those reformed countries (McMillan et al., 1989; Fan, 1991; Lin, 1992, 1997; Kalirajan et al., 1996). More recent studies have introduced weather effects into the accounting approach and concentrated on decomposing agricultural TFP growth in the US into weather effects, technological progress, technical efficiency and scale and mix efficiency changes (O'Donnell, 2012; Yang and Shumway, 2016; Njuki et al., 2018; Sabasi and Shumway, 2018; Chambers and Pieralli, 2020). To our best knowledge, Zhang and Carter (1997) is the only study that incorporated weather effects into accounting the agricultural growth in China from the 1980s to the 1990s prior to this paper. The major difference between Zhang and Carter (1997) and this paper in empirical strategy is that Zhang and Carter (1997) assume constant parameters that measure elasticities of inputs and weather effects in the Cobb-Douglas production function while this paper estimates time-varying production function that can help us document change in the input elasticities and weather effects as an important driver of agricultural growth.

Third, this paper provides a new framework for evaluating the roles of technological or input changes in moderating extreme temperature effects and agricultural growth. Incorporating both levels of inputs and interactions between inputs and temperature variables allows us to separate the direct contribution to growth of agricultural revenue from the contribution via inputs' moderation effects on temperature sensitivity of agriculture. With the OB decomposition, we can further separate the moderation effects on temperature sensitivity due to the expansion of inputs from the moderation effects due to improvement of marginal moderation effects over time with levels of inputs fixed. With the new setup for empirical strategy, this paper finds that improvement of marginal moderation effects of irrigation over time dominates expansion of irrigation coverage in explaining the decline of the extreme temperature effects, which is not documented in previous literature (Tack et al., 2017; Zaveri and Lobell, 2019; Wang et al., 2020). The new finding implies that investment in irrigation should not only be focused on increasing the quantities of irrigating facilities but also on improving the efficiency of irrigation technology.

Fourth, this paper contributes to the literature of applying the OB decomposition by conducting time-wise decomposition to explain the difference in the outcome variable over time. Traditional Oaxaca-Blinder decomposition is a regression-based decomposition method that attributes between-group differences in an outcome to differences in levels of predictors (explanatory variables) and differences in the corresponding coefficients. Groups (subsamples) of the whole sample are divided based on some *time invariant* characteristics (e.g. race). The method has frequently been applied to analyze gender and racial differences in wage gaps (Oaxaca, 1973; Blinder, 1973; Blau and Beller, 1988; Sandefur and Sakamoto, 1988; Wellington, 1993, 1994; Zipp, 1994; Sakamoto et al., 2000).

As researchers have become increasingly interested in research questions of developments over time, a dynamic OB decomposition approach using repeated cross-sectional or panel data has been developed to investigate what explains the changes in group differences over two points in time (Smith and Welch, 1989; Wellington, 1993; Makepeace et al., 1999; Deleire, 2000; Kim, 2010; Blau and Kahn, 2017; Kroger and Hartmann, 2020). The dynamic decomposition approach expresses the change in the outcome gap between groups over time as the temporal change in the component of predictors' differences between groups and the temporal change in the component of predictors' coefficient differences between groups.[1]

This paper extends the OB decomposition method from conducting group-wise decomposition to time-wise decomposition with the aid of time-varying panel fixed effect model. Previous applications of the Oaxaca-Blinder decomposition in the longitudinal data setting aims to investigate drivers of the temporal evolution of group differences

[1] To illustrate the dynamic OB decomposition, consider two groups A and B for which we have data for at least two points in time, t and s with $t > s$, the temporal change in the outcome difference between the two groups is given by $\Delta Y = \Delta Y_t - \Delta Y_s = (E(Y_t^A) - E(Y_t^B)) - (E(Y_s^A) - E(Y_s^B))$.

on the outcome of interest (e.g. wages) and conduct decomposition either by subtracting the difference between groups at one time point from another or by subtracting the difference between time-points within one group from that within the other group. As a comparison, the time-wise decomposition in this paper aims to investigate the drivers for the temporal evolution of the outcome of interest and only subtracts the average of the outcome variable in one period from the other period. The contributions of changes in predictors and of changes in the corresponding coefficients to the temporal change in the outcome variable are identified by the county-specific deviations from the county averages after controlling for the shocks common to all counties. Compared to the traditional decomposition method that relies on cross-sectional comparison of two groups, the advantage of our time-wise decomposition approach allowing us to restrict the endogeneity problem for the predictors by controlling for the time-invariant unobservables and time-trending unobservables.

The remainder of the paper is organized as follows. Section 2 describes the data sources and reports the summary statistics. Section 3 presents the econometric models used to examine the temporal evolution of the agricultural production function incorporating inputs and weather conditions and quantify the contributions of the change in predictors as well as changes in the coefficients to the growth of agricultural revenue. Section 4 reports the results from fitting the models in Section 3. Section 5 provides suggestive evidence for the mechanisms of the decline in the temperature sensitivity by examining the moderation effects of agricultural inputs on the temperature sensitivity. Section 6 concludes.

3.2 Data and Summary Statistics

3.2.1 Agricultural Data

We collect a county-level panel on the agricultural production in China from 1981 to 2010. The data is collected from the County-level Agricultural Database by the Ministry of Agriculture and Rural Affairs of China.[2] This dataset includes agricultural revenue, aggregate planted area, labor, fertilizer and machinery in each county on a yearly basis. We follow the literature in inputs and outputs selection for the agriculture in China (Wang et al., 2016). The output variable is the agricultural revenue per unit of planted area, which is the deflated gross value of agricultural outputs per hectare using the constant price in 1980. There are four inputs: labor (agricultural labor force per hectare), fertilizer (the gross weight of nitrogen, phosphate, potash and complex fertilizers per hectare) and machinery (kilowatts of total power per hectare) and irrigation (fraction of land that is effectively irrigated).

3.2.2 Weather

The weather data is from China Meteorological Data Service Center (CMDC) affiliated with the National Meteorological Information Center of China.[3] The CMDC collects weather conditions collected by 820 weather stations on a daily basis including minimum, maximum and average temperatures, precipitation, relative humidity, evaporation, wind speed and sunshine duration.[4] 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; Deschênes

[2] http://zzys.agri.gov.cn/nongqingxm.aspx.
[3] The data can be obtained at http://data.cma.cn/
[4] See the map of the 820 weather stations in Figure C.1

and Greenstone, 2007, 2011; Zhang et al., 2017). First, we choose a circle with a 200 km radius for each county's centroid following Deschênes and Greenstone (2011). 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.

3.2.3 Summary Statistics

Table 3.1 summarizes the agricultural revenue, inputs and climate conditions by period. The average of each variable is the national average of county's average within each time period (1981-1995 and 1996-2010) weighted by county's total planted area. To highlight differences over time, the summary statistics are reported separately for the 1981-1995 and 1996-2010 periods. From the pre-1996 period to the post-1996 period, the agricultural revenue of per unit of land in China more than doubled, increasing from 5,200 CNY to 13,100 CNY at a 1980's constant price. The increase in the agricultural revenue has been supported by sizable increase in the use of machinery, fertilizer and irrigation. Less use of labor and more use of the other three inputs echoes the agricultural modernization in China, which aims to convert the reliance on intensive labor input by encouraging mechanization and fertilizer use.

3.3 Empirical Strategy

This section first introduces a period-specific production function that models the agricultural production process for each period in which the parameters for the marginal productivity of the inputs and weather are not identical (hereafter we call the whole vector of inputs and weather variables as predictors). The production function serves as a data generating process to construct the empirical model for the relationship between weather and agricultural revenue by time periods. After estimating the parameters Using the Oaxaca-Blinder decomposition technique, we then estimate the effects of temporal change in the levels of inputs and weather conditions and of the temporal change in the marginal productivity of these predictors. We also quantify the contribution of the two components to the growth of agricultural revenue over time periods.

3.3.1 Period-specific Production Function

We construct a period-specific production function which incorporates agricultural inputs in logarithm form including labor, machinery, fertilizer and irrigation as well as climate variables including temperature and precipitation. We assume the production function to have a log-linear Cobb-Douglas form in order to justify the linear regression presented in equation (1).

$$\begin{aligned}\log y_{it} &= \phi_i + \sum_{d=a}^{b} X'_{it} \cdot \mathbf{1}\{period = d\} \cdot \beta_d + \eta_{pt} + \epsilon_{it} \\ &= \phi_i + \underbrace{\sum_{d=a}^{b} \sum_{m=1}^{M} \beta_{m,d} \cdot \mathbf{1}\{period = d\} \cdot \log x_{m,it}}_{\text{inputs}} + \underbrace{\sum_{d=a}^{b} \sum_{j=1}^{J} \beta_{j,d} \cdot \mathbf{1}\{period = d\} \cdot z_{j,it}}_{\text{weather}} + \eta_{pt} + \epsilon_{it}\end{aligned} \tag{3.1}$$

where y_{it} is county i's unit land revenue in year t (agricultural revenues per hectare) and the value of agricultural output is calculated by the county-level summation of the revenues of all crops; ϕ_i is county fixed effect controlling for county-specific time-invariant factors; X_{it} has two components: x_{it} is the input vector that includes labor, machinery(capital), fertilizer and irrigation; z_{it} is the climate vector that includes temperature and precipitation (regular climate variables) as well as humidity, evaporation, sunshine duration and wind speed (additional climate variables); a, b denotes the periods that indicate change in the production function. Following Wang et al. (2020), we choose 1981-1995 (the first 15 years in the data) and 1996-2010 (the second 15 years in the data) as the baseline specification for the periods. The period division is justified by the food self-sufficiency policy that was launched in 1996 by the central government of China and aims to achieve 95% self-sufficiency on grain consumption. This national priority of self-sufficiency has been supported by a series of agricultural policies that promote investment in agriculture, which may improve agricultural productivity and moderate the impacts of extreme heat on the agricultural revenue. In addition, the 15-year division allows us to construct two balanced time periods as there are 30 years of data in total.

η_{pt} is province-by-year fixed effect that accounts for the province-level shocks that may be correlated with inputs and weather conditions and affect the outcome variable. For example, shocks of product prices affect outputs but may be affected by weather shocks. Input price shocks are expected to affect the level of input use. According to Compilation of the Revenue and Cost Materials of Agricultural Products in China published by the central government of China, market prices and government-procuring prices of agricultural products and input prices are determined at the province level. Without high-quality data on product and input prices, the province-year fixed effects can control for the effects of input and product prices on revenue to some extent. With price controlled, the extreme temperature impacts on agricultural revenue is mostly driven by the extreme temperature impacts on outputs. ϵ_{it} is the error term.

3.3.2 Oaxaca-Blinder Decomposition

Oaxaca (1973) and Blinder (1973) initiated a regression-based decomposition to partition the gap in an outcome of interest between two groups into an "explained " component and an "unexplained" component. The explained portion of the gap is the difference in the outcome variable attributed to group differences in the levels of a set of predictor variables between the two groups. The unexplained portion arises from the differences in how the predictors are associated with the outcome for the two groups (i.e. the marginal effects of the predictors). This component would persist even if the discriminated (disadvantageous) group were to obtain the same average levels of predictors as the indiscriminated group (advantageous). The method has been frequently applied to analyze gender and racial differences in wage or earning gaps (Blau and Andrea, 1988; Sandefur and Sakamoto, 1988; Wellington, 1993, 1994; Zipp, 1994; Sakamoto et al., 2000; Deleire, 2000) and health status (Charasse-Pouee and Fournier, 2006; Sen, 2014).

The standard Oaxaca-Blinder decomposition relies on cross-sectional comparison of the relationship between two groups that are divided based on time-invariant characteristics (e.g. race). In this paper, we apply the decomposition method in a panel setting where the whole sample are divided by two periods based on the hypothesis that the relationship between the predictors and revenue varies over the two periods. We use the period-specific production function in equation (1) as the data generating process for the predictor-outcome relationship.

We construct long-run economic outcomes and temperature averages for a given location at two different points in time, over which the marginal effects of predictors on the outcome variable are assumed to change. The difference in the average of the outcome variable between the earlier period and the later period is decomposed into a portion attributable to the intertemporal change in the levels of predictors and the portion attributable to the change in the coefficients for the predictors. Consider two multiyear periods denoted "a" and "b" where period a stands for period 1981-1995 and period b stands for period 1996-2010. The OB decomposition approach expresses the mean outcome difference as the difference in the linear prediction at the group-specific means of the predictors. That is,

$$\begin{aligned} E(\log y_{ib}) - E(\log y_{ia}) &= E(\phi_i + X'_{ib}\beta_b + \eta_{pb}) - E(\phi_i + X'_{ia}\beta_a + \eta_{pa}) \\ &= \underbrace{E(X'_{ib} - X'_{ia})\beta_a}_{\text{Predictors Change}} + \underbrace{E(X'_{ib})(\beta_b - \beta_a)}_{\text{Coefficients Change}} + E(\Delta\eta) \end{aligned} \tag{3.2}$$

The decomposition shown in equation (2) is formulated from the viewpoint of period a because we are interested in the growth of the outcome variable and predictors and corresponding coefficients from period a to period b. The estimation of the components of the decomposition in equation (2) is straightforward. Let $\hat{\beta}_a$ and $\hat{\beta}_b$ be the least-squares estimates for β_a and β_b obtained from estimating the pooling model with period interactions shown in equation (1). Furthermore, we use the period(group) means $\overline{X}_a$ and $\overline{X}_b$ as estimates for $E(X_a)$ and $E(X_b)$. The estimates for the OB decomposition can be derived as

$$\begin{aligned} \overline{\log y}_b - \overline{\log y}_a &= \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=\underline{t}_b}^{\bar{t}_b}\log y_{it} - \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=\underline{t}_a}^{\bar{t}_a}\log y_{it} \\ &= \underbrace{(\overline{X}'_{ib} - \overline{X}'_{ia})\hat{\beta}_a}_{\text{Predictors Change}} + \underbrace{\overline{X}'_{ib}(\hat{\beta}_b - \hat{\beta}_a)}_{\text{Coefficients Change}} + \Delta\bar{\eta} + \Delta\bar{\epsilon} \end{aligned} \tag{3.3}$$

N is the total number of counties, T is the number years of a period. The temporal change in the province-year fixed effect $\Delta\overline{\eta} = \frac{1}{P}\frac{1}{T}\sum_{i=p}^{P}\sum_{t=\underline{t}_b}^{\bar{t}_b}\eta_{pt} - \frac{1}{P}\frac{1}{T}\sum_{p=1}^{P}\sum_{t=\underline{t}_a}^{\bar{t}_a}\eta_{pt}$ and so $\Delta\bar{\epsilon}$ is defined. $\Delta\bar{\epsilon}$ should be very close to zero and negligible.

In the period-specific data generating process, the unobserved differences in the average county-level predictor-outcome relationship are accounted for by the county fixed effect ϕ_i and any common shocks across counties within a given period are accounted for by the year fixed effects η_t. Because the decomposition regression in equation (3) is directly derived from the data generating process in equation (1), the β coefficients for the two periods are identified through within-county differences in the predictors over time after having controlled for the shocks common to all counties. We can obtain the standard errors for the coefficient estimators simply from the OLS regression and the variances for each decomposition components are derived in Appendix B according to Jann (2008).

$(\overline{X}'_{ib} - \overline{X}'_{ia})\hat{\beta}_a$ is the portion of the outcome difference over periods attributable to the change in the predictors while the predictability (coefficients) remain unchanged, which measures the contribution of the change in the levels of predictors to the growth of the outcome variable. $\overline{X}'_{ib}(\hat{\beta}_b - \hat{\beta}_a)$ is the portion of the outcome difference attributable to the change in how the predictors are associated with the outcome variable while the level of predictors changed to the second period (period b). This piece gives us a measurement of the counterfactual effect if the marginal effects of the predictors in the second period remained to be the one in the first period (period a).

The variable of central interest is the extreme temperature. 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 calendar year to get a measure of annual growing degree days for those bounds.[5] 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.

Daily average of precipitation, humidity, evaporation, sunshine duration and wind speed within a year and their quadratic forms are incorporated in the decomposition regression to succinctly account for the nonlinear impacts of these climate variables. In the estimation of equation (4), we set $l_0 = 10$ since GDD above 10 °C is beneficial to the agricultural sector (Chen and Gong, 2021) and allow the data to determine l_1 by looping over all possible thresholds from 26°C to 40°C and selecting the model that best fit the data based on the Bayesian Information Criterion. The selected thresholds for growing degree days is 33 °C which is consistent with the literature (Chen and Gong, 2021). We also conduct robustness checks with multiple thresholds other than the selected ones to avoid threshold misspecificiation.

3.4 Empirical Results

This section presents the estimates of the relationship between inputs, weather and revenue over time periods using the Oaxaca-Blinder decomposition method. Our

[5] 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).

primary analysis focuses on the evolutionary effects of period-to-period variation in temperature on the agricultural revenue per unit of land, which is a basic measure of agricultural productivity and a key determinant of farm income and welfare. We then conduct robustness checks on the temperature thresholds for the high piece of the growing degree days and functional forms of the growing degree days. At last, we explore the temporal evolution of the role of irrigation in moderating the extreme temperature impacts as a mechanism study.

3.4.1 The Temporal Evolution of Temperature-Revenue Relationship

Table 3.2 reports the estimation of the period-specific temperature-revenue relationship using the Oaxaca-Blinder decomposition method. The early period is 1981-1995 and the later period is 1996-2010. The first two columns present the estimates of the marginal effects of the inputs and climate variables. The "Decomposition" column for $\hat{\beta}_{1981}(\overline{X}_{1996} - \overline{X}_{1981})$ presents the estimation of the decomposition component of the change in the levels of the predictors and the corresponding "Percent" column presents the share of the predictors' change component in the overall change of the outcome variable which is estimated by $\frac{\hat{\beta}_{1981}(\overline{X}_{1996}-\overline{X}_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}}$. The "Decomposition" column for $\overline{X}_{1996}(\hat{\beta}_{1996} - \hat{\beta}_{1981})$ presents the estimation of the decomposition component for the change in the marginal effects of predictors (coefficients) and the corresponding "Percent" column reports the share of the coefficients' change in the overall change of the outcome variable, which is estimated by $\frac{\overline{X}_{1996}(\hat{\beta}_{1996}-\hat{\beta}_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}}$.[6] Period 1981-1995 is the

[6] The negative sign implies the contribution of the component to the agricultural growth is negative. For example, in Table 2, for the labor input, $\hat{\beta}_{1981}(\overline{X}_{1996} - \overline{X}_{1981}) = -0.0171$, which can be interpreted as that the growth rate of the agricultural revenue would have increased by 1.71 percentage points (the outcome variable is log of revenue) if the average labor level in the post-1996 period is the same as

reference period. We control for four inputs–labor, machinery, fertilizer and irrigation as well as climate variables–temperature (measured by degree days), precipitation, humidity, sunshine duration, evaporation and wind speed. To keep the table succinct, we report the aggregate effects of the additional climate variables due to change in the additional climate variables and the change in their marginal impacts.

The overall increase in the agricultural outputs from 1981-1995 to 1996-2010 is 113.25% ($\overline{Y}_{1996} - \overline{Y}_{1981}$). We first describe the evolutionary effects of the agricultural inputs. The roles of labor, machinery, fertilizer and irrigation in the agricultural growth have evolved significantly over time. Specifically, the role of labor has declined because both the elasticity of labor (marginal effects of the log labor on revenue) and labor input has significantly decreased over the two periods as shown in Table 1 about summary statistics. Both the production elasticity of machinery and levels of machinery use significantly increased in the last 30 years, contributing about 50 percentage points increase of agricultural revenue in total (0.2699+0.2239), which accounts for about 44% of the overall growth of agricultural revenues per hectare. The elasticity of fertilizer has doubled implying that fertilizer is used more efficiently over time and stimulating double expansion of fertilizer use from 1981-1995 to 1996-2010. The finding on the elasticity of machinery and fertilizer is consistent with the trend of mechanization of Chinese agricultural and previous studies about the evolution of Chinese agricultural production function (Gong, 2018). Irrigation expansion contributes about 23% of the

that in the pre-1996 period ($\overline{X}_{1981} = \overline{X}_{1996}$). In other words, that the average labor input per hectare decreased from 4.21 people per ha. in pre-1996 period to 3.92 people per ha. as summarized in Table 3.1 or by 7% has made the growth rate of revenue decrease by 1.71 percentage points, which is about 1.51% of the whole growth corresponding to $\frac{\overline{X}_{1996}(\hat{\beta}_{1996}-\hat{\beta}_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}} = -1.51\%$. The regression coefficient for log labor is the labor elasticity of production. $\overline{X}_{1996}(\hat{\beta}_{1996} - \hat{\beta}_{1981}) = -0.1229$ means that the decrease of labor elasticity from 0.24 to 0.13 as shown in Table 2 has made the agricultural growth decrease by 12.29 percentage points accounting for 10.86% of the whole growth, which corresponds to $\frac{\overline{X}_{1996}(\hat{\beta}_{1996}-\hat{\beta}_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}} = -10.86\%$.

output growth mainly through the increase in the marginal benefits of expansion of irrigation coverage.

Second, the decline in the extreme temperature effects on the agricultural revenue has made substantial contribution to the revenue growth. $\hat{\beta}_{1981}(\overline{X}_{1981} - \overline{X}_{1981})$ denotes the portion of the extreme temperature effects due to the change in the exposure to extreme temperatures while the temperature sensitivity remained as in the initial period. The increase in the extreme temperature exposure has caused 6.10 log points decrease in the agricultural revenue, which accounts for about 5.40% of the overall growth of agricultural growth in the last 30 years.

However, the impact on agricultural revenue of one additional daily exposure to temperatures above 33 °C every year on average during 1996-2010 is about 10 percentage points less than that during 1981-1995, which substantially contribute to the agricultural growth in the last 30 years. If the temperature sensitivity in the 1996-2010 period had been the one in the 1981-1985 period and the average level of extreme temperature exposure increased to the higher level in the 1996-2010 period, the revenue growth would have decreased by 6.10 percentage points, which accounts for 5.4% of the overall growth of the agricultural revenue. The growth rate of agricultural revenue would have decreased by about 6.1 percentage points if the temperature sensitivity had not declined. This finding is consistent with (Wang et al., 2020) which documents that the temperature sensitivities of corn and soybean yields (production of a unit piece of land) has declined in the same period of this study but does not quantify the contribution of the decline in the temperature sensitivity to the agricultural growth.

The results for the precipitation show that agricultural sensitivity to mild and excessive precipitation, which corresponds to the coefficient for the linear and quadratic form of annual average of daily precipitation respectively, is stable over the two periods.

In both the pre-1996 period and post-1996 period, the annual agricultural revenue increases as the daily average precipitation increases up to around 5mm beyond which revenue decreases as response to more precipitation. In Section 5, we will provide suggestive evidence on the role of irrigation in smoothing effects of precipitation shocks as a suggestive explanation for the stable evolution in the precipitation sensitivity. The aggregate contribution made by the additional climate variables is sizable but not significant, which makes it difficult to evaluate the role of those variables in the agricultural growth.

3.4.2 Robustness Check

The length of time periods and the time window used in the estimation are varied to test the sensitivity of estimation results to the choices of endpoint years of time periods and the number of years in a time period. We use 10 years as a period and choose 1981-2000 and 1991-2010 as the two time windows for robustness check.[7] The results for the window of 1981-2000 and 1991-2010 are shown in Figure 3.1 and Figure 3.2, respectively. In the two figures, we display the period-specific marginal effects of the predictors in Panel (a), the decomposition components of the revenue growth due to predictors' change and coefficients' change in Panel (b) and the corresponding shares of these two components in the overall growth in Panel (c). We find (1) temporal evolution of inputs elasticities and (2) the decline in the sensitivity of agricultural revenue to temperatures above 33 °C make contributions to the overall agricultural growth that are consistent with the decomposition results in the 15-year period setting

[7] 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.

that is reported in Table 3.2.

Varying temperature thresholds are applied to check the sensitivity of decomposition estimation to variation in temperature thresholds. It is a concern that the selected temperature threshold 33 °are misspecified. Figure 3.3 reports the estimated share that the temporal changes in the predictors' marginal effects account for the overall growth of the outcome variable ($\frac{\overline{X}_{1981}(\beta_{1996}-\beta_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}}$) in equation (1) using the temperature thresholds from 30°C to 35 °C except 33 °C. Panel (a) to (e) demonstrates similar temporal evolution of inputs elasticity estimated with models using the alternative thresholds. The role of labor in the growth of agricultural revenue has declined over time periods while the role of machinery, fertilizer and irrigation has increased. The marginal impact of extreme temperature on revenue has significantly declined over periods, which contributes 3 to 6 percentage points of the overall agricultural growth. Because the exposure to temperature above the thresholds decreases in response to threshold increase, the estimated share decreases as the temperature threshold rises from 30°C to 35°C.

The specification for the growing degree days is changed from a linear piece-wise specification to a more flexible binning specification that calculate the accumulation of heat for each 3°C or 5°C temperature interval that allows the data instead of parametric assumptions to determine the temperature-revenue relationship (Deschênes and Greenstone, 2011) . The specifications for precipitation, additional climate variables and agricultural inputs remain the same as those for the baseline regression. The results are presented in Figure 3.4. The results of significant decline in the sensitivity of revenue to extreme temperatures (above 33 °C for the 3°C interval or above 35 °C for the 5 °C interval) and the consequential effects on the growth of agricultural revenue remain to be robust when the specification for the growing degree days is switched from a linear piecewise form to a more flexible binning form.

A model without controlling for the input variables as an alternative for the model in equation (1) is estimated to investigate the impacts of input variables as bad controls on the empirical results. Inputs may be responsive to weather shocks and will generate a problem of bad control that may bias the weather effects on revenue if inputs are incorporated into the model of production function (Angrist and Pischke, 2008). We first evaluate the degree of bias caused by the input variables as bad controls in the following illustrative example. Suppose the outcome variable y is determined by a single input x, an index for extreme weather conditions z (e.g. extreme high temperatures) and the error term ν in equation (4). In equation (5) the input is also determined by the weather index and an error term e which is uncorrelated with the error term ϵ for the outcome variable. Leaving the input variable aside, we can estimate equation (6).

$$y_i = \beta \cdot x_i + \gamma \cdot z_i + \nu_i \tag{3.4}$$

$$x_i = \rho \cdot z_i + e_i \tag{3.5}$$

$$y_i = \pi \cdot z_i + u_i \tag{3.6}$$

It is straightforward to derive that $\pi = \gamma + \beta \cdot \rho$ and the estimator $\hat{\pi} = \hat{\gamma} + \hat{\beta} \cdot \hat{\rho}$ where $\hat{\beta}, \hat{\gamma}, \hat{\rho}$ is the least-squares estimator for β, γ and ρ, respectively. If extreme weather exposure negatively affects use of inputs, i.e. $\rho < 0$ and inputs increase agricultural outputs i.e. $\beta > 0$, the estimate of extreme weather effect on agricultural outputs (measured by revenue per capita) in equation (4) will be attenuated towards zero compared the estimate in equation (6). If we estimate a period-specific version of the model in equation (6), the Oaxaca-Blinder decomposition for the growth of the agricultural outputs between period a and b can be derived as following:

$$\begin{aligned}\overline{y}_b - \overline{y}_a &= \hat{\pi}_a(\overline{z}_b - \overline{z}_a) + \overline{z}_b(\hat{\pi}_b - \hat{\pi}_a) \\ &= \hat{\pi}_a \Delta\overline{z} + \overline{z}_b(\hat{\gamma}_b + \hat{\beta}_b \cdot \hat{\rho}_b - \hat{\gamma}_a - \hat{\beta}_a \cdot \hat{\rho}_a) \\ &= \hat{\pi}_a \Delta\overline{z} + \overline{z}_b(\Delta\hat{\gamma} + \hat{\beta}_a \cdot \Delta\hat{\rho} + \Delta\hat{\beta} \cdot \hat{\rho}_b) \end{aligned} \tag{3.7}$$

where $\Delta\hat{\beta} = \hat{\beta}_b - \hat{\beta}_a$, $\Delta\hat{\gamma} = \hat{\gamma}_b - \hat{\gamma}_a$ and $\Delta\rho = \hat{\rho}_b - \hat{\rho}_a$. $\Delta\hat{\gamma}$ is the temporal change in weather effects estimated in the model incorporating the input variable. If the input sensitivity to extreme weather shock ρ declined from period a to period b and the decline $\Delta\rho$ is sizable such that ρ_b is close to zero, $\Delta\hat{\pi} > \Delta\hat{\gamma} > 0$ i.e. the portion of the agricultural growth due to change in the weather sensitivity estimated in the model without controlling for input variables should be larger than that estimated in the model controlling for inputs variables. This is intuitive because the decline in weather sensitivity captured by the model omitting input variables incorporates the decline in the direct effects of extreme weather conditions on agricultural outcomes as well as the decline in the effects of extreme weather on inputs.

We next examine the input sensitivity to weather and how estimation of the decomposition components will be changed if input variables are dropped. Table 3.3 reports the impacts of weather shocks on use of inputs by time periods. The baseline 15-year period specification is used. It shows that labor and fertilizer input is significantly used less when there is additional exposure to temperatures above 33 °C or additional precipitation. Machinery and irrigation coverage are little responsive to extreme temperature shocks but are more responsive to precipitation shocks. Machinery may be used to substitute for labor when it is hard for farmers to work in the field. Excessive precipitation can provide sufficient water sources for irrigation. On the other hand, the temperature sensitivity of labor and fertilizer declined significantly as shown by the p value for the test of whether the temperature sensitivity of inputs remain unchanged across the two periods while precipitation sensitivity of the two inputs remained stable. Due to the substantial decline, the temperature sensitivity of labor and fertilizer in the post-1996 period is close to zero. In a nutshell, the temperature sensitivity of inputs either declined to a level close to zero or minimal, suggesting that (1) the negative impact of extreme temperature on agricultural revenue will become larger in magnitude and (2) the contribution of decline in the extreme temperature effects to the growth of agricultural revenue will become larger in the model without input variables.

Table 3.4 reports the empirical results of the OB decomposition model without input variables. The extreme temperature effects on the agricultural revenue become larger in magnitude compared to those in the model with inputs. This is intuitive because estimate of the extreme temperature impacts in the model without input variables captures both the direct impacts and impacts of extreme temperatures through the mechanism of negatively affecting inputs use. The extreme temperature effects decreased by 11.64 log points from the pre-1996 period to the post-1996 period, contributing to 7.15 log points of growth of agricultural revenue. The point estimate of the decomposition component for the decline in the extreme temperature effects is higher than the point estimate in the model with inputs controlled, which is 6.1 log points shown in Table 3.2. This is because decline in temperature sensitivity of labor and fertilizer adds to the decline in the direct effects of extreme temperatures on agricultural revenue, generating a larger extent of decline in the aggregate extreme temperature effects. However, we cannot conclude that the estimated components of the decline in temperature sensitivity in the two models are significantly different given the difference between the two estimates is less than the summation of the corresponding standard errors. So incorporation of inputs as outcomes of weather conditions does not generate significant bias on estimation.

3.5 Benefits of Inputs in Terms of Moderating Extreme Heat Impacts

Though the empirical analysis above documents the substantial contribution of the decline in the temperature sensitivity to the growth of agricultural revenue in the last 30 years but what are the mechanisms for the decline in the temperature sensitivity remains an open question. Following Wang et al. (2020), we will quantify the extent to which moderating extreme temperature impacts through the four inputs contributes to the growth of agricultural revenue. The Oaxaca-Blinder decomposition method allows us not only to quantify the contribution of the moderation effects through each input but also to figure out the respective role of inputs expansion and evolution of marginal moderation effects of each input in promoting the growth of revenue. To do this, we incorporate interactions of all the temperature and precipitation variables with the four inputs (labor, machinery, fertilizer and irrigation) into the period-specific production function in equation (1). We stick to the baseline 15-year period specification.

The results are reported in Table 3.5. The moderation effect of irrigation on temperature sensitivity has significantly increased from the pre-1996 period to the post-1996 period. Expansion of irrigation coverage from 0 to 100% in the post-1996 period is associated with about 12.27 percentage points decrease in the impacts of temperatures above 33 °C while the moderation effect in the pre-1996 period is only 2.64 percentage points decrease in extreme temperature effects. The significant improvement of the irrigation effects in terms of moderating extreme temperature impacts generates 2.68

percentage points of agricultural growth which account for 2.36% of the overall growth of agricultural revenue in the last 30 years. Irrigation coverage only increased by 3 percentage points from the pre-1996 period to the post-1996 period, contributing minimal of the growth. Therefore, improvement of marginal moderation effect of irrigation plays a dominant role in moderating extreme temperature impacts. The interaction effects between inputs and low temperature bins are presented in Table C.1 in Appendix C.

The extreme temperature impact on agricultural revenue that are not moderated through irrigation are captured by the variable of GDD above the threshold (GDD above T) and decreased by 7.08 percentage points (0.1556-0.848) , which contributes 3.84 percentage points of revenue growth accounting for 3.37% of the overall revenue growth. The decline in extreme temperature impacts either through the mechanism of irrigation or other unknown mechanisms generates 6.44 percentage points of revenue growth in total (0.0384+0.0268) and the increase in the moderation effects through irrigation explains about 41% of the aggregate effects of the decline in extreme temperature impacts in terms of agricultural growth.

This paper complements to Wang et al. (2020) that find that irrigation expansion can explain about 30% of the decline of extreme temperature impacts on crop yields by (1) quantifying the contribution of irrigation to the growth of agricultural revenue through the mechanism of moderating the temperature sensitivity and (2) pointing out that the irrigation benefits are achieved through improving the marginal benefits of irrigation in terms of moderating the extreme temperature effects rather than expanding irrigation coverage.

Irrigation is found to moderate the effects of precipitation shocks on agricultural revenue. Expansion of irrigation coverage from 0 to 100% is associated with 10.63 percentage points of decrease in the mild precipitation impacts on agricultural revenue and with 1.05 percentage points of increase in the excessive precipitation impacts. Agricultural sensitivity to extra amount of mild and excessive precipitation decreased significantly mainly because of improvement of marginal moderation effects of irrigation on precipitation effects rather than expansion of irrigation coverage. We do not find significant moderation effects of inputs other than irrigation.

3.6 Conclusion

A series of fundamental agricultural reforms since 1978 has dramatically stimulated the growth of agricultural productivity (Lin, 1992). During the same time period, China has experienced rapid temperature rise Wang et al. (2020). Though there are intensive studies on the climate-agriculture relationship in China (Chen et al., 2016; Zhang et al., 2017; Chen and Gong, 2021; Wang et al., 2020), few studies have analyzed how the impacts of extreme hot temperatures on agricultural outcomes account for the growth of agricultural productivity (Zhang and Carter, 1997). Inspired by the labor economics literature on decomposition methods starting with the seminal papers of Oaxaca (1973) and Blinder (1973), we apply the decomposition method to partition the agricultural growth into the changes in the predictors and the change of how the predictors are associated with the outcome variable and quantify the contribution Percentage of each predictor including extreme hot temperature, to the overall growth of agricultural outcome.

The empirical results show that labor elasticity is decreasing, machinery elasticity remains and fertilizer elasticity are increasing. The extreme temperature impact on agricultural revenue in the post-1996 period is more than 60% lower than that in the pre-1996 period, contributing 6.1 percentage points of growth of agricultural revenue, which is about 5.4% of the overall growth of agricultural revenue. The result is robust to the specification of 10-year period with rolling time window, binning specifications of growing degree days that calculate the accumulation of heat for 3 °C and 5 °C interval as well as model specification without input variables as an investigation of bad control problem. We provide suggestive evidence that irrigation plays an important role in moderating extreme temperature effects and precipitation effects. Dramatic increase in the marginal benefit of irrigation in terms of moderating extreme temperature effects and precipitation effects dominates increase in the irrigation coverage generates significant in contributing to the agricultural growth. Increase in the coefficient for irrigation's moderation effect (interaction between extreme temperature and irrigation coverage) contributes 2.36 percent of the agricultural growth, which accounts for about 40% of the contribution of the decline in the temperature sensitivity to the overall revenue growth. In addition to moderating extreme temperature effects, irrigation also contributes to the growth of agricultural revenue directly.

The empirical results can be interpreted in some lights. Perhaps the most relevant to the topic of climate change is to link the decline in extreme temperature impacts to climate change adaptation (Barreca et al., 2016; Wang et al., 2020). The irrigation-driven decline in the extreme temperature impacts suggest substantial effects of adaptation to climate change in Chinese agriculture. The sizable contribution of decline in extreme temperature impacts implies the pecuniary benefits of adaptation in terms of agricultural revenue. Irrigation contributes to agricultural growth through both the mechanism of moderating extreme temperature impacts and direct mechanism to fuel the growth of agricultural productivity, which implies that irrigation benefits are twofold and should not be underestimated when the investment decision is being made. Irrigation's contribution attributable to the increase of marginal moderation effects implies that more technology innovation to improve the moderation effects of irrigation are needed for controlling the extreme temperature impacts.

3.7 Tables for Chapter 3

Table 3.1: Summary Statistics

	1981-1995				**1996-2010**			
	Mean	Min	Max	Std.Dev.	Mean	Min	Max	Std.Dev.
Outcome Variable								
Agricultural Revenue (10,000 CNY/Ha)	0.52	0.04	19.76	0.33	1.31	0.06	62.18	126.86
Observations	26212				28921			
Inputs Variables								
Labor (persons/Ha)	4.21	0.01	51.18	2.33	3.92	0.00	129.28	2.58
Machinery (Kilowatt/Ha)	3.50	0.17	136.00	2.87	7.60	0.14	217.05	6.43
Fertilizer (Tons/Ha)	0.33	0.02	8.13	0.23	0.62	0.02	17.71	0.51
Irrigation (%)	0.57	0.00	1.00	0.28	0.60	0.00	1.00	0.27
Observations	26212				28865			
Weather Variables								
Temperature (Daily Average: °C)	14.00	-6.34	26.37	4.68	14.67	-5.77	27.00	4.76
Precipitation (Daily Average: mm)	2.60	0.01	34.42	1.39	2.59	0.00	9.89	1.43
Humidity (Daily Average: %)	71.80	25.83	90.62	8.88	69.95	25.30	89.64	8.88
Sunshine Duration (Daily Total: Hours)	5.63	1.91	9.63	1.43	5.49	0.19	9.72	1.42
Wind Speed (Daily Average: m/s)	2.26	0.30	9.51	0.96	2.17	0.21	8.29	0.88
Evaporation (Daily Average: mm)	4.13	1.83	13.02	0.90	3.54	0.40	12.02	1.18
Observations	26212				28921			

Notes: The mean value of each variable is weighted by the aggregate planted area.

Table 3.2: The Result for Oaxaca-Blinder Decomposition

	$\hat{\beta}_{1981}$	$\hat{\beta}_{1996}$	$\hat{\beta}_{1981}(\overline{X}_{1996} - \overline{X}_{1981})$		$\overline{X}_{1996}(\hat{\beta}_{1996} - \hat{\beta}_{1981})$	
			Decomposition	Percent	Decomposition	Percent
$\overline{Y}_{1996} - \overline{Y}_{1981}$			0.4036***	35.64%***	0.7289***	64.36%***
			(0.0289)	(0.0247)	(0.0302)	(0.0247)
Log Labor	0.2437***	0.1303***	-0.0171***	-1.51%***	-0.1229***	-10.86%***
	(0.0103)	(0.0071)	(0.0042)	(0.0038)	(0.0415)	(0.0361)
Log Machinery	0.1648***	0.2845***	0.2699***	23.83%***	0.2239***	19.77%***
	(0.0062)	(0.0084)	(0.0192)	(0.0167)	(0.0455)	(0.0401)
Log Fertilizer	0.2069***	0.2674***	0.1840***	16.25%***	-0.0395***	-3.49%**
	(0.0075)	(0.0066)	(0.0157)	(0.0136)	(0.0162)	(0.0143)
Irrigation (%)	0.1597***	0.5687***	0.0101***	0.89%***	0.2580***	22.78%***
	(0.0221)	(0.0170)	(0.0030)	(0.0026)	(0.0409)	(0.0363)
GDD between	-0.0062***	-0.0073***	-0.0191***	-1.68%***	-0.1349	-11.91%
0°C and 10 °C	(0.0006)	(0.0005)	(0.0049)	(0.0043)	(0.2390)	(0.2106)
GDD between	0.0035***	0.0051***	0.0314***	2.77%***	0.1946**	17.18%**
10 °C and T	(0.0003)	(0.0002)	(0.0055)	(0.0049)	(0.0976)	(0.0858)
GDD above T	-0.1421***	-0.0510***	-0.0251***	-2.22%**	0.0610***	5.40%***
	(0.0105)	(0.0092)	(0.0101)	(0.0098)	(0.0201)	(0.0184)
Precip.	0.1466***	0.1615***	-0.0041**	-0.36%*	0.0385	3.40%
	(0.0143)	(0.0121)	(0.0021)	(0.0019)	(0.0782)	(0.0691)
Precip. Square	-0.0159***	-0.0112***	0.0003	0.02%	0.0376**	3.30%**
	(0.0018)	(0.0015)	(0.0014)	(0.0013)	(0.0157)	(0.0141)
Additional	N/A	N/A	-0.0437***	-3.86%***	-0.3074	-26.96%
Climate Vars.	N/A	N/A	(0.0096)	(0.0073)	(0.5770)	(0.5096)
Average. of	-0.9405***	-0.4751***	N/A	N/A	0.4654**	41.19%**
Province-Year FEs	(0.1042)	(0.0831)	N/A	N/A	(0.2211)	(0.2021)
Observations	54584	54584	54584	54584	54584	54584
R squared	0.8820	0.8820	N/A	N/A	N/A	N/A
T threshold	33 °C	33 °C	33 °C	33 °C	33 ° C	33 ° C
No. of Clusters	1955	1955	1955	1955	1955	1955

Notes: The outcome variable is the difference in the average agricultural revenue between 1981-1995 and 1996-2010. The regression is weighted by the county-average farmed area from 1981 to 2010. Additional weather variables include linear and quadratic forms of accumulative precipitation, sunshine duration, average relative humidity, evaporation and wind speed. Standard errors listed in parentheses are clustered at the county level. The average of province-year fixed effects by time period are estimated by $\frac{1}{29}\frac{1}{15}\sum_{p=1}^{29}\sum_{t=1981}^{1995}\hat{\eta}_{pt}$ and $\frac{1}{29}\frac{1}{15}\sum_{p=1}^{29}\sum_{t=1996}^{2010}\hat{\eta}_{pt}$, where there are 29 provinces in the sample data. ***$p<0.01$, **$p<0.05$, * $p<0.1$

Table 3.3: The Impacts of Weather Shocks on use of Inputs by Period: 1981-1995 versus 1996-2010

	(1) Log Labor	(2) Log Machinery	(3) Log Fertilizer	(4) Irri. Ratio
period=1981 × GDD btw. 0°C and 10 °C	0.0011 (0.0009)	0.0010 (0.0012)	0.0010 (0.0013)	0.0011 (0.0006)
period=1996 × GDD btw. 0°C and 10 °C	-0.0018 (0.0011)	0.0009*** (0.0003)	-0.0001 (0.0014)	0.0005 (0.0004)
period=1981 × GDD btw. 10°C and 33°C	0.0032*** (0.0009)	0.0010 (0.0009)	-0.0005 (0.0008)	0.0007 (0.0005)
period=1996 × GDD btw. 10°C and 33°C	0.0025*** (0.0008)	-0.0007 (0.0009)	-0.0002 (0.0008)	0.0001 (0.0003)
period=1981 × GDD above 33°C	-0.0381*** (0.0082)	-0.0062 (0.0041)	-0.0201*** (0.0036)	-0.0053 (0.0033)
period=1996 × GDD above 33°C	-0.0079*** (0.0023)	0.0015 (0.0012)	-0.0052** (0.0025)	-0.0065* (0.0035)
period=1981 × Precip.	-0.0128*** (0.0045)	0.0290 (0.0166)	-0.0793*** (0.0167)	0.0080 (0.0055)
period=1996 × Precip.	-0.0156*** (0.0054)	0.0311*** (0.0174)	-0.0769*** (0.0157)	0.0092 (0.0059)
period=1981 × Precip. Square	-0.0020*** (0.0002)	-0.0012*** (0.0003)	-0.0003 (0.0002)	0.0002** (0.0001)
period=1996 × Precip. Square	-0.0005*** (0.0002)	-0.0008*** (0.0002)	-0.0007** (0.0003)	0.0003* (0.0002)
Constant	2.4168*** (0.2473)	2.1105*** (0.3367)	-0.0669 (0.3432)	0.6250*** (0.1089)
p-Value for test of $\beta^{1981}_{\text{GDD above T}} = \beta^{1996}_{\text{GDD above T}}$	0.0005	0.1162	0.0000	0.8010
Observations	48404	48140	48404	48117
R squared	0.9158	0.8986	0.8582	0.8825
Add. Climate Vars.	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Std. Error	Clustered	Clustered	Clustered	Clustered

Notes: Regressions are weighted by the county-average farmed area from 1981 to 2010. Additional climate variables include linear and quadratic forms of sunshine duration, average relative humidity, evaporation and wind speed. Standard errors listed in parentheses are clustered at the county level. ***p<0.01, **p<0.05, * p<0.1

Table 3.4: The Result for Oaxaca-Blinder Decomposition without Controlling Agricultural Inputs

	$\hat{\beta}_{1981}$	$\hat{\beta}_{1996}$	$\hat{\beta}_{1981}(\overline{X}_{1996} - \overline{X}_{1981})$		$\overline{X}_{1996}(\hat{\beta}_{1996} - \hat{\beta}_{1981})$	
			Decomposition	Percent	Decomposition	Percent
$\overline{Y}_{1996} - \overline{Y}_{1981}$			-0.0122	-1.07%	1.1528***	101.07%***
			(0.0127)	(0.0101)	(0.0188)	(0.0111)
GDD between	0.0119***	0.0107***	0.0354***	3.10%***	-0.0862***	-7.56%***
0°C and 10 °C	(0.0007)	(0.0006)	(0.0065)	(0.0053)	(0.0129)	(0.0107)
GDD between	0.0021***	0.0034***	0.0188***	1.65%***	0.1691**	14.83%**
10 °C and T	(0.0003)	(0.0004)	(0.0086)	(0.0054)	(0.838)	(0.0706)
GDD above T	-0.1688***	-0.0624***	-0.0371***	-3.25%***	0.0715**	6.27%**
	(0.0127)	(0.0109)	(0.0125)	(0.0106)	(0.0312)	(0.0262)
Precip.	0.1291***	0.1320***	-0.0063**	-0.55%**	0.0072	0.63%
	(0.0177)	(0.0122)	(0.0028)	(0.0026)	(0.0091)	(0.0082)
Precip. Square	-0.0088***	-0.0072***	0.0004	0.03%	0.0132	1.16%
	(0.0022)	(0.0020)	(0.0013)	(0.0010)	(0.0271)	(0.0201)
Additional	N/A	N/A	-0.0234**	-2.05%**	-0.2888	-25.33%
Climate Vars.	N/A	N/A	(0.0108)	(0.0095)	(0.6901)	(0.6054)
Average of	-2.8120***	-1.5452***	N/A	N/A	1.2668***	111.12%**
Province-year FEs	(0.1572)	(0.1317)	N/A	N/A	(0.4167)	(0.4029)
Observations	55132	55132	55132	55132	55132	55132
R squared	0.7214	0.7214	N/A	N/A	N/A	N/A
T threshold	33 °C	33 °C	33 °C	33 °C	33 °C	33 °C
No. of Clusters	1957	1957	1957	1957	1957	1957

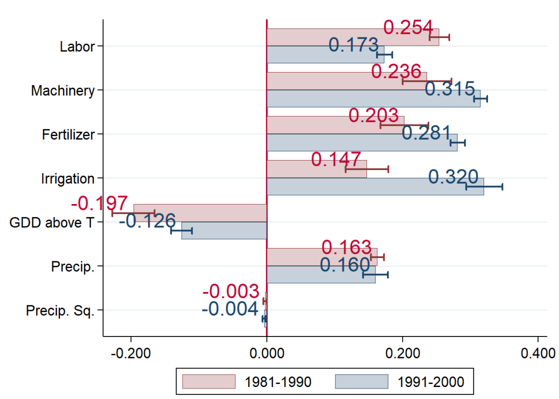
Notes: The outcome variable is the difference in the average agricultural revenue between 1981-1995 and 1996-2010. The regression is weighted by the county-average farmed area from 1981 to 2010. Additional weather variables include linear and quadratic forms of accumulative precipitation, sunshine duration, average relative humidity, evaporation and wind speed. Standard errors listed in parentheses are clustered at the county level. The average of province-year fixed effects by time period are estimated by $\frac{1}{29}\frac{1}{15}\sum_{p=1}^{29}\sum_{t=1981}^{1995}\hat{\eta}_{pt}$ and $\frac{1}{29}\frac{1}{15}\sum_{p=1}^{29}\sum_{t=1996}^{2010}\hat{\eta}_{pt}$, where there are 29 provinces in the sample data. ***$p<0.01$, **$p<0.05$, * $p<0.1$

Table 3.5: The Benefits of Inputs in terms of Moderating Extreme Temperature Impacts

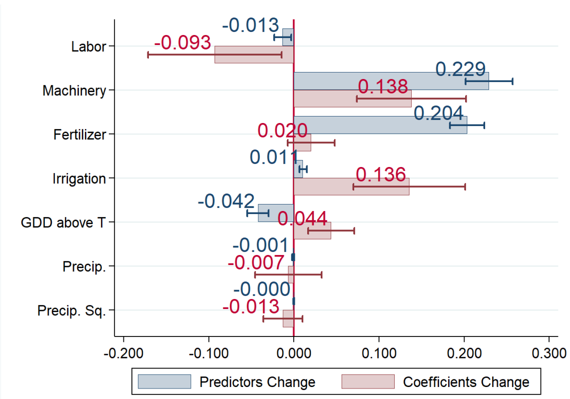
	$\hat{\beta}_{1981}$	$\hat{\beta}_{1996}$	$\hat{\beta}_{1981}(\overline{X}_{1996}-\overline{X}_{1981})$		$\overline{X}_{1996}(\hat{\beta}_{1996}-\hat{\beta}_{1981})$	
			Decomposition	Percent	Decomposition	Percent
$\overline{Y}_{1996}-\overline{Y}_{1981}$			0.3842***	33.92%***	0.7483***	66.08%***
			(0.0258)	(0.0217)	(0.0254)	(0.0228)
Log Labor	0.2998***	0.1875***	-0.0230***	-2.02%***	-0.1256***	-11.02%***
	(0.0101)	(0.0185)	(0.0079)	(0.0038)	(0.0305)	(0.0281)
Log Machinery	0.1712***	0.2970***	0.2573***	23.83%***	0.2203***	19.32%***
	(0.0171)	(0.0199)	(0.0484)	(0.0417)	(0.0456)	(0.0402)
Log Fertilizer	0.2273***	0.2814***	0.1786***	15.67%***	-0.0381**	-3.49%**
	(0.0255)	(0.0217)	(0.0372)	(0.0336)	(0.0192)	(0.0153)
Irrigation (%)	0.0936***	0.3292***	0.0056	0.49%	0.1487***	13.04%***
	(0.0185)	(0.0155)	(0.0070)	(0.0026)	(0.0309)	(0.0263)
GDD between	-0.0046***	-0.0071***	-0.0142***	-1.68%***	-0.3033	-26.78%
0°C and 10 °C	(0.0007)	(0.0006)	(0.0047)	(0.0043)	(0.2382)	(0.2095)
GDD between	0.0031***	0.0052***	0.0275***	2.77%***	0.2560***	22.61%**
10 °C and 33°C	(0.0003)	(0.0002)	(0.0055)	(0.0049)	(0.0955)	(0.0839)
GDD above 33°C	-0.1556***	-0.0848***	-0.0248**	-2.18%**	0.0384**	3.37%**
	(0.0232)	(0.0168)	(0.0106)	(0.0095)	(0.0185)	(0.0159)
Log Labor ×	-0.0094	-0.0050	-0.0022	-0.19%	0.0351	3.08%
GDD above 33°C	(0.0185)	(0.0103)	(0.0021)	(0.0240)	(0.0284)	(0.0250)
Log Machinery ×	0.0063	0.0102	0.0058	0.51%	0.0497	3.83%
GDD above 33°C	(0.0095)	(0.0084)	(0.0101)	(0.0086)	(0.0434)	(0.0384)
Log Fertilizer ×	-0.0068	-0.0048	-0.0097	0.85%	-0.0071	-0.63%
GDD above 33°C	(0.0165)	(0.0154)	(0.0111)	(0.0098)	(0.0114)	(0.0101)
Irrigation ×	0.0264***	0.1227***	0.0008	0.07%	0.0268**	2.36%***
GDD above 33°C	(0.0082)	(0.0197)	(0.0022)	(0.0017)	(0.0126)	(0.0097)
Precip.	0.1578***	0.2477***	-0.0044	-0.36%*	0.2242***	19.67%**
	(0.0143)	(0.0210)	(0.0039)	(0.0019)	(0.0701)	(0.0691)
Precip. Square	-0.0155**	-0.0146**	0.0001	0.02%	0.0072	0.63%
	(0.0071)	(0.0055)	(0.0025)	(0.0013)	(0.0107)	(0.0091)
Log Labor ×	-0.0096	-0.0050	-0.0036	-0.32%	0.0153	1.34%
Precip.	(0.0208)	(0.0103)	(0.0058)	(0.0044)	(0.0201)	(0.0184)
Log Machinery ×	0.0073*	0.0059*	0.0174	1.53%	-0.0025	-0.22%
Precip.	(0.0039)	(0.0031)	(0.141)	(0.0122)	(0.0192)	(0.0178)
Log Fertilizer ×	-0.0276	-0.0168	-0.0611	-5.39%	0.0207	1.81%
Precip.	(0.0197)	(0.0154)	(0.0794)	(0.0701)	(0.0167)	(0.0154)
Irrigation ×	-0.0192	-0.1063***	-0.0096	-0.84%	-0.0450**	-3.95%**
Precip.	(0.0158)	(0.0242)	(0.0076)	(0.0062)	(0.0101)	(0.0179)
Log Labor ×	-0.0044	-0.0029	-0.0048	-0.42%	0.0196	1.72%
Precip. Square	(0.0046)	(0.0033)	(0.0064)	(0.0062)	(0.0301)	(0.0292)
Log Machinery ×	0.0047	0.0054	0.0360	3.16%	0.0101	0.88%
Precip. Square	(0.0034)	(0.0032)	(0.0413)	(0.0314)	(0.0107)	(0.0094)
Log Fertilizer ×	0.0036	-0.0039	0.0253	2.19%	0.0306	2.68%
Precip. Square	(0.0033)	(0.0026)	(0.0111)	(0.0103)	(0.0301)	(0.0232)
Irrigation ×	0.0010	0.0105**	0.0019	0.17%**	0.0484**	4.24%***
Precip. Square	(0.0018)	(0.0042)	(0.0027)	(0.0073)	(0.0231)	(0.0184)
Observations	54584	54584	54584	54584	54584	54584
R squared	0.9239	0.9239	N/A	N/A	N/A	N/A
No. of Clusters	1955	1955	1955	1955	1955	1955

3.8 Figures for Chapter 3

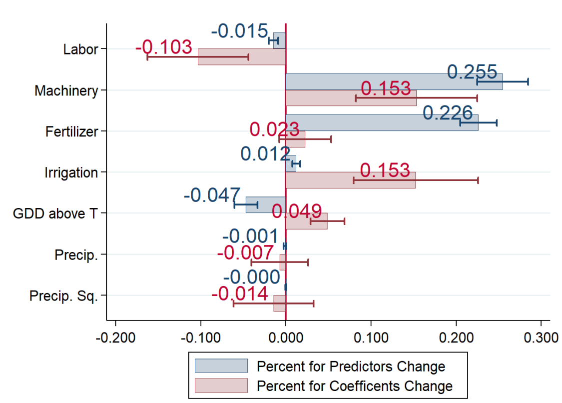
Figure 3.1: Sensitivity of Results to the Period Length of 10 Years: 1981-1990 and 1991-2010



(a) Coefficients for Predictors by time periods



(b) The Decomposition Components of Predictors' Change and Coefficients' Change

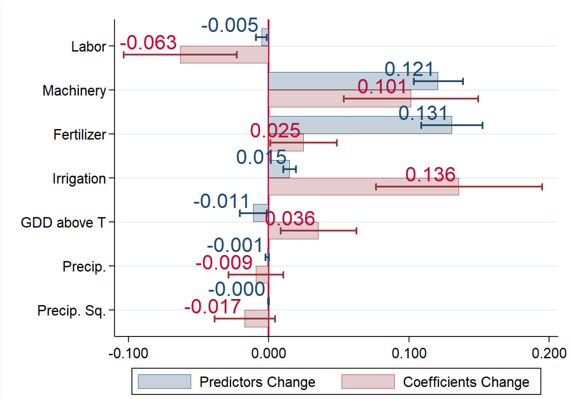


(c) The Share of Predictors' Change and Coefficients' Change in the Overall Growth of Agricultural Revenues

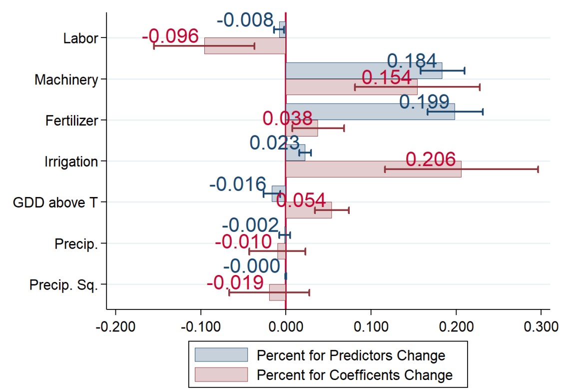
Notes: Panel (a) depicts $\hat{\beta}_{1981}$ and $\hat{\beta}_{1991}$ that are estimated in equation (1) using time periods of 1981-1990 and 1991-2000. Equation (1) is weighted by the county-level average of farmed area. Panel(b) depicts the estimates of $\hat{\beta}_{1981}(\overline{X}_{1991} - \overline{X}_{1981})$ (predictors' change) and $\overline{X}_{1991}(\hat{\beta}_{1991} - \hat{\beta}_{1981})$ (coefficients' change), respectively. Panel (c) depicts $\frac{\hat{\beta}_{1981}(\overline{X}_{1991}-\overline{X}_{1981})}{\overline{Y}_{1991}-\overline{Y}_{1981}}$ and $\frac{\overline{X}_{1991}(\hat{\beta}_{1991}-\hat{\beta}_{1981})}{\overline{Y}_{1991}-\overline{Y}_{1981}}$,the corresponding share of the two components in the overall growth of agricultural revenues per hectare.

Figure 3.2: Sensitivity of Results to the Period Length of 10 Years:
1991-2000 and 2001-2010

(a) Coefficients for Predictors by time periods



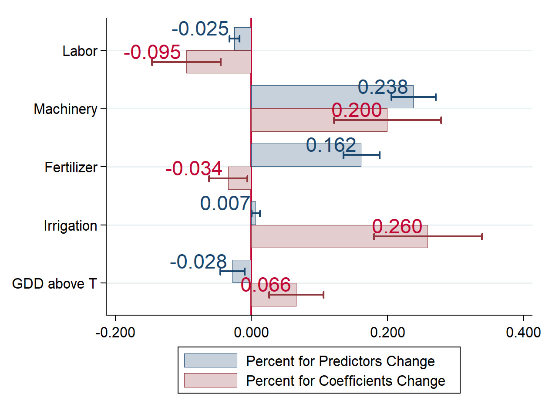
(b) The Decomposition Components of Predictors' Change and Coefficients' Change



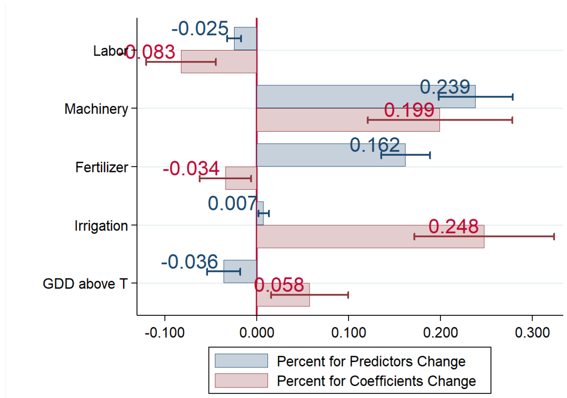
(c) The Share of Predictors' Change and Coefficients' Change in the Overall Growth of Agricultural Revenues

Notes: Panel (a) depicts $\hat{\beta}_{1991}$ and $\hat{\beta}_{2001}$ that are estimated in equation (1) using time periods of 1991-2000 and 2001-2010. Equation (1) is weighted by the county-level average of farmed area. Panel(b) depicts the estimates of $\hat{\beta}_{1991}(\overline{X}_{2001} - \overline{X}_{1991})$ (predictors' change) and $\overline{X}_{2001}(\hat{\beta}_{2001} - \hat{\beta}_{1991})$ (coefficients' change), respectively. Panel (c) depicts $\frac{\hat{\beta}_{1991}(\overline{X}_{2001}-\overline{X}_{1991})}{\overline{Y}_{2001}-\overline{Y}_{1991}}$ and $\frac{\overline{X}_{2001}(\hat{\beta}_{2001}-\hat{\beta}_{1991})}{\overline{Y}_{2001}-\overline{Y}_{1991}}$,the corresponding share of the two components in the overall growth of agricultural revenues per hectare.

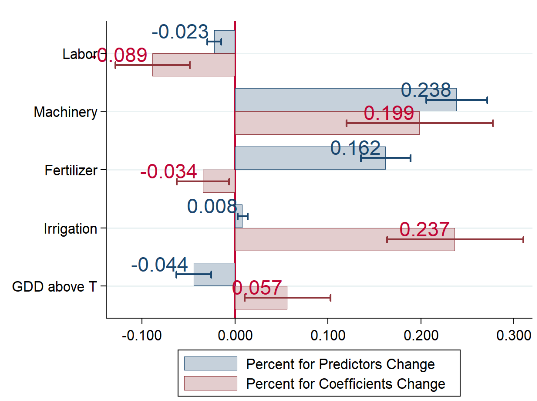
Figure 3.3: The Shares of Predictors' Change and Coefficients' Change in the Growth of Agricultural Revenues from 1981-1995 to 1996-2010 for Varying Temperature Thresholds:
–Sensitivity of Decomposition Estimation to Temperature Thresholds



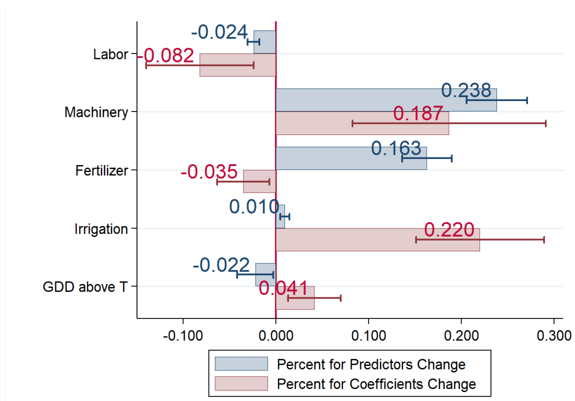
(a) Temperature Threshold $T = 30$ °C



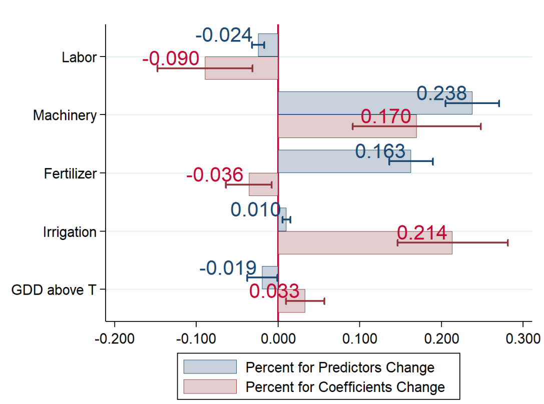
(b) Temperature Threshold $T = 31$ °C



(c) Temperature Threshold $T = 32$ °C

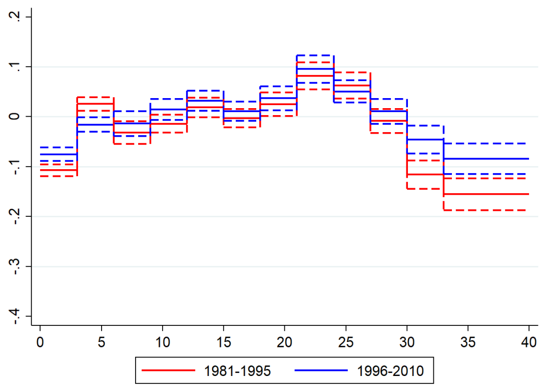


(d) Temperature Threshold $T = 34$ °C

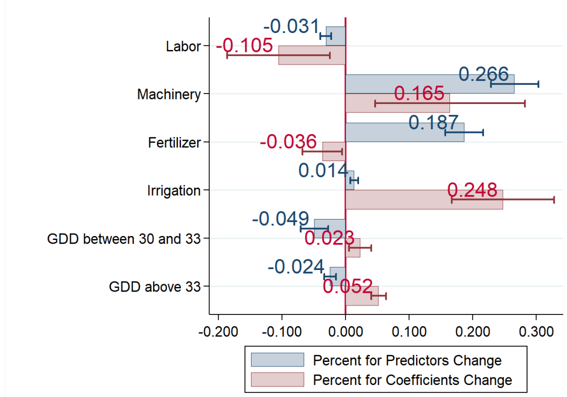


(e) Temperature Threshold $T = 35$ °C

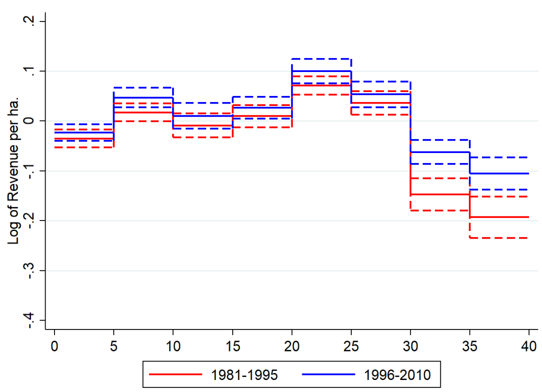
Figure 3.4: Sensitivity of Decomposition Estimation to A Temperature Bin Specification



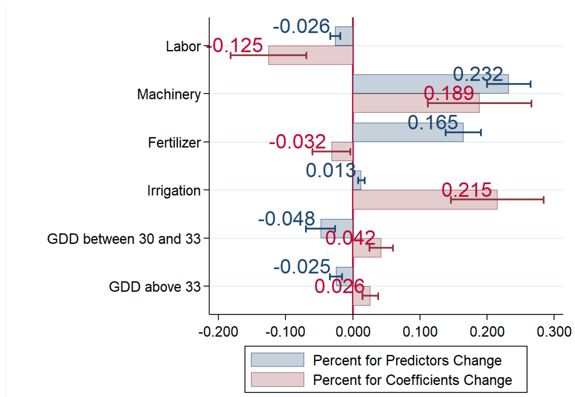
(a) Coefficients for Predictors by time periods: 3 °C Temperature Interval



(b) The Shares of Predictors' Change and Coefficients' Change in the Growth of Agricultural Revenues: 3 °C Temperature Interval



(c) Coefficients for Predictors by time periods: 5 °C Temperature Interval



(d) The Shares of Predictors' Change and Coefficients' Change in the Growth of Agricultural Revenues: 5 °C Temperature Interval

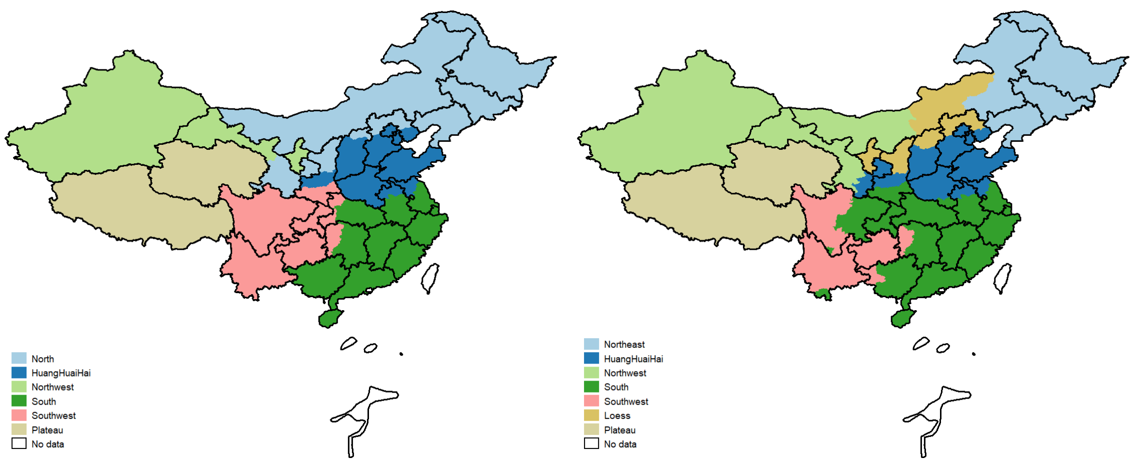
Notes: Figure 4 depicts depicts the period-specific temperature-revenue relationship that is estimated in equation (1) using a binning specification for growing degree days (in Panel (a) and (c)) and the shares of predictors' change and coefficients' change in the growth of agricultural revenues i.e. $\frac{\hat{\beta}_{1996}(\overline{X}_{1996}-\overline{X}_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}}$ and $\frac{\overline{X}_{1996}(\hat{\beta}_{1996}-\hat{\beta}_{1981})}{\overline{Y}_{1996}-\overline{Y}_{1981}}$ (in Panel (b) and (d)). Panel (a) and (b) are for the setting of 3 °C temperature interval while Panel (c) and (b) are for the 5 °C interval. The period 1981-1995 and 1996-2010 are used as the specification for period division. Each regression is weighted by the county-level average of farmed area.

Appendix A

Appendix for Chapter 1

A.1 Figures and Tables on Summary Statistics of Data

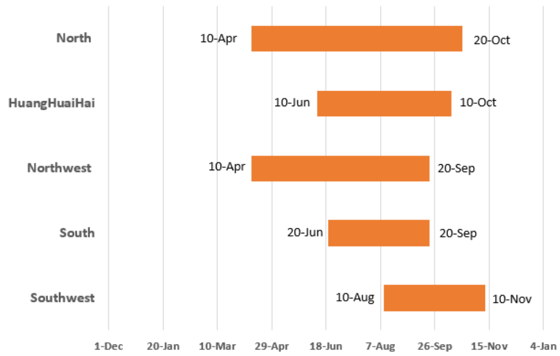
Figure A.1: The Maps of Crop Regions: Corn and Soybean



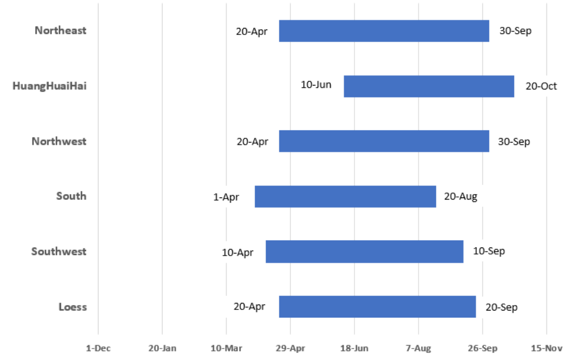
(a) The Map of Corn Regions (b) The Map of Soybean Regions

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



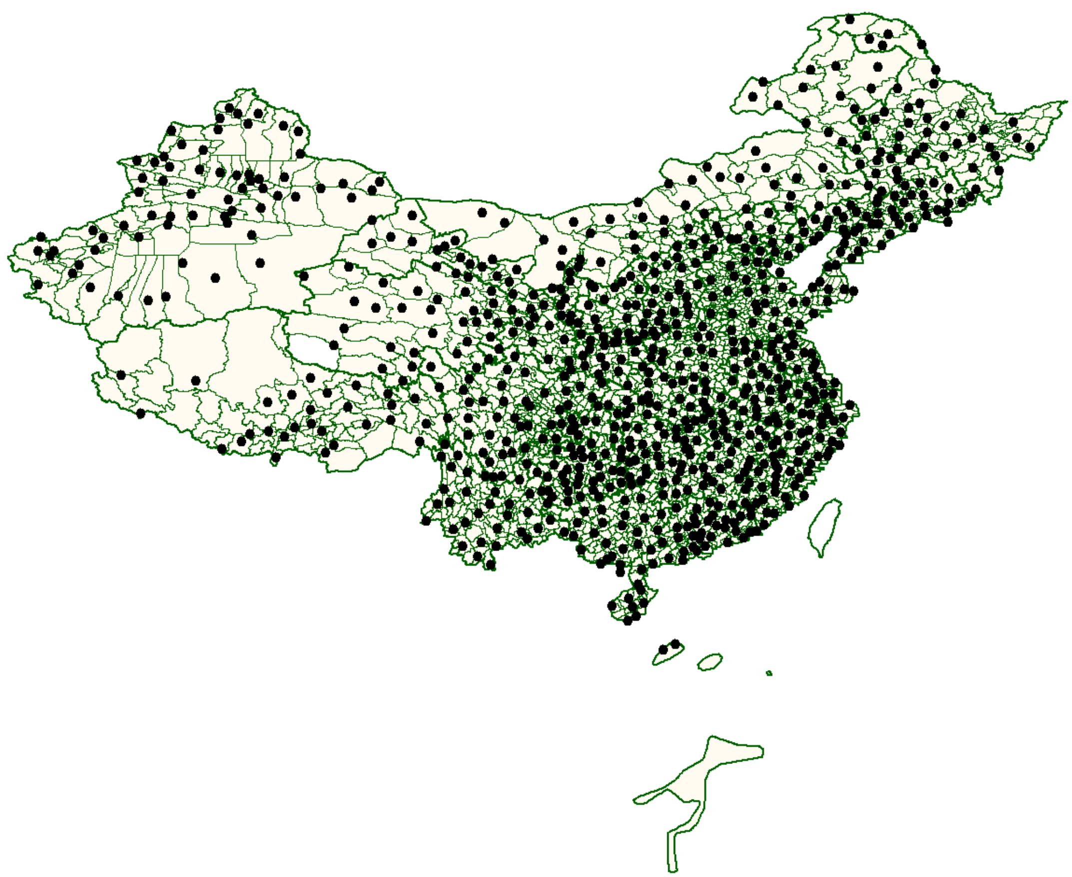
(a) Growing Seasons of Corn By Region



(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.

A.2 Temperature-Yield Relationship

A The Role of Additional Climate Variables in the Temperature-Yield Relationship

Table A.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
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 1.4 to present the impacts of additional climate variables on corn yields.

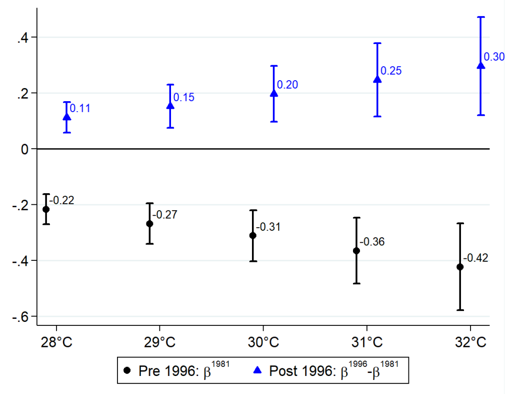
Table A.2: The Evolution of Temperature-Yield Relationship of Soybean: the Impacts of Additional Climate Variables

	(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
Distance	N/A	N/A	N/A	500 km	500 km
Years of Lag	N/A	N/A	N/A	5	5

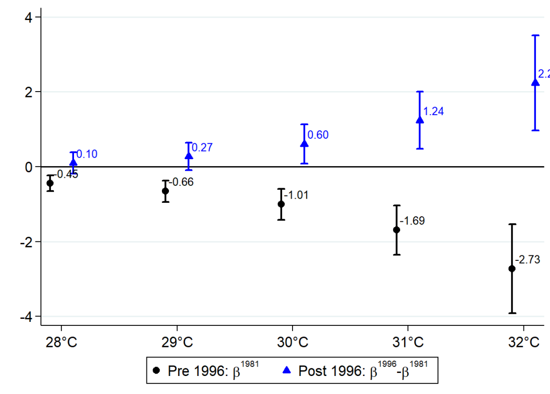
Note: This table follows Table 1.5 to present the impacts of additional climate variables on soybean yields.

Figure A.4 and A.5 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 A.4 is about corn and Figure A.5 is about soybean. All the figures depict the point estimate and the corresponding 95 % confidence interval for the coefficient for GDD above the threshold.

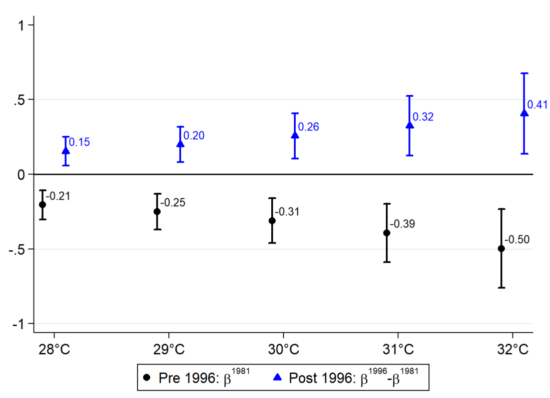
Figure A.4: Marginal Impacts of Extreme Temperatures on Corn Yields by Regions



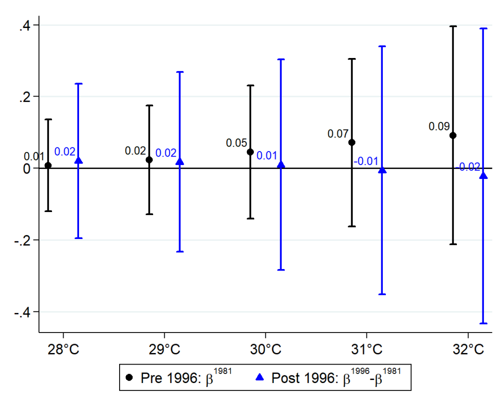
(a) Corn: Nationwide



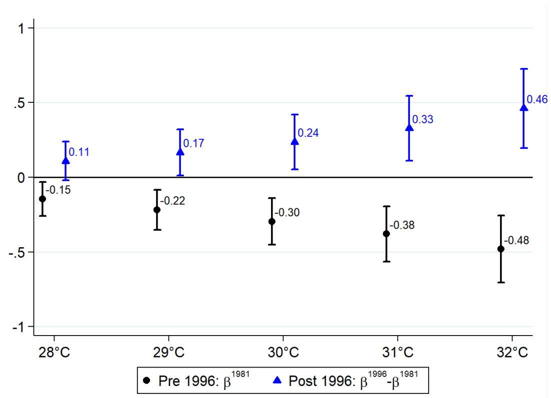
(b) Corn: North



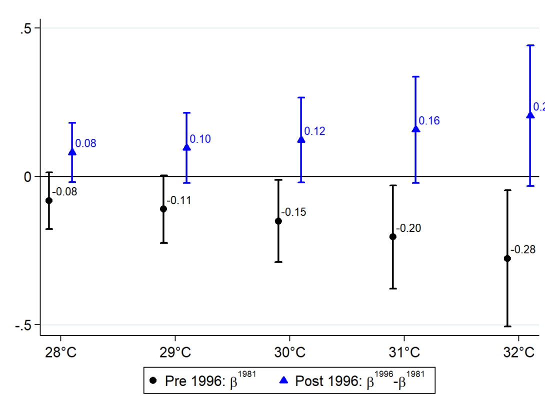
(c) Corn: Huanghuaihai (HHH)



(d) Corn: Northwest

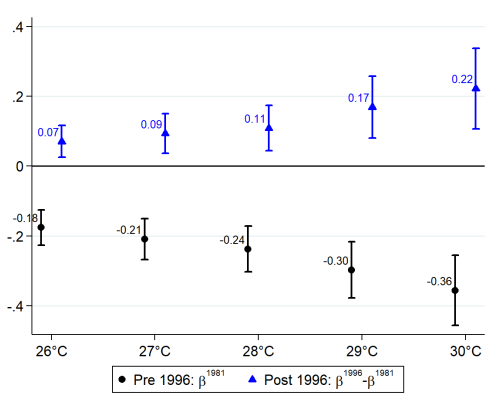


(e) Corn: South

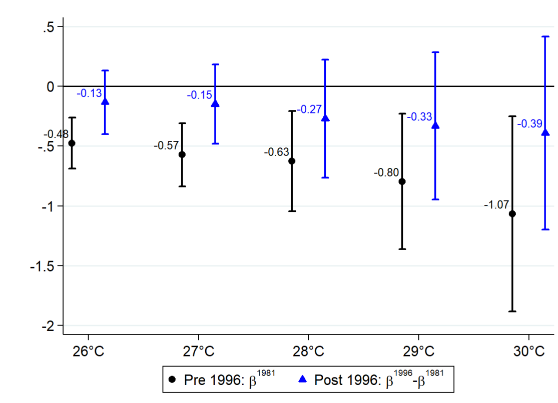


(f) Corn: Southwest

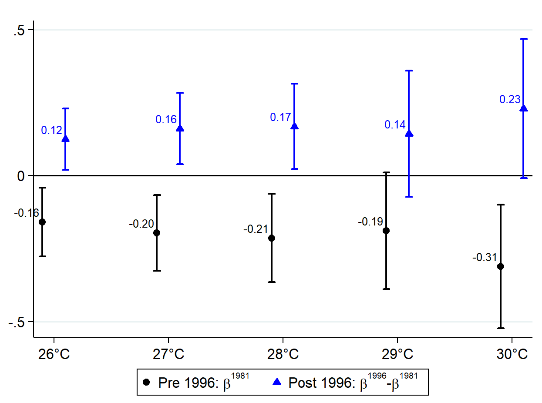
Figure A.5: Marginal Impacts of Extreme Temperatures on Soybean Yields by Regions



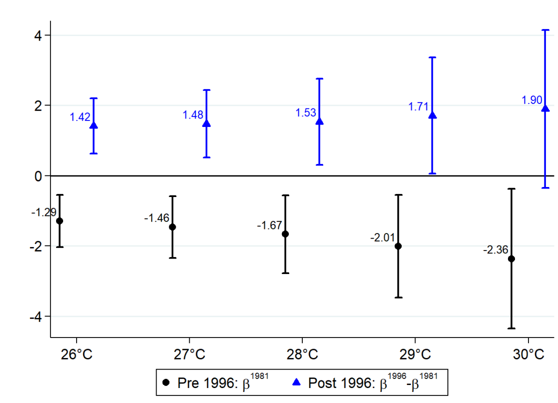
(a) Soybean: Nationwide



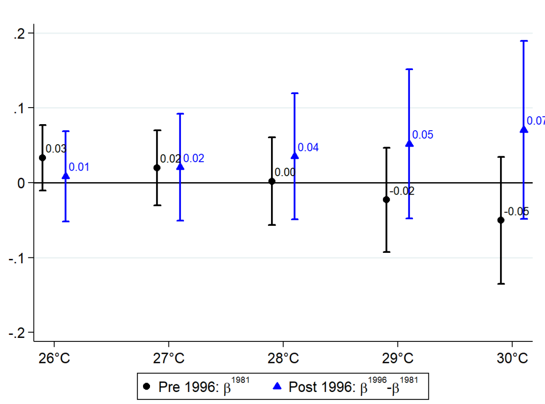
(b) Soybean: North



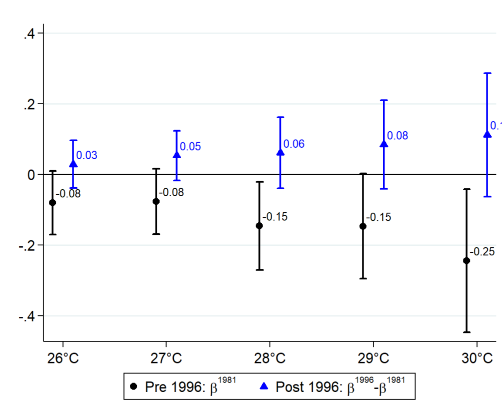
(c) Soybean: Huanghuaihai (HHH)



(d) Soybean: Northwest



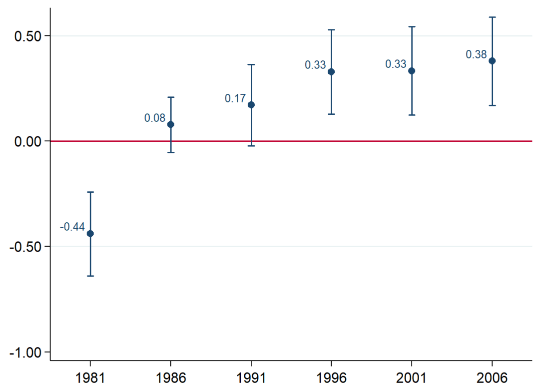
(e) Soybean: South



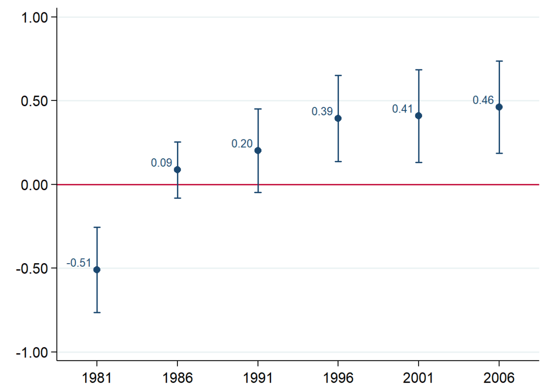
(f) Soybean: Southwest

Figure A.6 to A.9 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 A.6 and A.7 are about corn yields and Figure A.8 and A.9 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 A.6: Marginal Impacts of Extreme Temperatures on Corn Yields By Temperature Thresholds: 5 Years as a Period

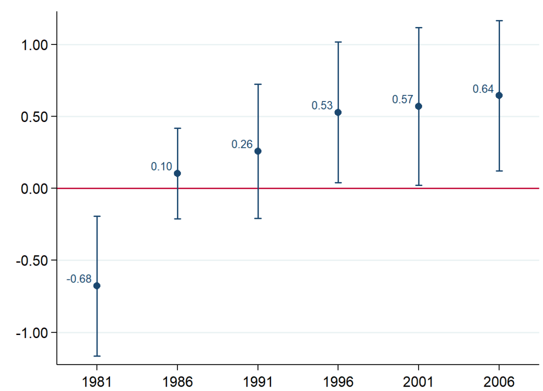


(a) GDD above 29 °C



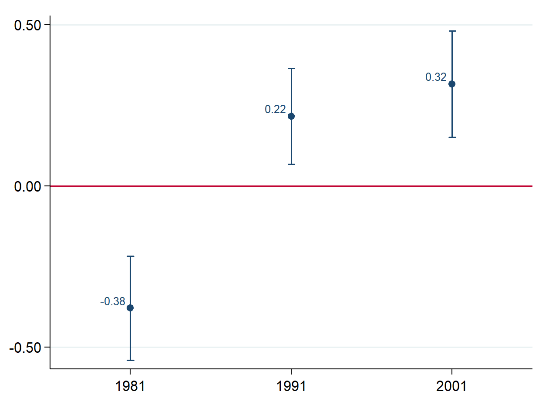
(b) GDD above 30 °C

(c) GDD above 31 °C

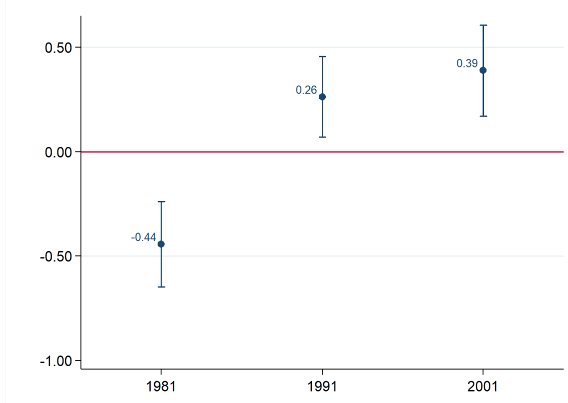


(d) GDD above 32 °C

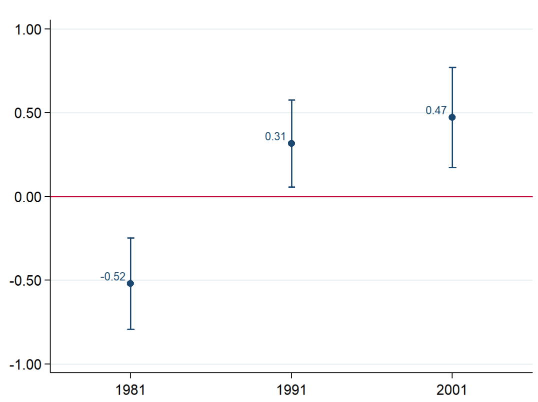
Figure A.7: Marginal Impacts of Extreme Temperatures on Corn Yields By Temperature Thresholds: 10 Years as a Period



(a) GDD above 29 °C



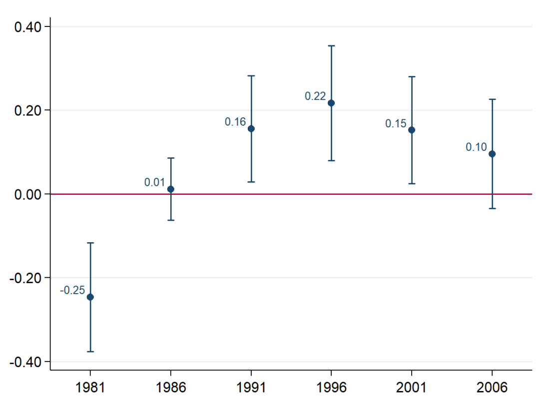
(b) GDD above 30 °C



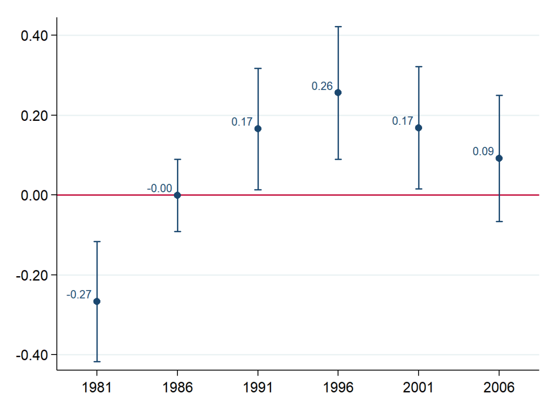
(c) GDD above 31 °C

(d) GDD above 32 °C

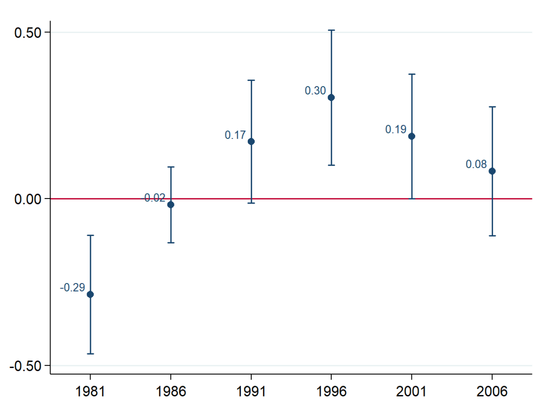
Figure A.8: Marginal Impacts of Extreme Temperatures on Soybean Yields By Temperature Thresholds: 5 Years as a Period



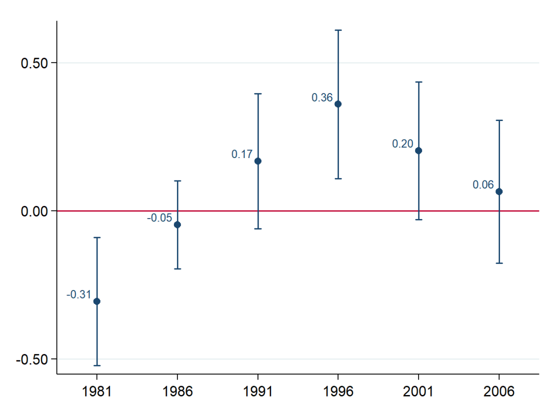
(a) GDD above 29 °C



(b) GDD above 28 °C

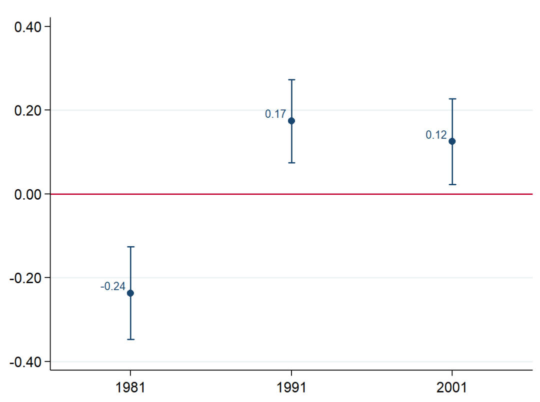


(c) GDD above 29 °C

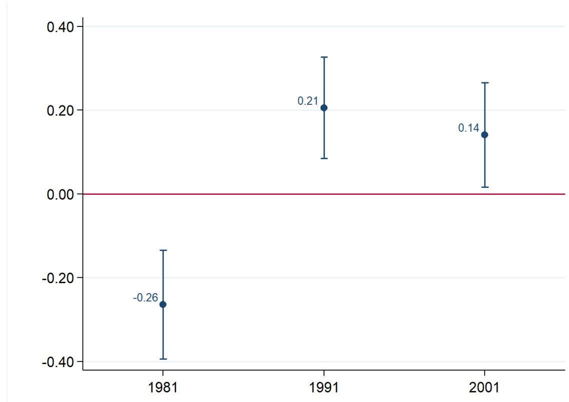


(d) GDD above 30 °C

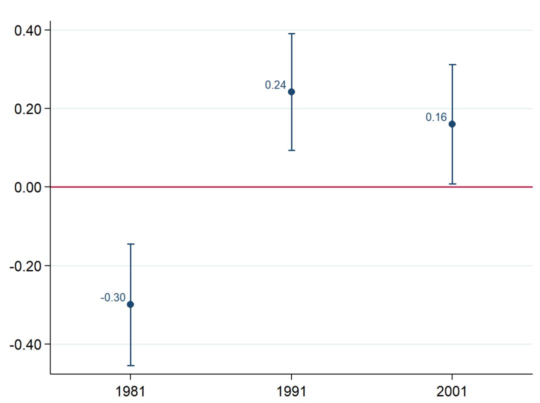
Figure A.9: Marginal Impacts of Extreme Temperatures on Soybean Yields By Temperature Thresholds: 10 Years as a Period



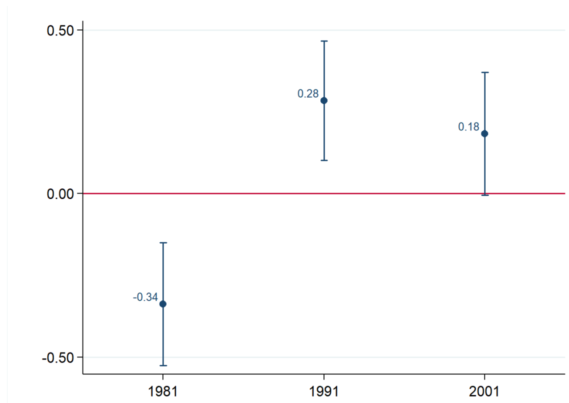
(a) GDD above 29 °C



(b) GDD above 28 °C



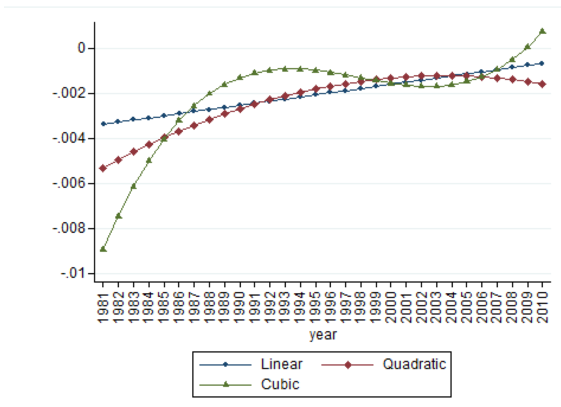
(c) GDD above 29 °C



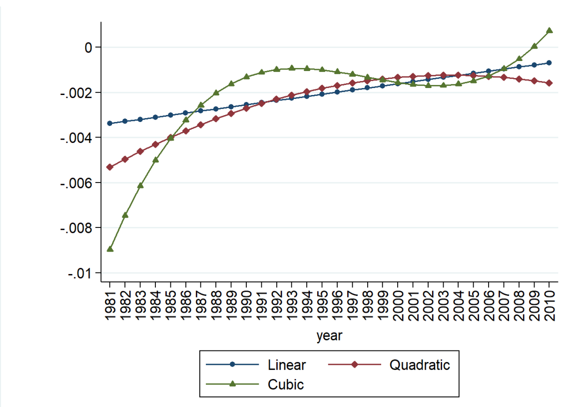
(d) GDD above 30 °C

Figure A.10 and A.11 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 A.10 is about corn and Figure A.11 is about soybean.

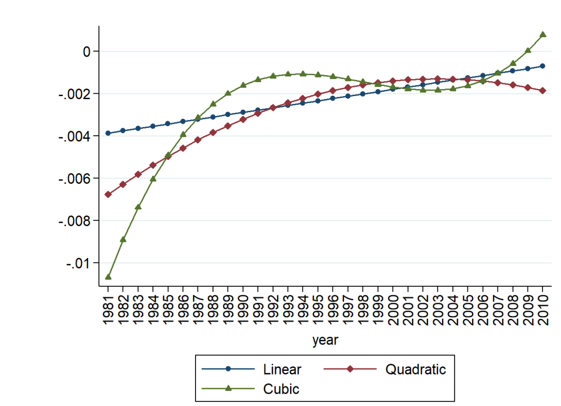
Figure A.10: Marginal Impacts of Extreme Temperatures on Corn Yields By Temperature Thresholds: Using Polynomial Model of Time Trend



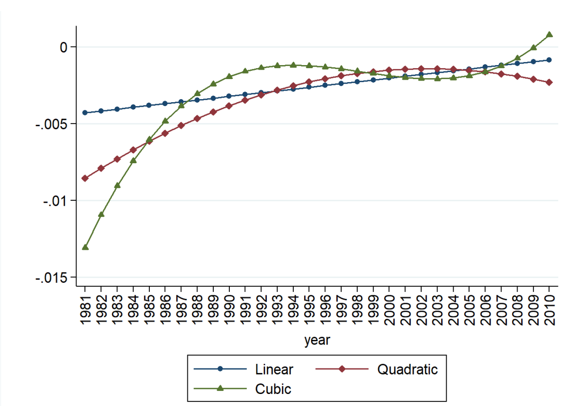
(a) GDD above 29 °C



(b) GDD above 28 °C

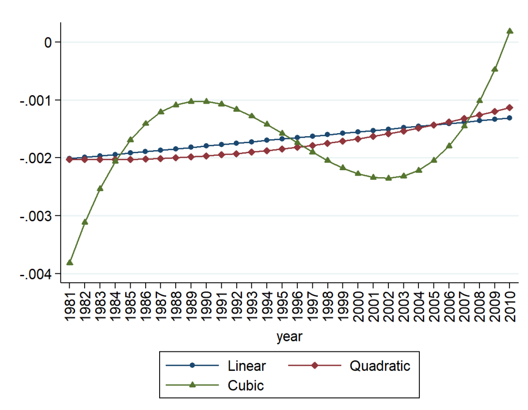


(c) GDD above 29 °C

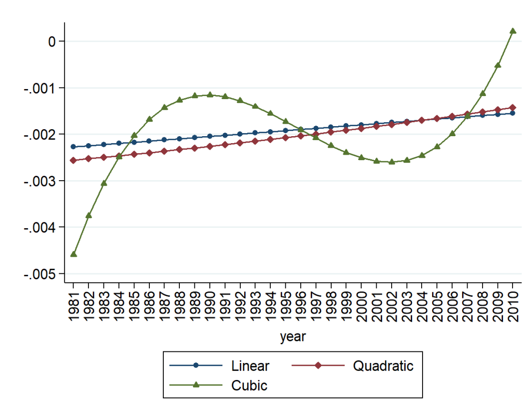


(d) GDD above 30 °C

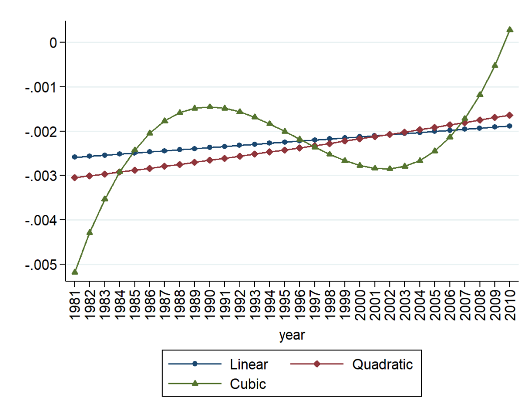
Figure A.11: Marginal Impacts of Extreme Temperatures on Soybean Yields By Temperature Thresholds: Using Polynomial Model of Time Trend



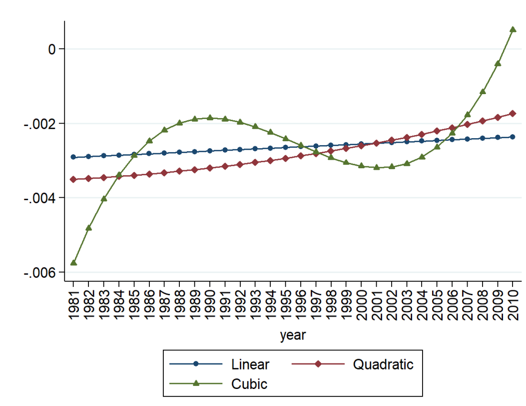
(a) GDD above 27 °C



(b) GDD above 28 °C



(c) GDD above 29 °C



(d) GDD above 30 °C

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

Table A.3 and A.4 report 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 A.5 and A.6 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 A.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 ×	-0.0002				0.0110
Δ Irrigation (%)	(0.0130)				(0.0132)
GDD below T ×		-0.0012			-0.0012
Δ Machinery (Kw./Ha.)		(0.0011)			(0.0012)
GDD below T ×			0.0487		0.0365
Δ Fertilizer (Tons of Ha.)			(0.0313)		(0.0278)
GDD below T ×				-0.0049	-0.0047
Δ Electricity (Kwh. per capita)				(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 A.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 ×	0.0011				-0.0066
Δ Irrigation (%)	(0.0242)				(0.0241)
GDD below T ×		-0.0010***			-0.0003
Δ Machinery (Kw./Ha.)		(0.0003)			(0.0018)
GDD below T ×			-0.0092***		-0.0066
Δ Fertilizer (Tons of Ha.)			(0.0024)		(0.0130)
GDD below T ×				0.0202	0.0195
Δ Electricity (Kwh. per capita)				(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 A.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 ×	0.2082***				0.1658***
Δ Irrigation Coverage (%)	(0.0435)				(0.0403)
GDD above T ×		0.0021			0.0009
Δ Machinery Power (Kw./Ha.)		(0.0017)			(0.0018)
GDD above T ×			0.0455		0.0209
Δ Fertilizer (Tons /Ha.)			(0.0431)		(0.0477)
GDD above T ×				0.0231*	0.0226*
Δ Electricity (Kwh. per capita)				(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 1.8. 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 (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 A.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 ×	0.1118**				0.0855**
Δ Irrigation Coverage (%)	(0.0544)				(0.0415)
GDD above T ×		-0.0002***			0.0036
Δ Machinery Power (Kw./Ha.)		(0.0001)			(0.0028)
GDD above T ×			-0.0019***		-0.0290*
Δ Fertilizer (Tons /Ha.)			(0.0004)		(0.0153)
GDD above T ×				-0.0035	-0.0036
Δ Electricity (Kwh. per capita)				(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 1.9. 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 A.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 $\times$ Δ Irrigation	0.0107	0.0074	-0.0073	0.0316
	(0.0135)	(0.0159)	(0.0243)	(0.0269)
GDD below T $\times$ Δ Machinery	-0.0011	-0.0013	-0.0003	-0.0009
	(0.0012)	(0.0012)	(0.0018)	(0.0019)
GDD below T $\times$ Δ Fertilizer	0.0383	0.0386	-0.0069	-0.0029
	(0.0282)	(0.0346)	(0.0130)	(0.0134)
GDD below T $\times$ Δ Electricity	-0.0047	-0.0076	0.0196	0.0283
	(0.0050)	(0.0052)	(0.0275)	(0.0306)
Δ GDP $\times$ Temperature	No	Yes	No	Yes
Δ (Cargo by Road) $\times$ Temperature	No	Yes	No	Yes
Temperature $\times$ 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

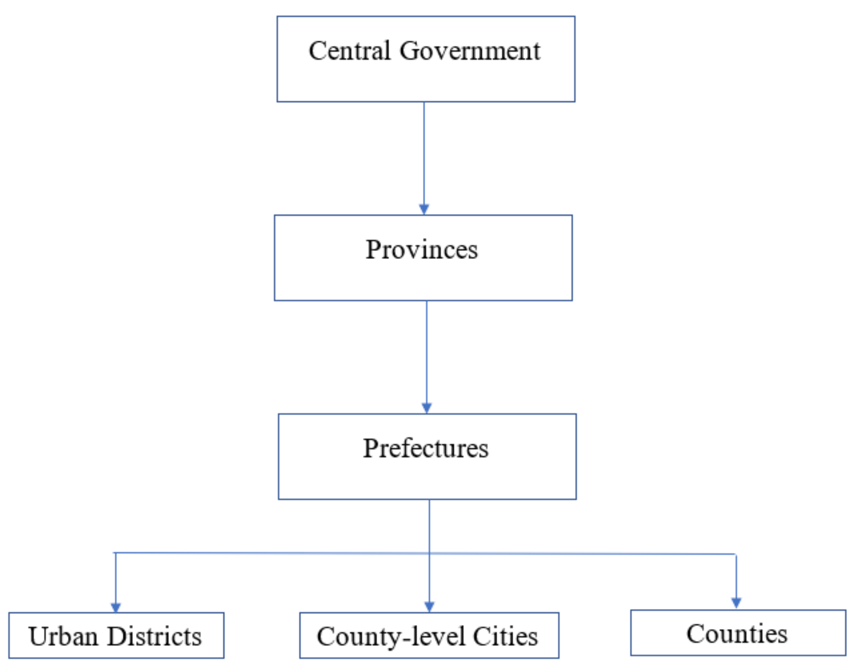
Note: This table presents the robustness analysis on the interaction effects of agricultural inputs with low temperatures. Each column is from a separate regression using different endogeneous controls. The dependent variable is log crop yields. The agricultural inputs, local GDP and cargo amount by 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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Appendix B

Appendix for Chapter 2

B.1 Background of the County-to-City Upgrading Policy

Figure B.1: The Structure and Hierarchies of the Governance System in China



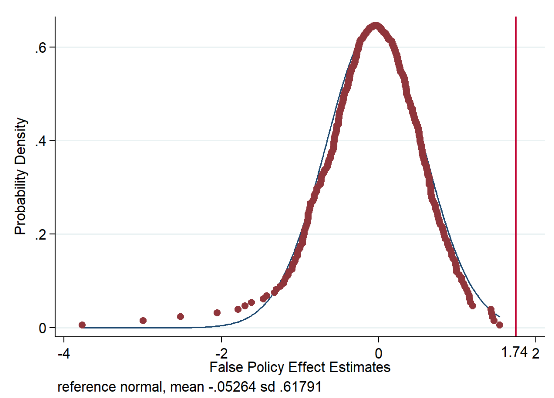
Note: Counties, county-level cities and urban districts are all county-level administrative divisions. Below the county-level division there are townships as the fourth level administrative units.

Table B.1: The Timetable for the County-to-City Upgrading Policy

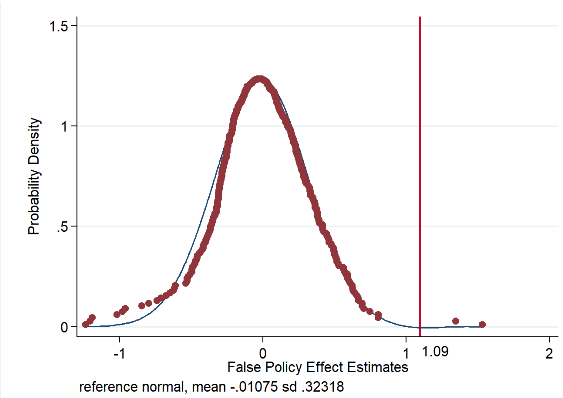
Year	Number of Upgraded Counties
1993	41
1994	40
1995	15
1996	21
1997	4

B.2 Robustness Checks on the Policy Effects on Air Pollutant Concentration and Economic Performance After 2004

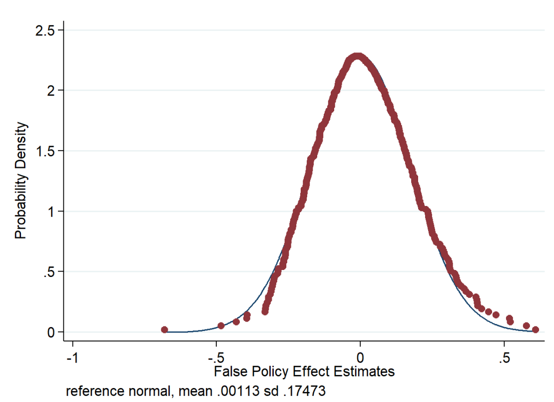
Figure B.2: Distribution of Estimated Falsified Policy Effect After 2004 for Falsification Test



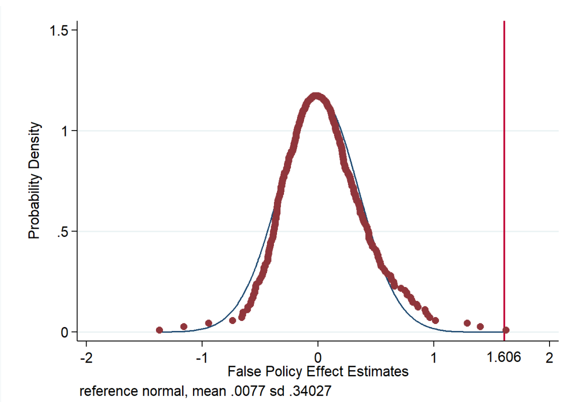
(a) The Falsified Policy Effects on $PM_{2.5}$ Concentration



(b) The Falsified Policy Effects on SO_2 Concentration



(c) The Falsified Policy Effects on Night Light Intensity



(d) The Falsified Policy Effects on Industrial Output per capita

Notes: This figure depicts the probability density distribution of the estimated policy effects after 2004 from 500 simulations randomly assigning the city status to counties as a robustness check of the results presented in Table 2.4. The vertical line presents the results in Table 2.4.

Table B.2: Policy Effects on Air Pollution and Economic Performance Estimated by PSM-DID Approach Based on Nearest Neighboring Matching Method: Before 2004 versus After 2004

	(1) PM 2.5	(2) SO_2	(3) Night Light	(4) Gross Value of Industrial Outputs Per Capita (10,000 CNY)
Upgrading Before 2004	0.7486	0.3304	0.2512	0.7097
	(0.4898)	(0.2824)	(0.2275)	(0.4581)
Upgrading After 2004	1.5942***	1.0082***	1.9258***	2.5842***
	(0.5710)	(0.3164)	(0.2970)	(0.4817)
Observations	8968	8968	5192	6136
R squared	0.9801	0.9749	0.9062	0.5995
County FE	Yes	Yes	Yes	Yes
Prov-by-Year FE	Yes	Yes	Yes	Yes
County Trend	Yes	Yes	Yes	Yes
Cluster	County	County	County	County
PSM	NN Matching	NN Matching	NN Matching	NN Matching

Note: *** denotes significance at 1%, ** at 5% and * at 10%. "NN" stands for the nearest neighboring matching The regressions control for county fixed effects, province-by-year fixed effects and county-specific time trends. The time trends are in quadratic forms. The standard errors are reported in parentheses, clustered by counties.

Table B.3: Policy Effects on Air Pollution and Economic Performance Estimated by PSM-DID Approach Based on Kernel Matching Method: Before 2004 versus After 2004

	(1) PM 2.5	(2) SO_2	(3) Night Light	(4) Gross Value of Industrial Outputs Per Capita (10,000 CNY)
Upgrading Before 2004	0.7416***	0.3254**	0.2422	0.6758***
	(0.2450)	(0.1412)	(0.1473)	(0.1384)
Upgrading After 2004	1.6015***	1.0133***	1.9370***	2.6185***
	(0.5708)	(0.3164)	(0.2988)	(0.4836)
Observations	36033	36033	21619	24654
R squared	0.9801	0.9749	0.9061	0.5988
County FE	Yes	Yes	Yes	Yes
Prov. Year FE	Yes	Yes	Yes	Yes
County Trend	Yes	Yes	Yes	Yes
Cluster	County	County	County	County
PSM	Kernel Matching	Kernel Matching	Kernel Matching	Kernel Matching

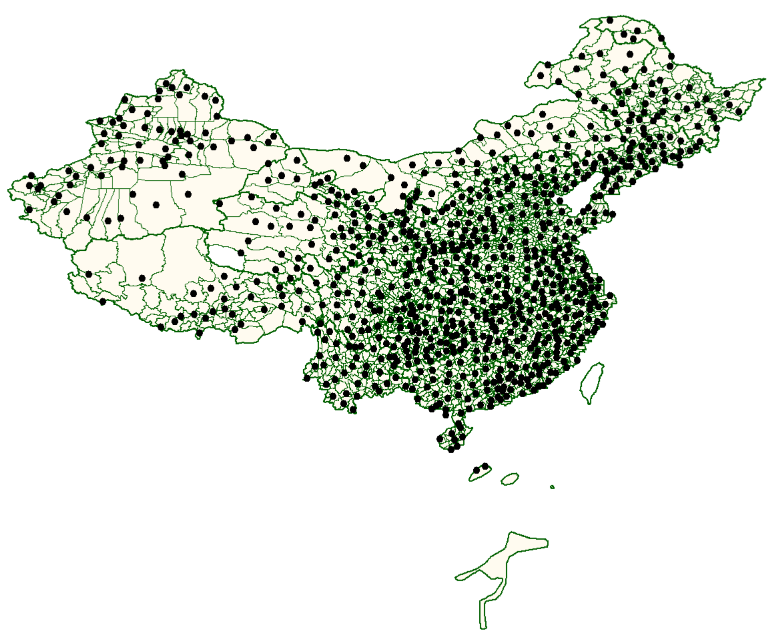
Note: *** denotes significance at 1%, ** at 5% and * at 10%. "Kernel" stands for kernel matching The regressions control for county fixed effects, province-by-year fixed effects and county-specific time trends. The time trends are in quadratic forms. The standard errors are reported in parentheses, clustered by counties.

Appendix C

Appendix for Chapter 3

C.1 Figures and Tables on Summary Statistics of Data

Figure C.1: 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.

C.2 Derivation of Standard Errors for Components of the Oaxaca-Blinder Decomposition

According to Jann (2008), we can derive the variances for each decomposition components as the following.

$$Var((\overline{X}_b - \overline{X}_a)' \cdot \hat{\beta}_a) = Var(\Delta\overline{X}' \cdot \hat{\beta}_a) \approx \Delta\overline{X}' Var(\hat{\beta}_a)\Delta\overline{X} + \hat{\beta}_a' Var(\Delta\overline{X})\hat{\beta}_a \quad \text{(B.1)}$$

$$Var(\overline{X}_b' \cdot (\hat{\beta}_b - \hat{\beta}_a)) = Var(\overline{X}_b' \cdot \Delta\beta) \approx \overline{X}_b' Var(\Delta\beta)\overline{X}_b + \Delta\beta' Var(\overline{X}_b)\Delta\beta \quad \text{(B.2)}$$

(C.1)

The last variance that needs to be estimated is the variance of the share of each decomposition component in the overall change in the outcome variable. Let R be one decomposition component and S be the overall change in the outcome variable $(\overline{Y}_b - \overline{Y}_a)$. The variance for the share can be derived thorough the delta method as the following.

$$Var(R/S) \approx \frac{1}{(\mu_S)^2} Var(R) - 2\frac{(\mu_R)}{(\mu_S)^3} Cov(R,S) + \frac{(\mu_R)^2}{(\mu_S)^4} Var(S) \quad \text{(B.4)}$$

C.3 The Effects of Interactions between Inputs and Low Temperatures

Table C.1: The Effects of Interactions between Inputs and Low Temperatures

	$\hat{\beta}_{1981}$	$\hat{\beta}_{1996}$	$\hat{\beta}_{1981}(\overline{X}_{1981} - \overline{X}_{1981})$		$\overline{X}_{1981}(\hat{\beta}_{1996} - \hat{\beta}_{1981})$	
			Decomposition	Percent	Decomposition	Percent
Log Labor × GDD between 0°C and 10 °C	0.0012 (0.0009)	0.0018 (0.0015)	-0.0052 (0.0042)	-0.0046% (0.0033)	0.0880 (0.0534)	7.72% (0.0489)
Log Machinery × GDD between 0°C and 10 °C	-0.0052 (0.0036)	-0.0044 (0.0025)	-0.6218 (0.4078)	-54.91%*** (0.3824)	0.2640 (0.2456)	23.16% (0.2106)
Log Fertilizer × GDD between 0°C and 10 °C	-0.0001 (0.0008)	0.0008 (0.0007)	-0.0102 (0.0.1643)	-0.89% (0.1450)	-0.0638 (0.1686)	-5.63% (0.1490)
Irrigation × GDD between 0°C and 10 °C	0.0012 (0.0013)	0.0041 (0.0027)	0.0136 (0.0279)	1.21% (0.0246)	0.2322 (0.2157)	20.51% (0.1907)
Log Labor × GDD between 10°C and 33 °C	-0.0052 (0.0042)	-0.0016 (0.0015)	-0.0182 (0.0102)	-1.60% (0.0091)	0.5416 (0.4426)	47.50% (0.4212)
Log Machinery × GDD between 10°C and 33 °C	0.0015 (0.0010)	-0.0020 (0.0014)	0.1861 (0.1669)	16.43% (0.1253)	-0.8020 (0.6964)	-70.82% (0.6616)
Log Fertilizer × GDD between 10°C and 33 °C	0.0014 (0.0015)	0.0019 (0.0013)	0.1313 (0.1395)	11.59% (0.1014)	-0.0347 (0.0799)	-3.07% (0.0705)
Irrigation × GDD between 10°C and 33 °C	0.0004 (0.0012)	-0.0031 (0.0026)	0.0053 (0.0278)	0.47% (0.0245)	-0.2852 (0.1859)	-25.19% (0.1668)
Additional Climate Vars.	N/A N/A	N/A N/A	-0.0453*** (0.0082)	-0.40%*** (0.0073)	-0.2421 (0.2420)	-21.24% (0.2163)
Average of Province-year FEs	-1.1057*** (0.1202)	-0.7417*** (0.1039)	N/A N/A	N/A N/A	0.3640** (0.1604)	31.93%** (0.1569)
Observations	54584	54584	54584	54584	54584	54584
R squared	0.9239	0.9239	N/A	N/A	N/A	N/A
T threshold	33 °C	33 °C	33 °C	33 °C	33 ° C	33 ° C
No. of Clusters	1936	1936	1936	1936	1936	1936

Notes: This table presents the results for the regressors that are not reported in Table 3.5 ***$p<0.01$, **$p<0.05$, * $p<0.1$

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