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The non-linear effect of daily weather on economic performance: Evidence from China

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ABSTRACT

This paper thoroughly examines the impacts of daily weather on the aggregate economic outcomes in China and identifies the underlying channels. Using within-county variations in daily weather between 1996 and 2012, we find that daily temperature and precipitation have non-linear effects on county-level economic outcomes. An additional day with an average temperature above 20 °C reduces county-level GDP by 0.05% to 0.08%, and the detrimental effects tend to intensify when the temperature rises. The precipitation does not have robust effects on county-level GDP. By examining the effects of daily weather on primary, secondary, and tertiary industries, we find that the primary industry is the main channel of the negative impacts of high temperatures. Heavy precipitation is inclined to harm agricultural output, especially grains and oil crop yields. Besides, we discover heterogeneous responses to weather extremes across counties and find suggestive evidence of adaptation.

1. Introduction

Climate change is a common concern of humankind. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change documents substantial variations in the frequencies of extreme weather events since the second half of the 20th century due to global warming (Pachauri et al., 2014). These changes in the worldwide climate have profound influences on human society.

This paper focuses on the economic impacts of two critical weather variables: temperatures and precipitation. Empirical studies have found that extreme temperature and precipitation adversely affect the economy through many channels (Dell, Jones, & Olken, 2014). For example, labor productivity and working hours decline on scorching days (Graff Zivin & Neidell, 2014; Seppanen, Fisk, & Lei, 2006). Extremely high temperatures reduce crop yields (Schlenker & Roberts, 2009) and the total factor productivity (TFP) of agriculture and manufacturing firms (Chen & Gong, 2021; Zhang, Deschênes, Meng, & Zhang, 2018). Precipitation significantly affects economic growth (Damania, Desbureaux, & Zaveri, 2020). All these studies confirm that the economic outcomes in a region are affected by the local temperature and precipitation.

Similar to the global trend, the climate of China has changed remarkably in the past several decades. Some studies have examined the effects of weather on several specific crop yields (Chen, Chen, & Xu, 2016; Zhang, Zhang, & Chen, 2017), agriculture production

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(Chen & Gong, 2021), and the output of large manufacturing firms in China (Chen & Yang, 2019; Zhang et al., 2018). But we have not seen any study that thoroughly examines the effects of daily temperature and precipitation on the aggregate economic outcomes in China and identifies the underlying channels, which have significant academic value and policy implications. Our study fulfills this research gap. In this paper, we explore the effects of daily temperature and precipitation on county-level aggregate economic output. We further study the impacts of daily weather on the primary industry, secondary industry, and tertiary industry to identify the main channel and investigate the heterogeneous effects of weather on different counties to identify potential adaptability.

Our study finds that high temperatures have significant adverse effects on county-level GDP. Relative to a day with an average temperature in [10, 15)°C bin, one day with an average temperature in [20, 25)°C, [25, 30)°C, and $\geq$ 30 °C bins reduces county-level GDP by 0.05%, 0.08%, and 0.08%, respectively. Other temperature bins do not have significant effects on GDP. These results are robust to various robustness checks. Relative to a day with zero precipitation, moderate daily rainfall in the (15, 20]mm bin has significant positive impacts on GDP. But the effect is not robust. Other precipitation levels do not show significant effects on GDP.

We find that the primary industry is the dominant channel for the effects of temperature and precipitation. The negative impacts of [25, 30)°C and $\geq$ 30 °C bins on the value added of primary industry are 2.8 and 4.1 times their impacts on the county-level GDP. Intensive precipitation over 35 mm significantly reduces the value added of primary industry. Further investigation shows that high temperatures and extreme precipitation substantially lower the output of grains and oil crops. In contrast, almost all the temperature bins and precipitation bins do not significantly impact the secondary and tertiary industries.

Counties with different characteristics respond very differently to high temperatures, suggesting they have heterogeneous adaptabilities. The GDP of counties that frequently experience extreme heat is not significantly impacted by high temperatures above 20 °C, while counties with fewer scorching days are affected considerably. The result suggests that more experiences of extreme heat nourish greater adaptability. High temperatures over 20 °C significantly hurt non-agricultural counties' primary industries, but the damaging effects of high temperatures are weaker and statistically insignificant in agricultural counties. Our analysis verifies that outputs of grains and oil crops of agricultural counties are less vulnerable to high temperatures. Our data support the following explanation for the heterogeneous effects: agricultural counties have much higher rural investment, more farm machinery, and more agricultural labor than non-agricultural counties. These inputs are essential to adaptation, as found by Chen and Gong (2021).

Our study contributes to the rapidly growing literature on the relationship between weather and economic performance. We are the first to thoroughly study the non-linear effects of daily weather on China's aggregate economic outcomes and the outputs of the primary, secondary, and tertiary industries.[1] Moreover, our study digs into different agricultural products, large manufacturing firms, and heterogeneous counties to unveil the mechanisms behind the effects. Quantifying the impact of weather conditions on economic output in China has significant policy implications because the results reveal the counterfactual benefits of tackling climate change. Heterogeneous effects of daily weather on different sectors imply that future industrial restructuring could partially counteract the adverse impacts of climate change on the overall economy. Industrial policies could smooth industrial restructuring and help to alleviate the damaging effects of climate change. The heterogeneous effects on different counties validate the importance of adaptation measures such as agricultural investment. In addition, our comprehensive study of China, the largest developing country, could help evaluate the economic losses of weather extremes in other developing countries and has substantial policy implications for them.

The effects of weather on agricultural production have been intensively studied in the literature. Dell et al. (2014) provide a comprehensive summary of the studies. We only highlight the most relevant papers here. Chen et al. (2016) and Zhang et al. (2017) study the effects of weather on corn, soybeans, rice, and wheat. Compared with their studies on specific crops, our research focuses on the aggregate value of agricultural outputs. We identify agricultural production as the main channel for weather extremes' effects on county-level GDP. In addition, we decompose the aggregate impact on agriculture into effects on grains, oil crops, cotton, and meat, each of which includes several agricultural products. Highly consistent with related studies (e.g., Burke & Emerick, 2016; Deschênes & Greenstone, 2007; Schlenker & Roberts, 2009), our study confirms the relationship between agricultural outputs and temperatures is non-linear, and high temperatures significantly reduce the yields of grains and oil crops. Chen and Gong (2021) find that high temperatures seriously harm China's agricultural TFPs, labor and fertilizer usage, and agricultural yields. Their study provides complementary evidence that high temperatures in China significantly hurt agriculture.

There are a few studies on weather and industrial output. Researches using aggregate data have mixed findings on whether high temperatures are detrimental to industrial output. Hsiang (2010) does not find a statistically significant effect of temperatures on manufacturing outputs in twenty-eight Caribbean countries. Jones and Olken (2010) find that high temperatures only significantly impact light manufacturing industries and barely affect heavy industries and raw materials production. Dell, Jones, and Olken (2012) find industrial losses from high temperatures only appear in poor countries. Newell, Prest, and Sexton (2021) do not find statistically significant evidence of temperatures affecting non-agricultural production. There is a clear result difference between studies using aggregate data and studies using firm-level data. At the firm level, Cachon, Gallino, and Olivares (2012), Zhang et al. (2018), and Chen & Yang (2019) all document significant detrimental effects of high temperatures on industrial output. Li, Cong, and Yin (2021) find that extreme heat has substantial adverse cumulative effects on Chinese exporting firms. Our result is consistent with studies using aggregate data. We find that almost all temperature and precipitation bins do not significantly impact the value added of secondary industry or the gross output of large manufacturing enterprises. Our result difference with Zhang et al. (2018) and Chen & Yang (2019) may be attributed to numerous efficient firm entrants in our extended data period. Our data spans from 1996 to 2012 (17 years), while their data covers 1998 to 2007 (10 years). According to their firm-level data, the number of firms in 1999 is around 160 thousand. The

[1] Li et al., 2020 is a related paper that studies the effects of annual weather conditions on the economic growth of Chinese counties. The detailed comparison with Li et al., 2020 is in the following literature review.

number rapidly grows to 330 thousand in 2007 and keeps increasing after 2007. Brandt, Van Biesebroeck, and Zhang (2012) find that entry accounts for over two-thirds of total TFP growth in Chinese manufacturing firms. Brandt, Van Biesebroeck, Wang, and Zhang (2019) find that entrants have higher initial productivity than incumbents in China's liberalized industries. Numerous efficient firms appear in our sample between 2008 and 2012, and they tend to be less affected by high temperatures. Our study would lead to a different policy recommendation on manufacturing firms from what firm-level studies would recommend. It is crucial and also debatable which result is more reliable.

Studies investigating the effects of weather on the tertiary industry are scarce. Niemela, Hannula, Rautio, Reijula, and Railio (2002) find that high temperatures adversely affect workers' productivity in call centers. Lee, Gino, and Staats (2014) show that bank workers in Japan have the highest productivity when outside weather is less attractive. These two papers focus on specific firms. Using aggregate data from more than 180 economies, Acevedo, Mrkaic, Novta, Pugacheva, and Topalova (2020) find that the value added of services sector is not significantly affected by temperature increase. Our study finds the same result as Acevedo et al. (2020) using county-level value added of tertiary industry in China.

Li, Cong, & Gu, 2020 study how annual average temperature and average precipitation affect the growth rate of GDP per capita of Chinese counties and calculate the cumulative effects of weather in the medium run (five years and ten years). The study also explores the possible channels of weather on economic growth. Highly consistent to Acevedo et al. (2020), it finds weather affects the growth rate of agricultural output, labor productivity, and investment. Different from studying the long-term growth in Li et al., 2020, this paper emphasizes how daily weather conditions, especially the weather extremes, impact the economic output in the short run. We find the primary industry is the dominant channel for the effects of weather extremes. The two papers' empirical findings provide very different but complementary angles to see the impacts of weather conditions on the Chinese economy.

The rest of this paper is organized as follows. Section 2 develops the conceptual framework to show how daily weather affects daily and annual economic outputs and sets up the empirical strategy. In Section 3, we introduce the data and provide summary statistics. Section 4 reports the main results, various robustness checks, and the channel of the results. Three extensions of the main results are shown in section 5. Section 6 concludes this paper.

2. Conceptual framework and empirical strategy

This section shows how daily weather affects annual economic outcomes and sets up the empirical strategy. An economy consists of the primary industry, secondary industry, and tertiary industry. Daily weather affects each sector's production process (Deryugina & Hsiang, 2014; Schlenker & Roberts, 2009; Zhang et al., 2018; Chen & Yang, 2019). Assume the daily production functions of three industries are $F_P(w_\tau)$, $F_S(w_\tau)$, and $F_T(w_\tau)$, in which the parameter w_τ indicates daily weather, such as daily temperature and precipitation. The available county-level economic statistics are at the annual frequency. Eq. (1) describes how annual aggregate output is affected by daily weather:

$$annual\ output = \sum_{\tau=1}^{365}[F_P(w_\tau) + F_S(w_\tau) + F_T(w_\tau)] = \sum_{\tau=1}^{365} F(w_\tau) \tag{1}$$

The annual output depends on how daily weather can affect daily production and relies on the distribution of weather conditions in a year.

Since weather variables are random and strictly exogenous, the central empirical challenge is precisely measuring the effect of weather on daily output when only annual output data are available. Eq. (1) establishes the conceptual relationship between annual output and daily weather and bridges this gap. We develop the following empirical approach following Deryugina and Hsiang (2014).

The function $F(w_\tau)$ in eq. (1) could be approximated by calculating its average value over several bins of w_τ. Suppose w_τ represents the temperature. We set up a sequence of temperature bins, such as 0 °C–5 °C, 5 °C–10 °C, 10 °C–15 °C and so on. The *nth* temperature bin is denoted as T^n. Its upper boundary and lower boundary are b_u^n and b_l^n, respectively. The average value of $F(w_\tau)$ in the temperature bin T^n is

$$\overline{F(T^n)} = \frac{1}{b_u^n - b_l^n}\int_{b_l^n}^{b_u^n} F(w_\tau)dw_\tau \tag{2}$$

The value $\overline{F(T^n)}$ measures the average effect of temperature bin T^n on daily output. In other words, the effect of a day with temperature $w_\tau \in T^n$ on daily output is approximated by $\overline{F(T^n)}$. Hence the function $F(w_\tau)$ is approximated as

$$F(w_\tau) \approx \sum_{n=1}^{N} \overline{F(T^n)} \cdot 1[w_\tau \in T^n] \tag{3}$$

in which $1[w_\tau \in T^n]$ is the indicator function whose value equals one if w_τ lies in the bin T^n and equals zero otherwise. With eqs. (2) and (3), we have

$$annual\ output = \sum_{\tau=1}^{365} F\left(w_\tau\right) \approx \sum_{\tau=1}^{365}\sum_{n=1}^{N} \overline{F(T^n)} \cdot 1[w_\tau \in T^n] = \sum_{n=1}^{N} \overline{F(T^n)} \sum_{\tau=1}^{365} 1[w_\tau \in T^n] \tag{4}$$

The part $\sum_{\tau=1}^{365} 1[w_\tau \in T^n]$ indicates the number of days in a year with temperature w_τ in the bin T^n.

The temperature bin method assumes that temperatures in the same bin equally affect the annual output, but temperatures in different bins have different effects. We can approximate the function $F(w_\tau)$ in the same way when w_τ contains other weather variables.

Based on eq. (4), we develop the following empirical specification

$$log(Y_{it}) = \rho log(Y_{it-1}) + \sum_{n=1}^{N} \alpha^n T\_bin_{it}^n + \sum_{m=1}^{M} \beta^m P\_bin_{it}^m + \gamma X_{it} + \eta X_{it}^2 + \mu_i + \delta_{jt} + \epsilon_{it} \tag{5}$$

where counties are indexed by i and years are indexed by t. The dependent variable Y_{it} is economic outcomes such as county-level GDP, agricultural output, industrial output and service output. The dependent variable is likely to be serially correlated, so the lagged dependent variable $log(Y_{it-1})$ is included in the regression.

The key independent variable $T\_bin_{it}^n$ is the number of days in county i and year t that the daily average temperatures lie in the *nth* temperature bin. In the main analysis, we set up 11 ($N = 11$) temperature bins. The first temperature bin is < -15 °C. $T\_bin^1{}_{it}$ is the number of days in county i and year t that the daily average temperatures are below -15 °C. The second bin is [-15, -10)°C. $T\_bin^2{}_{it}$ is the number of days in county i and year t that the daily average temperatures lie in [-15, -10)°C. The 11*th* temperature bin is $\geq$30 °C. We choose the 7*th* temperature bin, [10, 15)°C, as the reference temperature bin. The coefficient α^n, $n \neq 7$, measures the marginal effect of an additional day in the n*th* temperature bin on the dependent variable relative to a day with average temperatures in the reference bin.

We set 12 ($M = 12$) precipitation bins. The first precipitation bin is 0 mm. $P\_bin^1{}_{it}$ represents the number of days in county i and year t that the daily total precipitation is 0 mm. The second precipitation bin is (0,5] mm. $P\_bin^2{}_{it}$ represents the number of days in county i and year t that the daily precipitation lies in (0,5] mm. The 12*th* precipitation bin is $\geq$50 mm. We choose the first bin, i.e., 0 mm, as the reference precipitation bin. Coefficients β^m, $m \neq 0$, measure the marginal effect of an additional day in the m*th* precipitation bin on the dependent variable relative to a day with zero precipitation. Because both temperature and precipitation in a county tend to be serially correlated, lagged temperature bins and precipitation bins are included in the regression.

The X_{it} contains other weather variables, including the annual average relative humidity, annual average wind speed, annual average atmospheric pressure, and annual total sunshine hours. The square of other weather variables X_{it}^2 are included to control for the possible non-linear effects. Their lagged variables X_{it-1} and X_{it-1}^2 are also included in the regression unless specified otherwise (Zhang et al., 2018). μ_i is a set of county fixed effects that account for unobserved heterogeneities among counties. δ_{jt} is a set of region by year fixed effects which account for the common trends of counties in a region j.[2] ϵ_{it} is the disturbance term that may be correlated over time and across space. To account for this, we estimate eq. (5) using OLS method and allowing the disturbance term to be heteroscedastic and serially correlated within a county up to 5 years and be spatially correlated across contemporaneous counties up to a distance of 500 km (Conley, 1999; Deryugina & Hsiang, 2014; Schlenker & Roberts, 2009).

Following Deryugina and Hsiang (2014), we prefer the OLS method in this paper for the following two reasons. First, it allows us to estimate the Conley standard errors that account for spatial correlation across contemporaneous counties and heteroscedasticity and autocorrelation within counties over time. Second, it avoids using weak or internal instruments that may result in inconsistent estimations (Deryugina & Hsiang, 2014). For a dynamic panel model like eq. (5), if the panel length is less than ten periods, the coefficients estimated by OLS may be inconsistent, especially for the endogenous lagged dependent variables (Nickell, 1981). We are somewhat free from this concern since our interests center on the effects of exogenous weather variables, and our panel has 17 years. Other regression techniques, including 2SLS and GMM, are employed in the robustness check, and we find similar results.

3. Data and summary statistics

3.1. Data

Our weather data comes from the China Meteorological Data Service Center (CMDSC). We obtain station-day level data from 821 stations across China from 1986 to 2015. Almost all the major weather variables, including temperature, precipitation, wind speed, relative humidity, atmospheric pressure, and sunshine hours, are contained in the dataset. The inverse-distance weighting method, a widely used method in the literature (Deschênes & Greenstone, 2007, 2011), is used to aggregate weather data from the station level to the county level. The basic algorithm is as follows. We select all stations within a 200 km radius of a county's administrative center. The country's weather variables are the weighted average of the selected stations' records, in which the weights are the inverse distance between the weather station and the county's center. The final balanced panel of weather data contains each county's daily weather variables. We also use the weather data coming from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA) in the robustness check.

The economic data come from the Support System for China Statistics Application.[3] The dataset contains many county-level statistics, including GDP, agricultural output, industrial output, service output, crop output, investment, agricultural machinery,

[2] The eastern region of China contains 13 provinces: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Liaoning, Jilin, Heilongjiang. The middle region of China contains six provinces: Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan. The western region of China contains 12 provinces: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang. There are substantial development gaps among the three regions.

[3] The website is info.acmr.cn/index.aspx.

population, etc. It covers 1749 counties in mainland China, spanning from 1996 to 2012.[4]

The weather data and economic data are merged based on the county's name and administrative code. The final combined panel covers 1654 counties, highly representative of Chinese counties' economic statistics and weather conditions.

3.2. Summary statistics

Table 1 reports the key variables' summary statistics. Fig. 1 shows the distribution of daily average temperature in an average year from 1986 to 2015. An average year has almost 50.9 days with an average temperature below 0 °C and about 4.2 days hotter than 30 °C. Fig. 2 compares daily temperature distributions in two subintervals, 1986–2000 and 2001–2015. The number of days hotter than 20 °C demonstrates an apparent increase. Fig. 3 shows the distribution of daily total precipitation in an average year from 1986 to 2015. An average year has around 318.8 days with daily precipitation less than 5 mm. Fig. 4 shows the comparison of daily precipitation in 1986–2000 and 2001–2015. Zero precipitation days slightly increase in the latter period.

4. Empirical results

In this section, we first show the main results and various robustness checks. Then we explore the effects of daily weather on the primary industry, secondary industry, and tertiary industry to identify the channel of weather's effects.

4.1. Main results

Using the data on daily average temperature and daily total precipitation, we can calculate $T\_bin^n{}_{it}$ and $P\_bin^n{}_{it}$ for county i and year t in eq. (5) from 1996 to 2012. To avoid the potential unfavorable effect of the outliers, we truncate the county-level GDP variable before estimating eq. (5).[5] Our preferred regression specification contains the lagged dependent variable, lagged temperature and precipitation bins, county fixed effects, and region-by-year fixed effects. Following Zhang et al. (2017) and Zhang et al. (2018), the preferred regression specification also contains other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. Conley standard errors are used to account for spatial correlation across contemporaneous counties, heteroscedasticity, and serial correlation within a county.

Table 2 shows the estimation results of eq. (5). Different radius (100 km–500 km) and autocorrelation (AR(1)-AR(5)) specifications are chosen from column 1 to column 5 in Table 2. Column 2 of Table 2 shows the results of our preferred regression specification. We find that the effects of daily average temperature on GDP are non-linear. Relative to a reference day with an average temperature in [10,15)°C, a day hotter than 20 °C has significant negative effects on county-level GDP. The detrimental effects tend to increase as the temperature rises: a day with an average temperature of [20, 25)°C, [25, 30)°C, and $\geq$ 30 °C lowers county-level GDP by 0.05%, 0.08% 0.08%, respectively. In contrast, all coefficients of other temperature bins are statistically insignificant. As shown in column 2, relative to a zero precipitation day, only moderate precipitation bin (15, 20]mm positively affects county-level GDP. But this result is not stable in some robustness checks. Other columns of Table 2 show the results of different radius and autocorrelation specifications. Our main results are robust as the radius extends from 100 km to 500 km and autocorrelation extends from AR(1) to AR(5).

4.2. Robustness of the main results

In this part, we conduct a series of robustness checks by introducing alternative reference bins and bin width, different fixed effects, other regression techniques, and alternative weather data source.

4.2.1. Alternative reference bin

In the preferred regression specification, we choose [10, 15)°C as the reference temperature bin. This section selects two alternative reference bins, [5, 10)°C and [15, 20)°C, to check whether the main results are sensitive to the reference bin choice. The dashed curve and dotted curve in the left panel of Fig. 5 show the new estimates.[6] Temperatures higher than 20 °C still have significant adverse effects on county-level GDP, and other temperature bins do not show significant effects. Zero precipitation is chosen as the reference precipitation bin in the main results. Now, we choose the neighboring (0, 5] mm as the reference bin. The dotted curve in the right panel of Fig. 5 demonstrates the new estimates, which are almost identical to the main results.

4.2.2. Alternative bin width

In the preferred regression specification, the temperature bin's width is 5 °C, and the precipitation bin's width is 5 mm. Following the specification of Deryugina and Hsiang (2014), we narrow the temperature bins from 5 °C to 3 °C and broaden precipitation bins from 5 mm to 10 mm. Three different temperature bins, [9,12)°C, [12,15)°C, and [15,18)°C, are chosen as the reference bins

[4] Note that the counties in the data do not contain districts and boroughs in prefectures, which have the same administrative level as counties in China. These districts and boroughs are special because most of them do not have primary industry or even secondary industry.

[5] We drop the GDP observations above 99% and below 1% to avoid the potential bias that they may be misreported. The results are almost identical if we winsorize the data at 99% and 1% or use the total data, as shown in Appendix Table 1.

[6] The coefficients of all bins can be found in Appendix Table 2.

Table 1
Summary statistics of key variables.

Variables	Obs	Mean	Std. Dev	Min	Max
< -15 °C	44,631	5.492774	16.3624	0	138
$[-15,-10)$°C	44,631	7.15953	13.66172	0	82
$[-10,-5)$°C	44,631	13.43842	18.62705	0	113
$[-5,0)$°C	44,631	24.7653	23.80322	0	130
$[0,5)$°C	44,631	37.01295	21.95558	0	129
$[5,10)$°C	44,631	45.94795	19.21179	0	144
$[10,15)$°C	44,631	53.06507	19.33976	0	154
$[15,20)$°C	44,631	59.35693	20.52599	0	174
$[20,25)$°C	44,631	68.7363	30.88012	0	220
$[25,30)$°C	44,631	46.08391	41.57256	0	244
≥ 30 °C	44,631	4.20013	7.770389	0	69
0 mm	44,631	146.3534	55.67609	13	359
(0,5]mm	44,631	172.4608	39.39643	5	303
(5,10]mm	44,631	20.30754	10.02392	0	62
(10,15]mm	44,631	9.856826	6.081682	0	36
(15,20]mm	44,631	5.595998	4.145041	0	29
(20,25]mm	44,631	3.446013	2.964196	0	19
(25,30]mm	44,631	2.209675	2.198506	0	18
(30,35]mm	44,631	1.46685	1.681366	0	13
(35,40]mm	44,631	0.99693	1.29525	0	10
(40,45]mm	44,631	0.689969	1.028728	0	9
(45,50]mm	44,631	0.480003	0.816861	0	7
$>$ 50 mm	44,631	1.395308	2.029243	0	30
Annually average temperature (°C)	44,631	12.94746	5.537508	−5.77975	26.17939
Annually average relative humidity (%)	44,631	67.83773	10.59306	26.09176	88.80289
Annually average wind speed (m/s)	44,631	2.100039	0.686757	0.360956	7.147097
Annually average atmospheric pressure (hPa)	44,631	936.6894	94.83728	574.754	1017.608
Annually total precipitation (mm)	44,631	887.0858	526.4545	5.9	3299.855
Annually total sunshine hours (hour)	44,631	2117.338	539.3758	696.7247	3740.1
County-level GDP	27,085	53.579	93.471	0.040	2725.320
Value added of primary industry	27,579	10.330	10.839	0.010	114.960
Value added of secondary industry	27,534	25.713	55.593	0.000	1631.250
Value added of tertiary industry	26,545	19.719	138.924	0.010	10,818.000
Gross output value of large firms	27,649	63.909	200.604	0.000	7686.820
Agriculture output value	19,925	17.286	18.674	0.000	290.240
Grain output	27,673	23.728	25.865	0.000	350.450
Oil crops output	26,787	1.335	2.702	0.000	92.640
Cotton output	21,746	1.201	7.978	0.000	431.750
Meat output	26,790	3.212	4.241	0.000	105.050

Note: The weather data spans from January 1st, 1986 to December 31th, 2015. The economics data are from 1996 to 2012. Unit of observations is a county-year. All monetary amounts are in 100 million Chinese Yuan, and all output amounts are in 10 thousand tons.

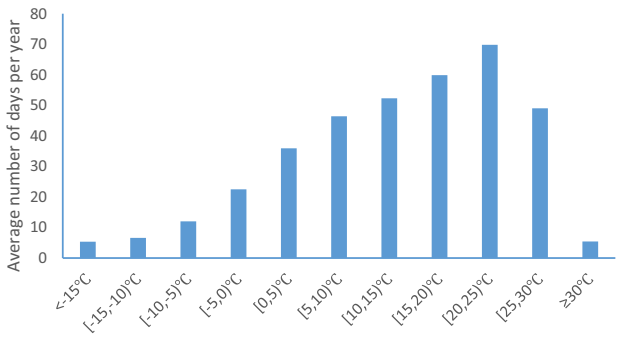

Fig. 1. Distribution of daily average temperature in an average year from 1986 to 2015.

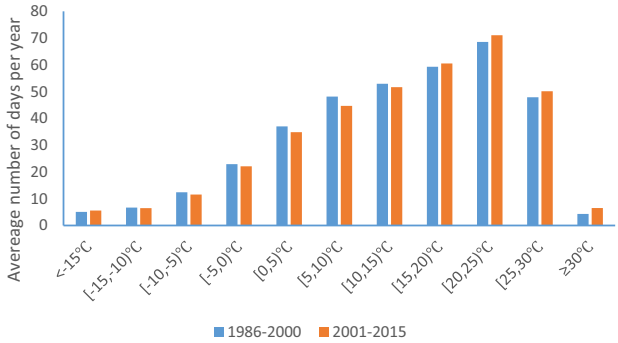

Fig. 2. Comparison of daily average temperature distribution in 1986–2000 and 2001–2015.

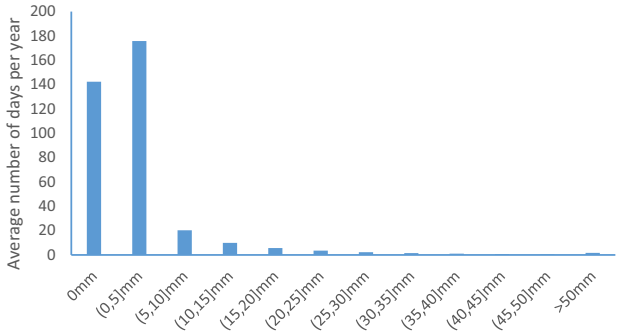

Fig. 3. Distribution of daily precipitation in an average year from 1986 to 2015.

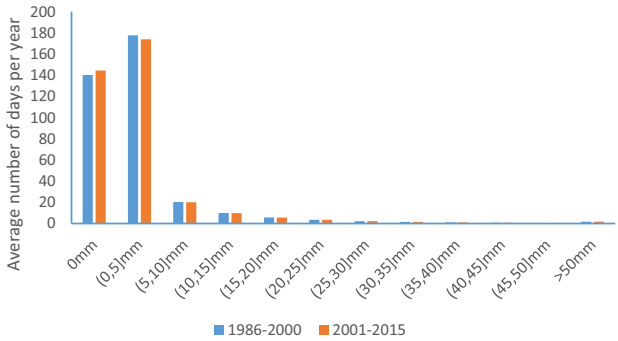

Fig. 4. Comparison of daily precipitation distribution in 1986–2000 and 2001–2015.

sequentially. The left panel of Fig. 6 shows the effects of temperature bins.[7] Similar to the main results, temperatures higher than 21 °C have significant adverse impacts on county-level GDP, and other temperature bins do not show any significant effects. The right panel of Fig. 6 shows the new estimates with 10 mm precipitation bins. Unsimilar to the main results, moderate precipitation in (20,30]mm demonstrates significant adverse effects on GDP while all other precipitation bins do not have significant effects. Therefore, we conclude that the effects of temperatures are insensitive to the choice of bin width, but the effects of precipitation are sensitive to bin width.

[7] The coefficients of all bins can be found in Appendix Table 3.

Table 2
The effects of daily temperature and precipitation on county-level GDP.

	(1)	(2)	(3)	(4)	(5)
	100 km, lag(1)	200 km, lag(2)	300 km, lag(3)	400 km, lag(4)	500 km, lag(5)
Variables	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
<−15 °C	−0.0008*	−0.0008	−0.0008	−0.0008	−0.0008
	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0007)
[−15, −10) °C	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
[−10, −5) °C	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
[−5, 0) °C	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
[0, 5) °C	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
[5, 10) °C	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
[10, 15) °C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 20) °C	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
[20, 25) °C	−0.0005***	−0.0005**	−0.0005**	−0.0005**	−0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
[25, 30) °C	−0.0008***	−0.0008***	−0.0008***	−0.0008**	−0.0008**
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
≥30 °C	−0.0008**	−0.0008**	−0.0008*	−0.0008*	−0.0008*
	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 5]mm	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
(5, 10]mm	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
(10, 15]mm	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
(15, 20]mm	0.0010**	0.0010**	0.0010**	0.0010**	0.0010**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
(20, 25]mm	−0.0008	−0.0008	−0.0008	−0.0008	−0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
(25, 30]mm	−0.0010	−0.0010	−0.0010	−0.0010	−0.0010
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
(30, 35]mm	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
(35, 40]mm	−0.0017	−0.0017*	−0.0017*	−0.0017*	−0.0017*
	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
(40, 45]mm	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
(45, 50]mm	−0.0017	−0.0017	−0.0017	−0.0017	−0.0017
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
>50 mm	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Log(Y_{it-1})	0.9724***	0.9724***	0.9724***	0.9724***	0.9724***
	(0.0023)	(0.0026)	(0.0029)	(0.0032)	(0.0034)
Observations	24,950	24,950	24,950	24,950	24,950
R-squared	0.9931	0.9931	0.9931	0.9931	0.9931

Note: Conley standard errors are reported in parentheses. All columns include region by year fixed effect, county fixed effect, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2.3. *Different fixed effects*

Our preferred regression specification includes county fixed effects and region by year fixed effects. We first use year fixed effects to replace the region-by-year fixed effects. The dotted curve in Fig. 7 shows the new estimates.[8] Temperatures have similar effects to the main results: detrimental effects of high temperature above 20 °C and no significant effects of other temperatures. But high temperatures' adverse effects are slightly larger. The effects of precipitation bins are very similar to the main results. We then use province-by-year fixed effects to replace the region-by-year fixed effects. As shown by the dashed curve in Fig. 7, the new estimates are pretty

[8] The coefficients of all bins can be found in Appendix Table 4.

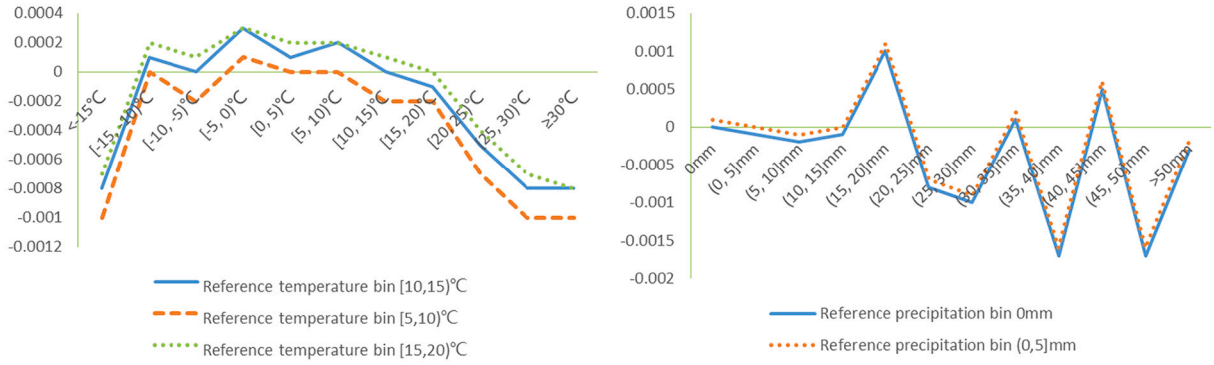

Fig. 5. Robustness test with alternative reference bins.

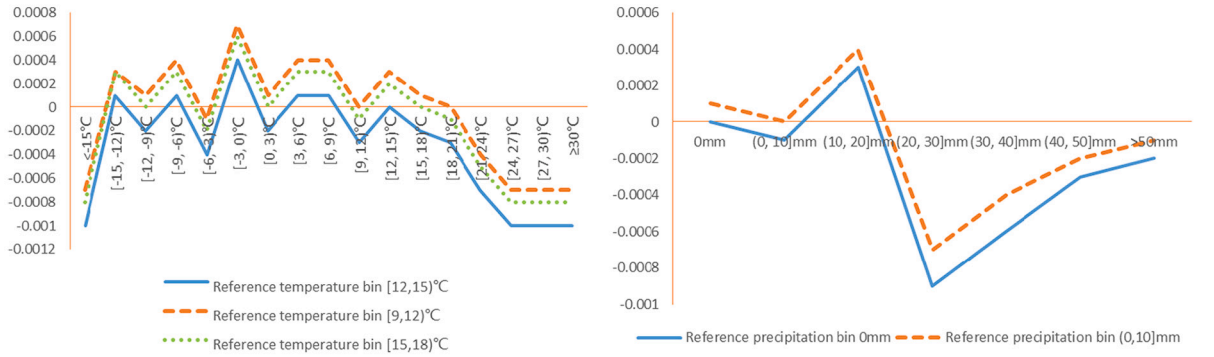

Fig. 6. Robustness test with alternative bin width.

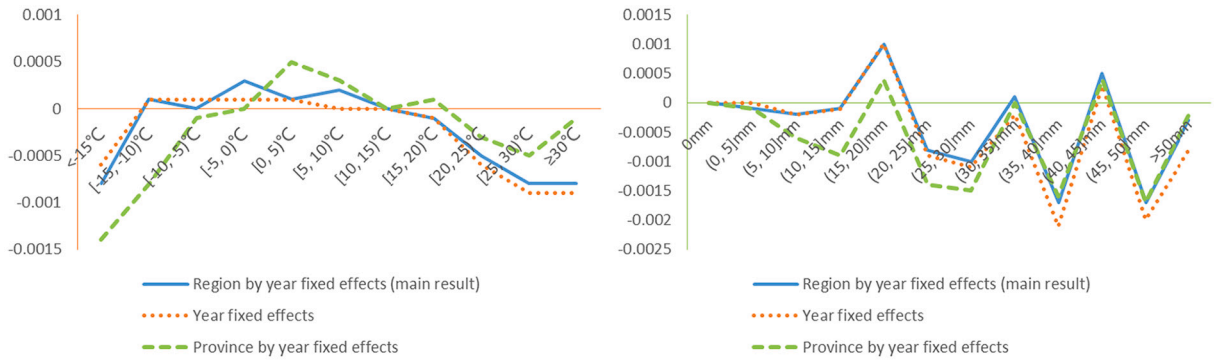

Fig. 7. Robustness test with alternative fixed effects.

different from the main results: high temperatures do not have significant adverse effects anymore. Fisher, Hanemann, Roberts, & Schlenker (2012) study the impact of weather on U.S. agriculture. They concern that using state-by-year fixed effects may remove too much of the identifying variation, thus causing attenuation bias to overwhelm the results. Deryugina and Hsiang (2014) have similar outcomes when they use state-by-year fixed effects with U.S. data. We believe the result differences are driven by the attenuated variation from province-by-year fixed effects. Such fixed effects control patterns in 31 provinces over 17 years, significantly reducing identifying variation.

4.2.4. Different regression techniques

As shown in Table 2, the coefficient of lagged dependent variable $log(Y_{it-1})$ is positive and statistically significant, implying a strong serial correlation of county-level GDP. Introducing a lagged dependent variable may cause the endogeneity problem when the panel is short. To test our main results' robustness, we use two alternative regression techniques, 2SLS and GMM. We use $\ln(GDP_{it-2})$ as the

instrument variable for $\ln(GDP_{it-1})$ and estimate the coefficients with 2SLS method. In the two-step system GMM method, IVs include lag (2, 6) of dependent variables, all exogenous variables, and one lag of all exogenous variables. Figure 8 compares the results using different regression techniques.[9] The new results have the same pattern as the main results. Temperatures higher than 20°C have significant adverse effects, and the magnitudes of the effect of different techniques are very similar. Precipitation bin (15, 20]mm has a robust significant positive impact on county-level GDP, while all other precipitation bins do not have stable effects. So we could conclude that the detrimental effects of high temperatures and the positive effects of moderate precipitation (15, 20]mm are robust to different regression techniques.

4.2.5. Different weather data source

In this robustness check, we use the weather data from NOAA and re-estimate equation (5).[10] The results using NOAA data are similar to the main results: high temperatures tend to reduce county-level GDP. Figure 9 compares the results using CMDSC data and NOAA data.[11] Two curves in the left panel have the same pattern, but the effect magnitudes of temperatures above 20°C using NOAA data are slightly smaller. In the right panel for precipitation, two curves have different patterns. Auffhammer, Hsiang, Schlenker, and Soel (2013) verify that correlation coefficients of temperature across different datasets tend to be high, but the correlation coefficients of precipitation are very low because precipitation is less smooth in space and time. Appendix Figure 1 shows that the distributions of daily temperature in the NOAA dataset and CMDSC dataset are very similar, while precipitation distributions are very different. We believe that is why the effects of temperature are robust to NOAA data, but the effects of precipitation do not.

4.3. The channel of weather effects

4.3.1. Heterogeneous effects of weather on three industries

The primary, secondary and tertiary industries may respond to temperature and precipitation shocks differently. This section decomposes the effects of daily weather on county-level GDP into these three sectors and identifies which sector is the dominant channel. We use the value added of these three sectors as the dependent variable and re-estimate eq. (5).

As shown in column 1 of Table 3, temperatures higher than 20 °C demonstrate significant negative impacts on the value added of primary industry (VAPI). The impacts become larger as the temperature rises. In particular, the damaging effect of [25, 30)°C and $\geq$ 30 °C bins are 2.8 and 4.1 times their counterparts in the main results, indicating the primary industry is more vulnerable to extreme heat. Column 1 also shows that heavy precipitation has significant negative effects on the value added of primary industry.

Column 2 of Table 3 shows that almost all temperature bins and precipitation bins do not significantly affect the value added of secondary industry (VASI). We use the gross output of enterprises above designated size (GOEDS) as the dependent variables and re-estimate eq. (5) to further confirm the results.[12] The results are unchanged: most temperature and precipitation bins do not show a significant effect. In the literature, several studies using sector-level aggregates do not find significant effects of high temperatures on industrial output, but studies using firm-level data find significant negative effects of high temperatures (Dell et al., 2014). At the sector level, Hsiang (2010) does not find a statistically significant impact of temperatures on manufacturing output; Jones and Olken (2010) find that temperatures do not have significant effects on heavy industry or raw materials production. Dell et al. (2012) find the industrial losses from high temperatures only exist in poor countries. However, at the firm level, Cachon et al. (2012) find that hot days significantly reduce the output of automobile plants in the United States; Chen & Yang (2019) and Zhang et al. (2018) find that extremely high temperatures have adverse effects on the value added of Chinese large manufacturing firms in many industries; Li et al. (2021) find that extreme heat has substantial adverse cumulative effects on Chinese exporting firms. Our finding here is consistent with the studies using sector-level aggregates but differs from Chen & Yang (2019) and Zhang et al. (2018). The result difference remains for China's secondary industry. Precipitation bins having no significant effects on large firms' output or VASI is consistent with Jones and Olken (2010) and Dell et al. (2012). Neither of them finds precipitation has a significant effect on industrial output. This is probably because most works in the industrial sector are indoors.

There are two possible reasons for our result difference with Chen & Yang (2019) and Zhang et al. (2018). First, our data contain

[9] The coefficients of all bins can be found in Appendix Table 5.

[10] The NOAA dataset reports global station-level weather data at three-hour intervals. This paper draws the data from weather stations covering China from 1985 to 2016. Almost all major weather variables, including temperature, dew point temperature, precipitation, wind speed, and atmospheric pressure, are contained in the dataset. The relative humidity is not reported directly in the data but is constructed based on NOAA's standard meteorological formula using the temperature and dew point temperature. We closely follow Zhang et al. (2018) and Graff Graff Zivin, Liu, Song, Tang, & Zhang, 2020 to process the weather data. Stations with accurate weather records for fewer than 364 days in a year are deleted because Zhang et al. (2018) emphasize the importance of continuous daily weather records for annual estimation. As the primary measurement of weather, we use the daily mean values of weather variables calculated as the averages of the three-hour values. The total precipitation is constructed as daily aggregates. After constructing weather variables in each station, we convert the weather variables from the station level to the county level using the inverse distance weighting (IDW) method (Deschênes & Greenstone, 2007, 2011) with a radius of 200 km.

[11] The coefficients of all bins using NOAA data can be found in Appendix Table 6.

[12] The term "enterprises above designated size/scale" is widely used to represent large enterprises in China. Before 2007, all state-owned enterprises (SOEs) and non-SOEs with an annual sale of over 5 million RMB are included in enterprises above designated size. After 2007, the SOEs with an annual sale below 5 million RMB are no longer included. Starting from 2011, the threshold of the annual sale increases from 5 million to 20 million. According to Zhang et al. (2018) and Chen & Yang (2019), the enterprises above designated size contribute more than 85%–90% of the secondary industry output.

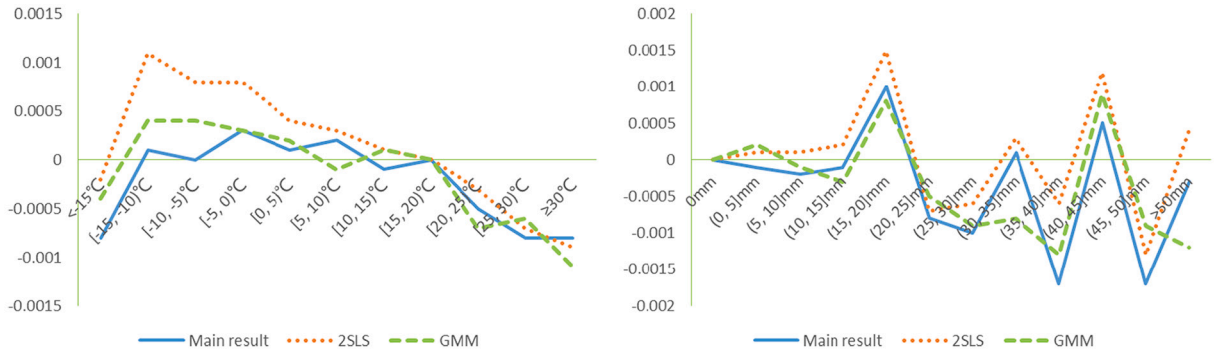

Fig. 8. Robustness test with different regression techniques.

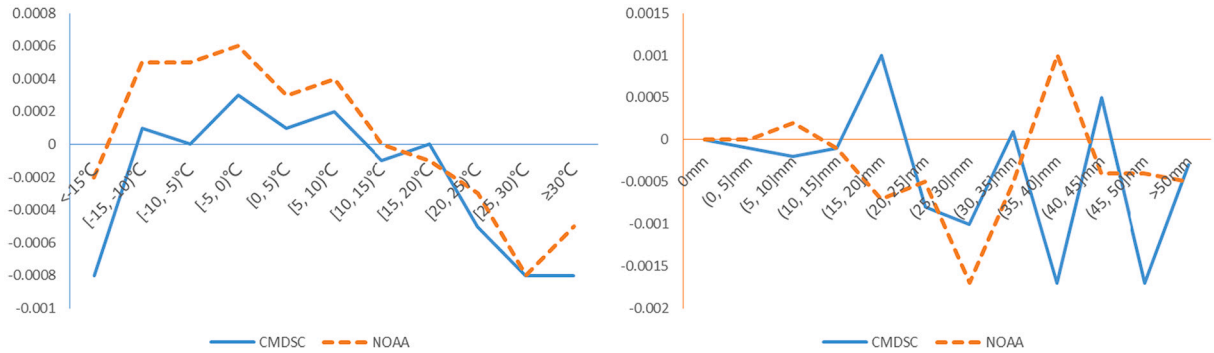

Fig. 9. Robustness test with NOAA weather data.

numerous efficient firm entrants. Our data spans from 1996 to 2012 (17 years), while their data covers 1998 to 2007 (10 years). According to their firm-level data, the number of firms in 1999 is around 160 thousand. The number rapidly grows to 330 thousand in 2007 and keeps increasing after 2007. Brandt et al. (2012) find that entry accounts for over two-thirds of total TFP growth in Chinese manufacturing firms. Brandt et al. (2019) find that entrants have higher initial productivity than incumbents in China's liberalized industries. Numerous new efficient firms appear in our sample between 2008 and 2012, and they tend to be less affected by high temperatures. Second, as Damania et al. (2020) pointed out, aggregation of firms' output may mask heterogeneity of impacts on different firms, causing statistical distortions that lead to different results.

Column 3 of Table 3 shows that almost all temperature bins and precipitation bins do not significantly affect the value added of tertiary industry (VATI). We further use the value added of non-agricultural sectors (VANA), i.e., the sum of the value added of secondary industry and tertiary industry, as the dependent variable and re-estimate eq. (5). The results are unchanged: most bins do not have a significant effect. To check the robustness of the results in Table 3, we change the temperature bin width to 3 °C and precipitation bin width to 10 mm. Appendix Table 7 reports the new results, which are almost the same as those in Table 3.

So we can conclude the primary industry is the main channel for the adverse effect of high temperatures over 20 °C. This finding suggests that future industrial restructuring in China could partially offset the impacts of climate change on the overall economy because the share of the primary industry will decline with economic development.

4.3.2. The effects of weather on agricultural products

To further explore the effects of temperature and precipitation on the primary industry, we investigate how they affect aggregate agricultural output and various agricultural products, including the gross value of agricultural outputs (GVAO), grains output, oil crops output, cotton output, and meat output. In our data, grains output is an aggregate term that includes rice, wheat, corn, beans, and tubers, almost all food crops in China. Oil crops include peanuts, rapeseed, and sesame. All major meat products in China, including pork, poultry, beef, and mutton, are included in the meat output. Since most grain crops, oil crops, and cotton grow from April to October, regressions in column 2 to column 4 of Table 4 only use the weather information in the growing season.[13]

[13] In China, cotton planting starts in April, continues through May, and is harvested from September to October. Corn, soybean, and spring wheat are planted near April and are harvested around October. April to October also roughly cover the growing season of rice. The growing seasons of two major oil crops, peanut and rapeseed, are different. We use April to October, the growing season of peanut, as the growing season for oil crops because there are no high temperatures in rapeseed's growing season.

Table 3
The effects of daily temperature and precipitation on three industries.

	(1)	(2)	(3)	(4)	(5)
Variables	log(VAPI)	log(VASI)	log(VATI)	log(GOEDS)	log(VANA)
<−15 °C	−0.0005	0.0004	−0.0011*	0.0014	−0.0007
	(0.0007)	(0.0008)	(0.0006)	(0.0012)	(0.0006)
[−15, −10)°C	−0.0008	0.0013*	0.0002	−0.0001	0.0004
	(0.0006)	(0.0007)	(0.0005)	(0.0012)	(0.0005)
[−10, −5)°C	0.0000	0.0005	−0.0000	0.0002	0.0003
	(0.0005)	(0.0006)	(0.0005)	(0.0011)	(0.0005)
[−5, 0)°C	0.0008*	0.0008*	−0.0001	0.0009	0.0001
	(0.0005)	(0.0005)	(0.0004)	(0.0008)	(0.0004)
[0, 5)°C	0.0004	0.0006	0.0001	0.0004	0.0002
	(0.0003)	(0.0004)	(0.0003)	(0.0006)	(0.0003)
[5, 10)°C	0.0002	0.0005*	−0.0001	−0.0007	0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0006)	(0.0002)
[10, 15)°C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 20)°C	0.0004	−0.0003	0.0001	−0.0001	0.0001
	(0.0002)	(0.0003)	(0.0002)	(0.0006)	(0.0002)
[20, 25)°C	−0.0005*	−0.0003	−0.0003	−0.0008	−0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0003)
[25, 30)°C	−0.0022***	−0.0006	−0.0001	0.0003	−0.0000
	(0.0004)	(0.0004)	(0.0003)	(0.0007)	(0.0003)
≥30 °C	−0.0033***	0.0005	0.0002	0.0013	0.0006
	(0.0006)	(0.0006)	(0.0005)	(0.0010)	(0.0005)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 5]mm	−0.0001	−0.0000	0.0001	0.0002	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0001)
(5, 10]mm	−0.0005	−0.0005	−0.0001	−0.0006	−0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0008)	(0.0003)
(10, 15]mm	−0.0006	−0.0004	0.0000	−0.0016*	−0.0001
	(0.0004)	(0.0006)	(0.0005)	(0.0010)	(0.0004)
(15, 20]mm	−0.0001	0.0020***	0.0011**	−0.0012	0.0017***
	(0.0005)	(0.0008)	(0.0005)	(0.0012)	(0.0005)
(20, 25]mm	−0.0016**	−0.0003	−0.0007	0.0007	−0.0004
	(0.0006)	(0.0009)	(0.0007)	(0.0014)	(0.0007)
(25, 30]mm	−0.0013*	−0.0003	−0.0001	0.0007	−0.0004
	(0.0007)	(0.0010)	(0.0008)	(0.0017)	(0.0007)
(30, 35]mm	−0.0016*	−0.0002	−0.0008	0.0007	0.0007
	(0.0009)	(0.0012)	(0.0011)	(0.0021)	(0.0010)
(35, 40]mm	−0.0029***	−0.0016	−0.0011	−0.0008	−0.0007
	(0.0011)	(0.0015)	(0.0012)	(0.0025)	(0.0012)
(40, 45]mm	−0.0022*	0.0032*	−0.0025	0.0081***	0.0011
	(0.0012)	(0.0018)	(0.0017)	(0.0028)	(0.0014)
(45, 50]mm	−0.0056***	−0.0015	0.0006	0.0016	0.0003
	(0.0015)	(0.0023)	(0.0016)	(0.0034)	(0.0015)
>50 mm	−0.0029***	−0.0000	0.0006	0.0019	0.0006
	(0.0010)	(0.0014)	(0.0009)	(0.0021)	(0.0009)
Observations	25,823	25,766	24,800	19,258	24,984
R-squared	0.9707	0.9724	0.9763	0.9641	0.9882

Note: VAPI is short for value added of primary industry. VASI is short for value added of secondary industry. VATI is short for value added of tertiary industry. GOEDS is short for gross output of enterprises above designated size. VANA is short for value added of non-agricultural sector. Conley standard errors are reported in parentheses. All columns include region by year fixed effect, county fixed effect, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As shown in column 1 of Table 4, temperatures higher than 20 °C have significant negative impacts on GVAO. The impacts become larger as the temperature rises. In particular, the damaging effect of [20, 25)°C, [25, 30)°C, and ≥ 30 °C bins are 4.4, 4.3, and 5 times their counterparts in the main results. Column 1 also shows that heavy precipitation tends to have significant adverse effects on GVAO. The results are consistent with the finding in column 1 of Table 3.

As shown in column 2 of Table 4, temperatures higher than 25 °C have significant adverse effects on grains output. This result is consistent with findings in the literature. Chen et al. (2016) find that temperatures higher than 29 °C are very harmful to corn growth. Zhang et al. (2017) find that temperatures above 30 °C are very detrimental to rice, corn, and wheat yields. Low precipitation and high precipitation above 30 mm significantly harm grains output. In column 3, high temperatures above 25 °C and intensive precipitation larger than 30 mm significantly damage oil crops' output. Almost all temperature bins and precipitation bins do not have significant effects on cotton output. The meat production responds to temperature and precipitation differently: days above 15 °C have positive

Table 4
The effects of daily temperature and precipitation on agricultural products.

	(1)	(2)	(3)	(4)	(5)
Variables	log(GVAO)	log(grains)	log(oil crops)	log(cotton)	log(meat)
<−15 °C	0.0517**	0.0488	0.1387	–	−0.0241
	(0.0214)	(0.0481)	(0.2769)	(−)	(0.0236)
[−15, −10)°C	−0.0122	0.0115	0.0728*	–	−0.0005
	(0.0137)	(0.0181)	(0.0427)	(−)	(0.0091)
[−10, −5)°C	−0.0023	0.0026	0.0321**	0.1520***	0.0075***
	(0.0027)	(0.0061)	(0.0131)	(0.0520)	(0.0029)
[−5, 0)°C	0.0007	0.0015	0.0107**	0.0287	0.0017
	(0.0021)	(0.0022)	(0.0046)	(0.0176)	(0.0014)
[0, 5)°C	0.0008	−0.0011	0.0007	−0.0066	0.0007
	(0.0009)	(0.0011)	(0.0017)	(0.0048)	(0.0008)
[5, 10)°C	−0.0004	−0.0013**	−0.0023*	−0.0003	−0.0004
	(0.0007)	(0.0006)	(0.0012)	(0.0025)	(0.0005)
[10, 15)°C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 20)°C	−0.0007	0.0006	0.0006	−0.0021	0.0009**
	(0.0006)	(0.0005)	(0.0008)	(0.0018)	(0.0004)
[20, 25)°C	−0.0022***	−0.0008	−0.0003	−0.0026	0.0009**
	(0.0008)	(0.0006)	(0.0010)	(0.0020)	(0.0005)
[25, 30)°C	−0.0034***	−0.0026***	−0.0029**	−0.0024	0.0016***
	(0.0009)	(0.0008)	(0.0012)	(0.0021)	(0.0006)
≥30 °C	−0.0040**	−0.0035***	−0.0041***	−0.0009	0.0022***
	(0.0016)	(0.0011)	(0.0016)	(0.0025)	(0.0008)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 5]mm	−0.0000	−0.0005	−0.0001	0.0002	0.0011***
	(0.0004)	(0.0003)	(0.0006)	(0.0009)	(0.0003)
(5, 10]mm	−0.0000	−0.0018***	−0.0027***	−0.0004	0.0017***
	(0.0007)	(0.0006)	(0.0010)	(0.0018)	(0.0005)
(10, 15]mm	−0.0015	−0.0023***	−0.0030**	0.0012	0.0032***
	(0.0010)	(0.0007)	(0.0012)	(0.0023)	(0.0007)
(15, 20]mm	−0.0029*	−0.0017**	−0.0000	0.0033	0.0011
	(0.0015)	(0.0008)	(0.0014)	(0.0026)	(0.0008)
(20, 25]mm	−0.0064***	−0.0024**	−0.0018	−0.0021	0.0019*
	(0.0018)	(0.0010)	(0.0018)	(0.0033)	(0.0011)
(25, 30]mm	−0.0045**	−0.0002	−0.0030	−0.0006	−0.0004
	(0.0021)	(0.0011)	(0.0020)	(0.0038)	(0.0012)
(30, 35]mm	−0.0032	−0.0043***	−0.0064***	0.0004	0.0023
	(0.0025)	(0.0014)	(0.0023)	(0.0046)	(0.0014)
(35, 40]mm	−0.0059**	−0.0054***	−0.0102***	−0.0012	−0.0000
	(0.0028)	(0.0017)	(0.0031)	(0.0052)	(0.0018)
(40, 45]mm	−0.0105***	−0.0048***	−0.0053*	−0.0036	0.0008
	(0.0039)	(0.0018)	(0.0032)	(0.0059)	(0.0019)
(45, 50]mm	−0.0033	−0.0082***	−0.0081**	−0.0039	0.0007
	(0.0038)	(0.0022)	(0.0038)	(0.0080)	(0.0022)
>50 mm	−0.0031	−0.0078***	−0.0060**	−0.0117**	0.0034**
	(0.0027)	(0.0015)	(0.0027)	(0.0048)	(0.0015)
Observations	17,283	25,772	23,824	12,015	25,043
R-squared	0.9589	0.9905	0.9308	0.9730	0.9617

Note: GVAO is short for the gross value of agricultural outputs. Dependent variables of the second to fifth columns are grain output, oil crops output, cotton output, and meat output. Grains include rice, wheat, corn, beans, and tubers. Oil crops include peanuts, rapeseed, and sesame. Major meat products in China are pork, poultry, beef, and mutton. Conley standard errors are reported in parentheses. Columns 2–4 use the weather data in the growing season, April to October. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. There are no coefficients for temperatures below −10 °C in column 4 because there is a limited number of days below −10 °C in cotton's growing season. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

effects on meat production, and low precipitation significantly enhances the meat output. Since most animal raising occurs indoors, the positive effects of high temperatures and low precipitation need to be further explored.

We use the weather conditions in the whole year, rather than the growing season, to test the robustness of the results in Table 4. The new estimates are reported in Appendix Table 8. Furthermore, we choose 3°C-width temperature bins and 10mm-width precipitation bins to perform a robustness check. Appendix Table 9 reports the new estimates. The two checks show that the effects of high temperatures on different agricultural products are very robust. The damaging impacts of high temperatures demand government policies such as introducing crop diversity, cultivating heat-resistant crops, and increasing agricultural investment.

5. Extensions of the main results

This section explores the heterogeneous effects of high temperatures on different counties and calculates GDP losses based on climate change predictions.

5.1. Heterogeneous effects on hot counties and cold counties

We explore whether counties with different climate experiences respond differently to extreme heat. We define a day with an average temperature higher than 30 °C as a scorching day. Based on the sample's long-run average from 1996 to 2012, an average county has 4.1 scorching days in a year. We define a county as a high-heat (low-heat) county if its long-run average of scorching days is more (less) than 4.1 days. As shown by column 1 and column 2 of Table 5, the impacts of temperatures above 20 °C on high-heat counties' GDP are insignificant and small in magnitude, while the effects on low-heat counties' GDP are significant, and the magnitudes are large.[14] To test the robustness of such heterogeneous effects, we further classify counties based on their long-run average temperature. A county is defined as a hot county if its long-run average temperature exceeds 12.9 °C, the sample mean of temperature from 1996 to 2012; otherwise, it is defined as a cold county. As shown by column 3 and column 4 of Table 5, high temperatures do not significantly affect hot counties' GDP. But the GDP of cold counties is significantly damaged by high temperatures.

The results here imply that the damaging effects of temperatures above 20 °C in the main results mainly come from low-heat counties or cold counties. These counties tend to have low adaptability to high temperatures because of fewer experiences with heatwaves. Using data of industrial firms in China, Chen & Yang (2019) find that the detrimental effects of high temperatures are smaller in high-temperature regions than those in low-temperature regions. They suggest that adaptation to heat may have been actively undertaken in high-temperature regions in China. Barreca, Clay, Deschênes, Greenstone, and Shapiro (2015) and Park (2016) find that extreme heat's impacts are notably smaller in states/counties that experience extreme heat more frequently. Our finding here also supports the conclusion that more heat experiences improve adaptation to hot weather.

Our further investigation shows that the adverse effects of high temperatures on agricultural production in high-heat and hot counties are considerably smaller. Appendix Table 10 reports the related results. No matter agricultural production is measured by the value added of primary industry (VAPI) or the gross value of agricultural outputs (GVAO), temperatures higher than 20 °C display significantly stronger adverse effects on agricultural production in low-heat and cold counties. There are two probable reasons for the better adaptation of high-heat counties. The first one is that high-heat counties exploit more resources to cope with high temperatures. Appendix Fig. 2 to Appendix Fig. 4 shows that high-heat counties tend to have much larger rural investments, more farm machinery, and more agricultural labor. The other reason is that frequent scorching temperatures induce them to be equipped with more air conditioning. Auffhammer and Schlenker (2014) find that areas experiencing more heatwaves are more likely to install air conditioning units. Appendix Fig. 5 shows that air conditioning penetration in China is remarkably higher in hot provinces than in cold provinces, no matter in the urban or rural areas. Appendix Table 11 shows that high temperatures only significantly affect the GDP and agricultural output in provinces with low air conditioning penetration. The findings here endorse the mitigating effects of agricultural investment, farm machinery, and air conditioning, which are informative to design climate change policies.

5.2. Different effects on agricultural and non-agricultural counties

The agricultural sector has been identified as the main channel of extreme heat's adverse effects. We further test whether agricultural counties and non-agricultural counties respond differently to extreme heat. A county is defined as an agricultural (non-agricultural) county if its average value added of the primary industry from 1996 to 2012 is greater (smaller) than the sample mean. As shown in column 1 and column 2 of Table 6, temperatures above 20 °C do not significantly affect the value added of primary industry (VAPI) and the gross value of agricultural outputs (GVAO) of agricultural counties. In contrast, temperatures above 20 °C have significant negative impacts on the VAPI and GVAO of non-agricultural counties. We identify the reasons behind the heterogeneous effects by investigating how temperatures affect agricultural products in different counties. The results are reported in Appendix Table 12. We find that temperatures above 25 °C do not significantly reduce the grains output in agricultural counties, but their adverse effects are significant and much stronger in non-agricultural counties. Temperatures higher than 20 °C reduce oil crop output in all counties, but the negative effects are statistically more statistically significant and larger in magnitude for non-agricultural counties.

The different effects on agricultural and non-agricultural counties suggest that they have diverse adaptations to hot weather. The probable reason for this is that agricultural production is critical to the GDP of agricultural counties. Both the government and farmers are willing to invest more to protect agricultural production from weather extremes, resulting in better adaptability. Chen and Gong (2021) point out that labor, fertilizer, and machinery are the three primary agricultural inputs in China. As shown in Appendix Fig. 6 to Fig. 8, agricultural counties have much higher rural investment, more farm machinery, and more agricultural laborers than non-agricultural counties. On average, an agricultural county has 596 million Yuan rural investment in a year, while a non-agricultural county only has 186 million Yuan. The agricultural machinery and agricultural labor comparisons are 491,481 kW vs. 146,581 kW

[14] The probably reason why the coefficient of the ≥30 °C bin in column 2 is insignificant is as follows. A low-heat county, on average, only has 0.7 days over 30 °C in a year. The sample of low-heat counties lacks sufficient variation to generate identification. The coefficient of ≥30 °C bin in column 4 of Table 5 is insignificant for the same reason because a typical cold county only has 0.4 days over 30 °C in a year.

Table 5
Different effects of high temperatures on hot counties and cold counties.

Variables	(1)	(2)	(3)	(4)
	log(GDP)	log(GDP)	log(GDP)	log(GDP)
	high-heat county	low-heat county	hot county	cold county
<−15 °C	0.0021	−0.0006	0.0042	−0.0009
	(0.0025)	(0.0006)	(0.0192)	(0.0008)
[−15, −10)°C	0.0023*	0.0002	−0.0002	−0.0001
	(0.0013)	(0.0005)	(0.0055)	(0.0007)
[−10, −5)°C	0.0004	0.0001	−0.0014	−0.0000
	(0.0015)	(0.0004)	(0.0009)	(0.0006)
[−5, 0)°C	0.0000	0.0003	0.0008	−0.0001
	(0.0006)	(0.0004)	(0.0005)	(0.0006)
[0, 5)°C	−0.0001	0.0003	0.0000	−0.0002
	(0.0005)	(0.0003)	(0.0003)	(0.0005)
[5, 10)°C	0.0002	0.0001	0.0001	−0.0002
	(0.0003)	(0.0003)	(0.0002)	(0.0005)
[10, 15)°C	0	0	0	0
	(−)	(−)	(−)	(−)
[15, 20)°C	−0.0001	−0.0003	0.0002	−0.0009**
	(0.0004)	(0.0002)	(0.0002)	(0.0004)
[20, 25)°C	−0.0003	−0.0007***	−0.0001	−0.0010**
	(0.0004)	(0.0003)	(0.0003)	(0.0004)
[25, 30)°C	−0.0001	−0.0010***	−0.0002	−0.0011*
	(0.0004)	(0.0003)	(0.0003)	(0.0006)
≥30 °C	0.0000	−0.0000	−0.0002	0.0015
	(0.0006)	(0.0009)	(0.0004)	(0.0019)
Observations	7311	17,639	14,495	10,455
R-squared	0.9975	0.9901	0.9961	0.9874

Note: Conley standard errors are reported in parentheses. All columns include region by year fixed effect, county fixed effect, lagged dependent variable, precipitation bins, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of machinery power and 194,397 people vs. 77,507 people. More agricultural investment leads to better adaptability has been supported by many empirical studies (e.g., Fishman, 2013; Fleischer, Mendelsohn, & Dinar, 2011; Manning, Goemans, & Maas, 2017; Taraz, 2017). Chen and Gong (2021) find that adjustment in labor, fertilizer, and machines significantly mitigates the agricultural output loss from climate change in China.

These findings are almost unchanged if agricultural and non-agricultural counties are defined differently. We define a county's primary industry ratio as $\frac{1}{17}\sum_{t=1996}^{2012}\frac{VAPI_t}{GDP_t}$. The mean of all counties' ratios is 0.3. A county is defined as an agricultural county if its primary industry ratio exceeds 0.3 and is classified as a non-agricultural county if this ratio is below 0.3. Appendix Table 13 reports the new estimates. We find that temperatures higher than 20 °C significantly lower the county-level GDP of non-agricultural counties, while their effects on agricultural counties are much less significant. Temperatures above 25 °C significantly harm the VAPI of all counties, but the effects are larger in non-agricultural counties. High temperatures only considerably damage the GVAO of non-agricultural counties.

5.3. Predicted impacts of climate change

With baseline estimates at hand, we forecast the impact of future climate change on Chinese counties' economic outcomes. We download the average climate projection from the Coupled Model Intercomparison Projection 5. Our forecast, to account for uncertainties in each climate projection model, focuses on four Representative Concentration Paths (RCPs): 2.6, 4.5, 6.0, and 8.5, in which 2.6 and 8.5 represent the slowest warming and fastest warming scenario respectively, and 4.5 and 6.0 represent two moderate warming scenarios. The Coupled Model Intercomparison Projection 5 provides weather projections until 2099 at a spatial resolution of 2.5° × 2.5°. We calculate the weather difference between 1996 and 2012 and 2070–2099 for each grid point in China and then assign weather changes to each county by inverse distance weighting all grid points within a 200 km radius. Finally, we multiply projected weather changes with our baseline model's estimated coefficients to calculate economic output changes.

Table 7 demonstrates an average county's predicted economic changes under four RCPs. A county's GDP will decrease by 3.04% under the slowest warming scenario (RCP2.6) and reduce by 6.15% under the fastest warming scenario (RCP8.5). The considerable GDP losses rationalize the necessity of the government's policies to deal with future climate change. Primary industry suffers the most from climate change. The warming climate harms secondary industry, but tertiary industry tends to benefit under all warming

Table 6
Different effects of high temperatures on agricultural and non-agricultural counties.

	Agricultural county		Non-agricultural county	
	(1)	(2)	(3)	(4)
Variables	log(VAPI)	log(GVAO)	log(VAPI)	log(GVAO)
<−15 °C	–	–	0.0514*	0.0724***
	(−)	(−)	(0.0294)	(0.0279)
[−15, −10)°C	0.0007	0.0565***	0.0099	0.0005
	(0.0168)	(0.0211)	(0.0130)	(0.0164)
[−10, −5)°C	−0.0072	0.0000	0.0025	0.0003
	(0.0070)	(0.0093)	(0.0026)	(0.0031)
[−5, 0)°C	0.0064***	0.0037	0.0038**	0.0031
	(0.0023)	(0.0040)	(0.0016)	(0.0025)
[0, 5)°C	−0.0030**	−0.0059***	0.0024***	0.0017
	(0.0013)	(0.0022)	(0.0008)	(0.0011)
[5, 10)°C	0.0010	−0.0010	−0.0004	−0.0007
	(0.0008)	(0.0020)	(0.0005)	(0.0007)
[10, 15)°C	0	0	0	0
	(−)	(−)	(−)	(−)
[15, 20)°C	0.0008	0.0007	0.0002	−0.0014**
	(0.0005)	(0.0010)	(0.0004)	(0.0007)
[20, 25)°C	0.0000	0.0008	−0.0005	−0.0027***
	(0.0006)	(0.0013)	(0.0006)	(0.0010)
[25, 30)°C	−0.0005	0.0010	−0.0020**	−0.0038***
	(0.0007)	(0.0015)	(0.0008)	(0.0013)
≥30 °C	−0.0012	−0.0006	−0.0035***	−0.0049**
	(0.0008)	(0.0021)	(0.0011)	(0.0019)
Observations	10,100	5972	15,723	11,311
R-squared	0.9888	0.9841	0.9567	0.9345

Note: VAPI is short for value added of primary industry. GVAO is short for the gross value of agricultural outputs. Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. The temperature bin below −15 °C in column 1 and column 2 does not have coefficients because our data has a limited number of days below −15 °C in agricultural counties. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Predicted changes of economic outcomes under different warming scenarios.

Economic outcomes	RCP2.6	RCP4.5	RCP6.0	RCP8.5
County-level GDP	−3.04%	−4.12%	−4.46%	−6.15%
Value added of primary industry	−7.40%	−11.63%	−13.36%	−20.92%
Value added of secondary industry	−1.23%	−1.64%	−1.63%	−1.60%
Value added of tertiary industry	1.41%	1.75%	1.81%	2.41%

Notes: The projected weather data are from Coupled Model Intercomparison Projection 5. The result is based on the weather difference between 1996 and 2012 and 2070–2099, assuming no adaptation.

scenarios.[15] The heterogeneous effects on different sectors imply that industrial restructuring could partially counteract the impacts of climate change on the overall economy. As the Chinese economy grows, the proportion of the primary industry will steadily decrease, and the tertiary industry segment will consistently rise. Industrial policies could smooth industrial restructuring and help to alleviate the adverse effects of climate change. But the future projections here should be treated with caution. We do not consider adaptation opportunities for the economy in the long run and overlook the transformation of industrial structure and the mitigating effects of related policies, all of which tend to reduce the damaging impacts of climate change.

6. Conclusion

This paper exploits weather data and economic data on Chinese counties to examine the relationship between daily weather and economic performance. We find that the effects of daily weather on economic output are non-linear. Relative to a day with an average temperature in the [10,15)°C bin, one additional day with an average temperature above 20 °C reduces county-level GDP by 0.05% to 0.08%. Temperature and precipitation mainly exert their effects through the agricultural sector. High temperatures and intense precipitation significantly harm agricultural output. We find heterogeneous responses to hot weather across counties and discover

[15] We should treat the result with caution because most coefficients of temperature and precipitation bins are statistically insignificant for the second and tertiary industries.

suggestive evidence of adaptation. Counties that frequently experience hot weather adapt to high temperatures better; agricultural production in agricultural counties is less affected by hot days.

Extreme weather events are occurring more frequently in China due to global climate change. Estimating the effects of weather conditions at the aggregate level reveals the counterfactual benefits of tackling climate change and has substantial policy implications. This paper serves as the first step in this direction and suggests an immense benefit of coping with climate change. However, due to data limitations, we cannot fully unveil the micro-mechanism behind the effects and cannot thoroughly explore the reasons behind the heterogeneous adaptabilities of different counties. These are important research topics when there are sufficient micro-level datasets. Unveiling the mechanisms behind the effects helps to design targeted policies to protect the economy from weather extremes.

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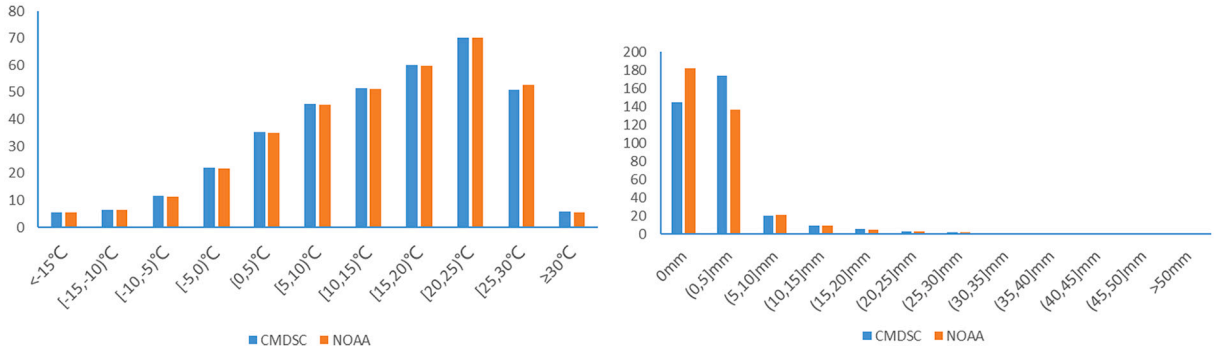
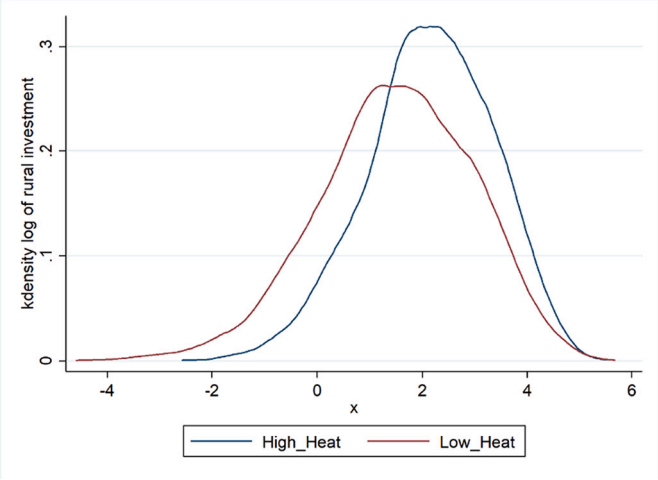
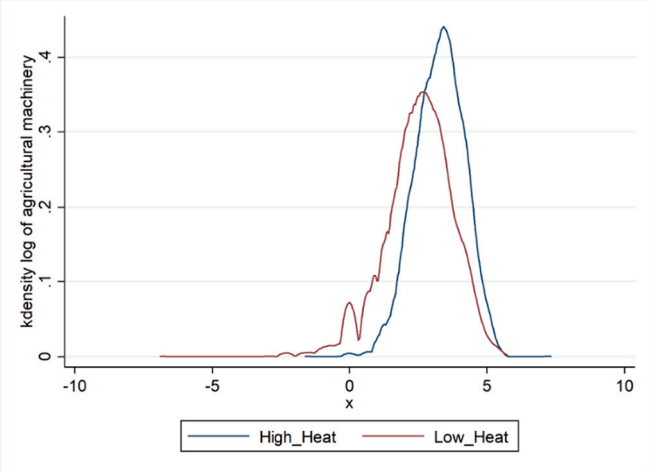
Appendix A. Appendix



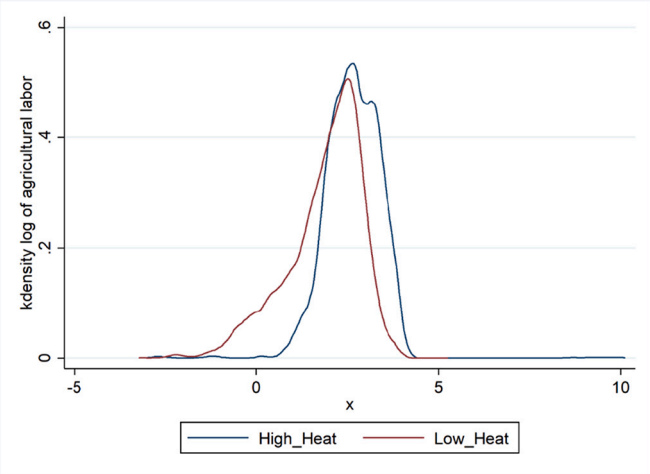
Appendix Fig. 1. Distribution of temperature and precipitation in CMDSC and NOAA datasets.



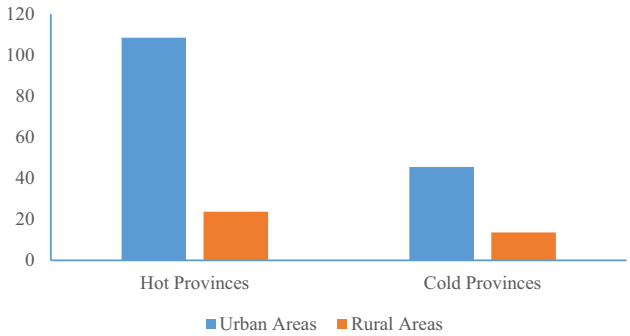
Appendix Fig. 2. Distribution of rural investment in high-heat and low-heat counties.



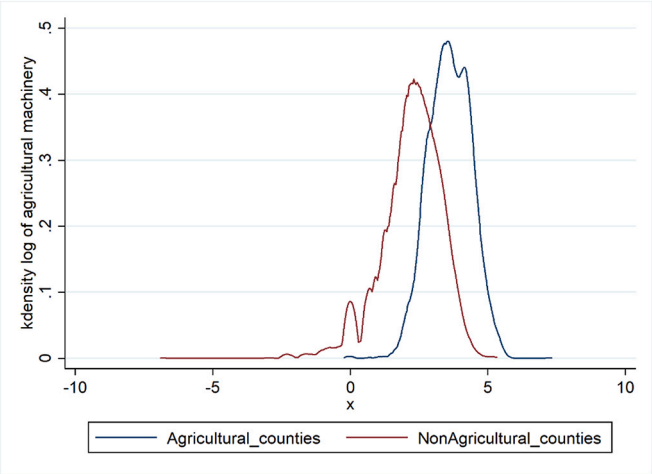
Appendix Fig. 3. Distribution of agricultural machinery in high-heat and low-heat counties.



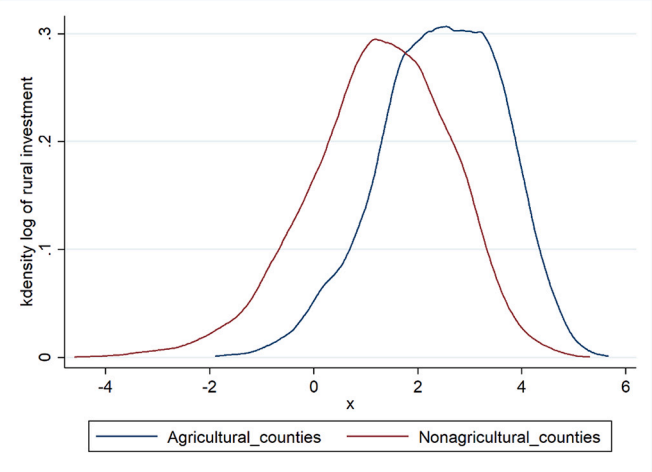
Appendix Fig. 4. Distribution of agricultural labor in high-heat and low-heat counties.



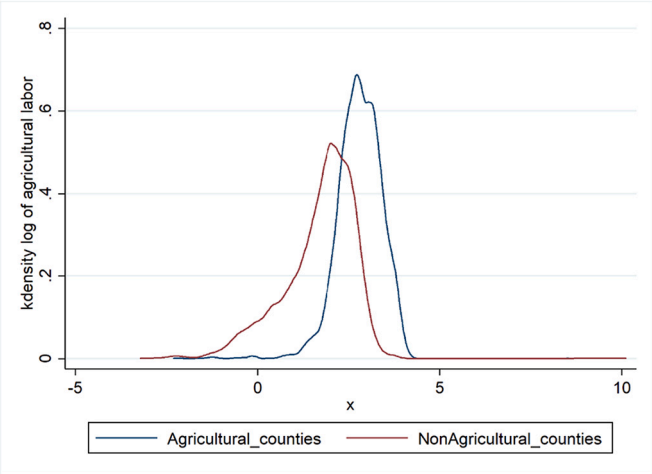
Appendix Fig. 5. Number of air conditioners per 100 households in hot provinces and cold provinces.



Appendix Fig. 6. Distribution of rural investment in agricultural and non-agricultural counties.



Appendix Fig. 7. Distribution of agricultural machinery in agricultural and non-agricultural counties



Appendix Fig. 8. Distribution of agricultural labor in agricultural and non-agricultural counties.

Appendix Table 1
The effects of temperature and precipitation on county-level GDP with alternative data processing.

Variables	Winsorized data			Complete data		
	(1)	(2)	(3)	(4)	(5)	(6)
	100 km, lag(1)	200 km, lag(2)	300 km, lag(3)	100 km, lag(1)	200 km, lag(2)	300 km, lag(3)
	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
<−15 °C	−0.0013***	−0.0013**	−0.0013**	−0.0009*	−0.0009*	−0.0009
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0006)
[−15, −10) °C	−0.0003	−0.0003	−0.0003	0.0001	0.0001	0.0001
	(0.0004)	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0005)
[−10, −5) °C	−0.0003	−0.0003	−0.0003	−0.0000	−0.0000	−0.0000
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)
[−5, 0) °C	−0.0000	−0.0000	−0.0000	0.0002	0.0002	0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
[0, 5) °C	−0.0003	−0.0003	−0.0003	0.0001	0.0001	0.0001
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
[5, 10) °C	−0.0001	−0.0001	−0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
[10, 15) °C	0	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)	(−)
[15, 20) °C	−0.0000	−0.0000	−0.0000	0.0000	0.0000	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
[20, 25) °C	−0.0005***	−0.0005**	−0.0005**	−0.0004**	−0.0004**	−0.0004*
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
[25, 30) °C	−0.0008***	−0.0008***	−0.0008**	−0.0007***	−0.0007***	−0.0007**
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
≥30 °C	−0.0010***	−0.0010**	−0.0010**	−0.0008**	−0.0008*	−0.0008*
	(0.0004)	(0.0004)	(0.0005)	(0.0003)	(0.0004)	(0.0005)
0 mm	0	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)	(−)
(0, 5]mm	−0.0003**	−0.0003*	−0.0003*	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
(5, 10]mm	−0.0005**	−0.0005*	−0.0005*	−0.0003	−0.0003	−0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
(10, 15]mm	−0.0006	−0.0006	−0.0006	−0.0001	−0.0001	−0.0001
	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
(15, 20]mm	0.0007	0.0007	0.0007	0.0010**	0.0010**	0.0010**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
(20, 25]mm	−0.0012**	−0.0012**	−0.0012**	−0.0010*	−0.0010*	−0.0010*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
(25, 30]mm	−0.0007	−0.0007	−0.0007	−0.0009	−0.0009	−0.0009
	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
(30, 35]mm	0.0004	0.0004	0.0004	−0.0000	−0.0000	−0.0000
	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
(35, 40]mm	−0.0018*	−0.0018*	−0.0018*	−0.0021*	−0.0021**	−0.0021**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0010)
(40, 45]mm	0.0007	0.0007	0.0007	0.0002	0.0002	0.0002
	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0012)
(45, 50]mm	−0.0006	−0.0006	−0.0006	−0.0019	−0.0019	−0.0019
	(0.0015)	(0.0016)	(0.0016)	(0.0014)	(0.0014)	(0.0014)
>50 mm	−0.0011	−0.0011	−0.0011	−0.0004	−0.0004	−0.0004
	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0009)
Log(Y_{it-1})	0.9558***	0.9558***	0.9558***	0.9727***	0.9727***	0.9727***
	(0.0030)	(0.0036)	(0.0041)	(0.0023)	(0.0026)	(0.0030)
Observations	25,425	25,425	25,425	25,425	25,425	25,425
R-squared	0.9923	0.9923	0.9923	0.9929	0.9929	0.9929

Note: Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 2
Robustness test with alternative reference bins.

Variables	(1)	(2)	(3)
	log(GDP)	log(GDP)	log(GDP)
<−15 °C	−0.0010**	−0.0007	−0.0008
	(0.0005)	(0.0006)	(0.0005)
[−15, −10)°C	−0.0000	0.0002	0.0001

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Appendix Table 2 (*continued*)

Variables	(1)	(2)	(3)
	log(GDP)	log(GDP)	log(GDP)
	(0.0004)	(0.0005)	(0.0005)
[−10, −5)°C	−0.0002	0.0001	0.0000
	(0.0003)	(0.0004)	(0.0004)
[−5, 0)°C	0.0001	0.0003	0.0003
	(0.0003)	(0.0004)	(0.0003)
[0, 5)°C	−0.0000	0.0002	0.0001
	(0.0002)	(0.0003)	(0.0002)
[5, 10)°C	0	0.0002	0.0002
	(−)	(0.0002)	(0.0002)
[10, 15)°C	−0.0002	0.0001	0
	(0.0002)	(0.0002)	(−)
[15, 20)°C	−0.0002	0	−0.0001
	(0.0002)	(−)	(0.0002)
[20, 25)°C	−0.0007**	−0.0004***	−0.0005**
	(0.0003)	(0.0002)	(0.0002)
[25, 30)°C	−0.0010***	−0.0007***	−0.0008***
	(0.0003)	(0.0002)	(0.0003)
≥30 °C	−0.0010**	−0.0008**	−0.0008**
	(0.0005)	(0.0004)	(0.0004)
0 mm	0	0	0.0001
	(−)	(−)	(0.0001)
(0, 5]mm	−0.0001	−0.0001	0
	(0.0001)	(0.0001)	(−)
(5, 10]mm	−0.0002	−0.0002	−0.0001
	(0.0003)	(0.0003)	(0.0002)
(10, 15]mm	−0.0001	−0.0001	−0.0000
	(0.0004)	(0.0004)	(0.0004)
(15, 20]mm	0.0010**	0.0010**	0.0011**
	(0.0005)	(0.0005)	(0.0005)
(20, 25]mm	−0.0008	−0.0008	−0.0007
	(0.0006)	(0.0006)	(0.0006)
(25, 30]mm	−0.0010	−0.0010	−0.0009
	(0.0007)	(0.0007)	(0.0007)
(30, 35]mm	0.0001	0.0001	0.0002
	(0.0009)	(0.0009)	(0.0009)
(35, 40]mm	−0.0017	−0.0017	−0.0016
	(0.0011)	(0.0011)	(0.0011)
(40, 45]mm	0.0005	0.0005	0.0006
	(0.0012)	(0.0012)	(0.0012)
(45, 50]mm	−0.0017	−0.0017	−0.0016
	(0.0014)	(0.0014)	(0.0014)
>50 mm	−0.0003	−0.0003	−0.0002
	(0.0009)	(0.0009)	(0.0009)
$log(Y_{it-1})$	0.9724***	0.9724***	0.9724***
	(0.0025)	(0.0025)	(0.0025)
Observations	24,950	24,950	24,950
R-squared	0.9931	0.9931	0.9931

Note: Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 3
Robustness test with alternative bin widths.

Variables	(1)	(2)	(3)	(4)
	log(GDP)	log(GDP)	log(GDP)	log(GDP)
<−15 °C	−0.0011*	−0.0008	−0.0009	−0.0011*
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
[−15, −12)°C	−0.0002	0.0002	−0.0000	−0.0002
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
[−12, −9)°C	−0.0002	0.0002	−0.0000	−0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
[−9, −6)°C	0.0002	0.0005	0.0003	0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
[−6, −3)°C	−0.0007	−0.0003	−0.0005	−0.0007
	(0.0005)	(0.0004)	(0.0005)	(0.0005)
[−3,0)°C	0.0004	0.0007**	0.0005	0.0004

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Appendix Table 3 (*continued*)

Variables	(1)	(2)	(3)	(4)
	log(GDP)	log(GDP)	log(GDP)	log(GDP)
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
[0,3)°C	−0.0003	0.0000	−0.0001	−0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0003)
[3, 6)°C	0.0000	0.0004	0.0002	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
[6, 9)°C	−0.0000	0.0003	0.0002	−0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
[9, 12)°C	−0.0003	0	−0.0002	−0.0003
	(0.0003)	(−)	(0.0003)	(0.0003)
[12, 15)°C	0	0.0003	0.0002	0
	(−)	(0.0003)	(0.0002)	(−)
[15, 18)°C	−0.0002	0.0002	0	−0.0002
	(0.0002)	(0.0003)	(−)	(0.0002)
[18, 21)°C	−0.0002	0.0002	−0.0000	−0.0002
	(0.0003)	(0.0003)	(0.0002)	(0.0003)
[21, 24)°C	−0.0007***	−0.0003	−0.0005**	−0.0007***
	(0.0003)	(0.0003)	(0.0002)	(0.0003)
[24, 27)°C	−0.0009***	−0.0006*	−0.0008***	−0.0009***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
[27, 30)°C	−0.0009***	−0.0006*	−0.0008***	−0.0009***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)
≥30 °C	−0.0009**	−0.0006	−0.0008*	−0.0009**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
0 mm	0	0	0	0.0002
	(−)	(−)	(−)	(0.0001)
(0,10]mm	−0.0002	−0.0002	−0.0002	0
	(0.0001)	(0.0001)	(0.0001)	(−)
(10,20]mm	0.0003	0.0003	0.0003	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
(20, 30]mm	−0.0010**	−0.0010**	−0.0010**	−0.0008*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
(30, 40]mm	−0.0007	−0.0007	−0.0007	−0.0006
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
(40, 50]mm	−0.0005	−0.0005	−0.0005	−0.0004
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
>50 mm	−0.0003	−0.0003	−0.0003	−0.0002
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$log(Y_{it-1})$	0.9725***	0.9725***	0.9725***	0.9725***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Observations	25,425	25,425	25,425	25,425
R-squared	0.9929	0.9929	0.9929	0.9929

Note: Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 4
Robustness test with alternative fixed effects.

Variables	(1)	(2)
	log(GDP)	log(GDP)
<−15 °C	−0.0006	−0.0014*
	(0.0005)	(0.0008)
[−15, −10)°C	0.0001	−0.0008
	(0.0005)	(0.0006)
[−10, −5)°C	0.0001	−0.0001
	(0.0004)	(0.0005)
[−5, 0)°C	0.0001	−0.0000
	(0.0003)	(0.0004)
[0, 5)°C	0.0001	0.0005
	(0.0002)	(0.0003)
[5, 10)°C	−0.0000	0.0003
	(0.0002)	(0.0002)
[10, 15)°C	0	0
	(−)	(−)
[15, 20)°C	−0.0001	0.0001
	(0.0002)	(0.0002)
[20, 25)°C	−0.0006***	−0.0003

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Appendix Table 4 (*continued*)

Variables	(1)	(2)
	log(GDP)	log(GDP)
	(0.0002)	(0.0003)
[25, 30)°C	−0.0009***	−0.0005
	(0.0003)	(0.0003)
≥30 °C	−0.0009**	−0.0001
	(0.0004)	(0.0005)
0 mm	0	0
	(−)	(−)
(0, 5]mm	0.0000	−0.0001
	(0.0001)	(0.0001)
(5, 10]mm	−0.0002	−0.0006*
	(0.0003)	(0.0003)
(10, 15]mm	−0.0001	−0.0009**
	(0.0004)	(0.0004)
(15, 20]mm	0.0010**	0.0004
	(0.0005)	(0.0005)
(20, 25]mm	−0.0009	−0.0014**
	(0.0006)	(0.0006)
(25, 30]mm	−0.0011*	−0.0015**
	(0.0007)	(0.0006)
(30, 35]mm	−0.0002	−0.0000
	(0.0009)	(0.0009)
(35, 40]mm	−0.0021**	−0.0016
	(0.0011)	(0.0011)
(40, 45]mm	0.0003	0.0004
	(0.0012)	(0.0011)
(45, 50]mm	−0.0020	−0.0017
	(0.0014)	(0.0014)
>50 mm	−0.0008	−0.0002
	(0.0009)	(0.0008)
$log(Y_{it-1})$	0.9735***	0.9690***
	(0.0025)	(0.0026)
Year fixed effect	Yes	No
Province×year fixed effect	No	Yes
Region×year fixed effect	No	No
County fixed effect	Yes	Yes
Observations	24,950	24,950
R-squared	0.9930	0.9937

Note: Conley standard errors are reported in parentheses. All columns include lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 5
Robustness test with alternative regression techniques.

	(1)	(2)	(3)
Variables	log(GDP) (main results)	log(GDP) (2SLS)	log(GDP) (GMM)
$\log(GDP_{it-1})$	0.9724***	0.8215***	0.9152***
	(0.0025)	(0.0068)	(0.0293)
<−15 °C	−0.0008	−0.0002	−0.0004
	(0.0005)	(0.0004)	(0.0004)
[−15, −10)°C	0.0001	0.0011***	0.0004
	(0.0005)	(0.0004)	(0.0003)
[−10, −5)°C	0.0000	0.0008**	0.0004
	(0.0004)	(0.0003)	(0.0003)
[−5, 0)°C	0.0003	0.0008***	0.0003
	(0.0003)	(0.0003)	(0.0002)
[0, 5)°C	0.0001	0.0004*	0.0002
	(0.0002)	(0.0002)	(0.0002)
[5, 10)°C	0.0002	0.0003*	−0.0001
	(0.0002)	(0.0002)	(0.0001)
[10, 15)°C	−0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0001)
[15, 20)°C	0	0	0
	(−)	(−)	(−)
[20, 25)°C	−0.0005**	−0.0003	−0.0007***
	(0.0002)	(0.0002)	(0.0002)

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Appendix Table 5 (*continued*)

	(1)	(2)	(3)
Variables	log(GDP) (main results)	log(GDP) (2SLS)	log(GDP) (GMM)
[25, 30)°C	−0.0008***	−0.0007***	−0.0006***
	(0.0003)	(0.0002)	(0.0002)
≥30 °C	−0.0008**	−0.0009**	−0.0011***
	(0.0004)	(0.0004)	(0.0003)
0 mm	0	0	0
	(−)	(−)	(−)
(0, 5]mm	−0.0001	0.0001	0.0002***
	(0.0001)	(0.0001)	(0.0001)
(5, 10]mm	−0.0002	0.0001	−0.0001
	(0.0003)	(0.0002)	(0.0002)
(10, 15]mm	−0.0001	0.0002	−0.0003
	(0.0004)	(0.0004)	(0.0003)
(15, 20]mm	0.0010**	0.0015***	0.0008**
	(0.0005)	(0.0005)	(0.0004)
(20, 25]mm	−0.0008	−0.0007	−0.0005
	(0.0006)	(0.0006)	(0.0005)
(25, 30]mm	−0.0010	−0.0006	−0.0009*
	(0.0007)	(0.0007)	(0.0005)
(30, 35]mm	0.0001	0.0003	−0.0008
	(0.0009)	(0.0009)	(0.0009)
(35, 40]mm	−0.0017	−0.0006	−0.0013
	(0.0011)	(0.0011)	(0.0008)
(40, 45]mm	0.0005	0.0012	0.0009
	(0.0012)	(0.0013)	(0.0010)
(45, 50]mm	−0.0017	−0.0013	−0.0009
	(0.0014)	(0.0015)	(0.0013)
>50 mm	−0.0003	0.0004	−0.0012*
	(0.0009)	(0.0008)	(0.0007)
Observations	24,950	23,178	23,192
R-squared	0.9931		

Note: All columns include region by year fixed effects and county fixed effects, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 6
Robustness test with NOAA data.

	(1)	(2)	(3)	(4)	(5)
	100 km, lag(1)	200 km, lag(2)	300 km, lag(3)	400 km, lag(4)	500 km, lag(5)
Variables	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
<−15 °C	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002
	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0007)
[−15, −10) °C	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
[−10, −5) °C	0.0005	0.0005	0.0005	0.0005	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
[−5, 0) °C	0.0006**	0.0006**	0.0006*	0.0006*	0.0006*
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
[0, 5) °C	0.0003	0.0003	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
[5, 10) °C	0.0004**	0.0004*	0.0004*	0.0004	0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
[10, 15) °C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 20) °C	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
[20, 25) °C	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
[25, 30) °C	−0.0008***	−0.0008***	−0.0008***	−0.0008***	−0.0008***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
≥30 °C	−0.0005	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 5]mm	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000

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Appendix Table 6 (*continued*)

	(1)	(2)	(3)	(4)	(5)
	100 km, lag(1)	200 km, lag(2)	300 km, lag(3)	400 km, lag(4)	500 km, lag(5)
Variables	log(GDP)	log(GDP)	log(GDP)	log(GDP)	log(GDP)
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
(5, 10]mm	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
(10, 15]mm	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
(15, 20]mm	−0.0007*	−0.0007	−0.0007	−0.0007	−0.0007
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
(20, 25]mm	−0.0005	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
(25, 30]mm	−0.0017**	−0.0017**	−0.0017**	−0.0017**	−0.0017**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
(30, 35]mm	−0.0005	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0009)	(0.0009)	(0.0009)	(0.0010)	(0.0010)
(35, 40]mm	0.0010	0.0010	0.0010	0.0010	0.0010
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
(40, 45]mm	−0.0004	−0.0004	−0.0004	−0.0004	−0.0004
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
(45, 50]mm	−0.0004	−0.0004	−0.0004	−0.0004	−0.0004
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
>50 mm	−0.0005	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Log(Y_{it-1})	0.9788***	0.9788***	0.9788***	0.9788***	0.9788***
	(0.0021)	(0.0023)	(0.0026)	(0.0028)	(0.0029)
Observations	22,341	22,341	22,341	22,341	22,341
R-squared	0.9947	0.9947	0.9947	0.9947	0.9947

Note: Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 7

The effects of temperature and precipitation on three industries with different bin widths.

	(1)	(2)	(3)	(4)	(5)
Variables	log(VAPI)	log(VASI)	log(VATI)	log(GOEDS)	log(VANA)
<−15 °C	−0.0006	0.0007	−0.0014**	0.0018	−0.0008
	(0.0007)	(0.0008)	(0.0006)	(0.0014)	(0.0007)
[−15, −12)°C	−0.0008	0.0008	0.0003	0.0006	0.0001
	(0.0009)	(0.0010)	(0.0007)	(0.0016)	(0.0007)
[−12, −9)°C	−0.0008	0.0016*	−0.0006	0.0006	0.0002
	(0.0007)	(0.0008)	(0.0006)	(0.0018)	(0.0006)
[−9, −6)°C	0.0003	0.0013*	0.0005	0.0004	0.0007
	(0.0006)	(0.0008)	(0.0005)	(0.0014)	(0.0006)
[−6, −3)°C	0.0002	−0.0004	−0.0008	0.0007	−0.0008
	(0.0006)	(0.0006)	(0.0006)	(0.0013)	(0.0005)
[−3, 0)°C	0.0010*	0.0019***	0.0000	0.0015	0.0005
	(0.0005)	(0.0006)	(0.0004)	(0.0011)	(0.0004)
[0, 3)°C	0.0002	0.0003	−0.0004	0.0011	−0.0001
	(0.0004)	(0.0005)	(0.0004)	(0.0009)	(0.0004)
[3, 6)°C	0.0005	0.0009**	−0.0000	−0.0007	0.0001
	(0.0003)	(0.0005)	(0.0004)	(0.0008)	(0.0003)
[6, 9)°C	0.0001	0.0008*	−0.0002	−0.0000	0.0001
	(0.0003)	(0.0005)	(0.0003)	(0.0008)	(0.0003)
[9, 12)°C	−0.0006*	−0.0000	−0.0005*	−0.0005	−0.0003
	(0.0003)	(0.0004)	(0.0003)	(0.0007)	(0.0003)
[12, 15)°C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 18)°C	0.0001	−0.0002	0.0001	0.0001	0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0008)	(0.0003)
[18, 21)°C	−0.0001	−0.0006	−0.0003	−0.0009	−0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0007)	(0.0003)
[21, 24)°C	−0.0011***	−0.0003	−0.0003	−0.0013*	−0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0007)	(0.0003)
[24, 27)°C	−0.0023***	−0.0008*	−0.0003	−0.0006	−0.0002
	(0.0004)	(0.0004)	(0.0003)	(0.0008)	(0.0003)
[27, 30)°C	−0.0032***	−0.0007	−0.0000	0.0003	0.0000

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Appendix Table 7 (*continued*)

	(1)	(2)	(3)	(4)	(5)
Variables	log(VAPI)	log(VASI)	log(VATI)	log(GOEDS)	log(VANA)
	(0.0006)	(0.0005)	(0.0004)	(0.0009)	(0.0004)
≥30 °C	−0.0040***	0.0003	0.0002	0.0012	0.0006
	(0.0007)	(0.0007)	(0.0005)	(0.0011)	(0.0005)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 10]mm	−0.0001	−0.0000	0.0000	0.0002	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0001)
(10, 20]mm	−0.0006*	0.0003	0.0002	−0.0013*	0.0005
	(0.0003)	(0.0005)	(0.0004)	(0.0008)	(0.0004)
(20, 30]mm	−0.0016***	−0.0002	−0.0006	0.0007	−0.0004
	(0.0005)	(0.0007)	(0.0005)	(0.0012)	(0.0005)
(30, 40]mm	−0.0021***	−0.0005	−0.0009	0.0003	0.0002
	(0.0008)	(0.0010)	(0.0008)	(0.0016)	(0.0008)
(40, 50]mm	−0.0036***	0.0015	−0.0011	0.0057**	0.0009
	(0.0010)	(0.0015)	(0.0011)	(0.0023)	(0.0010)
>50 mm	−0.0028***	0.0004	0.0009	0.0025	0.0008
	(0.0010)	(0.0014)	(0.0009)	(0.0020)	(0.0009)
Observations	25,823	25,766	24,800	19,258	24,984
R-squared	0.9708	0.9724	0.9763	0.9641	0.9882

Note: VAPI is short for value added of primary industry. VASI is short for value added of secondary industry. VATI is short for value added of tertiary industry. GOEDS is short for gross output of enterprises above designated size. VANA is short for value added of non-agricultural sector. Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 8

The effects of daily temperature and precipitation on agricultural products.

	(1)	(2)	(3)	(4)	(5)
Variables	log(GVAO)	log(grains)	log(oil crops)	log(cotton)	log(meat)
<−15 °C	0.0014	−0.0029***	−0.0017	0.0069	−0.0006
	(0.0011)	(0.0011)	(0.0019)	(0.0043)	(0.0008)
[−15, −10)°C	−0.0002	−0.0027***	−0.0025	−0.0055*	0.0001
	(0.0010)	(0.0010)	(0.0017)	(0.0028)	(0.0007)
[−10, −5)°C	0.0002	−0.0023***	−0.0010	0.0002	−0.0000
	(0.0009)	(0.0008)	(0.0013)	(0.0022)	(0.0006)
[−5, 0)°C	0.0008	0.0002	−0.0006	−0.0024	0.0005
	(0.0008)	(0.0007)	(0.0010)	(0.0019)	(0.0005)
[0, 5)°C	0.0018***	−0.0006*	0.0001	0.0009	−0.0001
	(0.0006)	(0.0004)	(0.0007)	(0.0014)	(0.0004)
[5, 10)°C	0.0008*	−0.0001	−0.0002	0.0002	−0.0002
	(0.0005)	(0.0003)	(0.0006)	(0.0012)	(0.0003)
[10, 15)°C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 20)°C	−0.0002	0.0002	0.0003	−0.0025*	0.0005*
	(0.0004)	(0.0003)	(0.0006)	(0.0014)	(0.0003)
[20, 25)°C	−0.0019***	−0.0009**	0.0000	−0.0022	0.0007**
	(0.0005)	(0.0004)	(0.0007)	(0.0016)	(0.0003)
[25, 30)°C	−0.0034***	−0.0036***	−0.0031***	−0.0019	0.0010**
	(0.0007)	(0.0006)	(0.0010)	(0.0018)	(0.0004)
≥30 °C	−0.0046***	−0.0047***	−0.0045***	−0.0031	0.0015**
	(0.0014)	(0.0009)	(0.0014)	(0.0023)	(0.0007)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 5]mm	−0.0001	0.0002	0.0006	0.0004	0.0005**
	(0.0004)	(0.0003)	(0.0004)	(0.0007)	(0.0002)
(5, 10]mm	0.0013	−0.0005	−0.0019**	0.0001	0.0008**
	(0.0009)	(0.0005)	(0.0008)	(0.0014)	(0.0004)
(10, 15]mm	0.0001	−0.0013**	−0.0029***	0.0011	0.0014**
	(0.0009)	(0.0006)	(0.0010)	(0.0018)	(0.0006)
(15, 20]mm	−0.0015	−0.0009	0.0003	0.0051**	−0.0002
	(0.0012)	(0.0007)	(0.0012)	(0.0022)	(0.0007)
(20, 25]mm	−0.0049***	−0.0014	−0.0009	0.0008	0.0009
	(0.0015)	(0.0009)	(0.0016)	(0.0028)	(0.0010)
(25, 30]mm	−0.0029	0.0003	−0.0042**	−0.0001	−0.0014
	(0.0019)	(0.0010)	(0.0019)	(0.0034)	(0.0011)
(30, 35]mm	−0.0023	−0.0033**	−0.0054**	0.0034	0.0004
	(0.0023)	(0.0013)	(0.0022)	(0.0043)	(0.0013)

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Appendix Table 8 (*continued*)

	(1)	(2)	(3)	(4)	(5)
Variables	log(GVAO)	log(grains)	log(oil crops)	log(cotton)	log(meat)
(35, 40]mm	−0.0042*	−0.0055***	−0.0120***	−0.0032	−0.0027
	(0.0025)	(0.0015)	(0.0030)	(0.0049)	(0.0018)
(40, 45]mm	−0.0075*	−0.0037**	−0.0046	−0.0026	−0.0015
	(0.0039)	(0.0016)	(0.0031)	(0.0057)	(0.0019)
(45, 50]mm	−0.0029	−0.0076***	−0.0100***	−0.0037	−0.0028
	(0.0038)	(0.0021)	(0.0038)	(0.0078)	(0.0022)
>50 mm	−0.0037	−0.0079***	−0.0075***	−0.0139***	0.0010
	(0.0026)	(0.0014)	(0.0026)	(0.0046)	(0.0014)
Observations	17,283	25,772	23,824	12,015	25,043
R-squared	0.9589	0.9904	0.9300	0.9730	0.9617

Note: GVAO is short for the gross value of agricultural outputs. Dependent variables of the second to fourth columns are grain output, oil crops output, and meat output. Grains include rice, wheat, corn, beans, and tubers. Oil crops include peanuts, rapeseed, and sesame. Major meat products in China are pork, poultry, beef, and mutton. Conley standard errors are reported in parentheses. All columns include region by year fixed effect, county fixed effect, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 9
The effects of temperature and precipitation on agricultural products with different bin widths.

	(1)	(2)	(3)	(4)	(5)
Variables	log(GVAO)	log(grains)	log(oil crops)	log(cotton)	log(meat)
<−15 °C	0.0008	−0.0029**	−0.0020	0.0053	−0.0003
	(0.0012)	(0.0011)	(0.0019)	(0.0045)	(0.0008)
[−15, −12)°C	−0.0020	−0.0029*	−0.0011	−0.0077*	0.0001
	(0.0016)	(0.0016)	(0.0026)	(0.0041)	(0.0011)
[−12, −9)°C	0.0003	−0.0027**	−0.0046**	−0.0039	0.0005
	(0.0012)	(0.0012)	(0.0019)	(0.0035)	(0.0008)
[−9, −6)°C	−0.0008	−0.0022**	−0.0001	−0.0014	−0.0004
	(0.0011)	(0.0010)	(0.0016)	(0.0027)	(0.0007)
[−6, −3)°C	0.0001	−0.0010	−0.0007	−0.0025	0.0012*
	(0.0010)	(0.0009)	(0.0016)	(0.0024)	(0.0007)
[−3, 0)°C	0.0005	0.0006	−0.0005	−0.0038*	0.0003
	(0.0009)	(0.0008)	(0.0012)	(0.0022)	(0.0006)
[0, 3)°C	0.0003	−0.0009	−0.0010	0.0003	0.0002
	(0.0009)	(0.0006)	(0.0010)	(0.0017)	(0.0005)
[3, 6)°C	0.0022***	−0.0004	0.0008	−0.0003	−0.0000
	(0.0008)	(0.0005)	(0.0008)	(0.0017)	(0.0004)
[6, 9)°C	0.0003	−0.0001	−0.0006	−0.0006	−0.0002
	(0.0006)	(0.0004)	(0.0008)	(0.0015)	(0.0004)
[9, 12)°C	−0.0002	−0.0005	−0.0012*	−0.0020	0.0000
	(0.0006)	(0.0004)	(0.0007)	(0.0015)	(0.0004)
[12, 15)°C	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
[15, 18)°C	−0.0005	−0.0001	−0.0005	−0.0046***	0.0002
	(0.0006)	(0.0004)	(0.0007)	(0.0016)	(0.0003)
[18, 21)°C	−0.0003	−0.0002	0.0004	−0.0017	0.0011***
	(0.0005)	(0.0004)	(0.0007)	(0.0019)	(0.0004)
[21, 24)°C	−0.0027***	−0.0015***	−0.0005	−0.0042**	0.0005
	(0.0007)	(0.0005)	(0.0008)	(0.0020)	(0.0004)
[24, 27)°C	−0.0040***	−0.0038***	−0.0031***	−0.0032	0.0008*
	(0.0008)	(0.0006)	(0.0010)	(0.0020)	(0.0004)
[27, 30)°C	−0.0048***	−0.0047***	−0.0043***	−0.0038*	0.0012**
	(0.0010)	(0.0008)	(0.0012)	(0.0023)	(0.0006)
≥30 °C	−0.0059***	−0.0055***	−0.0055***	−0.0051*	0.0014*
	(0.0016)	(0.0009)	(0.0015)	(0.0026)	(0.0007)
0 mm	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)
(0, 10]mm	−0.0002	0.0001	0.0004	0.0002	0.0004**
	(0.0004)	(0.0003)	(0.0004)	(0.0007)	(0.0002)
(10, 20]mm	−0.0013	−0.0012**	−0.0021**	0.0017	0.0006
	(0.0008)	(0.0005)	(0.0008)	(0.0014)	(0.0005)
(20, 30]mm	−0.0047***	−0.0007	−0.0020	−0.0002	−0.0001
	(0.0014)	(0.0008)	(0.0013)	(0.0024)	(0.0008)
(30, 40]mm	−0.0035*	−0.0040***	−0.0075***	0.0005	−0.0010
	(0.0019)	(0.0011)	(0.0019)	(0.0037)	(0.0011)
(40, 50]mm	−0.0059*	−0.0052***	−0.0062**	−0.0029	−0.0020
	(0.0032)	(0.0014)	(0.0026)	(0.0050)	(0.0015)

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Appendix Table 9 (*continued*)

	(1)	(2)	(3)	(4)	(5)
Variables	log(GVAO)	log(grains)	log(oil crops)	log(cotton)	log(meat)
>50 mm	−0.0038	−0.0077***	−0.0071***	−0.0145***	0.0010
	(0.0026)	(0.0014)	(0.0026)	(0.0045)	(0.0014)
Observations	17,283	25,772	23,824	12,015	25,043
R-squared	0.9591	0.9904	0.9301	0.9731	0.9617

Note: GVAO is short for gross value of agricultural outputs. Dependent variables of the second to fifth columns are grain output, oil crops output, cotton output, and meat output. Grains include rice, wheat, corn, beans, and tubers. Oil crops include peanuts, rapeseed, and sesame. Major meat products in China are pork, poultry, beef, and mutton. Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 10
Temperatures' effects on agriculture in hot counties and cold counties.

Variables	(1)	(2)	(3)	(4)
	high-heat county	low-heat county	hot county	cold county
	log(VAPI)	log(VAPI)	log(VAPI)	log(VAPI)
<−15 °C	–	0.0357	–	0.0351
	(−)	(0.0269)	(−)	(0.0293)
[−15, −10)°C	–	0.0138	–	0.0169
	(−)	(0.0124)	(−)	(0.0121)
[−10, −5)°C	–	0.0005	–	−0.0010
	(−)	(0.0025)	(−)	(0.0026)
[−5, 0)°C	−0.0872	0.0039***	–	0.0042***
	(0.0736)	(0.0014)	(−)	(0.0014)
[0, 5)°C	−0.0009	0.0018***	−0.0010	0.0012*
	(0.0062)	(0.0007)	(0.0059)	(0.0007)
[5, 10)°C	−0.0007	−0.0003	−0.0003	−0.0006
	(0.0014)	(0.0005)	(0.0008)	(0.0005)
[10, 15)°C	0	0	0	0
	(−)	(−)	(−)	(−)
[15, 20)°C	0.0006	0.0000	0.0005	−0.0008*
	(0.0007)	(0.0004)	(0.0004)	(0.0005)
[20, 25)°C	0.0010	−0.0009*	0.0010**	−0.0021***
	(0.0008)	(0.0005)	(0.0005)	(0.0007)
[25, 30)°C	0.0009	−0.0026***	0.0008	−0.0043***
	(0.0009)	(0.0007)	(0.0005)	(0.0010)
≥30 °C	0.0011	−0.0031**	0.0008	−0.0027
	(0.0010)	(0.0015)	(0.0006)	(0.0023)
Observations	8028	17,795	15,005	10,818
R-squared	0.9876	0.9648	0.9839	0.9629
Variables	log(GVAO)	log(GVAO)	log(GVAO)	log(GVAO)
<−15 °C	–	0.0560**	–	0.0425*
	(−)	(0.0222)	(−)	(0.0238)
[−15, −10)°C	–	−0.0019	–	0.0001
	(−)	(0.0145)	(−)	(0.0139)
[−10, −5)°C	–	−0.0011	–	−0.0049
	(−)	(0.0030)	(−)	(0.0032)
[−5, 0)°C	−0.4532*	0.0018	–	0.0012
	(0.2466)	(0.0023)	(−)	(0.0022)
[0, 5)°C	−0.0211	0.0012	0.0166	0.0009
	(0.0159)	(0.0009)	(0.0128)	(0.0010)
[5, 10)°C	−0.0012	−0.0008	−0.0015	−0.0009
	(0.0035)	(0.0007)	(0.0025)	(0.0007)
[10, 15)°C	0	0	0	0
	(−)	(−)	(−)	(−)
[15, 20)°C	−0.0007	−0.0011*	0.0017	−0.0016**
	(0.0017)	(0.0007)	(0.0012)	(0.0008)
[20, 25)°C	−0.0012	−0.0019*	0.0027*	−0.0020*
	(0.0024)	(0.0010)	(0.0015)	(0.0012)
[25, 30)°C	−0.0007	−0.0028**	0.0035*	−0.0039***
	(0.0027)	(0.0011)	(0.0018)	(0.0014)
≥30 °C	−0.0033	−0.0009	0.0029	−0.0042
	(0.0034)	(0.0026)	(0.0024)	(0.0030)
Observations	5402	11,881	9842	7441
R-squared	0.9746	0.9539	0.9716	0.9515

Note: VAPI is short for value added of primary industry. GVAO is short for the gross value of agricultural outputs. Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature

and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. Some bins do not have coefficients because our data has a limited number of days in these bins. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 11
The mitigating effect of air conditioning.

	high AC penetration		low AC penetration	
	(1)	(2)	(3)	(4)
Variables	log(GDP)	log(VAPI)	log(GDP)	log(VAPI)
<−15 °C	−0.00068	0.00264	−0.00047*	−0.00009
	(0.00100)	(0.00166)	(0.00024)	(0.00030)
[−15, −10)°C	0.00016	−0.00259**	−0.00003	−0.00027
	(0.00086)	(0.00126)	(0.00042)	(0.00052)
[−10, −5)°C	−0.00108*	−0.00178**	0.00037	0.00044
	(0.00063)	(0.00069)	(0.00035)	(0.00045)
[−5, 0)°C	−0.00030	−0.00050	0.00002	0.00135**
	(0.00049)	(0.00048)	(0.00037)	(0.00053)
[0, 5)°C	−0.00018	−0.00071**	−0.00006	0.00058
	(0.00032)	(0.00032)	(0.00034)	(0.00038)
[5, 10)°C	0.00009	0.00007	0.00004	0.00002
	(0.00025)	(0.00027)	(0.00033)	(0.00033)
[10, 15)°C	0	0	0	0
	(−)	(−)	(−)	(−)
[15, 20)°C	0.00063**	0.00056*	−0.00060**	−0.00051
	(0.00031)	(0.00031)	(0.00030)	(0.00036)
[20, 25)°C	0.00020	0.00043	−0.00097***	−0.00158***
	(0.00033)	(0.00032)	(0.00035)	(0.00050)
[25, 30)°C	−0.00016	−0.00053	−0.00093**	−0.00287***
	(0.00038)	(0.00036)	(0.00043)	(0.00064)
≥30 °C	−0.00035	−0.00063	0.00329*	−0.00204
	(0.00047)	(0.00047)	(0.00198)	(0.00245)
Observations	14,314	14,570	11,111	11,253
R-squared	0.99653	0.98412	0.98298	0.95818

Note: VAPI is short for value added of primary industry. Data of air conditioning is cross-section data in the year 2008 at the province level. A province is defined as high (low) penetration province if its air conditioning penetration rate is larger (smaller) than the sample average. Conley standard errors are reported in parentheses. Controls include county and year fixed effects, precipitation, lagged weather variables, and lagged dependent variables. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table 12
Temperatures' effects on crops in agricultural and non-agricultural counties.

Variables	Agricultural county		Non-agricultural county	
	(1)	(2)	(3)	(4)
	log(grains)	log(oil crops)	log(grains)	log(oil crops)
<−15 °C	–	–	0.0482	0.1099
	(−)	(−)	(0.0502)	(0.2978)
[−15, −10)°C	0.0150	0.0012	0.0063	0.1076**
	(0.0411)	(0.0525)	(0.0198)	(0.0497)
[−10, −5)°C	−0.0070	0.0874***	0.0026	0.0374**
	(0.0075)	(0.0275)	(0.0075)	(0.0147)
[−5, 0)°C	0.0083*	0.0228***	−0.0012	0.0175***
	(0.0045)	(0.0087)	(0.0028)	(0.0060)
[0, 5)°C	−0.0065**	0.0039	−0.0015	0.0043**
	(0.0025)	(0.0046)	(0.0012)	(0.0021)
[5, 10)°C	−0.0033**	0.0028	−0.0016**	−0.0022*
	(0.0014)	(0.0026)	(0.0008)	(0.0013)
[10, 15)°C	0	0	0	0
	(−)	(−)	(−)	(−)
[15, 20)°C	0.0017*	−0.0010	0.0002	−0.0010
	(0.0009)	(0.0015)	(0.0006)	(0.0010)
[20, 25)°C	0.0011	−0.0012	−0.0009	−0.0036**
	(0.0011)	(0.0018)	(0.0009)	(0.0015)
[25, 30)°C	−0.0004	−0.0039*	−0.0026**	−0.0078***
	(0.0013)	(0.0021)	(0.0013)	(0.0019)
≥30 °C	−0.0013	−0.0053**	−0.0035**	−0.0097***
	(0.0015)	(0.0026)	(0.0017)	(0.0024)
Observations	10,178	9648	15,594	14,176
R-squared	0.9960	0.9140	0.9831	0.9397

Note: Grains include rice, wheat, corn, beans, and tubers. Oil crops contain peanuts, rapeseed, and sesame. Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. The

temperature bin below −15 °C in column 1 and column 2 does not have coefficients because our data has a limited number of days below −15 °C in agricultural counties during the growing season. *** p < 0.01, ** p < 0.05, * p < 0.1.

Appendix Table 13

Temperatures' effects on agricultural and non-agricultural counties.

	Agricultural county		Non-agricultural county			
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	log(GDP)	log(VAPI)	log(GVAO)	log(GDP)	log(VAPI)	log(GVAO)
<−15 °C	−0.0011*	0.0016	0.0166	−0.0006	0.0729	–
	(0.0007)	(0.0194)	(0.0265)	(0.0007)	(0.0900)	(−)
[−15, −10)°C	−0.0001	0.0314**	0.0130	0.0003	0.0074	0.0307*
	(0.0006)	(0.0125)	(0.0189)	(0.0006)	(0.0155)	(0.0175)
[−10, −5)°C	0.0003	−0.0004	0.0033	−0.0004	0.0042	0.0010
	(0.0005)	(0.0030)	(0.0044)	(0.0005)	(0.0037)	(0.0044)
[−5, 0)°C	0.0003	0.0026*	−0.0013	0.0001	0.0047**	0.0054*
	(0.0005)	(0.0014)	(0.0025)	(0.0004)	(0.0022)	(0.0032)
[0, 5)°C	−0.0003	0.0007	0.0008	0.0001	0.0032***	0.0018
	(0.0004)	(0.0007)	(0.0011)	(0.0003)	(0.0011)	(0.0015)
[5, 10)°C	0.0004	0.0006	0.0002	−0.0000	−0.0005	−0.0023**
	(0.0003)	(0.0005)	(0.0008)	(0.0003)	(0.0006)	(0.0010)
[10, 15)°C	0	0	0	0	0	0
	(−)	(−)	(−)	(−)	(−)	(−)
[15, 20)°C	0.0001	0.0005	0.0003	−0.0003	0.0002	−0.0012
	(0.0003)	(0.0004)	(0.0007)	(0.0002)	(0.0005)	(0.0008)
[20, 25)°C	−0.0005*	−0.0005	−0.0005	−0.0006**	−0.0006	−0.0026**
	(0.0003)	(0.0005)	(0.0009)	(0.0003)	(0.0006)	(0.0012)
[25, 30)°C	−0.0007*	−0.0015**	−0.0008	−0.0009***	−0.0024***	−0.0036**
	(0.0004)	(0.0006)	(0.0011)	(0.0003)	(0.0008)	(0.0014)
≥30 °C	−0.0008	−0.0020**	−0.0022	−0.0010**	−0.0038***	−0.0032
	(0.0006)	(0.0009)	(0.0022)	(0.0005)	(0.0010)	(0.0020)
Observations	11,623	12,103	7719	13,327	13,720	9564
R-squared	0.9879	0.9711	0.9581	0.9954	0.9742	0.9636

Note: VAPI is short for value added of primary industry. GVAO is short for the gross value of agricultural outputs. Conley standard errors are reported in parentheses. All columns include region by year fixed effects, county fixed effects, lagged dependent variable, lagged temperature and precipitation bins, other weather variables X_{it}, and their quadratic terms X_{it}^2 and their lagged terms X_{it-1} and X_{it-1}^2. *** p < 0.01, ** p < 0.05, * p < 0.1.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., & Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics, 65*, 103207.

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Soel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy, 7*(2), 181–198.

Auffhammer, M., & Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics, 46*, 555–561.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., & Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900–2004. *American Economic Review, 105*, 247–251.

Brandt, L., Van Biesebroeck, J., Wang, L., & Zhang, Y. (2019). WTO accession and performance of Chinese manufacturing firms: Corrigendum. *American Economic Review, 109*, 1616–1621.

Brandt, L., Van Biesebroeck, J., & Zhang, Y. (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics, 97*, 339–351.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from U.S. agriculture. *American Economic Journal: Economic Policy, 8*, 106–140.

Cachon, G., Gallino, S., & Olivares, M. (2012). *Severe weather and automobile assembly productivity* (Working Paper).

Chen, S., Chen, X., & Xu, J. (2016). Impacts of climate change on agriculture: Evidence from China. *Journal of Environmental Economics and Management, 76*, 105–124.

Chen, S., & Gong, B. (2021). Response and adaptation of agriculture to climate change: Evidence from China. *Journal of Development Economics, 148*, 102557.

Chen, X., & Yang, L. (2019). Temperature and industrial output: Firm-level evidence from China. *Journal of Environmental Economics and Management, 95*, 257–274.

Conley, T. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics, 92*, 1–45.

Damania, R., Desbureaux, S., & Zaveri, E. (2020). Does rainfall matter for economic growth? Evidence from global sub-national data (1990-2014). *Journal of Environmental Economics and Management, 102*, 102335.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics, 4*, 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature, 52*, 740–798.

Deryugina, T., & Hsiang, S. M. (2014). *Does the environment still matter? Daily temperature and income in the United States* (Working Paper).

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review, 97*, 354–385.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the U.S. *American Economic Journal: Applied Economics, 3*, 152–185.

Fisher, A. C., Michael Hanemann, W., Roberts, M. J., & Schlenker, W. (2012). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Comment. *The American Economic Review, 102*, 3749–3760.

Fishman, R. M. (2013). *Climate change, rainfall variability, and adaptation through irrigation: Evidence from Indian agriculture* (Working Paper).

Fleischer, A., Mendelsohn, R., & Dinar, A. (2011). Bundling agricultural technologies to adapt to climate change. *Technological Forecasting and Social Change, 78*, 982–990.

Graff Zivin, J., Liu, T., Song, Y., Tang, Q., & Zhang, P. (2020). The unintended impacts of agricultural fires: Human capital in China. *Journal of Development Economics, 147*, 102560.
Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics, 32*, 1–26.
Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences, 107*, 15367–15372.
Jones, B. F., & Olken, B. A. (2010). Climate shocks and exports. *American Economic Review, 100*, 454–459.
Lee, J. J., Gino, F., & Staats, B. R. (2014). Rainmakers: Why bad weather means good productivity. *Journal of Applied Psychology, 99*, 504–513.
Li, C., Cong, J., & Gu, H. (2020). Could weather fluctuations affect local economic growth? Evidence from counties in the People's Republic of China. *Asian Development Review, 37*, 201–224.
Li, C., Cong, J., & Yin, L. (2021). Extreme heat and exports: Evidence from Chinese exporters. *China Economic Review, 66*, 101593.
Manning, D. T., Goemans, C., & Maas, A. (2017). Producer responses to surface water availability and implications for climate change adaptation. *Land Economics, 93*, 631–653.
Newell, R., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: Implication for climate change damages. *Journal of Environmental Economics and Management, 108*, 102445.
Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica, 49*, 1417–1426.
Niemela, R., Hannula, M., Rautio, S., Reijula, K., & Railio, J. (2002). The effect of air temperature on labor productivity in call centers: A case study. *Energy and Buildings, 34*, 759–764.
Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., , … Dasgupta, P., et al. (2014). *Climate change 2014: Synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change*. IPCC.
Park, J. (2016). *Will we adapt? Temperature shocks, labor productivity, and adaptation to climate change in the United States* (Working Paper).
Schlenker, W., & Roberts, M. J. (2009). Non-linear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences, 106*, 15594–15598.
Seppanen, O., Fisk, W. J., & Lei, Q. H. (2006). *Effect of temperature on task performance in office environment* (Working Paper).
Taraz, V. (2017). Adaptation to climate change: Historical evidence from the Indian monsoon. *Environment and Development Economics, 22*, 517–545.
Zhang, P., Deschênes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management, 88*, 1–17.
Zhang, P., Zhang, J., & Chen, M. (2017). Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. *Journal of Environmental Economics and Management, 83*, 8–31.