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Temperature and industrial output: Firm-level evidence from China☆

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ABSTRACT

We pair a firm-level panel of annual industrial output with a fine-scale daily weather data set, to estimate the responses of industrial output to temperature changes in China. We have four primary findings. First, industrial output is nonlinear in temperature changes. With seasonal average temperatures as temperature variables, output responds positively to higher spring temperatures and negatively to elevated summer temperatures. With temperature bins as temperature variables, output increases linearly with temperature up to 21–24 °C, and then declines sharply at higher temperatures. Second, lagged temperature changes exert large and significant impacts on current year's output. Third, higher summer temperatures have larger detrimental effects on output in low-temperature regions than in high-temperature regions, which suggests that adaptation to warming may have been actively undertaken in high-temperature regions in China. Lastly, industrial output in China is projected to decrease by 3–36% by 2080 under the slowest warming scenario (B1) and by 12–46% under the most rapid warming scenario (A2) under the global climate models UKMO-HadCM3 and PCM.

Introduction

With accumulating evidence that the world is becoming warmer, many studies have assessed the effects of high temperatures on economic output, estimated impacts that may occur under different warming scenarios, and discussed how economies should adapt to a warmer climate. Because of agriculture's direct link with atmospheric conditions, that sector's vulnerability to high temperatures has been the focus of many studies estimating the impacts of climate change (see Chen et al. (2016), Deschênes and Greenstone (2007), Mendelsohn et al. (1994), Schlenker and Roberts (2009)). Compared to the agricultural sector, the industrial sector accounts for a much larger share of gross domestic product (GDP) in many countries around the world. However, studies evaluating the impacts of temperature changes on industrial output, particularly studies using fine-scale, micro-level data, remain scant. That may be the case because micro-level data at the sub-country level or firm level are not readily available, particularly in developing countries.

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An exception is Zhang et al. (2016). Using a panel data set of Chinese manufacturing firms from 1998 to 2007, they analyze the effects of temperature on output, total factor productivity (TFP), and input use. They find that output and TFP exhibit nonlinear responses to temperature, while temperature has very limited impacts on input use. Building on Zhang et al. (2016), we also examine whether industrial output in China has been affected by temperature changes, and, if so, to what extent. Using the same firm-level panel data from 1998 to 2007 as in Zhang et al. (2016), combined with a fine-scale daily weather data set during the same period, we exploit random variations in temperature within firms over time to identify the effects of temperature on industrial output in China. Although our paper is similar to Zhang et al. (2016), it differs in several key aspects. First, we identify the temperature effects on output more comprehensively, as we use two different approaches to construct temperature variables. In addition to using temperature bins as temperature variables, as in Zhang et al. (2016), we examine the temperature effects on output using seasonal average temperatures as temperature variables. This allows us to combine our parameter estimates of seasonal average temperature variables with existing global climate projections, which are typically only available at monthly or seasonal frequencies, to assess potential impacts of future warming. Second, we include sunshine duration as an explanatory variable. Because sunlight has been considered an important factor affecting human health and labor productivity (De Witte and Saal, 2010; Lambert et al., 2002; Patz et al., 2005) and is highly correlated with temperature, omitting this variable in the regression analysis could lead to biased parameter estimates of the temperature effects on output. Third, when using temperature bins as temperature variables, we identify the critical temperature threshold above and below which is detrimental to industrial output, whereas Zhang et al. (2016) focus only on the effects of high temperatures (above 32 °C) on output. Identification of this critical temperature threshold is essential for the development of strategies to adapt to an uncertain future in global climate change (Hallegatte, 2009).

For the reasons discussed above, we have different findings than Zhang et al. (2016).[1] Zhang et al. (2016) find very limited impacts of lagged temperatures on output and limited adaptation to high temperatures. In contrast, we show that lagged temperature changes have significant impacts on current year's output. We also provide suggestive evidence that adaptation to warming may have been actively undertaken in high-temperature regions in China. In addition to the output effect, we also want to understand the mechanisms through which temperature affects output. While Zhang et al. (2016) find that output losses stem mainly from the negative response of TFP to high temperatures, we show that the reduction in firms' investment and the increase in inventory levels in response to high temperatures are two other drivers behind output losses.

To obtain the net economic impact of temperature on output, while accounting for simultaneous variations in temperature and other weather variables, we include a comprehensive set of weather variables in the regression analysis. In addition to temperature, we incorporate rainfall, sunshine duration, air pressure, relative humidity and average wind speed. To minimize the estimation biases originating from omitted variables, we also control for time-invariant firm fixed effects and industry × year fixed effects. We intentionally exclude non-weather variables (such as input/output prices and adaptation variables) in the regression analysis, to obtain the total marginal effects of temperature on output. These marginal effects are the sum of the direct effect of temperature on output and the indirect effect of temperature on output (through temperature's influence on input productivity, prices of inputs and output, and adaptation actions).

As noted above, we use two different approaches to construct temperature variables. We first use seasonal average temperatures as temperature variables to examine whether there exist differential effects of temperature on industrial output. We find that key results remain similar when temperature bins are used to represent the relationship between temperature and industrial output. Our central finding is that industrial output exhibits nonlinear responses to temperature changes. When seasonal average temperatures are used as temperature variables, output exhibits a *positive* response to higher spring temperatures and a *negative* response to higher summer temperatures. Our estimates of the negative effect on output stemming from increased summer temperatures (3.5–5.6%/1 °C) are larger than the previous assessments for other countries (Dell et al., 2012; Deryugina and Hsiang, 2014; Hsiang, 2010). When temperature bins are used as temperature variables, output increases with temperature up to 21–24 °C, and then declines sharply at higher temperatures. The critical temperature threshold identified here is consistent with prior studies based on high-frequency micro-level data (Zivin and Neidell, 2014). We also find that temperature changes in prior years exert large and significant impacts on current year's output. These findings remain broadly consistent to variations in model specifications, econometric estimation strategies, and data.

Moreover, we find substantial heterogeneity in the effects of temperature on output across industries. Ferrous metal mining, timber, and rubber are the three industries most affected by higher summer temperatures, while stationary and office machinery are most affected by higher winter temperatures. We also find that higher temperatures lead to a much larger reduction in industrial output in low-temperature regions than in high-temperature regions. This finding suggests possible human adaptation to global warming in high-temperature regions. Even with this apparent adaptation, industrial output in China is projected to experience a significant reduction before the end of this century under warming scenarios provided by the most recent versions of global climate models.

[1] To investigate the possible causes of the differences in findings between our study and Zhang et al. (2016), we use the same model specification as in Zhang et al. (2016) to replicate their results. However, the differences in findings still exist. There are two possible explanations. One, we use different weather data. We collect the most detailed weather data available from the China Meteorological Data Sharing Service System (CMDSSS), which records daily weather outcomes for 820 weather stations. Zhang et al. (2016) rely on the weather data reported by the US National Oceanic and Atmospheric Administration, which has only 400 stations covering China. Two, Zhang et al. (2016) control for visibility, which is not reported by the CMDSSS and thus cannot be incorporated in our analysis.

Based on coarse macro-level data, several studies have found large correlations between temperature and industrial output (Burke et al., 2015; Dell et al., 2012; Hsiang, 2010). For instance, using a sample of 28 Caribbean and Central American countries over the 1970–2006 period, Hsiang (2010) analyzes the effects of temperature and cyclones on economic output (measured by value added per capita), while controlling for rainfall. He finds that, for a 1 °C increase in surface temperature during the hottest season, national output falls 2.5%, with output losses in nonagricultural industries significantly exceeding the losses in agricultural industries (2.4%/1 °C vs. 0.1%/1 °C). Dell et al. (2012) examine how variations in temperature and rainfall affect the growth of industrial output, with a sample of 125 counties over the 1950–2003 period. They find that the growth of industrial output declines approximately 2.4% for a 1 °C increase in annual average temperature, but only in poor countries. More recently, Burke et al. (2015) analyze a global sample of 166 countries from 1960 to 2010 and show that global economic productivity exhibits nonlinear responses to temperature in all countries. They find that productivity increases with annual average temperature up to 13 °C and declines sharply at higher temperatures. Cachon et al. (2012) analyze a micro-level data set of weekly production from 64 automobile plants in the US over the 1994–2005 period, and find that a week with six or more days above 32 °C can reduce that week's production by roughly 8%.

With the exception of Cachon et al. (2012), the estimates of the temperature effects on output center around a 2–3% output loss for each 1 °C increase in temperature. These estimates are slightly higher than those obtained by studies estimating the temperature effects on national income. For instance, Dell et al. (2012) show that, by reducing agricultural output, industrial output, and political stability, a 1 °C increase in annual average temperature reduces income per capita in poor countries by 1.4%. Deryugina and Hsiang (2014) analyze a county-level panel of weather and income data in the US during the period 1969–2011, and find that income per capita drops about 1.7% for each 1 °C increase in daily average temperature beyond 15 °C.

This paper contributes to the related literature in at least three regards. First, we add to the sparse literature examining the temperature effects on industrial output by using a particularly comprehensive firm-level data set for a large country other than the US. Because the industrial sector contributes about 43% of China's GDP and is the most important economic sector in China, understanding how temperature has affected China's industrial output provides useful information for the development of long-term adaptation strategies to cope with future climate change. Second, in contrast to the previous studies (see Burke et al. (2015), Dell et al. (2012), Hsiang (2010), Zhang et al. (2016)), our empirical analysis includes sunshine duration as an explanatory variable to increase the precision of estimated temperature effects on output. Third, our study provides new suggestive evidence that adaptation to global warming may have been actively undertaken in high-temperature regions in China. This finding goes beyond previous empirical findings, because prior studies only find that countries/regions are better able to cope with environmental changes when they become wealthier (Dell et al., 2012; Hsiang, 2010; Kahn, 2005), not that certain regions may have actually undertaken adaptation in response to high temperatures for a long period of time.

The remainder of the paper is organized as follows. Section Conceptual framework presents a conceptual framework. Section Empirical strategy describes our empirical estimation strategy. Section Data provides data sources and reports descriptive statistics. Section Results presents the main results and considers a number of robustness checks. Section Heterogeneity in the temperature effects across industries examines heterogeneity in the effects of temperature on output across industries. Section Adaptation to high temperatures explores whether adaptations have been undertaken. Section Impacts of future climate change presents the impacts of future climate change. Section Conclusions and discussion concludes.

Conceptual framework

In this section, we develop a simple framework to illustrate the mechanisms through which temperature affects industrial firms' economic performance, such as profit and industrial output. For ease of illustration, here we explain how temperature affects profit. The same logic applies to industrial output.

Consider a profit-maximizing firm that operates in competitive markets and uses N inputs $\mathrm{x} = \{x_1, x_2, \ldots, x_N\}$ to produce an output (y). Let λ_x denote a productivity vector for inputs. The production function of the output is assumed to be constant returns to scale and can be stylized as $\mathrm{y} = \mathrm{Y}(\lambda_x * x)$. Let P_y be the market price of the output and P_x be a non-negative price vector for inputs.

Several studies have demonstrated that temperature (T) can affect market prices of output and inputs by affecting investment decisions and storage levels (Cao and Wei, 2005; Roberts and Schlenker, 2013). Input productivities (λ_x) might also change with temperature (see Dell et al. (2014), Moore and Diaz (2015), Zivin and Neidell (2014)). A firm's adaptation effort, denoted by $\mathrm{A}(T)$, also depends on temperature, and may effectively alleviate the negative effect of high temperatures on input productivities. For example, air conditioners could be installed to mitigate thermal stress on workers. Thus, λ_x depends not only on temperature, but also on $\mathrm{A}(T)$.

The total quantities of some inputs used to produce y might be held fixed in the short term because they cannot be adjusted in response to temperature changes. With this constraint, the firm's profit maximization problem can be represented as follows:

$$\begin{aligned} \pi(P_x, P_y, F) &= Max\{P_y(T) * y - P_x(T) * x - A(T)\} \\ \text{subject to y} &= \mathrm{Y}(\lambda_x(T, A(T)) * x; F) \end{aligned} \tag{1}$$

where F is a vector of the inputs held constant and $Y(\lambda_x(T, A(T)) * x; F)$ is the production function when some inputs are fixed at given levels. Because temperature is an exogenous shift variable, the firm decides the amount of variable inputs and the level of adaptation effort to maximize its profit. By solving the above profit-maximization problem and substituting derived x and $A(T)$ into Eq. (1), we can obtain the restricted profit function $\pi(P_x, P_y, F)$.

From Eq. (1), we can see that the effect of temperature changes on this firm's profit (industrial output) depends on the extent to which temperature affects input productivities, market prices of inputs and output, and the adaptation effort undertaken by the firm. As discussed above, our empirical analysis includes only temperature and other relevant weather variables as explanatory variables and excludes input and output prices and climate adaptation variables, for two reasons. First, we intend to obtain the total marginal effect of temperature on output, defined as the sum of the direct effect and the indirect effect through the channels of input productivities, inputs and output prices, and adaptation. Second, we want to examine whether temperature has any remaining effects on industrial output, net of firms' adjustment in input use and net of all potential climate adaptations in response to temperature changes.

Empirical strategy

We use two different approaches to construct temperature variables and examine the effects of temperature on industrial output. In this section, we describe the two approaches.

Seasonable average temperatures as temperature variables

We first use seasonal average temperatures as temperature variables and examine whether there exist differential effects of temperature on output:

$$\log VA_{r,t} = \alpha_0\, Temp_{r,t} + \sum_{L\geq 1}\alpha_L Temp_{r,t-L} + \beta_0 W_{r,t} + \sum_{L\geq 1}\beta_L W_{r,t-L} + \gamma\Psi^i_t + c_r + \varepsilon_{r,t} \tag{2}$$

where firms are indexed by r, industries are indexed by i and years are indexed by t. Following Hsiang (2010) and Dell et al. (2012), we measure a firm's industrial output using value added per worker.[2] The natural log of value added per worker for firm r in year t is denoted by $\log VA_{r,t}$. Most regions in China have clear distinctions of four seasons. Spring usually begins in March and ends in May, while summer starts in June and ends in August. Fall is September, October and November, and winter includes December, January, and February. To accurately capture the relationship between temperature and industrial output, we construct temperature variables by season, which are denoted by $Temp_{r,t}$. To account for simultaneous variations in temperature and other weather variables, we include rainfall, sunshine duration, air pressure, relative humidity and average wind speed as additional weather variables. We incorporate sums of rainfall and sunshine hours and means of air pressure, relative humidity and average wind speed for each season, which are denoted by $W_{r,t}$. We also include lagged values of weather variables, represented by $Temp_{r,t-L}$ and $W_{r,t-L}$, to examine whether industrial output in year t is affected by weather variations in prior years.

Ψ^i_t denotes two-digit industry × year fixed effects, in order to remove the unobserved factors that are common to all firms in a given year but differ across industries, such as the introduction of a new production technology or changes in trade policies that are specific to industry i. c_r denotes time-invariant firm fixed effects which are used to control for the unobserved firm characteristics that are unique to firm r, such as geographical location. $\varepsilon_{r,t}$ are the error terms that capture the impacts on output of other factors that are not included in Eq. (2).

With the semi-log specification of the regression model, estimated coefficients of temperature variables (α_0 and α_L) can be interpreted as the percentage changes in output with a 1 °C increase in seasonal average temperatures. The main hypothesis is to test whether $\alpha_0 = \alpha_L = 0$, namely, to test the null hypothesis that temperature has no effect on output.

Temperature bins as temperature variables

Following Deryugina and Hsiang (2014), we define temperature variables as a vector of temperature bins, as shown in Eq. (3):

$$\log VA_{r,t} = \sum_m\left[\alpha^m_0 Tbin^m_{r,t} + \sum_{L\geq 1}\alpha^m_L Tbin^m_{r,t-L}\right] + \lambda_0 Weather_{r,t} + \sum_{L\geq 1}\lambda_L Weather_{r,t-L} + \gamma\Psi^i_t + c_r + \varepsilon_{r,t} \tag{3}$$

where $Tbin^m_{r,t}$ denotes the number of days in year t on which daily average temperatures fall into the mth temperature bin in the county where firm r is located. We divide daily average temperatures, measured in °C, into sixteen bins, each of which is

[2] As explained below in the data section, value added is the difference between total output and intermediate input. We will use (industrial) output and value added per worker interchangeably in the remainder of the paper.

3 °C wide. We define $Tbin^1_{r,t}$= number of days when daily average temperature is below − 12 °C, $Tbin^2_{r,t}$= number of days when daily average temperature falls into the range of [− 12 °C, − 9 °C), and so on. Finally, $Tbin^{16}_{r,t}$ = number of days when daily average temperature is above 30 °C. The implicit assumption made here is that the temperature effect on output is consistent within each bin, which is reasonable given the small size of each temperature bin. To avoid multicollinearity, we set the temperature bin [21 °C, 24 °C) as the omitted category (we explain how this bin is selected in Section Robustness checks).[3] The coefficients of the other temperature bins, α^m_0 and α^m_L, thus measure the marginal effect on output of an additional day in the *m*th temperature bin, relative to a day in the [21 °C, 24 °C) bin.

We also include linear and quadratic forms of sums of rainfall and sunshine duration and means of air pressure, relative humidity and average wind speed to capture the potential nonlinear effects of these weather variables on output. These weather variables are denoted by $Weather_{r,t}$. Moreover, lagged values of weather variables, represented by $Tbin^m_{r,t-L}$ and $Weather_{r,t-L}$, are included to examine the effects on output of weather variations in prior years. Two-digit industry × year fixed effects (Ψ^i_t) and firm fixed effects (c_r) included in Eq. (3) are defined in the same way as in Eq. (2).

Method of estimation

The temperature effects on output are identified from the random variations in temperature over time. This identification strategy is consistent with the approaches used by previous studies (Chen et al., 2016; Deryugina and Hsiang, 2014; Deschênes and Greenstone, 2007). The error terms $\varepsilon_{r,t}$ may be spatially correlated because of the omission of spatially correlated explanatory variables and may be serially correlated within a given firm over time. To account for both spatial correlation and serial correlation of the error terms, we estimate standard errors that are clustered within firms and within prefecture-level city-years, using the two-way clustering approach proposed by Cameron et al. (2011). The former (clustering standard errors within firms) accounts for serial correlation within each firm, while the latter (clustering standard errors within prefecture-level city-years) accounts for spatial correlation across firms within each prefecture-level city-year. We also allow for the heteroskedasticity of the error terms.

China has five administrative levels below the central level, namely provincial level (1st), prefectural level (2nd), county level (3rd), township level (4th) and village level (5th). Relative to a county, a prefecture-level city is larger in size and has greater political power to design/change policies that may affect industrial firms located in that prefecture-level city. Moreover, firms may be spatially correlated with other firms located in the same prefecture-level city but in different counties, as these counties may have experienced similar levels of urbanization and industrial agglomeration. Thus, allowing for spatial correlation within a prefecture-level city-year is more appropriate than allowing the error terms to be spatially correlated within a county-year as in Zhang et al. (2016). We test the sensitivity of our results using other cluster options in the robustness check section.

Data

We compile a rich firm-level panel on industrial output and weather from 1998 to 2007. This section describes data sources and reports summary statistics.

Weather data

We obtain daily weather data from the CMDSSS, which reports daily average temperature, rainfall, sunshine duration, air pressure, relative humidity and average wind speed for 820 weather stations in China from 1998 to 2007. The data set also contains detailed information on coordinates of each weather station, enabling us to construct weather variables at the county level. Of the 2806 counties included in the sample, 19 counties have more than one weather station. For counties with multiple weather stations, we construct county-level weather variables by taking the simple average of the weather variables across weather stations within each county. For counties without a weather station, we impute the weather information for this county from its nearest neighboring county.[4]

Industrial output

We collect firm-level industrial output data for the period 1998–2007 from the Annual Survey of Industrial Firms database compiled by the National Bureau of Statistics of China (NBS). This data set contains detailed information on total output,

[3] In the baseline analysis, we remove weather data on February 29 in leap years to ensure that the sum of temperature bins is equal to 365 in any given year during our sample period. Our main findings hold if we do not drop February 29 and normalize temperature bins in leap years by 365/366 to ensure that the sum of temperature bins equals 365. These results are reported in the robustness check section.

[4] For counties without a weather station, we also use weather data from their neighboring counties (based on whether they share a common boundary) and distances between counties as weights to construct weather variables. We obtain similar results compared to our baseline findings. For brevity, they are not reported, but are available upon request.

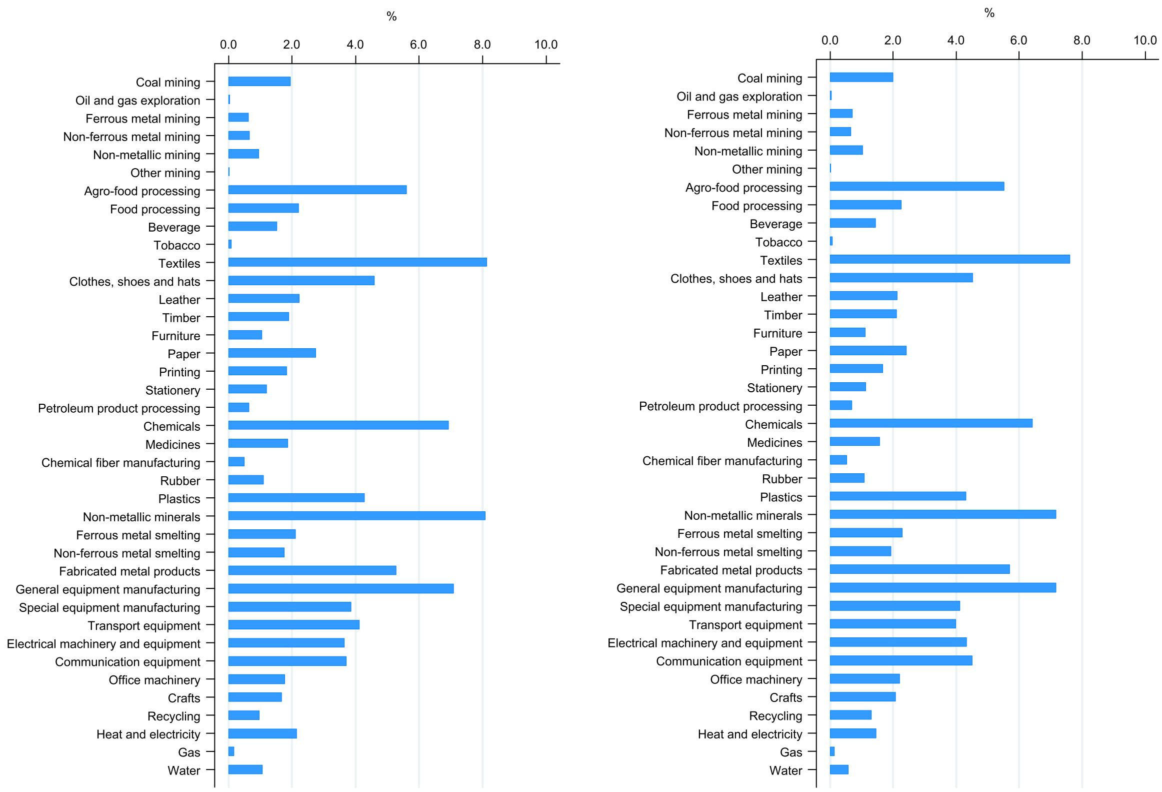
intermediate input, number of workers, and other accounting information for firms with annual sales above 5 million RMB, equivalent to US $0.75 million at the average exchange rate in 2010. Industrial output is measured by value added per worker, while value added is the difference between total output and intermediate input.

This data set includes 530,370 firms located in 31 provinces and province-equivalent municipal cities. The total output produced by firms covered in this data set accounts for more than 85% of China's total industrial output. In the data set, each firm is classified into a two-digit Chinese Industry Classification Code and the data set contains 39 two-digit industries. The left panel of Fig. 1 shows the percentage distributions of observations in the sample for each of the 39 two-digit industries, while the right panel of Fig. 1 displays the percentage distributions of the number of firms in the sample for these industries. We find that, of the 39 two-digit industries, general equipment manufacturing, non-metallic minerals, chemicals, textiles and agro-food processing are the five large industrial sectors. Their shares of observations (the number of firms) in the sample are 7.1% (7.2%), 8.1% (7.2%), 6.9% (6.4%), 8.1% (7.6%) and 5.6% (5.5%), respectively.

The NBS assigns a legal identification number (ID) to each firm included in the data set and specifies its type of ownership. There are six primary ownership categories for firms covered by the data set, namely state-owned enterprises, private firms, collective firms, foreign firms, Hong Kong, Macao and Taiwan firms, and mixed-ownership firms. Many firms occasionally receive a new ID as a result of restructuring, merger, acquisition, or changes in ownership. We follow the procedure described in Brandt et al. (2012) to generate unique IDs to link firms over time.

Before merging the firm-level output data with the county-level weather data, following the common practices used by prior studies (for example, see Cai and Liu (2009)), we delete observations from the original data set to avoid potential estimation biases originating from misclassified observations. Specifically, we drop observations if (*i*) one of the following key variables, including value added, the number of workers, total assets, fixed assets and total annual sales, has missing values; (*ii*) the values of fixed assets and total annual sales are below 10 million RMB; (*iii*) the number of workers is less than 8; (*iv*) value added is either larger than the 99th percentile or smaller than the 1st percentile; and (*v*) basic accounting principles are clearly violated, such as total assets are smaller than liquid assets, total fixed assets or net values of fixed assets.

Finally, we merge the firm-level output data with the county-level weather data by county and year. Thus, weather information in a county is assigned to all firms located in that county. We have an unbalanced panel with 1,803,482 observations for years 1998–2007, and the panel includes 530,370 firms in 2806 Chinese counties. Table A1 in the Appendix shows



(a) Observations (b) Number of firms

Fig. 1. Percentage distributions of observations and the number of firms in the sample for each two-digit industry. Notes: the left panel (a) shows the percentage distributions of observations in the sample for each of the 39 two-digit industries. The right panel (b) shows the percentage distributions of the number of firms in the sample for these industries. In the sample, the number of observations = 1,803,482 and the number of firms = 530,370.

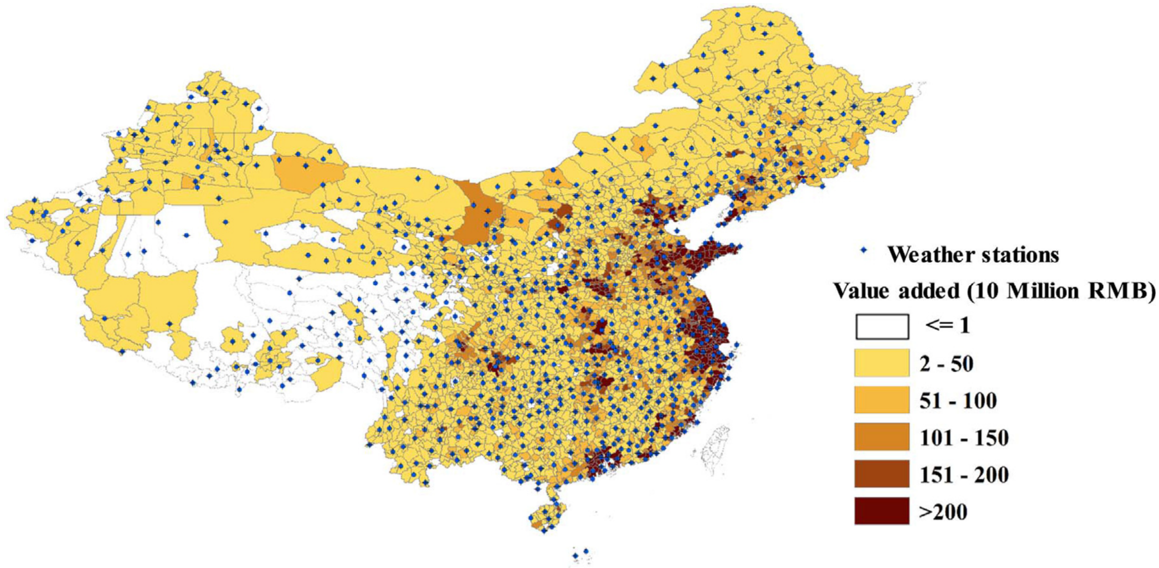


Fig. 2. Spatial distributions of weather stations and industrial value added in China. Notes: the figure overlays weather stations and county-level industrial value added in China. Weather stations are shown in blue dots. The county-level industrial value added, aggregated from the firm-level value added and averaged over the period 1998–2007, is shown in shades of yellow, with darker yellow indicating a larger amount of value added. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

that output and weather variables exhibit considerable variability, while Table A2 in the Appendix shows that weather variables are highly correlated during the sample period. Fig. 2 displays the spatial distributions of weather stations and county-level value added that is aggregated from the firm-level value added and averaged over the period 1998–2007. This figure depicts that weather stations are widely distributed in China, and China's industrial activities are concentrated mostly in east coastal regions.

Results

Main results: Seasonal average temperatures as temperature variables

We examine the effects of weather on industrial output using models with no lags and lagged values of the weather variables. We first consider two model specifications with no lagged values of the weather variables in Models 1 and 2. In Model 1, we include all weather variables, except sunshine hours, as explanatory variables to assess the temperature effects on industrial output during the sample period. In Model 2, we add sunshine hours as an additional explanatory variable to examine whether estimated temperature effects are sensitive to the inclusion of the sunshine variables.

We then consider two model specifications with up to four lags of the weather variables to examine whether weather shocks in prior years had any direct impacts on industrial output in the current year. In Model 3, we consider a model with one lag of the weather variables. In Model 4, we incorporate four lags of the weather variables. We select the two models with up to four lags, because we find that temperature changes exert significant effects on output with at most a four-year lag. Specifically, we find that, with four lags, estimated coefficients of temperature variables are broadly consistent in sign, magnitude and statistical significance as we add more lags, and that parameter estimates of the lagged temperature variables beyond four years are statistically insignificant. We report estimated coefficients of temperature variables obtained using Models 1–3 in Table 1, while parameter estimates of temperature variables based on Model 4 are displayed in Fig. 3.[5] All model specifications incorporate time-invariant firm fixed effects and two-digit industry $\times$ year fixed effects.

Contemporaneous temperature effects

Across various model specifications that we considered, we find that the coefficient estimates of $Temp^{spring}$ are positive and statistically significant at the 5% level, indicating that output is positively correlated with higher spring temperatures during the sample period. Specifically, a 1 °C increase in $Temp^{spring}$ is associated with a 1.6–3.0% increase in output, depending on model specifications. Parameter estimates of $Temp^{summer}$ are negative and statistically significant at the 1%

[5] The main focus of this paper is to examine the temperature effects on output. For brevity, we report only parameter estimates of temperature variables in Table 2 and Fig. 3. Parameter estimates of other weather variables are not reported but are available upon request.

Table 1
Effects of temperature on output: main results (dependent variable is log value added per worker).

	Models with no lags		Model with one lag
	(1)	(2)	(3)
$Temp^{spring}$	0.0217^{***}	0.0163^{**}	0.0182^{**}
	(0.0068)	(0.0070)	(0.0073)
$Temp^{summer}$	-0.0346^{***}	-0.0451^{***}	-0.0563^{***}
	(0.0075)	(0.0084)	(0.0085)
$Temp^{fall}$	−0.0018	0.0024	0.0124
	(0.0068)	(0.0068)	(0.0076)
$Temp^{winter}$	0.0030	0.0038	0.0047
	(0.0057)	(0.0058)	(0.0060)
L1: $Temp^{spring}$			0.0391^{***}
			(0.0078)
L1: $Temp^{summer}$			-0.0201^{**}
			(0.0096)
L1: $Temp^{fall}$			0.0216^{***}
			(0.0078)
L1: $Temp^{winter}$			-0.0175^{***}
			(0.0061)
Sum of all $Temp^{spring}$ coefficients	0.0217^{***}	0.0163^{**}	0.0573^{***}
	(0.0068)	(0.0070)	(0.0112)
Sum of all $Temp^{summer}$ coefficients	-0.0346^{***}	-0.0451^{***}	-0.0764^{***}
	(0.0075)	(0.0084)	(0.0130)
Sum of all $Temp^{fall}$ coefficients	−0.0018	0.0024	0.0339^{***}
	(0.0068)	(0.0068)	(0.0122)
Sum of all $Temp^{winter}$ coefficients	0.0030	0.0038	−0.0128
	(0.0057)	(0.0058)	(0.0095)
Observations	1,803,482	1,803,482	1,801,581
R^2	0.7401	0.7401	0.7408
Sunshine variables	NO	YES	YES
Other weather variables	YES	YES	YES

Notes: This table shows coefficient estimates of seasonal temperature variables. Columns (1) and (2) show contemporaneous temperature effects on output. Column (3) shows contemporaneous, one-year lagged, and cumulative temperature effects on output. These estimated temperature effects can be interpreted as the percentage changes in output with a 1 °C increase in temperature. Results reported in Column (1) are obtained by estimating Eq. (2) and including temperature, rainfall, air pressure, relative humidity, and average wind speed as weather variables. Results reported in Column (2) are obtained by adding sunshine hours. Results reported in Column (3) are obtained with one lag of the weather variables and the inclusion of sunshine hours as an additional weather variable. All regressions include firm fixed effects and two-digit industry × year fixed effects. Standard errors, shown in parentheses, are clustered within firms and within prefecture-level city-years. Units for explanatory variables: 1 °C for temperature. Observations decline slightly as more lags are added, because several new weather stations were built over the sample period.

$p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

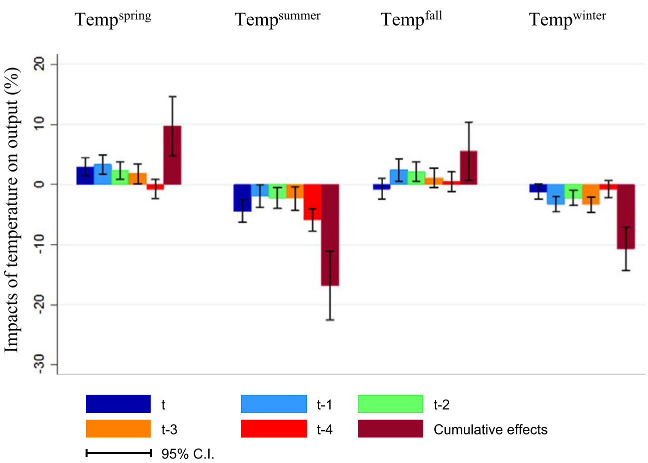


Fig. 3. Estimated temperature effects on output. Notes: this figure shows estimated temperature effects on output in percentage terms. The four clusters show the effects on output for each 1 °C increase in spring, summer, fall and winter temperatures, respectively. In each cluster, coefficient estimates of temperature variables for years t, t-1, t-2, t-3 and t-4 are shown in dark blue, light blue, light green, orange, and red, respectively. Cumulative temperature effects are shown in brown. The 95% confidence bands are added as black solid lines. Results are obtained by estimating Eq. (2) with four lags of the weather variables; by including temperature, sunshine hours, rainfall, air pressure, relative humidity and average wind speed as weather variables; and by incorporating firm fixed effects and two-digit industry × year fixed effects. Standard errors are clustered within firms and within prefecture-level city-years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

level, suggesting that output declines with increased summer temperatures. The reduction in output stemming from higher summer temperatures is quite large. Holding all else the same, a 1 °C increase in average $Temp^{summer}$ can reduce output by 3.5–5.6%. The effects on output of temperature changes during the fall and winter are not statistically significant in Models 1–3. In Model 4 with four lags of the weather variables, the coefficient estimate of $Temp^{winter}$ is negative and statistically significant at the 10% level, which suggests that output might be negatively correlated with higher winter temperatures during the sample period.

Given the large correlations between temperature and sunshine hours during the spring and summer (see Table A2 in the Appendix), the inclusion of sunshine hours has a large influence on parameter estimates of $Temp^{spring}$ and $Temp^{summer}$. Specifically, it causes the $Temp^{spring}$ parameter estimate to be 25% smaller, decreasing from 2.2% in Model 1 to 1.6% in Model 2, and increases the absolute value of the parameter estimate of $Temp^{summer}$ by 30%, from − 3.5% in Model 1 to − 4.5% in Model 2 (see Columns 1–2 in Table 1). Therefore, our results show the importance of jointly analyzing the impacts of temperature and sunshine hours on industrial output, and indicate that excluding sunshine hours would lead to biased parameter estimates of the temperature variables.

Recent studies by Hsiang (2010), Dell et al. (2014), and Deryugina and Hsiang (2014) have discovered that high temperatures are associated with losses in, respectively, industrial output (2.5%/1 °C), average country-level GDP per capita (1.0%/1 °C), and county-average income per capita (1.7%/1 °C). Our estimated summer temperature effects on industrial output are higher in magnitude (3.5–5.6%/1 °C) than these earlier estimates. Moreover, our finding of the positive temperature effects on industrial output during the spring is different from that reported in Hsiang (2010), which focuses on the Caribbean and Central America and finds that industrial output in these countries responded negatively to increased temperatures only during the hottest season. The difference in this finding might be driven by the large differences in seasonal average temperatures between the Caribbean and Central America and China. For example, in our sample, average $Temp^{spring}$, $Temp^{fall}$ and $Temp^{winter}$ were 16.0 °C, 17.5 °C, and 4.9 °C, respectively, all of which are lower than average $Temp^{summer}$ (26.4 °C). In contrast, the difference in temperature across seasons is fairly small in the Caribbean and Central America (see Table S1 in Hsiang (2010)). Our findings suggest that, when examining the temperature effects on economic output, it is important to use seasonal average temperatures as temperature variables rather than using annual average temperature, especially for countries like China with clear distinctions of four seasons.

Lagged temperature effects

The last column in Table 1 and Fig. 3 show that the effects of temperature changes in the previous year on current year's output are statistically significant, with negative temperature effects during the summer and winter and positive temperature effects during the spring and fall. Holding all else the same, each 1 °C increase in $Temp^{summer}$ and $Temp^{winter}$ in year *t-1* can reduce output in year *t* by 1.9–2.0% and 1.8–3.2%, respectively, while each 1 °C increase in $Temp^{spring}$ and $Temp^{fall}$ in the previous year can increase current year's output by 3.4–3.9% and 2.2–2.4%. Fig. 3 also shows that the effects of temperature changes in prior years on current year's output do not exhibit any particular trends over time. For instance, the absolute value of the coefficient estimate of summer temperature is 4.4% in year *t*, decreases to 1.9% in year *t-1*, and then jumps to 5.9% in year *t-4*.

Cumulative temperature effects

The cumulative effect of $Temp^{summer}$ remains substantially negative and increases in magnitude as more lags are included. With no lagged weather variables, a 1 °C increase in $Temp^{summer}$ reduces output by 3.5–4.5%. With one lag included, the cumulative effect of $Temp^{summer}$ is a reduction of 7.6% in output. With four lags included, the cumulative effect of $Temp^{summer}$ is a reduction of 16.8% in output. The cumulative effect of $Temp^{spring}$ is positive and also increases when we add more lags, ranging from 1.6–2.2% with no lags to 9.8% with four lags. As more lags are included, the cumulative effects of $Temp^{fall}$ and $Temp^{winter}$ become statistically significant and are positive and negative, respectively. In Model 4 with four lags, the cumulative effect of $Temp^{fall}$ is an increase of 5.6% in output, while the cumulative effect of $Temp^{winter}$ is a reduction of 10.7% in output.

In summary, our results suggest that there exist differential effects of temperature on output and that the response of output to temperature is nonlinear. It is worth noting that our estimate of the cumulative effect of $Temp^{summer}$ on output (−16.8%/1 °C) is quite large, for three possible reasons. First, we find that within-group standard deviations (SDs) of $Temp^{summer}$ are small, ranging from 0.03 °C to 1.37 °C across the 2806 counties included in the sample. Average summer temperatures are 21.5–27.2 °C for counties with a SD of 0.03 °C and are 26.8 °C for counties with a SD of 1.37 °C. That partly explains why a 1 °C increase in $Temp^{summer}$ can cause such a big reduction in output. Second, unlike the studies mentioned above that use annual average temperature to examine the effect of temperature on output (with the exception of Hsiang (2010)), we use seasonal average temperatures as temperature variables. If we use annual average temperature as the temperature variable, the cumulative effect of temperature is found to be − 13.6% (rather than − 16.8%).[6] Lastly, we find that, when analyses are conducted using detailed micro-level data, estimated temperature effects on output are substantially larger than those obtained using coarse macro-level data. As noted above, when Cachon et al. (2012) used a micro-level data set of weekly production from 64

[6] That may be the case because the positive effects of higher spring and fall temperatures on output can partially offset the negative effects of higher summer and winter temperatures on output.

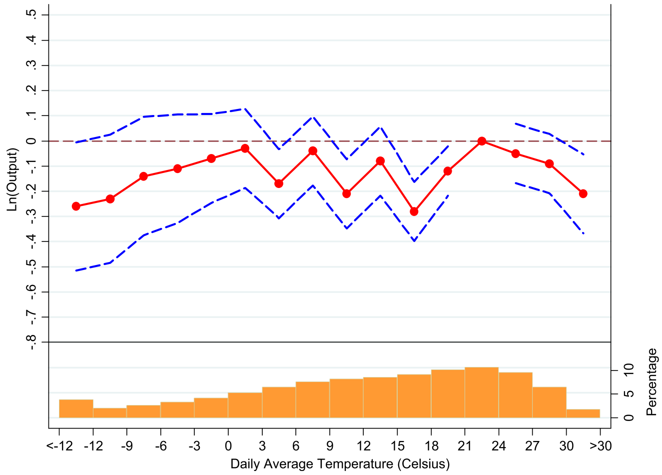


Fig. 4. Nonlinear relationship between temperature and output based on the model with no lags. Notes: This figure displays the effect of daily average temperature on log value added per worker in percentage terms. The red curve represents point estimates of temperature bins, while the 95% confidence bands are added as blue dashed lines. Histograms at the bottom show the percentage distribution of each temperature bin in the sample. The regression uses temperature bins as temperature variables and includes linear and quadratic forms of sums of rainfall and sunshine duration and means of air pressure, relative humidity and average wind speed as additional weather variables. The regression also incorporates firm fixed effects and two-digit industry × year fixed effects and does not include lagged values of the weather variables. Standard errors are clustered within firms and within prefecture-level city-years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

automobile plants in the US, they found that a week with six or more days above 32 °C can reduce that week's production by roughly 8%. Similarly, using a subnational level data set, Dell et al. (2009) found that per capital GDP fell 8.9% for each 1 °C increase in temperature. These estimates are considerably larger than the estimates (− 2 to 3%/1 °C) noted above based on the macro-level data. When we replicate the above regression analysis using a county-level data set that is aggregated from the firm-level data set, the estimate of the cumulative effect of $Temp^{summer}$ is only − 11.1% (see the Robustness check section).

Given that output is positively correlated with higher spring and fall temperatures, our finding of the negative effect of higher winter temperatures on output seems counterintuitive, because one might expect that output increases with higher winter temperatures. Here, we provide two possible explanations for this finding. First, with higher winter temperatures, winter may become more pleasantly temperate, which might cause workers to take additional time off, resulting in reduced total hours worked. Second, although the underlying mechanisms are not very clear, we find that higher winter temperatures increase the share of female workers and reduce the share of male workers, with an insignificant impact on the total number of workers employed (see Table A3 in the Appendix).[7] Because some of the industrial jobs in our sample are physically demanding jobs, a higher share of female workers in the labor force is expected to reduce output.

Main results: Temperature bins as temperature variables

We use temperature bins as temperature variables to further investigate whether the nonlinear relationship between temperature and industrial output identified above holds and to determine the critical temperature threshold above and below which is harmful for output. To achieve these goals, we estimate Eq. (3) iteratively by setting different temperature bins as the omitted category. We find that, when the bin [21 °C, 24 °C) is set as the omitted category, the coefficients of other temperature bins are non-positive. This suggests that, relative to a day in the [21 °C, 24 °C) bin, the marginal effects on industrial output of an additional day in other temperature bins are negative (or zero) and that [21 °C, 24 °C) is the critical temperature threshold. When temperature bins are used as temperature variables, we find that temperature changes have significant effects on output only with a two-year lag. Thus, we estimate Eq. (3) by including all weather variables and we consider models with no lags and two lags of the weather variables.

Contemporaneous temperature effects

Fig. 4 displays point estimates and the 95% confidence bands of coefficient estimates of temperature bins, which are obtained by estimating Eq. (3) with no lags. The horizontal axis of Fig. 4 is temperature, while the vertical axis denotes the log value added per worker. This figure shows that the relationship between temperature and output is nonlinear and exhibits an inverted-U shape when temperature is above 15 °C. Output responds negatively to low temperatures (< − 12 °C). When temperature is above − 12 °C and below 15 °C, the responses of output to temperature changes are statistically insignificant, except for bins [3 °C, 6 °C) and [9 °C, 12 °C), where the coefficient estimates of the two bins are negative and statistically

[7] This finding is in line with Zhang et al. (2016).

significant at the 5% level and the 1% level, respectively. When temperature is above 15 °C, the responses of output to temperature changes become statistically significant. Industrial output increases approximately linearly with temperature up to 21–24 °C, and then declines sharply with temperatures above 30 °C.

Relative to a day with an average temperature of 21–24 °C, an additional day at 30 °C can lead to a reduction in annual industrial output by roughly 0.21%, while output declines 0.26% with an additional day at − 12 °C, holding all else the same. During the sample period, the number of days with average temperatures [21 °C, 24 °C) accounts for about 10% of the 365 days in a year (see histograms at the bottom of Fig. 4). Thus, replacing days at [21–24 °C) temperatures with full days at 30 °C will decrease output by 0.21% * 10% * 365 = 7.7%, holding all else the same. The reduction in output by replacing days at [21–24 °C) temperatures with full days at − 12 °C will be larger, by 0.26% * 10% * 365 = 9.5%. When Eq. (3) is estimated with two lags of the weather variables, Panel A in Fig. 5 shows that the relationship between temperature and output is similar to that presented in Fig. 4.

Lagged temperature effects

Panels B and C in Fig. 5 show that, when temperature is above 3 °C, the responses of current year's output to temperature changes in the prior two years are also highly nonlinear and exhibit inverted-U shapes. These findings suggest that the negative effects on output of elevated temperatures in the prior two years can be carried over into the following years. Panel D in Fig. 5 shows the cumulative effect of temperature on output. This figure depicts that, relative to a day with an average

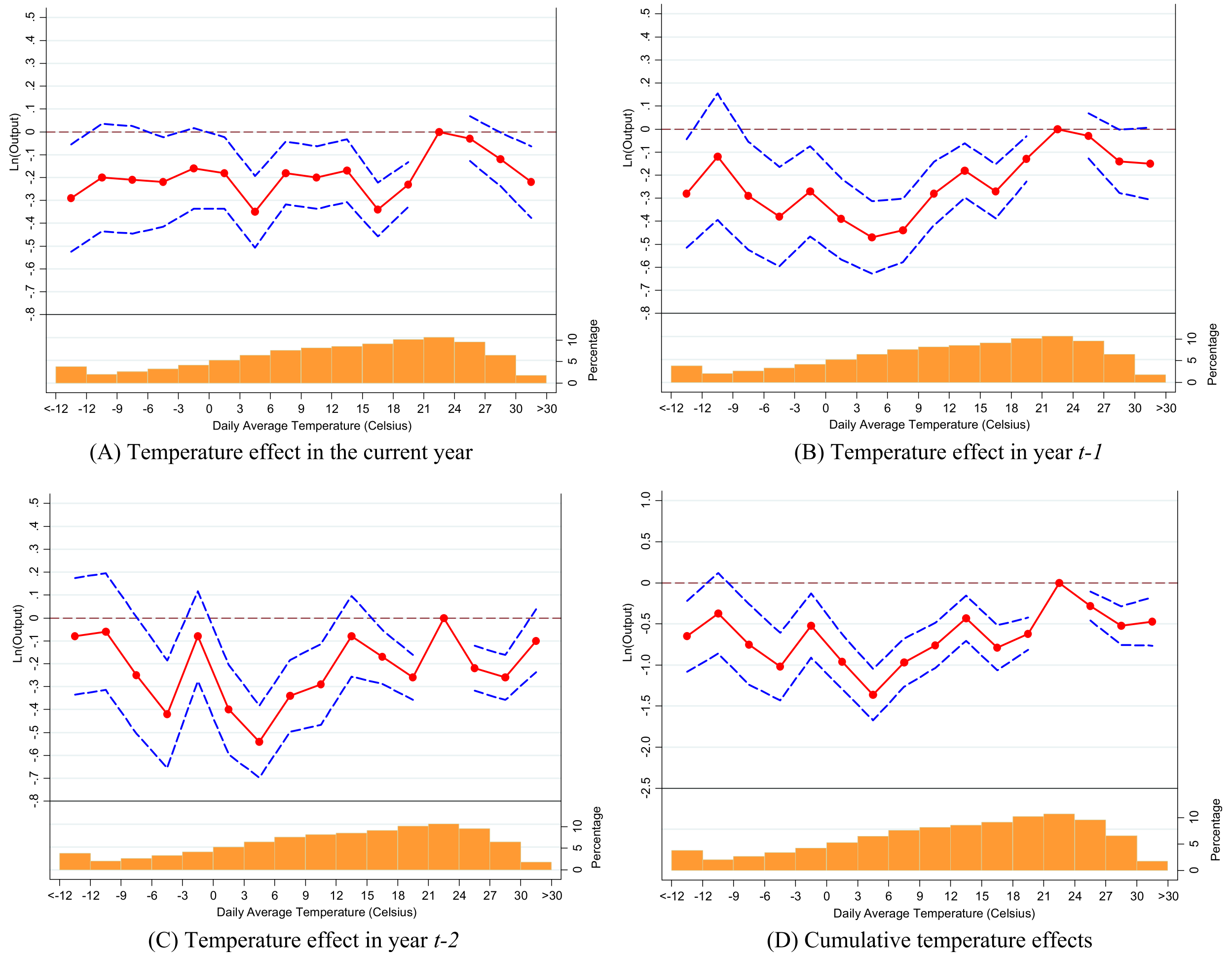


Fig. 5. Nonlinear relationship between temperature and output based on the model with two lags. Notes: these figures display the effect of daily average temperature on log value added per worker in percentage terms. Panel (A) shows the effect of daily average temperature in the current year on log value added per worker. Panels (B) and (C) show the effects of daily average temperature in the prior two years on log value added per worker. Panel (D) shows the cumulative effect of daily average temperature on log value added per worker. The red curve in each panel represents point estimates of temperature bins, while the 95% confidence bands are added as blue dashed lines. Histograms at the bottom in each panel show the percentage distribution of each temperature bin in the sample. The regression uses temperature bins as temperature variables and includes linear and quadratic forms of sums of rainfall and sunshine duration and means of air pressure, relative humidity and average wind speed as additional weather variables. The regression incorporates firm fixed effects and two-digit industry × year fixed effects and includes two lags of the weather variables. Standard errors are clustered within firms and within prefecture-level city-years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

temperature of 21–24 °C, the cumulative effects on output of an additional day in other temperature bins are negative and statistically significant, with an exception for the bin [− 12 °C, − 9 °C). When temperature is above 3 °C, the cumulative temperature effect on output exhibits a clear inverted-U shape. Panel D also shows that the critical temperature threshold identified above, [21 °C, 24 °C), is robust to variations in model specifications.

Robustness checks

We examine the robustness of estimated temperature effects on output to variations in econometric estimation strategies and data in eight different scenarios. Specifically, in Scenario (1), we estimate standard errors that are clustered within firms and within county-years to account for autocorrelation and spatial correlation of the error terms. As mentioned above, we obtain weather data from 820 weather stations and the same weather station data sometimes are used for multiple counties. Thus, the error terms may be correlated within a weather-station-year. To account for this, we estimate standard errors that are clustered within firms and within weather-station-years in Scenario (2). In Scenario (3), in addition to the fixed effects considered in the baseline scenario, we include region × year fixed effects to account for shocks occurring in a region in a given year that are the same for all firms located in that region in that year.[8] In the baseline analysis, we drop observations from the original data set based on certain criteria (discussed in the Data section). In Scenario (4), we remove entire firms from the sample if they violate these criteria at a given point in time.

So far, weather variables have been constructed by incorporating weather information on all days in a year, including weekdays, weekends and holidays. Most industrial activities in China occur on weekdays. In Scenario (5), we re-construct our weather variables by removing weather information on weekends and holidays and using weather data on weekdays only, and then replicate the regression analyses using the newly constructed weather variables. In Scenario (6), we replicate the above analyses using a balanced sample from 1998 to 2007. To examine whether our results are sensitive to data aggregation, in Scenario (7) we aggregate the firm-level data into a county panel with county-industry-year as the unit of observation. Lastly, in Scenario (8), we estimate Eqs. (2) and (3) using a dynamic panel data approach that includes the lagged dependent variable as an explanatory variable to examine whether our results are sensitive to variations in model specifications.[9]

We conduct these sensitivity analyses using seasonal average temperatures and temperature bins as temperature variables, respectively. Tables A4 and A5 in the Appendix report coefficient estimates of seasonal temperature variables, which are obtained by estimating Eq. (2) with four lags of the weather variables. We present coefficient estimates of temperature bins for these scenarios in Fig. A1 in the Appendix, which are obtained by estimating Eq. (3) with two lags of the weather variables.

Our key findings of the temperature effects on output are broadly consistent across the various scenarios that we considered. The negative contemporaneous temperature effects on output stemming from rising $\text{Temp}^{\text{summer}}$ are statistically significant at the 1% level, ranging between 2.7% in Scenario (5) and 5.6% in Scenario (3). The negative effects of each 1 °C increase in $\text{Temp}^{\text{winter}}$ lie between 1.2% in Scenario (1) and 3.4% in Scenario (7), although the coefficient estimates of the $\text{Temp}^{\text{winter}}$ variable do not show high significance levels in some scenarios. Our finding of the positive temperature effects on output in the spring is also robust across these scenarios.

Moreover, we find that signs and statistical significance of the cumulative temperature effects estimated in Scenarios (1)–(8) are similar to our baseline estimates. The cumulative effects of $\text{Temp}^{\text{summer}}$ and $\text{Temp}^{\text{winter}}$ on output are negative and statistically significant, at (-)8.9–26.5% and (-)6.2–14.2%, respectively. The cumulative effect of $\text{Temp}^{\text{spring}}$ on output is also statistically significant and ranges between 5.9% and 14.6%, with an exception in Scenario (8), where the cumulative effect of $\text{Temp}^{\text{spring}}$ is insignificant. The cumulative effect of $\text{Temp}^{\text{fall}}$ on output is positive and statistically significant, ranging from 5.6% to 14.8%, with an exception in Scenario (6), where the cumulative effect of $\text{Temp}^{\text{fall}}$ has a positive sign but is not significant. Because the sum of the absolute values of the negative effects of $\text{Temp}^{\text{summer}}$ and $\text{Temp}^{\text{winter}}$ is considerably larger than the sum of the absolute values of the positive effects of $\text{Temp}^{\text{spring}}$ and $\text{Temp}^{\text{fall}}$, future global warming is expected to lead to a reduction in output.

We also consider a Scenario (9) when using temperature bins as temperature variables. In this scenario, rather than removing weather data on February 29 in leap years, we do not drop February 29 and normalize temperature bins in leap years by 365/366 to ensure that the sum of temperature bins is equal to 365 in any given year during our sample period. The left panels in Fig. A1 in the Appendix show that the critical temperature threshold identified in the baseline scenario, [21 °C, 24 °C), remains remarkably consistent across the various scenarios that we considered. The right panels illustrate that the cumulative temperature effects on output in these scenarios are also broadly consistent with our baseline findings.[10]

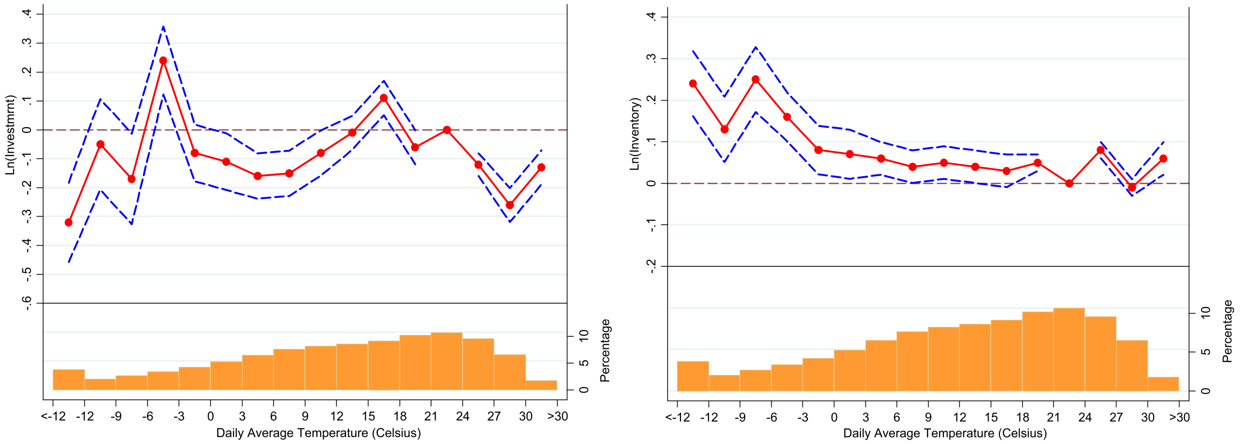
Channels for the lagged temperature effects on output

Our finding that output can be affected by temperature changes in prior years is line with Dell et al. (2012), who find that temperature shocks have long-lasting effects. But this finding is different from those reported in Deryugina and Hsiang (2014)

[8] China can be divided into six regions, including North China, Northeast China, East China, South Central China, Southwest China and Northwest China. Provinces included in each region can be found at: https://en.wikipedia.org/wiki/List_of_regions_of_the_People's_Republic_of_China.

[9] When conducting the sensitivity analysis described in Scenario (8), we use GMM and the aggregated county-level data for computational ease.

[10] There is one exception in Scenario (8) with the GMM estimation, where most of the coefficient estimates of temperature bins are not significant.



(A) Temperature effects on investment

(B) Temperature effects on inventory

Fig. 6. Effects of temperature on investment and inventory. Notes: Panel (A) shows the effect of daily average temperature on log investment in percentage terms. Panel (B) shows the effects of daily average temperature on log inventory in percentage terms. The red curve in each panel represents point estimates of temperature bins, while the 95% confidence bands are added as blue dashed lines. Histograms at the bottom in each panel show the percentage distribution of each temperature bin in the sample. All regressions use temperature bins as temperature variables and incorporate linear and quadratic forms of sums of rainfall and sunshine duration and means of air pressure, relative humidity and average wind speed as additional weather variables. All regressions incorporate firm fixed effects and two-digit industry × year fixed effects, and do not include lagged values of the weather variables. Standard errors are clustered within firms and within prefecture-level city-years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and Zhang et al. (2016), who find limited effects of lagged temperatures on current year's output. In this section, we apply our panel methodology to explore possible channels through which temperature in prior years might affect current year's output.

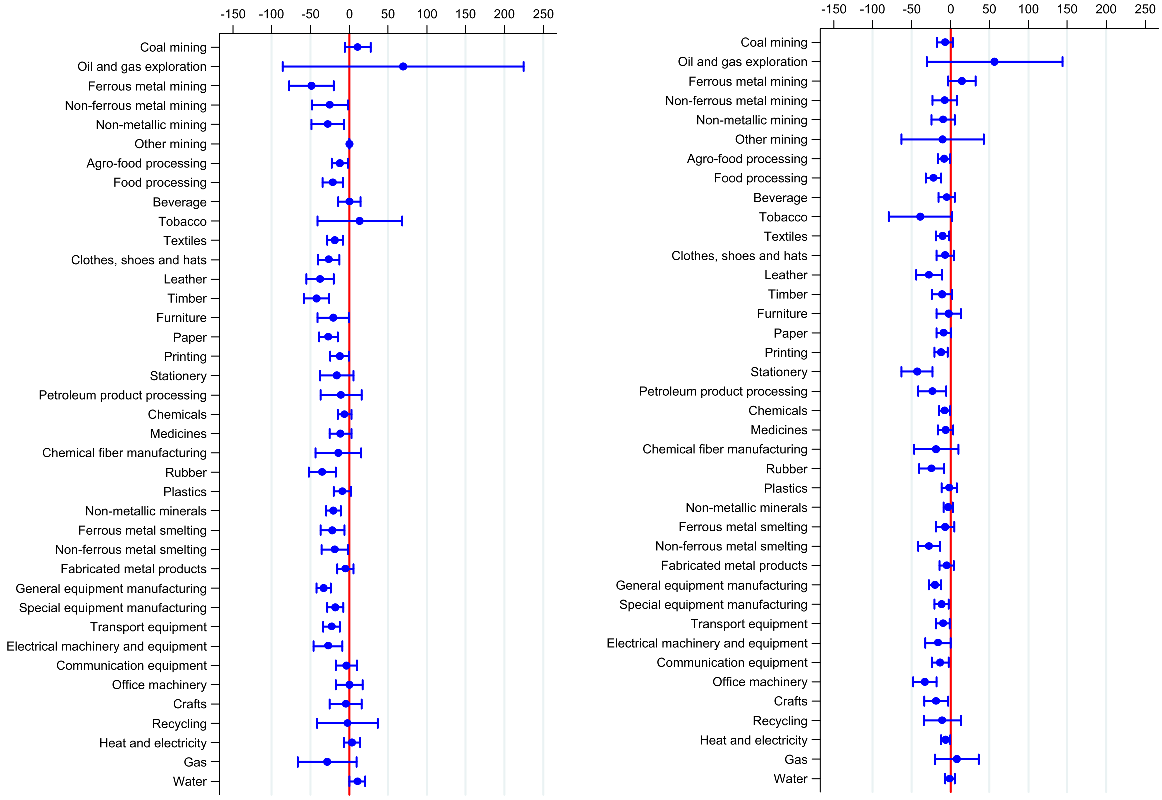
Fig. 6 shows the impacts of temperature on firms' investment and inventory levels. Although the relationships between the two variables and temperature do not exhibit particular shapes, we find that low and high temperatures have influenced firms' investment and inventory levels. The left panel of this figure shows negative effects of low and high temperatures on firms' investment. Relative to a day with an average temperature of 21–24 °C, an additional day at 30 °C or − 12 °C can lead to reductions in firms' investment by about 0.1% and 0.3%, respectively, holding other factors constant. Dell et al. (2012) also document the similar negative impacts of high temperatures on investment in poor countries, although their results are not statistically significant. The right panel of this figure shows that inventory is positively correlated with temperature. Relative to a day at 21–24 °C, an additional day with average temperatures below − 3 °C or above 30 °C can cause a significant increase in firms' inventory levels. That may be the case because temperatures below − 3 °C and above 30 °C can negatively affect the performance of drivers and vehicles (Daanen et al., 2003). These two findings indicate that, by influencing firms' investment and inventory levels, temperature changes in prior years can affect industrial firms' production in the following years.

Using both seasonal average temperatures and temperature bins as temperature variables, we have demonstrated that output is nonlinear in temperature changes and output exhibits negative responses to low and high temperatures. For brevity, we will use seasonal average temperatures as temperature variables for the analyses conducted in Sections Heterogeneity in the temperature effects across industries, Adaptation to high temperatures and Impacts of future climate change.

Heterogeneity in the temperature effects across industries

The temperature effects on output discovered above may differ across industries due to the differences in the length of time that inputs in each industry, such as labor and capital, are exposed to low and high temperatures, their resilience to temperature changes, and/or the ability of different industries to adapt to temperature changes. To examine which industries are most affected by temperature changes, we estimate Eq. (2) with four lags of the weather variables for each two-digit industry. Fig. 7 displays point estimates and the 95% confidence bands of coefficient estimates of the cumulative effects of summer and winter temperatures for these industries. We present the temperature effects for the summer and winter, because the cumulative effects of temperature changes on output during the two seasons are negative and statistically significant.

We find substantial heterogeneity in the effects of temperature on output across industries. The left panel of Fig. 7 shows that, among the 39 two-digit industries, ferrous metal mining, timber, and rubber are the three industries affected most by higher summer temperatures, which is expected given that the three industries involve outdoor production activities. Workers in the timber and rubber industries are highly exposed to high temperatures during the summer, while running air conditioners is an almost infeasible (or costly) option to mitigate thermal stress for ferrous metal mine workers. The cumulative effects of a 1 °C increase in $Temp^{summer}$ are output reductions of 48.7%, 41.2% and 34.7%, respectively, in the three industries. The right panel of Fig. 7 depicts that, relative to other industries, stationary and office machinery are most affected



(A) Summer temperature effects (%) (B) Winter temperature effects (%)

Fig. 7. Heterogeneity in temperature effects across industries. Notes: the two figures show the cumulative temperature effects on log value added per worker for each of the 39 two-digit industries in percentage terms. Panel (A) shows the cumulative effect of summer temperature on log value added per worker. Panel (B) shows the cumulative effect of winter temperature on log value added per worker. Blue dots in each panel represent point estimates and blue bars denote the 95% confidence bands. Results displayed in the two panels are obtained by estimating Eq. (2) and including temperature, sunshine hours, rainfall, air pressure, relative humidity, and average wind speed as weather variables. All regressions incorporate four lags of the weather variables, while including firm fixed effects and year fixed effects. Standard errors are clustered within firms and within prefecture-level city-years. Estimated coefficients of temperature variables are interpreted as the percentage changes in output with a 1 °C increase in temperature. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

by higher winter temperatures. The cumulative effect of a 1 °C increase in $Temp^{winter}$ is a reduction of 42.9% in stationary output and a reduction of 33% in office machinery output. Higher winter temperatures also lead to substantial output losses in other industries, such as food processing, leather, rubber and non-ferrous metal smelting.

Adaptation to high temperatures

We have demonstrated that higher summer temperatures have large and negative impacts on output. In this section, we explore whether adaptation actions have been undertaken to reduce the negative effects on output of rising summer temperatures. In exploring the scope for climate adaptation, we focus our attention on the temperature effects in regions with different temperature levels.[11] High-temperature regions might be better than low-temperature regions at coping with high temperatures. When a region has been exposed to high temperatures for a long period of time, some types of adaptation might have been developed to mitigate thermal stress. For instance, individuals can work flexibly by reallocating time on hot days (Zivin and Neidell, 2014).

To proceed, we modify Eq. (2) and construct one new set of weather variables, by interacting weather variables with a dummy for a "high-temperature" county, according to the Huai River-Qin Mountains line that is the natural boundary

[11] Here, we do not focus on regions with different income levels, because rich regions in China are typically located in coastal regions and have different industrial compositions relative to poor regions. Thus, it is not clear what a heterogeneity analysis by income would pick up.

Table 2
Effect of temperature on output in "high-temperature" regions (dependent variable is log value added per worker).

	"high-temperature" regions are defined based on the Huai River-Qin Mountains line (1)	"high-temperature" regions are hot and have above-median humidity (2)	"high-temperature" regions are hot and have above-median rainfall (3)
$Temp^{summer}$	-0.0751^{***}	-0.0740^{***}	-0.0527^{***}
	(0.0168)	(0.0156)	(0.0130)
$Temp^{summer}$ × "high-temperature" region dummy	0.0480^{**}	0.0468^{**}	0.0227
	(0.0212)	(0.0203)	(0.0186)
Temperature effect in high-temperature regions	-0.0271^{**}	-0.0271^{**}	-0.0300^{**}
	(0.0118)	(0.0121)	(0.0130)
Observations	1,801,581	1,801,581	1,801,581
R^2	0.7417	0.7417	0.7419

Notes: This table shows the effects of summer temperature on output in different temperature regions. Column (1) shows the regression results when "high temperature" regions are defined based on the Huai River-Qin Mountains line that is the natural boundary between Northern (low-temperature) China and Southern (high-temperature) China. Column (2) shows the regression results when "high-temperature" regions include both hot (located in Southern China) and humid (having above-median relative humidity) regions. Column (3) shows the regression results when "high-temperature" regions are hot (located in Southern China) and have above-median rainfall. To obtain these results, we construct one new set of weather variables by interacting weather variables with a dummy for a "high-temperature" county. We then estimate Eq. (2) with the inclusion of the new set of weather variables and one lag of the weather variables. All regressions include temperature, sunshine hours, rainfall, air pressure, relative humidity, and average wind speed as weather variables, and incorporate firm fixed effects and two-digit industry × year fixed effects. These estimated temperature effects can be interpreted as the percentage changes in output with a 1 °C increase in temperature. For brevity, we only report coefficient estimates of $Temp^{summer}$ in the current year. Standard errors, shown in parentheses, are clustered within firms and within prefecture-level city-years. Units for explanatory variables: 1 °C for temperature.
$p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

between Northern (low-temperature) China and Southern (high-temperature) China. For computational ease, we estimate Eq. (2) with only one lag of the weather variables and report coefficient estimates of $Temp^{summer}$ in Table 2.[12]

Column (1) in Table 2 shows that the coefficient estimate of the interaction term between the "high-temperature" dummy and $Temp^{summer}$ is positive and statistically significant at the 5% level, which suggests that, compared to low-temperature regions, high-temperature regions are better at adapting to elevated summer temperatures. Columns (2)–(3) report parameter estimates of these interaction terms when we change the definition of "high-temperature" regions. We find that the parameter estimates of the interaction term between $Temp^{summer}$ and the "high-temperature" dummy remain consistent, if (*i*) "high-temperature" regions include both hot (located in Southern China) and humid (having above-median relative humidity) regions; and (*ii*) "high-temperature" regions are hot (located in Southern China) and have above-median rainfall.[13]

Moreover, our adaptation findings remain broadly consistent across the various scenarios that we considered in the robustness check section, with a few exceptions (see Tables A6 and A7 in the Appendix). Although we do not have direct evidence showing that adaptation has been undertaken in high-temperature regions, estimated coefficients of temperature variables presented here suggest that some types of adaptation might have been undertaken in these regions to alleviate the negative effects of local thermal conditions on output.

Impacts of future climate change

We use point estimates of the sum of the contemporaneous and lagged marginal effects of seasonal average temperatures on output obtained from Model 4, under the baseline scenario and the scenarios considered in the robustness check section, to quantify the potential impacts of future climate change. Projections of future climate variables are taken from Climate-Wizard,[14] which provides climate predictions based on the most recent global climate models under three warming scenarios, including the B1 scenario, the A1B scenario and the A2 scenario. These scenarios differ substantially by assumed population growth, economic development, technological change, and use of clean and resource-efficient technologies. The B1, A1B and A2 scenarios describe low, medium and high rates of warming, respectively, by the end of this century. The climate variables provided by ClimateWizard include monthly average temperature and monthly total rainfall for the medium term (mid-Century, 2050s) and the long term (end of century, 2080s). Following Meehl et al. (2005) and Schlenker and Roberts (2009), we use the climate data based on the global climate models UKMO-HadCM3 developed by the UK Met Office and PCM

[12] We do not estimate Eq. (2) with four lags because our weather variables are seasonal averages. With the inclusion of the "high-temperature" dummy, the model with no lags already contains 48 weather variables. If we incorporated four lags, this would result in 240 weather variables and the model is unlikely to have sufficient statistical power to identify temperature effects on output.

[13] In this case, the parameter estimate of the interaction term between $Temp^{summer}$ and the "high-temperature" dummy has a positive sign, but it is insignificant.

[14] http://www.climatewizard.org/; last accessed March 10, 2016.

Table 3
Effects of warming on output under different warming scenarios (%).

		Baseline and Scenarios (1)–(2) (1)	Scenario (3) (2)	Scenario (4) (3)	Scenario (5) (4)	Scenario (6) (5)	Scenario (7) (6)	Scenario (8) (7)
UKMO-HadCM3								
A2	Medium term	− 21.6	− 27.2	− 21.8	− 20.4	− 23.1	− 10.6	− 12.2
	Long term	− 38.0	− 45.6	− 38.1	− 35.2	− 42.8	− 14.8	− 24.4
A1B	Medium term	− 27.7	− 35.9	− 28.0	− 25.7	− 30.7	− 12.9	− 16.8
	Long term	− 37.6	− 45.7	− 37.8	− 35.2	− 42.2	− 15.8	− 25.0
B1	Medium term	− 13.9	− 19.6	− 14.1	− 12.0	− 15.8	− 5.2	− 6.8
	Long term	− 28.7	− 36.0	− 28.9	− 27.7	− 30.2	− 16.1	− 17.7
PCM								
A2	Medium term	− 8.4	− 10.3	− 8.6	− 9.2	− 6.8	− 7.5	− 5.2
	Long term	− 18.9	− 20.8	− 19.0	− 19.7	− 18.8	− 11.9	− 13.8
A1B	Medium term	− 14.4	− 17.0	− 14.6	− 15.1	− 12.3	− 11.1	− 7.4
	Long term	− 19.5	− 21.9	− 19.6	− 20.5	− 18.6	− 13.5	− 13.7
B1	Medium term	− 4.2	− 3.2	− 4.4	− 6.6	0.2	− 8.5	− 3.0
	Long term	− 7.0	− 8.9	− 7.1	− 7.5	− 4.9	− 6.7	− 2.8

Notes: This table reports projected impacts of future warming on output in percentage terms under three warming scenarios (the B1, A1B and A2 scenarios) in the medium term (2050s) and the long term (2080s) under the climate models UKMO-HadCM3 and PCM. To obtain these projections, we first calculate the projected changes in seasonal average temperatures across regions, which are computed by using the temperature data based on the ClimateWizard database minus seasonal average temperatures in our sample. Using the coefficient estimates of the cumulative temperature effects on output, we then compute firm-specific predicted changes in output, weighted by each firm's share in total output, to get the estimates of the impacts of future warming on China's industrial output. Column (1) reports the projections based on the coefficient estimates obtained in the baseline scenario, in Scenario (1) with standard errors clustered within firms and within county-years, and in Scenario (2) with standard errors clustered within firms and within weather-station-years. Column (2) reports the projections based on the coefficient estimates obtained in Scenario (3) with the addition of region × year fixed effects. Column (3) reports the projections based on the coefficient estimates obtained in Scenario (4) by removing entire firms from the sample if they violate the criteria discussed in the data section at a given point in time. Column (4) reports the projections based on the coefficient estimates obtained in Scenario (5) from using weather information on weekdays only. Column (5) reports the projections based on the coefficient estimates obtained in Scenario (6) from using a balanced panel. Column (6) reports the projections based on the coefficient estimates obtained in Scenario (7) from using a county-level data set. Column (7) reports the projections based on the coefficient estimates obtained in Scenario (8) from using a dynamic panel data approach.

developed by the US National Center for Atmospheric Research. We download the data at 50 km spatial resolution, which enables us to obtain future climate variables for all Chinese counties included in our sample.

To obtain the impacts of future warming on output, we first calculate the projected changes in seasonal average temperatures across regions, which are computed by using the temperature data based on the ClimateWizard database minus seasonal average temperatures in our sample. Using the coefficient estimates of the cumulative temperature effects on output, we then compute firm-specific predicted changes in output, weighted by each firm's share in total output, to get the estimates of the impacts of future warming on China's industrial output.

Tables A8 in the Appendix reports descriptive statistics of projected changes in seasonal temperature variables under the three warming scenarios based on the climate models PCM and UKMO-HadCM3 in the medium term and the long term. The UKMO-HadCM3 model projects that, under the B1, A1B and A2 scenarios, average summer temperature in the medium term would increase by 0.9 °C, 2.1 °C and 1.3 °C, respectively, while the corresponding temperature increases in the long term would be 1.9 °C, 3.3 °C and 3.4 °C. The increases in temperature during other seasons projected by the UKMO-HadCM3 model are considerably smaller relative to the projected increase in summer temperature. Compared to the UKMO-HadCM3 model, temperature changes predicted by the climate model PCM are modest: the absolute values of temperature changes during all seasons are less than 1 °C in the medium term, and less than 2 °C in the long term.

We present the effects of future warming on output in Table 3. We find that the effects of warming on output depend on climate models and warming scenarios. If climate projections are based on the UKMO-HadCM3 model, output in China in the medium term is projected to decrease by 10.6–27.2% under the A2 scenario, 12.9–35.9% under the A1B scenario, and 5.2–19.6% under the B1 scenario. If climate projections are based on the PCM model, the corresponding output reductions in the medium term are projected to be 5.2–10.3% under the A2 scenario, 7.4–17.0% under the A1B scenario, and 3.0–8.5% under the B1 scenario.[15] In the long term, the reduction in output is expected to be considerably larger. Specifically, output is projected to decrease by 14.8–45.6% under the A2 scenario, 15.8–45.7% under the A1B scenario, and 16.1–36.0% under the B1 scenario, if we take climate variables from the UKMO-HadCM3 model. Output would decrease by 11.9–20.8% under the A2 scenario, 13.5–21.9% under the A1B scenario, and 2.8–8.9% under the B1 scenario, if we take climate variables from the PCM model.

The main factor causing future output reductions is the projected increase in summer temperature, which is found to have negative effects on output across various model specifications. However, the estimated future climate impacts on industrial output presented here are likely to be larger than the damage that actually will be caused by global warming in the long term,

[15] Output in the medium term is projected to slightly increase by 0.2% under the B1 scenario if we use projections based on the PCM model and the coefficient estimates of temperature variables based on the balanced panel.

because our coefficient estimates of temperature variables are based on the observed outcomes in a relatively short period of time and cannot capture adaptation that will be undertaken by industrial firms in the long term.

Conclusions and discussion

In this paper, we use a firm-level panel of annual industrial output, combined with a fine-scale daily weather data set, to assess the impacts of temperature changes on industrial output in China. Our results suggest that industrial output exhibits nonlinear responses to temperature changes. This finding is insensitive to how temperature variables are constructed. Industrial output responds positively to increased spring temperatures and negatively to elevated summer temperatures. Estimated negative effects on industrial output due to higher summer temperatures are larger than previous estimates for other countries (Dell et al., 2012; Deryugina and Hsiang, 2014; Hsiang, 2010), suggesting that industrial firms in China may be more vulnerable to higher summer temperatures. Because of the large differences in temperature during different seasons in China, the positive temperature effects on industrial output during the spring discovered here are different from previous findings in other countries. These findings suggest that, when examining temperature effects on economic performance for countries/regions that have clear distinctions of four seasons, one should construct weather variables by season. We also find that lagged temperature changes in prior years exert large and significant impacts on current year's output, with positive cumulative temperature effects during the spring and fall and negative cumulative temperature effects during the summer and winter.

We use temperature bins as temperature variables to identify the critical temperature threshold above and below which is harmful for industrial output. The temperature threshold identified here, [21–24 °C), is broadly consistent with studies that examine the effects of temperature on labor supply (Zivin and Neidell, 2014) and labor productivity (Hsiang, 2010), but considerably higher than that reported in studies using macro-level data (Burke et al., 2015) and data in the US (Deryugina and Hsiang, 2014). In addition to the difference in data analyzed, a possible explanation is that this paper focuses on industrial production, while Burke et al. (2015) and Deryugina and Hsiang (2014) analyze the temperature effects on GDP and income per capita, respectively, which include not only the industrial sector but also other economic sectors.

Our finding that high-temperature regions are better able to cope with high temperatures provides new suggestive evidence that adaptation to high temperatures may have been undertaken in hot Chinese counties. Coefficient estimates of the contemporaneous and lagged temperature variables are used to predict the impacts of future global warming on industrial output. Industrial output in China is projected to decrease by 3–36% before the end of this century under the slowest warming scenario and decrease by 12–46% under the most rapid warming scenario under the climate models UKMO-HadCM3 and PCM.

Two major caveats apply. The primary caveat of this work is that our data set covers observations for only a short period of time. Our estimates of the future damage to industrial output suffer particularly from this data disadvantage. Because firms may undertake a variety of adaptation actions in the long run in response to global warming, our parameter estimates of temperature variables cannot capture this long-term adaptation. As a result, we may have over-estimated the damage relative to the actual damages that will occur. Another caveat is that, although we find that increased winter temperatures affect shares of male and female workers in the labor force, the underlying mechanisms are not clear. Identifying mechanisms is thus an important area for future research.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at https://doi.org/10.1016/j.jeem.2017.07.009.

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