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Temperature and Industrial Output

Micro-level Evidence from China

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Abstract

We pair a county-level panel of annual industrial output with a fine-scale daily weather dataset to estimate the responses of industrial output to temperature changes in China. We have three primary findings. First, industrial output is nonlinear in temperature changes. With seasonal average temperatures as temperature variables, industrial output increases by 0.7–1.0% for each 1°C increase in average spring temperature, and falls by 1.3–2.3% for each 1°C increase in average summer temperature. With temperature bins as temperature variables, industrial output increases linearly with temperature up to 24–27°C, and then declines sharply at higher temperatures. Second, increased summer temperature substantially reduces industrial output in low-temperature regions, while the effect of elevated summer temperature on industrial output is insignificant in high-temperature regions. Third, total industrial output in China could decrease by as much as 8.5% by 2080.

Key Words: temperature, industrial output, adaptation, China

JEL Codes: Q51, Q54, D24, O14, O44

Contents

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1. Introduction

With accumulating scientific evidence suggesting that the world is becoming warmer, many studies have assessed the effects of high temperature on economic output, estimated impacts that may occur under different warming scenarios, and discussed how economies should adapt to a warmer climate. Because of its direct link with atmospheric conditions, agriculture's vulnerability to high temperature has been the main focus of many existing studies estimating the impacts of climate change (for example, see Chen et al., 2016; Deschênes and Greenstone, 2007; Lobell et al., 2011; Mendelsohn et al., 1994; Schlenker and Roberts, 2009; Welch et al., 2010). 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. There are at least two possible reasons for this. First, some economists posit that geography and institutional causes are the main factors driving a country's economic growth (Acemoglu et al., 2001; Rodrik et al., 2004), and believe that the industrial sector is not sensitive to climate change (Schelling, 1992). Second, micro-level data at the sub-country level or firm level are not readily available, particularly in developing countries.

In this paper, we examine whether industrial output is affected by temperature changes in the world's largest developing economy, and, if so, to what extent. Using a county-level panel of annual industrial output with a fine-scale daily weather dataset from 1999 to 2007, we exploit random variations in temperature over time within counties to identify the effects of temperature on industrial output in Chinese counties. Although China has the world's largest agricultural economy, agriculture only accounts for

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approximately 10% of its GDP. In contrast, the industrial sector contributes about 43% of China's GDP. Thus, understanding the relationship between temperature and industrial output has important implications for China's economic development and climate change policy.

There are at least three channels through which temperature can impact industrial output. First, high temperature can affect labor productivity by causing discomfort, fatigue, pain, and even cognitive dysfunction, depending on the length of time that workers are exposed to high temperature (González-Alonso et al., 1999; Zivin and Neidell, 2014). Second, by affecting investors' behavior (Cao and Wei, 2005) and storage levels (Roberts and Schlenker, 2013), temperature can influence prices of output and of inputs used for industrial production. Third, industrial firms may take actions to adapt to rising temperatures, and the nature and extent of such adaptations also depend on temperature. If these adaptations are too costly, it may affect the amount of resources used for industrial production and thus negatively affect output.

To obtain the net economic impact of temperature on industrial output, we incorporate rainfall and sunshine hours as additional weather variables in the regression analysis and estimate the impacts of the two weather variables on output. When estimating the effects of temperature on economic output, several studies have controlled for rainfall (Dell et al., 2012; Hsiang, 2010). However, none of these studies has incorporated sunshine hours 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 and rainfall, omitting this variable in the regression analysis may lead to biased parameter estimates of the effects of temperature variables on output. To minimize the estimation biases originating from omitted variables, we also control for a variety of fixed effects, including time-invariant county × industry fixed effects, year fixed effects, and industry × year fixed effects. We intentionally exclude non-climate variables (such as input and output prices and climate adaptation variables) as explanatory variables in the regression analysis, in order 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 climate adaptation actions).

We use two different approaches to construct temperature variables. We first construct temperature variables using seasonal average temperatures. We find that 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, we find that a 1°C increase in average spring temperature can raise industrial output by 0.7-1.0%, but a 1°C increase in average summer temperature is associated with a 1.3-2.3% reduction in industrial output. Estimated negative effects stemming from increased summer temperature on output are similar in magnitude to the previous assessments for other countries (Dell et al. 2012; Deryugina and Hsiang 2014; Hsiang 2010). When temperature bins are used as temperature variables, industrial output increases linearly with temperature up to 24-27°C, and then declines sharply at higher temperatures. The critical temperature threshold identified here is also consistent with prior studies based on high-frequency micro-level data (Zivin and Neidell 2014). Moreover, we find that higher temperatures can lead to a substantial reduction in industrial output in low-temperature regions, while the effect of elevated temperature on industrial output is statistically insignificant in high-temperature regions. This finding suggests possible human adaptation to global warming in high-temperature regions. Using warming scenarios from the most recent versions of global climate models, we project that total industrial output in China is expected to decrease before the end of this century. These findings remain robust to variations in model specifications, econometric estimation strategies, and data.

This paper is not the only attempt to assess the temperature effects on industrial output. 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 by 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 world 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. In contrast to the above studies that rely upon aggregate macro-level data, Cachon et al. (2012) use a micro-level dataset of weekly production from 64 automobile plants in the US over the 1994-2005 period. They 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 industrial output center around on 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, using a world sample of 125 counties over the 1950-2003 period, Dell et al. (2012) show that, by reducing agricultural and industrial output, scientific research, and political stability, a 1°C increase in annual average temperature reduces income per capita by 1.4% in poor countries. Deryugina and Hsiang (2014) analyze county-level weather and income data in the US during the period 1969-2011. They 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 existing literature in at least three regards. First, it provides new micro-level evidence on the temperature effects on industrial output for a large country other than the US. Because the industrial sector 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 (for example, see Burke et al., 2015; Dell et al., 2012; Hsiang, 2010), we include sunshine hours as an explanatory variable in the empirical analysis to increase the precision of estimated temperature effects on output. Third, this 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 they can actually undertake adaptation when they are exposed to high temperature for a long period of time.

The remainder of the paper is organized as follow. Section 2 presents a conceptual framework. Section 3 describes our empirical estimation strategy. Section 4 provides data sources and reports descriptive statistics. Section 5 presents the main results and considers a number of robustness checks. Section 6 explores whether adaptations to high temperature have been undertaken. Section 7 presents the impacts of future climate change. Section 8 concludes.

2. 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 the 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 $x = \{x_1, x_2, ..., x_N\}$ to produce an output (*y*). Let λ_x denote input productivity. The production function of the output is assumed to be constant returns to scale and can be stylized as $y = Y(\lambda_x x)$. 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 (Cao and Wei, 2005; Roberts and Schlenker, 2013) by affecting investment decisions and storage levels. 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 $A(T)$, 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 $A(T)$.

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:

$$\pi(P_x, P_y, F) = Max\{P_y(T)y - P_x(T)x - A(T)\} \tag{1}$$

subject to $y = Y(\lambda_x(T, A(T))x; F)$, 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 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 effects of temperature on output, defined as the sum of the direct effect of temperature on output and the indirect effect of temperature on output through temperature's effects on input productivities, market prices of inputs and output, and climate adaptation effort. Second, we want to examine whether temperature has any remaining effects on industrial output, net of firms' adjustment in input use and all potential climate adaptations in response to temperature changes.

3. 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.

3.1 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 county-average industrial output:

$$\log VA_{r,t}^{i} = \rho \log VA_{r,t-1}^{i} + \alpha_1 Temp_{r,t} + \alpha_2 Temp_{r,t-1} + \beta_1 W_{r,t} + \beta_2 W_{r,t-1} + c_r^i + \psi_t^i + \theta_t + \varepsilon_{r,t}^i \qquad (2)$$

where counties are indexed by r, industries are indexed by i and years are indexed by t. Following Hsiang (2010) and Dell et al. (2012), we use value added per capita to measure industrial output1. $\log VA_{r,t}^{i}$ denotes log value added per capita for industry i in county r and year t. $\log VA_{r,t-1}^{i}$ is a lagged dependent variable which is included as an explanatory variable to capture possible serial correlation in county-average industrial output over time. ρ is the coefficient of the serial correlation. c_r^i denotes time-invariant industry ×

[1] We will use (industrial) output and value added per capita interchangeably in the remainder of the paper.

county fixed effects which are used to control for the unobserved variables that are unique to industry i in county r, such as geography. ψ_t^i denotes industry × year fixed effects to remove the unobserved factors that are common to all counties 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. θ_t denotes year fixed effects that account for common temporal shocks which are the same for all industries and counties in a given year, such as trends in global climate.

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. Autumn 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 using seasonal average temperatures, which are denoted by $Temp_{r,t}$ in Eq. (2). To account for simultaneous variations in temperature, rainfall, and sunshine duration, sums of rainfall and sunshine hours in each season are also included as additional weather variables, which are denoted by $W_{r,t}$. We include lagged values of weather variables as additional explanatory variables, represented by $Temp_{r,t-1}$ and $W_{r,t-1}$, to examine whether industrial output in year t is affected by weather conditions in the previous year. With the semi-log specification of the regression model, estimated coefficients of temperature variables (α_1 and α_2) can be interpreted as the percentage changes in industrial output with a 1°C increase in seasonal average temperature. The main hypothesis is to test whether $\alpha_1 = \alpha_2 = 0$, namely to test the null hypothesis that temperature has no effect on output. $\varepsilon_{r,t}^i$ are the error terms that capture the impacts on output of other factors that are not included in Eq. (2).

3.2 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):

$$\log VA_{r,t}^i = \rho \log VA_{r,t-1}^i + \sum_m [\alpha_1^m Tbin_{r,t}^m + \alpha_2^m Tbin_{r,t-1}^m] + \beta_1 W_{r,t} + \beta_2 W_{r,t-1} + c_r^i + \psi_t^i + \theta_t + \varepsilon_{r,t}^i \quad (3)$$

where $Tbin_{r,t}^m$ denotes the number of days in county r and year t on which daily average temperatures fall into the mth temperature bin. We divide daily average temperatures, measured in °C, into seventeen bins, each of which is 3°C wide. We define $Tbin_{r,t}^{1}$ = number of days when daily average temperature is below -15°C, $Tbin_{r,t}^{2}$ = number of days when daily average temperature falls into the range of [-15°C, -12 °C), $Tbin_{r,t}^{3}$ = number of days when daily average temperature falls into the range of [-12°C, -9 °C), and so on. Finally, $Tbin_{r,t}^{17}$ = 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 [24°C, 27°C) as the omitted category. The coefficients of the other temperature bins, α_1^m, thus measure the marginal effect on $\log VA_{r,t}^{i}$ of an additional day in the mth temperature bin, relative to a day in the [24°C, 27°C) bin. However, our results do not hinge on the selection of this reference group. Other explanatory variables included in Eq. (3) are defined in the same way as in Eq. (2).

3.3 Identification

The temperature effects on industrial 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; Schlenker and Roberts, 2009). Given that our econometric models include a lagged dependent variable and our panel has a short period of time and a large number of industry-counties, we estimate our econometric models using the Arellano-Bond Generalized Method of Moments (GMM) approach (Arellano and Bond, 1991).

If our dependent variable is close to a random walk, the GMM estimator based on the Arellano-Bond approach will be inconsistent and a system GMM estimator is more appropriate (Blundell and Bond, 1998). Compared to difference GMM, system GMM uses lagged differences of $\log VA_{r,t}^{i}$ as instruments for the equation in levels, in addition to lagged values of $\log VA_{r,t}^{i}$ as instruments for the equation in first differences. The validity of the additional instruments in system GMM depends on the assumption that the lagged differences of $\log VA_{r,t}^{i}$ are uncorrelated with the time-invariant fixed effects (Roodman, 2009).

When determining whether difference GMM or system GMM is more appropriate for our study, we rely upon several specification tests. First, we find that the lagged differences of $\log VA_{r,t}^{i}$ are not valid instruments for the equation in levels, because they are correlated with the time-invariant fixed effects.[2] This finding is also supported by the Hansen test statistics. Second, based on the unit-root test statistics (Levin et al., 2002), we find that $\log VA_{r,t}^{i}$ is stationary, suggesting that the lagged values of $\log VA_{r,t}^{i}$ contain useful information about its future changes and that they are valid instruments for the equation in first differences. The validity of the lagged values of $\log VA_{r,t}^{i}$ as instrumental variables is also supported by the Hansen test statistics. Hence, we estimate the econometric models (2)-(3) using the Arellano-Bond two-step GMM approach. Reported standard errors are estimated using the Windmeijer finite-sample correction to adjust the downward bias in the two-step estimation and are adjusted for autocorrelation and heteroscedasticity of the error terms.[3]

4. Data

We compile a rich county-level panel on industrial output and weather from 1999 to 2007. This section describes data sources and reports summary statistics.

4.1 Weather Data

We obtain daily weather data from the China Meteorological Data Sharing Service System, which reports daily average temperature, rainfall, and sunshine duration for 820 weather stations in China. The dataset also contains detailed information on coordinates of each weather station, enabling us to construct weather variables at the county level. Of the 2862 Chinese counties included in the sample, 19 counties have

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[2] Specifically, we use OLS to estimate Eqs. (2) and (3) and obtain predicted values of $c_r^i + \varepsilon_{r,t}^i$. We find that the correlations between $\Delta \log VA_{r,t-1}^{i}$ ($\Delta \log VA_{r,t-2}^{i}$, $\Delta \log VA_{r,t-3}^{i}$) and the predicted values of $c_r^i + \varepsilon_{r,t}^i$ are statistically significant at the 1% level.

[3] The error terms may also be spatially correlated because of the omission of spatially correlated explanatory variables. Cameron et al. (2011) suggest that two-way clustering at both the county and year level can account for spatial correlation and serial correlation of the error terms. Consistent estimates from the two-way clustering requires both large *N* and large *T*. Because our panel has a large *N* but a small number of years, we cannot use their approach to account for the potential spatial correlation of the error terms. As a result, we may have over-estimated *t*-statistics. However, because we include in the regression analysis a variety of fixed effects to minimize estimation biases originating from omitted variables, the effect of not accounting for the spatial correlation of the error terms on our coefficient estimates is expected to be small.

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]

4.2 Industrial Output

Data on industrial output are initially collected at the firm level for the period 1999-2007 from the Annual Survey of Industrial Firms database compiled by the National Bureau of Statistics of China (NBS). This dataset contains detailed information on total value added, number of workers, and other accounting information for firms with annual sales above 5 million RMB. The dataset covers 37 two-digit manufacturing industries for 31 provinces and province-equivalent municipal cities. The total output produced by firms covered in this dataset accounts for more than 85% of China's total industrial output.

The NBS assigns a legal identification number (ID) to each firm included in the dataset and specifies its type of ownership. There are six primary ownership categories for firms covered by the dataset, namely state-owned enterprises, private firms, collective firms, foreign firms, Hong Kong, Macao and Taiwan firms, and mixed-ownership firms. However, many firms occasionally receive a new ID as a result of restructuring, merger, acquisition, or changes in ownership. Thus, it is fairly difficult to generate unique IDs to link firms over time. To circumvent this data difficulty, we transform the original firm-level data into county-level data, with county-industry-year as the unit of observation. Before the data transformation, following Cai and Liu (2009), we delete observations from the original dataset to avoid estimation bias originating from misclassified observations, if the values of fixed assets and total annual sales are below 10 million RMB and the number of workers is less than 30. Observations are also excluded if value added per capita is either larger than the 99th percentile or smaller than the 1st percentile.

Table 1 reports summary statistics of the sample. We have an unbalanced panel with 186,558 observations for years 1999-2007. Value added per capita varied

[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 in Section 5, but are available upon request.

substantially in the sample, ranging between 2.5-846.8 thousand RMB, with a national average of 81.7 thousand RMB. Weather variables also exhibit considerable variability. For instance, average spring temperature ($Temp^{spring}$) ranged from -6.2°C to 27.4°C in China, with an average of 15.5°C. Average autumn temperature ($Temp^{autumn}$) has a similar distribution, ranging between -6.2°C to 27.6°C (averaged at 16.3°C). Average winter temperature ($Temp^{winter}$) varied between -22.2°C and 24.1°C, with an average of 7.3°C. Compared to mean temperatures during the other three seasons, average summer temperature ($Temp^{summer}$) is considerably higher (about 9.5°C -18.4°C higher), with an average of 25.7°C.

5. Results

5.1 Data Correlations

Before presenting the main results, we first examine the correlations of weather variables during the sample period. As shown in Table 2, we find that correlations of weather variables are statistically significant at the 1% level during all seasons. Temperature and sunshine variables were positively correlated, with coefficients of correlation ranging between 0.18 and 0.64. Both variables were negatively correlated with rainfall, except for the relationship between the temperature and rainfall variables during the winter, where the correlation of the two variables was positive. These test results suggest that, to obtain accurate estimates of temperature effects on industrial output, the three weather variables should be incorporated in the empirical analysis.

5.2 Main Results: Seasonal Average Temperatures as Temperature Variables

We examine the effects of weather on industrial output using four different model specifications. In Model 1, we include only four temperature variables, namely $Temp^{spring}$, $Temp^{summer}$, $Temp^{autumn}$, and $Temp^{winter}$, as explanatory variables to assess the temperature effects on industrial output during the sample period. In Model 2, we add rainfall as additional explanatory variables, including $Rain^{spring}$, $Rain^{summer}$, $Rain^{autumn}$, and $Rain^{winter}$. Sunshine variables are incorporated in Model 3. Lastly, we add lagged values of weather variables in Model 4 to examine whether weather shocks in year *t-1* had any direct impacts on industrial output in year *t*. All model specifications include the lagged dependent variable in year *t-1* as an explanatory variable and incorporate time-invariant industry × county fixed effects, industry × year fixed effects, and year fixed effects.

Coefficient estimates of temperature variables and the 95% confidence bands are displayed in Figure 1, while parameter estimates are reported in Table A1 in the appendix.

When employing the Arellano-Bond GMM approach to estimate Models 1-4, we find that Arellano-Bond test statistics for AR(1) and AR(2) are statistically significant, while the corresponding test statistics for AR(3) are insignificant. Thus, following Roodman (2009), we use the third and deeper lags of the dependent variable as instruments for the equation in first differences.[5] The validity of our instruments is supported by the Hansen test statistics, as shown in Table A1.

Across various model specifications that we considered, parameter estimates of temperature variables indicate that increased $Temp^{summer}$ is associated with a substantial reduction in industrial output. Specifically, a 1°C increase in average $Temp^{summer}$ can reduce industrial output by 1.2-1.5% (depending on model specifications), holding all else the same (Figure 1a). This negative temperature effect on industrial output is statistically significant at the 1% level.

The effects of temperature changes on industrial output during the other three seasons are statistically insignificant in Models 1-3. In Model 4, with the inclusion of lagged values of weather variables, the coefficient estimate of $Temp^{spring}$ is positive and statistically significant at the 10% level, suggesting that industrial output might be positively correlated with higher spring temperature during the sample period. Specifically, a 1°C increase in $Temp^{spring}$ is associated with an 0.8% increase in industrial output. We also find that the effects of spring and winter temperatures in year *t-1* on industrial output in year *t* are positive (light blue bars in Figure 1b). Holding all else the same, each 1°C increase in $Temp^{spring}$ and $Temp^{winter}$ in year *t-1* can raise industrial output in year *t* by 0.8% and 0.5%, respectively. Effects of the changes in $Temp^{summer}$ and $Temp^{autumn}$ in the previous year on current year's output are statistically insignificant. Therefore, our results suggest that there exist differential effects of temperature on industrial output and that the response of industrial output to temperature is nonlinear.

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

[5] We estimate our econometric models using the Stata command "xtabond2".

on industrial output are similar in magnitude (1.2-1.5%/1°C) to these earlier studies. However, our finding of the positive temperature effects on industrial output during the spring and winter is different from that reported in Hsiang (2010), which focuses on Caribbean and Central American countries and finds that industrial output in these countries only responded negatively to increased temperature during the hottest season. This might be driven by the large difference between average summer temperature and average temperatures during all other seasons in our sample. For example, average $Temp^{spring}$, $Temp^{autumn}$ and $Temp^{winter}$ in our sample were 10.2°C, 9.4°C, and 18.4°C, respectively, lower than average $Temp^{summer}$. In contrast, the difference in temperature during different seasons is fairly small in Caribbean and Central American countries (see Table S1 in Hsiang, 2010). Our findings suggest that, when examining the temperature effects on economic output, it is important to construct temperature variables by season rather than using annual average temperature, especially for countries like China with clear distinctions of four seasons.

The coefficient estimates of the rainfall and sunshine variables in the current year do not demonstrate strong statistical significance in Models 2, 3 and 4. Parameter estimates of the $Rain^{spring}$ and $Sunshine^{winter}$ variables in the prior year are statistically significant at the 1% level. Although the parameter estimates of the two variables are small in magnitude (<0.2%), they are positive, which suggests that increased rainfall during the spring and higher sunshine hours during the winter in the prior year raised current year's industrial output. A possible explanation for these findings is that, by mitigating air pollution and increasing labor productivity,[6] the positive effect on labor productivity of increased rainfall and sunshine hours in the prior year was carried over into the next year. Finally, we find that, across the various model specifications, coefficient estimates of the lagged dependent variable are statistically significant at the 1% level, with a coefficient estimate of 0.64, indicating that there exists substantial serial correlation in industrial output at the industry-county level.

In summary, our results displayed in Figure 1 indicate that the response of industrial output to temperature is nonlinear, with a negative effect of $Temp^{summer}$ and a positive effect of $Temp^{spring}$. Because the coefficient estimate of $Temp^{spring}$ is statistically

[6] Atmospheric studies suggest that increased rainfall can mitigate air pollution (see Arya, 1999). Reduced sunlight during the winter is found to be a major cause of the reduction in labor productivity (Lambert et al., 2002).

significant only at the 10% level in Model 4, we use temperature bins as temperature variables to further investigate whether a nonlinear relationship between temperature and industrial output exists. In our sample, mean $Temp^{spring}$ is 15.5°C, while mean $Temp^{summer}$ is 25.7°C. Thus, the critical temperature threshold above which is harmful for industrial output is likely to lie between 16°C and 26°C. Therefore, when using temperature bins as temperature variables, we set the bin [24°C, 27°C) as the omitted category. The coefficients of other temperature bins measure the marginal effect on industrial output of an additional day in the respective temperature bins, relative to a day in the [24°C, 27°C) bin.

5.3 Main Results: Temperature Bins as Temperature Variables

Figure 2 displays point estimates and the 95% confidence bands of coefficient estimates of various temperature bins, which are obtained using Model 4 with the inclusion of lagged weather variables. We report these parameter estimates in Table A2 in the appendix. The horizontal axis of Figure 2 is temperature, while the vertical axis in each frame denotes the log value added per capita. The left panel of Figure 2 shows that the responses of industrial output to temperature are statistically insignificant when temperature is below 15°C. When temperature is above 15°C, the responses of industrial output to temperature changes become statistically significant. Industrial output increases approximately linearly with temperature up to 24-27°C, and then declines sharply with temperatures above 30°C. Relative to a day with an average temperature of 24-27°C, an additional day at 30°C can lead to a reduction in annual industrial output by roughly 0.12%, holding all else the same. During the sample period, the number of days with average temperatures [24°C, 27°C) accounts for about 9.5% of the 365 days in a year (see histogram at the bottom of Figure 2). Thus, replacing days at [24-27°C) temperatures with full days at 30°C will decrease output by 0.12%*9.5%*365=4.2%, holding all else the same. The temperature threshold identified here is consistent with our findings when seasonal average temperatures are used as temperature variables. These results also confirm that the relationship between temperature and industrial output is indeed nonlinear.

The right panel of Figure 2 displays the estimated effects of temperature in the previous year on current year's output, which are jointly estimated with the contemporaneous temperature effects shown in the left panel of Figure 2. We find that, except for the temperature bin [27°C, 30°C), coefficient estimates of other temperature bins are statistically significant and negative, suggesting that the increasing number of hot days in the previous year also negatively affected industrial output in the following year. Parameter estimates of other weather variables are similar to our findings when seasonal average temperatures are used as temperature variables. For brevity, they are not reported.

5.4 Robustness Checks

We conduct a variety of sensitivity analyses to examine the robustness of our estimated temperature effects on industrial output. Specifically, in Scenario (1), we drop industry × year fixed effects and consider only industry × county fixed effects and year fixed effects. In Scenario (2), in addition to the fixed effects considered in the baseline scenario, we include regional-specific time trends.[7] In Scenario (3), we replicate the above analysis using a balanced sample from 1999 to 2007. So far, weather variables are constructed by incorporating weather information on all days in a year, including both weekdays and weekends. Most industrial activities in China occur on weekdays. In Scenario (4), we re-construct our weather variables using weather information on weekdays only, and replicate the regression analysis using the newly constructed weather variables. To account for the urban heat island effect, in which temperature might be affected by industrial activities, in Scenario (5) we treat temperature variables as endogenous variables and use their lags as instruments to address this potential endogeneity issue. We conduct these sensitivity analyses using Model 4 with lagged weather variables and the lagged dependent variable. Table 3 reports coefficient estimates of temperature variables, which are obtained using seasonal average temperatures as temperature variables. To facilitate comparison, we repeat the relevant results from Table A1 in the first column of Table 3. We present coefficient estimates of temperature bins for Scenarios (1)-(5) in Figure A1 and Table A2 in the appendix.

We find that our key findings of the temperature effects on industrial output are broadly consistent across the various scenarios that we considered. The negative temperature effects on industrial output stemming from rising $Temp^{summer}$ are statistically significant, ranging between 1.3% in Scenario (4) and 2.3% in Scenario (5). Our findings of the positive temperature effects on industrial output during the spring are also robust

[7] 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.

across these scenarios, with exceptions in Scenarios (3) and (4), where the effect of Temp^{spring} on industrial output is statistically insignificant. Parameter estimates of other weather variables in Scenarios (1)-(5) are similar to our baseline estimates. For brevity, they are not reported in Table 3. As shown in Figure A1, we find that the critical temperature threshold identified in the baseline scenario, [24°C, 27°C), remains remarkably consistent across the various scenarios that we considered in this section.

6. Climate Adaptation

After demonstrating that industrial output is negatively correlated with high temperature, in this section we explore whether adaptation actions have been undertaken to reduce the negative temperature effects on industrial output. In exploring the scope for climate adaptation, we focus our attention on the temperature effects in regions with different income and temperature levels. On the one hand, it is well noted that, as regions become richer, they become better equipped to cope with natural disasters and sudden environmental changes (Dell et al., 2012; Hsiang, 2010; Kahn, 2005). Adaptation to high temperature can take many forms. For instance, firms located in rich regions may install and run air conditioners to mitigate thermal stress on workers, let workers work less on hot days, or shift to capital-intensive production technology, although the costs of these adaptation strategies could be considerable. On the other hand, high-temperature regions might be better than low-temperature regions at coping with high temperature. When a region is exposed to high temperature for a long period of time, some types of adaptation can be developed and undertaken. For instance, individuals can work flexibly by reallocating time on hot days (Zivin and Neidell, 2014).

To proceed, we modify Eq. (2) and construct two new sets of weather variables. The first set of new variables is constructed by interacting weather variables with a dummy for a county being “rich”, defined as having above-median GDP per capita in 1998 (the year before the first year of the sample period). The second set of new variables is constructed by interacting weather variables with a dummy for a “high-temperature” county, according to the Huai River-Qin Mountains line, which is the natural boundary between Northern (low-temperature) China and Southern (high-temperature) China. We conduct the analyses using seasonal average temperatures as temperature variables as specified in Eq. (2), and using Model 4. For the ease of comparison, we report only coefficient estimates of Temp^{summer} in Table 4, whose effect on output is found to be negative.

Column (1) of Table 4 shows that the coefficient on the interaction term between the "rich" dummy and temperature is not statistically significant, suggesting that the negative effect of $Temp^{summer}$ does not differ between poor and rich counties in China. Column (2) in this table shows that the coefficient estimate of the interaction term between the "high-temperature" dummy and temperature is positive and statistically significant at the 1% level, which suggests that, compared to low-temperature regions, high-temperature regions are better at adapting to elevated summer temperature. Column (3) controls for the interaction term between temperature and "rich" and the interaction term between temperature and "high-temperature." Once again, we find that higher temperatures caused a substantial reduction in industrial output in low-temperature regions, and the effect of elevated summer temperature on industrial output is statistically insignificant in high-temperature regions (see last row of Table 4). These findings remain robust across the various scenarios that we considered in the robustness check section (see Table A3 in the appendix).[8] Although we do not have direct evidence showing that adaptation has been undertaken in high-temperature regions, estimated coefficients of temperature variables in Table 4 suggest that some types of adaptation might have been undertaken in these regions to alleviate the negative effect of local thermal conditions on output.

7. Future Climate Change

We use parameter estimates obtained from Model 4, which utilizes seasonal average temperatures as temperature variables, under the baseline scenario and the scenarios considered in the robustness check (reported in Table 3) to quantify the potential impacts of future climate change. Projections of future climate variables are taken from ClimateWizard,[9] 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 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

[8] In Scenario (3) with a balanced sample, we find that the negative $Temp^{summe}$ effects on industrial output in rich regions are smaller than in poor regions.

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

ClimateWizard include monthly average temperature and monthly total rainfall for the medium term (Mid Century, 2050s) and the long term (End 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 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.

Table 5 reports descriptive statistics of projected changes in seasonal temperature variables under the three warming scenarios by the climate models PCM and UKMO-HadCM3 in the medium and long term. Projected changes in temperature variables are computed by using the temperature data based on the ClimateWizard database minus mean temperatures in our sample. The UKMO-HadCM3 model projects that, under the B1 scenario, average summer temperature would increase by 0.9°C in the medium term and 1.9°C in the long term. The UKMO-HadCM3 model projects that, under the A2 scenario, average summer temperature would increase by 1.3°C and 3.4°C in the medium and long term, respectively, while the corresponding increases in average summer temperature under the A1B scenario are 2.1°C and 3.3°C. Compared to the UKMO-HadCM3 model, the increases in summer temperature predicted by the climate model PCM are considerably smaller. Both climate models predict that average winter temperature will decrease, by 2.6-3.5°C in the medium term and by 1.0-3.6°C in the long term.

We present the effects of future climate change on industrial output in Table 6. We find that the effects of warming on industrial output depend on climate models and warming scenarios. If climate projections are based on the UKMO-HadCM3 model, total industrial output in China in the medium term is expected to decrease by 1.0-3.3% under the B1 scenario, 1.2-4.1% under the A2 scenario, and 1.6-6.4% under the A1B scenario. If climate projections are based on the PCM model, total industrial output in the medium term is expected to decrease by 0.1-2.2% under the B1 scenario (with an exception in Scenario (5), under which total industrial output would slightly increase by 0.3%), 0.3-2.6% under the A2 scenario, and 0.7-2.2% under the A1B scenario.

In the long term, industrial output is expected to decrease under all warming scenarios. Specifically, total industrial output is expected to decrease by 1.6-6.1% under the B1 scenario, 0.4-8.3% under the A2 scenario, and 0.5-8.5% under the A1B scenario, if we take climate variables from the UKMO-HadCM3 model. The output reductions would decrease by 0.6-2.6% under the B1 scenario, 0.2-2.5% under the A2 scenario, and 0.3-2.5% under the A1B 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. One should note that the estimated future climate impacts on industrial output presented here are likely to be larger than the damage that will be actually caused by global warming in the long term, because the coefficient estimates of temperature variables used here are based on the observed outcomes in a relatively short period of time and cannot capture adaptations that will be undertaken by industrial firms in the long term.

8. Conclusions and Discussion

In this paper, we use a county-level panel of annual industrial output with a fine-scale daily weather dataset 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 temperature and negatively to elevated summer temperature. Estimated negative effects on industrial output due to higher summer temperature (1.3-2.3%/1°C) are in line with previous assessments. Because of the large difference 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 use temperature bins as temperature variables to identify the critical temperature threshold above which is harmful for industrial output. The temperature threshold identified here [24-27°C) is 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 per capita and income per capita, respectively, which include not only the industrial sector but also other economic sectors.

Unlike what has been previously hypothesized (for instance, see Dell et al., 2012; Hsiang, 2010), we discover that poor and rich counties in China exhibit similar responses to temperature changes. This finding could be driven by the difference between the data analyzed in this study and that used in the previous studies. It is also possible that our sample spans only a short period of time and cannot capture adaptations undertaken before the first year of the sample period. Our finding that high-temperature regions are better able to cope with high temperature provides new suggestive evidence that adaptations to high temperature may have been undertaken in hot Chinese counties. Estimated parameter estimates of temperature variables are used to predict the impacts of future global warming on industrial output in China. We find that county-average industrial output could decrease by as much as 8.5% before the end of this century.

The primary caveat is that our dataset covers observations for only a short period of time. With a longer time period of observations, we may find that rich regions are better equipped to adapt to high temperatures relative to poor regions. Our estimates of the future damage to industrial output also suffer from this data disadvantage. Because industrial 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.

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Tables and Figures

Table 1. Summary Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Value added per capita	1000 RMB	81.721	87.066	2.482	846.777
$Temp^{spring}$	°C	15.528	4.077	-6.243	27.432
$Temp^{summer}$	°C	25.749	2.767	4.843	32.757
$Temp^{autumn}$	°C	16.257	4.849	-6.195	27.636
$Temp^{winter}$	°C	7.305	6.383	-22.213	24.110
$Rain^{spring}$	Cm	24.590	19.964	0.000	112.240
$Rain^{summer}$	Cm	47.552	24.563	0.030	253.860
$Rain^{autumn}$	Cm	16.625	11.573	0.000	121.580
$Rain^{winter}$	Cm	15.193	11.356	0.000	72.040
$Sunshine^{spring}$	10 hours	53.210	17.556	16.970	100.950
$Sunshine^{summer}$	10 hours	56.298	12.131	18.550	110.380
$Sunshine^{autumn}$	10 hours	48.626	12.772	7.450	90.810
$Sunshine^{winter}$	10 hours	41.338	14.084	7.300	85.880

Notes: N=186,558. Unit of observation is a county-industry-year.

Table 2. Correlations among Weather Variables

	Spring			Summer	
	$Temp^{spring}$	$Rain^{spring}$		$Temp^{summer}$	$Rain^{summer}$
$Rain^{spring}$	-0.316*	-	$Rain^{summer}$	-0.517*	-
$Sunshine^{spring}$	0.413*	-0.408*	$Sunshine^{summer}$	0.636*	-0.468*
	Autumn			**Winter**	
	$Temp^{autumn}$	$Rain^{autumn}$		$Temp^{winter}$	$Rain^{winter}$
$Rain^{autumn}$	-0.164*	-	$Rain^{winter}$	0.039*	-
$Sunshine^{autumn}$	0.179*	-0.384*	$Sunshine^{winter}$	0.179*	-0.185*

Notes: Correlations are computed using residual variations in weather variables after removing the fixed effects of the unobserved factors that are unique to each county or common to all counties in a given year.

* denotes $P < 1\%$

Table 3. Robustness Checks (Dependent Variable: Log Value Added Per Capita)[a]

	Baseline	Scenario (1): Industry × county fixed effects and year fixed effects only	Scenario (2): All fixed effects and regional specific time trends	Scenario (3): Balanced sample	Scenario (4): Weekday	Scenario (5): Endogenous temperature variables
$Temp^{spring}$	0.0077*	0.0072*	0.0073*	0.0035	0.0055	0.0101**
	(0.0041)	(0.0041)	(0.0042)	(0.0053)	(0.0037)	(0.0047)
$Temp^{summer}$	-0.0147***	-0.0150***	-0.0153***	-0.0140**	-0.0133***	-0.0227***
	(0.0043)	(0.0044)	(0.0044)	(0.0058)	(0.0042)	(0.0068)
$Temp^{autumn}$	0.0054	0.0055	0.0061	0.0088*	0.0043	0.0100*
	(0.0038)	(0.0038)	(0.0038)	(0.0050)	(0.0037)	(0.0057)
$Temp^{winter}$	0.0024	0.0025	0.0029	0.0075**	-0.0012	-0.0034
	(0.0021)	(0.0021)	(0.0022)	(0.0030)	(0.0018)	(0.0036)
$L1.Temp^{spring}$	0.0079**	0.0079**	0.0076**	0.0035	0.0132***	0.0000
	(0.0037)	(0.0037)	(0.0037)	(0.0050)	(0.0035)	(0.0037)
$L1.Temp^{summer}$	0.0023	0.0019	0.0016	0.0025	-0.0004	-0.0172***
	(0.0043)	(0.0043)	(0.0044)	(0.0056)	(0.0041)	(0.0059)
$L1.Temp^{autumn}$	0.0057	0.0056	0.0063*	0.0017	0.0030	0.0050
	(0.0037)	(0.0037)	(0.0038)	(0.0052)	(0.0035)	(0.0047)
$L1.Temp^{winter}$	0.0051**	0.0051**	0.0055**	0.0041	-0.0006	0.0048
	(0.0022)	(0.0022)	(0.0022)	(0.0029)	(0.0018)	(0.0038)
AR(3)[b]	0.608	0.567	0.610	0.751	0.588	0.631
Hansen test [b]	0.745	0.770	0.745	-	0.754	0.646
Observations	186,558	186,558	186,558	103,537	186,558	186,558

Notes: [a]All scenarios include the lagged dependent variable, lagged weather variables, industry × county fixed effects, year fixed effects, and industry × year fixed effects unless otherwise noted. Robust standard errors are in parentheses, adjusted for autocorrelation and heteroscedasticity of the error terms. Units for explanatory variables: 1°C for temperature.

[b] *p*-values of test statistics. In Scenario (3), because the model is just-identified, the Hansen *J*-statistic is not reported.

*** significant at 1%; ** significant at 5%; * significant at 10%

Table 4. Effect of Temperature on Log Value Added Per Capita in Different Income and Temperature Regions[a]

	(1)	(2)	(3)
$Temp^{summer}$	-0.0178***	-0.0203***	-0.0231***
	(0.0057)	(0.0064)	(0.0074)
$Temp^{summer}$ × rich region dummy	0.0104		0.0075
	(0.0084)		(0.0087)
$Temp^{summer}$ × high-temperature region dummy		0.0210**	0.0018**
		(0.0094)	(0.0007)
Temperature effect in high-temperature regions		0.0007	-0.0008
		(0.0068)	(0.0079)
AR(3)[b]	0.679	0.743	0.719
Hansen test[b]	0.751	0.790	0.787

Notes: [a] Results are obtained using seasonal average temperatures as temperature variables and Model 4 that includes the lagged dependent variable, lagged weather variables, industry × county fixed effects, year fixed effects and industry × year fixed effects. Robust standard errors are in parentheses, adjusted for autocorrelation and heteroscedasticity of the error terms. Units for explanatory variables: 1°C for temperature. N=186,558.

[b] *p*-values of test statistics.

*** significant at 1%; ** significant at 5%; * significant at 10%

Table 5. Predicted Changes in Temperature by Climate Models PCM and UKMO-HadCM3

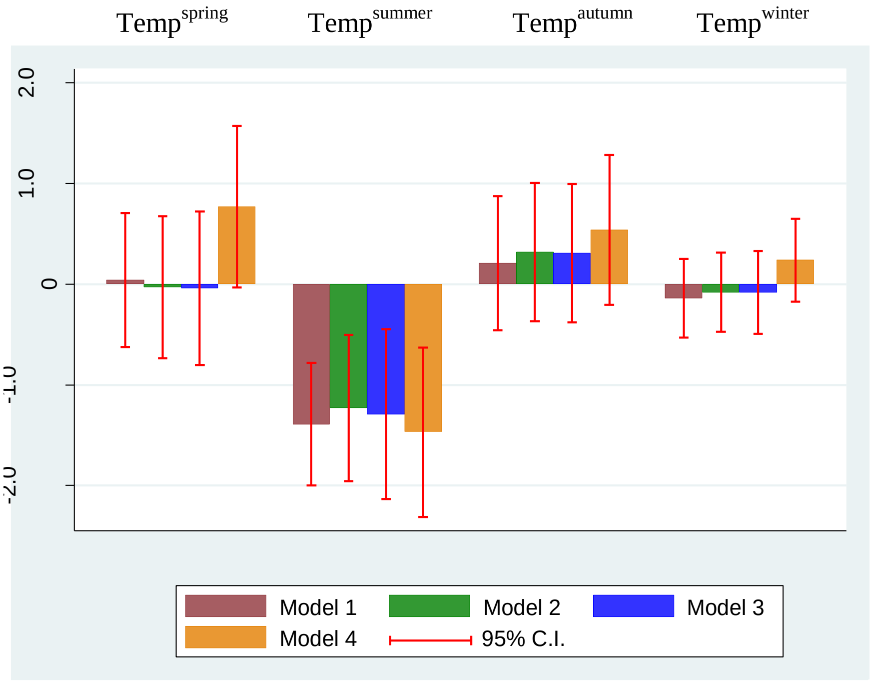
	Mid Century (2050s)				End Century (2080s)			
	PCM		UKMO-HadCM3		PCM		UKMO-HadCM3	
A1B								
$Temp^{spring}$	-0.35	(2.28)	0.91	(2.35)	0.56	(2.34)	2.10	(2.36)
$Temp^{summer}$	0.20	(2.26)	2.05	(2.40)	0.81	(2.26)	3.29	(2.45)
$Temp^{autumn}$	0.35	(2.20)	1.42	(2.20)	0.88	(2.16)	2.77	(2.26)
$Temp^{winter}$	-2.81	(2.41)	-2.57	(2.57)	-2.13	(2.31)	-1.26	(2.57)
A2								
$Temp^{spring}$	-0.25	(2.35)	0.39	(2.34)	0.83	(2.31)	2.11	(2.31)
$Temp^{summer}$	0.04	(2.27)	1.28	(2.33)	0.95	(2.23)	3.39	(2.42)
$Temp^{autumn}$	0.06	(2.19)	1.02	(2.22)	1.06	(2.17)	3.04	(2.24)
$Temp^{winter}$	-3.38	(2.37)	-2.71	(2.52)	-1.97	(2.27)	-1.01	(2.55)
B1								
$Temp^{spring}$	-0.60	(2.36)	0.13	(2.39)	-0.61	(2.34)	0.72	(2.34)
$Temp^{summer}$	-0.54	(2.27)	0.90	(2.33)	-0.18	(2.27)	1.92	(2.42)
$Temp^{autumn}$	-0.43	(2.21)	0.60	(2.22)	-0.18	(2.20)	1.26	(2.17)
$Temp^{winter}$	-3.42	(2.44)	-3.49	(2.60)	-3.57	(2.51)	-2.40	(2.53)

Notes: Numbers presented in parentheses are standard deviations.

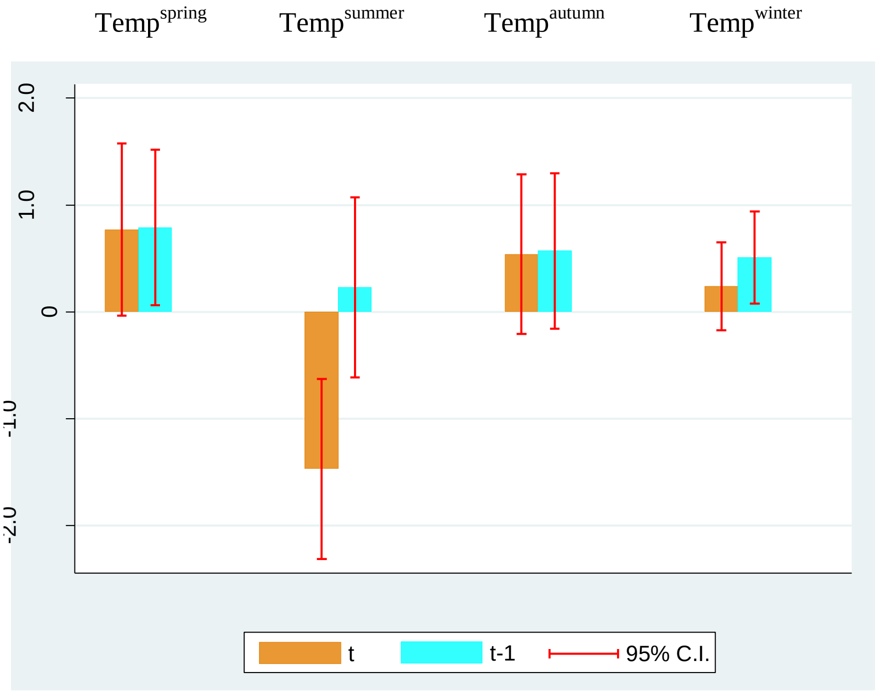
Table 6. Effects of Warming on Total Industrial Output under Different Warming Scenarios and Model Specifications (%)

		Baseline	Industry × county fixed effects and year fixed effects only	All fixed effects and regional specific time trends	Balanced sample	Weekday	Endogenous temperature variables
UKMO-HadCM3							
A1B	Medium term	-2.64	-2.77	-1.94	-3.39	-1.56	-6.35
	Long term	-1.97	-2.19	-0.53	-2.92	-1.65	-8.46
A2	Medium term	-2.34	-2.42	-1.79	-2.71	-1.17	-4.12
	Long term	-3.42	-2.20	-0.38	-2.57	-1.74	-8.27
B1	Medium term	-1.98	-2.61	-2.27	-3.12	-1.00	-3.32
	Long term	-2.66	-2.78	-2.05	-3.23	-1.63	-6.13
PCM							
A1B	Medium term	-2.09	-2.10	-1.92	-2.17	-0.73	-1.51
	Long term	-1.21	-1.29	-0.79	-2.05	-0.34	-2.54
A2	Medium term	-1.83	-1.85	-1.85	-2.56	-0.32	-1.13
	Long term	-0.93	-1.02	-0.41	-1.94	-0.16	-2.50
B1	Medium term	-1.63	-1.61	-1.85	-2.18	-0.07	0.32
	Long term	-2.24	-2.24	-2.32	-2.56	-0.56	-0.85

Figure 1. Estimated Temperature Effects on Log Value Added Per Capita



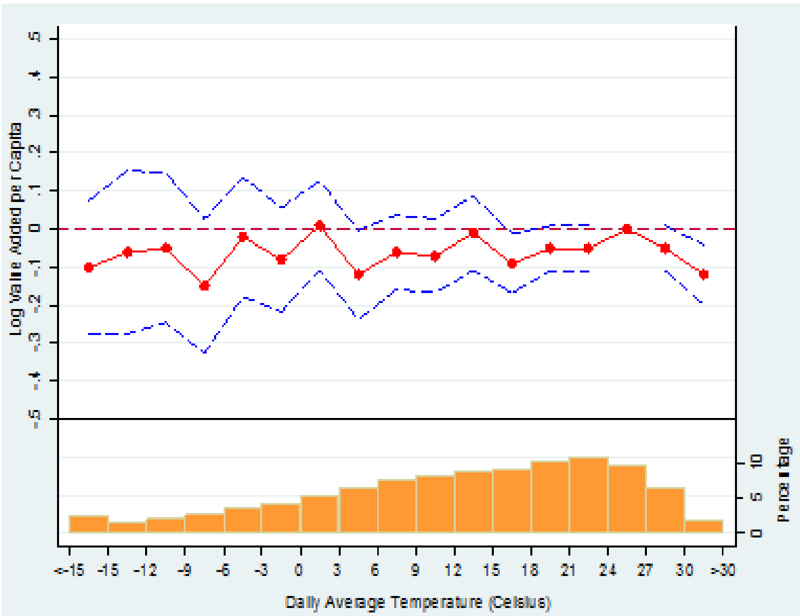
(a) Percentage change in industrial output per 1°C increase in temperature (effect of current year)



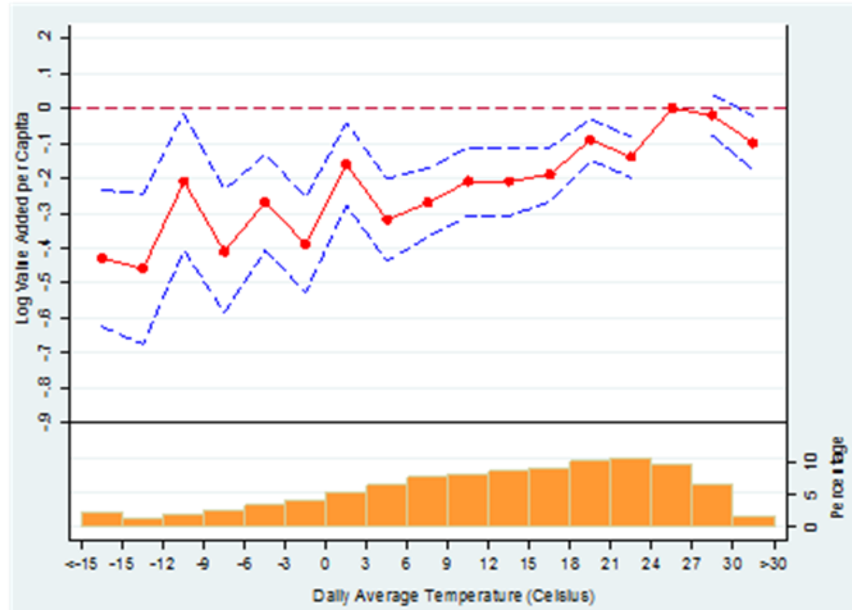
(b) Percentage change in industrial output per 1°C increase in temperature (effect of prior year)

Notes: Results presented in Panel (a) are estimated temperature effects on industrial output in current year under Models 1-4. Results presented in Panel (b) are estimated temperature effects on industrial output based on Model 4. Orange bars in this panel show the temperature effect in the current year, while light blue bars show the temperature effect in the prior year. The 95% confidence intervals are added (red lines) in both panels.

Figure 2. Nonlinear Relation between Temperature and Log Value Added Per Capita



(a) Temperature effect in the current year



(b) Temperature effect in the previous year

Notes: Graph in Panel (a) displays the effect of daily average temperature in the current year on log value added per capita × 100, while the graph in Panel (b) shows the effect of daily average temperature in the prior year on log value added per capita × 100. Results presented in the two graphs are estimated using Model 4 with temperature bins as temperature variables. Red curves represent point estimates, while the 95% confidence bands are added as blue dashed lines. Histograms at the bottom of each graph display the percentage distribution of each temperature bin among all counties in the data.

Appendix

Table A1. The Effect of Weather on Log Value Added Per Capita: Main Results[a]

	Model 1	Model 2	Model 3	Model 4	Model 4: lagged weather variables
Lag dependent Variable	0.6382***	0.6386***	0.6385***	0.6375***	
	(0.0278)	(0.0279)	(0.0279)	(0.0279)	
$Temp^{spring}$	0.0004	-0.0003	-0.0004	0.0077*	0.0079**
	(0.0034)	(0.0036)	(0.0039)	(0.0041)	(0.0037)
$Temp^{summer}$	-0.0139***	-0.0123***	-0.0129***	-0.0147***	0.0023
	(0.0031)	(0.0037)	(0.0043)	(0.0043)	(0.0043)
$Temp^{autumn}$	0.0021	0.0032	0.0031	0.0054	0.0057
	(0.0034)	(0.0035)	(0.0035)	(0.0038)	(0.0037)
$Temp^{winter}$	-0.0014	-0.0008	-0.0008	0.0024	0.0051**
	(0.0020)	(0.0020)	(0.0021)	(0.0021)	(0.0022)
$Rain^{spring}$		-0.0001	-0.0000	0.0002	0.0005***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
$Rain^{summer}$		0.0001	0.0001	-0.0000	-0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
$Rain^{autumn}$		0.0003*	0.0003*	0.0002	-0.0002
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
$Rain^{winter}$		0.0003	0.0003	0.0005	0.0004
		(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Sunshine^{spring}$			0.0001	-0.0003	-0.0002
			(0.0004)	(0.0004)	(0.0004)
$Sunshine^{summer}$			0.0001	0.0002	0.0001
			(0.0003)	(0.0004)	(0.0003)
$Sunshine^{autumn}$			0.0000	-0.0000	-0.0001
			(0.0004)	(0.0004)	(0.0004)
$Sunshine^{winter}$			-0.0001	0.0004	0.0013***
			(0.0004)	(0.0005)	(0.0005)
AR(3)[b]	0.602	0.595	0.595	0.608	
Hansen test[b]	0.797	0.765	0.761	0.745	

Notes: [a] We report parameter estimates of lagged weather variables in Model 4 in the last column of this table. All model specifications include industry × county fixed effects, year fixed effects, and industry × year fixed effects. Robust standard errors are in parentheses, adjusted for autocorrelation and heteroscedasticity of the error terms. Units for explanatory variables: 1°C for temperature, 10 hours for sunshine, and 1 cm for rainfall. N=186,558.

[b] *p*-values of test statistics.

*** significant at 1%; ** significant at 5%; * significant at 10%

Table A2. The Effect of Temperature on Log Value Added Per Capita: Temperature Bins[a]

Temperature	Baseline results	Industry × county fixed effects and year fixed effects only	All fixed effects and regional specific time trends	Balanced Sample	Weekday	Endogenous temperature variables
<-15°C	-0.0010	-0.0010	-0.0011	-0.0011	-0.0001	0.0001
	(0.0009)	(0.0009)	(0.0010)	(0.0013)	(0.0013)	(0.0011)
[-15°C,-12°C)	-0.0006	-0.0006	-0.0008	-0.0000	0.0008	0.0005
	(0.0011)	(0.0011)	(0.0011)	(0.0016)	(0.0016)	(0.0013)
[-12°C,-9°C)	-0.0005	-0.0005	-0.0006	-0.0021	0.0000	0.0009
	(0.0010)	(0.0010)	(0.0010)	(0.0014)	(0.0014)	(0.0012)
[-9°C,-6°C)	-0.0015	-0.0015	-0.0017*	-0.0021	-0.0008	-0.0006
	(0.0009)	(0.0009)	(0.0009)	(0.0013)	(0.0013)	(0.0011)
[-6°C,-3°C)	-0.0002	-0.0002	-0.0003	-0.0010	0.0004	0.0016*
	(0.0008)	(0.0008)	(0.0008)	(0.0011)	(0.0010)	(0.0009)
[-3°C,0°C)	-0.0008	-0.0008	-0.0009	-0.0011	-0.0005	0.0001
	(0.0007)	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0009)
[0°C,3°C)	0.0001	0.0001	0.0000	-0.0005	0.0009	0.0007
	(0.0006)	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0008)
[3°C,6°C)	-0.0012**	-0.0011**	-0.0012**	-0.0017**	-0.0004	-0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0008)	(0.0008)	(0.0008)
[6°C,9°C)	-0.0006	-0.0006	-0.0006	-0.0011	-0.0004	-0.0000
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0008)
[9°C,12°C)	-0.0007	-0.0006	-0.0007	-0.0010	-0.0004	0.0003
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0008)
[12°C,15°C)	-0.0001	-0.0001	-0.0001	-0.0006	0.0001	0.0010
	(0.0005)	(0.0005)	(0.0005)	(0.0007)	(0.0006)	(0.0007)
[15°C,18°C)	-0.0009**	-0.0008**	-0.0009**	-0.0016***	-0.0009*	-0.0009
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)
[18°C,21°C)	-0.0005*	-0.0005	-0.0005	-0.0005	-0.0007	0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
[21°C,24°C)	-0.0005*	-0.0005*	-0.0005*	-0.0006	-0.0006	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
[24°C,27°C)	0	0	0	0	0	0
	-	-	-	-	-	-
[27°C,30°C)	-0.0005	-0.0005	-0.0005	-0.0004	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
≥ 30°C	-0.0012***	-0.0013***	-0.0013***	-0.0017***	-0.0013**	-0.0017**

	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0008)
AR(3)[b]	0.626	0.584	0.626	0.699	0.576	0.660
Hansen test[b]	0.774	0.801	0.778	-	0.760	0.756
Observations	186,558	186,558	186,558	103,537	186,558	186,558

Notes: [a] All scenarios include the lagged dependent variable, lagged weather variables, industry × county fixed effects, year fixed effects, and industry × year fixed effects unless otherwise noted. Robust standard errors are in parentheses, adjusted for autocorrelation and heteroscedasticity of the error terms. Units for explanatory variables: 1°C for temperature. Omitted temperature category is 24-27°C.

[b] *p*-values of test statistics. In Scenario (3), because the model is just-identified, the Hansen *J*-statistic is not reported.

*** significant at 1%; ** significant at 5%; * significant at 10%

Table A3. Climate Adaptation: Robustness Checks [a]

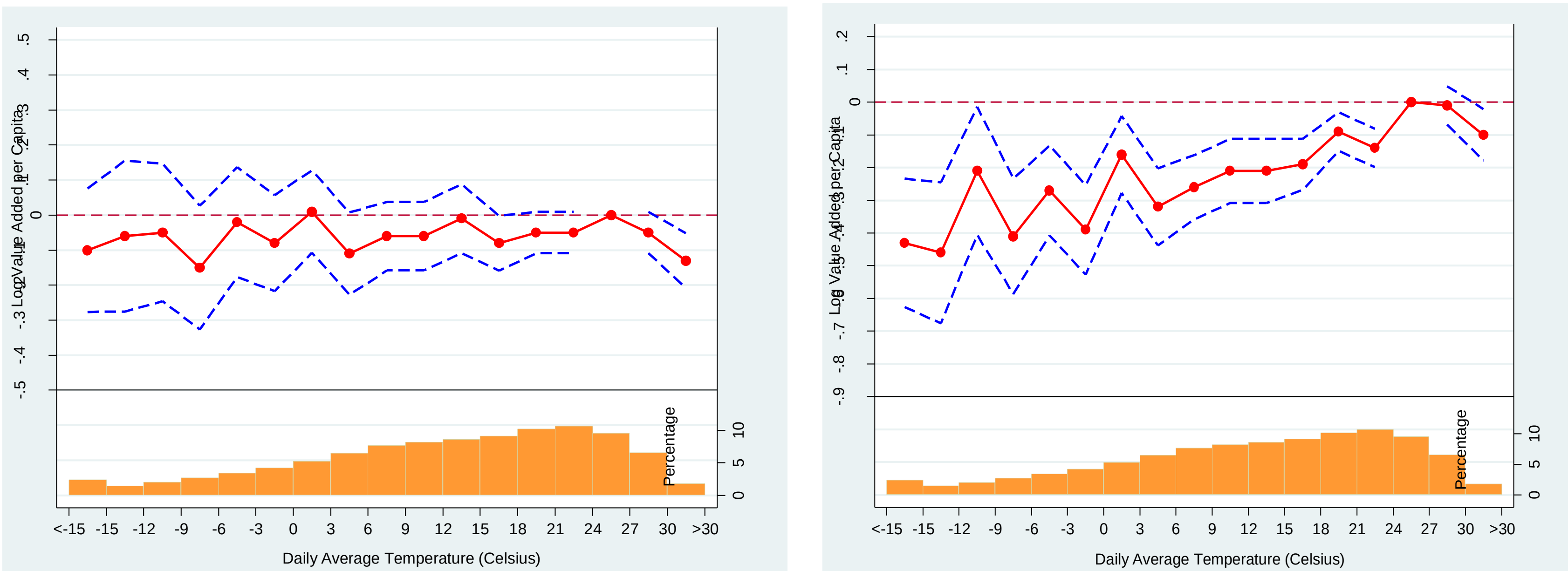
	Baseline	Industry × county fixed effects and year fixed effects only	All fixed effects and regional specific time trends	Balanced Sample	Weekday	Endogenous temperature variables
$Temp^{summer}$	-0.0231***	-0.0228***	-0.0240***	-0.0347***	-0.0144**	-0.0418***
	(0.0074)	(0.0074)	(0.0075)	(0.0108)	(0.0070)	(0.0121)
$Temp^{summer}$ × rich region dummy	0.0075	0.0067	0.0084	0.0286**	-0.0113	-0.0045
	(0.0087)	(0.0087)	(0.0088)	(0.0118)	(0.0081)	(0.0128)
$Temp^{summer}$ × high-temperature region dummy	0.0018**	0.0218**	0.0223**	0.0309**	0.0270***	0.0418***
	(0.0007)	(0.0097)	(0.0097)	(0.0136)	(0.0091)	(0.0139)
Temperature effect in high-temperature regions	-0.0008	-0.0010	-0.0017	-0.0038	-0.0257***	-0.0000
	(0.0079)	(0.0079)	(0.0080)	(0.0107)	(0.0080)	(0.0111)
AR(3)[b]	0.597	0.559	0.597	0.674	0.604	0.625
Hansen test[b]	0.787	0.798	0.786	-	0.800	0.772

Notes: [a] Results are obtained using seasonal average temperatures as temperature variables. All scenarios include the lagged dependent variable, lagged weather variables, industry × county fixed effects, year fixed effects, and industry × year fixed effects unless otherwise noted. Robust standard errors are in parentheses, adjusted for autocorrelation and heteroscedasticity of the error terms. Units for explanatory variables: 1°C for temperature.

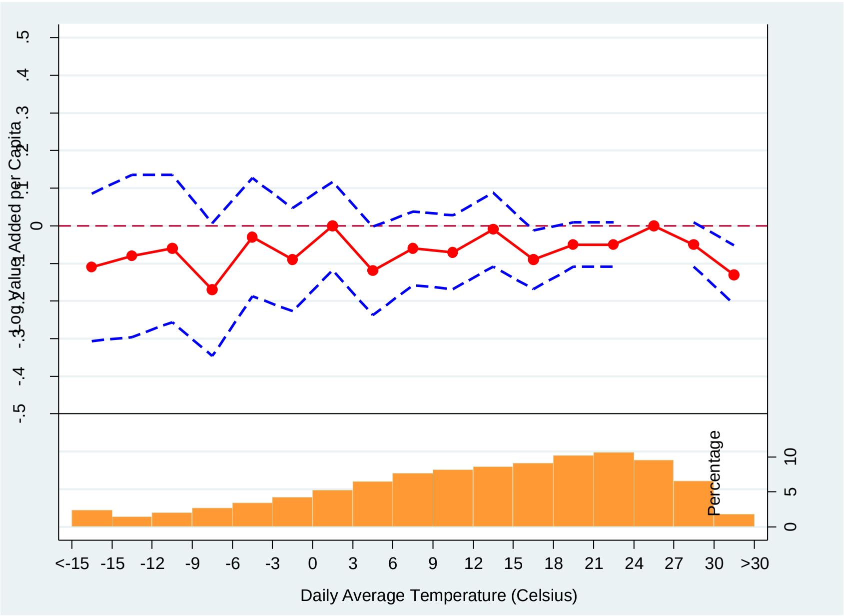
[b] *p*-values of test statistics. In Scenario (3), because the model is just-identified, the Hansen *J*-statistic is not reported.

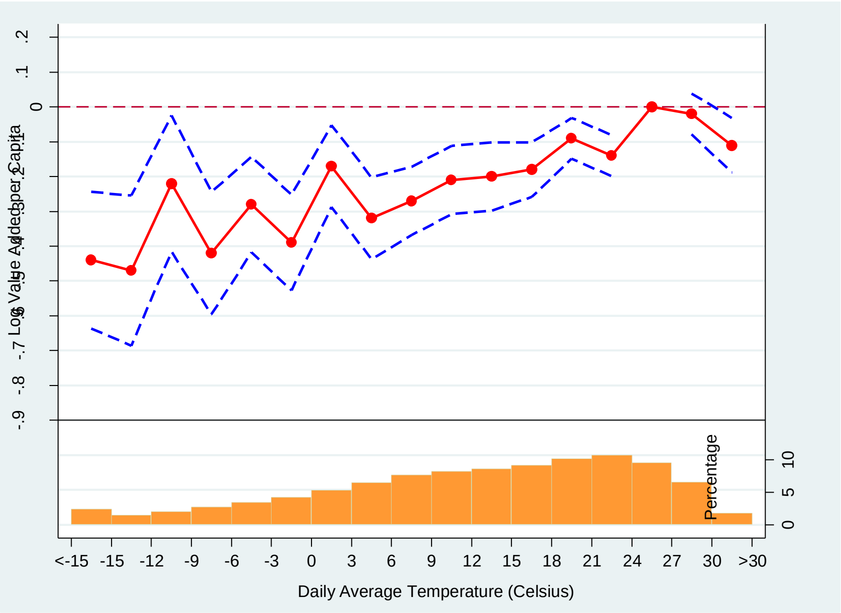
*** significant at 1%; ** significant at 5%; * significant at 10%

Figure A1. Nonlinear Relation between Temperature and Log Value Added Per Capita

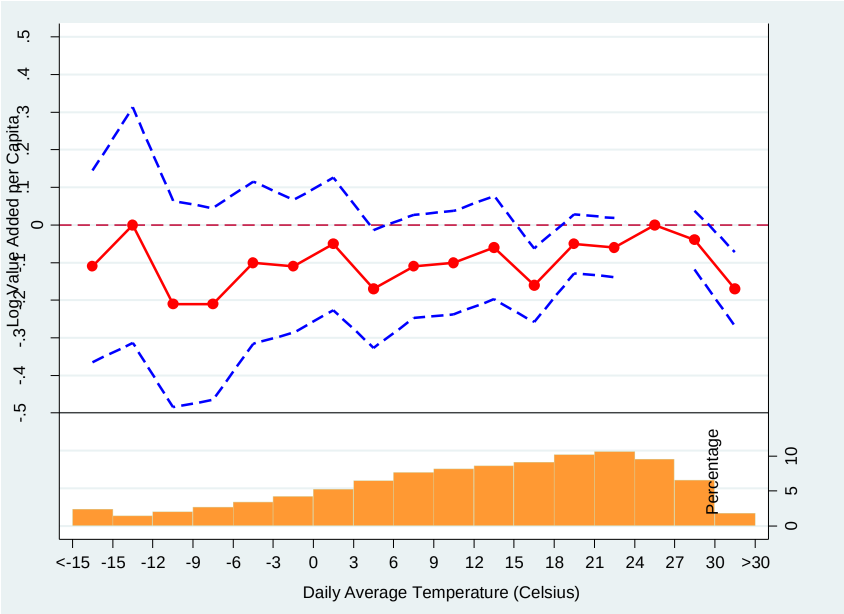


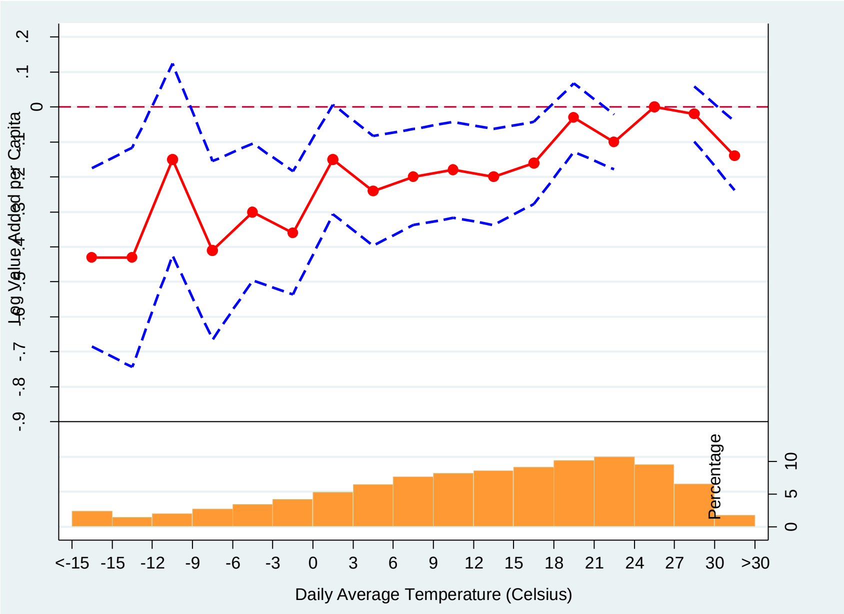
(a) Scenario (1): Industry × county fixed effects and year fixed effects only



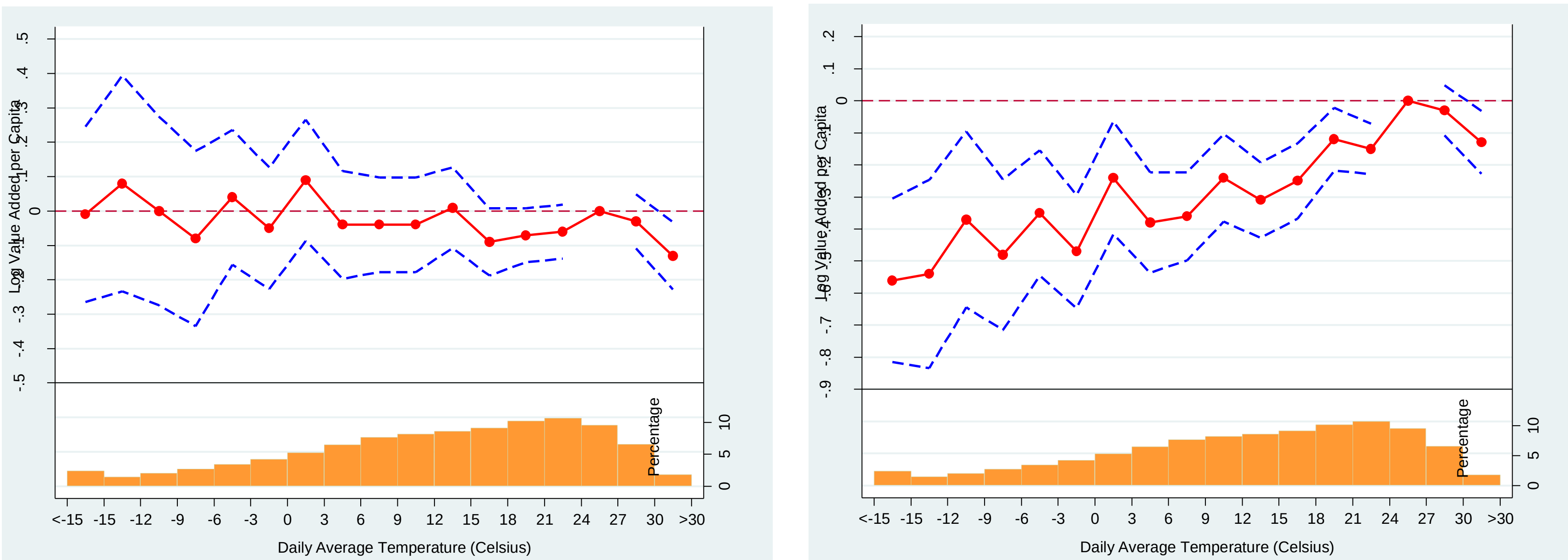


(b) Scenario (2): All fixed effects and regional specific time trends

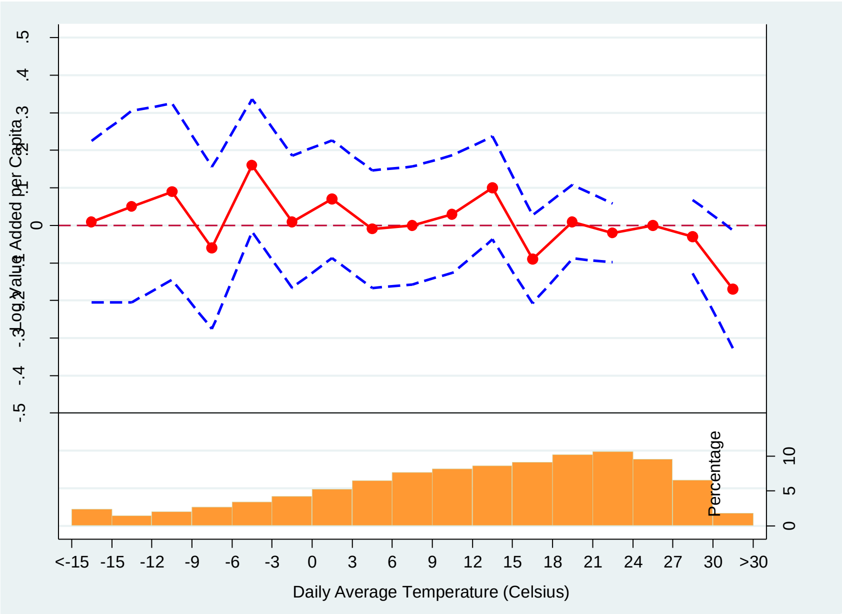


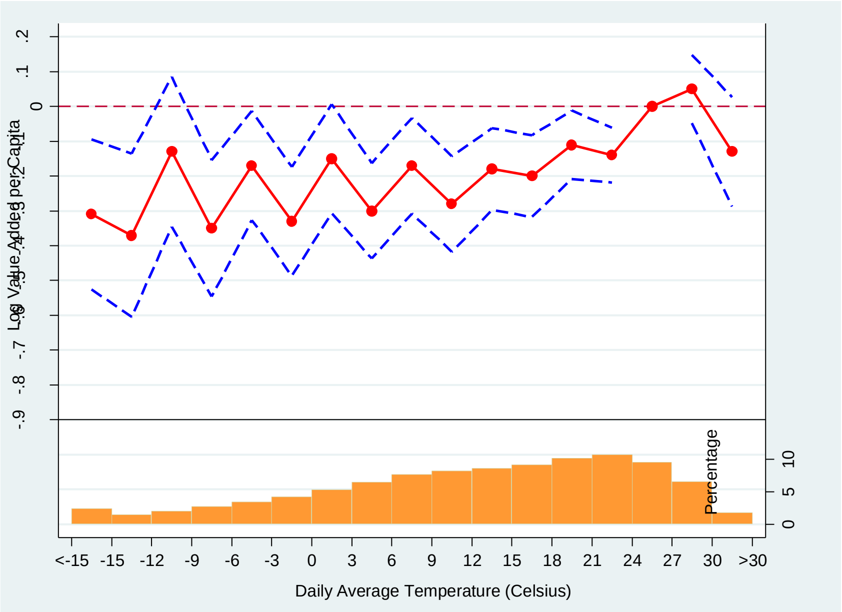


(c) Scenario (3): Balanced sample



(d) Scenario (4): Weekday





(e) Scenario (5): Endogenous temperature variables

Notes: Graphs displayed above are based on scenarios considered in the sensitivity analysis. Graphs in the left panel display the effect of daily average temperature in current year on log value added per capita × 100, while the graphs in the right panel shows the effect of daily average temperature in the prior year on log value added per capita × 100. Results presented in the graphs are estimated using Model 4 with temperature bins as temperature variables. Red curves represent point estimates, while the 95% confidence bands are added as blue dashed lines. Histograms at the bottom of each graph display the percentage distribution of each temperature bin among all counties in the data.