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# Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants ☆

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ABSTRACT

This paper uses detailed production data from a half million Chinese manufacturing plants over 1998–2007 to estimate the effects of temperature on firm-level total factor productivity (TFP), factor inputs, and output. We detect an inverted U-shaped relationship between temperature and TFP and show that it primarily drives the temperature-output effect. Both labor- and capital- intensive firms exhibit sensitivity to high temperatures. By mid 21st century, if no additional adaptation were to occur, we project that climate change will reduce Chinese manufacturing output annually by 12%, equivalent to a loss of $39.5 billion in 2007 dollars. This implies substantial local and global economic consequences as the Chinese manufacturing sector produces 32% of national GDP and supplies 12% of global exports.



## Introduction

High temperatures have been linked with lower aggregate economic output in many parts of the world (Hsiang, 2010; Dell et al., 2012; Deryugina and Hsiang, 2014; Burke et al., 2015; Chen and Yang, 2017). The design of climate change adaptation policy requires understanding the mechanisms responsible for these temperature-driven output losses. If they are due to costly factor reallocation, adaptation investments should focus on lowering factor adjustment costs. If they are due to direct productivity effects, investments should prioritize reducing the sensitivity of productivity to temperature.

We address this question by conducting the first joint empirical analysis of temperature effects on total factor productivity (TFP), factor inputs, and output using firm-level data. Specifically, we estimate the effects of temperature on manufacturing

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activity using plausibly exogenous year-to-year variation in a firm's exposure to the annual distribution of daily temperatures. Using a detailed dataset covering the near-universe of Chinese manufacturing plants during 1998-2007, we find an inverted U-shaped relationship between temperature and TFP with particularly large negative effects at high temperatures. In our benchmark specification, a day with temperature above 90 °F decreases TFP by 0.56%, relative to a day with temperature between 50–60 °F.

Importantly, we find that the response function between daily temperature and manufacturing output is nearly identical to that of TFP. Compared to a day with temperature between 50–60 °F, a day with temperature above 90 °F lowers manufacturing output by 0.45%, or by $8160 in 2007 dollars for the average firm. In contrast, temperature effects on labor and capital inputs are less responsive. This implies that TFP losses in response to high temperatures is the primary channel through which temperature alters manufacturing output in our setting.

Projecting future climate change onto our empirical estimates, we consider the impact of climate change on the Chinese manufacturing sector. Like other climate impact calculations in the empirical literature, our calculations assume no additional adaptation that could potentially reduce the sensitivity of output to high temperatures. Under this scenario, we find that climate change will reduce Chinese manufacturing output annually by 12% on average during the 2040-2059 period. At the national level, if China's manufacturing output share remains at its current 32% of GDP, climate-driven losses in manufacturing alone could reduce annual Chinese GDP by 3.8% by mid-century. This is equivalent to a loss of $39.5 billion in 2007 dollars. Such projected losses could also have large consequences for the global economy given that China's manufacturing sector currently supplies 12% of global exports (World Bank, 2013).

Our analysis provides several contributions. To the best of our knowledge, this is the first study to jointly examine the effects of temperature fluctuations on TFP, factor inputs, and output within the same data environment. By detecting temperature effects on TFP, we improve our understanding of how temperature directly affects an economic parameter that is essential for economic growth (Aghion and Durlauf, 2005; Syverson, 2011).[1] Furthermore, by demonstrating the similarity between TFP and output effects, we quantify the limited extent to which factor reallocation dampens the temperature-TFP relationship.

Examining TFP allows us to look at the combined effect of labor and capital productivity. High temperatures could reduce labor productivity by causing discomfort, fatigue, and cognitive impairment in workers. In addition, high temperatures could also affect machine performance and lower capital productivity. Previous studies have largely focused on labor productivity (e.g., see Adhvaryu et al., 2014 and Somanathan et al., 2014), without examining capital productivity. Although one cannot explicitly disentangle TFP as labor and capital productivity, we look for differential TFP effects for labor- and capital-intensive firms. Our results suggest that high temperatures affect both labor and capital productivity.

Finally, most prior sectoral analyses of temperature impacts have focused on agriculture (Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009). However, focusing solely on the agricultural sector cannot fully explain GDP losses given its relatively small output share in many national economies. For example, agriculture accounts for only 1% and 10% of U.S. and China's GDP, respectively. By contrast, the manufacturing sector constitutes 12% and 32% of each country's GDP (U.S. Bureau of Economic Analysis, 2013; China Statistical Yearbook, 2014). This paper adds to recent firm-level studies (Adhvaryu et al., 2014; Somanathan et al., 2014; Chen and Yang, 2017) along with subnational (Colmer, 2017) and national-level (Hsiang, 2010; Dell et al., 2012; Burke et al., 2015) studies that have examined temperature effects on manufacturing activity around the world. In particular, consistent with Hsiang (2010) and Dell et al. (2012)'s evidence from other parts of the world, we find that a 1 °F shift in the annual distribution of daily temperature reduces China's GDP by 0.92% through manufacturing sector impacts alone. For China specifically, a recent parallel paper by Chen and Yang (2017) examines temperature effects on firm-level manufacturing output over the same period. Our paper complements (Chen and Yang, 2017) and provides new insights by isolating the mechanism underlying the temperature-output relationship.

Several policy implications may be drawn from this paper. First, our results can help inform climate adaptation policy. If high temperatures only affected labor productivity, then the Chinese manufacturing sector could adapt by shifting from labor- to capital-intensive production. However, our results suggest that temperature increases could induce shifts in production isoquants rather than along isoquants. Thus, the Chinese manufacturing sector may be less able to avoid damages under climate change simply by reallocating labor and capital inputs. Instead, technologies that expand the possibilities frontier for all inputs are needed to offset the temperature-driven TFP losses. Second, these new estimates of manufacturing sector damages could help revise cost-benefit analyses underlying Chinese climate mitigation policy. This may be globally consequential given China's position as the world's largest greenhouse gas emitter.

The rest of the paper is organized as follows. Section 2 presents a simple conceptual framework that informs our empirical analysis. Section 3 describes the data sources and summary statistics. Section 4 presents our empirical strategy while Section 5 describes our results. Section 6 predicts mid-century climate change impacts on manufacturing output and TFP. Section 7 offers policy implications and concludes.

[1] A growing literature in macroeconomics, industrial organization, labor, and trade seeks to understand the determinants of productivity across firms and nations (Syverson, 2011). This paper documents that temperature may be a new cause of productivity dispersion.

## Conceptual framework

To illustrate the channels through which temperature can affect output, we consider a standard firm-level Cobb-Douglas production function for manufacturing output $Q$, taking labor $L$ and capital $K$ as inputs:

$$Q = (A_L L)^{\sigma_L} (A_K K)^{\sigma_K}$$

where $A_L$ and $A_K$ denote labor and capital productivity. Output elasticities for labor and capital are captured by $\sigma_L$ and $\sigma_K$. Taking natural logs:

$$\ln Q = \ln TFP + \sigma_L \ln L + \sigma_K \ln K \tag{1}$$

where log total factor productivity (TFP) is defined as $\ln TFP = \sigma_L a_L + \sigma_K a_K$. It is the average of labor and capital productivity, weighted by the output elasticities of each input. Temperature can potentially affect log output, $\ln Q$, directly through productivity and indirectly through factor reallocation.

Temperature effects on labor productivity are well documented. High temperatures not only cause physical discomfort and fatigue but can also affect cognitive functioning (Hancock et al., 2007). Existing studies have documented these biological effects in both laboratory (Niemelä et al., 2002; Seppanen et al., 2003, 2006) and observational data settings (Adhvaryu et al., 2014; Somanathan et al., 2014; Graff Zivin et al.). Temperature can also affect capital productivity, as suggested by various engineering studies. For example, higher temperatures lower the ability of lubricants to reduce surface friction between mechanical components (Mortier et al., 1992); increase failure rates by expanding the volume of input materials (Collins, 1963); and lower the processing speed of computers (Lilja, 2000).

Some of these direct productivity effects may be offset by adjustments in factor inputs. Previous work has documented the effects of high temperatures on reduced labor supply in the U.S. (Graff Zivin and Neidell, 2014) and India (Somanathan et al., 2014).[2] It is also possible that firms respond to extreme temperature by adjusting capital input.

Our objective is to assess how temperature's impact on log output is decomposed along each components shown in Eq. (1). If the temperature-TFP relationship largely mirrors the temperature-output relationship in magnitude and shape, then adjustments in factor inputs have played a relatively small role in offsetting the direct productivity effects of temperature. Conversely, factor inputs that respond to temperature suggest that factor reallocation may have dampened temperature's direct productivity effects.

## Data

### *Firm data*

The firm level data used in this study come from the annual surveys conducted by the National Bureau of Statistics (NBS) in China. This survey covers all industrial firms with annual sales over nominal CNY 5 million (USD 0.66 million) from 1998 to 2007 (hereafter referred to as the “above-scale” industrial firms).[3] The industrial sectors included in the NBS data are mining, manufacturing, and public utilities, of which manufacturing represents 94% of the total observations. Given that manufacturing is by far the largest industrial sector in the NBS data, we use the terms manufacturing sector and industrial sector interchangeably throughout the paper.

We process the NBS data to address several issues. First, each firm in the NBS data has a unique numerical ID. However, firms may change their IDs because of restructuring, acquisition, or merging. We use the matching algorithm provided in Brandt et al. (2012) to match firms over time.[4]

Second, the NBS data contain outliers which we address by following procedures established in prior papers that have used this data (Cai and Liu, 2009; Brandt et al., 2012; Yu, 2014). In particular, we drop observations with missing or negative values for value added output, employment, and capital stock. We then drop observations with employment less than 10, because these small firms may have unreliable accounting. We also drop observations that violate basic accounting principles such as when liquid, fixed, or net fixed assets are larger than total assets and when current depreciation is larger than cumulative depreciation. Finally, we drop observations for which our key variables - value added output, employment, and capital stock - have values outside the 0.5 to 99.5 percentile range. Overall, we remove approximately 10% of the initial NBS sample.

Third, each firm is classified using a four-digit Chinese Industry Classification (CIC) code, which is similar to the U.S. Standard Industrial Classification (SIC) code. However, in 2003, the NBS adopted a new CIC system, during which several existing sectors were combined and new sectors were created. Following Brandt et al. (2012), we reclassify the pre-2003 codes to make them consistent with post-2003 codes. The final estimation sample contains 39 two-digit sectors, 193 three-digit sectors, and 497 four-digit sectors.

[2] See Heal and Park (2013) for a conceptual framework regarding the effects of temperature on labor supply.

[3] According to the census of manufacturing firms conducted by NBS in 2004, above-scale firms contribute over 91% of total output.

[4] This algorithm involves first matching firms according to their IDs and then linking them over time using information on firm names, staff member names, industry codes, and other characteristics.

*Measuring firm-level TFP*

Several approaches were used to estimate firm-level TFP. These methods are debated in the literature as each requires a different set of assumptions (Biesebroeck, 2007). We use the Olley-Pakes estimator (Olley and Pakes, 1996) as the primary approach to estimate TFP. We also use the index number approach (Syverson, 2011) as a robustness check.

To estimate log TFP, we recast the log-linearized Cobb-Douglas production function in Eq. (1) for firm $i$ in county $c$ during year $t$ as

$$\ln Q_{ict} = \sigma_L \ln L_{ict} + \sigma_K \ln K_{ict} + \mu_{ict}, \tag{2}$$

where from the NBS, $\ln Q_{ict}$ is log value added output, $\ln L_{ict}$ is log employment, and $\ln K_{ict}$ is log fixed capital stock. $\mu_{ict}$ is a residual term. The estimated residual $\hat{\mu}_{ict} = \ln Q_{ict} - \hat{\sigma}_L \ln L_{ict} - \hat{\sigma}_K \ln K_{ict}$ captures log TFP, where $\hat{\sigma}_L$ and $\hat{\sigma}_K$ are estimated output elasticities of labor and capital. Eq. (2) is estimated separately for each two-digit industry.

The OLS estimates of the parameters from Eq. (2) may be biased because of simultaneity and sample selectivity. Simultaneity bias arises when firms can observe productivity and endogenously choose labor and capital inputs. In that case, $\ln L_{ict}$ and $\ln K_{ict}$ would be correlated with $\mu_{ict}$. Furthermore, firms with lower productivity may be more likely to exit, resulting in the remaining firms observed in the sample having higher productivity.

Olley and Pakes (1996) propose an estimator that addresses both simultaneity and selection biases. Their basic idea is to use investment as a proxy for unobserved productivity shocks, and use a firm's survival probability to correct for selection bias.[5] The Olley-Pakes estimator is widely used in the literature,[6] and thus serves as our baseline TFP measurement.[7]

A limitation of the Olley-Pakes estimator is that it requires parametric estimation of the production function. As an alternative, the index number approach is less parametrically restrictive. Rather, it uses the share of the wage bill on value added output to measure the output elasticity of labor, $\sigma_L$, and use $1 - \sigma_L$ to measure the output elasticity of capital, $\sigma_K$. However, the index number approach requires assuming perfect competition and constant returns to scale in production. As these assumptions may be overly strong for our empirical setting, we use the index number approach as a robustness check.

*Weather data*

The weather data are drawn from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA). The NCDC data reports global station-level weather data at three-hour intervals from 1901-2015. We extract data from the roughly 400 stations covering China from 1998-2007.[8] Auffhammer et al. (2013) note the importance of keeping a continuous weather record when using daily weather data because missing values may contaminate annual estimates derived from daily data. As such, we choose stations with valid weather records for 364 days in a year.[9]

The NCDC data contain temperature, precipitation, dew point temperature, visibility, and wind speed. Relative humidity is not reported in the NCDC data, but is instead constructed using a standard meteorological formula provided by combining temperature and dew point temperature (see Appendix A). We use the daily mean values of each weather variable calculated as the average of three-hour values as our daily weather variable. The exception is precipitation which is constructed as the daily hourly total.

*Climate prediction data*

To project the future impact of of climate change on productivity and output in the Chinese manufacturing sector, we obtain predictions for the future daily distribution of all weather variables used in our empirical analysis. These predictions come from the Hadley Centre's Third Coupled Ocean-Atmosphere General Circulation Model (HadCM3), which is commonly used in the literature (Schlenker et al., 2006; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011). We do not use data from other Global Circulation Models because other models typically produce only temperature and precipitation projections. HadCM3 reports global grid-level daily temperature, precipitation, relative humidity, and wind speed from 1990 to 2099. The grid points are separated by 2.5° latitude and 3.75° longitude. We focus on the A1FI scenario, a "business-as-usual" scenario and choose the 2040-2059 horizon for our predictions.

In order to account for any systematic error in the HadCM3 model, we implement the error-correction method proposed by Deschênes and Greenstone (2011). This approach allows for any baseline difference between the observed weather from NOAA and the modeled weather from HadCM3 over the 1998-2007 period.

[5] Investment is constructed using the perpetual inventory method. All monetary variables are deflated using industry-level price indexes following Brandt et al. (2012).

[6] For example, see Pavcnik (2002); Javorcik (2004); Amiti and Konings (2007); Brandt et al. (2012).

[7] Levinsohn and Petrin (2003) argue that the use of investment to control for unobserved productivity shocks may be inappropriate in certain empirical settings because investment must be strictly positive in the Olley-Pakes estimator. We think this is a relatively minor issue in our empirical setting as there are few observations with negative or zero investment.

[8] Fig. 6 shows the geographical distribution of the weather stations.

[9] We do not choose stations that are operational for all 365 days because all stations are missing one day's weather records for the years 1999 and 2007. Temperature for the remaining missing day is interpolated using temperature from preceding and subsequent days.

*Matching firm and weather data*

The NBS firm-level data and station-level weather data are merged by year and county, the smallest geographical unit available for each firm.[10] We transform weather data from station to county level by using an inverse-distance weighting method. Specifically, we assign weather measures to counties by using a weighted average of data from weather stations that lie within a 200 km radius of each county's centroid. The weights are defined as the inverse distance between each station and the centroid. A similar inverse-distance weighting approach (using a radius of 300 km) is used to transform the HadCM3 data from the grid to the county level. The final merged sample is an unbalanced panel from 1998–2007 with 511,352 firms. It has nearly two million observations.

Table 1 presents summary statistics for the estimation sample. The sample contains all state-owned firms and non-state-owned firms with sales over CNY 5 million (USD 0.66 million) from 1998 to 2007 for which we can match weather data. The industrial sectors include mining (3.81%), manufacturing (93.52%), and utilities (2.67%). The unit of observation is a firm-year and all monetary units are expressed in 2007 dollars.[11]

Firm output is measured by valued added, which is the difference between total output and the value of intermediate inputs. From 1998 to 2007, the annual average output of each firm in the sample is $1.82 million. As shown in Fig. 7 there is notable geographical heterogeneity in the average level of output across firms over the sample period. Generally, aggregate output is larger in the south and the east.

The average log TFP is 2.9, but varies from -3.6 to 8.8, suggesting a large degree of dispersion of TFP across firms. Labor is measured by total employment, with an average of 204 workers per firm. Capital is measured by fixed capital stock and averages $2.26 million in value.

Table 1 reports summary statistics for observed historical weather variables during 1998-2007 and for predicted weather variables during 2040-2059 from HadCM3.[12] The average observed temperature during 1998-2007 is 61.5 °F and average precipitation is 73.2 inches. HadCM3 predictions indicate that average temperature will reach 65.2 in 2040-2059, an increase of 3.6 °F (2.0 °C). Precipitation is expected to increase by 10.8 inches over the same time horizon. Average relative humidity and wind speed are mostly unchanged during this period.

## Empirical approach

*Measuring the effect of daily temperature on annual TFP*

Our firm-level variables are observed annually. To estimate the effects of daily temperatures on annual outcomes, we employ a widely-used method which discretizes the annual distribution of daily temperatures into a fixed set of temperature bins (e.g. Deschênes and Greenstone, 2011; Deryugina and Hsiang, 2014). This semi-parametric approach allows flexible estimation of nonlinear temperature effects across various daily temperature values.

In practice, we divide the annual distribution of daily temperature in each county, measured in degrees Fahrenheit, into $m = 1\ldots10$ bins. $T_{ct}^{m}$ is the number of days in year $t$ experienced by county $c$ with daily temperature that fall in bin $m$. $T_{ct}^{1}$ is the number of days in county $c$ during year $t$ with daily temperature below 10 °F (-12 °C). Each interior bin is 10 °F wide. At the upper tend, $T_{ct}^{10}$ is the number of days with temperature above 90 °F (32 °C).

Fig. 1 plots the annual distribution of daily temperatures averaged across Chinese counties and years in our sample. The height of each bar represents the number of days in a year with daily temperature falling in each temperature bin, $T_{ct}^{m}$, averaged across counties and years. Blue bars indicate the average daily temperature distribution for our 1998–2007 sample period. To preface our projections of future climate-driven effects in Section 6, the red bars indicate the average daily temperature distribution for 2040-2059 projected under a business-as-usual climate change scenario. Climate change is expected to shift the daily temperature distribution to the right, replacing cold with hot days.

*Empirical specification*

We estimate the effects of temperature on each term in the production function shown in Eq. (1): output, TFP, labor and capital. For firm $i$ in county $c$ in year $t$, we model outcome $y_{ict} \in \{\ln Q_{ict}, \ \ln TFP_{ict}, \ \ln L_{ict}, \ \ln K_{ict}\}$ using the following regression specification

$$y_{ict} = \sum_{m} \beta^{m} T_{ct}^{m} + \delta' \mathbb{W}_{it} + \theta' \mathbb{Z}_{ict} + \varepsilon_{ict} \tag{3}$$

[10] The NBS data are collected at the firm level, not at the plant level, and so the assigned weather to multiple-plant firms may be mis-measured. Crucially, more than 95% of firms in the sample are single-plant firms (Brandt et al., 2012), and thus measurement error is unlikely to have a large impact on our results.

[11] The USD to CNY exchange rate in 2007 was 7.61.

[12] The HadCM3 model does not predict for visibility.

**Table 1**
Summary statistics.

| | Historical (1998–2007) | | | Predicted (2040–2059) | | | Obs | Firms |
|---|---|---|---|---|---|---|---|---|
| | Mean | Min | Max | Mean | Min | Max | | |
| **Firm Data** | | | | | | | | |
| Output (thousand USD) | 1820 | 11 | 54,218 | – | – | – | 1,833,408 | 511,352 |
| TFP | 31.25 | 0.03 | 6887.59 | – | – | – | 1,833,408 | 511,352 |
| Log TFP | 2.90 | -3.56 | 8.84 | – | – | – | 1,833,408 | 511,352 |
| Labor (person) | 204 | 10 | 3013 | – | – | – | 1,833,408 | 511,352 |
| Capital (thousand USD) | 2258 | 9 | 51,906 | – | – | – | 1,833,408 | 511,352 |
| **Weather Data** | | | | | | | | |
| Temperature (°F) | 61.54 | 23.84 | 80.57 | 65.18 | 29.06 | 81.99 | 1,833,408 | 511,352 |
| Precipitation (inch) | 73.17 | 0.06 | 845.07 | 84.01 | 0.01 | 833.54 | 1,833,408 | 511,352 |
| Relative humidity (%) | 68.75 | 10.79 | 99.93 | 68.99 | 12.49 | 99.99 | 1,833,408 | 511,352 |
| Wind speed (mile/hour) | 5.79 | 0.56 | 16.70 | 5.80 | 0.44 | 16.19 | 1,833,408 | 511,352 |
| Visibility (mile) | 6.64 | 2.97 | 10.00 | – | – | – | 1,833,408 | 511,352 |

*Notes*: Unit of observation is a firm-year. Sample includes state- and non-state owned firms with sales greater than nominal CNY 5 million during 1998-2007. Output is measured by value added. TFP is obtained using the Olley-Pakes approach. Labor is measured by employment. Capital stock is constructed following Brandt et al. (2012). All monetary units are in 2007 USD. Temperature, wind speed, visibility, and relative humidity are calculated as annual mean value from daily observations. Precipitation is calculated as the annual sum from daily observations. Predicted climate variables are obtained from the HadCM3 model running the A1FI scenario.

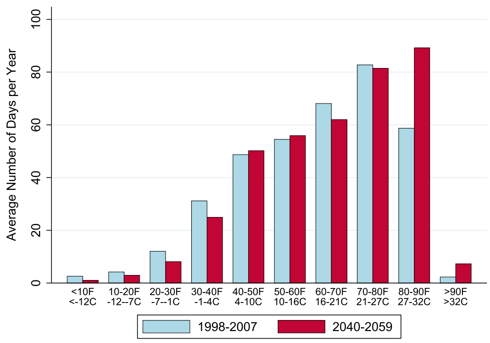


**Fig. 1.** Daily Temperature Distribution (1998–2007) and Predicted Daily Temperature Distribution (2040–2059). *Notes:* Daily temperature distribution averaged across all firms and years. Blue (red) bars correspond the 1998–2007 (2040–2059) periods. Predicted climate variables are obtained from the HadCM3 model running the A1FI scenario. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

where the vector $\mathbb{W}_{ct}$ include other county-year level weather controls including precipitation, relative humidity, wind speed, and visibility.[13] $\mathbb{Z}_{ict}$ is a vector of semi-parametric controls. It contains firm fixed effects to control for time-invariant firm-level characteristics; year-by-geographical region fixed effects to control for annual shocks common to each region, such as regional economic policy[14]; and year-by-two-digit-sector controls for annual shocks common to each manufacturing subsector such as input and output prices. To address potential spatial and serial correlation in the error term $\varepsilon_{ict}$, we cluster standard errors at both firm and county-year levels (Cameron et al., 2011). This permits arbitrary forms of serial correlation within a firm and spatial correlation across firms within a given county and year.

Our coefficient of interest is the semi-elasticity $\beta^m$, the marginal effect of an extra day with temperature in bin $m$ relative to a day in the reference temperature bin between 50-60 °F, which is omitted from Eq. (3).[15] Identification of $\beta^m$ in Eq. (3) requires that year-to-year temperature fluctuations experienced within a firm to be exogenous (Deschênes and Greenstone, 2007). Additionally, our identifying temperature variation is purged of potential correlation with other weather variables which has been shown to be important for the temperature-cereal yield relationship in China (Zhang et al., 2017).

[13] Zhang et al. (2017) demonstrate the importance of additional weather variables beside temperature and precipitation for predicting crop yields in China. This motivates our inclusion of relative humidity and wind speed as control variables. Additionally, air pollution can be correlated with weather, and may affect productivity (Zivin and Neidell, 2012). To address this, we use visibility as a proxy for air pollution since we do not have national Chinese daily air pollution data (Ghanem and Zhang, 2014). Each non-temperature weather term is modeled quadratically to account for potential nonlinear relationships.

[14] Geographical region classifications are shown in Table 7.

[15] Because $\sum_m T_{ct}^m = 365$ for every county and year, dropping one of the $m$ temperature bins is required to avoid multicollinearity. We omit the 50–60 °F bin because it is in the middle of our temperature range. Our results do not depend on this choice.

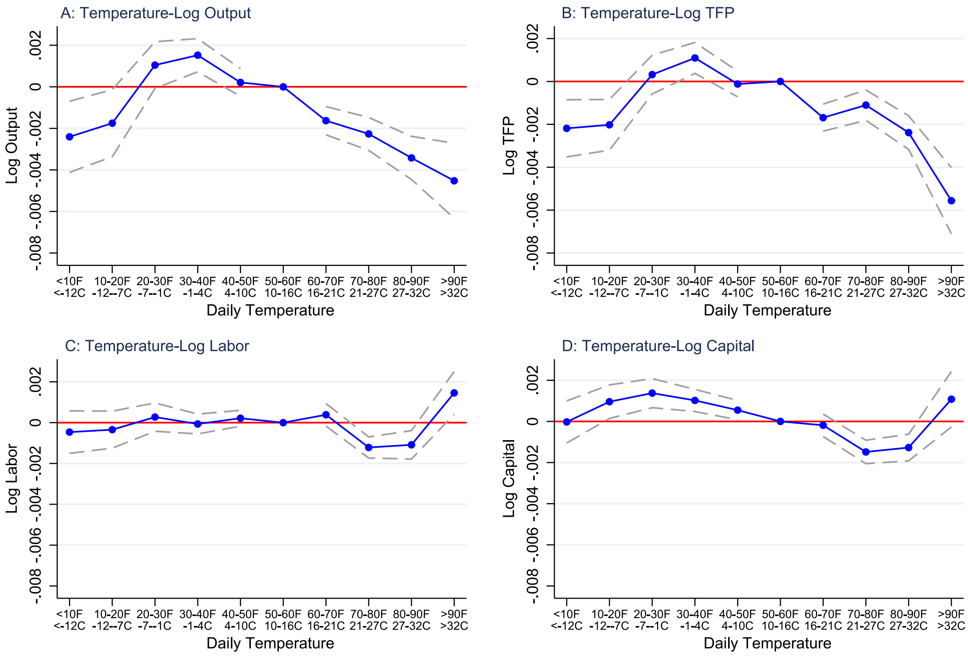


**Fig. 2.** Estimated Effects of Daily Temperature on Manufacturing Output, TFP, Labor Input, and Capital Input *Notes:* Panels show the estimated temperature-log output relationship (panel A), temperature-log TFP relationship (panel B), temperature-log labor relationship (panel C), and temperature-log capital relationship (panel D). Figures show point estimates in blue and the associated 95% confidence intervals in gray. Each panel is a separately estimated regression using Eq. (3) and includes firm fixed effects, year-by-region fixed effects, and year-by-sector fixed effects. 50–60 °F is the omitted temperature category. Standard errors are clustered at firm and county-year levels. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

## Results

### *Main results*

We first present baseline regression results estimated using Eq. (3). To visualize these estimates, Fig. 2 plots the response function between daily temperature and output, as well as the three components of output: TFP, labor, and capital inputs. Specifically, it plots the point estimates and associated 95% confidence intervals for $\beta^m$ in Eq. (3) for each outcome. Estimates are relative to daily temperature between 50–60 °F, the omitted reference group, and are shown for each temperature bin in degrees Fahrenheit as well as in degrees Centigrade.[16]

Panel A in Fig. 2 depicts the temperature-output relationship and shows an inverted U-shaped relationship. The negative effects of extremely high temperatures (above 90 °F) are both economically and statistically significant. The point estimate suggests that an extra day with temperature larger than 90 °F decreases output by 0.45%, relative to an extra day with temperature between 50–60 °F.

To put this in value terms, the average output of a sample firm was $1.82 million in 2007 dollars. Thus, the effect of an extra day with temperature above 90 °F lowers output by $8,160 for the average firm. At the aggregate level, the average total output of manufacturing firms in our sample during 1998-2007 was $334 billion in 2007 dollars. If all firms in our sample were to jointly experience an extra day with temperatures above 90 °F instead of a day between 50–60 °F, total output would decrease by $1.50 billion.

To provide a point of comparison with prior other studies, if there were a 1 °F shift to the entire annual distribution of daily temperature and the manufacturing output share of Chinese GDP were to remain 32%, our results imply a 0.92% reduction in Chinese GDP from temperature impacts in the manufacturing sector alone. This is consistent with Hsiang (2010) and Dell et al. (2012)'s evidence from other parts of the world.

We next turn to exploring which component of output drives the temperature-output relationship shown in panel A. Panels B, C, and D of Fig. 2 plot the response function between daily temperature and TFP, labor, and capital inputs, respectively. The temperature-TFP relationship closely mirrors the shape of the temperature-output relationship. The magnitudes of each set of point estimates are also mostly similar. The extreme high temperature effect depicted in panel B is slightly larger than in panel A, though the two point estimates do not appear to be statistically different.

[16] Centigrade bin boundaries are converted from Fahrenheit and rounded to the nearest integer to conserve space.

**Table 2**
Estimated effects of temperature on manufacturing output and TFP.

| **A: Output** | Mean Temperature | | | | Max Temp | Heat Index | |
|---|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | |
| 80–90 °F | −0.0009** (0.0004) | −0.0034*** (0.0004) | −0.0007** (0.0004) | −0.0034*** (0.0005) | 0.0005 (0.0004) | −0.0024*** (0.0005) | |
| >90 °F | −0.0028*** (0.0008) | −0.0047*** (0.0009) | −0.0022*** (0.0008) | −0.0045*** (0.0009) | −0.0010** (0.0004) | −0.0046*** (0.0005) | |
| $p$-value of joint test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | |
| **B: TFP** | TFP using Olley-Pakes method | | | | | | TFP using Index method |
| | Mean Temperature | | | | Max Temp | Heat Index | Mean Temperature |
| | (1a) | (1b) | (1c) | (1d) | (2a) | (2b) | (3) |
| 80-90 °F | −0.0011*** (0.0003) | −0.0024*** (0.0004) | −0.0009*** (0.0003) | −0.0024*** (0.0004) | 0.0007* (0.0004) | −0.0018*** (0.0004) | −0.0015*** (0.0003) |
| >90 °F | −0.0041*** (0.0007) | −0.0057*** (0.0008) | −0.0036*** (0.0007) | −0.0056*** (0.0008) | −0.0010*** (0.0004) | −0.0033*** (0.0004) | −0.0029*** (0.0007) |
| $p$-value of joint test | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Observations | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 |
| Firm FE | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | NO | NO | NO | NO | NO | NO |
| Year-by-region FE | NO | YES | NO | YES | YES | YES | YES |
| Year-by-two-digit-sector FE | NO | NO | YES | YES | YES | YES | YES |

*Notes*: Dependent variables are log output (panel A) and log TFP (panel B). Models include all temperature bins. Only coefficients on 80–90 °F and >90 °F bins are shown. In columns (1a)–(2b), log TFP is measured using the Olley-Pakes method. In column (3), TFP is measured using Index method. In columns (1a)–(1d), bins are constructed using daily mean temperature. In columns (2a) and (2b), bins are constructed using daily maximum temperature and daily heat index. The estimates in column (1d) correspond to Fig. 2. Standard errors are clustered at firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

On the other hand, the response function of labor (panel C) and capital (panel D) to temperature appear much flatter. Furthermore, the estimates for most temperature bins are not statistically significant. There is, however, a small and marginally statistically significant increase in labor input under extremely high temperatures. This suggests that firms may be employing additional labor in response to extremely high temperatures though this response is much smaller than the TFP effect. Overall, the evidence in FIg. 2 suggests that TFP effects it the primary driver of the temperature-output relationship. For this reason, the remainder of this paper will focus only on output and TFP effects.

Table 2 further documents the effects of daily temperatures on output (panel A) and TFP (panel B) using various specifications. Due to space limitations, we only report the coefficients on the two highest temperature bins: 80–90 °F and above 90 °F. We also report the $F$ statistic testing the null hypothesis that all temperature bin coefficients are jointly zero.

Columns (1a) to (1d) test the robustness of our results to the inclusion and exclusion of different sets of fixed effects. In column (1a), we start with a specification that includes only firm and year fixed effects. Identification in this model comes form within firm temperature variation and purges the potential biases due to annual nation-wide shocks such as policy, technological, and price changes common to all counties. To allow spatial heterogeneity in these annual shocks, the model in column (1b) replaces year fixed effects with year-by-geographical region fixed effects. In column (1c), we replace year fixed effects with year-by-sector fixed effects to control for shocks that are common to two-digit industries in a given year. Finally, column (1d) shows our preferred specification as shown Fig. 2, which includes both year-by-region and year-by-sector fixed effects. The negative effects of high temperatures are evident across the four different sets of controls. Estimates are generally more negative when year-by-region fixed effects are included while year-by-sector fixed effects do little to alter our estimates.

Temperature bins are constructed using daily mean temperature across columns (1a)-(1d). In column (2a), we alternatively construct temperature bins using daily maximum temperature to isolate the effects of peak temperatures within a day. The estimated coefficients becomes attenuated possibly because maximum daily temperature may not adequately capture the full exposure of temperature during the course of a day. Finally, in column (2b), we construct temperature bins using a daily heat index (see Appendix A for details), which jointly incorporates the effects of temperature and humidity. The estimated coefficients are relatively unaffected.

The TFP measure used in columns (1a) to (2b) of panel B is constructed using the Olley-Pakes estimator (Olley and Pakes, 1996). As a further robustness check, column (3) estimates the same model as in column (1d) but uses a TFP measure constructed following the index number approach (Syverson, 2011). These coefficients have a smaller magnitude but remain statistically significant.

To conserve space, Table 2 suppresses the coefficients on other weather variable controls, $\mathbb{W}_{ct}$. Quadratic coefficients on precipitation, humidity, wind speed, and visibility are shown in Table 8 and come from the benchmark model in column (1d) of Table 2.

Past temperatures may affect current economic outcomes and may be correlated with current temperature. To examine this potential source of bias, we add one-year lagged temperature bins into our baseline regression model in Eq. (3). Fig. 8 presents the effects of jointly estimated current and lagged temperatures on output (panels A and B) and on TFP (panels C and D). When controlling for lagged temperature, the shape of the output (panel A) and TFP (panel C) response to contemporaneous temperature is similar to that of our benchmark model in panels A and B of Fig. 2. Furthermore, there does not appear to be a systematic pattern in the lagged temperature-output (panel B) and lagged temperature-TFP (panel D) relationships.

*Heterogeneity across labor and capital-intensive firms*

Fig. 2 and Table 2 show that the negative effects of high temperature on output are primarily driven by TFP losses. Given that TFP is a weighted average of labor and capital productivity, we now turn to exploring whether these negative effects primarily originate from labor productivity, capital productivity, or both. Previous studies have predominantly focused on labor productivity (e.g., see Adhvaryu et al., 2014; Somanathan et al., 2014). Because TFP cannot be separated into labor and capital productivity in our production function approach, we instead indirectly test for the relative role of each component. The intuition is as follows. Recall from Section 2 that $\ln TFP = \sigma_L a_L + \sigma_K a_K$. Suppose that the negative effects of high temperature on TFP operate primarily through its effects on labor productivity, $a_L$. In that case, one should expect the effects on TFP to be more negative in labor-intensive firms where the output elasticity of labor, $\sigma_A$, is typically larger.

We use two measures of labor intensity to classify firms. The first measure is wage bill over output, a common measurement of labor intensity. The second measure is labor over sales, following Dewenter and Malatesta (2001). Both measures are defined using the firm-level average across sample years.

Table 3 presents the effects of temperature on TFP between labor- and capital-intensive firms. In columns (1a)–(1c), labor intensity is measured by wage bill over output. In columns (2a)–(2c), labor intensity is measured by employment over sales. To capture the heterogeneous impacts across labor- and capital-intensive firms, we interact the two highest temperature bins (80–90 °F and above 90 °) with variables that distinguish firms as either labor- or capital-intensive. In columns (1a) and (2a), we interact two highest temperature bins with raw labor intensity. In columns (1b) and (2b), we define a dummy variable equal to one if a firm's labor intensity is above the median for all firms, indicating it is a labor-intensive firm. In columns (1c) and (2c), labor intensity is classified based on the mean labor intensity value.

If the effects of high temperatures on TFP were mostly through labor productivity, capital-intensive firms would be relatively unaffected and one should see much smaller effects for the two uninteracted high temperature bins. However, each specification in Table 3 shows statistically significant negative effects for the uninteracted high temperature terms suggesting that high temperatures lower capital productivity. In general, we detect similar high temperature effects for labor and capital intensive firms though the relative magnitudes of these two effects depend on the measure of labor intensity.

*Heterogeneity across industrial sectors*

The effects of temperature on output and TFP may differ across industrial sectors because of differences in temperature exposures and sensitivity to temperatures. To explore heterogeneity across industrial sectors, Fig. 3 depicts point estimates and 95% confidence intervals for the effect of temperatures above 90 °F on output (panel A) and TFP (panel B) within each two-digit sector. The regression models underlying Fig. 3 are estimated separately for each two-digit sector using Eq. (3).[17] The average output share for each sector is shown in parentheses with sectors sorted according to their shares. Each sector is classified as either a light (labeled in red) or a heavy (labeled in blue) industry.[18]

We find that temperatures above 90 °F have statistically significant negative effects on output for 15 out of the 33 industries. There is, however, strong heterogeneity across sectors. One more day with temperatures above 90 °F reduces output in timber manufacturing sector by 1.26%, but has insignificant impacts on certain sectors such as medicine manufacturing. These output effects are largely patterned by sector-specific TFP effects in panel B.

Fig. 3 suggests that temperatures above 90 °F have significantly negative effects on both light and heavy industries. Light industries, such as food processing, food manufacturing, and timber, are typically labor-intensive. By contrast, heavy industries, such as non-metallic minerals, general machinery, raw chemicals, transport equipment, are generally capital-intensive. Consistent with findings in Section 5.2, these results demonstrate that high temperatures may be affecting both labor and capital productivity.

[17] We exclude sectors with fewer than 10,000 observations. This includes the oil and natural gas mining, other mining, tobaccos, chemical fibers, waste recycling, and gas utility, sectors.

[18] The classification is based on the standards published by the Shanghai Bureau of Statistics. http://www.stats-sh.gov.cn/tjfw/201103/88317.html.

**Table 3**
Estimated effects of temperature on TFP across labor- and capital-intensive firms.

| | Labor intensity = wage bill/output | | | Labor intensity = labor/sales | | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (1c) | (2a) | (2b) | (2c) |
| 80-90 °F | -0.0035*** | −0.0015*** | −0.0017*** | −0.0024*** | −0.0023*** | −0.0025*** |
| | (0.0003) | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0005) |
| > 90 °F | -0.0042*** | −0.0050*** | −0.0052*** | −0.0055*** | −0.0068*** | −0.0061*** |
| | (0.0008) | (0.0009) | (0.0009) | (0.0008) | (0.0009) | (0.0008) |
| 80-90 °F × Labor Intensity | 0.0041*** | – | – | −0.0001 | – | – |
| | (0.0003) | – | – | (0.0002) | – | – |
| > 90 °F × Labor Intensity | -0.0008 | – | – | -0.0094 | – | – |
| | (0.0016) | – | – | (0.0060) | – | – |
| 80-90 °F × Above Median | – | -0.0016*** | – | – | -0.0002 | – |
| | – | (0.0002) | – | – | (0.0002) | – |
| > 90 °× Above Median | – | -0.0012* | – | – | 0.0023*** | – |
| | – | (0.0007) | – | – | (0.0007) | – |
| 80-90 °F × Above Mean | – | – | -0.0016*** | – | – | 0.0006** |
| | – | – | (0.0002) | – | – | (0.0003) |
| > 90 °× Above Mean | – | – | -0.0008 | – | – | 0.0030*** |
| | – | – | (0.0007) | – | – | (0.0008) |
| Observations | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 | 1,833,408 |

*Notes*: Dependent variable is log TFP. Regression models based on Eq. (3) and include firm fixed effects, year-by-region fixed effects, and year-by-sector fixed effects. Models include all temperature bins. Only coefficients on 80-90 °F and > 90 °F bins are shown. In columns (1a)-(1c), labor intensity is measured using wage bill over output. In columns (2a)-(2c), labor intensity is measured using labor over sales. Columns (1a) and (2a) interact temperature with labor intensity. In columns (1b) and (2b), labor-intensive firms are classified as having above median labor intensity. In columns (1c) and (2c), labor-intensive firms are classified as having above mean labor intensity. Standard errors are clustered at firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we examine the heterogeneity in temperature effects across high and low-technology industries as defined by the NBS.[19] High-technology industries include medicine manufacturing, electronic and telecommunication manufacturing, aviation and aerospace manufacturing, computer manufacturing, medical equipment manufacturing, and information chemicals manufacturing. Table 4 reports estimates on log output (panel A) and log TFP (panel B) for the full sample (column (1)), firms in high-technology industries (column (2)), and firms in low-technology industries (column (3)). The coefficients are quite similar across these two subsample of firms. This is striking as firms in high-technology industries tend to operate in air-conditioned environments.

*Heterogeneity across firm ownership types*

Firms in China are required to implement protective measures such as providing hydration, air conditioning, and bonus pay for workers during extremely hot days.[20] Because enforcement of labor regulations is typically more stringent in state-owned firms than in private firms, the effects of high temperatures on TFP and output may be weaker in state-owned firms. To explore heterogeneity by type of firm ownership, Table 5 presents the effects of temperature on log output (panel A) and log TFP (panel B) across ownership types. The regression models underlying the estimates in Table 5 are estimated separately using Eq. (3) for each type of ownership. The coefficients are identified from deviations from the mean within each firm, not by a change in ownership. Table 5 also shows that the mean annual temperature faced by each subsample of firms is very similar.

Private firms constitute the largest share in the Chinese manufacturing sector and bear the most severe damages induced by high temperatures. An additional day with temperature above 90 °F reduces output and TFP by 1.12% and 1.05%, respectively. The second largest ownership type is foreign firms, which comprise 19.03% of the entire sample and experience moderate damages from high temperatures. Collectively owned firms constitute 12.98% of the entire sample, and the negative effects of high temperatures on output and TFP are generally small or statistically insignificant. State-owned firms comprise the smallest share, at 9.14%, and the effects of temperature above 90 °F on output and TFP are significantly positive.

[19] See http://www.stats.gov.cn/tjsj/tjbz/201310/P020131021347576415205.pdf) for details.
[20] See, for example: http://www.chinasafety.gov.cn/newpage/Contents/Channel_20697/2012/0704/173399/content_173399.htm.

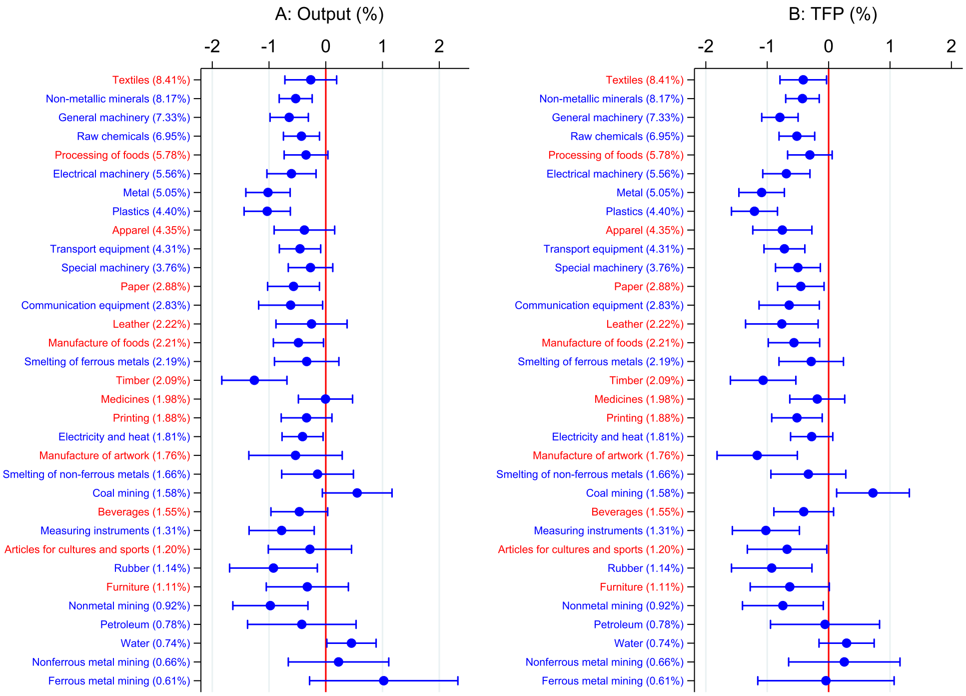


**Fig. 3.** Estimated Effects of Temperatures Above 90 °F on Output and TFP for Each Manufacturing Subsector *Notes*: Panels show estimated effect of temperature above 90 °F on log output (panel A) and log TFP (panel B). Average output shares for each manufacturing subsector shown in parentheses. Sectors are sorted according to their shares. Temperature effects estimated using Eq. (3). Light (heavy) industries labeled in red (blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**Table 4**
Estimated effects of temperature on output and TFP across technology types.

| | Full sample (1) | High-tech industries (2) | Low-tech industries (3) |
|---|---|---|---|
| **A: Output** | | | |
| 80-90 °F | -0.0034*** | −0.0020 | −0.0035*** |
| | (0.0005) | (0.0015) | (0.0004) |
| > 90 °F | −0.0045*** | −0.0040** | −0.0045*** |
| | (0.0009) | (0.0018) | (0.0009) |
| **B: TFP** | | | |
| 80-90 °F | −0.0024*** | −0.0033*** | −0.0023*** |
| | (0.0004) | (0.0009) | (0.0004) |
| > 90 °F | −0.0056*** | −0.0051*** | −0.0056*** |
| | (0.0008) | (0.0015) | (0.0008) |
| Mean Temp ( °F) | 61.54 | 62.81 | 61.46 |
| Percentage | 100% | 6.51% | 93.49% |
| Observations | 1,833,408 | 119,304 | 1,714,104 |

*Notes*: Dependent variables are log output (panel A) and log TFP (panel B). Regression models are estimated separately for the full sample, for firms in high-technology industries, and for firms in low-technology industries using Eq. 3 and include firm fixed effects, year-by-region fixed effects, and year-by-sector fixed effects. Models include all temperature bins. Only coefficients on 80-90 °F and > 90 °F bins are shown. Following NBS definitions, high-technology industries include medicine manufacturing, electronic and telecommunication manufacturing, aviation and aerospace manufacturing, computer manufacturing, medical equipment manufacturing, and information chemicals manufacturing. Standard errors are clustered at both firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 5**
Estimated effects of temperature on output and TFP across ownership types.

| | Full sample (1) | Private (2) | Foreign (3) | Collective (4) | State-Owned (5) |
|---|---|---|---|---|---|
| **A: Output** | | | | | |
| 80-90 °F | −0.0034*** | −0.0067*** | −0.0009 | −0.0039*** | 0.0009 |
| | (0.0005) | (0.0007) | (0.0015) | (0.0007) | (0.0008) |
| > 90 °F | −0.0045*** | −0.0112*** | −0.0026* | −0.0025* | 0.0033*** |
| | (0.0009) | (0.0012) | (0.0015) | (0.0014) | (0.0012) |
| **B: TFP** | | | | | |
| 80-90 °F | −0.0024*** | −0.0050*** | 0.0004 | −0.0028*** | 0.0009 |
| | (0.0004) | (0.0007) | (0.0008) | (0.0007) | (0.0005) |
| > 90 °F | −0.0056*** | −0.0105*** | −0.0049*** | −0.0020 | 0.0022** |
| | (0.0008) | (0.0011) | (0.0015) | (0.0013) | (0.0011) |
| Mean Temp ( °F) | 61.54 | 61.64 | 64.52 | 60.25 | 59.03 |
| Percentage | 100% | 38.46% | 19.03% | 12.98% | 9.14% |
| Observations | 1,833,408 | 705,078 | 348,985 | 237,942 | 167,648 |

*Notes*: Dependent variables are log output (panel A) and log TFP (panel B). Regression models are estimated separately for each ownership category using Eq. 3 and include firm fixed effects, year-by-region fixed effects, and year-by-sector fixed effects. Models include all temperature bins. Only coefficients on 80-90 °F and > 90 °F bins are shown. Column (1) reports estimates for the full sample. Columns (2)-(5) report estimates for each ownership type. Standard errors are clustered at both firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These results demonstrate the potential importance of labor regulations; private firms may be bearing higher damages from high temperatures because of weaker enforcement of labor regulations.

*Heterogeneity across regions*

Firms in different geographical regions may exhibit varied responses to high temperatures. For example, regions that are hotter on average may have differentially adapted to extreme hot days than regions that are cooler on average. To detect whether there is geographical heterogeneity, Table 6 presents the effects of high daily temperature log output (panel A) and log TFP (panel B) estimated separately for each region. The average daily temperature for each region is also reported.

The northeast has the lowest annual mean temperature, whereas the south has the highest annual mean temperature. As shown in column (6) of panel A, the negative output effects of temperatures above 90 °F for firms in the south are larger in magnitude than the full sample estimates in column (1) of panel A and statistically significant. Conversely, we do not detect statistically significant output effects for firms in the much cooler northeast. Panel B shows a similar pattern when the outcome variable is log TFP. This evidence indicates that firms in locations that are warmer on average are more sensitive to extreme heat than those located in cooler places. This suggests that adaptation based on long-term average temperature may be incomplete.

## Predicted impacts of climate change

We now interpret the main empirical results of the paper through the lens of ongoing climate change to assess the vulnerability of the Chinese manufacturing sector to climate change. To this end, we combine the estimated relationship between temperature fluctuations and manufacturing output and TFP with predictions about future climate change.

To predict impacts of climate change on output and TFP, we use the regression coefficient estimates for each weather variable from Eq. (3). We then calculate the predicted difference in each weather variable between the periods 2040–2059 (as projected by HadCM3 A1FI) and 1998–2007 for each firm. The firm-specific differences in the weather variables are then averaged to a representative firm. For example, Fig. 1 reports the predicted number of days in each temperature bin by 2040–2059, for the average firm in the sample. In that case, the predicted difference is simply the difference in the height of the bars representing the number of days in each temperature bin. These predicted differences are then multiplied by the relevant estimated regression coefficient to infer the impacts of climate change on output for the average firm in the sample. Standard errors are calculated using the delta method. In addition, we predict the impact on TFP using the same method.

It is important to note the strong assumptions behind these calculations. Namely, while we allow climate change to alter the distribution of temperature, precipitation, relative humidity and wind speed, we hold all other determinants of manufacturing output fixed to mean values over our 1998–2007 sample period. This includes, among other things, fixing

**Table 6**
Estimated effects of temperature on TFP across geographical regions.

| | Overall (1) | North (2) | Northeast (3) | East (4) | Central (5) | South (6) | Southwest (7) | Northwest (8) |
|---|---|---|---|---|---|---|---|---|
| **A: Output** | | | | | | | | |
| 80-90 °F | −0.0024*** | −0.0059*** | −0.0004 | −0.0041*** | −0.0052*** | −0.0022 | 0.0004 | −0.0002 |
| | (0.0004) | (0.0013) | (0.0019) | (0.0007) | (0.0013) | (0.0013) | (0.0008) | (0.0013) |
| > 90 °F | −0.0056*** | −0.0118*** | 0.0187 | −0.0081*** | −0.0023 | −0.0213*** | 0.0016 | 0.0025 |
| | (0.0008) | (0.0045) | (0.0174) | (0.0012) | (0.0017) | (0.0058) | (0.0015) | (0.0032) |
| **B: TFP** | | | | | | | | |
| 80-90 °F | −0.0034*** | −0.0061*** | −0.0013 | −0.0060*** | −0.0078*** | −0.0047*** | 0.0012 | −0.0014 |
| | (0.0005) | (0.0015) | (0.0022) | (0.0008) | (0.0015) | (0.0015) | (0.0009) | (0.0013) |
| > 90 °F | −0.0045*** | −0.0164*** | 0.0289 | −0.0066*** | −0.0029 | −0.0256*** | 0.0038** | 0.0022 |
| | (0.0009) | (0.0048) | (0.0192) | (0.0014) | (0.0018) | (0.0071) | (0.0016) | (0.0036) |
| Mean Temp ( °F) | 61.54 | 53.99 | 46.77 | 62.27 | 61.45 | 73.20 | 61.74 | 50.93 |
| Percentage | 100% | 9.94% | 6.08% | 51.08% | 10.93% | 13.45% | 5.82% | 2.71% |
| Observations | 1,833,408 | 182,189 | 111,506 | 936,478 | 200,397 | 246,515 | 106,676 | 49,647 |

*Notes*: Dependent variables are log output (panel A) and log TFP (panel B). Regression models are estimated separately for each geographical region and include firm fixed effects and year-by-sector fixed effects. Models include all temperature bins. Only coefficients on 80-90 °F and > 90 °F bins are shown. See Table 7 for regional definitions. Column (1) reports estimates for the full sample. Columns (2)-(8) report estimates for each region. Standard errors are clustered at both firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

baseline productivity and technology to historical levels. Furthermore, our calculations assume that firm entry, exit, and location decisions are not affected by climate change. Finally, our calculations rely on predictions from a single climate model, which does not allow for uncertainty associated with climate predictions (Burke et al., 2015).

The predicted mid-century impacts suggest that climate change will reduce manufacturing output by 12% and TFP by 9% annually for the average firm. Both estimates are statistically significant at the 5% level.[21] At the national level, if China's manufacturing output share remains fixed at 32% of national GDP, climate-driven losses in manufacturing alone could reduce Chinese GDP by 3.8% annually by mid century.

The climate change impact on output can be converted into monetary damages by multiplying the percent impact by the average annual aggregate output for all firms during 1998–2007 period. This amounts to a predicted loss of $39.5 billion in 2007 dollars.[22] To put this large estimate in perspective, we can compare it to country-level GDP data from the World Bank (World Bank, 2013). In 2007, 129 countries had GDP below this amount. The predicted output loss under climate change in the Chinese manufacturing sector roughly corresponds to the GDP of Tunisia or Lithuania.

*Industry-specific predicted impacts*

As shown in Fig. 3, there is considerable heterogeneity in the effects of high temperatures on output and TFP across manufacturing subsectors. It is interesting to consider if such heterogeneity is also detectable in the predicted climate impacts. Fig. 4 presents the predicted impacts on output (panels A and B) and on TFP (panel C), for 33 two-digit sectors along with the 95% confidence intervals. Like in Fig. 3, the underlying regression models are estimated separately for each two-digit sector and the average output share for each sector is shown in parentheses with sectors sorted according to their shares. Panel B monetizes the predicted climate impacts on output for each sector by multiplying by the average annual aggregate output.

Several findings emerge from Fig. 4. First, there is a high degree of heterogeneity in both the sign and magnitude of the predicted impacts across sectors. The point estimates vary from negative 24.85% for rubber to positive 6.12% for ferrous metal mining. Consequently, the monetized climate damages in panel B greatly vary across sectors as well. Textile will bear the largest climate change damage, with a loss of $4.30 billion, while the impacts on water utility, non-ferrous and ferrous metal mining, smelting of non-ferrous metals, and coal mining are all negligible.

Second, most sectors are predicted to have reduced output under climate change. In 20 of the 33 sectors, the predicted effects of climate change in percentage points (panel A) are statistically significantly negative at the 5% level.

Third, for large manufacturing subsectors, climate change impact predictions are both economically and statistically significant. Sectors with output shares greater than 5% are expected to face 10.48-17.01% output losses, with corresponding $1.93–4.30 billion losses. In addition, both light (in red) and heavy industries (in blue) exhibit negative responses to climate

[21] The 95% confidence intervals are [−15.76, −7.93] and [−11.79, −6.32] for output and TFP, respectively.
[22] The 95% confidence interval is [−51.16, −26.92] billion USD.

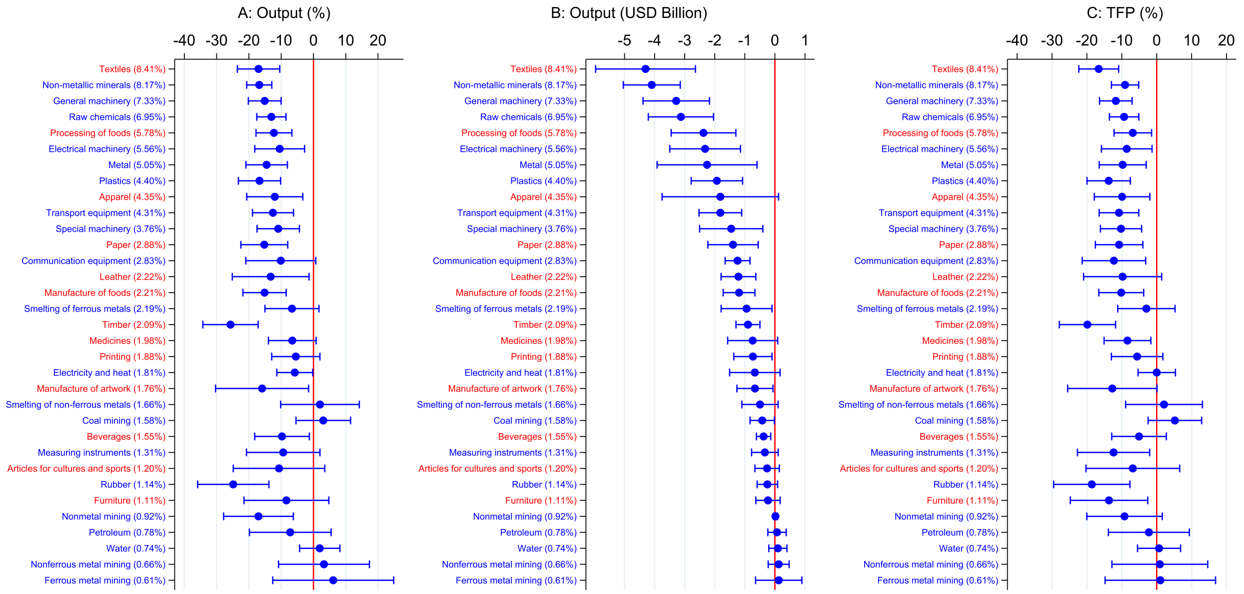


**Fig. 4.** Predicted Climate Change Impacts on Output and TFP for Each Manufacturing Subsector *Notes:* Panels show predicted average annual climate impact in 2040–2059 on output in percentage points (panel A), output in 2007 billion USD (panel B), and TFP in percentage points (panel C). Average output shares for each manufacturing subsector shown in parentheses. Sectors are sorted according to their shares in panels A and C. Sectors are sorted by climate impacts in panel B. Light (heavy) industries labeled in red (blue). Predicted climate variables are obtained from the HadCM3 model running the A1FI scenario. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

change. This is consistent with findings in Section 5.2 showing both labor and capital productivity effects as light industries are typically more labor-intensive while heavy industries are more capital-intensive.

Lastly, the sector-specific predicted impacts on TFP shown in panel C are similar to the predictions on output in panel A.

*Region-specific predicted impacts*

The HadCM3 A1FI scenario predicts a warmer climate in China in the foreseeable future. As shown in Table 1, between now and the 2040–2059 period, average temperatures are predicted to increase by 3.64 °F (2.02 °C). There are also notable differences across region in the extent of warming. For example, panel A of Fig. 5 displays the difference in number of days with temperatures above 90 °F between the 1998-2007 and 2040-2059 periods. Eastern and southern China are expected to gain more extremely hot days. As a result, the impact of climate change on manufacturing activity could vary spatially across China. To demonstrate such regional heterogeneity, Fig. 5 presents the climate change predictions on output in percentage points (panel B), in million USD (panel C), and on TFP in percentage points (panel D) for each county. The county-specific effects are calculated as the county-level averages of the firm-level prediction detailed earlier.[23]

The predicted climate damages in southern and eastern China are particularly severe with losses of 15% or more, corresponding to roughly $260 million in most of the counties. Notably, those regions are where most manufacturing firms are located. On average, the northern and northeastern China are subject to more moderate output losses.

The predicted damages on TFP are generally similar to the ones on output. Southern China and eastern China are expected to experience severe losses, whereas the damages are more muted for northern China. A large area in northwestern China is predicted to experience moderate TFP increases. Overall, the results indicate strong heterogeneity across geographical regions and suggest that an important response to climate change in China could be the relocation of manufacturing plants to areas where damages are expected to be lower. The analysis of such long-run responses is beyond the scope of this paper.

## Discussion

This paper estimates the effects of temperature on manufacturing activity in China using data from the near-universe of Chinese manufacturing firms. Over 1998–2007, we find that one day with temperature above 90 °F reduces manufacturing output by 0.45%, or by $8,160 in 2007 dollars for the average firm.

To better understand the mechanism behind this temperature-output relationship, we implement the first study that examines how temperature affects three components of output: TFP, labor input, and capital input. We show that the

[23] Thus, the county-specific predictions reported here only capture the effect of county-level heterogeneity in the predicted changes in the weather variables, and not the heterogeneity in the historical relationship between output and temperature.

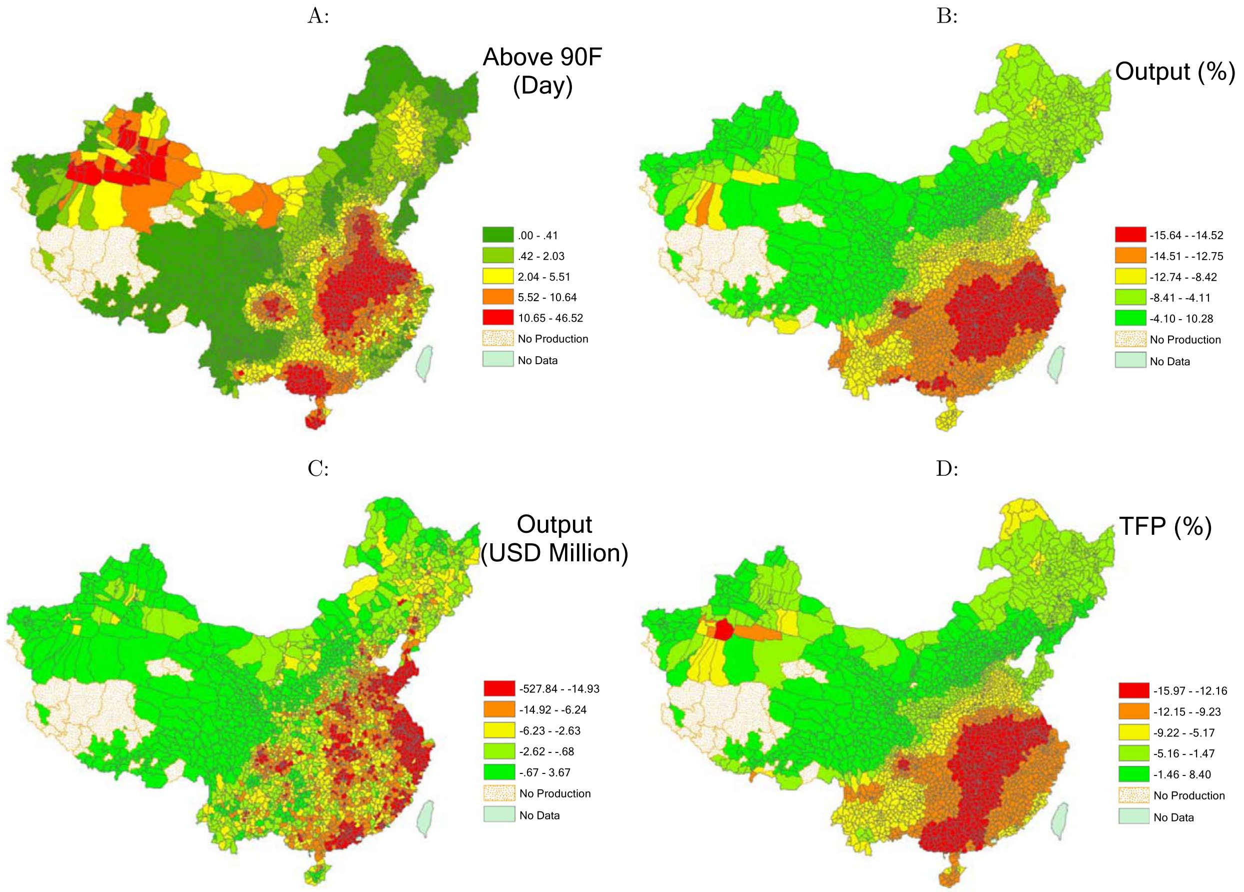


**Fig. 5.** Predicted Climate Change Impacts on Temperature, Output, and TFP for Each County *Notes:* Panel A shows change in days per year with temperatures above 90 °F between 1998–2007 and 2040–2059 periods. Panel B shows average annual climate change impact in 2040–2059 on output in percentage points. Panel C shows average annual climate change impact in 2040–2059 on output in 2007 million USD. Panel D shows average annual climate change impact in 2040–2059 on TFP in percentage points. Predicted climate variables are obtained from the HadCM3 model running the A1FI scenario.

temperature-TFP relationship largely mirrors that of the temperature-output relationship while factor inputs are much less sensitive to temperature. This implies that in our context, high temperatures lower output primarily through productivity losses with factor reallocation playing a more limited role. Finally, we find similar productivity effects across both labor- and capital- intensive firms suggesting that high temperature may be lowering both labor and capital productivity.

Taking our historical estimates into a climate change projection, we calculate that climate change would reduce manufacturing output by 12% annually by mid 21st century or by $39.5 billion in 2007 dollars. If China's manufacturing output share remains fixed at 32% of national GDP, climate-driven losses in manufacturing alone would reduce Chinese GDP by 3.8% annually by mid century. These projected damages assume nothing else changes in the future besides the climate. Additional climate adaptation during this future period could ultimately reduce climate damages.

These results have several policy implications. First, climate change adaptation policy for the Chinese manufacturing sector should prioritize investments that reduce the responsiveness of productivity to high temperatures. In particular, investments should be made to reduce both the sensitivities of labor and capital productivity to temperature.

Second, even with adaptation, optimal policy is unlikely to completely eliminate climate damages. The resulting climate damages on the Chinese manufacturing sector could have global consequences. China is currently the world's largest exporter. It provides 13% of global exports in 2016 of which manufacturing goods comprise 94%.[24] As a consequence, any climate change damage to the Chinese manufacturing sector is likely to affect global prices and thus welfare around the world.

Third, China is currently the world's largest emitter of greenhouse gases (U.S. Energy Information Administration, 2012) and thus plays a major role in global climate mitigation efforts. While China currently has policies to reduce emissions,[25]

[24] See: http://stat.wto.org/CountryProfile/WSDBCountryPFView.aspx?Country=CN

[25] For example, under the Paris Agreement, China proposed to peak $CO_2$ emissions, increase non-fossil energy share to 20%, and lower carbon intensity by 60%, all by 2030.

these new estimates of manufacturing sector damages could inform revised cost-benefit analyses of Chinese climate policy. We leave such an exercise, which includes estimating the cost of Chinese climate policy, for future research.

## Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at https://doi.org/10.1016/j.jeem.2017.11.001.

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