Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants*

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Abstract

Understanding the relationship between temperature and economic growth is critical to the design of optimal climate policies. A large body of literature has estimated a negative relationship between these factors using aggregated data. However, the micro-mechanism behind this relationship remains unknown; thus, its usefulness in shaping adaptation policies is limited. By applying detailed firm-level production data derived from nearly two million observations of the Chinese manufacturing sector in the period of 1998-2007, this paper documents the relationship between daily temperature and four components in a standard Cobb-Douglas production function: output, total factor productivity (TFP), labor, and capital inputs. We detect an inverted U-shaped relationship between daily temperature and TFP; by contrast, the effects of temperature on labor and capital inputs are limited. Moreover, the response function between daily temperature and output is almost identical to that between temperature and TFP, thereby suggesting that the reduction in TFP in response to high temperatures is the primary driver behind output losses. In addition, temperature affects both labor and capital productivity. A medium-run climate prediction indicates that climate change will reduce TFP by 4.18%, and result in output losses of 5.71%. This loss corresponds to CNY 208.32 billion (USD 32.57 billion) in 2013 values. Given that TFP is

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invariant to the intensity of use of labor and capital inputs and reflects both labor and capital productivity, the Chinese manufacturing industry is unlikely to avoid climate damages simply by implementing factor allocation. Thus, new innovations that expand the technology frontier for all inputs should be developed to offset weather-driven TFP losses if other adaptation strategies are infeasible.

Keywords: Climate Change, TFP, Manufacturing, China

JEL Classification Codes: Q54, Q56, L60, O14, O44

1 Introduction

Understanding the effect of temperature on economic activity is critical to the design of optimal climate policies (Dell et al., 2012). A growing body of literature has estimated the historical effects of temperature on economic growth using reduced-form statistical methods (e.g., see Nordhaus and Yang (1996); Hsiang (2010); Dell et al. (2012); Burke et al. (Forthcoming)), and strong negative effects have been detected in various parts of the world. However, most of these studies are based on aggregated economic data; therefore, the specific micro-mechanism behind this relationship remains unknown. The usefulness of these works is thus limited in terms of informing climate adaptation policies. In particular, the sector whose losses are most responsible for GDP losses is unclear. Furthermore, whether or not temperature affects output primarily through costly factor reallocation or productivity losses remains unknown.

This paper fills this research gap in two ways. First, prior studies that use micro data primarily examined productivity in the agricultural sector (e.g., see 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 the small share of agricultural output in many national economies. For example, agriculture accounts for only 1% and 10% of the GDPs of the U.S. and of China, respectively; by contrast, the manufacturing sector constitutes 12% and 32% of these GDPs (U.S. Bureau of Economic Analysis, 2013; China Statistical Yearbook, 2014). Therefore, this paper selects the Chinese manufacturing sector as the empirical setting because of its significance to the Chinese economy. Furthermore, this sector comprises 12% of global exports (World Bank, 2013a); thus, the output losses can have global general equilibrium consequences. In addition, China is the world's largest carbon dioxide (CO_2) emitter (U.S. Energy Information Administration, 2012); hence, the potential climate damages to the Chinese manufacturing sector may motivate this country to develop more aggressive carbon reduction policies, which is critical to mitigating global climate change.

Second, this paper documents the relationship between temperature and the four components in a standard Cobb-Douglas production function: output, total factor productivity (TFP), labor, and capital inputs, using detailed firm-level production data from nearly two million observations in the manufacturing sector in China from 1998 to 2007. The primary focus is TFP, which combines both labor and capital productivity and is invariant to the intensity of use of labor and capital inputs (Syverson, 2011). TFP has been employed to measure technology progress and is essential to economic growth (Aghion and Durlauf, 2005). While recent works have investigated labor productivity in Indian manufacturing (Adhvaryu et al., 2014; Somanathan et al., 2014), no study to date has jointly examined productivity and factor allocation effects of temperature.

To identify the causal effects of temperature on TFP and other variables, we employ year-to-year variation in a firm's exposure to the distribution of daily temperatures, modeled as 10-degree Fahrenheit (F) bins (Deschênes and Greenstone, 2011). We find an inverted U-shaped relationship between daily temperature and TFP. The negative effect of extreme high temperatures, above 90°F, is particularly large in magnitude. In our preferred specification, one more day with temperatures above 90°F decreases TFP by 0.56%, relative to temperatures between 50-60°F. Importantly, we find that the response function between daily temperature and output is almost identical to that of TFP. By contrast, the effects on labor and capital inputs are limited. This implies that the reduction in TFP in response to high temperatures is the primary channel through which temperature affects manufacturing output.

Given that TFP combines both labor and capital productivity, disentangling the effects separately is important. Previous studies have largely focused on labor productivity (e.g., see Adhvaryu et al. (2014); Somanathan et al. (2014)), and ignored capital productivity. High temperatures could cause discomfort, fatigue, and cognitive impairment on workers, and reduce labor productivity. In addition, such temperatures could also affect machine performance and lower capital productivity. Although one cannot explicitly disentangle TFP as labor and capital productivity in a Cobb-Douglas production function, we can examine differential TFP effects for labor- or capital-intensive firms. Various specifications suggest that high temperatures affect both labor and capital productivity.

Firms are required to provide some protection for workers, such as hydration, air conditioning, and subsidies during extremely hot days in China.[1] Given the relative rigidity of labor regulations in state-owned firms compared with those of private firms, one may expect effects of high temperatures on TFP to differ based on firm ownership. Our empirical results support this argument. We find that the effects of high temperatures on TFP for state-owned firms are slightly positive. On the contrary, TFP in private firms exhibits larger negative response to high temperatures. This implies that labor regulations could play an important role in mitigating the negative effects of high temperatures.

Lastly, using the estimated coefficients of climatic variables on output and TFP, we predict a medium-run climate effect on output and TFP. Compared with the periods from 1998-2007, climate change is likely to reduce output by 5.71% by 2020-2049, which is mainly caused by the reduction in TFP. This is equivalent to CNY 208.32 billion (USD 32.57 billion) losses in 2013 values. Given that China is the world's largest exporter and manufacturing goods comprise 94% of total exports (World Bank, 2013a), the output losses could have global general equilibrium consequences via trade.

This paper contributes to the existing literature in three aspects. First, to our best knowledge, this paper is the first to present a possible micro-mechanism for considerable studies that focus on temperature and economic growth (Nordhaus and Yang, 1996; Hsiang, 2010; Dell et al., 2012; Burke et al., Forthcoming). We find that a 1°F (1° Celsius (C)) increase in annual mean temperature reduces China's GDP by 0.92% (1.66%). This finding is consistent with Hsiang (2010) and Dell et al. (2012); they find that a 1°F (1°C) increase in annual mean temperature leads to 1.39% (2.5%) and 0.56% (1.0%) GDP reduction in other developing countries. Our results suggest that the reduction of TFP in the manufacturing

[1] http://www.chinasafety.gov.cn/newpage/Contents/Channel_20697/2012/0704/173399/content_173399.htm.

sector as a response to high temperatures is primarily responsible for the negative relationship between temperature and economic growth.

Second, this paper provides the first study that documents the relationship between daily temperature and TFP. Unlike single-factor productivity which heavily depends on the intensity of use of the excluded factor, TFP is invariant to labor and capital inputs, and thus is more likely to capture the true productivity. Furthermore, high temperatures affect both labor and capital productivity, the latter of which has been ignored in the literature.

Third, a large body of literature in macroeconomics, industrial organization, labor, and trade seeks to understand the determinants of productivity (Syverson, 2011). This paper provides a new channel: weather, or specifically, temperature. High temperatures, especially above 90°F, have a significantly negative effect on TFP. Given the typical fluctuation of temperature across space and over time, this exogenous variation could further cause TFP dispersion across firms.

The results of this paper have considerable policy implications. If high temperatures only affect labor productivity, then manufacturing could adapt to climate change by simply shifting from being labor-intensive to being capital-intensive. However, because TFP reflects both labor and capital productivity, and is invariant to the intensity of inputs, temperature could induce shifts in isoquants rather than along isoquants. Therefore, Chinese manufacturing is less likely to avoid damages under climate change simply by reallocating labor and capital inputs. Indeed, new innovations that expand the technology frontier for all inputs need to occur to offset weather-driven TFP losses if other adaptation strategies are infeasible.

In addition, the empirical setting is Chinese manufacturing, which is critical for the Chinese economy. The new findings of potential damages on the manufacturing sector could be incorporated in the cost-benefit analysis in designing climate policies, and motivate China to aggressively act on reducing carbon emissions with self interest in mind. As the world's largest emitter of CO_2 (U.S. Energy Information Administration, 2012), China's effort is critical in mitigating global climate change.

Finally, transitioning from agriculture to manufacturing is recognized as a feasible way to aid Sub-Saharan Africa in adapting to climate change (Henderson et al., 2015). Nonetheless, climate change may also impact the African manufacturing industry given the significant climate damages to the Chinese manufacturing sector described in this paper. Therefore, the estimates in this research need to be generalized to other countries to improve the support for adaptation policy design.

The rest of the paper is organized as follows. Section 2 presents a simple conceptual framework that helps the empirical analysis. Section 3 describes data sources and summary statistics. Section 4 presents the empirical strategy and the identification. Section 5 describes the results and interpretation. Section 6 predicts the impacts of climate change on output and TFP. Section 7 offers economic and policy implications and Section 8 concludes.

2 Background and Conceptual Framework

This section provides a simple conceptual framework and the channels that how temperature might affect the four components in a production function: output, TFP, labor, and capital inputs.

Consider a standard Cobb-Douglas production function for an industry

$$Y(T) = A(T)L(T)^{\alpha}K(T)^{\beta}. \tag{1}$$

Here, Y denotes output and L and K denote labor and capital, respectively. In practice, output is measured by value added; therefore, material input is excluded from the production function. The Hicks-neutral efficiency level, or TFP, is represented by A. Output elasticities of labor and capital are measured by α and β. Temperature, denoted as T, could affect output through productivity and inputs.

Taking natural logs of the above equation leads to the following function

$$y(T) = a(T) + \alpha l(T) + \beta k(T), \tag{2}$$

where lowercase symbols represent natural logs of variables. It is worth noting that TFP is a weighted average of labor and capital productivity. To see this, consider a Cobb-Douglas production function that distinguishes labor and capital productivity

$$Y(T) = (A_L(T)L(T))^{\alpha}(A_K(T)K(T))^{\beta}, \tag{3}$$

where A_L and A_K denote the labor and capital productivity, respectively. Taking natural logs of the above equation results in the following equation

$$y(T) = \alpha a_L(T) + \beta a_K(T) + \alpha l(T) + \beta k(T). \tag{4}$$

Comparing the above equation with Equation (2), one can obtain

$$a(T) = \alpha a_L(T) + \beta a_K(T), \tag{5}$$

which suggests that TFP is a weighted average of labor and capital productivity, where the weights are output elasticities of labor and capital inputs. However, in practice, one cannot estimate Equation (4) because of two unknowns (a_L and a_K) within one equation. It is common practice for labor productivity to be measured by output per worker, i.e., Y/L. Similarly, capital productivity is sometimes measured by output per capital, or Y/K. However, this single-factor productivity measurement heavily depends on the intensity of excluded factor, and may not reflect the true productivity (Syverson, 2011). For example, two firms with the same technology could have different labor productivity levels because one happens to use more capital.[2]

[2] To see this, consider two firms within the same industry that share the following Cobb-Douglas produc-

Temperature could affect TFP through labor productivity. High temperatures not only physiologically affect human body and cause discomfort and fatigue, it may also affect cognition function and psychomotor ability (Hancock et al., 2007; Graff Zivin et al., 2015). Several studies have estimated the impacts of temperature on labor productivity using either lab experiments (e.g., see Niemelä et al. (2002); Seppanen et al. (2003, 2006)) or reduced-form statistical methods (e.g., see Graff Zivin and Neidell (2014), Adhvaryu et al. (2014), and Somanathan et al. (2014).)[3]

Temperature also affects TFP through capital productivity. Evidence shows that high temperatures could dramatically impact machine performance. For example, lubricant helps reduce friction between surfaces in machines. It also helps transmit forces and transport foreign particles, and has been regarded as one of the key factors for machine performance (Ku, 1976). High temperatures could negatively affect lubricant efficiency by influencing their viscosity and pour point (Mortier et al., 1992). Moreover, high temperatures could expand most materials used in manufacturing by altering their coefficients of thermal expansion (Collins, 1963), and further increase gaging error in the manufacturing process. Computers play a major role in modern manufacturing. Excessive heat could lower the electrical resistance of objects and increase the current, which may slow down the processing performance of a computer (Lilja, 2000). It is noteworthy that the evidence presented above is mainly suggestive. To date, no rigorous study has focused on temperature and capital productivity.

Furthermore, temperature could affect labor inputs. Given the negative effects of high temperatures, workers may reduce working hours or even be absent from work. Several studies estimate the effects of temperature on labor supply (e.g., see Graff Zivin and Neidell (2014) and Somanathan et al. (2014)).[4] Temperature could also affect capital stock. For

tion function $Y = AL^{1/2}K^{1/2}$. The following values are assigned to firm 1: $A_1 = 1$, $L_1 = 1$, $K_1 = 1$. One can obtain $Y_1 = 1$, and labor productivity $Y_1/L_1 = 1$. Similarly, the following values are assigned to firm 2: $A_2 = 1$, $L_2 = 1$, $K_2 = 4$. One can obtain $Y_2 = 2$, and labor productivity $Y_2/L_2 = 2$. Both firms have the same TFP levels, but the second firm exhibits higher labor productivity than the first because the second firm uses more capital.

[3] See a detailed review in Dell et al. (2014).

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

example, high temperatures may abrade machines and lead to faster capital depreciation. Given the possible effect of temperatures on all the three inputs in the production function, naturally, temperatures may also affect output.

3 Data

3.1 Firm Data

Firm-level data come from the annual surveys conducted by the National Bureau of Statistics (NBS) in China. This survey covers all industrial firms, either state-owned or non-state with sales over CNY 5 million (USD 0.8 million) from 1998 to 2007 (hereafter referred to as the "above-scale" industrial firms).[5] The industrial sectors here include mining, manufacturing, and public utilities, in which manufacturing composes 93.52% of the total observations. Given that manufacturing composes the largest share of the industrial sector, we use the terms manufacturing sector and industrial sector interchangeably throughout the paper.[6]

We address several empirical issues. First, each firm 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.[7]

Second, the data contain outliers. We take standard procedures in the literature that have used this data (Cai and Liu, 2009; Brandt et al., 2012; Yu, 2014). First, we drop observations with missing or negative values for value added, employment, and fixed capital stock. Second, we drop observations with employment less than 10, because these small firms may not have a reliable accounting system. Third, we drop observations that apparently violate accounting principles: liquid assets, fixed assets, or net fixed assets larger than total assets; current

[5] According to the census of manufacturing firms conducted by NBS in 2004, the above-scale firms contribute more than 91% of the total output. Therefore, the sample used in this study is representative of the Chinese industrial sector.

[6] The main results are robust when we focus on manufacturing sector only.

[7] The basic idea involves first matching firms according to their IDs and then linking them using information on firms' names, legal persons, industry codes, and others.

depreciation larger than accumulative depreciation. Finally, we drop observations with the values of key variables outside the range of 0.5 to 99.5 percentile. Overall, approximately 10% of observations are dropped.[8]

Third, in the data, each firm is classified into 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. Several sectors were merged whereas new sectors were created. Following Brandt et al. (2012), we revise codes before 2003 to make them consistent with codes after 2003. Overall, the sample contains 39 two-digit sectors, 193 three-digit sectors, and 497 four-digit sectors.

3.2 Measuring Firm-level TFP

Several approaches are used to estimate firm-level TFP. These methods are debated in the literature and each requires particular assumptions (Van Biesebroeck, 2007). Fortunately, all these measurements are sufficiently robust to empirical specifications (Syverson, 2011). In this paper, we use the Olley-Pakes estimator (Olley and Pakes, 1996) to estimate TFP. The index number approach (Syverson, 2011) is used for a robustness check.

Consider a standard linearized Cobb-Douglas production function

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + u_{it}, \tag{6}$$

where y_{it} is the log output for firm i in year t; l_{it} and k_{it} are log values of labor and capital inputs, respectively; β_l and β_k are output elasticities of labor and capital that need to be estimated; u_{it} is the error term. Hence, the log TFP is the residual $\hat{u}_{it} = y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}$.

The OLS estimates of Equation (6) may be biased because of simultaneity and sample selection. Simultaneity bias arises because firms can observe productivity and then make decisions on labor and capital inputs. Thus, l_{it} and k_{it} are likely to be correlated with u_{it}.

[8]Generally, the results are robust to those outliers.

Furthermore, firms with lower productivity may be more likely to exit from the market, and thus result in selection bias.

Olley and Pakes (1996) propose an estimator that controls for the simultaneity and selection biases. The basic idea is to use investment to proxy for unobserved productivity shocks, and use a firm's survival probability to correct for selection bias. The Olley-Pakes estimator is widely used in the literature,[9] and thus serves as the baseline measurement of TFP in this paper.[10]

The Olley-Pakes estimator requires parametric estimation of the production function. The index number approach, however, is free of the parametric assumption. Indeed, we simply use the share of wage bill in value added to measure output elasticity of labor input β_l, and use $1 - \beta_l$ to measure output elasticity of capital input β_k.[11] The index number approach requires the assumptions of perfect competition and constant returns to scale. These assumptions seem strong in our empirical setting, and thus the index number approach will serve as a robustness check.

In practice, y_{it} is measured by value added; l_{it} is measured by employment, and k_{it}, is measured by fixed capital stock. Investment is constructed using the perpetual inventory method. All monetary variables are deflated using the industry-level price indexes following Brandt et al. (2012). Furthermore, Equation (6) is estimated separately for each two-digit industry.

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

[10] 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. Nonetheless, this issue is minor in our empirical setting. Given the rapid development in China, few observations indicate negative or zero investment. Furthermore, the Levinsohn-Petrin estimator does not control for selection bias; thus, we prefer the Olley-Pakes estimator. Nonetheless, the results remain robust when we use the Levinsohn-Petrin estimator.

[11] It would be ideal to use capital share to measure β_k; however, data on capital rental rate is not available.

3.3 Weather Data

The weather data are drawn from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA).[12] NCDC reports global station-level weather data at three-hour intervals from 1901-2015. We extract the data covering China from 1998-2007.[13] Auffhammer et al. (2013) suggest the importance of keeping a continuous weather record when using daily weather data because missing values may contaminate the estimates. As such, we choose stations with valid weather records for 364 days in a year and fill in the rest of the missing values using the average between the preceding and subsequent days.[14]

The weather data contain major climatic variables, including temperature, precipitation, dew point temperature, visibility, and wind speed. Relative humidity is not reported in the NCDC data, but is constructed from the standard meteorological formula provided by NOAA using temperature and dew point temperature.[15] Zhang et al. (2015) demonstrate the importance of additional climatic variables other than temperature and precipitation. Thus, we include temperature, precipitation, relative humidity, and wind speed in our empirical specifications. We use the daily mean values of each climatic variable calculated as the averages of the three-hour values as the main measurement of weather, except precipitation which is constructed as daily total values. In addition, we use visibility as a proxy for air pollution (Ghanem and Zhang, 2014). Air pollution is typically correlated with climatic variables (Jayamurugan et al., 2013) and affects productivity as well (Graff Zivin and Neidell, 2012). Therefore, omitting air pollution may induce the omitted-variable bias.

The variable of interest in this analysis is temperature. Temperature may have a joint impact with humidity on productivity. For example, when temperature is high, the human

[12] The data can be downloaded from the website ftp://ftp.ncdc.noaa.gov/pub/data/noaa/.

[13] Approximately 400 stations cover China. Refer to Figure B.10 for a detailed distribution of weather stations.

[14] 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.

[15] A detailed explanation is provided in the online appendix.

body may cool itself down through perspiration. However, this process is hard in a more humid environment. Consequently, we also use the heat index to measure the joint influence of temperature and humidity on productivity as a robustness check. Heat index is constructed following the standard formula provided by the NOAA.[16]

3.4 Climate Prediction Data

The climate prediction data are drawn from the Hadley Centre, one of the world's leading institutes in climate prediction. We focus on the Hadley Centre's Third Coupled Ocean-Atmosphere General Circulation Model (HadCM3), which has been commonly used in the literature (Schlenker et al., 2006; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011).[17] 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 "business-as-usual" (A1FI) scenario and choose the years from 2020-2049, a medium-run period. We do not choose a long period such as 2070-2099 because technology could be much advanced at that time and may be insensitive to high temperatures. Given that technology advancement may still be limited in a short time frame, the climate prediction could be more realistic and meaningful.

Systematic model errors may exist between HadCM3 and NOAA, which may lead the predictions to be inaccurate.[18] Therefore, we implement the error-corrected method proposed by Deschênes and Greenstone (2011). First, we calculate the difference in weather data from 1998-2007 between NOAA and HadCM3. We then add the difference to the prediction by HadCM3, to correct for systematic model errors.

[16]The online appendix presents a detailed explanation of heat index calculation.

[17]The data can be downloaded at `http://browse.ceda.ac.uk/browse/badc/hadcm3`. We do not use other climatic models because such models typically report only temperature and precipitation data.

[18]The systematic model errors are indeed severe in our sample. The average temperature for the period of 1998-2007 in China is 54°F according to NOAA but only 49°F as per HadCM3.

3.5 Matching Firm and Weather Data

Firm-level data and station-level weather data are merged by county and year.[19] First, we transform weather data from station level to county level using the inverse-distance weighting method, which is widely used in the literature (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007, 2011). The basic algorithm of this approach is to first choose a circle with a 200 km radius for each county's centroid. Then, the weighted average of weather data for each station within the circle is assigned to that county, where the weights are the inverse of the distance between each station and the county's centroid. Finally, we assign each firm with the weather data in that county where the firm is located.[20] A similar way is used to transform climate prediction data from the grid level to the county level.[21] The merged data leave an unbalanced panel from 1998-2007 for 511,352 firms with nearly two million observations.

Table 1 presents the summary statistics of the merged data. The data cover all state-owned firms and non-state firms with sales over CNY 5 million (USD 0.8 million) from 1998 to 2007. The industry sectors include mining (3.81%), manufacturing (93.52%), and utilities (2.67%). Unit of observation is a firm-year. All monetary values are expressed in constant 1998 CNY.

Output is measured by valued added, which is the difference between total output and intermediate input. From 1998 to 2007, the annual average output is approximately CNY 12 million (USD 2 million). To demonstrate the regional heterogeneity in output, Figure 1 depicts the average annual aggregate output in each county during 1998-2007. Generally, aggregate output is the largest in the south and the east, suggesting that manufacturing firms are mostly located in those regions.

[19] We do not observe the specific latitude and longitude of firms. Indeed, county is the smallest geographic unit representing a firm's geographic location.

[20] The firm data are presented at firm level and not plant level; therefore, firms with multiple branches located in different regions may be assigned erroneous weather data. Nonetheless, more than 95% of firms in the sample are single-plant firms (Brandt et al., 2012); thus, this issue should exert little effect on the estimates.

[21] A 300 km radius is assigned to ensure that each county has a valid observation for the period of 2020-2049.

TFP is measured by the Solow residual in a Cobb-Douglas production function using the Olley-Pakes estimator (Olley and Pakes, 1996). The average log TFP is 2.90, but varies from -3.56 to 8.84, suggesting a large dispersion of TFP across firms exists. The dispersion of TFP could be caused by many factors, and temperature may be an important one. Labor is measured by employment, with an average of 200 people. Capital is measured by the fixed capital stock. The average is CNY 15 million (USD 2.35 million).

Temperature, wind speed, visibility, and relative humidity are calculated as annual mean value using daily observations. Precipitation is calculated as annual cumulative value using daily observations. Past climate is calculated during the period 1998-2007 from NOAA, whereas the future climate is calculated over the period 2020-2049 from HadCM3 with error correction.[22] The average temperature during 1998-2007 in the sample is 61.54°F (16.41°C).[23] In general, temperature is expected to increase by 2°F (1.11°C), whereas precipitation is expected to increase by 3 inches under climate change in China. Relative humidity and wind speed are relatively unchanged when comparing 2020-2049 to 1998-2007, which is only a medium-run prediction. In a long-run prediction (2070-2099), climate change is expected to significantly increase temperature, precipitation, relative humidity, and wind speed in China (Zhang et al., 2015).

4 Empirical Strategy

4.1 Measuring the Effect of Daily Temperature on Annual TFP

The TFP measurement is constructed at annual level because output and input are only observed annually. To measure the effects of daily temperatures on annual TFP, We employ a semi-parametric method, the so called bin approach, which has been widely used in the

[22]HadCM3 A1FI scenario does not predict for visibility.

[23]Firm-average temperature is higher than county-average temperature because 67% of firms are located in the south, which is typically warmer than the north. Similarly, precipitation and relative humidity levels are also higher in this area.

literature (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Deryugina and Hsiang, 2014). The basic idea of the bin approach is to divide daily temperature into small bins and then count the number of days falling into each bin. This semi-parametric approach allows flexible model specifications of measuring nonlinear effects of temperature and also preserves daily variations in temperature.

To develop the intuition of measuring annual TFP using daily temperatures, we present a thought experiment motivated by Deryugina and Hsiang (2014). Suppose that only two days are in a year, and each day could be either hot or normal. Considering the possible effect of high temperatures on productivity, a firm could only produce one product given a certain amount of labor and capital inputs on a hot day, but could produce two products given the same inputs on a normal day. In addition, we assume only two years: year t and year $t+1$, each with only two days. In year t, one day is normal and other other day is hot. In year $t+1$, both days are hot. Suppose that a typical firm uses the same inputs in both years,[24] then, it will produce 3 goods in year t and 2 goods in year t+1. Thus, one more hot day decreases productivity by 1, or 33%.

Furthermore, using annual TFP measurement could capture adaptations of firms in response to high temperatures within a year. For example, firms may adjust their production period from hot to cool days. This adjustment behavior will be absorbed by annual TFP measurement. Thus, our estimates are more likely to have considered within-year adaptation.

In practice, we divide daily temperature, measured in °F, into ten bins. Temperatures below 10°F are defined as the 1$^{\text{st}}$ bin, and temperatures between 10-20°F are defined as the 2$^{\text{nd}}$ bin, etc. Finally, temperatures above 90°F are defined as the 10$^{\text{th}}$ bin, which represents extremely high temperatures.

Figure 2 plots average annual distribution of daily temperatures across different bins. The blue bar "1998-2007" indicates past climate, i.e., during the period 1998-2007, whereas the red bar "2020-2049" denotes future climate (2020-2049). The height of each bin represents

[24] Temperature may also affect labor and capital inputs, but TFP is invariant to inputs.

the average number of days falling into that bin's range per year. For example, the height of the bin above 90°F is approximately 2, which indicates that on average, there are two days per year with temperature over 90°F. As expected, climate change is likely to shift the distribution of temperature to the right, and lead to more extremely hot days.

It is important to know that the changes in temperature distribution are not uniform across China. To demonstrate the regional heterogeneity in climate change, Figure 3 depicts the changes in days with temperatures above 90°F for each county under a medium-run climate prediction. Each observation records the difference in days with temperatures above 90°F between the periods of 2020-2049 and 1998-2007. The east and the south will generally experience more extremely hot days.

Other than temperature, this paper also includes precipitation, relative humidity, visibility, and wind speed. For simplicity, those variables are constructed as annual means, except precipitation calculated as annual cumulative value. We also include a quadratic for those variables to account for nonlinearity.[25]

4.2 Regression Model and the Identification

To explore the effects of temperature on the four components of the Cobb-Douglas production function (see Equation (2)), especially TFP, we estimate the following fixed-effect regression models

$$\ln y_{it} = \beta' \mathrm{Temp}_{it} + \delta' w_{it} + \theta' z_{it} + \alpha_i + \varepsilon_{it}, \tag{7}$$

where i indexes a firm, and t references a year.

In this form, y_{it} denotes the four components in Equation (2): output, TFP, labor, and capital inputs. All these variables are represented in logarithms, and thus, our estimates can be illustrated as semi-elasticities. The variable of interest, Temp_{it}, contains a vector

[25] Readers interested in the changes in the distribution of precipitation, relative humidity, and wind speed under climate change in China can refer to Zhang et al. (2015).

of temperature bins $[\text{Tbin}_{it1}, \cdots, \text{Tbin}_{it10}]$, in which Tbin_{itj} denotes the number of days falling into the j^{th} temperature bin for firm i in year t. Other climatic variables, including precipitation, relative humidity, wind speed, and visibility, are included in vector w_{it}. The vector z_{it} contains a set of fixed effects, including year-by-region fixed effects and year-by-two-digit-sector fixed effects.[26] Year-by-region fixed effects control for shocks common to each geographic region in a year, such as climate trends, technology, and policy shocks within each geographic region. Year-by-two-digit-sector fixed effects control for shocks common to each two-digit sector in a given year, such as input and output price shocks and technology shocks within each two-digit industry. We use firm fixed effects α_i to control for firm-specific time invariant characteristics, such as geographic locations. Lastly, ε_{it} is an unobservable error term.

Several noteworthy econometric details exist. First, it is likely that the error terms are both spatial and serial correlated. Thus, standard errors are clustered in two ways: within firm and within county-year (Cameron et al., 2011). The former will control for the serial correlation along time within each firm, whereas the latter will account for the spatial correlation across firms within each county in a given year.

Second, because each day is assigned into different bins, the sum of all bins $\sum_j \text{Tbin}_{itj}$ is exactly equal to 365.[27] To avoid multicollinearity, we normalize the coefficient for the 50-60°F bin to zero. Thus, all estimates of other temperature bins are impacts relative to the reference group 50-60°F. We choose 50-60°F as the reference group because it is in the middle of temperature ranges and thus makes the illustration of results more intuitive. However, our conclusion does not hinge on the choice of this reference group.

The coefficient of central interest is the estimate for each temperature bin. Considering

[26] We do not use more disaggregated fixed effects such as year-by-four-digit-sector fixed effects and year-by-province fixed effects because of the computational constraints (Greenstone et al., 2012). Furthermore, year-by-province fixed effects are likely to absorb a significant share of exogenous variations in weather given that weather is typically homogeneous within a province (Fisher et al., 2012). Region classification data are shown in Table B.8.

[27] In 2000 and 2004, the sum of all days is equal to 366. We drop February 29$^{\text{th}}$ to ensure that the sum of all days is constant for the period of 1998-2007.

that the dependent variables are all measured in logarithms, temperature effect β_j measures the percentage change, or the semi-elascticities in the four components of the production function for a firm if it has one more day falling into the j^{th} temperature bin, relative to the 50-60°F bin. The marginal effects of each temperature bin could be used to evaluate the marginal cost of increasing temperatures induced by climate change.

The identification of the key parameter relies on year-to-year weather fluctuations within firms over time. Formally, for the j^{th} temperature bin, the identification assumption is

$$\mathbb{E}\left[\text{Tbin}_{itj}\varepsilon_{it}|\text{Tbin}_{it,-j}, w_{it}, z_{it}, \alpha_i\right] = 0. \tag{8}$$

As suggested by Deschênes and Greenstone (2007), weather fluctuations are generally random and less predictable. Thus, we can reasonably assume that the j^{th} temperature bin is orthogonal to the error term, conditional on other controls. Furthermore, Zhang et al. (2015) argue that climatic variables are generally inter-correlated. As such, omitting other climatic variables apart from temperature and precipitation may bias the estimates. This study includes a rich set of climatic variables other than temperature and precipitation, including relative humidity, wind speed, and visibility. This will further solidify the identification assumption.

5 Results

5.1 Baseline Results

This section presents the baseline regression results estimated using Equation (7). To visualize the effects, Figure 4 plots the response function between daily temperature and the four components in a Cobb-Douglas production function: output, TFP, labor, and capital inputs. Specifically, it plots the point estimates as well as the 95% confidence intervals for each temperature bin estimated in four regressions. Bin 50-60°F is normalized to zero. As such, other estimates are relative to the reference group.

Panel A in Figure 4 depicts the response function between daily temperatures and log output. In general, we find an inverted U-shaped relationship between temperature and output.[28] The shape is relatively smooth and precisely estimated. The negative effects of extremely high temperatures (above 90°F) are both economically and statistically significant. The point estimate suggests that one more day with temperatures larger than 90°F decreases output by 0.45%, relative to the impact of temperature bin 50-60°F. In the sample, the average annual aggregate output for all firms is CNY 2.69 trillion (USD 0.43 trillion) in 1998 values. This suggests that, one more day with temperatures above 90°F decreases output by CNY 12.11 billion (USD 1.89 billion), relative to the impact of temperature bin 50-60°F. Given that climate change will shift the distribution of temperature to the right and induce more extreme hot days (Figure 2), a substantial economic loss in the manufacturing sector in China under climate change may be expected.[29]

Given that temperatures, particularly high temperatures, have a significantly negative effect on output, the mechanism, i.e., which component leads to the reduction in output, may be the next concern. Thus, panels B, C, and D plot the response function between daily temperature and TFP, labor, and capital inputs.

Several findings can be made from these figures. First, the response function between daily temperature and TFP is very close to daily temperature and output. An inverted U-shaped relationship is observed in both panels A and B. The magnitudes of the point estimates are close. However, the gradient depicted in panel B is slightly steeper than presented in panel A in the high-temperature ranges. For example, one more day with temperature higher than 90°F reduces output by only 0.45% but lowers TFP by 0.56%.

[28] Surprisingly, bin 30-40°F, which is a relatively cold range, reports the largest point estimate and is statistically significant. This outcome is because TFP combines both labor and capital productivity; while 30-40°F is cold for human behaviors, this range may be suitable for machine performance.

[29] Extremely cold days, such as those with temperatures below 10°F, are reduced under climate change. This occurrence may benefit the manufacturing sector. However, the losses induced by the increased number of extremely hot days should dominate these gains because the point estimate of extremely hot days is much larger than that of extremely cold days.

The effects of daily temperature on labor (panel C) and capital (panel D) do not take a particular shape. Furthermore, the estimates of most temperature bins are statistically insignificant; however, a slight increase is observed in the highest temperature range depicted in panel C, and the effect is statistically significant at conventional levels. This outcome suggests that firms may employ additional labor in response to high temperatures, to partially compensate the output losses driven by TFP losses. This result explains why the TFP losses are slightly greater than the output losses in response to high temperatures. By contrast, the effect on capital is statistically insignificant because capital is generally unadjustable in the short run.

Table 2 further presents the effects of daily temperatures on output and TFP using various specifications. Due to space limitations, we only report the regression results of the two highest temperature bins: 80-90°F and above 90°F. Furthermore, the F-statistic of the null hypothesis, that the coefficients of all temperatures bins are jointly equal to zero, are also reported.

In column (1a), we start with a simple specification of only firm fixed effects and year fixed effects. Thus, the identification is from plausibly exogenous variations in weather within firms over time after we adjusted nationwide shocks in a given year. These shocks may include policy changes, technology progress, or price shocks of inputs and output that are common to the country. However, some shocks may be region-specific. Thus, in column (1b), we replace year fixed effects with year-by-region fixed effects, which control for any common shocks for a specific geographic region in a given year.

In column (1c), we replace year fixed effects with year-by-two-digit-sector fixed effects to control for shocks that are common to two-digit industries in a given year. These shocks may include sector-specific price shocks of inputs and output. In addition, technology progress within each industry are included in year-by-two-digit-sector fixed effects. Column (1d) includes both year-by-region and year-by-two-digit-sector fixed effects, which will control for common shocks within geographic regions and two-digit sectors.

Through columns (1a)-(1d), temperature bins are constructed using daily mean temperature. In column (2a), temperature bins are constructed using daily maximum temperature to capture the daily extremely hot effects that may be missed using daily mean temperature. In column (2b), we construct temperature bins using daily heat index, which incorporates the effects of both temperature and humidity.

TFP is estimated as the Solow residual in a Cobb-Douglas function using the Olley-Pakes estimator (Olley and Pakes, 1996) through columns (1a) to (2b). In column (3), TFP is estimated using the index number approach (Syverson, 2011) to verify the robustness of different TFP measures. Temperature bins are constructed using daily mean temperature and the model includes firm fixed effects, year-by-region fixed effects, and year-by-two-digit-sector fixed effects.

The major conclusion that high temperatures have a significantly negative effect on both output and TFP is robust across various specifications. The F-statistic for all temperature bins are all statistically significant, suggesting that the effects of all temperature bins are jointly different from zero.

Columns (1a) to (1d) test the robustness of fixed effects. In general, controlling for geographic shocks produces larger estimates. This is likely because manufacturing plants built in hot regions may be equipped with heat-proof materials. When year-by-region fixed effects are included, we are comparing firms within each geographic region; thus, this protection measure was absorbed. Therefore, the model with year-by-region fixed effects produces larger estimates. The estimates are relatively unchanged when including year-by-two-digit-sector fixed effects. The most robust specification, column (1d), controls for both geographic and industrial shocks. Thus, this specification will serve as the baseline in this paper.

Column (2a) tests the robustness of daily temperature measures, and produces the smallest negative estimates. This is because when temperature bins are constructed using daily maximum temperatures, above 90°F are actually not particularly hot. Column (2b) incorporates the joint effects of temperature and humidity, and produces slightly smaller effects, indicating that the effects of humidity may be limited. Column (3) tests the robustness of TFP measures. The results suggest that our estimates are robust to alternative TFP measures using the index number approach, though the magnitude is smaller.

In terms of climatic variables other than temperature, precipitation and wind speed generally have a significantly negative impact on output and TFP; by contrast, the effects of relative humidity and visibility are statistically insignificant. The results are listed in Table B.9, which is provided in the online appendix.

5.2 Effects of Lagged Temperatures

The temperatures in previous years may have an effect on current economic outcomes (Dell et al., 2012; Deryugina and Hsiang, 2014). For example, hot temperatures in the prior year may reduce the output, and further reduce investment. This outcome may affect capital accumulation, and reduce current output. Therefore, in this section, we include one-year lagged temperature, measured in 10°F bins, in the baseline regression model.[30] Both current and lagged temperatures are estimated simultaneously in one regression.

Figure 5 presents the effects of both current and lagged temperatures on output and TFP. Panel A depicts the response function between current daily temperature and output, whereas panel B depicts the response function between lagged daily temperature and output. Panels C and D also depict the response function, but with the dependent variable as log TFP.

Panels A and C show that the effects of current temperatures on both output and TFP still remain as inverted-U shapes when we include lagged temperatures. The response function between current daily temperature and output and TFP are qualitatively almost the same, with and without including lagged temperature. As shown in panels B and D, the effects of lagged temperatures on output and TFP are not clear. Overall, the point estimates

[30] We do not include further lags because temperature is measured in 10 bins, and 2-year lags already result in 30 dependent variables. Therefore, we are unlikely to generate adequate statistical power to identify the effects of temperature on output and TFP.

are mostly noisy results, and do not exhibit any particular shapes. Thus, lagged temperatures, especially lagged high temperatures, seem to have limited effects on both output and TFP.[31]

5.3 Effects of Temperature on TFP Growth

Temperatures may not only affect the level of TFP, but also influence growth rate through investments or institutions (Dell et al., 2012). To verify this hypothesis, Equation (7) is estimated with the dependent variable as TFP growth rate. Given that the effects of temperature on TFP growth rate may be time lagged, we include one-year lagged temperature bins.

Figure 6 plots the response function between daily temperature and TFP growth rate. Panel A is for current daily temperature, while panel B is for one-year lagged daily temperature. Surprisingly, we do not find an effect of either current or lagged temperatures on TFP growth rate. In panel A, the response function is relatively flat. Although the temperature range above 90°F slightly dropped, it is statistically insignificant. Moreover, in panel B, most estimates, particularly high temperature ranges, are statistically insignificant. Panels C and D further depict the response function between daily temperature and log investment. We do not find a significant effect of either current or lagged daily temperature on investment. Most estimates are statistically insignificant and not well-estimated. This suggests that the effects of temperatures are mostly significant on the level of TFP, instead of the growth rate.

5.4 Disentangling TFP into Labor and Capital Productivity

We have shown that the negative effects of temperature on TFP is the major force that drives the reduction in output. Given that TFP is a weighted average of labor and capital productivity, whether the negative effects primarily originate from labor productivity, capital

[31] In general, we do not detect the significant impacts of both current and lagged temperature on labor and capital inputs either.

productivity, or both, is a question of interest. Previous studies have predominantly focused on labor productivity (e.g., see Adhvaryu et al. (2014); Somanathan et al. (2014)), while ignoring capital productivity. Because one cannot estimate labor and capital productivity separately in a Cobb-Douglas production, we have to implicitly test the hypothesis that the negative effects of TFP are mostly from labor productivity. The intuition is as follows. We recall Equation (5) ($a(T) = \alpha a_L(T) + \beta a_K(T)$) and suppose the negative effects of temperature on TFP (a) are primarily from the effect on labor productivity (a_L). As such, the effects on TFP (a) should be larger in labor-intensive industries because output elasticity of labor (α) is typically larger in those industries. Thus, if we cannot find such effects, this result implicitly suggests that temperature affects both labor and capital productivity.

To classify firms by either labor- or capital-intensive, we use two measurements of labor intensity. The first measurement is wage bill over output, a common measurement of labor intensity. The second measurement is labor over sales, following Dewenter and Malatesta (2001).

Table 3 presents the effects of temperature on TFP between labor- and capital-intensive firms. Regression models are estimated using Equation (7). Due to space limitations, we only report the effects of the two highest temperature bins. In columns (1a)-(1c), labor intensity is measured by wage bill over output. In columns (2a)-(2c), labor intensity is measured by labor over sales. To be able to capture the heterogeneous impacts of labor- and capital-intensive firms, we make the two highest temperature bins (80-90°F and above 90°) interact with variables that distinguish firms as either labor- or capital-intensive. In columns (1a) and (2a), we simply interact two highest temperature bins with raw labor intensity. In columns (1b) and (2b), labor intensity is classified as either above median (=1) or below median (=0). Thus, the dummy variable "Above Median" would indicate labor-intensive firms. Similarly in columns (1c) and (2c), labor intensity is classified based on the mean value, and thus the dummy variable "Above Mean" indicates labor-intensive firms.

If the effects of high temperatures on TFP are mostly from the effects on labor productivity, the interaction terms are expected to be significantly negative. However, in all these specifications, the interaction terms are either significantly positive or statistically insignificant. To be more specific, we take column (1b) as an example. Given that the variable "Above Median" is defined as equal to 1 if the firm's labor intensity is larger than the median, the marginal effect of temperature above 90°F for labor-intensive firms is $-0.0081 + 0.0064 = -0.0017$, whereas the marginal effect for capital-intensive firms is -0.0081. Similarly with temperature bin 80-90°F, the marginal effect for labor-intensive firms is $-0.0030 + 0.0009 = -0.0021$, while that for capital-intensive firms is -0.0030. This suggests that the negative effects of two highest temperature bins on TFP are actually smaller in labor-intensive firms. One can observe the same pattern when interactions are constructed using either raw labor intensity or mean values. All these implicitly suggest that high temperatures affect both labor and capital productivity.

5.5 Industrial Heterogeneity in the Effects of Temperature on Output and TFP

The effects of temperature on output and TFP may differ across industrial sectors because of the differences in climate exposures, sensitivity to temperatures, or the presence of air conditioning for protection. To explore the heterogeneity across industrial sectors, Figure 7 depicts the point estimates and the 95% confidence intervals of temperatures above 90°F on output (panel A) and TFP (panel B) for each two-digit sector. Regression models are estimated separately for each two-digit sector using Equation (7).[32] The share of each sector in the entire sample is enumerated in the parenthesis; sectors are sorted according to their shares. Each sector is classified as either a light or a heavy industry (labeled in red or blue, respectively).[33]

[32] We do not include sectors with observations smaller than 10,000, including the sectors for oil and natural gas mining, other mining, tobaccos, chemical fibers, waste recycling, and gas utility, because these industries have too few observations to produce accurate estimates.

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

Several findings can be made from Figure 7. First, temperatures above 90°F exhibit statistically significant and negative effects on output for most industries. The effects on industries with a considerable share in the whole sample, such as textiles, non-metallic minerals, general machinery, raw chemicals, are precisely estimated. Second, there is strong heterogeneity across industrial 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. Third, the impacts of temperatures above 90°F on TFP for each two-digit sector in panel B are almost identical with the effects on output in panel A, which again indicates that the reduction in TFP in response to high temperatures are mostly responsible for output losses.

Last, results in Figure 7 suggest that temperatures above 90°F have significantly negative effects on both light (in red) and heavy (in blue) industries. Light industries, such as processing of foods, manufacture of foods, 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 5.4, the result demonstrates that high temperatures may affect both labor and capital productivity.

5.6 Role of Air Conditioners

Air conditioners (ACs) can mitigate the negative effects of high temperatures; therefore, their use is regarded as an effective method of adapting to climate change (Barreca et al., Forthcoming). Unfortunately, firms do not report either the application of AC or electricity consumption in our data; thus, we have to rely on other aggregated measures of AC use. In this study, we utilize the province-level AC penetration rate per 100 urban households as a proxy for AC use by firms, which is reported in the China Statistical Yearbooks. The average AC penetration rate for each province over the period of 1998-2007 is presented in Table B.10 in the online appendix. The provinces are sorted according to their AC penetration rates; Guangdong is one of the hottest regions in China and has the highest AC penetration rate, followed by Shanghai, Chongqing, Beijing. All these rates are greater than 100. By contrast, the two provinces Yunnan and Qinghai report the lowest AC penetration rates; the average rate for China is 53.21.

To determine the role of AC in mitigating the negative effects of high temperatures, we classify provinces as either high or low intensity based on the median AC penetration rate across provinces, as listed in Table B.10. This median is 46.18; therefore, provinces with AC penetration rates above and below 46.18 are classified as high and low intensity, respectively. As a robustness check, we also classify provinces based on the mean AC penetration rate; the results are identical because the mean (45.08) is highly similar to the median (46.18).

Table 4 reports the effects of AC on temperature-output and temperature-TFP relationships. The dependent variables are output presented in columns (1a)-(1b) and TFP listed in columns (2a)-(2b). Furthermore, the regression models are estimated using Equation (7). We interact the two highest temperature bins with the dummy variable "AC Above Median" in columns (1a) and (2a); the value of this variable is one if the AC penetration rate of a particular province is above the median. Otherwise, the value is zero. Similarly, the dummy variable "AC Above Mean" in columns (1b) and (2b) is one if the AC penetration rate in that province is above the mean; otherwise, the value is zero.

If manufacturing firms are well protected by AC, then we expect the interactions to be significantly positive; however, the interactions are significantly negative in all specifications. This result indicates that the regions reporting high-intensity AC use still display strongly negative responses to high temperatures. This outcome implicitly suggests that firms are indeed not very well protected by AC. Given that China is still a developing country, AC adaptation behavior may be limited.

5.7 Role of Ownership Types

Firms in China are required to implement protective measures such as hydration, air conditioning, and subsidies for workers during extremely hot days.[34] Given that labor regulations are typically more stringent in state-owned firms than in private firms, the effects of high temperatures on TFP can be weaker in state-owned firms than in private firms. To explore the heterogeneity in ownership, Table 5 presents the effects of temperature on output and TFP across ownership types; the estimates for the full sample are also reported for comparison purposes. Regression models are estimated separately using Equation (7) for each type of ownership; moreover, we report the mean temperature and the percentage of each type of ownership in the entire sample.

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 1.16% 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. Collective firms constitute 12.98% of the entire sample, and the negative effects of high temperatures on output and TFP are generally weak or statistically insignificant. State-owned firms comprise the smallest share, and the effects of temperature above 90°F on output and TFP are significantly positive.

These results demonstrate the importance of labor regulations; private firms bear the most severe damages from high temperatures because of lax regulations. On the contrary, the effects of the highest temperatures on state-owned firms are slightly positive because of the stringent regulations and heavy subsidies. However, firms under the same type of ownership may be located in the same geographic region; thus, the results may be driven by geographic differences. Therefore, the bottom of Table 5 reports the mean temperature for each ownership type. The mean temperature for the full sample is 61.54°F while those for

[34] http://www.chinasafety.gov.cn/newpage/Contents/Channel_20697/2012/0704/173399/content_173399.htm.

private and state-owned firms are 61.64°F and 59.03°F, respectively. This finding suggests that the mean temperatures of private and state-owned firms do not differ significantly; therefore, the results are unlikely to be driven by geographic differences. Furthermore, the findings are unlikely to be driven by sector differences because no clear pattern has been generated of industrial sectors, as depicted in Figure 7.

5.8 Regional Heterogeneity in the Effects of Temperature on Output and TFP

Firms in different regions may exhibit various responses to high temperatures. For example, economically developed regions are more likely to be able to implement costly defensive devices such as air conditioners. If this is the case, the negative effects of high temperatures on TFP in more developed regions are expected to be smaller. People living in hot regions are more likely to adapt to hot weather through complete physiological acclimatization (Graff Zivin and Neidell, 2014). Therefore, TFP should be less sensitive to high temperatures in hot regions.

To detect such adaptation behaviors, Table 6 presents the regression estimates for the two highest temperature bins (80-90°F and above 90°F) on TFP for each economic and geographic region. Regression models are separately estimated for each region using Equation (7). The average TFP for each economic region and the average annual mean temperature for each geographic region are also reported.

Among the economic regions, the east has the highest TFP, whereas the west has the lowest TFP. However, the negative effects of temperatures above 90°F are statistically insignificant for northeast, central, and west. Given that high temperatures have significantly negative effects on TFP in the most developed region, the adaptation behaviors are limited in developed regions. This is also consistent with finding in Section 5.6.

In terms of the geographic regions, the northeast has the lowest annual mean temperature, whereas the south has the highest annual temperature. The effects of temperatures above

90°F are significantly negative for the south, but insignificant for the northeast. Furthermore, if one compares the negative effects of temperatures above 90°F in the south with other regions that have significantly negative effects but with lower annual mean temperature, such as north and east, we can find that the negative effects in those regions are lower in magnitude. This suggests that the adaptation behavior in hot regions are also limited.[35]

6 Climate Prediction

This section presents the climate prediction on output and TFP. Firms may adapt to climate change by adopting new technology, by increasing the use of air conditioners, or by migrating to cooler areas. As such, the prediction may be overestimated. Furthermore, climate models are regarded with much uncertainty (Burke et al., 2015). Nonetheless, we believe that the predictions remain instructive for climate policy design.

6.1 Main Results

To predict impacts of climate change on output, we first estimate regression coefficients for each climatic variable from Equation (7). We then calculate the difference in each climatic variable between the periods 2020-2049 and 1998-2007 for each firm. The firm-specific climate differences are averaged to a representative firm. Lastly, we use estimated coefficients multiplying by the climate differences to infer the impacts of climate change on output. Standard errors are calculated using the Delta method. In addition, we calculate the climate prediction on TFP using the same method.

Table 7 presents the climate prediction on output in both percentage points and billion CNY, and TFP for the full sample and for each ownership category. The point estimates,

[35]The estimates of the two highest temperature bins on output for each region are reported in Table B.11; We detect a similar pattern. Other methods to identify adaptation behaviors have been developed, such as the long-difference approach or the comparison of regression estimates in different time periods (Dell et al., 2014). Nonetheless, the time period for our data is only 10 years (1998-2007), we are unlikely to implement such approaches.

standard errors, as well as the 95% confidence intervals are reported. In the last row, we report the percentage of each ownership in the full sample.

Column (1) reports the climate prediction on output for the full sample. Compared with the period 1998-2007, output will be reduced by 5.71% under a medium-run climate change. In addition, the effect is statistically significant at 1% level. The climate prediction on output in percentage points could be further translated into monetary damages by multiplying by the average annual aggregate output for all firms during 1998-2007, which yields a loss of CNY 208.32 billion (USD 32.57 billion) in 2013 values. To illustrate how large the damage is, we used each country's GDP from the World Bank (World Bank, 2013b). In 2013, 99 countries have GDPs below this amount. The output loss under climate change in the Chinese manufacturing sector corresponds to the GDP of Cameroon or Bolivia.

Column (1) also reports the climate prediction on TFP. The model predicts that climate change will decrease TFP by 4.18%, which is statistically significant at 1% level. The prediction on TFP is quantitatively close to the prediction on output, suggesting that the reduction in TFP is the major driver behind output losses under climate change.

Columns (2) to (5) report climate predictions on output and TFP for each ownership category. Consistent with the findings in Table 5, climate prediction is the largest in private firms because of lax labor regulations. Overall, private firms will bear economic damages in CNY 168.72 billion (USD 26.28 billion). By contrast, the prediction is trivial for state-owned firms. Foreign and collective firms will bear moderate damages under climate change.

6.2 Industrial Heterogeneity in Climate Prediction

As shown in Figure 7, the effects on high temperatures on TFP across two-digit industrial sectors have a strong heterogeneity. As a result, one may expect similar heterogeneity in climate predictions. Figure 8 presents the predictions on output (panel A) and TFP (panel B), for 33 two-digit sectors at the 95% confidence interval. The regression models are estimated separately for each two-digit sector. The percentage of each sector in the full sample are presented in the parenthesis. Sectors are ordered by their shares. Six sectors are not presented because of excessively small sample sizes and too large standard errors.[36] Panel C further monetizes the climate predictions on output for each sector by multiplying by the average annual aggregate output. Sectors in panel C are sorted by their climate impacts.

Several findings can be made from Figure 8. First, the climate prediction on output have a strong heterogeneity in both sign and magnitude across sectors. The point estimates vary from -12.22% for rubber and 1.95% for ferrous metal mining. Consequently, monetary climate damages (panel C) greatly vary across sectors as well. Textile will bear the largest climate damages, with a loss of CNY 20 billion (USD 3.11 billion), while the impacts on water utility, non-ferrous and ferrous metal mining, smelting of non-ferrous metals, and coal mining are approximately non-exist.

Second, most sectors will bear output damages under climate change. Among the 33 sectors, the effects of climate change on output in percentage points (panel A) in 22 sectors are statistically significantly negative at the 5% level. Third, for sectors with a larger share in the whole sample, the climate predictions are both economically and statistically significant. In general, these sectors will bear 5-8% output losses under climate change, with corresponding CNY 10-20 billion (USD 1.56-3.11 billion) losses. For sectors with a smaller share, the predictions are generally insignificant because of large standard errors, which is likely caused by small sample size.

The results in Figure 8 also confirm the findings in Section 5.4. Both light (in red) and heavy industries (in blue) exhibit negative responses to climate change. With light industries being typically labor-intensive and heavy industries being generally capital-intensive, the results imply that climate change affect both labor and capital productivity. Lastly, the climate predictions for each sector on TFP in panel B is almost identical to predictions on output in panel A. This similarity demonstrates that the reduction in TFP in response to

[36]These sectors include oil and natural gas mining, other mining, tobaccos, chemical fibers, waster recycling, and gas utility, with observations smaller than 10,000.

climate change are mostly responsible for output damages.

6.3 Regional Heterogeneity in Climate Prediction

HadCM3 A1FI scenario predicts a warmer climate in China in the foreseeable future. On average, the temperature will increase by 2°F (1.11°C). However, the changes of temperature across regions display a strong heterogeneity. For example, panel D in Figure 9 depicts the differences in number of days with temperatures above 90°F between the periods 2020-2049 and 1998-2007. Generally, eastern and southern China will gain more extremely hot days. As a result, the climate predictions could vary across China. To demonstrate such regional heterogeneity, Figure 9 presents the climate predictions on output in percentage points (panel A) and in CNY billion (panel B) and TFP in percentage points (panel C) for each county. The county-specific effects are calculated as follows: First, we estimate the regression model (Equation (7)) for the whole sample; we then calculate the climate difference for each firm between the periods of 2020-2049 and 1998-2007; Third, we use estimated coefficients and multiply them by climate difference to infer the climate effects for each firm; Lastly, the firm-specific climate effects are averaged to the county level.[37] The monetary damages for each county are obtained using predicted output losses in percentage points (panel A) multiplying by the county-specific aggregate output.

Overall, the climate damages in southern and eastern China are particularly severe with more than 6% losses and corresponding CNY 0.06 billion in most counties. Notably, those regions are where most manufacturing firms are located. On average, the northern and north-eastern China are subject to moderate output losses. In general, the loss varies from 2-4%, or CNY 0.02-0.04 billion (USD 3.12-6.25 million). In addition, a large area in northwestern China are predicted to slightly increase output under climate change.

The climate prediction on TFP is generally similar to the prediction on output. Southern

[37] We do not run regression models separately for each county because the sample is too small. Therefore, the county-specific predictions in this study merely capture the heterogeneity in the changes of temperature and not the heterogeneity in the historical relationship between output and temperature.

China and eastern China are expected to experience severe losses, whereas the damages are moderate for northern China. A large area in northwestern China are predicted to moderately increase TFP. Overall, the results demonstrate a strong heterogeneity across geographic regions.

7 Economic and Policy Implications

In the previous section, we predict the effects of climate change on output and TFP in the medium run, and explore the heterogeneity across industrial sectors and geographic regions. These results have significant economic and policy implications.

First, this paper helps explain the micro-mechanism for a large body of literature that estimates the relationship between temperature and economic growth (Nordhaus and Yang, 1996; Hsiang, 2010; Dell et al., 2012; Burke et al., Forthcoming). Our model predicts that a medium-run climate change will reduce output by 5.71%. Given that the manufacturing sector contributes 32% of China's GDP, this result can be translated as $5.71\% \times 0.32 = 1.83\%$ GDP losses. Mean temperature increases by approximately 2°F (1.11°C) under medium-run climate change; this outcome suggests that a 1°F (1°C) increase in annual mean temperature reduces the Chinese GDP by 0.92% (1.66%). This finding is consistent with Hsiang (2010) and Dell et al. (2012), in which they find that a 1°F (1°C) increase in annual mean temperature leads to 1.39% (2.5%) and 0.56% (1.0%) GDP reduction in other developing countries. We determine that the TFP reduction in response to high temperatures in the manufacturing sector is primarily responsible for the negative relationship between temperature and economic growth.

Second, the baseline model predicts an output loss by 5.71%. This is equivalent to losses of CNY 208.32 billion (USD 32.57 billion) in the Chinese manufacturing sector in 2013 values. This damage could be incorporated in the cost-benefit analysis when China is making its own climate policies. As the world's largest emitter of CO_2 (U.S. Energy Information

Administration, 2012), China's effort to reduce CO_2 emissions is critical in tackling global climate change. Although China has made various actions to reduce CO_2 emissions under international pressure,[38] the new findings of potential damages on manufacturing sector in this study could motivate China to make more stringent policies on carbon reduction with self interest in mind.

Third, the baseline model predicts a TFP loss by 4.18% under climate change. This TFP reduction in response to climate change is mostly responsible for output losses. As TFP is invariant to the intensity of use of labor and capital inputs, Chinese manufacturing is less likely to avoid these damages simply through factor reallocation. If only labor productivity is negatively affected by high temperatures, a natural way to avoid climate damage is to simply replace workers with machines. However, because we find that temperature affects both labor and capital productivity, the factor reallocation is less likely to be a feasible way of adapting to climate change.

Fourth, China is the world's largest exporter, wherein manufacturing goods compose 94% of total exports (World Bank, 2013a). As a result, climate damages on Chinese manufacturing sector could further affect global welfare via trading. For example, reduction in TFP and output under climate change may reduce exports, and increase prices of manufacturing goods, which may further affect the economic welfare in the imported country. As such, the climate damages on Chinese manufacturing sector could spill over to other countries.

Fifth, Sub-Saharan Africa is one of the regions most vulnerable to climate change because rain-fed agriculture is the primary source of food production in this area and is the main income source for a rural population that numbers nearly 350 million (Cooper et al., 2008). It is thought that transitioning from agriculture to manufacturing can feasibly facilitate adaptation to climate change (Henderson et al., 2015). Given the severe climate damages to the Chinese manufacturing sector, climate change may also affect the African manufacturing industry significantly. Therefore, additional researches should be conducted in Africa and

[38] For example, China agreed to reduce its carbon intensity (carbon dioxide emissions/GDP) by 40 to 45% by 2020 in the 2009 Copenhagen Accord.

possibly in other countries, to enhance the support for optimal adaptation policy design.

Sixth, the results suggest that climate damages are severe in private firms, whereas the effects on state-owned firms are trivial. This finding reveals that labor regulations could play an important role in mitigating the negative effects of high temperatures. In addition, we find strong heterogeneity in climate damages across industrial sectors. This finding suggests that climate change may generally have a negative affect on Chinese manufacturing. However, climate change may also alter the composition of industrial sectors. Some sectors may gain more shares, while others may lose. Given that the manufacturing sector composes 32% of China's GDP and employs 30% of labor forces (China Statistical Yearbook, 2014), the climate shock on composition of the manufacturing sector could further have a profound effect on the Chinese economy.

Lastly, climate damages across geographic regions display a strong heterogeneity. Overall, southern and eastern China is expected to experience severe losses, whereas northern China is expected to experience moderate losses or even slight gains in certain regions. This prediction provides a potential migration opportunity for Chinese manufacturing firms to adapt to climate change. As manufacturing are largely limited by infrastructure, and Chinese manufacturing is centered in the south and the east, the Chinese government may promote more infrastructure construction in the north to adapt to climate change.

8 Conclusion

This paper estimates the economic effects of temperature on the four components of a production function using firm-level manufacturing data in China: output, TFP, labor, and capital inputs. We determine that the reduction in TFP in response to high temperatures is the major channel that leads to output losses. This finding helps contribute to a growing number of studies estimating the relationship between temperature and economic growth.

The model predicts that climate change may reduce TFP by 4.18%, and cause output losses by 5.71%. This result is equivalent to losses in CNY 208.32 billion (USD 32.57 billion) in 2013 values. As Chinese manufacturing is a critical component in both the country's GDP and world's export market, the potential climate damages could have a profound effect on global welfare.

Chinese manufacturing firms may mitigate climate damages through more stringent environmental regulations or by migrating to the north. However, China and probably other countries are less likely to be able to avoid these damages simply by reallocating labor and capital inputs. Therefore, new technology that expands the production frontier should be developed to compensate the weather-driven TFP losses if other adaptation strategies are less feasible.

In terms of future study, one direction involves applying other production functions, such as the constant-elasticity-of-substitution production function that enables researchers to estimate labor and capital productivity explicitly, and then exploring the responses of these factors to temperature separately. Furthermore, the present study evaluates climate damages to the Chinese manufacturing sector alone; thus, generalizing these estimates to other countries is particularly important in the design of global climate policies.

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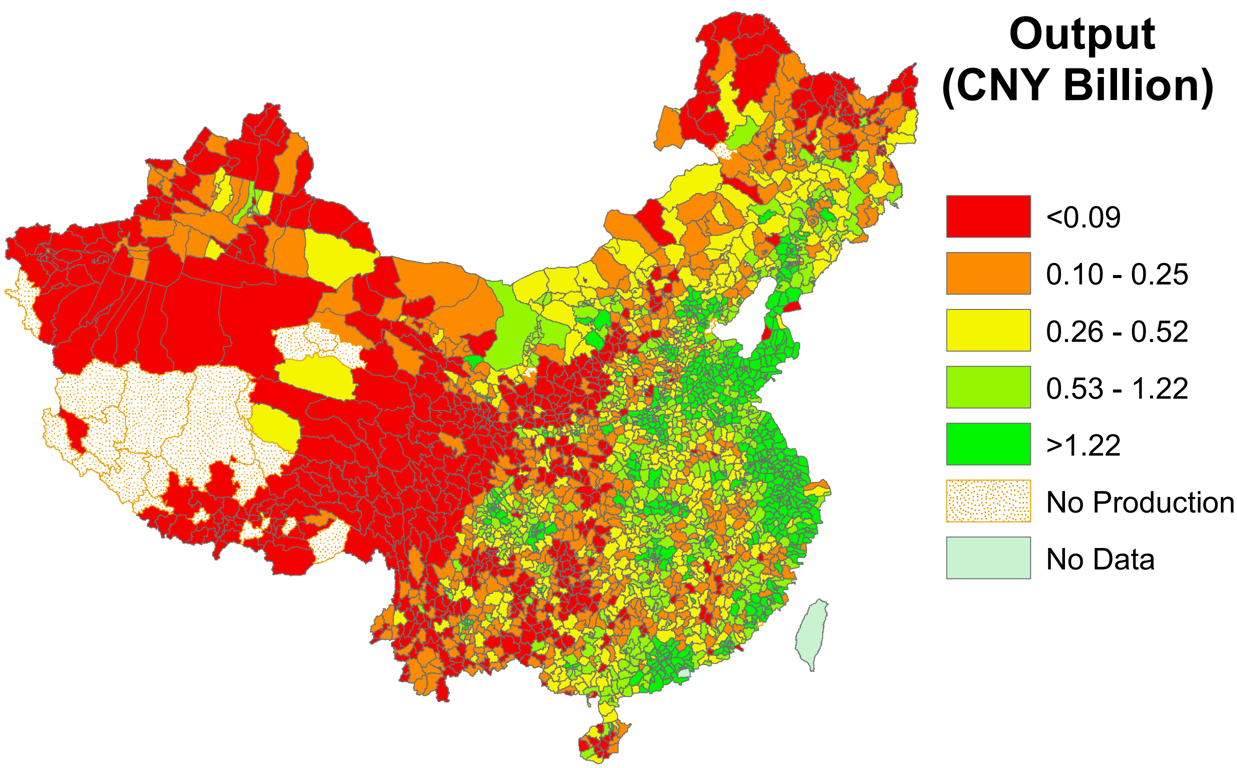
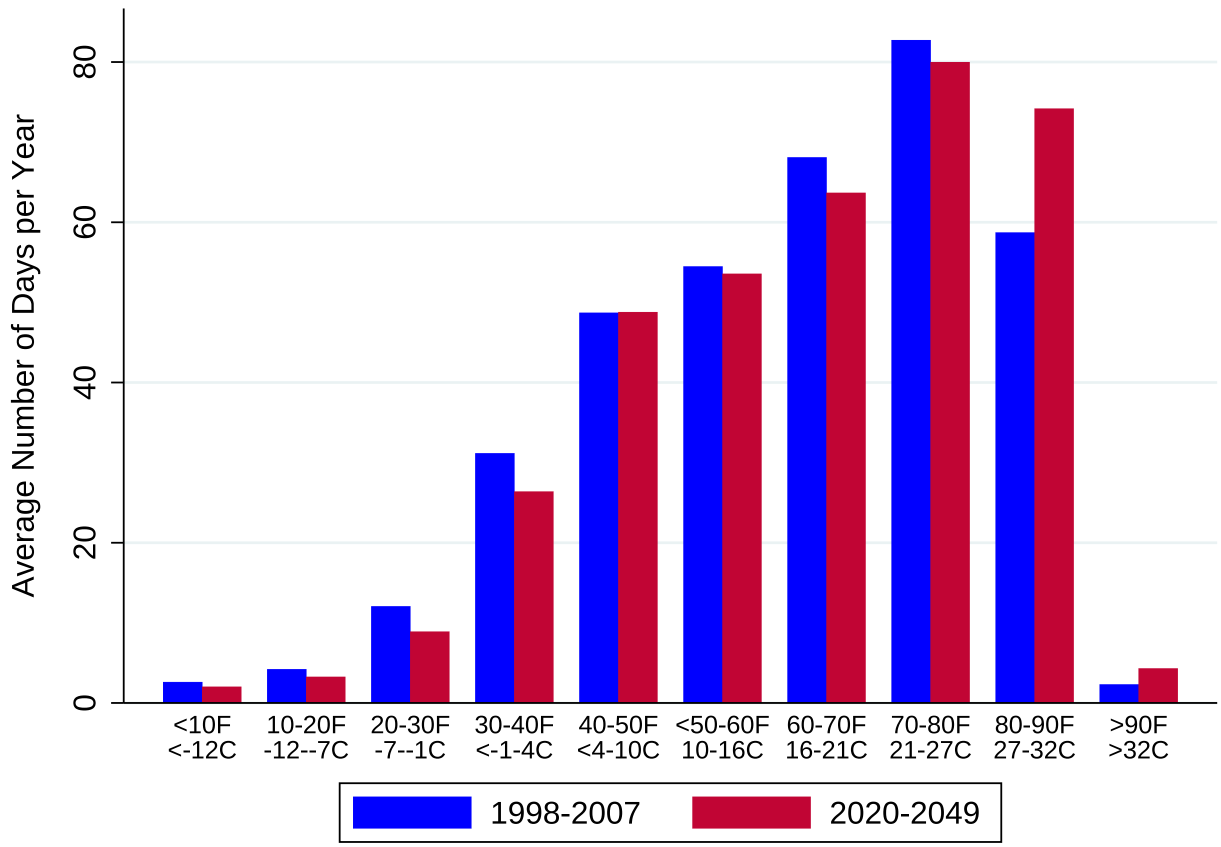
A Appendix

Figure 1: Geographic Distribution of Output, 1998-2007



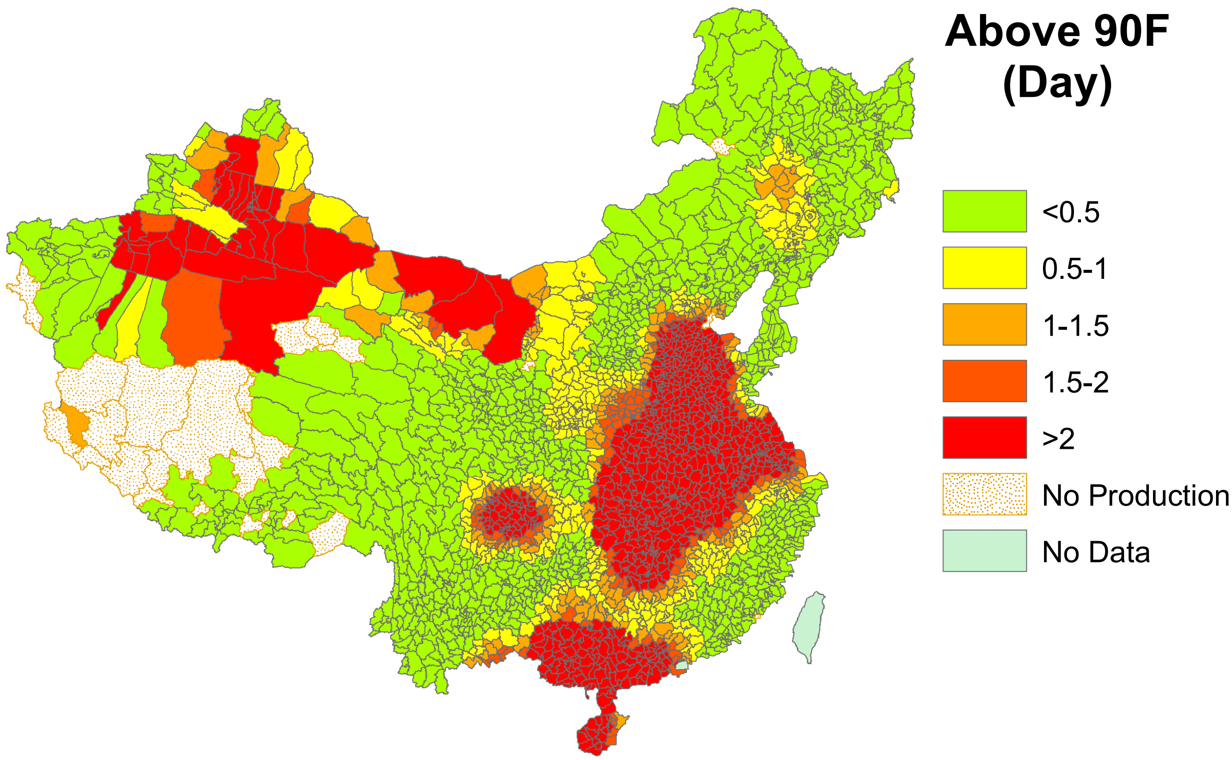
Notes: This figure presents the average annual aggregate output for each county during the period of 1998-2007. The county-level aggregate is calculated with the firm-level output, and the unit is CNY billion in 1998 values.

Figure 2: Distribution of Daily Temperatures, 1998-2007 and 2020-2049



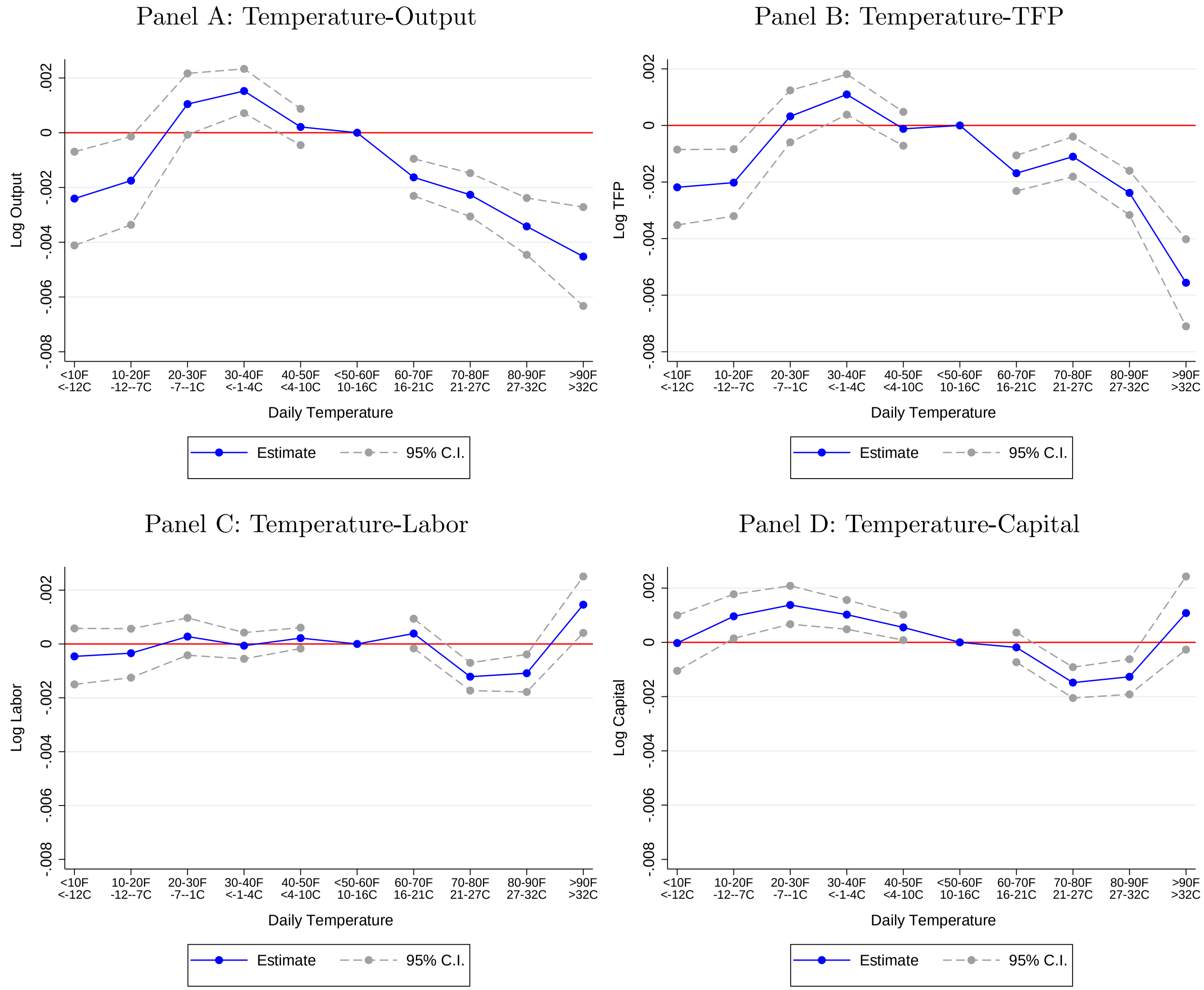
Notes: This figure illustrates the distribution of daily temperatures for the periods 1998-2007 and 2020-2049. The "1998-2007" and "2020-2049" bars represent the average number of days per year in each temperature category over these time periods. The climate prediction is obtained from the HadCM3 A1FI scenario.

Figure 3: Geographic Distribution of Changes in Days with Temperatures above 90°F



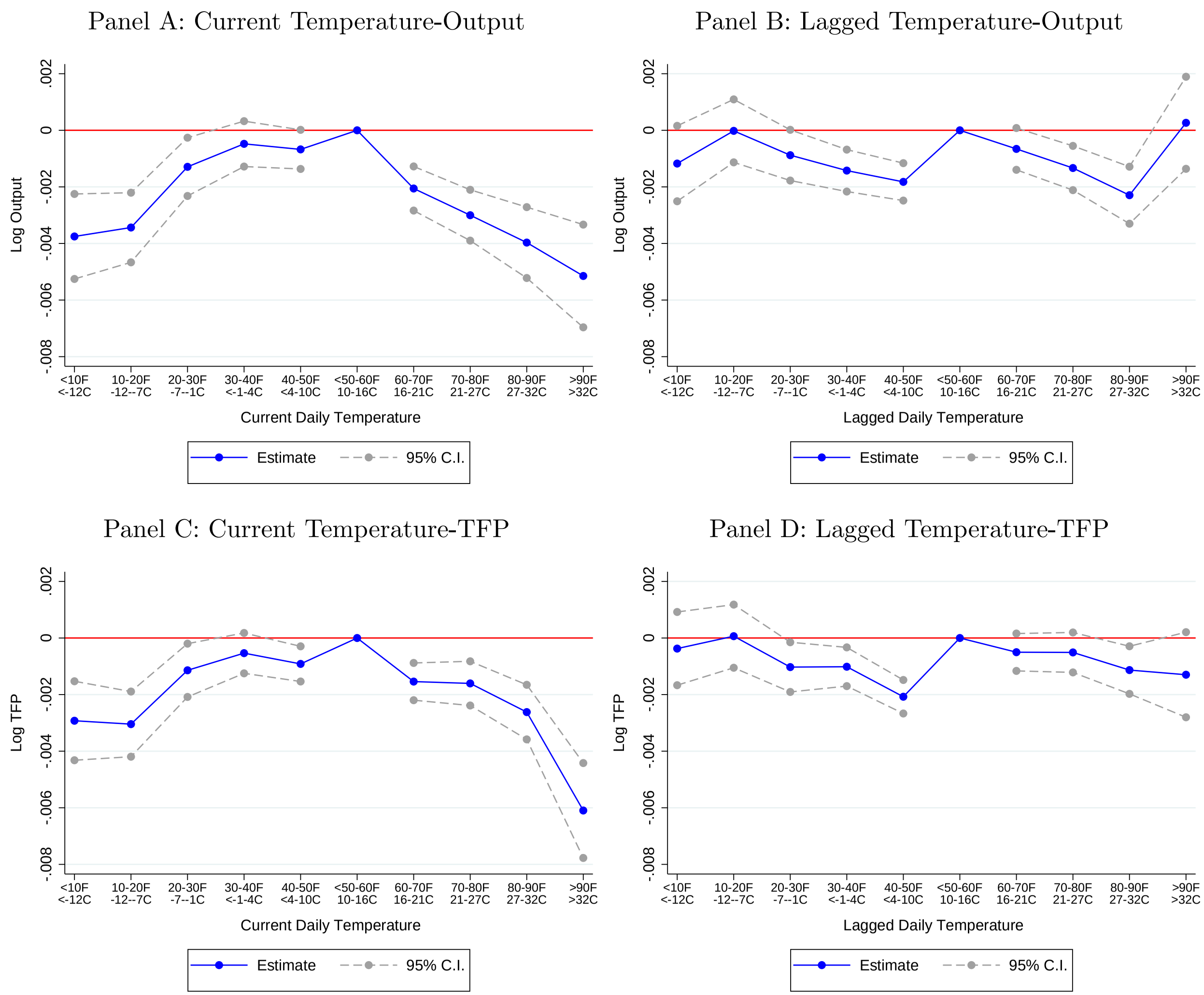
Notes: This figure depicts the changes in days with temperatures above 90°F under a medium-run climate change. The unit is the difference in days with temperatures above 90°F between the periods 2020-2049 and 1998-2007.

Figure 4: Effects of Daily Temperature on Output, TFP, Labor, and Capital Inputs



Notes: Panel A: Estimated Temperature-Output Relationship. Panel B: Estimated Temperature-TFP Relationship. Panel C: Estimated Temperature-Labor Relationship. Panel D: Estimated Temperature-Capital Relationship. Regression models are estimated for each component separately using Equation (7).

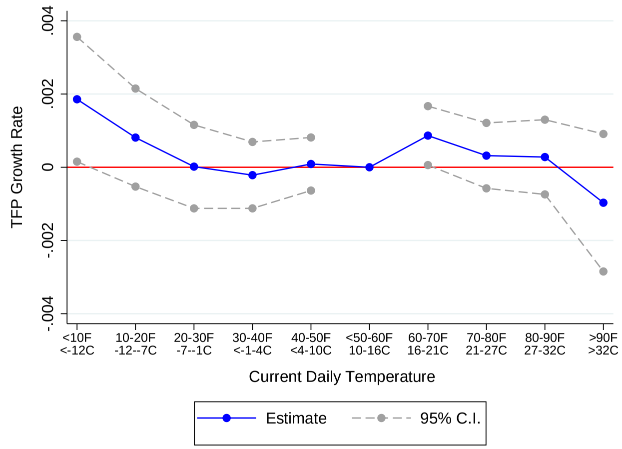
Figure 5: Effects of Current and Lagged Temperature on Output and TFP



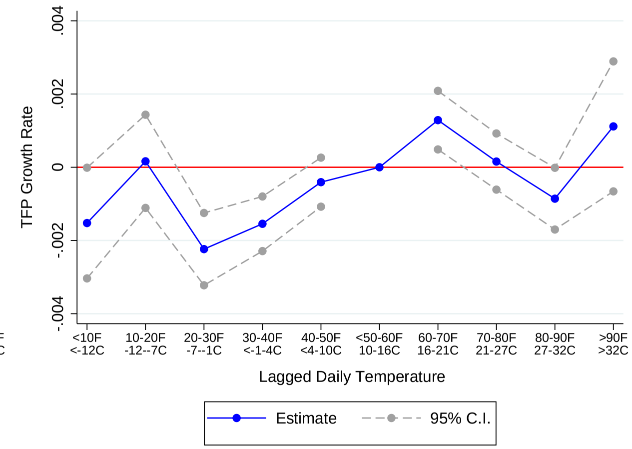
Notes: Panel A: Estimated Current Temperature-Output Relationship. Panel B: Estimated Lagged Temperature-Output Relationship. Panel C: Estimated Current Temperature-TFP Relationship. Panel D: Estimated Lagged Temperature-TFP Relationship. Panels A and B are estimated simultaneously in one regression, and so are panels C and D.

Figure 6: Effects of Current and Lagged Temperatures on TFP Growth Rate and Investment

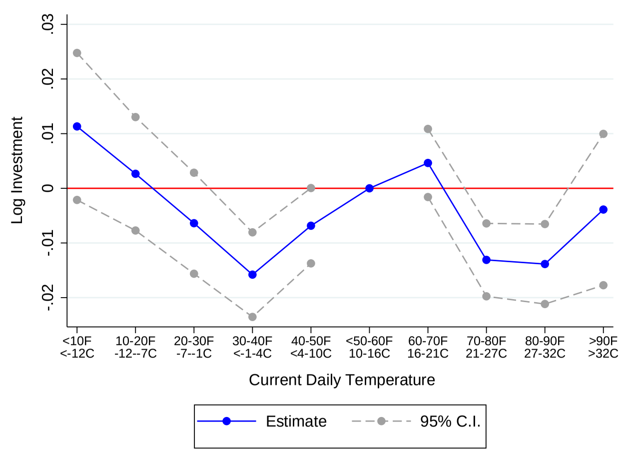
Panel A: Current Temperature-TFP Growth Rate



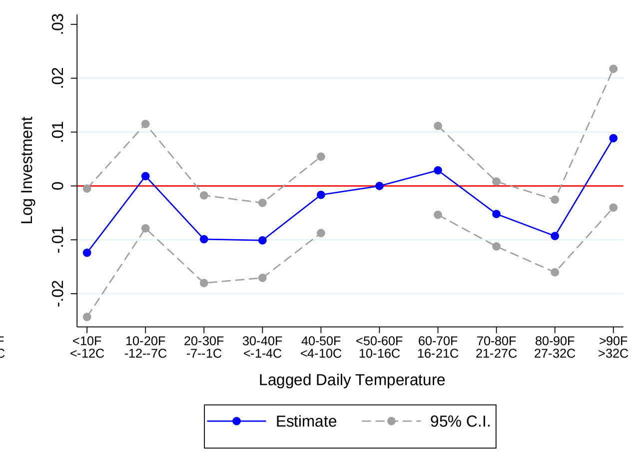
Panel B: Lagged Temperature-TFP Growth Rate



Panel C: Current Temperature-Investment



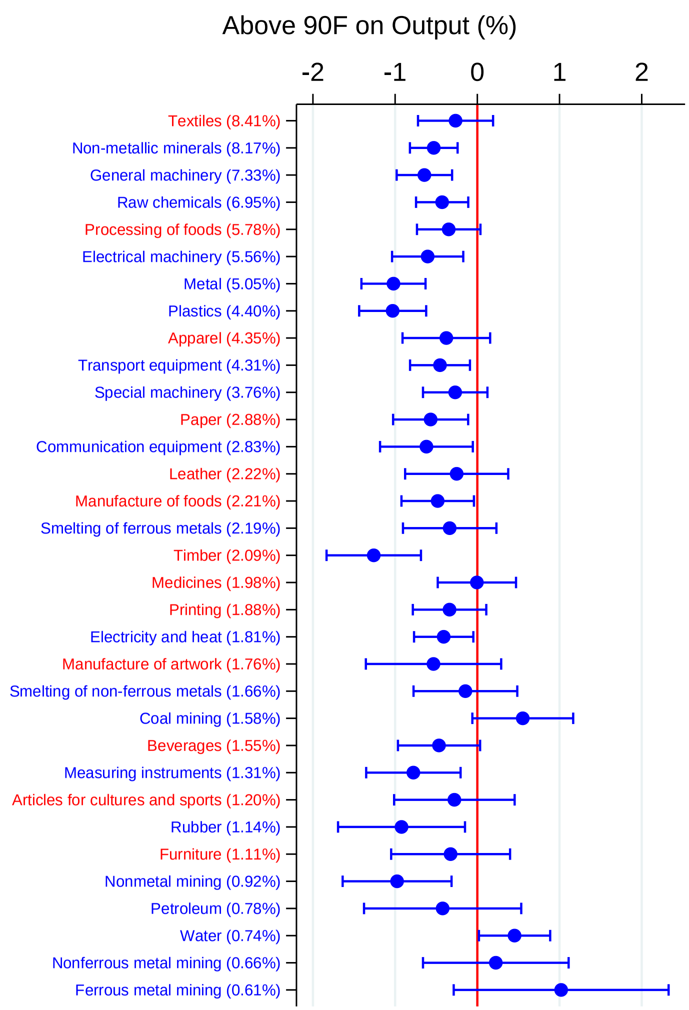
Panel D: Lagged Temperature-Investment



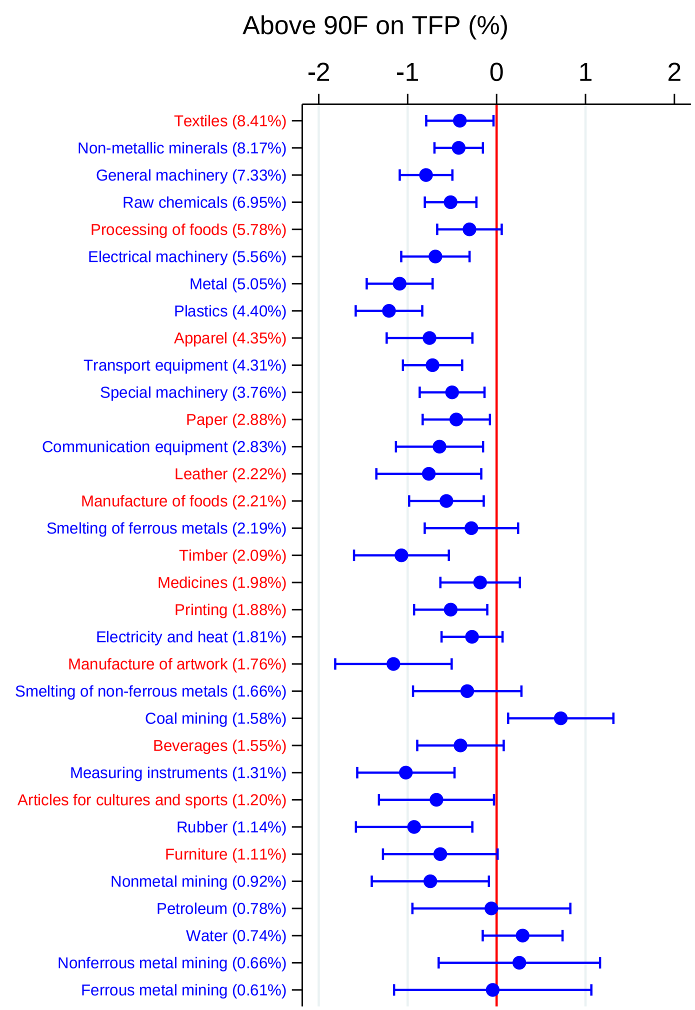
Notes: Panel A: Estimated Current Temperature-TFP Growth Rate Relationship. Panel B: Estimated Lagged Temperature-TFP Growth Rate Relationship. Panel C: Estimated Current Temperature-Investment Relationship. Panel D: Estimated Lagged Temperature-Investment Relationship. Panels A and B are estimated simultaneously in one regression, as are panels C and D.

Figure 7: Effects of Temperatures Above 90°F on Output and TFP for Each Sector

Panel A

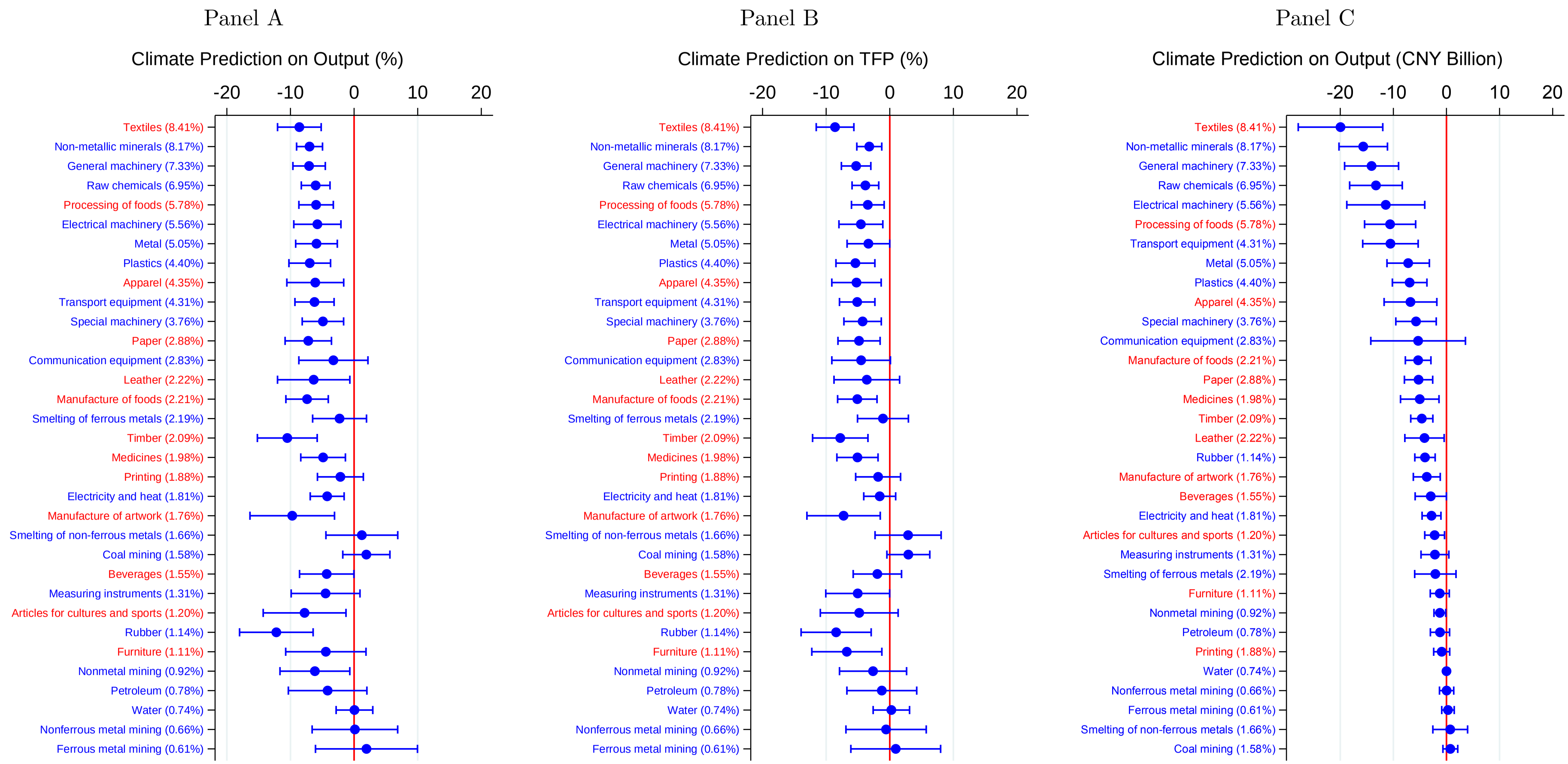


Panel B



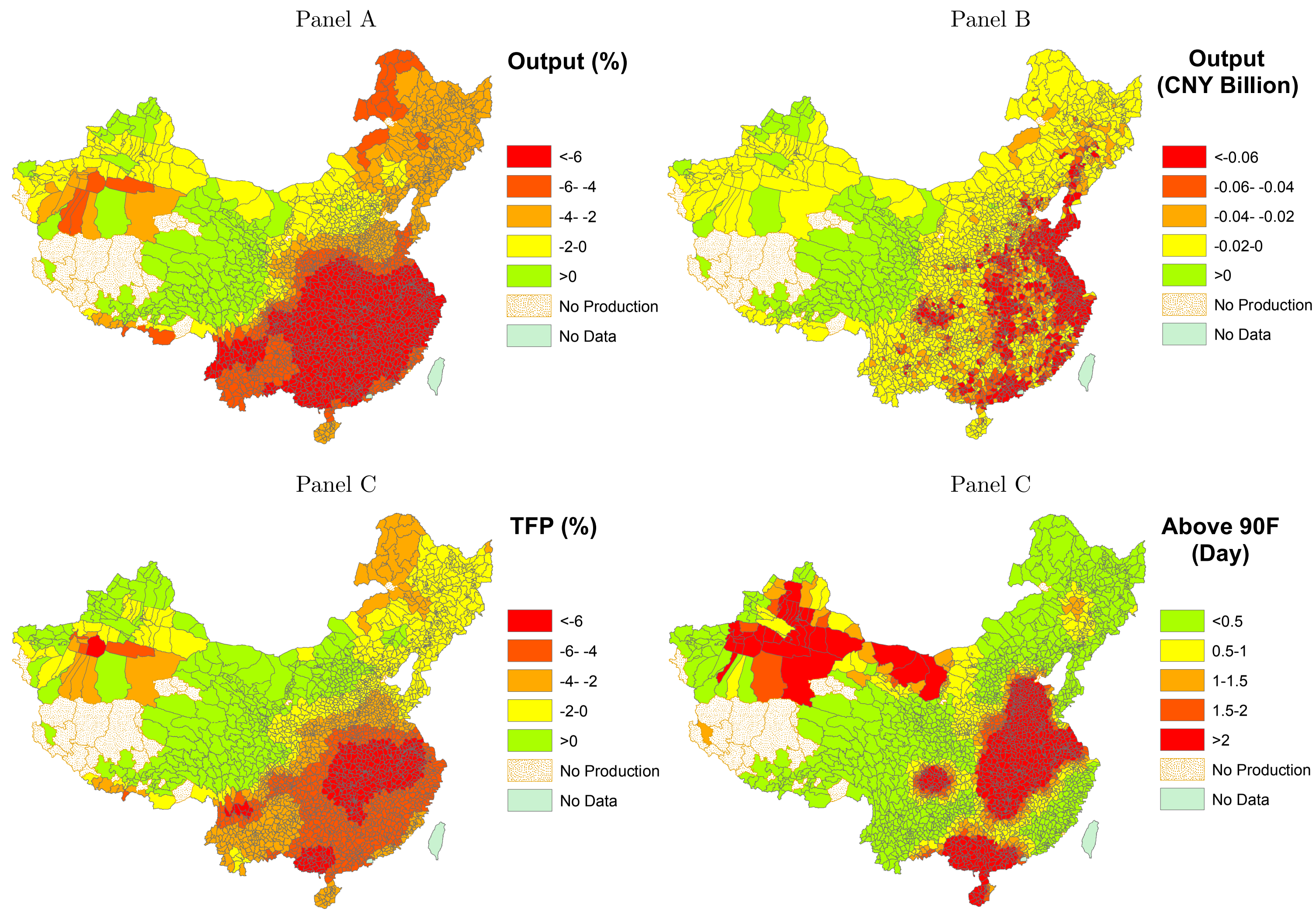
Notes: Panel A: Effect of Temperatures Above 90°F on Output. Panel B: Effect of Temperatures Above 90°F on TFP. The shares of the sectors in the full sample are enumerated in the parenthesis. Sectors are sorted according to their shares. All temperature bins are estimated using Equation (7), although the effects of the highest temperature bin alone are reported. Light industries are labeled in red, whereas heavy industries are in blue.

Figure 8: Climate Predictions on Output and TFP for Each Sector



Notes: Panel A: Climate Prediction on Output in Percentage Points. Panel B: Climate Prediction on TFP. Panel C: Climate Prediction on Output in CNY Billion. The shares of the observations in the full sample of all sectors are listed in the parenthesis. In panels A and B, sectors are sorted according to their shares. In panel C, sectors are sorted based on their climate impacts. Light industries are labeled in red, whereas heavy industries are in blue.

Figure 9: Climate Predictions on Output and TFP for Each County



Notes: Panel A: Climate Prediction on Output in Percentage Points. Panel B: Climate Prediction on Output in CNY Billion. Panel C: Climate Prediction on TFP. Panel D: Changes in Days with Temperatures Above 90°F between the Periods 2020-2049 and 1998-2007.

Table 1: Summary Statistics of Firm and Weather Data

	Past (1998-2007)			Future (2020-2049)				
	Mean	Min	Max	Mean	Min	Max	Obs	Firms
Firm Data								
Output (thousand CNY)	12,301	74	366,426	—	—	—	1,833,408	511,352
Log of TFP (number)	2.90	-3.56	8.84	—	—	—	1,833,408	511,352
Labor (person)	204	10	3,013	—	—	—	1,833,408	511,352
Capital (thousand CNY)	15,260	64	350,801	—	—	—	1,833,408	511,352
Weather Data								
Temperature (F)	61.54	23.84	80.57	63.51	26.86	81.04	1,833,408	511,352
Precipitation (inch)	73.17	0.06	845.07	76.56	0.34	824.45	1,833,408	511,352
Relative humidity (%)	69.21	24.98	87.35	68.86	12.88	100.00	1,833,408	511,352
Wind speed (mile/hour)	5.79	0.56	16.70	5.82	0.46	16.21	1,833,408	511,352
Visibility (mile)	6.64	2.97	10.00	—	—	—	1,833,408	511,352

Notes: The data cover all state-owned and non-state firms with sales greater than CNY 5 million in the period of 1998-2007. Output is measured by value added, and TFP is estimated according to the Solow residual in a Cobb-Douglas production function using the Olley-Pakes estimator (Olley and Pakes, 1996). Labor is measured by employment. Capital stock is constructed following in Brandt et al. (2012). All monetary units are deflated based on 1998 values. Temperature, wind speed, visibility, and relative humidity are calculated as annual mean value using daily observations. Precipitation is calculated as annual cumulative value as per daily observations. Unit of observation is a firm-year. The climate prediction data are obtained from the HadCM3 A1FI scenario.

Table 2: Effects of Temperature on Output and TFP

	TFP by OP						TFP by Index
	Mean Temp				Max Temp	Heat Index	Mean Tem
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(3)
Output							
80-90°F	-0.0009**	-0.0034***	-0.0007**	-0.0034***	0.0005	-0.0024***	-0.0034***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
>90°F	-0.0028***	-0.0047***	-0.0022***	-0.0045***	-0.0010**	-0.0046***	-0.0045***
	(0.0008)	(0.0009)	(0.0008)	(0.0009)	(0.0004)	(0.0005)	(0.0009)
F-statistic (All Bins)	11.78***	11.81***	10.83***	11.61***	14.08***	13.95***	11.61***
TFP							
80-90°F	-0.0011***	-0.0024***	-0.0009***	-0.0024***	0.0007*	-0.0018***	-0.0015***
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
>90°F	-0.0041***	-0.0057***	-0.0036***	-0.0056***	-0.0009**	-0.0033***	-0.0029***
	(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0004)	(0.0004)	(0.0007)
F-statistic (All Bins)	12.28***	11.64***	11.41***	11.40***	12.45***	12.46***	8.28***
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: The dependent variables are logarithms of output and TFP. Regression models are estimated using Equation (7). Through columns (1a)-(2b), TFP is measured by Olley-Pakes estimator. In column (3), TFP is measured with the index number approach. Bins are constructed according to daily mean temperature as per columns (1a)-(1d). In columns (2a) and (2b), bins are constructed using daily maximum temperature and daily heat index. Column (1d) is the baseline specification throughout the study. Due to space limitations, we report only the effects of the two highest temperature bins. Standard errors are clustered at both firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. See the text for more details.

Table 3: Effects of Temperature on TFP between Labor- and Capital-Intensive Firms

	Intensity = Wage Bill/Output			Intensity = Labor/Sales		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
80-90°F	-0.0035***	-0.0030***	-0.0029***	-0.0024***	-0.0024***	-0.0022***
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
>90°F	-0.0042***	-0.0081***	-0.0076***	-0.0055***	-0.0083***	-0.0062***
	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(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	—	0.0009***	—	—	0.0008***	—
	—	(0.0001)	—	—	(0.0001)	—
>90°× Above Median	—	0.0064***	—	—	0.0072***	—
	—	(0.0006)	—	—	(0.0006)	—
80-90°F × Above Mean	—	—	0.0010***	—	—	0.0004***
	—	—	(0.0001)	—	—	(0.0001)
>90°× Above Mean	—	—	0.0061***	—	—	0.0042***
	—	—	(0.0006)	—	—	(0.0008)
Observations	1,833,408	1,833,408	1,833,408	1,833,408	1,833,408	1,833,408

Notes: The dependent variable is the log of TFP. Regression models are estimated using Equation (7) and include firm fixed effects, year-by-region fixed effects, and year-by-two-digit-sector fixed effects. In columns (1a)-(1c), labor intensity is measured by wage bill/output. In columns (2a)-(2c), labor intensity is determined through labor/sales. In columns (1a) and (2a), we interact the two highest temperature bins with raw labor intensity. In columns (1b) and (2b), labor intensity is classified as either above median (=1) or below median (=0); subsequently, we interact the two highest temperature bins with a dummy variable for above median. The dummy variable for below median is omitted for multicollinearity. In columns (1c) and (2c), labor intensity is classified as either above mean (=1) or below mean (=0); then, we interact the two highest temperatures bins with a dummy variable for above mean. The dummy variable for below mean is omitted for multicollinearity. Due to space limitations, we report only the effects of the two highest temperature bins. Standard errors are clustered at both firm and county-year levels. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. See the text for more details.

Table 4: Effects of Air Conditioner Penetration Rate on the Temperature-Ouput and Temperature-TFP Relationships

	Output		TFP	
	(1a)	(1b)	(2a)	(2b)
80-90°F	-0.0001	-0.0001	0.0004	0.0004
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
>90°F	0.0040**	0.0040**	0.0037**	0.0037**
	(0.0016)	(0.0016)	(0.0017)	(0.0017)
80-90°F × AC Above Median	-0.0040***	—	-0.0035***	—
	(0.0005)	—	(0.0005)	—
>90°× AC Above Median	-0.0100***	—	-0.0109***	—
	(0.0017)	—	(0.0017)	—
80-90°F × AC Above Mean	—	-0.0040***	—	-0.0035***
	—	(0.0005)	—	(0.0005)
>90°× AC Above Mean	—	-0.0100***	—	-0.0109***
	—	(0.0017)	—	(0.0017)
Observations	1,833,408	1,833,408	1,833,408	1,833,408

Notes: The dependent variables are the log of output (1a-1b) and TFP (2a-2b). Regression models are estimated using Equation (7) and include firm fixed effects, year-by-region fixed effects, and year-by-two-digit-sector fixed effects. In columns (1a) and (2a), air conditioner penetration rate is classified as either above median (=1) or below median (=0); subsequently, we interact the two highest temperature bins with a dummy variable for above median. The dummy variable for below median is omitted for multicollinearity. In columns (1b) and (2b), air conditioner penetration rate is classified as either above mean (=1) or below mean (=0); then, we interact the two highest temperatures bins with a dummy variable for above mean. The dummy variable for below mean is omitted for multicollinearity. Due to space limitations, we report only the effects of the two highest temperature bins. Table B.10 reports the province-level air conditioner penetration rate per 100 urban households. Standard errors are clustered at both firm and county-year levels. * p <0.10, ** p <0.05, *** p <0.01. See the text for more details.

Table 5: Effects of Temperature on Output and TFP Across Ownership Types

	Full sample (1)	Private (2)	Foreign (3)	Collective (4)	State-Owned (5)
Output					
80-90°F	-0.0034***	-0.0067***	-0.0006	-0.0040***	0.0008
	(0.0005)	(0.0007)	(0.0010)	(0.0007)	(0.0006)
>90°F	-0.0045***	-0.0116***	-0.0028*	-0.0023*	0.0031***
	(0.0009)	(0.0012)	(0.0015)	(0.0014)	(0.0012)
TFP					
80-90°F	-0.0024***	-0.0049***	0.0004	-0.0029***	0.0007
	(0.0004)	(0.0007)	(0.0008)	(0.0007)	(0.0006)
>90°F	-0.0056***	-0.0105***	-0.0051***	-0.0021	0.0021**
	(0.0008)	(0.0011)	(0.0015)	(0.0013)	(0.0010)
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	705,129	358,413	237,976	167,373

Notes: The dependent variables are output and TFP. Regression models are estimated separately for each ownership category using Equation (7) and includes firm fixed effects, year-by-region fixed effects, and year-by-two-digit-sector fixed effects. Column (1) reports the estimates for the full sample while columns (2)-(5) report the estimates for each ownership type. Due to space limitations, we report only the effects of the two highest temperature bins. Standard errors are clustered at both firm and county-year levels. * p <0.10, ** p <0.05, *** p <0.01. See the text for more details.

Table 6: Effects of Temperature on TFP across Regions

Economic Region	Overall	Northeast	East	Central	West			
	(1a)	(1b)	(1c)	(1d)	(1e)			
80-90°F	-0.0024***	-0.0004	-0.0045***	-0.0035***	0.0003			
	(0.0004)	(0.0019)	(0.0007)	(0.0008)	(0.0006)			
>90°F	-0.0056***	0.0187	-0.0100***	0.0013	0.0004			
	(0.0008)	(0.0164)	(0.0014)	(0.0013)	(0.0013)			
Mean TFP	2.90	2.71	2.98	2.85	2.63			
Observations	1,833,408	111,506	1,226,702	298,702	196,498			
Geographic Region	Overall	North	Northeast	East	Central	South	Southwest	Northwest
	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)	(2h)
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)
Mean Temp (°F)	61.54	53.99	46.77	62.27	61.45	73.20	61.74	50.93
Observations	1,833,408	182,189	111,506	936,478	200,397	246,515	106,676	49,647

Notes: The dependent variable is TFP. Regression models are estimated separately for each region using Equation (7). In the first panel, firms are classified according to their respective economic regions. In the second panel, firms are classified based on geographic regions. The region classification is detailed in Table B.8 in the online appendix. We also report the average annual mean temperature for each geographic region and the average TFP for each economic region. Due to space limitations, we present only the effects of the two highest temperature bins. Standard errors are clustered at both firm and county-year levels. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. See the text for more details.

Table 7: Climate Predictions on Output and TFP

	Full Sample	Private	Foreign	Collective	State-Owned
	(1)	(2)	(3)	(4)	(5)
Output (%)					
Point Estimate	-5.71	-11.26	-2.56	-3.48	-0.26
S.E.	0.61	1.02	1.51	0.89	0.73
95% C.I.	[-6.91, -4.51]	[-13.25, -9.27]	[-5.52, 0.39]	[-5.23, -1.73]	[-1.71, 1.18]
Output (CNY Billion)					
Point Estimate	-208.32	-168.72	-27.11	-10.91	-0.68
S.E.	22.27	15.22	15.94	2.80	1.89
95% C.I.	[-251.97, -164.68]	[-198.55, -138.90]	[-58.36, 4.14]	[-16.40, -5.41]	[-4.39, 3.03]
TFP					
Point Estimate (%)	-4.18	-8.32	-0.81	-1.83	-0.35
S.E. (%)	0.55	0.96	1.27	0.86	0.75
95% C.I. (%)	[-5.27, -3.10]	[-10.20, -6.44]	[-3.31, 1.68]	[-3.51, -0.15]	[-1.81, 1.12]
Ownership Percentage	100%	38.46%	19.03%	12.98%	9.14%

Notes: The top part presents the climate prediction on output in percentage points. The middle part presents the climate prediction on output in CNY billion in 2013 values. The bottom part presents the climate prediction on TFP.

B Online Appendix

B.1 Data

B.1.1 Calculating Relative Humidity using Temperature and Dew Point Temperature

The NOAA does not report data on relative humidity. Thus, we use the following meteorological formula provided by the NOAA to calculate relative humidity:[39]

$$RH \approx 100(\frac{112 - 0.1T + Td}{112 + 0.9T})^8, \tag{9}$$

where RH denotes relative humidity in percent, T represents the air temperature in °C, and T_d represents the dew point temperature in °C.

B.1.2 Calculating Heat Index using Temperature and Relative Humidity

Heat index, or the apparent temperature, is an index that measures the sensation of temperature when combined with humidity. The human body can cool itself down through perspiration; however, this process is hard in a humid environment. For example, if the air temperature is 90°F and the relative humidity is 60%, then the air temperature feels as if it is at 100°F.[40]

To calculate heat index, we use the following formula provided by the National Weather Service:[41]

$$\begin{aligned} HI = &-42.379 + 2.04901523 * T + 10.14333127 * RH - .22475541 * T * RH \\ &-.00683783 * T * T - .05481717 * RH * RH + .00122874 * T * T * RH \\ &+.00085282 * T * RH * RH - .00000199 * T * T * RH * RH, \end{aligned} \tag{10}$$

[39] http://www.erh.noaa.gov/bgm/tables/rh.shtml
[40] http://www.srh.noaa.gov/ama/?n=heatindex
[41] http://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml

where HI represents heat index in °F, T denotes temperature in °F, and RH indicates relative humidity in percent.

When the relative humidity is less than 13% and the temperature is between 80-112°F, the following formula is used to calculate the heat index:

$$
\begin{aligned}
HI = -42.379 + 2.04901523 * T + 10.14333127 * RH - .22475541 * T * RH \\
-.00683783 * T * T - .05481717 * RH * RH + .00122874 * T * T * RH \\
+.00085282 * T * RH * RH - .00000199 * T * T * RH * RH \\
-((13 - RH)/4) * ((17 - |T - 95|)/17)^{0.5}.
\end{aligned}
\tag{11}
$$

On the other hand, if the relative humidity is larger than 85% and the temperature is between 80-87°F, we use the following formula:

$$
\begin{aligned}
HI = -42.379 + 2.04901523 * T + 10.14333127 * RH - .22475541 * T * RH \\
-.00683783 * T * T - .05481717 * RH * RH + .00122874 * T * T * RH \\
+.00085282 * T * RH * RH - .00000199 * T * T * RH * RH \\
+((RH - 85)/10) * (87 - T)/5).
\end{aligned}
\tag{12}
$$

Lastly, if the calculated heat index from above formulas is smaller than 80°F, the following formula is used:

$$HI = 0.5 * (T + 61.0 + ((T - 68.0) * 1.2) + (RH * 0.094)). \tag{13}$$

B.2 Figures and Tables

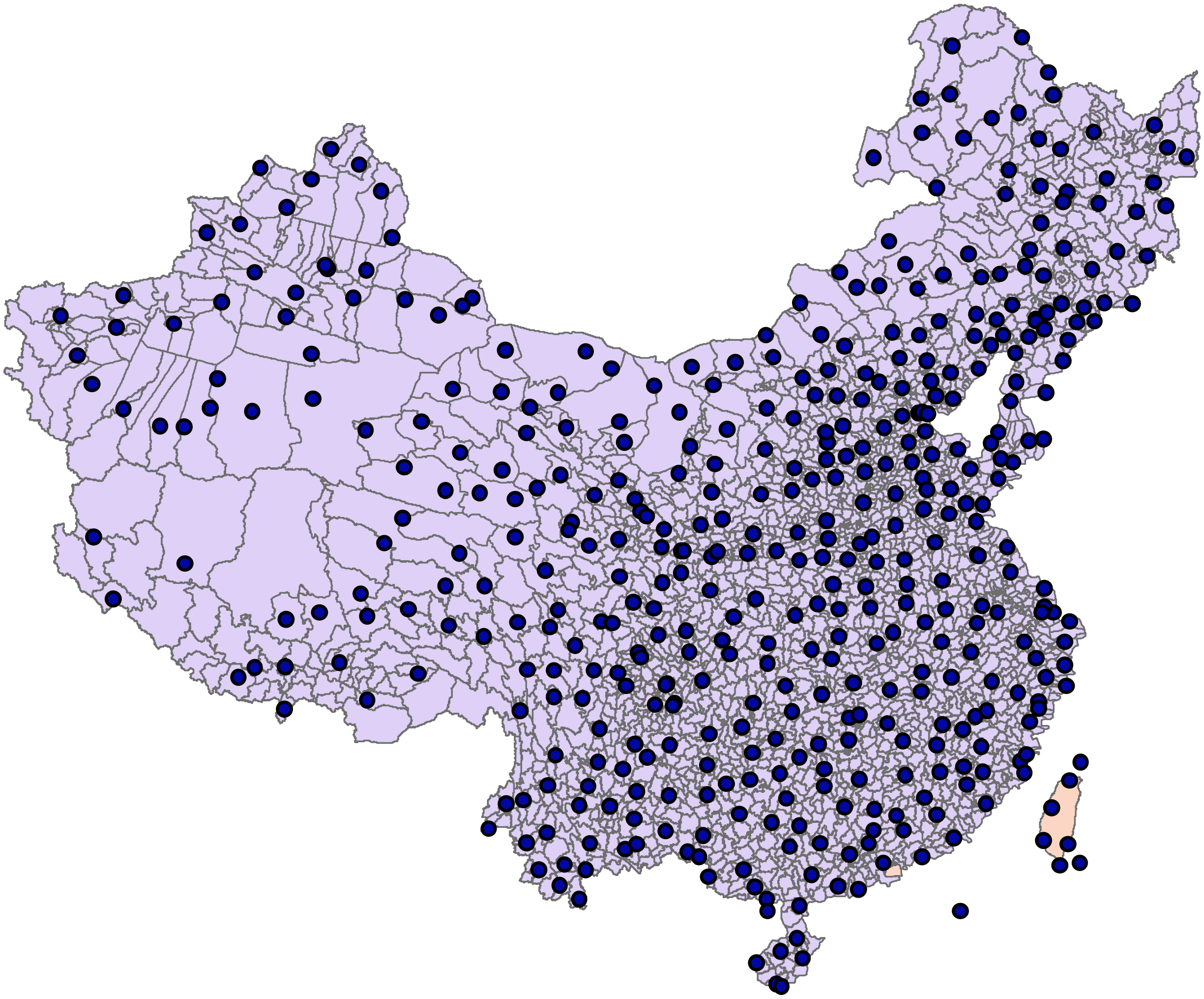


Figure B.10: Distribution of Weather Stations in China. *Notes*: Each dot represents a weather station and each polygon represents a county.

Table B.8: Region Classification

Geographic Regions	Provinces
North	Beijing, Tianjin, Hebei, Shanxi, Nei Mongol
Northeast	Liaoning, Jilin, Heilongjiang
East	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
Central	Henan, Hubei, Hunan
South	Guangdong, Guangxi, Hainan
Southwest	Chongqing, Sichuan, Guizhou, Yunan, Xizang (Tibet)
Northwest	Shaanxi, Gansu, Qinghai, Ningxia Hui, Xinjiang Uygur
Economic Regions	**Provinces**
Northeast	Liaoning, Jilin, Heilongjiang
East	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan
West	Nei Mongol, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang (Tibet), Shaanxi, Gansu, Qinghai, Ningxia Hui, Xinjiang Uygur

Notes: Geographic regions are classified based on traditional standards. Economic regions are classified according to the standards published on the NBS website http://www.stats.gov.cn/ztjc/zthd/sjtjr/dejtjkfr/tjkp/201106/t20110613_71947.htm.

Table B.9: Regression Results for Climate Variables Other than Temperature

	Output	TFP
	(1)	(2)
Precipitation	-0.0005***	-0.0004***
	(0.0001)	(0.0001)
Precipitation Square	0.0000	0.0000
	(0.0000)	(0.0000)
Humidity	-0.0011	-0.0015
	(0.0010)	(0.0010)
Humidity Square	0.0000	0.0000
	(0.0000)	(0.0000)
Wind Speed	-0.0116	-0.0202**
	(0.0104)	(0.0094)
Wind Speed Square	-0.0016**	-0.0001
	(0.0008)	(0.0007)
Visibility	-0.0456*	-0.0341
	(0.0277)	(0.0241)
Visibility Square	0.0032	0.0025
	(0.0020)	(0.0018)
Observations	1,833,408	1,833,408

Notes: This table supplements Table 2. The dependent variables are logarithms of output and TFP. Regression models are estimated using Equation (7). This table reports additional estimates for climatic variables other than temperature. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Air Conditioner Penetration Rate per 100 Urban Households

Provinces	AC Penetration Rate	Intensity
Guangdong	126.68	High
Shanghai	124.74	High
Chongqing	113.13	High
Beijing	101.31	High
Zhejiang	95.77	High
Tianjin	82.70	High
Fujian	82.00	High
Jiangsu	77.80	High
Hubei	66.27	High
Henan	60.60	High
Anhui	54.14	High
Hunan	53.92	High
Heibei	51.60	High
Shaanxi	47.07	High
Shandong	46.61	High
Guangxi	46.18	High
Jiangxi	42.71	Low
Sichuan	42.67	Low
Hainan	28.78	Low
Shanxi	14.28	Low
Liaoning	8.69	Low
Guizhou	6.07	Low
Xinjiang Uygur	4.66	Low
Nei Mongol	3.95	Low
Heilongjiang	3.74	Low
Ningxia Hui	3.11	Low
Jilin	2.88	Low
Xizang (Tibet)	2.79	Low
Gansu	1.92	Low
Yunnan	0.50	Low
Qinghai	0.31	Low
China	53.21	

Notes: This table presents the average air conditioner penetration rate per 100 urban households in each province over the periods 1998-2007 in China. The provinces are sorted by the air conditioner penetration rate. The last row reports the average air conditioner penetration rate for the whole China. Provinces are classified by either high intensity (above median) or low intensity (below median) based on the median of air conditioner penetration rate.

Table B.11: Effects of Temperature on Output across Regions

Economic Region	Overall	Northeast	East	Central	West			
	(1a)	(1b)	(1c)	(1d)	(1e)			
80-90°F	-0.0034***	-0.0013	-0.0063***	-0.0052***	0.0007			
	(0.0005)	(0.0022)	(0.0010)	(0.0010)	(0.0007)			
>90°F	-0.0045***	0.0289	-0.0082***	0.0008	0.0021			
	(0.0009)	(0.0186)	(0.0016)	(0.0014)	(0.0013)			
Mean TFP	2.90	2.71	2.98	2.85	2.63			
Observations	1,833,408	111,506	1,226,702	298,702	196,498			
Geographic Region	Overall	North	Northeast	East	Central	South	Southwest	Northwest
	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)	(2h)
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
Observations	1,833,408	182,189	111,506	936,478	200,397	246,515	106,676	49,647

Notes: This table supplements Table 6. The dependent variable is output. Regression models are estimated using Equation (7). In the first panel, firms are classified according to their respective economic regions. In the second panel, firms are classified based on their geographic regions. Due to space limitations, we report only the effects of the two highest temperature bins. We also present the average annual mean temperature for each geographic region and the average TFP for each economic region. Standard errors are clustered at both firm and county-year levels. * p <0.10, ** p <0.05, *** p <0.01.