Temperature and Economic Growth:
New Evidence from Total Factor Productivity

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Abstract

Understanding the relationship between temperature and economic growth is a critical component in designing optimal climate policies. This paper provides the first study that documents the relationship between daily temperature and total factor productivity (TFP). Using detailed firm-level production data from nearly two million observations in the Chinese manufacturing sector from 1998 to 2007, I find 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 with temperature and TFP, suggesting that reduction in TFP in response to high temperatures is the primary driver behind output losses. A medium-run climate prediction indicates that climate change will reduce TFP by 4.18%, and result in output losses by 5.71%. This corresponds to CNY 208.32 billion (USD 32.57 billion) losses in 2013 values. Given the invariance of TFP to the intensity of labor and capital inputs, Chinese manufacturing may be less likely to avoid climate damages simply by factor allocation. New innovations that expand the technology frontier for all inputs need to occur to offset weather-driven TFP losses if other adaptation strategies are not feasible.

Keywords: Climate Change, TFP, Manufacturing, China

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1 Introduction

Understanding the relationship between temperature and economic growth is a critical component in designing optimal climate policies (Dell et al., 2012). A growing body of literature has estimated the causal effects of temperature on aggregate economic outcomes using reduced-form statistical methods (e.g., see Nordhaus and Yang (1996); Hsiang (2010); Dell et al. (2012); Deryugina and Hsiang (2014)). This literature finds that a one-degree Celsius (C) increase in annual mean temperature is associated with a 1-3% reduction in economic output (Hsiang, 2010; Dell et al., 2012). The negative effect is particularly strong in developing countries. These results are further incorporated into the damage function in the Integrated Assessment Models (IAMs), to assess possible policy responses to global climate change (Dell et al., 2014).

It is crucial to understand the specific micro-mechanism behind this negative relationship between temperature and economic growth. Abundant studies have focused on the impacts of temperature on agricultural productivity (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 agriculture sector is insufficient because agriculture typically accounts for only a small share of a country’s GDP.¹ Therefore, several papers have focused on the manufacturing sector and argue that the reduction in labor productivity in response to high temperatures is a major force that drives output losses (Adhvaryu et al., 2014; Somanathan et al., 2014). However, because labor is only one factor in the production function, ignoring other factors such as capital may produce factor-biased estimates. Furthermore, single-factor productivity such as output per capita heavily depends on the allocation of inputs, and may not represent the true productivity (Syverson, 2011).

Using detailed firm-level production data from nearly two million observations in the manufacturing sector in China from 1998 to 2007, this paper documents the relationship between temperature and four components in a standard Cobb-Douglas production function:

¹For example, agriculture accounts for 1% of the U.S. GDP and 10% of China’s GDP.
output, total factor productivity (TFP), labor, and capital inputs. The primary focus is TFP, a combination of both labor and capital productivity and is invariant to factor allocation. TFP has been used to measure technology progress and is considered essential to economic growth (Aghion and Durlauf, 2005).

To identify the causal effects of temperature on TFP and other variables, I 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). I 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 the most preferred specification, I find that one more day with temperatures above 90°F decreases TFP by 0.56%, relative to temperatures between 50-60°F. Importantly, I 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 channel that leads to output losses.

Given that TFP is a combination of labor and capital productivity, disentangling the effects separately is important. Previous studies have largely focused on labor productivity (e.g., see Zivin and Neidell (2014); 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 because of two unknowns within one equation, the hypothesis that temperature only affects labor productivity could be implicitly tested by classifying firms as labor or capital intensive. Various specifications suggest that high temperatures affect both labor and capital productivity.

Firms are required to provide protections such as summer drinks and air-conditioning for
workers during extremely hot days in China.\(^2\) Given the relative rigidity of environmental regulations in state-owned firms compared with those of private firms, the negative effects of high temperatures on TFP could be smaller in state-owned firms. My empirical results support this argument. On the contrary, I find that negative effects of high temperatures are the strongest in private firms. This implies that environmental 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, I predict a medium-run climate effect on output and TFP. Comparing 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,\(^3\) the output losses could be spread to the world via trade.

This paper contributes to the literature in three aspects. First, to my best knowledge, this paper provides the first study documenting the relationship between daily temperature and TFP. Given the TFP’s invariance to the intensity of use of labor and capital inputs, I am able to separate the effect on productivity from that on factor reallocation. Furthermore, high temperatures affect both labor and capital productivity, the latter of which has been ignored in the literature.

Second, this paper presents a possible micro-mechanism for considerable literature that focuses on temperature and economic growth (Nordhaus and Yang, 1996; Hsiang, 2010; Dell et al., 2012; Deryugina and Hsiang, 2014). I find that a 1°F (1°C) increase in annual mean temperature decreases Chinese GDP by 0.92\% (1.65\%). This finding is consistent with Hsiang (2010) and Dell et al. (2012); they find that a 1°C increase in annual mean temperature leads to 2.5\% and 1.0\% GDP reduction in other developed countries. My results suggest that TFP reduction as a response to high temperatures is mostly responsible.

for the negative relationship between temperature and economic growth.

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, temperatures, particularly extremely high temperatures, have large and negative effects on TFP. Given that TFP reflects both labor and capital productivity, and is invariant to input reallocation, 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 not feasible.

In addition, the empirical setting is Chinese manufacturing, which composes 32% of the country’s GDP and employs 30% of the labor force. 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 carbon dioxide (CO₂), China’s effort is critical in mitigating global climate change.

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

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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 mechanisms 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

\[ Y(T) = A(T)L(T)^\alpha K(T)^\beta. \] (1)

Here, \( Y \) denotes output and \( L \) and \( K \) denote labor and capital, respectively.\(^6\) The Hicks-neutral efficiency level, or TFP, is represented by \( A \). Output elasticities of labor and capital are measured by \( \alpha \) and \( \beta \). Temperature, denoted as \( T \), could affect output through productivity and inputs.

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

\[ y(T) = a(T) + \alpha l(T) + \beta k(T), \] (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

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

where \( A_L \) and \( A_K \) denote the labor and capital productivity, respectively. Taking natural

\(^6\)Since output is measured by value added, material input is excluded from the production function.
logs of the above equation results in the following equation

\[ y(T) = \alpha a_L(T) + \beta a_K(T) + \alpha l(T) + \beta k(T). \]  \hspace{1cm} (4)

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

\[ a(T) = \alpha a_L(T) + \beta a_K(T), \]  \hspace{1cm} (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 may have the same labor productivity because of various input allocations, but may have markedly different TFP levels.\(^7\)

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; Zivin et al., 2015). Several studies have been estimating 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 Zivin and Neidell (2014), Adhvaryu et al. (2014), and Somanathan et al. (2014)).\(^8\)

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\(^7\)To see this, consider two firms within the same industry sharing the following Cobb-Douglas production function \( Y = AL^{1/2}K^{1/2} \). Assign the following values for firm 1: \( A_1 = 1, L_1 = 25, K_1 = 400 \), one can obtain \( Y_1 = 100 \), and labor productivity \( Y_1/L_1 = 4 \). Similarly, assign the following values for firm 2: \( A_2 = 2, L_2 = 25, K_2 = 100 \), one can obtain \( Y_2 = 100 \), and labor productivity \( Y_2/L_2 = 4 \). For these two firms, labor productivity are the same, but TFP are quite different.

\(^8\)See a detailed review in Dell et al. (2014).
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).

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 estimated the effects of temperature on labor supply (e.g., see Zivin and Neidell (2014) and Somanathan et al. (2014)). Temperature could also affect capital stock. For example, high temperatures may abrade machines and lead to faster capital depreciation. High temperatures are likely to reduce output, subsequently damage the investment, and further reduce capital accumulation. 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 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

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9See Heal and Park (2013) for a conceptual framework about the impacts of temperature on labor supply.
“above-scale” industrial firms). The industrial sectors here include mining, manufacturing, and public utilities, in which manufacturing composes 93% of the total observations. Given that manufacturing composes the largest share of the industrial sector, I use the terms manufacturing sector and industrial sector interchangeably throughout the paper.

I address several empirical issues. First, each firm has a unique numerical ID. However, firms may change their IDs because of restructuring, acquisition, or merging. I use the matching algorithm provided in Brandt et al. (2012) to match firms over time.11

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

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), I 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.

10 According to the census of the 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 for the Chinese industrial sector.

11 The basic idea is to match firms firstly by their IDs, and then link them using information on firms’ name, legal person name, industry code, and others.
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, I use the Olley-Pakes estimator (Olley and Pakes, 1996) to estimate TFP. The index number approach (Caves et al., 1982) is used for a robustness check.

Consider a standard linearized Cobb-Douglas production function

\[ y_{it} = \beta_l l_{it} + \beta_k k_{it} + u_{it}, \]  

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; \( \beta_l \) and \( \beta_k \) 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 \( u_{it} \). 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,\(^{12} \) and thus serves as the baseline measurement of TFP in this paper.\(^{13} \)

\(^{12}\)For example, see Pavcnik (2002); Javorcik (2004); Amiti and Konings (2007); Brandt et al. (2012).

\(^{13}\)Levinsohn and Petrin (2003) argue that using investment to control for unobserved productivity shocks may be inappropriate in some empirical settings because investment has to be strictly positive in the Olley-Pakes estimator. However, this is a minor issue in my empirical setting. Given the rapid development in China, there are few observations with negative or zero investment. Furthermore, because the Levinsohn-Petrin estimator does not control for selection bias, I prefer to use the Olley-Pakes estimator. Nonetheless, the results are robust when I use the Levinsohn-Petrin estimator.
The Olley-Pakes estimator requires parametric estimation of the production function. The index number approach, however, is free of the parametric assumption. Indeed, I simply use wage bill share in value added to measure output elasticity of labor input \( \beta_l \), and use \( 1 - \beta_l \) to measure output elasticity of capital input \( \beta_k \).\(^{14}\) The index number approach requires the assumptions of perfect competition and constant returns to scale. These assumptions seem strong in my 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.\(^{15}\)

### 3.3 Weather Data

The weather data are drawn from the National Climatic Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA).\(^{16}\) NCDC reports global station-level weather data at three-hour intervals from 1901-2015. I extract the data covering China from 1998-2007.\(^{17}\) 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, I 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.\(^{18}\)

The weather data contain major climatic variables, including temperature, precipitation,

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\(^{14}\)It would be ideal if one can use capital share to measure \( \beta_k \). However, the data on capital rental rate is not available.

\(^{15}\)Certain industries have few observations and thus are merged to the similar industry to enable more accurate estimates.


\(^{17}\)There is around 400 stations covering China. See Figure B.9 for detailed distribution of weather stations.

\(^{18}\)I do not choose stations that are operational for all 365 days because all stations are missing one day weather record in 1999 and 2007.
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.\textsuperscript{19} Zhang et al. (2015) demonstrate the importance of additional climatic variables other than temperature and precipitation. Thus, I include all these climatic variables in my empirical specifications. I 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.

The variable of interest in this analysis is temperature. However, temperature may have a joint impact with humidity on productivity. For example, when temperature is high, the human body may cool itself down through perspiration. However, this process is hard in a more humid environment. Consequently, I 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.\textsuperscript{20}

3.4 Climate Prediction

The climate prediction data are drawn from the Hadley Centre, one of the world’s leading institutes in climate prediction. I 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).\textsuperscript{21} 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. I focus on the “business-as-usual” (A1FI) scenario and choose the years from 2020-2049, a medium-run period. I 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

\textsuperscript{19}See the formula at http://www.erh.noaa.gov/bgm/tables/rh.shtml.
\textsuperscript{20}The explanation and the construction formula of the heat index can be found at http://www.srh.noaa.gov/ama/?n=heatindex.
\textsuperscript{21}The data can be downloaded at http://browse.ceda.ac.uk/browse/badc/hadcm3.
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 too high or too low. Therefore, I implement the error-corrected method proposed by Deschênes and Greenstone (2011). First, I calculate the difference in weather data from 1998-2007 between NOAA and HadCM3. I then add the difference to the prediction by HadCM3, to correct for systematic model errors.

3.5 Matching Firm and Weather Data

Firm-level data and station-level weather data are merged by county and year. First, I 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, I assign each firm with the weather data in that county where the firm is located. A similar way is used to transform climate prediction data from the grid level to the county level. 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.

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22 The systematic model errors are indeed severe in my sample. The average temperature during 1998-2007 in China are 54°F according to NOAA, but only 49°F during the same period by HadCM3.
23 I do not observe the specific latitude and longitude of firms. Indeed, county is the smallest geographic unit representing firms’ geographic locations.
24 The firm data are at firm level, not plant level. Firms with multiple branches may located in different regions and lead to wrong weather information assigned. However, this should be a minor issue because more than 95% of firms in this data are single-plant firms (Brandt et al., 2012).
25 A 300km radius is assigned to ensure that every county has a valid observation during 2020-2049.
(2.68%). Unit of observation is a firm-year. All monetary values are expressed in constant 1998 CNY. Column (1) presents the summary statistics for the full sample, while columns (2)-(5) report the summary statistics for each ownership. These four types of ownership are constructed following Brandt et al. (2012) and remain as the major ownership in China.\textsuperscript{26}

Output is measured by valued added. From 1998 to 2007, the average output is approximately CNY 12 million (USD 2 million) in the full sample. Among the subsamples, foreign firms have the largest average output, while collective firms have the smallest average output. 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 2.06 in state-owned firm to 3.07 in private firms. This suggests that private firms remain the highest efficiency. Labor is measured by employment, with an average of 200 people, and state-owned firms seem to hire the most workers on average. Capital is measured by the fixed capital stock. The average is CNY 15 million (USD 2.35 million), with state-owned firms having the largest share. To demonstrate the regional heterogeneity in output, Figure 1 depicts the aggregate output in each county during 1998-2007. Generally, county-level aggregate output is the largest in the south and the east, suggesting that most manufacturing firms are located in those regions.

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. The average temperature during 1998-2007 in the sample is 61.54°F (16.41°C), which is higher than other studies using county averages. This is because the observation is a firm-year, and 67% of firms are located in the south, where is typically hotter. The average temperatures in state-owned, collective, and private firms are quantitatively close to the average temperature in the full sample, while the average temperature in foreign firms is 3°F higher than the full sample. This implies that foreign firms may be mostly

\textsuperscript{26}The sum of observations in each ownership is not equal to the total observations, because there are other types of ownership, such as limited liability corporation. See http://www.stats.gov.cn/tjsj/tjbz/200610/t20061018_8657.html
located in the south.

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, I employ a semi-parametric method, the so called bin approach, which has been widely used in the literature (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011; 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, I 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, I 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, 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 production.

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27Temperature may also affect labor and capital inputs, but TFP is invariant to inputs.
measurement. Thus, my estimates are more likely to have considered within-year adaptation.

In practice, I divide daily temperature, measured in F, into ten bins. Temperatures below 10°F are defined as the 1st bin, and temperatures between 10-20°F are defined as the 2nd bin, etc. Finally, temperatures above 90°F are defined as the 10th 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 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, which may have a dramatic effect on TFP.

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. I also include a quadratic for those variables to account for nonlinearity.

4.2 Regression Model and the Identification

To explore the effects of temperature on the components in the production function (see Equation (5)), especially TFP, I estimate the following fixed-effect regression models

$$\ln y_{it} = \beta' \text{Temp}_{it} + \delta' w_{it} + \theta' z_{it} + \alpha_i + \varepsilon_{it},$$  \hspace{1cm} (7)

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

In this form, $y_{it}$ denotes the four components in Equation (5): output, TFP, labor, and capital inputs. All these variables are represented in logarithms, and thus, my estimates
can be illustrated as semi-elasticities. The variable of interest, Temp_{it}, contains a vector of temperature bins \([Tbin_{it1}, \cdots, Tbin_{it10}]\), in which \(Tbin_{ij}\) 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-two-digit-sector fixed effects and year-by-region fixed effects.\(^{28}\) 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. 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. I use firm fixed effects \(\alpha_i\) to control for firm-specific time invariant characteristics, such as geographic locations. Lastly, \(\varepsilon_{it}\) 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 \(\sum_j Tbin_{ij}\) is exactly equal to 365.\(^{29}\) To avoid multicollinearity, I 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. I 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, my conclusion does not hinge on the choice of this reference group.

\(^{28}\)I 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 more likely to absorb a great share of exogenous variations in weather, since weather are typically homogeneous within a province (Fisher et al., 2012). Region classification is shown in Table B.7.

\(^{29}\)In 2000 and 2004, the sum of all days are equal to 366. I simply drop the day on February 29th, to make sure all days sum up to a constant number from 1998 to 2007.
The coefficient of central interest is the estimate for each temperature bin. Considering that the dependent variables are all measured in logarithms, temperature effect $\beta_j$ measures the percentage change, or the semi-elasticities 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

$$E[T\text{bin}_{itj}|T\text{bin}_{it,-j}, w_{it}, z_{it}, \alpha_i] = 0. \quad (8)$$

As suggested by Deschênes and Greenstone (2007), weather fluctuations are generally random and less predictable. Thus, I 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 3 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 3 depicts the response function between daily temperatures and log output. In general, I find an inverted U-shaped relationship between temperature and output. 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.\textsuperscript{30}

Given that temperatures, particularly high temperatures, have a significant 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 plotted 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 almost identical 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 very close, particularly in the highest temperature range. For example, one more day with temperature larger than 90°F decreases output and TFP by 0.45% and 0.56%, respectively, relative to temperature 50-60°F. All these negative effects of the highest temperature ranges are statistically significant.

\textsuperscript{30}Surprisingly, bin 30-40°F, which is a relatively cold range, has the largest point estimate and is statistically significant. Recall that TFP combines both labor and capital productivity. It is possible that 30-40°F is relatively cold for human behaviors, but is suitable for machine performance.
However, the effects of daily temperature on labor (panel C) and capital (panel D) do not exhibit any particular shapes. The estimates of most temperature bins are noisy and statistically insignificant. Even the effects of several high temperature bins, such as 70-80°F, 80-90°F, and above 90°F, are statistically significant, the magnitudes are relatively small, compared with the impacts of temperature on TFP and output. This suggests that, the effects of temperature on labor and capital inputs are limited. Thus, the effects of temperature on output are more likely from the effect on TFP. In the remainder of the paper, I will mostly focus on the effects of temperature on output and TFP.

Table 2 further presents the effects of daily temperatures on output and TFP using various specifications. Due to space limitation, I 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), I 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 I 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), I 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), I 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 temper-
ature. 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), I construct temperature bins using daily heat index, which incorporates the effects of both temperature and humidity.

TFP are 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 (Caves et al., 1982) 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. Generally, controlling for geographic shocks produce larger estimates, whereas controlling for industrial shocks produce smaller estimates. 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 my 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, in general, I find a significantly negative impact of precipitation on output and TFP. However, the effects of relative humidity,
wind speed, and visibility, are statistically insignificant. The results are not reported and are available upon request.

5.2 The 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, I include one-year lagged temperature, measured in $10^\circ$F bins, in the baseline regression model. Both current and lagged temperatures are estimated simultaneously in one regression.

Figure 4 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 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 I 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 in Figure 4, in terms of lagged daily temperature, the effects on output and TFP are not clear. Overall, the point estimates are mostly noisy results, and do not exhibit any particular shapes. Thus, lagged temperatures, especially lagged high temperatures, seem to not have a significant effect on both output and TFP. Therefore, in the baseline regression model, I will only include current temperatures.\footnote{In general, I do not find a significant impact of both current and lagged temperature on labor and capital inputs.}

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5.3 Disentangling TFP into Labor and Capital Productivity

I 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 productivity, or both, is a question of interest. Previous studies have predominantly focused on labor productivity (e.g., see Zivin and Neidell (2014); 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, I 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 of the wage share, or output elasticity of labor \( \alpha \) is typically larger in those industries. Thus, if I cannot find such effects, this result implicitly suggests that temperature may affect both labor and capital productivity.

To classify firms by either labor- or capital-intensive, I use two measurements of labor intensity. The first measurement is wage bill share, defined as the fraction of wage bill in output. 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 limitation, I 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, I make the two highest temperature bins (80-90°F and above 90°F) interact with variables that distinguish firms as either labor- or capital-intensive. In columns (1a) and (2a), I simply interact two highest temperature bins with labor intensity. In columns
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. The dummy variable for below median is omitted for multicollinearity. In columns (1c) and (2c), labor intensity is divided into 4 quartiles. Each quartile is a dummy variable for firms with labor intensity falling into that quartile range. For example, the dummy variable quartile 4 equal to 1 corresponds to firms with labor intensity above 75th percentile. Then each quartile variable is interacted with two highest temperatures bins. Quartile 1 is omitted for multicollinearity.

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 quartiles. All these implicitly suggest that high temperatures may have an effect on both labor and capital productivity.

### 5.4 The 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., 2014). 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, I include one-year lagged temperature
Figure 5 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, I 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. I 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.

5.5 The Role of Ownership

Firms are required to provide protection, such as summer drinks and air conditioning for workers during extremely hot days in China.\footnote{http://www.chinasafety.gov.cn/newpage/Contents/Channel_20697/2012/0704/173399/content_173399.htm} Given that labor regulations are typically more stringent in state-owned firms than in private firms, the negative effects of high temperatures on TFP could be smaller in state-owned firms.

To explore heterogeneity in ownership, Table 4 presents the effects of temperature on TFP across firms with different ownership. In comparison, the estimates for the full sample are also reported. Regression models are estimated using Equation (7). In each column, I interact two highest temperature bins (80-90°F and above 90°F) with dummy variables representing for each ownership. For example, in column (2), a dummy variable “state-owned” equals to 1 if ownership is state-owned and 0, if otherwise. Considering space limitation, I only report the results for two highest temperature bins and their interactions with ownership. I also report the percentage of each ownership in the whole sample.

The results suggest that the negative effect of the highest temperature bin (above 90°F)
on TFP is smaller in state-owned firms. Overall, the negative effect of temperature above 90°F on TFP for state-owned firms is 0.39 percentage points smaller than non-state owned firms. This difference is statistically significant. This finding confirms my hypothesis that state-owned firms have more regulated practices.

Column (3) reports the results for collective and non-collective firms. Collective firms are in between state-owned firms and privates. Generally, the negative effects of temperatures above 90°F in collective firms are 0.12% smaller than non-hybrid firms. In column (4), I report the results for private and non-private firms. On average, the magnitude of the negative effect of temperature above 90°F on TFP for private firms is 0.19 percentage points larger than non-private firms. This implies that private firms may bear the largest damages of high temperatures on TFP.

Column (5) reports the results between foreign firms and domestic firms. Surprisingly, the negative effects of temperatures above 90°F on TFP is 0.19 percentage points larger than domestic firms. This result indicates that foreign firms may not fully obey the regulated practices in China. All these results suggest that labor regulations may play a major role in mitigating the negative effects of high temperatures.

5.6 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 and whether protected by air conditioning. To explore the heterogeneity across industrial sectors, Figure 6 depicts the point estimates and the 95% confidence intervals of temperatures above 90°F on output and TFP for two-digit sectors. Regression models are estimated separately for each two-digit sector using Equation (7). The share of each sector in the whole sample is reported in the parenthesis. Panel A reports

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33 I do not include sectors with observations smaller than 10,000, including oil and natural gas mining, other mining, tobaccos, chemical fibers, waster recycling, and gas utility, because these industries have too few observations to produce accurate estimates.
the impacts of temperatures above 90°F on output in percentage points. Panel B monetizes the impacts on output using estimated coefficients on panel A multiplying by the average annual aggregate output for each sector. The damages on output are converted from 1998 to 2013 values. Panel C presents the estimated coefficients of temperatures above 90°F on TFP in percentage points.

Several findings can be made from Figure 6. First, temperatures above 90°F exhibit statistically significant and negative effects on output for most industries. The effects on industries with a considerable share, such as foods processing, textiles, raw chemicals manufacturing, non-metallic minerals manufacturing, in the whole sample are precisely estimated. Those industries with a considerable share also experience large monetary damages. Though the point estimates for certain industries, such as water utility, non-ferrous metal mining, are positive, the effects are statistically insignificant at 5% level.

Second, there is strong heterogeneity across industrial sectors. One more day with temperatures above 90°F reduces output in general machinery sector by CNY 1.28 billion (USD 0.21 billion). The economic damages for medicines, however, is only CNY 0.005 billion (USD 0.0008 billion). Third, the impacts of temperatures above 90°F on TFP for each 2-digit sector in panel C 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 6 suggest that temperatures above 90°F have significantly negative effects on both light and heavy industries. Light industries, such as textiles, apparel, leather, timber, and furniture, are typically labor intensive. By contrast, heavy industries, such as paper, raw chemicals manufacturing, and transport equipment, are generally capital intensive. Consistent with findings in Section 5.3, the result demonstrates that high temperatures may affect both labor and capital productivity.
5.7 Adaptation

Firms may employ various strategies to adapt to high temperatures. For example, air conditioning is regarded as an effective strategy to protect human beings from extremely hot days (Barreca et al., Forthcoming). However, this defensive investment is costly. Thus, economically developed regions are more likely to be able to implement such devices.\textsuperscript{34} 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 (Zivin and Neidell, 2014). Therefore, TFP should be less sensitive to high temperatures in hot regions.

To detect such adaptation behaviors, Table 5 presents the regression estimates for the two highest temperature bins (80-90°F and above 90°F) on TFP for each geographic and economic region. Regression models are separately estimated for each region using Equation (7). The average annual mean temperature for each geographic region and the average TFP for each economic region are also reported.

Among 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. Such a result is most likely because observations with daily temperature above 90°F to generate accurate estimates are too few. 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 may be limited.

In terms of 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 in-

\textsuperscript{34} The use of air conditioning, or expenditures of electricity are not reported in the data, and thus I cannot directly test the adaptation behavior through the use of air conditioning.
significant 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.\textsuperscript{35}

6 Climate Prediction

This section presents the climate prediction on output and TFP. It is worth noting that firms may adapt to climate change with new technology. As such, the prediction may be overestimated. However, because I predict for a medium-run time frame, the technology advancement could be limited. Thus, the predictions are instructive for designing climate policies.

6.1 Main Results

To predict impacts of climate change on output, I first estimate regression coefficients for each climatic variable from Equation (7). I then calculate the difference in each climatic variable between the periods 1998-2007 and 2020-2049 for each firm. The firm-specific climate differences are averaged to a representative firm. Lastly, I 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, I calculate the climate prediction on TFP using the same method.

Table 6 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, standard errors, as well as the 95\% confidence intervals are reported. In the last row, I report the percentage of each ownership in the full sample. Column “State-owned” denotes firms that are state-owned, while columns “collective”, “private”, and “foreign” indicate firms that

\textsuperscript{35}There are other ways to identify adaptation behaviors, such as long-difference approach, or comparing regression estimates in different time periods (Dell et al., 2014). However, since the time period in my data is only ten years (1998-2007), it is unlikely that I will be able to implement such approaches.
are collective, private, and foreigner-owned, respectively.

Column (1) reports the climate prediction on output for the full sample. Compared with the period between 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, I used each country’s GDP from the World Bank.\footnote{World Bank, 2013. \url{http://data.worldbank.org/indicator/NY.GDP.MKTP.CD}} 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 4, 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 6, the effects on high temperatures on TFP across two-digit industry sectors have a strong heterogeneity. As a result, one may expect similar heterogeneity in climate predictions. Figure 7 presents the predictions on output in both percentage points (panel A) and in billion CNY (panel B), as well as TFP in percentage points (panel C), for 33 two-digit industry 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 monetary damages under climate change. Six sectors are not presented because of excessively small sample sizes and too large standard errors.37

Several findings can be made from Figure 7. First, the climate prediction on output in percentage points (panel A) across sectors have a strong heterogeneity in both sign and magnitude. The point estimates vary from -12.22% for rubber and 1.95% for ferrous metal mining. Consequently, monetary climate damages (panel B) greatly vary across industry 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 (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 7 also confirm the findings in Section 5.3. Both light (textile, foods processing, plastics, apparel, and so on) and heavy industries (non-metallic minerals manufacturing, general machinery, raw chemicals machinery, electrical machinery, metal manufacturing, and so on) 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 C is almost identical to predictions on

37These sectors include oil and natural gas mining, other mining, tobaccos, chemical fibers, waster recycling, and gas utility, with observations smaller than 10,000.
output in panel A. This similarity demonstrates that the reduction in TFP in response to 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. However, the changes of temperature across regions display a strong heterogeneity. For example, panel D in Figure 8 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 8 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, I estimate regression model (Equation (7)) for the whole sample; I calculate the climate difference for each firm between the periods of 2020-2049 and 1998-2007; Third, I use estimated coefficients and multiplied them by climate difference to infer the climate effects for each firm; Lastly, the firm-specific climate effects are averaged to the county level.\(^{38}\) 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, China will experience moderate output losses under climate change. 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 northeastern 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

\(^{38}\) I do not run regression models separately for each county because of too small sample size. Therefore, the county-specific predictions here only capture the heterogeneity in the changes of temperature, not the heterogeneity in the historical relationship between output and temperature.
to slightly increase output under climate change.

The climate prediction on TFP is generally similar to the prediction on output. Southern 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, I 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 literature that estimates the relationship between temperature and economic growth. My model predicts that a medium-run climate change will reduce output by 5.71%. With the manufacturing sector composing 32% of China’s GDP, this could be translated as $5.71\% \times 0.32 = 1.83\%$ GDP losses. Because mean temperature will increase by around $2^\circ F$ ($1.11^\circ C$) under a medium-run climate change, this suggests that a $1^\circ F$ ($1^\circ C$) increase in annual mean temperature decreases Chinese GDP by 0.92% (1.65%). This finding is consistent with Hsiang (2010) and Dell et al. (2012); they find that a $1^\circ C$ increase in annual mean temperature leads to 2.5% and 1.0% GDP reduction in other developed countries. The results suggest that TFP reduction in response to high temperatures is mostly 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 CO₂, China’s effort to reduce CO₂ emissions is critical in tackling climate change for the world. Although China has made various actions to reduce CO₂ emissions under international pressure, 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 factor allocation, 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, given the empirical findings in this study, 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. As a result, climate damages on Chinese manufacturing sector could further affect global welfare through trade. 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, 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 and adapting to climate change.

Sixth, I find strong heterogeneity in climate damages across industrial sectors. This finding suggests that climate change may generally have a negative affect on Chinese man-

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41For example, China agreed to reduce its carbon intensity (carbon dioxide emissions/GDP) by 40 to 45% by 2020 in the 2009 Copenhagen Accord.

ufacturing. 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, 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 four components of a production function using firm-level manufacturing data in China: output, TFP, labor, and capital inputs. I 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. Indeed, new innovations that expand the production frontier must occur to offset those weather-driven TFP losses if other adaptation strategies are not feasible.
References


Figure 1: Geographic Distribution of Output, 1998-2007

Notes: This figure presents the average annual aggregate output for each county during the periods 1998-2007. The county-level aggregate is calculated using firm-level output. The unit is CNY billion in 1998 values.
Figure 2: Distribution of Daily Temperatures, 1998-2007 and 2020-2049

Notes: This figure presents the distribution of daily temperatures for periods 1998-2007 and 2020-2049. The “1998-2007” bars and the “2020-2049” bars represent the average number of days per year in each temperature category over the periods 1998-2007 and 2020-2049, respectively. The climate prediction is from the HadCM3 A1FI scenario.
Figure 3: The Effect of Daily Temperature on Output, TFP, Labor, and Capital Inputs

Panel A: Output

Panel B: TFP

Panel C: Labor

Panel D: Capital

Figure 4: The Effect of Current and Lagged Temperature on Output and TFP

Panel A: Current Temperature-Output

Panel B: Lagged Temperature-Output

Panel C: Current Temperature-TFP

Panel D: Lagged Temperature-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 5: The Effect of Current and Lagged Temperature 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, and so are panels C and D.
Figure 6: The Effect of Temperature above 90°F on Output and TFP for Each Sector

Panel A: The Effect of Temperature above 90°F on Output in Percentage Points.
Panel B: The Effect of Temperature above 90°F on Output in CNY Billion.
Panel C: The Effect of Temperature above 90°F on TFP in Percentage Points.

Notes: Panel A: The Effect of Temperature above 90°F on Output in Percentage Points. Panel B: The Effect of Temperature above 90°F on Output in CNY Billion. Panel C: The Effect of Temperature above 90°F on TFP in Percentage Points. The share of the observations in the full sample of each sector are reported in the parenthesis. All temperatures bin are estimated in Equation (7), while only the effects of the highest temperature bin are reported. All monetary terms are in 2013 values.
Figure 7: Climate Prediction on Output and TFP for Each Sector

Panel A: Climate Prediction on Output in Percentage Points. Panel B: Climate Prediction on Output in CNY Billion. Panel C: Climate Prediction on TFP in Percentage Points. The share of the observations in the full sample of each sector are reported in the parenthesis. All monetary terms are in 2013 values.

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 in Percentage Points. The share of the observations in the full sample of each sector are reported in the parenthesis. All monetary terms are in 2013 values.
Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full Sample (1)</th>
<th>State-owned (2)</th>
<th>Collective (3)</th>
<th>Private (4)</th>
<th>Foreign (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Firm Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Output (thousand RMB)</td>
<td>12,301</td>
<td>10,583</td>
<td>8,948</td>
<td>9,125</td>
<td>18,545</td>
</tr>
<tr>
<td>Log of TFP (number)</td>
<td>2.90</td>
<td>2.06</td>
<td>2.85</td>
<td>3.07</td>
<td>3.06</td>
</tr>
<tr>
<td>Labor (person)</td>
<td>204</td>
<td>329</td>
<td>193</td>
<td>131</td>
<td>254</td>
</tr>
<tr>
<td>Capital (thousand RMB)</td>
<td>15,260</td>
<td>29,016</td>
<td>9,358</td>
<td>7,609</td>
<td>22,322</td>
</tr>
<tr>
<td><strong>Weather Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Temperature (°F)</td>
<td>61.54</td>
<td>59.03</td>
<td>60.25</td>
<td>61.64</td>
<td>64.52</td>
</tr>
<tr>
<td>Precipitation (inch)</td>
<td>73.17</td>
<td>63.61</td>
<td>63.20</td>
<td>76.36</td>
<td>80.43</td>
</tr>
<tr>
<td>Relative humidity (%)</td>
<td>68.75</td>
<td>67.75</td>
<td>68.50</td>
<td>68.64</td>
<td>69.80</td>
</tr>
<tr>
<td>Wind speed (mile/hour)</td>
<td>5.79</td>
<td>5.18</td>
<td>5.71</td>
<td>5.76</td>
<td>6.38</td>
</tr>
<tr>
<td>Visibility (mile)</td>
<td>6.64</td>
<td>7.10</td>
<td>6.76</td>
<td>6.58</td>
<td>6.37</td>
</tr>
<tr>
<td>Obs</td>
<td>1,833,408</td>
<td>167,648</td>
<td>237,942</td>
<td>705,078</td>
<td>348,985</td>
</tr>
<tr>
<td>Number of firms</td>
<td>511,352</td>
<td>52,173</td>
<td>81,559</td>
<td>247,021</td>
<td>94,187</td>
</tr>
</tbody>
</table>

Notes: Output is measured by valued added. TFP is measured by 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 in 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 using daily observations. Unit of observation is a firm-year. The data cover all state-owned firms and non-state firms with sales larger than CNY 5 million from 1998 to 2007. The industry sectors include mining (3.81%), manufacturing (93.52%), and utilities (2.68%). Columns (2)-(4) presents the summary statistics for each ownership.
Table 2: The Effects of Temperature on Output and TFP

<table>
<thead>
<tr>
<th></th>
<th>TFP by OP</th>
<th></th>
<th>TFP by Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1a)</td>
<td>(1b)</td>
<td>(1c)</td>
</tr>
<tr>
<td>Log of Output</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>80-90°F</td>
<td>-0.0009**</td>
<td>-0.0034***</td>
<td>-0.0007**</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>&gt;90°F</td>
<td>-0.0028***</td>
<td>-0.0047***</td>
<td>-0.0022***</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0009)</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>F-statistic (All Bins)</td>
<td>11.78***</td>
<td>11.81***</td>
<td>10.83***</td>
</tr>
<tr>
<td>Log of TFP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>80-90°F</td>
<td>-0.0011***</td>
<td>-0.0024***</td>
<td>-0.0009***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0004)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>&gt;90°F</td>
<td>-0.0041***</td>
<td>-0.0057***</td>
<td>-0.0036***</td>
</tr>
<tr>
<td></td>
<td>(0.0007)</td>
<td>(0.0008)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>F-statistic (All Bins)</td>
<td>12.28***</td>
<td>11.64***</td>
<td>11.41***</td>
</tr>
<tr>
<td>Observations</td>
<td>1,833,408</td>
<td>1,833,408</td>
<td>1,833,408</td>
</tr>
<tr>
<td>Firm FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year FE</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>Year-by-region FE</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Year-by-2-digit-sector FE</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
</tbody>
</table>

Notes: Dependent variables are logarithms of TFP and output. Regression models are estimated using Equation (7). Through columns (1a)-(2b), TFP are measured by Olley-Pakes estimator. In column (3), TFP are measured by the index approach. Through columns (1a)-(1d), bins are constructed using daily mean temperature. In columns (2a) and (2b), bins are constructed using daily maximum temperature and daily heat index. Column (1d) is the baseline specification throughout the paper. Standard errors are clustered at both firm and county-year level. * p <0.10, ** p <0.05, *** p <0.01. See the text for more details.
<table>
<thead>
<tr>
<th>Intensity Measured by Wage/Output</th>
<th>Intensity Measured by Labor/Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1a)</td>
</tr>
<tr>
<td>80-90°F</td>
<td>-0.0035***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
</tr>
<tr>
<td>&gt;90°F</td>
<td>-0.0042***</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
</tr>
<tr>
<td>80-90°F × Intensity</td>
<td>0.0041***</td>
</tr>
<tr>
<td></td>
<td>(0.0016)</td>
</tr>
<tr>
<td>&gt;90°F × Intensity</td>
<td>-0.0008</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>80-90°F × &gt; Median</td>
<td>0.0009***</td>
</tr>
<tr>
<td>80-90°F × Quartile 2</td>
<td>0.0009***</td>
</tr>
<tr>
<td>80-90°F × Quartile 3</td>
<td>0.0012***</td>
</tr>
<tr>
<td>80-90°F × Quartile 4</td>
<td>0.0017***</td>
</tr>
<tr>
<td>&gt;90°F × Quartile 2</td>
<td>0.0033***</td>
</tr>
<tr>
<td>&gt;90°F × Quartile 3</td>
<td>0.0037***</td>
</tr>
<tr>
<td>&gt;90°F × Quartile 4</td>
<td>0.0046***</td>
</tr>
</tbody>
</table>

Observations 1,833,408 1,833,408 1,833,408 1,833,408 1,833,408 1,833,408

Notes: Dependent variable is log of TFP. Regression models are estimated using Equation (7) and includes firm fixed effects, year-by-region fixed effects, and year-by-2-digit-sector fixed effects. In columns (1a)-(1c), labor intensity is measured by wage/output. In columns (2a)-(2c), labor intensity is measured by labor/sales. In columns (1a) and (2a), I interact two highest temperature bins with labor intensity. In columns (1b) and (2b), labor intensity is classified as either above median (=1) or below median (=0), and then I interact two highest temperature bins with dummy variable for above median. Dummy variable for below median is omitted for multicollinearity. In columns (1c) and (2c), labor intensity is classified as 4 quartiles, and then I interact two highest temperatures bins with each quartile. Quartile 1 is omitted for multicollinearity. Standard errors are clustered at both firm and county-year level. * p <0.10, ** p <0.05, *** p <0.01. See the text for more details.
Table 4: The Effects of Temperature on TFP Across Ownership

<table>
<thead>
<tr>
<th></th>
<th>Full sample</th>
<th>State-Owned</th>
<th>Collective</th>
<th>Private</th>
<th>Foreign</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-90°F</td>
<td>-0.0024***</td>
<td>-0.0024***</td>
<td>-0.0024***</td>
<td>-0.0023***</td>
<td>-0.0024***</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>&gt;90°F</td>
<td>-0.0056***</td>
<td>-0.0060***</td>
<td>-0.0059***</td>
<td>-0.0048***</td>
<td>-0.0053***</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0008)</td>
<td>(0.0008)</td>
<td>(0.0008)</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>80-90°F × Ownership</td>
<td>-0.0001</td>
<td>0.0001</td>
<td>-0.0002*</td>
<td>-0.0000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(0.0002)</td>
<td></td>
</tr>
<tr>
<td>&gt;90°F × Ownership</td>
<td>0.0039***</td>
<td>0.0012**</td>
<td>-0.0019***</td>
<td>-0.0019**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0009)</td>
<td>(0.0006)</td>
<td>(0.0006)</td>
<td>(0.0008)</td>
<td></td>
</tr>
<tr>
<td>Ownership Percentage</td>
<td>100%</td>
<td>9.14%</td>
<td>12.98%</td>
<td>38.46%</td>
<td>19.03%</td>
</tr>
<tr>
<td>Observations</td>
<td>1,833,408</td>
<td>1,833,408</td>
<td>1,833,408</td>
<td>1,833,408</td>
<td>1,833,408</td>
</tr>
</tbody>
</table>

Notes: Dependent variable is logarithm of TFP. Regression models are estimated using Equation (7) and includes firm fixed effects, year-by-region fixed effects, and year-by-2-digit-sector fixed effects. Column (1) reports the estimates for the full sample. In column (2), the variable “Ownership” equals to 1 if firms are state-owned, and 0 if otherwise. Two highest temperatures bins (80-90°F and above 90°F) are interact with dummy variables for each ownership. Therefore the effect of bin above 90°F on TFP for state-owned firms is $-0.0060 + 0.0039 = -0.0021$, while the effect for non-state firms is $-0.0060$. Similarly for columns (3)-(5). Standard errors are clustered at both firm and county-year level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. See the text for more details.
Table 5: The Effects of Temperature on TFP across Regions

<table>
<thead>
<tr>
<th>Geographic Region</th>
<th>Overall (1a)</th>
<th>North (1b)</th>
<th>Northeast (1c)</th>
<th>East (1d)</th>
<th>Central (1e)</th>
<th>South (1f)</th>
<th>Southwest (1g)</th>
<th>Northwest (1h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-90°F</td>
<td>-0.0024***</td>
<td>-0.0059***</td>
<td>-0.0004</td>
<td>-0.0041***</td>
<td>-0.0052***</td>
<td>-0.0022</td>
<td>0.0004</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0013)</td>
<td>(0.0019)</td>
<td>(0.0007)</td>
<td>(0.0013)</td>
<td>(0.0013)</td>
<td>(0.0008)</td>
<td>(0.0013)</td>
</tr>
<tr>
<td>&gt;90°F</td>
<td>-0.0056***</td>
<td>-0.0118***</td>
<td>0.0187</td>
<td>-0.0081***</td>
<td>-0.0023</td>
<td>-0.0213***</td>
<td>0.0016</td>
<td>0.0025</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0045)</td>
<td>(0.0174)</td>
<td>(0.0012)</td>
<td>(0.0017)</td>
<td>(0.0058)</td>
<td>(0.0015)</td>
<td>(0.0032)</td>
</tr>
<tr>
<td>Mean Temperature (°F)</td>
<td>61.54</td>
<td>53.99</td>
<td>46.77</td>
<td>62.27</td>
<td>61.45</td>
<td>73.20</td>
<td>61.74</td>
<td>50.93</td>
</tr>
<tr>
<td>Observations</td>
<td>1,833,408</td>
<td>182,189</td>
<td>111,506</td>
<td>936,478</td>
<td>200,397</td>
<td>246,515</td>
<td>106,676</td>
<td>49,647</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Economic Region</th>
<th>Overall (2a)</th>
<th>Northeast (2b)</th>
<th>East (2c)</th>
<th>Central (2d)</th>
<th>West (2e)</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-90°F</td>
<td>-0.0024***</td>
<td>-0.0004</td>
<td>-0.0045***</td>
<td>-0.0035***</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
<td>(0.0019)</td>
<td>(0.0007)</td>
<td>(0.0008)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>&gt;90°F</td>
<td>-0.0056***</td>
<td>0.0187</td>
<td>-0.0100***</td>
<td>0.0013</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0164)</td>
<td>(0.0014)</td>
<td>(0.0013)</td>
<td>(0.0013)</td>
</tr>
<tr>
<td>Mean TFP</td>
<td>2.90</td>
<td>2.71</td>
<td>2.98</td>
<td>2.85</td>
<td>2.63</td>
</tr>
<tr>
<td>Observations</td>
<td>1,833,408</td>
<td>111,506</td>
<td>1,226,702</td>
<td>298,702</td>
<td>196,498</td>
</tr>
</tbody>
</table>

Notes: Dependent variable is logarithm of TFP. Regression models are estimated using Equation (7). In the first panel, firms are classified by geographic regions. In the second panel, firms are classified by economic regions. See the detailed region classification in Table B.7 in the online appendix. Due to space limitations, I only report the impacts of two highest temperature bins. I also report 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 level. * p < 0.10, ** p < 0.05, *** p < 0.01. See the text for more details.
Table 6: Climate Predictions on Output and TFP

<table>
<thead>
<tr>
<th></th>
<th>Full Sample (1)</th>
<th>State-Owned (2)</th>
<th>Collective (3)</th>
<th>Private (4)</th>
<th>Foreign (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Output (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point Estimate</td>
<td>-5.71</td>
<td>-0.26</td>
<td>-3.48</td>
<td>-11.26</td>
<td>-2.56</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.61</td>
<td>0.73</td>
<td>0.89</td>
<td>1.02</td>
<td>1.51</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>[-6.91, -4.51]</td>
<td>[-1.71, 1.18]</td>
<td>[-5.23, -1.73]</td>
<td>[-13.25, -9.27]</td>
<td>[-5.52, 0.39]</td>
</tr>
<tr>
<td><strong>Output (Billion RMB)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point Estimate</td>
<td>-208.32</td>
<td>-0.68</td>
<td>-10.91</td>
<td>-168.72</td>
<td>-27.11</td>
</tr>
<tr>
<td>S.E.</td>
<td>22.27</td>
<td>1.89</td>
<td>2.80</td>
<td>15.22</td>
<td>15.94</td>
</tr>
<tr>
<td><strong>TFP (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point Estimate</td>
<td>-4.18</td>
<td>-0.35</td>
<td>-1.83</td>
<td>-8.32</td>
<td>-0.81</td>
</tr>
<tr>
<td>S.E.</td>
<td>0.55</td>
<td>0.75</td>
<td>0.86</td>
<td>0.96</td>
<td>1.27</td>
</tr>
<tr>
<td>95% C.I.</td>
<td>[-5.27, -3.10]</td>
<td>[-1.81, 1.12]</td>
<td>[-3.51, -0.15]</td>
<td>[-10.20, -6.44]</td>
<td>[-3.31, 1.68]</td>
</tr>
<tr>
<td><strong>Ownership Percentage</strong></td>
<td>100%</td>
<td>9.14%</td>
<td>12.98%</td>
<td>38.46%</td>
<td>19.03%</td>
</tr>
</tbody>
</table>

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, which is calculated using the prediction in percentage points multiplying by the mean aggregate output over the periods 1998-2007. The bottom part presents the climate prediction on TFP. See the text for more details.
Figure B.9: The Distribution of Weather Stations in China. *Notes:* Each dot represents a weather station and each polygon represents a county.
Table B.7: Region Classification

<table>
<thead>
<tr>
<th>Geographic Regions</th>
<th>Provinces</th>
</tr>
</thead>
<tbody>
<tr>
<td>North</td>
<td>Beijing, Tianjin, Hebei, Shanxi, Nei Mongol</td>
</tr>
<tr>
<td>Northeast</td>
<td>Liaoning, Jilin, Heilongjiang</td>
</tr>
<tr>
<td>East</td>
<td>Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong</td>
</tr>
<tr>
<td>Central</td>
<td>Henan, Hubei, Hunan</td>
</tr>
<tr>
<td>South</td>
<td>Guangdong, Guangxi, Hainan</td>
</tr>
<tr>
<td>Southwest</td>
<td>Chongqing, Sichuan, Guizhou, Yunnan, Xizang (Tibet)</td>
</tr>
<tr>
<td>Northwest</td>
<td>Shaanxi, Gansu, Qinghai, Ningxia Hui, Xinjiang Uygur</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Economic Regions</th>
<th>Provinces</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>Liaoning, Jilin, Heilongjiang</td>
</tr>
<tr>
<td>East</td>
<td>Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan</td>
</tr>
<tr>
<td>Central</td>
<td>Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan</td>
</tr>
<tr>
<td>West</td>
<td>Nei Mongol, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang (Tibet), Shaanxi, Gansu, Qinghai, Ningxia Hui, Xinjiang Uygur</td>
</tr>
</tbody>
</table>

Notes: The classification of geographic regions is based on the tradition. The classification of economic regions is based on the standards published in the NBS website [http://www.stats.gov.cn/ztjc/zthd/sjtjr/dejtjkfr/tjkp/201106/t20110613_71947.htm](http://www.stats.gov.cn/ztjc/zthd/sjtjr/dejtjkfr/tjkp/201106/t20110613_71947.htm).