The Impacts of Temperature on Chinese Food Processing Firms

by Xiaoguang Chen, Madhu Khanna, and Lu Yang

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Xiaoguang Chen[1,4], Madhu Khanna[2,4], Lu Yang[3,4]

[1.] Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, China

[2.] Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, Urbana, USA

[3.] School of Accountancy, Nanjing University of Finance and Economics, Nanjing, China

[4.] All authors contributed equally to this work

Correspondence to be sent to: Xiaoguang Chen, Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, China, 610074. Fax: +86 (0)28 8735 6958. Phone: +86 (0)28 8709 9164. Email: cxg@swufe.edu.cn.

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Abstract

This article investigates the impacts of temperature variations on industrial output and accounting profits of food processing firms, using rich panel data of Chinese food processing firms for the 1998-2007 period. We find that both industrial output and accounting profits peaked at a daily average temperature of 21-24 ℃ and declined sharply at higher temperatures. Higher temperatures reduced firms' output and profits primarily by hurting total factor productivity and reducing investment in capital and thus capital stock. Without additional adaptation, the total profits and industrial output of Chinese food processing firms are projected to experience significant decline by 2080.

Key words: Temperature; food processing firms; industrial output; profits

JEL Codes: Q18, Q54, O13, O14

1. Introduction

With global average temperatures predicted to continue to rise, a large body of research has shown that rising temperatures will have significant adverse effects on crop productivity and farmland values in the absence of adaptation (Mendelsohn, Nordhaus and Shaw 1994; Lobell, Schlenker and Costa-Roberts 2011; Schlenker and Roberts 2009; Chen, Chen and Xu 2016; Costinot, Donaldson and Smith 2016). These studies have primarily focused on impacts at the farm-gate level and not considered the downstream effects of a warmer climate on agro-food industries. A resilient food processing sector is essential for building sustainable and productive agro-food systems, ensuring value addition to agricultural products and meeting the world's growing demand for processed food products (FAO and OECD 2019). Vulnerability of this sector to climatic factors has also been rapidly growing with climate change, possibly through the impact of temperature on labor productivity (Stevens 2018; Zivin and Neidell 2014) and food processing firms' energy expenditures (Auffhammer and Mansur 2014; Mansur, Mendelsohn and Morrison 2008). However, the literature has so far overlooked the impact of rising temperatures on the food processing sector.

Using an annual firm-level data set of Chinese food processing firms from 1998 to 2007 with fine-scale daily weather data over the same period, in this article we assess the supply and demand side impacts of temperature variations. On the supply side, we focus on examining the impact of temperature on food processing firms' industrial output (measured by value added). By affecting consumer demand (Henley and Peirson 1998), temperature variations are also expected to influence market prices of final products and firms' profits. We thus assess the demand side impact by investigating the impact of temperature on firms' accounting profits. Both supply and demand side indicators are vital for a firm to survive from highly competitive markets and remain attractive to investors. There is a long list of factors through which temperature affects food processing firms' output and profits, such as technology, input use, consumer demand, etc. Here, we primarily investigate whether temperature influences firms' output and profits by affecting total factor productivity (TFP) and input use (i.e. labor, capital).

China provides a compelling setting to study the temperature effect on the food processing sector for at least two reasons. First, China has witnessed significant warming over the past century. Annual average surface temperature has increased by approximately 0.5-0.8 ℃ over the past 100 years, which is higher than the average global temperature rise over the same period (Ding et al. 2007). Second, China is the world's largest consumer, producer, and importer of agro-food commodities, with imports totaling approximately $130 billion in 2019 (The World Bank 2020). Therefore, impacts in China could have broad implications for prices and supply of processed food worldwide. Understanding the impacts of temperature variations on Chinese food processing firms is a critical first step before efficient strategies can be developed to cope with future warming.

The firm-level data set includes all major food processing firms in mainland China with annual sales above CNY 5 million. The number of firms covered by the data set varies from approximately 6,000 in 1998 to approximately 18,000 in 2007. Figure 1 shows that these firms are widely distributed across China's agricultural heartland. In addition to firms' operation and performance information, the firm-level data also report firms' primary ownership types. In China, enforcement of labor regulations is typically weaker in privately owned firms than in firms with other ownership types (Ngai 2005) and thus private firms are less likely to take good protective measures for workers on hot days. Reported ownership information in the data set allows us to explore the heterogeneity in the impacts of temperature across ownership types. Due to substantial differences in exposure to high temperatures across regions, we also explore whether temperature impacts on food processing firms are regionally heterogeneous. We are unaware of a comparable data set used for assessing the effect of temperature on the food processing sector in any other developing country.

Our weather data are compiled from the China National Environmental Monitoring Center (CNEMC) that reports daily weather outcomes for 820 weather stations in mainland China. We use the daily weather data to compute the number of days that firms are exposed to each three-degree Celsius temperature intervals in a year. That facilitates estimation of a flexible model specification to examine whether food processing firms responded differently to temperature intervals.

We identify the temperature impacts on food processing firms by exploiting year-to-year fluctuations in temperature within firms. We isolate the temperature effect from other confounding factors by including a comprehensive set of weather variables that exhibit simultaneous variations with temperature. As additional weather variables, we incorporate rainfall, sunshine hours, air pressure, relative humidity, and wind speed. Time-invariant firm fixed effects, industry × year fixed effects, and region × year fixed effects are incorporated to minimize the estimation biases stemming from omitted variables.

Because firms' true accounting profits are not directly observable, following the literature on tax avoidance, we use firms' reported accounting profits as a proxy for firms' true accounting profits. Our regression results indicate that accounting profits and industrial output of Chinese food processing firms exhibited nonlinear responses to temperature changes, with both peaking at a daily average temperature of 21-24 ℃ and declining sharply at higher temperatures. The adverse temperature impacts are particularly large at temperatures above 30 ℃. Holding all else equal, we estimate that one more day with temperatures above 30 ℃ is expected to reduce an average food processing firm's profit by 0.68%, while the corresponding reduction in output is 0.58%. Further analysis reveals that higher temperatures reduced firms' output and profits primarily by hurting TFP and reducing investment in capital and thus capital stock, while temperature variations had no significant impact on labor use. If no additional adaptation is undertaken, the total profits and industrial output of Chinese food processing firms are projected to decline annually by 15-24% and 14-22% respectively under the most severe climate scenario (Representative Concentration Pathway 8.5) of the global climate models HadGEM2-ES and NorESM1-M by 2080.

The remainder of the paper is organized as follows. Section 2 reviews related literature. Section 3 presents a conceptual framework. Section 4 reports data sources. Section 5 describes our empirical model. Section 6 presents the results. Section 7 concludes.

2. Related Literature

A large body of research has examined the impacts of rising temperatures on crop yields (for example, see Schlenker and Roberts 2009; Asseng et al. 2015; Challinor et al. 2014; Chen, Chen, and Xu 2016b), farmland values (Mendelsohn, Nordhaus and Shaw 1994; Schlenker, Hanemann and Fisher 2006; Bozzola et al. 2018), and changes in cropland use (Miao, Khanna and Huang 2016; Cui 2020). These studies have shown that a warmer climate is expected to have significant detrimental impacts on global food production in the absence of adaptation.

There is a rapidly growing literature evaluating the impacts of rising temperatures on the industrial sector and most studies find that industrial output declines with higher temperatures (Dell, Jones, and Olken 2012; Hsiang 2010; Burke, Hsiang, and Miguel 2015; Cachon, Gallino, and Olivares 2012; Chen and Yang 2019; Zhang et al. 2018). However, only two studies, namely Zhang et al. (2018) and Chen and Yang (2019), estimate the relationship between temperature and industrial output for China. Both studies show that the response of industrial output to temperature is nonlinear and output declines strongly with higher temperatures above 30 ℃.

The most relevant study pertains to Zhang et al. (2018). By analyzing a firm-level data set of Chinese manufacturing firms with 33 industries, the researchers quantify how temperature affects firms' industrial output and analyze the channels by which temperature affects output. They find that an additional day with temperatures above 32 ℃ leads to an output reduction by 0.45%. The negative impact of higher temperatures on industrial output is mainly through the effect of temperature on TFP, while higher temperatures have insignificant impacts on labor and capital stock. Among the 33 industries, Zhang et al. (2018) find that one more day above 32 ℃ lowers output in the food processing sector by approximately 0.5%, while the temperature impact on TFP is not statistically significant.

Although our work is similar to Zhang et al. (2018), it differs in three major aspects. First, Zhang et al. (2018)'s focus is on estimating the supply side impact of temperature, ignoring that the demand side may also be influenced by temperature. If the demand for final products declines with temperature, higher temperatures may not only reduce the supply of final goods, but also lower their market prices, resulting in a more pronounced impact on profits than the impact on output. In contrast to Zhang et al. (2018), we examine both the supply and demand side impacts of temperature, by assessing the impacts of higher temperatures on firms' industrial output and profits. As noted above, while the responses of industrial output to temperature variations have been well studies, however, little is known about the effect of temperature on firms' profits. Similar to Zhang et al. (2018), Chen and Yang (2019) have also exclusively focused on the supply side impact of temperature variations.

Second, our weather data based on 820 weather stations are richer than the weather data used in Zhang et al. (2018). The researchers collect weather data from the US National Oceanic and Atmospheric Administration, which has only 400 stations covering China. We also include sunshine duration as a weather covariate, as prior studies document that sunlight is directly linked to labor productivity (De Witte and Saal 2010; Lambert et al. 2002; Patz et al. 2005). This variable is omitted in Zhang et al. (2018).

Finally, our findings are different. We find a significant, negative response of TFP to temperatures above 30℃, whereas Zhang et al. (2018) find an insignificant TFP-temperature relationship in the food processing sector. We also discover that capital stock declines with higher temperatures, which is another major factor driving the output and profit losses. Zhang et al. (2018)'s finding of the limited temperature impact on capital stock is based on a sample of 33 industries and the extent to which this finding applies specifically to food processing firms is unclear. The differences in these findings are possibly due to the differences in weather data used and specifications considered between our work and theirs.

The primary contribution of our work is to present the first firm-level evidence from China that temperature affects food processing firms' accounting profits and industrial output, and show that the adverse impacts of higher temperatures on TFP and capital stock are the two main factors driving the output and profit losses. These results are useful for the design of efficient strategies to mitigate the negative effects of higher temperatures on Chinese food processing firms.

3. Conceptual framework

This section sketches a conceptual framework to illustrate channels through which temperature may affect a firm's accounting profit and industrial output. Because firms' accounting profits and economic profits are likely to be positively correlated, for ease of illustration, here we explain how temperature affects a firm's economic profit. The same logic applies to accounting profit.

We assume that all firms are profit-maximizing and operate in perfectly competitive markets. Consider a representative firm that uses a Cobb-Douglas production technology and two inputs, labor (L) and capital (K), to produce a single final good (Y). Labor and capital may change with temperature (T). The quantity of the final good produced can be written as:

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

Here, $A(T)$ refers to this firm's TFP, which might respond to temperature. α and β denote output elasticities of labor and capital, respectively. Let $P(T)$, $\omega_L(T)$ and $\omega_K(T)$ denote the market prices of the final good, labor, and capital, respectively, all of which might also change with temperature. The firm's economic profit can be written as in Equation (2):

$$\pi(T) = P(T) * Y(T) - \omega_L(T)L(T) - \omega_K(T)K(T) \tag{2}$$

Equation (3) below shows that the firm's year-end capital stock is the sum of the year-end capital stock in the previous year (denoted by $K_{-1}(T)$) and the investment made in the current year (denoted by $I(T)$), net of capital depreciation (denoted by $D(T)$). Here, investment and capital depreciation might respond to temperature changes.

$$K(T) = K_{-1}(T) + I(T) - D(T) \tag{3}$$

From Equations (1), (2) and (3), we note that temperature may affect a firm' industrial output and economic profit through two mechanisms.

(A). Temperature may affect industrial output by affecting input productivity and input costs.

Equation (1) shows that temperature may affect industrial output by influencing input productivity and costs of inputs. First, high temperatures are found to have direct impacts on productivities of labor and capital (González-Alonso et al. 1999; Zivin and Neidell 2014;

Mostafavi and Agnew 1996). Because TFP is a weighted average of productivities of inputs used for production, temperature changes are expected to affect TFP. Second, temperature can affect the market prices of inputs. For instance, high temperatures are expected to increase labor costs in China, because the Chinese government requires that employers provide high-temperature subsidies to workers on extremely hot days (Zhao et al. 2016). Responding to changes in input prices, labor and capital inputs may also change with temperature. Third, prior studies have provided evidence suggesting that temperature significantly affects investors' behavior and stock market returns (Cao and Wei 2005). By influencing investment decisions ($I(T)$), temperature may affect capital stock (see Equation 3) and thus industrial output.[1]

(B). Temperature may affect profit by altering market demand.

Several studies have demonstrated that temperature can affect consumer demand (Henley and Peirson 1998). If the demand is affected, the equilibrium quantity sold and the market price of the final product are also altered by temperature. As a result, temperature changes are expected to influence a firm's revenue and profit (see Equation 2).

However, we cannot empirically examine the effect of temperature on input and output prices because of the limited availability of the price data and also because these prices are unlikely to vary substantially across regions in a given year, due to improved transportation infrastructure and market integration in China in the past two decades (Zheng and Kahn 2013).[2] Thus, in the empirical analyses presented below, we mainly focus on estimating whether

[1] In the empirical analyses, we do not examine the temperature effect on capital depreciation, because this variable is typically computed based on an assumed depreciation rate and the year in which the capital was purchased (Nadiri and Prucha 1996). Thus, it is unlikely to be affected by temperature.
[2] In addition to weather variables, our empirical model also incorporates industry $\times$ year fixed effects and region $\times$ year fixed effects, which may absorb most of the variations in prices. As a result, the effect of temperature on prices would likely be insignificant, if we were able to collect the price data.

temperature affects firms' profits and industrial output by influencing TFP, and altering investment, labor and capital inputs.

4. Data Sources

4.1. Firm-level data for food processing industries in China

We obtained firm-level data for food processing industries from the annual surveys of Chinese manufacturing firms conducted by the National Bureau of Statistics of China (NBS) for the period of 1998 to 2007. This data set covers state-owned enterprises (SOE) and non-state-owned enterprises, with annual sales above CNY 5 million. The non-state-owned enterprises include privately owned firms, collectively owned firms, foreign firms, Hong Kong, Macao and Taiwan firms, and mixed-ownership firms. The data set contains four two-digit food processing industries specified based on Chinese Industry Classification Codes, namely agro-food processing, food processing, beverage and tobacco industries. The number of food processing firms covered by these surveys varies over time and increases from 6,098 in 1998 to 17,962 in 2007. The data set also contains firm identification number (ID) and operation and accounting information. When the firms were first surveyed, they received a unique ID from the NBS. However, many firms received a new ID due to restructuring, merger, acquisition, or changes in ownership. To construct a firm-level longitudinal data set, we followed the procedure described in Brandt et al.(Brandt, Biesebroeck and Zhang 2012) to link firms across the sample period.

The firm-level data set contains the number of workers employed, total industrial output values, intermediate input values, and the pre-tax accounting profit reported by each firm. Firms' true accounting profits are not observable due to firms' incentives to avoid corporate income tax. Thus, we used firms' reported accounting profits as a proxy for firms' true accounting profits. As an alternative, following Cai and Liu (2009), we computed a firm's imputed profit, by deducting intermediate inputs, financial charges (primarily interest payments), total wage paid to workers, current depreciation and value added tax from this firm's gross output. We measured a firm's industrial output using value added, which is the difference between total output and intermediate input. Following the prior literature (Zhang et al. 2018), we estimated firm-level TFP using the Olley-Pakes estimator (Olley and Pakes 1996). Investment in capital, which is used in the Olley–Pakes estimator, is simply obtained from the equation of motion for the capital stock.

We excluded observations from the original data set if (*i*) a firm's reported accounting profit to sales ratio is either below the 0.1% level or above the 99.9% level; (*ii*) value added is either below the 1.0% level or above the 99.0% level; and (*iii*) the number of workers is below 8. We also dropped observations if value added, the number of workers, total assets, fixed assets, or total annual sales have missing values or when basic accounting principles are violated, in order to ensure that our regression results are not biased due to outliers. The NBS also released firm-level data from 2008 to 2013. However, we could not include the newly released data in our analysis, because these new data do not report several key variables, such as value added and intermediate input values, which are essential for calculations of industrial output and TFP.

4.2. Historical and future weather data

We collected daily weather data, including average temperature, rainfall, sunshine hours, air pressure, relative humidity, and wind speed, from the CNEMC. The CNEMC reports daily weather outcomes for 820 weather stations in China and the coordinates of each weather station. The historical weather data are publicly available online at http://data.cma.cn/. For counties with more than one weather station, we used the average of the weather variables across weather stations to construct county-level weather variables. We constructed weather variables for counties without a weather station from their nearest neighboring counties. We merged the firm-level data with the county-level weather data by county and year. Thus, food processing firms located in the same county have the same values of weather variables.

Projections of climate data were taken from WorldClim for future years (2021-2100). WorldClim provides future climate data under four Representative Concentration Pathways (RCPs), namely RCP2.6, RCP4.5, RCP6.0, and RCP8.5, which differ by assumed greenhouse gas (GHG) concentration trajectory. We selected RCP2.6 and RCP8.5 for this analysis because the two pathways cover the entire range for the projected speeds of future GHG emissions. Following (Warszawski et al. 2014; Miao, Khanna, and Huang 2016; Chen and Chen 2018), we used the climate data projected by the global climate models HadGEM2-ES and NorESM1-M, because the two models provide distinct contrast on future global temperature changes. We downloaded the data at the spatial resolution of 2.5 minutes of a degree of longitude and latitude, and thus we obtained future climate variables for all Chinese counties. The future climate data that support the analysis are publicly available online at https://www.worldclim.org/data/v1.4/cmip5_10m.html.

Supplementary Table S1 reports summary statistics of our key economic and weather variables. Our sample is an unbalanced panel with 119,019 observations for years 1998-2007. Table S1 shows that both economic and weather variables exhibit considerable variability during the sample period.

5. Regression Models

To detect whether food processing firms' economic performance exhibited nonlinear responses to temperature changes, following prior studies (for example, see Schlenker and Roberts 2009; Zhang et al. 2018), we define temperature variables as a vector of temperature bins and estimate the following model:

$$\log E_{i,t} = \sum_{m} \alpha_0^m Tbin_{i,t}^m + \lambda_0 W_{i,t} + \gamma Z_{i,t} + c_i + \varepsilon_{i,t} \qquad (4)$$

where firms are indexed by *i* and years are indexed by *t*. $E_{i,t}$ refers to variables of interest, which can be profit, industrial output, TFP, labor, capital stock, and capital investment. We took the natural logs for these variables and thereby estimated coefficients of weather variables are interpreted as the percentage changes in $E_{i,t}$ with a one-unit increase in weather variables.

In equation (4), $Tbin_{i,t}^m$ denotes the number of days in year *t* with daily average temperatures falling into the *m*th temperature bin in the county where firm *i* is located. Daily average temperatures are measured in ℃ and are divided into twelve bins, with each bin 3 ℃ wide. The first temperature bin, $Tbin_{i,t}^1$, is defined as the number of days when daily average temperatures are below 0 ℃, and the last temperature bin, $Tbin_{i,t}^{12}$, is defined as the number of days when daily average temperatures are above 30 ℃. We set the temperature bin 21-24 ℃ as the omitted category to avoid multicollinearity. The coefficients of the other temperature bins, α_0^m, thus measure the marginal effect on $E_{i,t}$ of an additional day when daily average temperatures fall into the *m*th bin, relative to a day in the 21-24 ℃ bin. Our main findings do not hinge on the selection of this reference bin.

Other weather variables, represented by $W_{i,t}$, incorporate sums of rainfall and sunshine hours and means of air pressure, relative humidity, and average wind speed in year *t* and their quadratic terms. $Z_{i,t}$ contains two-digit industry × year fixed effects and region × year fixed effects. The former controls for the unobserved factors that are common to each two-digit industry in a given year, such as changes in industrial policies and production technology that are specific to a given industry. The latter accounts for common shocks occurring in a region in a given year that are the same for all firms located in that region in that year, such as trends in climate and/or changes in regional energy supply infrastructure. c_i is the time-invariant firm fixed effects. $\varepsilon_{i,t}$ are the error terms.

The temperature effects are identified from the random variations in temperature over time. Note that the error terms $\varepsilon_{i,t}$ may be spatially and serially correlated. To account for this, we estimate standard errors that are clustered in two dimensions: within firms and within (prefecture-level) city-years (Cameron, Gelbach and Miller 2011). Clustering standard errors within firms accounts for autocorrelation within each firm, while clustering standard errors within city-years accounts for spatial correlation across contemporary firms within each city. We also control for the heteroskedasticity of the error terms.

6. Results

Our baseline analysis used firms' reported accounting profits as a proxy for firms' true accounting profits, as the two variables are positively correlated (Cai and Liu 2009; Desai 2005). To test the sensitivity of the results, we also computed a firm's imputed profit based on the national income account by deducting intermediate inputs from gross output as another proxy for firms' true accounting profits (Cai and Liu 2009).

6.1. Impacts of Temperature on Food Processing Firms' Profits and Industrial Output

We present the impacts of temperature on food processing firms' profit and industrial output in Figure 2, while point estimates of weather variables are reported in Table 1. Figure 2 has two frames, where the left frame displays point estimates and the 95% confidence intervals of the temperature impacts on profit and the right frame shows the effect of temperature on industrial output. The horizontal axis of the two figures is temperature, while the vertical axis denotes the log of profit (or the log of industrial output). The two figures show that profit and output exhibit similar responses to temperature changes, increasing modestly with temperature up to a critical temperature threshold, 21-24 ℃, and then declining sharply with higher temperatures.

The negative impacts on profit and industrial output are particularly large when daily average temperatures are above 30 ℃. Holding all else the same, relative to a day with an average temperature of 21-24 ℃, profit is projected to decline by approximately 0.68% ($P < 0.01$) for each additional day at temperatures above 30 ℃. In comparison, the reduction in output is smaller: one more day at temperatures above 30 ℃ reduces output by 0.58% ($P < 0.01$). The number of days with an average temperature of 21-24 ℃ accounted for approximately 10% of the 365 days in a year in our sample. Thus, holding all else the same, replacing days at 21-24 ℃ temperatures with full days at 30 ℃ results in a projected reduction in profit by 25% (≈ 0.68%*10%*365) and a projected reduction in industrial output by 21% (≈ 0.58%*10%*365). The finding of a larger adverse impact on profit than the impact on industrial output indicates that the demand for food and thus food prices might have declined with rising temperatures.

Coefficients for other weather variables (rainfall, sunshine hours, air pressure, relative humidity, and average wind speed) are reported in Table 1. Rainfall had small, negative impacts on profit and output. Holding all else the same, a 1-cm increase in total annual rainfall was associated with a reduction of 0.16% in profit ($P < 0.05$) and a reduction of 0.17% in industrial output ($P < 0.01$). We find that profit and industrial output increased with higher levels of sunshine hours. Coefficients for air pressure, relative humidity, and wind speed are not economically or statistically significant.

6.2. Robustness Checks

This section checks the robustness of estimated temperature effects on profit and output in four scenarios. Our baseline model specification incorporates firm fixed effects, two-digit industry × year fixed effects, and region × year fixed effects. Here, we start by considering a very simple specification with only firm fixed effects and year fixed effects in Scenario (a). In this specification, year fixed effects control for shocks that are common to all firms in a given year, such as policy changes, trends in global climate, or shocks to international trade, regardless of the differences in firm characteristics and location. In Scenario (b), we incorporate firm fixed effects and region × year fixed effects, due to the concern that some shocks may vary by region. We consider these two scenarios to see whether our baseline estimates of temperature variables are sensitive to variations in model specifications. In Scenario (c), we replicate the above analyses by removing observations if a firm's reported accounting profit to sales ratio is either below the 0.5% level or above the 99.5% level (rather than below the 0.1% level or above the 99.9% level in the baseline analysis) to further ensure that our results are not affected by potentially mis-specified outliers. In the baseline analysis, we construct weather variables using weather information on all days in a year, including weekdays and non-weekdays (i.e., weekends and holidays). Finally, in Scenario (d), we use log (imputed profit) as our dependent variable rather than log (reported accounting profit) to examine whether our results are sensitive to how the profit variable is constructed. Sensitivity analyses are conducted by estimating Equation (1). Supplementary Figure S1 presents coefficient estimates of temperature bins for these scenarios.

We find that our main results are robust to alternative specifications and data. The profit (output)-temperature relationships hold even in models with simple year fixed effects or region × year fixed effects to control for technology and time effects (Supplementary Figures S1a and S1b).

Similarly, using a stringent criterion on profit to sales ratio to drop potential outliers does not alter the main findings reported in Figure 2 (Supplementary Figure S1c). Our main findings remain broadly consistent when using the imputed firm profit as the proxy for the true accounting profit (Supplementary Figure S1d).

6.3. Channels

As noted above in the conceptual framework, temperature may influence firms' profits and industrial output by affecting TFP, investment and factor inputs (i.e. labor, capital). In this section, we empirically examine whether temperature affects firms' profits and output through the impacts on these variables. Such analysis provide useful information for food processing firms to develop efficient strategies to cope with heat stress.

Our results summarized in Figure 3 indicate that the negative impacts of higher temperatures on TFP and capital stock are the two key factors driving the adverse responses of economic output to higher temperatures above 30 ℃, with the negative impact on TFP being twice larger than the impact on capital stock. Figure 3A shows that estimated temperature effects on TFP are nearly identical to those depicted in Figure 2. Holding all else equal, each additional day of temperature above 30 ℃ was associated with a reduction of 0.41% in TFP ($P < 0.01$).

Figure 3B illustrates that capital stock declined by 0.21% ($P < 0.05$) for each additional day at temperatures above 30 ℃, holding all else the same. The decrease in capital stock was mainly due to the adverse impacts of temperatures above 30 ℃ on investment in capital (Coefficient = -0.25%, $P < 0.10$, Table 1). Responses of TFP and capital stock to variations in other temperature bins are not statistically significant. We do not find strong evidence for statistically significant impacts of high temperatures on labor use (Table 1).

Our finding of a significant, negative response of TFP to higher temperatures above 30 ℃ is different from Zhang et al. (2018) who find an insignificant response of TFP to higher temperatures in the food processing sector. The differences in weather data and specifications between our work and their study could be possible reasons causing the differences in finding. Moreover, we show that the reduction in capital stock in response to higher temperatures is another major driver behind profit and output losses. Zhang et al. (2018) did not examine the temperature impacts on input use for the food processing sector.

6.4. Heterogeneity

We examine whether the estimated impacts of temperature on food processing firms' profits and industrial output differ across regions and ownership types. There exist substantial differences in exposure to high temperatures across regions in China. For example, although growing evidence indicates that hot temperatures above 30 ℃ can reduce firms' productivity, Northeast China has a cold climate and may benefit from rising temperatures. Estimated temperature impacts may vary across ownership types. In contrast to firms with other ownership types, enforcement of labor regulations is weaker in privately owned firms (Ngai 2005) and as a result private firms are less likely to take good protective measures for workers on hot days.

When dosing so, we first split the full sample into subsamples by region to examine whether the estimated temperature impacts on profits and output are regionally heterogeneous. Figure 4A shows that food processing firms in North China are most affected by high temperatures, with profit and output declining by 1.7% (P < 1%) and 1.4% (P < 1%) respectively for each additional day at temperatures above 30 ℃ (Coefficient estimates of temperature variables are reported in Supplementary Table S2). High temperatures above 30 ℃ also exerted large and detrimental impacts in East China, which is the traditional hub of China's industrial activity and has experienced significant warming since 1960 (Piao et al. 2010). Holding all else the same, firms' profit and industrial output in East China declined by 1.2% (P < 1%) and 0.9% (P < 1%), respectively, for each additional day at temperatures above 30 ℃. Higher temperatures above 30 ℃ in the South Central region were also associated with reduced industrial output (Coefficient = -0.065%, P < 1%), while the effect on profit is not statistically significant.

We find that firms' economic output was positively associated with higher temperatures in the Southwest and Northeast regions (Figure 4A). As a cold region, higher temperatures may have been favorable for the rapid expansion of the alcoholic beverage industry (such as, beer, liquor and wine) in Northeast China (Liang et al. 2017). Southwest China, which is home to several top-ranking Chinese liquor factories (such as Kweichow Moutai, Wuliangye), is also a major tobacco planting and manufacturing area. Higher temperatures are beneficial for the tobacco industry in this region, because they produce natural heat to dry out the tobacco leaves in heated barns and reduce the need to burn firewood (Bendix 2019). The correlations of profit and industrial output with temperatures above 30 ℃ in Northwest China are neither statistically nor economically significant (Figure 4A).

Figure 4B displays that domestic firms that are privately owned were most impacted by higher temperatures possibly due to the weak enforcement of labor regulations in private firms. We find no strong evidence on significant impacts of higher temperatures above 30 ℃ on profit for foreign firms, collectively owned firms, and SOE. Holding all else equal, each additional day at temperatures above 30 ℃ is associated with a reduction of 0.67% (P < 1%) in profit for privately owned firms, relative to a day with an average temperature of 21-24 ℃. Except SOE, industrial output declined for all types of food processing firms, ranging from -0.48% (P < 5%) for foreign firms to -0.69% ($P < 1\%$) for privately owned firms, for each additional day at temperatures above 30 ℃.

6.5. Future Warming Impacts

We quantified the potential impacts of future warming on food processing firms' accounting profits and industrial output, using the coefficient estimates of temperature variables presented in Figure 3 and the climate projections based on two widely-adopted global climate model HadGEM2-ES and NorESM1-M under two Representative Concentration Pathways (RCP), namely RCP2.6 and RCP8.5. We projected the impacts of future warming for the medium term (2041-2060) and the long term (2061-2080). The predictions were weighted by firm-specific industrial value added in 2007 and summarized in Figure 5.

We find that future warming is expected to reduce food processing firms' profit and industrial output, but the extent to which the reductions occur depends on the severity of future warming and global climate models. If we use climate projections from the HadGEM2-ES model, the total profits of China's food processing firms are expected to decrease annually by 5.5% under RCP2.6 and by 12.5% under RCP8.5 in the midst of this century. The corresponding predicted profit reductions are smaller, by 1.2% under RCP2.6 and by 6.2% under RCP8.5, if climate projections from the climate model NorESM1-M are utilized. By 2080, the total profits may decline annually by 14.5-23.7% under the most severe climate scenario (RCP8.5). In 2007, the total reported accounting profit of Chinese food processing firms was approximately CNY 95 billion. These projected profit losses due to future warming are, therefore, equivalent to CNY 13.8-22.5 billion (equivalent to USD 1.8-3.0 billion) in 2007 values.

Figure 5 also shows that the magnitudes of the reductions in industrial output are nearly identical to the reductions in profits. Under RCP8.5, industrial output is expected to decline annually by 6.7-12.3% during the mid-21st century and by 14.2-21.9% by 2080. Under RCP2.6, the reductions in industrial output are modest, by 1.7-5.7% by 2050 and by 2.5-5.5% by 2080. The primary driving force of the predicted profit and output reductions is the projected increase in the number of days with temperatures above 30 ℃ (Supplementary Figure S2). The red bars in Figure 5 depict that, under RCP8.5, TFP may decrease by as much as 11.1-17.1% by 2080, if no additional adaptation actions are undertaken.

7. Conclusions and Discussion

To build a climate-resilient food processing sector in China, policy makers need specific information on whether rising temperatures have affected industrial output and profits of food processing firms and channels through which the impacts occurred. We used a comprehensive firm-level data set for major Chinese food processing firms with daily weather data to estimate the relationship between temperature and food processing firms' profit and industrial output and to illustrate the mechanisms through which temperature impacts firms' industrial output and profits. Our statistical evidence indicates that firms' profit and output responded negatively to higher temperatures above 30 ℃ and these negative impacts mainly stemmed from the adverse impacts of higher temperatures on firms' TFP and capital stock.

These results have a number of policy implications. Our findings suggest that climate adaptation polices focusing on China's food processing sector should prioritize developing strategies to reduce the adverse impacts of high temperatures on firms' productivity. As privately owned firms were most impacted by higher temperatures, our results call for a strong need for improved enforcement of labor regulations in privately owned firms. Our results of heterogeneous impacts of higher temperatures also suggest that the development of strategies to cope with future warming should also consider heterogeneity in the effects of temperature across regions.

There are several limitations of this study. Our data set only covers large food processing firms with annual sales above CNY 5 million for a short period of time, yet our results remain remarkably statistically significant and robust across a wide range of variations in specifications, data and variables (Supplementary Figure S1). Utilizing a longer time period of observations is expected to enable us to detect whether Chinese food processing firms have undertaken adaptation actions to cope with heat stress. Although these food processing firms account for a significant share in China's agricultural economy, they may respond differently to a warmer climate relative to small firms. When estimating the future climate impacts, the coefficients of the temperature variables used are based on the short-term observations. Because these coefficient estimates cannot capture the adaptation actions that firms may undertake in the long-term in response to climate change, our estimates of the projected declines in economic output due to temperature rises are expected to be greater than the actual damages that will occur.

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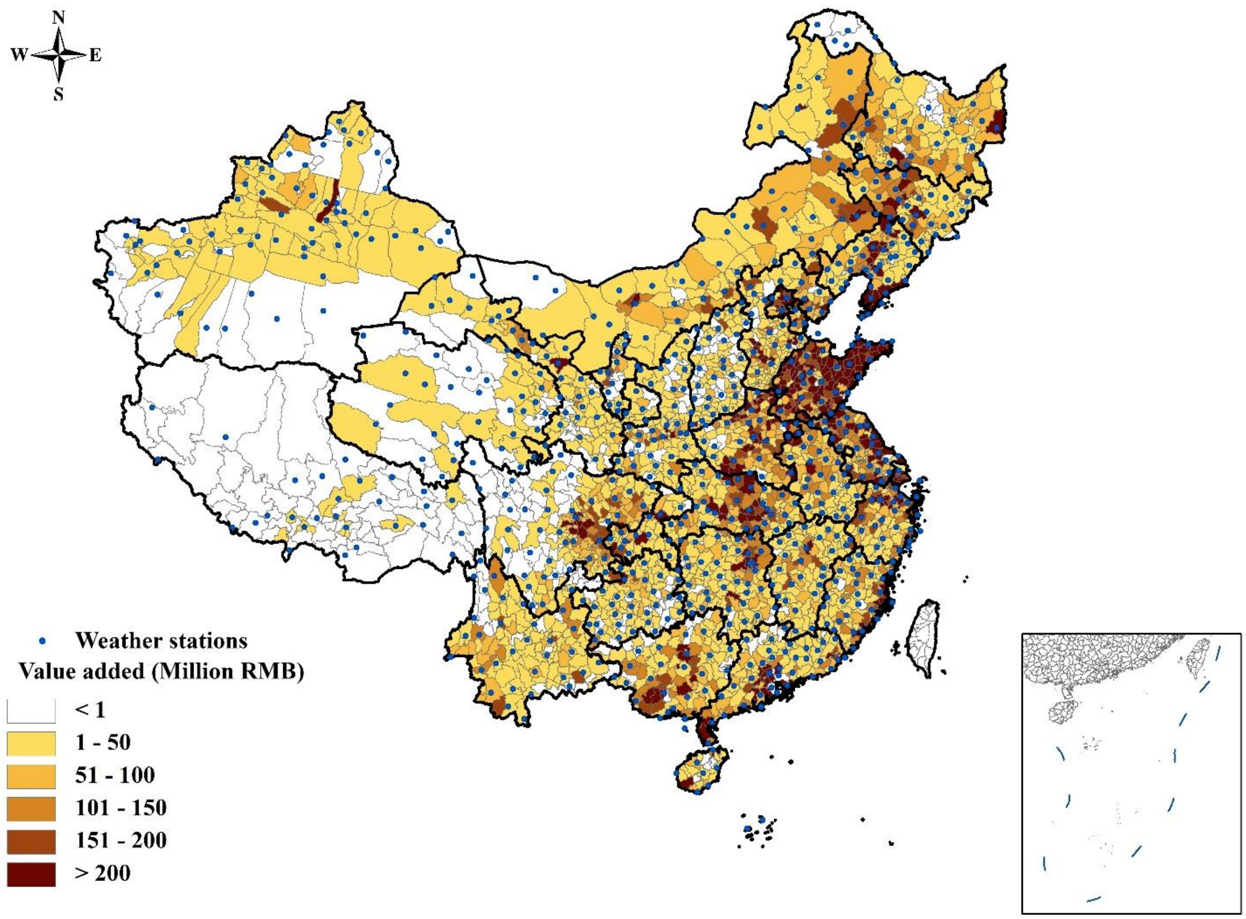


Figure 1. Spatial distributions of weather stations and industrial value added of food processing firms in China. Notes: This figure overlays weather stations (denoted by blue dots) and county-level industrial value added of food processing firms in China. The county-level industrial value added (shown in shades of yellow) are aggregated from the firm-level value added and averaged over 1998-2007.

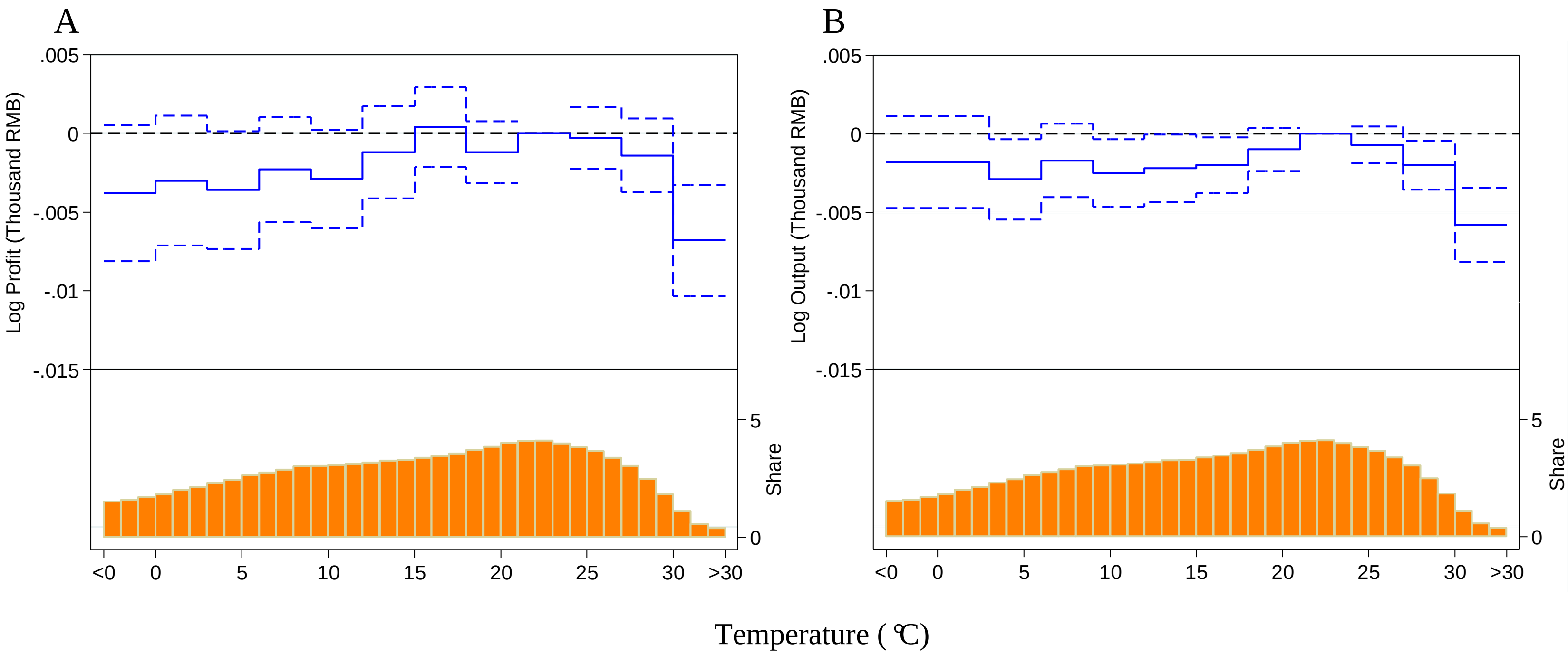


Figure 2. Profit and output responses to temperature changes. Graphs at the top of each frame display the changes in log profit (A) and log industrial output (B) when food processing firms are exposed to different temperature intervals. The solid blue curve in each frame represents point estimates of temperature bins, while the 95% confidence bands are added as blue dashed lines. These coefficient estimates are obtained by estimating Equation (1) and including rainfall, sunshine hours, air pressure, relative humidity, and average wind speed as additional weather variables. Histograms at the bottom in each frame show the percentage distribution of each temperature bin in the data.

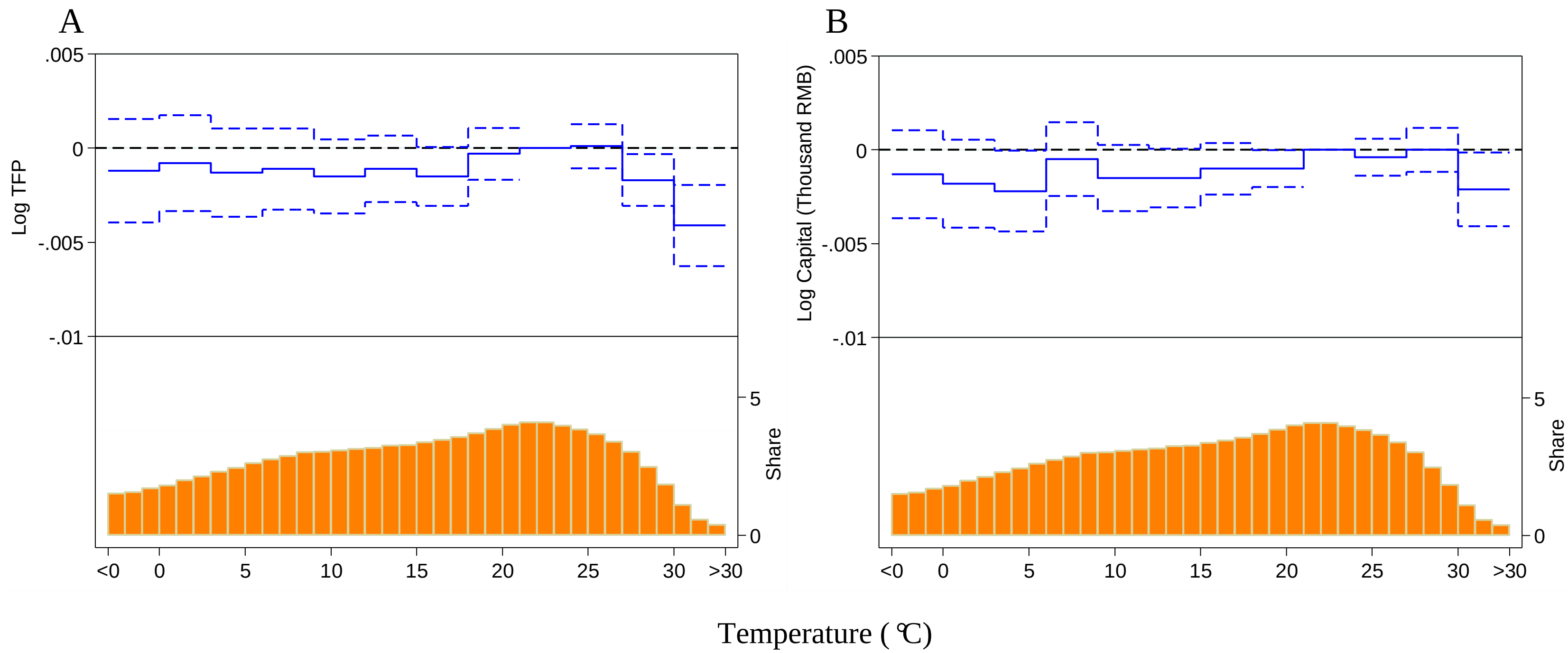


Figure 3. Productivity and capital stock responses to temperature changes. Graphs at the top of each frame display the changes in log TFP (A) and log capital stock (B) when food processing firms are exposed to different temperature intervals. The solid blue curve in each frame represents point estimates of temperature bins, while the 95% confidence bands are added as blue dashed lines. These coefficient estimates are obtained by estimating Equation (1) and including rainfall, sunshine hours, air pressure, relative humidity, and average wind speed as additional weather variables. Histograms at the bottom in each frame show the percentage distribution of each temperature bin in the data.

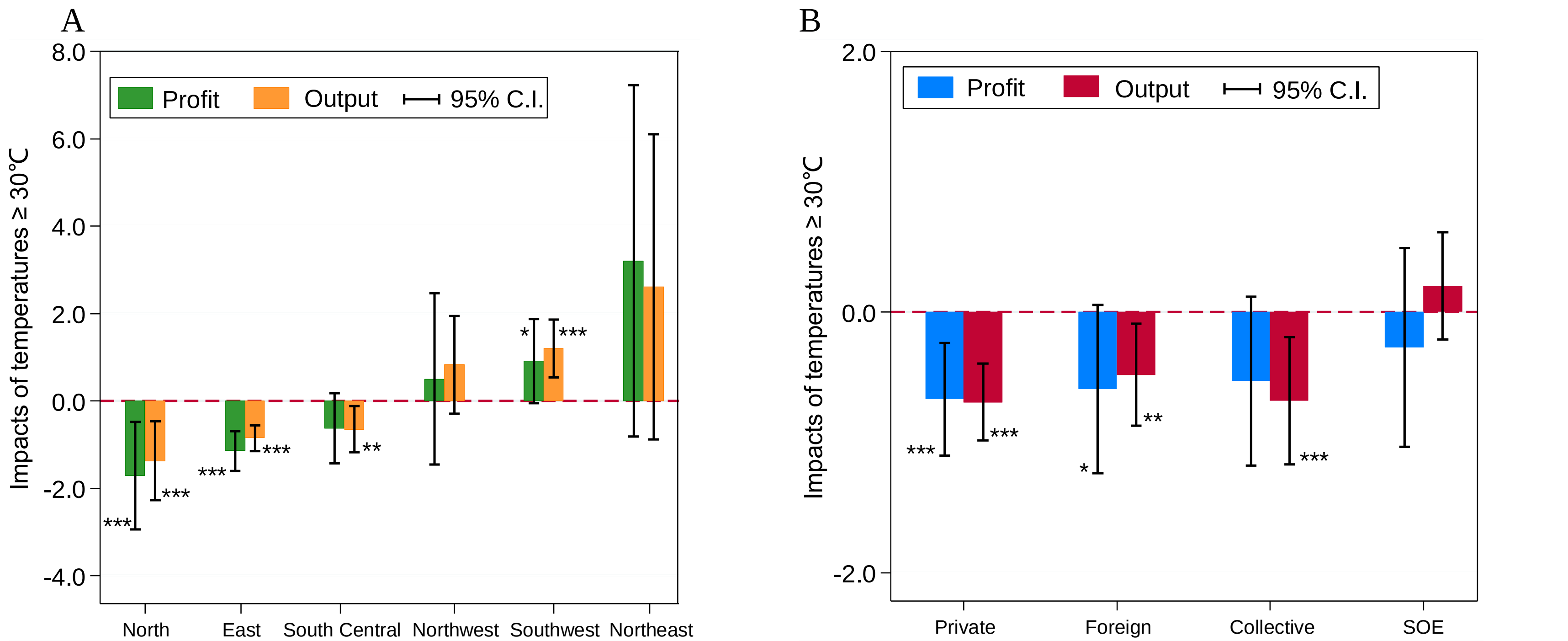


Figure 4. Heterogeneous temperature effects. Graphs at the top of each frame display the changes in log profit and log industrial output across regions (A) and ownership types (B). Bars in each frame represent point estimates of the impacts of one additional day at temperatures above 30 ℃, holding all else equal, while whiskers represent the 95% confidence bands. These coefficient estimates are obtained by using respective subsamples by region and by types of ownership and estimating Equation (1).

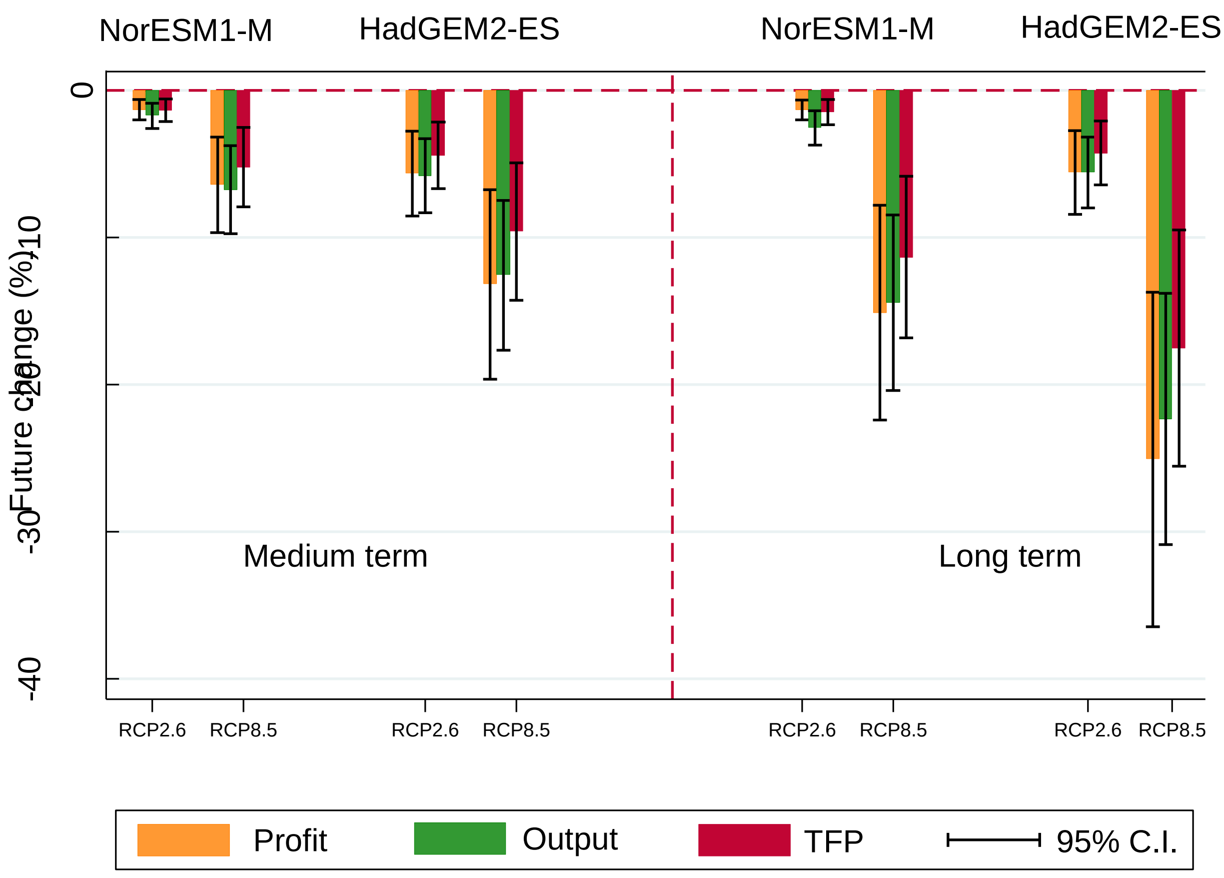


Figure 5. Predicted changes in profit, industrial output and TFP from future warming. This figure displays the predicted percentage changes due to variations in temperature distribution under RCP2.6 and RCP8.5 scenarios of the HadGEM2-ES and NorESM1-M models in the medium term (2041-2060) and the long term (2061-2080). Yellow, green and red bars correspond to the point estimates in profit, output and TFP changes, while whiskers represent 95% confidence bands.

Table 1. Estimated impacts of weather in baseline regressions

	Log (profit)	Log (output)	Log (TFP)	Log (capital stock)	Log (investment)	Log (labor)
<0 ℃	-0.0038*	-0.0018	-0.0012	-0.0013	-0.0030	0.0021**
	(0.0022)	(0.0015)	(0.0014)	(0.0012)	(0.0020)	(0.0009)
[0 ℃, 3 ℃)	-0.0030	-0.0018	-0.0008	-0.0018	-0.0031*	0.0013
	(0.0021)	(0.0015)	(0.0013)	(0.0012)	(0.0019)	(0.0008)
[3 ℃, 6 ℃)	-0.0036*	-0.0029**	-0.0013	-0.0022**	-0.0014	0.0006
	(0.0019)	(0.0013)	(0.0012)	(0.0011)	(0.0018)	(0.0007)
[6 ℃, 9 ℃)	-0.0023	-0.0017	-0.0011	-0.0005	-0.0002	0.0011
	(0.0017)	(0.0012)	(0.0011)	(0.0010)	(0.0017)	(0.0007)
[9 ℃, 12 ℃)	-0.0029*	-0.0025**	-0.0015	-0.0015	-0.0030*	0.0001
	(0.0016)	(0.0011)	(0.0010)	(0.0009)	(0.0016)	(0.0006)
[12 ℃, 15 ℃)	-0.0012	-0.0022**	-0.0011	-0.0015*	-0.0025*	0.0002
	(0.0015)	(0.0011)	(0.0009)	(0.0008)	(0.0014)	(0.0006)
[15 ℃, 18 ℃)	0.0004	-0.0020**	-0.0015*	-0.0010	-0.0032***	0.0005
	(0.0013)	(0.0009)	(0.0008)	(0.0007)	(0.0012)	(0.0005)
[18 ℃, 21 ℃)	-0.0012	-0.0010	-0.0003	-0.0010*	-0.0027**	-0.0001
	(0.0010)	(0.0007)	(0.0007)	(0.0005)	(0.0011)	(0.0004)
[21 ℃, 24 ℃)	-	-	-	-	-	-
[24 ℃, 27 ℃)	-0.0003	-0.0007	0.0001	-0.0004	-0.0001	-0.0006
	(0.0010)	(0.0006)	(0.0006)	(0.0005)	(0.0010)	(0.0004)
[27 ℃, 30 ℃)	-0.0014	-0.0020**	-0.0017**	0.0000	0.0017	0.0000
	(0.0012)	(0.0008)	(0.0007)	(0.0006)	(0.0011)	(0.0005)
≥ 30 ℃	-0.0068***	-0.0058***	-0.0041***	-0.0021**	-0.0025*	-0.0002
	(0.0018)	(0.0012)	(0.0011)	(0.0010)	(0.0015)	(0.0006)
Total rainfall	-0.0016**	-0.0017***	-0.0011**	-0.0010**	-0.0007	-0.0001
	(0.0008)	(0.0005)	(0.0005)	(0.0004)	(0.0008)	(0.0003)
Total sunshine	0.0054**	0.0068***	0.0051***	0.0026**	0.0019	0.0029***
	(0.0022)	(0.0015)	(0.0013)	(0.0012)	(0.0021)	(0.0009)
Average air pressure	-0.0259	-0.0198	-0.0215	0.0061	0.0153	0.0198*
	(0.0229)	(0.0185)	(0.0147)	(0.0161)	(0.0374)	(0.0117)

Average relative humidity	-0.0489**	-0.0201	-0.0064	-0.0250*	0.0608***	0.0007
	(0.0239)	(0.0174)	(0.0155)	(0.0132)	(0.0221)	(0.0101)
Average wind speed	-0.1030	-0.0461	-0.0436	-0.0502	-0.1265*	0.0331
	(0.0654)	(0.0433)	(0.0396)	(0.0392)	(0.0682)	(0.0333)
Total rainfall squared	0.0000	0.0000*	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Total sunshine squared	-0.0000**	-0.0000***	-0.0000***	-0.0000**	-0.0000	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Average air pressure squared	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Average relative humidity squared	0.0004**	0.0002	0.0001	0.0002**	-0.0004**	-0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
Average wind speed squared	0.0056	-0.0056	-0.0009	0.0025	0.0164	-0.0076
	(0.0106)	(0.0070)	(0.0066)	(0.0067)	(0.0115)	(0.0061)
Observations	119,019	119,019	118,795	118,725	119,006	119,019
R^2	0.7848	0.8248	0.6992	0.8860	0.6394	0.8878

Note: This table shows estimated coefficients of weather variables in the baseline regressions. These coefficient estimates are obtained by estimating Equation (4) and including rainfall, sunshine hours, air pressure, relative humidity, and average wind speed as additional weather variables. The two regressions include firm fixed effects, two-digit industry × year fixed effects, and region × year fixed effects. Standard errors, shown in parentheses, are clustered within firms and within prefecture-level city-years. ****p*<0.01, ** *p*<0.05, **p*<0.1

Supporting Information

The impacts of temperature on Chinese food processing firms

Table S1. Summary statistics

Variable	Unit	Observations	Mean	Std. Dev.	Min	Max
Economic variables						
Accounting profit	Thousand RMB	119,019	3409.55	9218.38	1	546,835
Imputed profit	Thousand RMB	103,668	11628.22	21785.19	1	258,549
Industrial value added	Thousand RMB	119,019	17130.67	30551.62	115	262,286
Log TFP	-	118,795	3.46	1.00	-1.57	8.25
Capital stock	Thousand RMB	118,725	16714.92	44858.87	1	3403,929
Labor	Persons	119,019	181.73	337.27	8	16,029
Investment	Thousand RMB	49,452	5552.33	17945.71	1	669,879
Weather variables						
# of days at temperatures ≥ 30 ℃	days	119,019	10.56	12.24	0	88
Total rainfall	cm	119,019	95.75	48.77	0.80	382.48
Total sunshine	10 hours	119,019	200.54	45.69	64.36	353.96
Average air pressure	hPa	119,019	995.27	36.69	800.74	1017.62
Average relative humidity	%	119,019	70.20	7.86	30.07	89.63
Average wind speed	m/s	119,019	2.39	0.96	0.21	8.88

Notes: This table shows summary statistics of our key economic and weather variables. The sample covers 17,962 food processing firms for years 1998-2007. Unit of observation is a firm-year.

Table S2. Estimated temperature impacts on profit and output across regions and ownership types

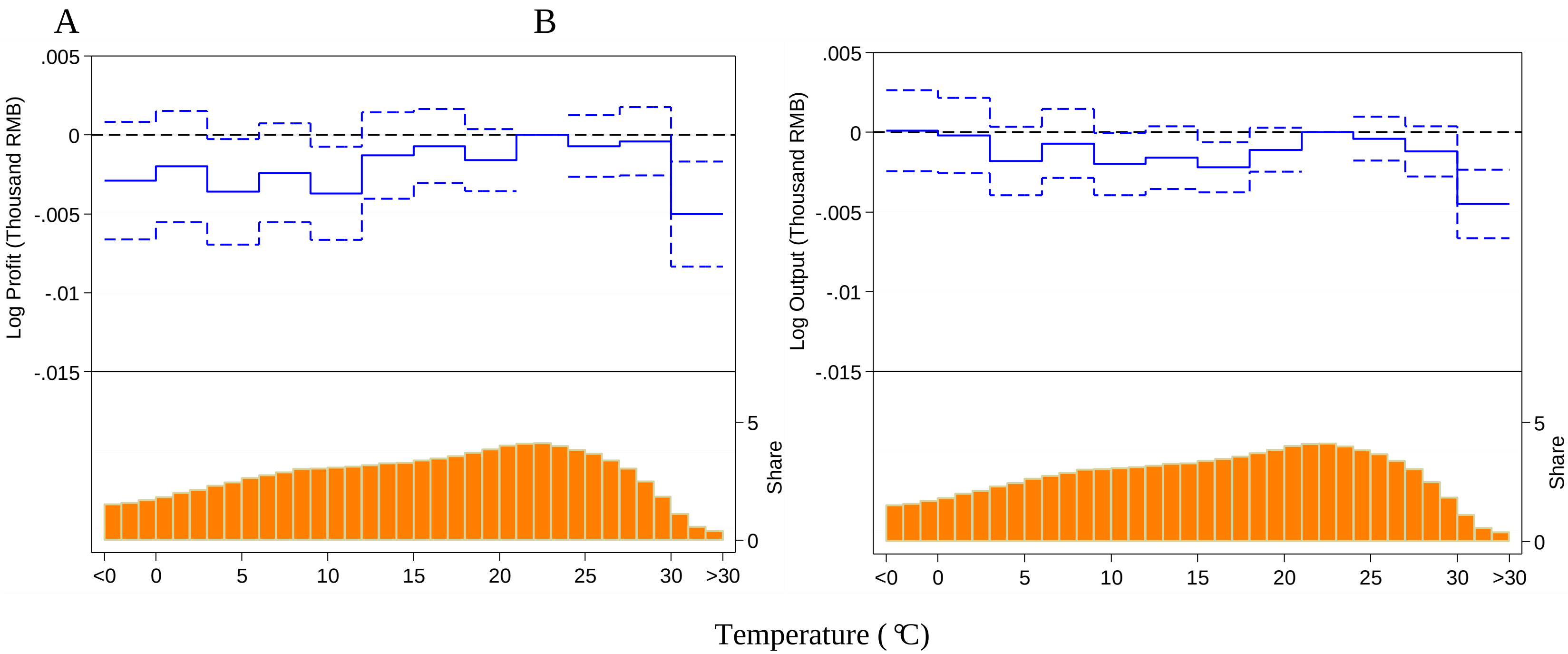
Panel A: Estimated temperature impacts on log (profit)

	North	East	South Central	Northwest	Southwest	Northeast	Private	Foreign	Collective	SOE
	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)
≥ 30 ℃	-0.0171***	-0.0115***	-0.0063	0.0050	0.0091*	0.0320	-0.0067***	-0.0059*	-0.0053	-0.0027
	(0.0063)	(0.0023)	(0.0041)	(0.0100)	(0.0049)	(0.0205)	(0.0022)	(0.0033)	(0.0033)	(0.0039)
Observations	11,930	53,793	29,344	5,031	8,983	9,933	60,439	17,968	14,131	12,979
R^2	0.8047	0.7815	0.7920	0.8071	0.7967	0.7254	0.7633	0.7764	0.8353	0.8443

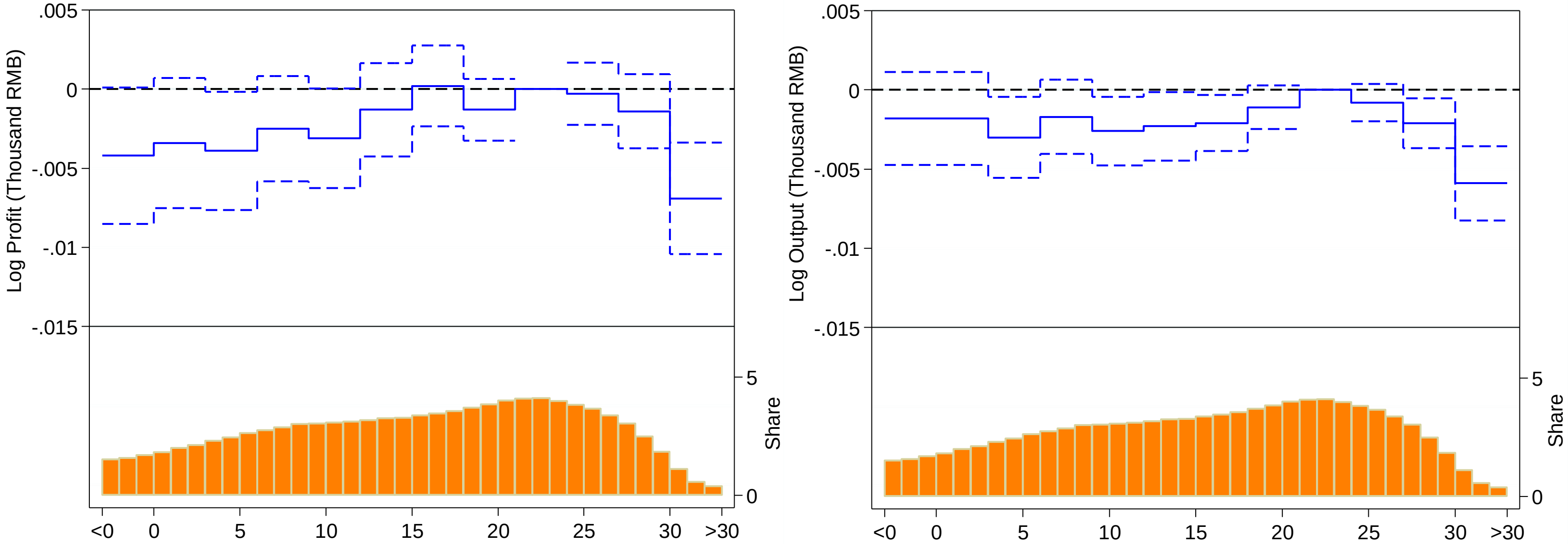
Panel B: Estimated temperature impacts on log (output)

	North	East	South Central	Northwest	Southwest	Northeast	Private	Foreign	Collective	SOE
≥ 30 ℃	-0.0137***	-0.0085***	-0.0065**	0.0083	0.0120***	0.0261	-0.0069***	-0.0048**	-0.0068***	0.0020
	(0.0046)	(0.0015)	(0.0027)	(0.0057)	(0.0034)	(0.0178)	(0.0015)	(0.0020)	(0.0025)	(0.0021)
Observations	11,930	53,793	29,344	5,031	8,983	9,933	60,439	17,968	14,131	12,979
R^2	0.8201	0.8250	0.8340	0.8526	0.8419	0.7891	0.8029	0.8358	0.8531	0.8996

Note: This table shows estimated impacts of temperature above 30 ℃ on profit and output across regions and types of ownership. These coefficient estimates are obtained by estimating Equation (4) and including rainfall, sunshine hours, air pressure, relative humidity, and average wind speed as additional weather variables. For brevity, coefficients of other temperature bins are not reported in this table. These regressions include firm fixed effects, two-digit industry × year fixed effects, and region × year fixed effects. Standard errors, shown in parentheses, are clustered within firms and within prefecture-level city-years. ****p*<0.01, ** *p*<0.05, **p*<0.1

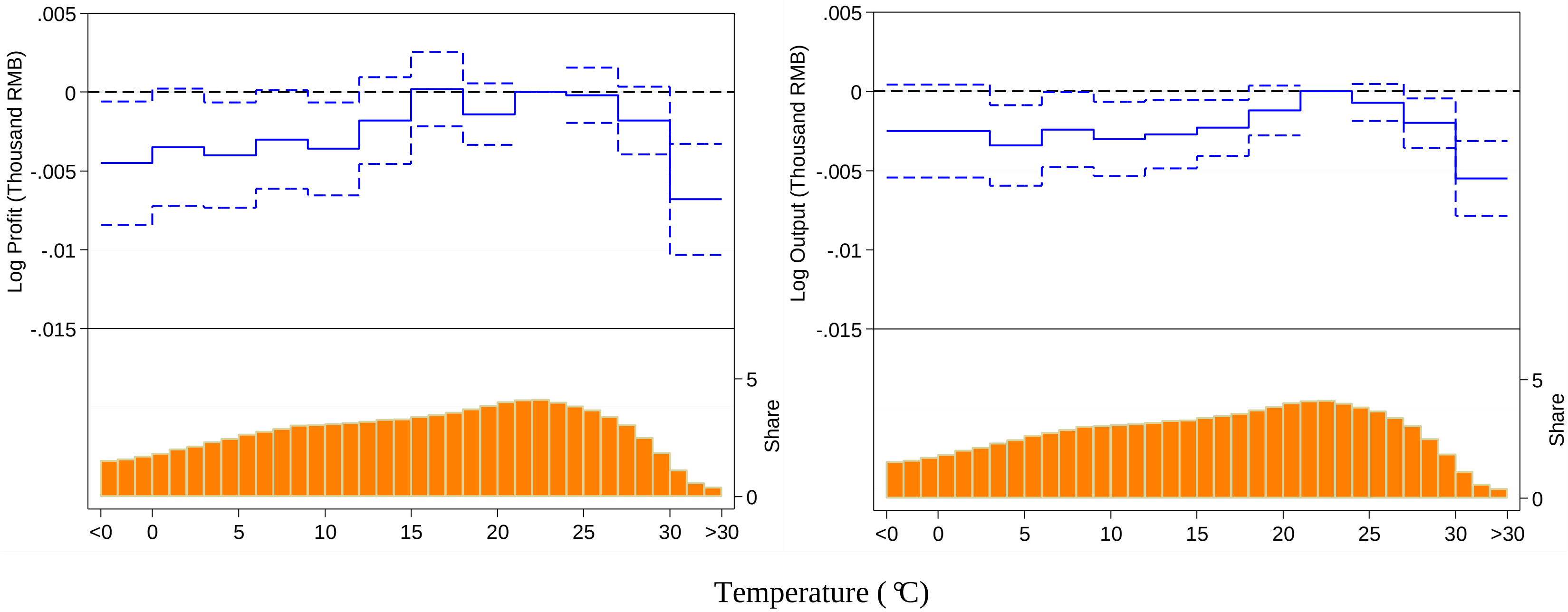


(a). Year fixed effects only

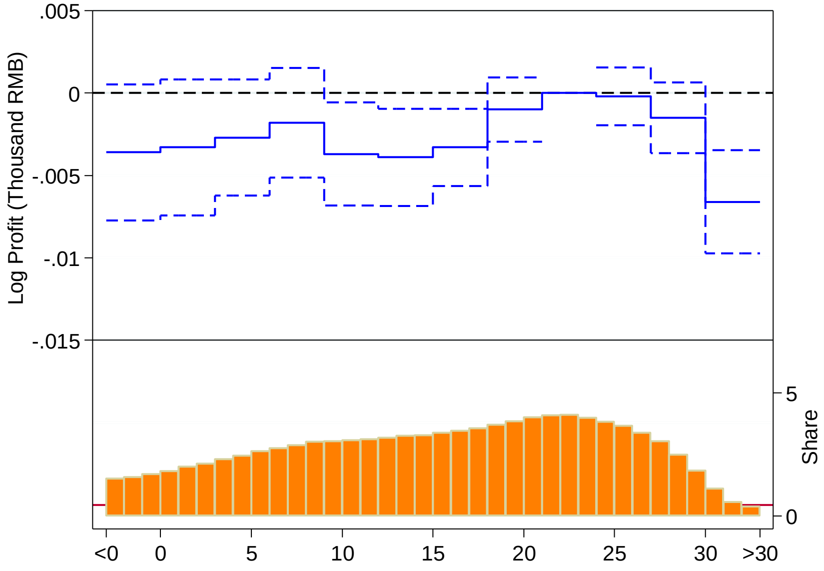


Temperature (℃)

(b). Region × year fixed effects only



(c). Dropping observations with a stringent criterion on accounting profit to sales ratio



Temperature (℃)

(d). Log (imputed profit) as the dependent variable

Figure S1. Robustness checks for estimated profit (output)-temperature relationships. Notes: The figures in the left frame display the effect of daily average temperature on log profit, while the right frame shows the effects of daily average temperature on log output. The blue curve in each figure represents point estimates of temperature bins, while the 95% confidence bands are added as blue dashed lines. Histograms at the bottom show the percentage distribution of each temperature bin in the sample. In Scenario (a), we consider firm fixed effects and year fixed effects only. In Scenario (b), we incorporate firm fixed effects and region × year fixed effects. In Scenario (c), we replicate the analyses by removing observations if a firm's accounting profit to sales ratio is either below the 0.5% level or above the 99.5% level. In Scenario (d), we use the log imputed profit as the dependent variable. These coefficient estimates are obtained by estimating Equation (4) and including rainfall, sunshine hours, air pressure, relative humidity, and average wind speed as additional weather variables. These regressions also include firm fixed effects, two-digit industry × year fixed effects, and region × year fixed effects, unless otherwise noted.

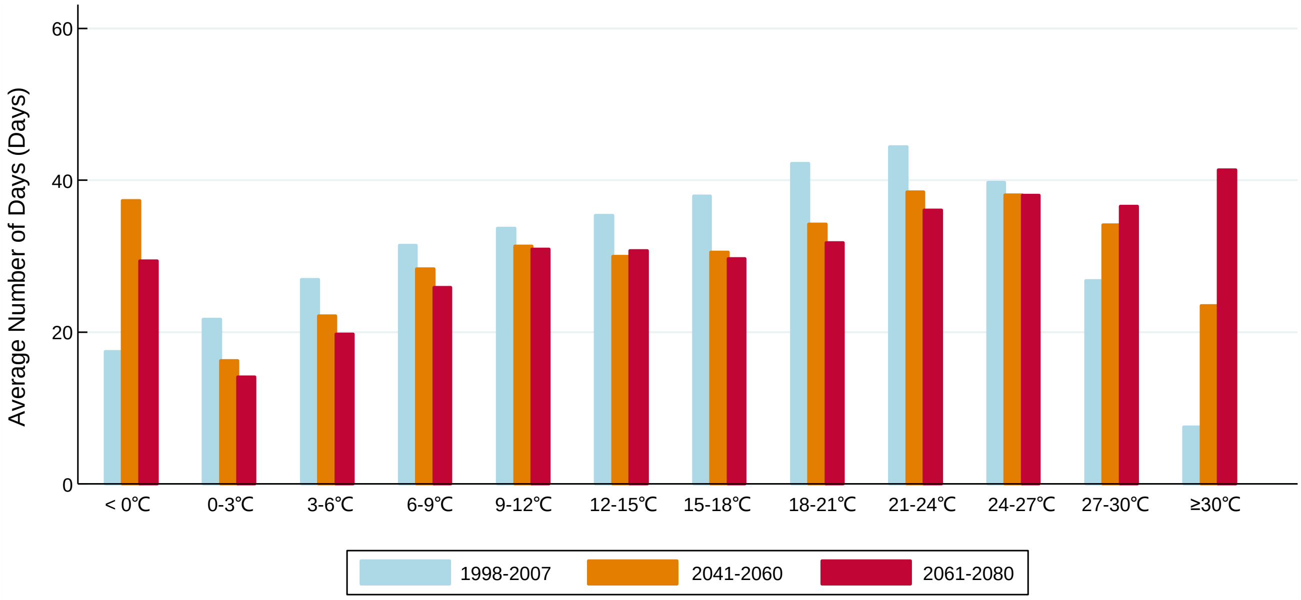


Figure S2. Historical and predicted distributions of daily average temperatures. Light blue, yellow and red bars correspond the 1998-2007, 2041-2060, and 2061-2080 periods, respectively. Predicted average numbers of days with different temperature intervals are obtained from the global climate model HadGEM2-ES under RCP8.5.