High Temperature, Power Rationing, and Firm Performance

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ABSTRACT

This paper investigates the impacts of power rationing on firm performance during heat-induced power shortages and the economic rationales for the government's power rationing strategy in a system characterized by a lack of market mechanisms and price signals. We combine panel data from Chinese firms with fine-scale meteorological data to document robust evidence that high temperatures significantly reduce firms' electricity usage and performance. Leveraging inter-provincial hydropower dispatching and precipitation anomalies, we provide causal evidence that the decline in firms' electricity usage is primarily driven by power rationing during high-temperature days. We further developed a framework to theoretically and quantitatively analyze the social planner's optimal allocation of electricity between sectors and the welfare implications of prioritizing the power demand of household sector. Our results highlight that climate change-intensified inter-sectoral competition for electricity and market inefficiencies can explain power rationing in China.

Key words: High temperatures, electricity usage, power rationing, market mechanism, hydropower
JEL classification: Q54, L51, L60, L94, P21

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1. Introduction

The impact of temperature extremes on firms and industries underscores a critical link between climate change and economic performance in a warming world (IPCC, 2021). Research indicates that climate change not only increases the frequency of heat-induced peak electricity loads but also intensifies regional supply and demand imbalances (Franco and Sanstad, 2008; Auffhammer, 2022). While numerous studies have highlighted the importance of power availability for firm operations and productivity (Fisher-Vanden et al., 2015; Allcott et al., 2016; Cole et al., 2018; Mensah, 2024), there remains a significant gap in understanding how climate change-induced temperature extremes affect firms and industries through the electricity system.

This question becomes even more critical given that the the government's dominant role in allocating electricity resources in China, where a siginificant portion of the power sector is state-owned (Cicala, 2022; Guo et al., 2020). In the summer of 2022, China experienced the most severe heatwaves in the last six decades, coupled by droughts in southwestern China. To manage the surging cooling demand and insufficient power supply, the Sichuan provincial government suspended all factory operations in 19 out of 21 cities for six days, affecting major companies like Apple, Foxconn, and Intel. In such cases, the government was forced to balance the competing electricity demands between the residential and industrial sectors. In China, the government has made commitments and regulations to prioritize the provision of electricity to the residential sector[1]. As global climate change intensifies, heat-induced power shortages and rationing are expected to increasingly disrupt local economies, not only in China but worldwide. While a substantial body of research has examined the effects of high temperatures on electricity consumption, the focus has predominantly been on the household sector (Deschenes and Greenstone, 2011; Auffhammer and Mansur, 2014; Davis and Gertler, 2015; Barreca et al., 2016; Yu et al., 2019; Zhang et al., 2022). However, there is a notable gap in understanding how high temperatures induced supply shock affect electricity usage within firms.

We answer this question by combining panel data from the National Tax Surveys (NTS) of manufacturing firms in China and fine-scale meteorological data from 2007 to 2016. This dataset provides information on the firm's address, annual electricity usage, and other inputs and outputs, enabling a comprehensive analysis of the impact of temperature exposure on firms. Our

[1] For instance, in 2011, the National Development and Reform Commission of China issued the "Regulations on Orderly Electricity Management", prioritizing residential electricity demands.

baseline empirical strategy employs within-province year-by-year ambient temperature variation to identify the effect of local high temperatures on firms' electricity usage.

To start with, we show that holding all else constant, for each additional standard deviation increase of days (4.86 days, or 1.94% of annual working days) with a daily average temperature exceeding 31°C compared to a reference day[2], there is a 3.50% decrease in a firm's electricity usage. Our estimates remain robust across various alternative empirical specifications, displaying both statistical significance and consistent magnitudes. Together with the previous literature highlighting high temperatures increasing residential sector electricity consumption, our results suggest that the government's prioritization of electricity supply to residents reduces firms' electricity availability. This implies that high temperatures represent a negative shock to the electricity supply for firms, consistent with the anecdotal evidence reflected in the 2022 heatwave and power rationing in Sichuan province. Further analysis indicates that high temperatures significantly reduce firms' performance and output via the availability of electricity. Meanwhile, we do not observe any significant effects of high temperatures on firms' factor reallocation or the substitution effects of coal and oil.

To validate heat-induced power rationing, we employ a strategy that leverages an exogenous variable that only affects firms' electricity availability during high temperatures without influencing their electricity demand. The rationale behind this strategy is that if no power rationing occurs, it can be assumed that firms have unlimited access to electricity. Consequently, their electricity usage should remain unaffected by variations in exogenous pure electricity supply shock. Conversely, if firms' electricity usage is sensitive to the pure electricity supply shock, it implies that power rationing is taking place, indicating that the available electricity supply for firms cannot meet their power demand.

We construct a province-level pure electricity supply shock using hydropower availability, inspired by the approach employed by Allcott et al. (2016) and Cole et al. (2018). Firstly, we identify each province's hottest month of the year based on monthly average temperatures. Then, we calculate precipitation anomalies in the province and its hydropower-sourcing provinces prior to the hottest month. We assume that precipitation anomalies before the hottest month may affect firms' availability of electricity from hydropower but are exogenous to firms' electricity demand

[2] Daily average temperature between 11°C and 16°C.

during the hottest month. Meanwhile, we construct and incorporate the inter-provincial hydropower transmission matrix to account for hydropower dispatching. The final pure electricity supply shock is an average of precipitation anomalies weighted by the hydropower dependence between provinces.

Our results reveal that firms' electricity usage is highly sensitive to exogenous electricity supply during high temperatures, indicating that industrial firms in China experience power rationing. Furthermore, we find that firms' electricity-usage-high-temperature sensitivity is more pronounced at lower levels of hydropower availability. This implies that when high temperatures overlap with inadequate hydropower supply, the severity of power rationing experienced by firms intensifies. We also provide empirical evidence supporting the role played by the government. We show that state-owned enterprises (SOEs) exhibit a greater sensitivity of electricity usage to high temperatures than non-SOEs. This suggests that the government may sacrifice the demand of SOEs first when considering power rationing. We also conduct a falsification test by constructing a supply shock using precipitation anomalies a month *after* the hottest month and do not find any significant results.

Several alternative explanations that can potentially account for our baseline results and threaten the power rationing channel are excluded. High temperatures and surging residential electricity demand may lead to an increase in electricity prices (Ponticelli et al., 2023). However, if this were the case, we would expect to observe a smaller impact of high temperatures on firms' electricity usage with better profitability. Additionally, the literature has found that industrial firms in China are insensitive to short-term electricity price adjustments, as the costs associated with reorganizing production far outweigh the magnitude of electricity cost increases (Zhou et al., 2019). We also do not expect timely adjustments in contract prices by China's electricity wholesalers or retailers in response to high temperatures. We collect monthly electricity price indices for industrial firms in 36 major cities in China from 2007 to 2016. We do not find significant evidence indicating that industrial electricity prices respond to high temperatures. On the contrary, industrial electricity prices exhibit relative stability, often remaining unchanged for consecutive months in China.

High temperatures can reduce firm output through decreased productivity or other channels unrelated to electricity supply (Zivin and Neidell, 2014; Zhang et al., 2018; Chen and Yang, 2019; Agarwal et al., 2021). The reduction in electricity usage may be merely a side effect of the decrease in firm output. Our results may be trivial if these channels dominate the effect. To address this concern, we include labor, capital, and total factor productivity (TFP) in our baseline regression. Our results remain robust with the productivity channels controlled. Furthermore, we find no evidence that high temperatures increase equipment failures or lead to significant adjustments in firms' labor and capital inputs.

Taking a step forward, we elucidate the economic rationales behind the government's power rationing strategy. Both government dominance and the transitory nature of high temperatures render the electricity market inefficient in responding to heat-induced power shortages. We attempt to explain why the government prioritizes the household sector and implements power rationing in the industrial sector from the perspective of social welfare maximization. We first directly compare the household sector's willingness to pay (WTP) to avoid power interruptions with the industrial value-added losses resulting from power rationing. Our findings indicate that the household sector's welfare loss due to power interruptions is four times the marginal industrial value-added output. Then, we construct a static model to analyze the trade-off faced by the social planner in allocating electricity resources between the household and industrial sectors in the absence of market mechanisms and price signals. We discover that the optimal allocation depends on the electricity substitution elasticities in both sectors. Our estimation of electricity substitution elasticities supports the conclusions of our direct comparison.

Finally, we investigate potential ways to reduce the welfare losses associated with power rationing by analyzing the rationing mechanism employed by the Chinese government. We demonstrate that larger firm size, greater profitability, and higher productivity do not exempt firms from power rationing. Therefore, we postulate that the Chinese government implements *random* regional rationing. We suggest that reducing the welfare losses caused by high-temperature-induced power shortages can be achieved by implementing *efficient* rationing that prioritizes regions with lower social costs for rationing.

Our paper makes several contributions to the literature. Firstly, this paper enhances our understanding of the impacts of high temperatures on firms and the economy. Previous research has found that high temperature reduces firms' labor productivity, TFP, revenues, and output (Zivin and Neidell, 2014; Zhang et al., 2018; Chen and Yang, 2019; Agarwal et al., 2021; Pankratz et al., 2023), and consequently lowers regional economic growth, particularly in developing countries (Hsiang et al., 2017; Kalkuhl and Wenz, 2020; Kahn et al., 2021). To understand the underlying mechanisms, some research has provided evidence that high temperature increases residents' or regions' electricity consumption and costs (Deschenes and Greenstone, 2011; Auffhammer and Mansur, 2014; Davis and Gertler, 2015; Barreca et al., 2016; Yu et al., 2019; Zhang et al., 2022). Tang and He (2024) find that high temperature reduces the adoption of robots and automation by firms in China. In this paper, we show that power rationing induced by high temperature is another explanation for the productivity loss. To the best of our knowledge, we are the first to analyze the impact of high temperatures on firms' electricity usage in developing countries. The study most closely related to ours is by Ponticelli et al. (2023), which demonstrates that high-temperature shocks increase energy costs for US firms in a highly marketized electricity sector. Our paper examines how the government allocates resources among sectors with competing demands in the absence of a pricing mechanism. We find that, in this setting, firms experience a reduction in electricity consumption due to heat-induced power rationing, contrasting with the increase observed in more market-driven environments. Although our study is based on China's institutional framework, the challenges of climate shocks and non-market-oriented electricity systems are prevalent globally, especially in developing countries.

Secondly, our study reveals the economic rationales behind power rationing on firms. Extensive research has examined the economic consequences of electricity shortages (Reichl et al., 2013; Allcott et al., 2016; Cole et al., 2018; Chen et al., 2023; Mensah, 2024). Some studies have utilized cooling degree days (CDD) as an instrument to investigate the impact of power shortages on firms, particularly in China, such as Fisher-Vanden et al. (2015). However, when and why this strategy works remain unclear. Our study elucidates that the government prioritizes residential electricity demand, leading to power rationing for industrial firms during periods of high temperatures. Further analysis reveals that the government's power rationing strategy is shaped by a trade-off for maximizing social welfare, which depends on the electricity elasticity of substitution in both the residential and industrial sectors.

Lastly, our study shed light on how to address resource scarcity when market mechanisms are absent. The shift from government dominance to liberalization in the energy sector is a common trend internationally, particularly in developed countries like the United States (Cicala, 2022), the United Kingdom (Sweeting, 2007), and Spain (Ito and Reguant, 2016). Literature has found that liberalizing energy markets can reduce power plants' costs and improve market efficiency (Davis and Wolfram, 2012; Kabir et al., 2011; Cicala, 2022). We provide empirical evidence that insufficient energy supply lowers firm performance, particularly during power shortages induced by climate extremes. One way of solving resource scarcity is to accelerate the ongoing energy market liberalization reforms in China (Guo et al., 2020; Chen et al., 2022; Cao et al., 2024). Apart from the market reforms, we also provide insights on reducing welfare losses by improving the power rationing mechanism. Our results demonstrate that the government implements random regional rationing when facing a power shortage. The costs of power rationing could be reduced through efficient rationing by linking power cut schedules with social costs of rationing.

2. Data

2.1 Firm data

The firm-level data used in this study come from the National Tax Surveys conducted by the Chinese State Administration of Taxation from 2007 to 2016. This survey annually samples about 700,000 firms from all industries, sizes, and ownership types. The sampled firms are legally obligated to report operational and tax-related data, including annual electricity usage, to the local tax bureaus using standardized forms.

We process the NTS data to address several issues. First, we create a unique ID for each firm. Each firm is assigned a 15-digit (18-digit after 2015) registration ID in the NTS database. However, the registration ID for firms with the same name and address can vary over the years[3]. To address this, we generate a unified, unique ID for each firm by considering two factors: (1) treating firms with the same name and address as the same firm, and (2) considering the firms with the same juridical person ID (the 7th-14th digits of the registration ID) as one firm.

Second, we unify different versions of Chinese Industry Classification (CIC) codes used in the NTS data. Each firm in the database is classified into a 4-digit Chinese Industry Classification (CIC) code. The CIC standard switched from *GB/T 4754-2002* to *GB/T 4754-2011* in 2013. We unify two versions of the industry codes at the 3-digit level.

Third, due to frequent changes in China's administrative division coding system, we unify the 6-digit county codes system in the NTS data. To validate the unified geocoding of firms, we utilize the *AMap* geocoding service to parse the latitude and longitude based on their reported

[3] For instance, missing values or transitioning from a 15-digit to an 18-digit format.

addresses, enabling us to determine the corresponding county. Subsequently, we compare the parsed locations with each firm's county codes reported by the NTS. The firms are excluded if the parsed and reported locations differ at the municipality level. Firms for which the county could not be determined have also been removed. Approximately 7% of observations are removed during this process.

Finally, we remove irregular observations that exhibit non-positive values for total assets or value-added output. Furthermore, we eliminate firms with electricity usage, prime operating revenue, or fixed assets smaller than 1. We also exclude firms with no more than four employees, as many of these entities are typically individual businesses that resemble households rather than formal enterprises. We detail the steps for cleaning the data in Appendix C.

We measure firms' TFP using several approaches. We employ the LP approach proposed by Levinsohn and Petrin (2003) as the primary approach to estimate firms' TFP due to its advantages in estimation consistency. We use the OP approach (Olley and Pakes, 1996), also commonly used in the literature, to calculate firm-level TFP for robustness checks. Our results remain consistent across different TFP estimation approaches. To examine the significance of electricity in firm production, we calculate TFP both with and without controlling for electricity as an input factor[4] (Fisher-Vanden et al., 2015).

2.2 Meteorological data

The meteorological data in this paper comes from the *China Surface Climate Data Daily Value Dataset* (V3.0) from the National Meteorological Information Center, which includes the daily air pressure, temperature, precipitation, relative humidity, wind speed, sunshine hours, and evaporation of 824 weather stations in China. We first interpolate the meteorological data into gridded data with a resolution of 0.1 degrees by 0.1 degrees using inverse distance weighting. Then, we take the within-region average to obtain daily weather data in China from 1975 to 2016 at the county level.

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[4] Theoretical equations for firm-level TFP with and without controlling for electricity using a classical Cobb-Douglas framework can be expressed as follows: (1) $TFP_{it}^{E} = \ln Q_{it} - \sigma_L \ln L_{it} - \sigma_K \ln K_{it} - \sigma_E \ln E_{it}$ and (2) $TFP_{it}^{NE} = \ln Q_{it} - \sigma_L \ln L_{it} - \sigma_K \ln K_{it}$, where Q, L, K, and E represent firm's value-added output and labor, capital, and electricity inputs, respectively. The superscripts "E" and "NE" indicate TFP with and without controlling for electricity, respectively.

2.3 Interprovincial electricity dispatching data

We obtain interprovincial electricity dispatching data from the "*Compilation of Statistical Information on China's Electric Power Industry*" from 2006 to 2016. We manually clean and encode this data into an interprovincial electricity transmission matrix. Some of the interprovincial transmission records are labeled with specific transmission grid lines. Therefore, we can identify whether the transmitted electricity is from hydropower or thermal power if the specific transmission line is known to transmit hydropower or thermal power exclusively. For the cases where the source of electricity cannot be determined, we estimate the amount of hydropower dispatched across provinces based on the proportion of provincial hydropower production to total electricity production in that year.

Interprovincial electricity allocation plays a crucial role in China's power supply system. Figure 1 illustrates the flow of interprovincial electricity dispatching in 2007. In northern China, the primary transmission lines transport electricity from provinces such as Inner Mongolia, Shanxi, and Ningxia in the west to provinces like Beijing and Hebei in the east. These transmission lines predominantly carry thermal power, leveraging the coal resources in northwest China. In southern China, the main transmission lines transfer electricity from provinces such as Guizhou, Yunnan, and Hubei in the west to provinces like Guangdong and Shanghai in the east. These southern transmission lines have a significant proportion of hydropower sourced from the abundant water resources in southwest China. Figure A1 illustrates the proportions of hydropower in total electricity consumption across China, southern provinces, and northern provinces from 2006 to 2016. The average dependence on hydropower exceeds 20% for an average province in China, with southern provinces surpassing 30%.

[Insert Figure 1 about here]

2.4 Matching firm and weather data

We match the firm-level data with weather data by county and year. Approximately 95% of the firms in the NTS dataset are classified as small and medium-sized enterprises according to the government's standards. For larger firms and conglomerates that may have multiple plants, their different branches and plants registered separately are treated as distinct firms as long as they have different registration IDs. Therefore, our data is seemingly establishment-level, and we are not concerned about substantial mismeasurement of firm-level temperature exposure due to our merging strategy. In Appendix C, we detail the steps for cleaning the data and discuss the results using different samples[5]. After the data cleaning steps and removing singletons, our final regression dataset consists of unbalanced panel data with 171,270 distinct manufacturing firms and 586,168 observations from 2007 to 2016.

Panel A of Table 1 represents summary statistics for the main variables in our sample. The dataset shows an average firm's annual value-added output of approximately \$0.77 million. It requires an input of 1.24 million kWh of electricity, \$1.01 million capital value, and employs 129 workers. The differences in TFP calculated using the LP and OP methods for firms are insignificant. However, the TFP is slightly lower when controlling for electricity as an input factor. We also report weather conditions at the firms' locations, including annual average temperature (*Temp*), cumulative precipitation (*Pre*), average relative humidity (*Rhu*), average wind speed (*Win*), and average sunshine hours (*Sun*). The annual average temperature (*Temp*) is calculated as the mean of daily average temperatures over a year. *Temp* has a mean value of 15.82 in our sample and exhibits substantial variation across different firms ($\sigma = 4.56$).

[Insert Table 1 about here]

3. Estimation strategy

3.1 Empirical approach

To investigate how temperature exposure affects firms' electricity usage, we follow the model of Schlenker and Roberts (2009) and Addoum et al. (2023) by assuming that the firm's production process nonlinearly depends on regional temperature. We provide a more detailed discussion of this estimation strategy in Appendix B. Consistent with the approach adopted by Deschênes and Greenstone (2011), Dell et al. (2014), and Zhang et al. (2018), we estimate the nonlinear impact of temperature on firm's electricity usage using the equation (1).

$$\ln y_{it} = \sum_{n \neq 6, n=1}^{10} \beta^n \cdot TemB_{it}^n + \delta \boldsymbol{X}_{it} + \mu_i + \lambda_{pt} + I_{st} + \boldsymbol{\epsilon}_{it} \tag{1}$$

[5] Using the sample containing all industries, we find that the impact of high temperatures significantly reduces firms' electricity usage. However, this effect is primarily driven by manufacturing firms. Manufacturing firms constitute about 40% of all firms and 69% of electricity usage in the NTS. Based on anecdotal evidence and policy documents (e.g., "*Regulations on Orderly Electricity Management*" issued in 2011), manufacturing firms are more likely to be subject to electricity rationing compared to other industries, such as agriculture and services. Therefore, our research primarily focuses on manufacturing firms. Refer to Appendix C for further discussion on the impact of high temperatures on non-manufacturing firms.

where $\ln y_{it}$ denotes firm i's electricity usage in year t in log form. $TemB_{it}^{n}$ is the number of days experienced by firm i in year t with daily average temperature that falls in the n[th] temperature bin. We lump the first bin as the number of days with a daily average temperature below -9°C and the last (10[th]) bin as the daily average temperature that exceeds 31°C. The 6[th] bin (11°C–16°C) is omitted to avoid multicollinearity in estimating equation (1). Thus, the semi-elasticity coefficients β^{n} should be interpreted as the marginal effect of an extra day with temperature in the n[th] bin relative to a day with temperature between 11°C and 16°C. Other factors are denoted $\boldsymbol{X}_{it}$ and include quadratic of precipitation, average relative humidity, average wind speed, and sunshine hours. μ_i is the firm fixed effect proxy for time-invariant firm characteristics. Considering that the impact of temperature may exhibit substantial industry heterogeneity (Addoum et al., 2023), we control for two-digit-industry-by-year fixed effects (I_{st}).

Figure 1 shows the importance of including the province-year fixed effect (λ_{pt}). Due to interprovincial electricity dispatching in the grid system, firms' electricity usage may be influenced by temperature shocks in other regions. By introducing province-year fixed effects, we analyze the impact of temperature shocks on firms' electricity usage within provinces, holding the local electricity supply potential constant. Including province-year fixed effects also mitigates the potential influence of factors such as electricity policy changes and new power generation units within the provincial grid.

We choose the sixth bin as the reference because it is the middle bin and corresponds to the annual average temperature experienced by the firms in our sample. The middle-bin specification also aligns with the literature (Zhang et al., 2018; Agarwal et al., 2021), and our results are independent of the reference bin selection. In the robustness check, we also report results for alternative specifications for the temperature bins, including a step function with 3°C intervals and Chebyshev polynomials estimated with 1°C intervals, following Schlenker and Roberts (2009), Burke et al. (2015), and Addoum et al. (2023).

We report the descriptive statistics for two sets of temperature bins in Panel B and C of Table 1. In this study, we are particularly interested in the temperature bins representing high temperatures due to the global warming trend. The results show that the number of days with a daily average temperature exceeding 31°C is relatively small, with an average of only 5.32 days per year, indicating rare occurrences. However, it has a significantly bigger coefficient of variation

(1.54), much larger than other temperature bins, which boosts our confidence in considering high temperatures as exogenous shocks.

We also calculate temperature anomalies at the bin level by subtracting the average temperature bin over the past ten years. Figure 2 illustrates the mean temperature anomalies experienced by an average county in China from 2003 to 2020 at each 1°C interval. We observe a significant increase in high-temperature anomalies and a significant decrease in low-temperature anomalies among Chinese firms, with a clear threshold at 15°C. The results show that between 2007 and 2016, the number of days with a daily average temperature falling within the (29, 30] and (30, 31] ranges increased by more than one day compared to the previous ten years, which reveals a clear warming trend in China.

[Insert Figure 2 about here]

3.2 Hydropower transmission and climate-induced electricity supply shock

One identification challenge is that regional high temperatures may simultaneously affect both electricity supply and demand. To further investigate whether high temperatures lead to power rationing, we leverage an exogenous electricity supply shock using interregional hydropower transmission and precipitation anomalies. Due to the water-storage-dominated characteristic of hydropower generation, the precipitation patterns and water inflows in the past few months can significantly affect the supply potential of hydropower in the focal month. Inspired by Allcott et al. (2016) and Cole et al. (2018), we assume that, for a given province, the hydropower availability can be exogenously influenced by precipitation anomalies in the province and its hydropower-sourcing provinces one month prior. In contrast, the prior precipitation anomalies is unrelated to high temperatures and the heat-induced changes in electricity demand of firms in the hottest month.

For province p, we have the following identity:

$$C_{pt} = G_{pt} + Import_{pt} - Export_{pt} \tag{2}$$

where C_{pt} and G_{pt} represent the hydropower consumption and generation in province p during year t. $Import_{pt}$ is the amount of hydropower received by province p from other provinces, while $Export_{pt}$ is the amount of hydropower allocated by province p to other provinces. Based on the interprovincial allocation of hydropower, we calculate the degree of dependency of province p on hydropower from other provinces in year t using the following approach:

$$Dep_{pjt} = \frac{e_{jpt}}{C_{pt} + Export_{pt}} \quad (3)$$

where e_{jpt} represents the amount of hydropower dispatched from province j to province p in the year t. When $j = p$, e_{jpt} indicates the amount of hydropower generated and used within provinces p itself. We have $\sum_j Dep_{pjt} \equiv 1$. Subsequently, we construct an indicator of hydropower supply potential for the hottest month in province p.

$$HydropowerPotential_{pt} = \sum_j (Dep_{pjt-1} \cdot PrecAno_{j,[m-3,m-2]}) \quad (4)$$

where m represents the hottest month in province p during year t. We identify the hottest month in a year as the month with the highest monthly average temperature. $PrecAno_{j,[m-3,m-2]}$ refers to the anomaly of cumulative precipitation in province j during months $m-3$ to $m-2$ in year t. The precipitation anomalies are calculated as the difference between the precipitation and the 10-year historical average of the corresponding months.

Then, we employ the following equation to estimate how firms respond to exogenous electricity supply shocks overlapping with high-temperature periods.

$$\ln y_{it} = \theta \cdot HydropowerPotential_{pt} + \delta \boldsymbol{X}_{it} + \mu_i + I_{st} + \boldsymbol{\epsilon}_{it} \quad (5)$$

Figure A2 illustrates the implications for different values of θ. When $\theta = 0$, it implies that exogenously increasing or decreasing electricity supply during high temperatures does not affect firm electricity usage, resulting in a vertical curve along the x-axis. This indicates the absence of electricity constraints during high temperatures. However, if $\theta > 0$, it signifies that firm electricity usage during high-temperature periods increases with the exogenous increase in electricity supply. This implies that electricity supply shortages restrict firms' electricity usage during high temperatures; in other words, firms are "electricity-constrained" or power-rationed.

4. Results

4.1 Main Results

We aim to examine whether and how firms respond to high temperatures in electricity usage. Table 2 presents the estimation results for Equation (1), visually represented in Figure 3. The first column of Table 2 reveals a significant negative correlation between a firm's electricity usage and high-temperature exposure. This conclusion remains significant and robust as columns

(2) and (3) successively introduce other weather control variables and two-digit industry-year fixed effects. The results indicate that holding all else constant, for an extra day increase with a daily average temperature exceeding 31°C compared to the reference bin (11°C–16°C), there is a 0.72% decrease in a firm's electricity usage. Moreover, for each additional standard deviation increase of days (4.86 days[6]) with a daily average temperature exceeding 31°C, there is a 3.50% decrease in a firm's electricity usage. The scale of this effect is highly robust across different empirical specifications. This effect holds significant economic significance compared to the existing literature's relevant findings[7].

[Insert Table 2 about here]

[Insert Figure 3 about here]

We then perform several robustness tests to ensure that specific empirical specifications do not drive the observed results. Columns (1) and (2) of Table 3 present the results when replacing the reference bin with the fifth (6°C–11°C) and seventh (16°C–21°C) bins, respectively. While the choice of the reference bin may affect the magnitude of the estimated coefficients slightly, our conclusions remain significant both statistically and economically. In columns (3) and (4) of Table 3, we explore clustering the standard errors at different levels. Our findings remain robust even when two-way clustering the standard errors at the firm and province-year level or simply clustering at the province level (31 provinces).

[Insert Table 3 about here]

Our conclusions remain robust after substituting different measures of temperature exposure. In column (5) of Table 3, we employ temperature anomalies as a proxy for firm-specific temperature exposure. In columns (6) and (7) of Table 3, we construct temperature bins and anomalies with a 3°C interval. In column (8), we proxy high temperatures using the cooling degree days. Additionally, we adopt the Chebyshev polynomials approach proposed by Schlenker and Roberts (2009) to relax specifications regarding the temperature bins and functional form as much as possible. The estimated results are presented in Figure 4. Our estimation consistently demonstrates statistical and economic significance across various empirical specifications.

[6] 4.86 days is equivalent to 1.94% of working days (based on 250 working days per year).

[7] For instance, Zhang et al. (2018) show that an extra day with temperature larger than 90°F (32°C) decreases output by 0.45%, relative to an extra day with temperature between 50–60°F (10–16°C), for the above-scale industrial firms in China.

[Insert Figure 4 about here]

4.2 Power rationing

A logical question arises as to why there is a negative correlation between high temperatures and firms' electricity usage. Intuitively, firms may increase their electricity usage during high temperatures to maintain a comfortable working environment, similar to how households respond to high temperatures. Existing studies have consistently shown that high temperatures significantly increase household electricity demand and usage (Davis and Gertler, 2015; Barreca et al., 2016; Zhang et al., 2022). However, our empirical findings indicate a negative correlation between high temperatures and firms' electricity usage. Although high-temperature shocks are often transitory and idiosyncratic compared to the vast electricity grid, it does not indicate the absence of heat-induced power supply shortages (relative to total demand). Actually, existing research has demonstrated that rapid ramping services and power dispatching cannot fully cover peak electricity demand (An and Zhang, 2023). Theoretically, households and industrial sectors compete for electricity resources in situations of inadequate electricity supply. Therefore, it is also reasonable to postulate that in a context where the government has the authority to allocate electricity resources and prioritize electricity supply for households, the surge in electricity demand from the residential sector due to high temperatures may crowd out firms' electricity availability.

Our baseline estimates utilize localized temperature exposure and thus cannot differentiate between heat-induced electricity supply and demand shock. To address this challenge, we employ equation (4) to construct an exogenous measure of pure electricity supply shock during high temperatures in the province where the firms are located. Then, we employ equation (5) to further examine whether firms' electricity supply is constrained during high temperatures by testing "usage-supply sensitivity". Table 4 shows the estimations of θ are significantly positive under different empirical specifications. The result implies that during high temperatures, if the province where the firms are located enjoys a greater electricity supply, the firms' electricity usage also increases. This indicates that firms are power rationed during high temperatures.

[Insert Table 4 about here]

We provide additional support to validate the legitimacy of the electricity supply shocks by examining whether the shock variable constructed using precipitation anomalies in the months *following* the hottest month is related to firms' electricity usage. Table A1 shows the results of this falsification test. The regression coefficients of $HydropowerPotential_{pt,[m+2,m+3]}$ and firm electricity consumption are positive but not statistically significant. This falsification test also sheds light on the exact timing of the heat-induced power rationing. Here, we test the sensitivity of the firm's electricity usage to power supply in the surrounding months of the hottest month to verify the presence of power rationing, despite our electricity usage data and baseline model being annual-based. In the baseline results, we show that high temperatures significantly reduce electricity usage, while the impact of low temperatures is not significant. These results suggest that power rationing due to extreme high temperatures in summer (hot months) may be the reason for firms' reduced electricity usage rather than the effects of extreme low temperatures.

Figure 5 provides further evidence of the power rationing. We divide the sample based on the median of electricity supply shocks and perform subsample regressions. We find that a greater impact of high temperatures on firm electricity consumption is observed in scenarios where high temperatures overlap with inadequate hydropower supply. In subsamples with greater extra hydropower supply, the effect of high temperatures on firm electricity consumption is smaller. The results indicate that the power rationing effect is more prominent when high temperatures overlap with droughts. Furthermore, we find that SOEs exhibit greater sensitivity in electricity usage to high temperatures. This suggests that the government may sacrifice the SOEs and prioritize non-SOEs' demand during periods of strained electricity supply.

[Insert Figure 5 about here]

We further divide our sample into three sub-samples based on the abundance of hydropower resources in each province, with each sub-sample containing ten provinces. Table A3 presents the regression results using these sub-samples. The results verify our expectations, showing that in regions with lower hydropower abundance and greater dependence on imported hydropower, the firm's electricity usage has a significantly higher sensitivity to electricity supply shocks during high temperatures.

4.3 Alternative explanations

One possible explanation for our baseline results is the price effect. The increase in electricity demand during high temperatures may surge electricity prices, prompting firms to reduce their electricity usage (Ponticelli et al., 2023). However, we tend to rule out the price effect in China. In China, the electricity prices for manufacturing firms depend on their contracts with electricity retailers. Retailers may not be able to promptly respond to high temperatures and adjust electricity prices. Furthermore, literature has found that industrial firms in China are insensitive to short-term electricity price adjustments, as the costs associated with reorganizing production far exceed the magnitude of electricity cost increases (Zhou et al., 2019). To test the price effect, we collect monthly electricity price indices for industrial firms with a voltage level of 35kV or above in 36 major cities in China from 2007 to 2016, as published by the Price Monitoring Center of the National Development and Reform Commission. We find no economically significant correlation between monthly electricity price indices (ln*EPI*) and the city's temperature, as shown in Table A4. In Figure A3, we present the trend of the average EPI across 36 cities. It reveals that industrial electricity prices in China exhibit relative stability, often remaining unchanged for consecutive months.

Another possible explanation is that high temperatures reduce firms' output through mechanisms unrelated to electricity supply or demand, leading to decreased electricity usage only as a side effect. Previous literature has documented that high temperatures significantly reduce industrial firms' labor productivity, TFP, and output (Zivin and Neidell, 2014; Zhang et al., 2018; Chen and Yang, 2019; Agarwal et al., 2021). If such side effects entirely drive our results, we expect the sensitivity of firm electricity usage to high temperatures to disappear after controlling for variables such as labor, capital, and total factor productivity. In columns (1)–(3) of Table 5, we sequentially add labor productivity, capital productivity, and TFP as control variables in the baseline model. We find that including labor and capital productivity does not affect the sensitivity of firm electricity usage to high temperatures. Indeed, after controlling for TFP, the sensitivity decreases but remains significant at the 5% level. After accounting for the TFP channel, the marginal effect of an extra day with an average temperature exceeding 31°C on the firm's electricity usage reduction is estimated to be 0.49%.

[Insert Table 5 about here]

If high temperatures lead to an increase in equipment failure rates and subsequent shutdowns, it may also result in a decrease in firm electricity usage. To investigate this possibility further, we regress the firm's equipment repair and maintenance expenses (*Ln(1+R&M)*) on temperature bins. However, our regression results do not indicate a significant positive correlation between the firm's equipment repair and maintenance expenses and high temperatures, as shown in Table 6.

[Insert Table 6 about here]

4.4 Economic consequences

We further investigate whether heat-induced power rationing and the decline in electricity usage affect firms' output. Previous research on the relationship between high temperatures and output has overlooked electricity as a crucial input factor of firms' production process. In column (1a) of Table 7, we show that high temperatures significantly reduce firms' output. The results indicate that for each additional day with a temperature exceeding 31°C compared to the reference bin, an average firm's output decreases by approximately 0.4%. Our estimates are similar to those of previous studies (Zhang et al., 2018; Chen and Yang, 2019). However, column (1b) shows that when we include electricity input as a control variable in the regression model, the sensitivity of firm output to high temperatures significantly decreases by 13%–30%. In columns (1c) and (1d) of Table 7, we replicate this analysis using temperature bins with a 3°C interval and arrive at the same conclusion. TFP is considered one of the primary channels explaining the output-high temperature sensitivity in the literature. In column (2a), we validate that high temperatures indeed reduce firms' TFP in our sample. However, when we incorporate electricity input into the firm's production function and recalculate TFP, we find a significant decrease in the sensitivity of TFP to high temperatures, as shown in column (2b). In columns (2c) and (2d), we obtain consistent results using alternative temperature bins. Our findings demonstrate robustness when estimating TFP using the OP method in untabulated results.

A plausible postulation is that firms may have backup power generators to cope with electricity shortages during high temperatures. In Panel B of Table 7, we analyze the impact of high temperatures on firms' factor reallocation. However, we do not find significant evidence of the change in labor and capital due to high temperatures, consistent with previous literature (Zhang et al., 2018; Chen and Yang, 2019). As shown in Panel C of Table 7, the sensitivity of firms' coal and oil consumption in response to high temperatures is close to zero and not statistically significant, either at the extensive or intensive margin. These results combined suggest that while high temperatures may affect firms' performance by reducing the availability of electricity, they may not have made sufficient adjustments to address this transitory shock, at least in the short term.

[Insert Table 7 about here]

5. Welfare implications

5.1 Direct comparison

One insightful question is how to understand the decision of the Chinese government to prioritize residential electricity demand during high-temperature periods in terms of social welfare. To shed light on this question, we first compare the marginal reduction in industrial value-added due to power rationing with the residents' marginal willingness to pay (WTP) to avoid power interruptions for the same amount of electricity. Following the literature estimating the "value of the lost load" (de Nooij et al., 2007; 2009; Zachariadis and Poullikkas, 2012), we estimate the loss in industrial firms' value-added due to power rationing using the production-function approach. For convenience, we employ a Cobb-Douglas production function to estimate the average economic value-added loss when firms reduce their electricity input by 10MWh. The production function is estimated using a 2SLS method, considering hydropower potential as instrumental variables for electricity input. The estimation results are detailed in Table A5. Our results show that, on the margin, removing 10 MWh of electricity from an average firm yields an economic value-added loss of approximately US$1,010.

Estimating the welfare losses for the residential sector due to power interruptions is typically challenging since no market allows households to trade power interruptions directly. However, the contingent valuation method (CVM) combined with survey studies offers a viable approach [8] to estimating the impact of power interruptions based on the residents' stated preferences (Hartman et al., 1991; Baik et al., 2020; Zhao et al., 2022). Nevertheless, relevant surveys and empirical studies in this area remain scarce. The only estimation available for Chinese residents that we could find is provided by Zhao et al. (2022), which estimated the residents' WTP to avoid air conditioning interruptions induced by electricity outages during summer electricity peaks based on a survey study conducted in a major Chinese city in 2020. Their results showed that the median WTP for avoiding a half-hour air conditioning interruption was CN￥2.91, while the median WTP reached as high as CN￥6.75 for avoiding a one-hour interruption. These estimates are lower than the WTP of residents in other more developed regions and countries for

[8] Introductions and comparisons of other related methods, such as household production-function-based approaches, market-behavior-based approaches, and case studies, can be found in de Nooij et al. (2007) and Baik et al. (2020).

avoiding power interruptions, as revealed by other studies[9] (Woo et al., 2014; Baik et al., 2020). Then, our calculation yields that the welfare of allocating 10 MWh of electricity to the residential sector during high temperatures is $3,702. We visualize the comparison of the value of the lost loads in Figure 6.

[Insert Figure 6 about here]

In estimating China household's MWTP, Zhao et al. (2022) only consider the interruption of air conditioning, which may underestimate the impact of power interruptions on household welfare via all appliances, despite the literature emphasizing the importance of air conditioning as the primary means for residents to cope with heat-related physical damages (Naughton, 2002; Basu, 2009; Agarwal et al., 2021; Xi et al., 2024). Nevertheless, our back-of-envelope calculation reveals that the marginal welfare effect of allocating more electricity to households during high-temperature periods is four times greater than the marginal economic value-added of allocating it to firms.

5.2 A static model of the optimal allocation

Taking a step further, we construct a simple yet intuitive static model to analyze the social planner's optimal allocation of electricity resources between the household and industrial sectors under the premise of inadequate supply. We detail the model specification, solution, and calibration in Appendix D. In our model, the total electricity output of the power sector E_S is featured by a Leontief production function so that the maximum electricity output is a constant N.

$$E_S = \min\,(A_E L_E, N)$$

where A_E denotes the productivity of the power sector, and L_E is the labor employed in the power sector. We then analyze how a social planner, aiming to maximize social welfare, should allocate electricity resources between representative households and firms. The utility function U of the representative household is defined as

$$U = \left[\lambda_1 Y^{\frac{s_1-1}{s_1}} + (1-\lambda_1) E_H^{\frac{s_1-1}{s_1}}\right]^{\frac{s_1}{s_1-1}}$$

[9] Using a similar estimation strategy, Woo et al. (2014) found that residents in Hong Kong had a WTP of up to $45 to avoid a one-hour power interruption, while Baik et al. (2020) documented that U.S. residents had a WTP ranging from approximately $1.7 to $2.3 per kWh for avoiding power interruptions.

where Y and E_H indicate the consumption of normal goods and electricity, respectively. λ_1 is the share parameter, and s_1 denotes the household's elasticity of substitution. Normal goods are produced by the firm with the technology $Y = A_I \left[\lambda_2 L_I^{\frac{s_2-1}{s_2}} + (1-\lambda_2) E_I^{\frac{s_2-1}{s_2}}\right]^{\frac{s_2}{s_2-1}}$, where A_I denotes the firm's productivity. L_I and E_I represent the labor and electricity inputs, and s_2 represents the elasticity of substitution between the two composites.

We define the allocation share $\mu = \frac{E_H}{E_S}$. The social planner is facing a trade-off featured by

$$\frac{\partial U}{\partial \mu} = \underbrace{U^{\frac{1}{s_1}} \lambda_1 Y^{-\frac{1}{s_1}} \frac{\partial Y}{\partial \mu}}_{\text{Utility loss due to less products}} + \underbrace{U^{\frac{1}{s_1}} (1-\lambda_1) (E_H)^{-\frac{1}{s_1}} \frac{\partial E_H}{\partial \mu}}_{\text{Utility gain due to more electricity}} = 0$$

Thus, the effect of change in μ on utilities can be decomposed into two parts. The first component refers to the change in utility resulting from a change in the consumption of the product, while the second component represents the change in utility resulting from a change in the consumption of electricity. By solving the social planner's problem, we have the optimal allocation ($r = E_I/E_H$) characterized by

$$r^* = A_I^{s_2-1} \left(\frac{\lambda_1}{1-\lambda_1}\right)^{s_1 \frac{1-s_2}{1-s_1}} \theta^{\frac{s_2-s_1}{1-s_1}}$$

were $\theta = pY/eE_H$, and we assume that high temperatures increase household electricity demand, and the social planner always prioritizes the household sector, resulting in a decrease in θ.

Our model reveals that in an electricity market characterized by a constrained total supply and the absence of market mechanisms, an increase in residential electricity consumption due to high temperatures leads to a decline in industrial output (see proof in Appendix D). To maximize welfare, the social planner must weigh the trade-off between increased electricity consumption and reduced consumption of normal goods. Furthermore, we elucidate that the optimal allocation is characterized by the substitution elasticities in both the household and industrial sectors. The social planner should allocate more electricity to the industrial sector only when the substitution elasticity of the household sector exceeds that of the industrial sector ($s_2 < s_1 < 1$). However, based on our calibration, the electricity substitution elasticity of the household sector in China is significantly lower[10]. This implies that the welfare loss from electricity interruptions in the

[10] $\hat{s_1} = 0.616$ and $\hat{s_2} = 0.863$. See Appendix D3 for more details.

household sector is much greater than that from power rationing in the industrial sector. Consistent with our findings in Section 5.1, more electricity should be directed toward the household sector during heat-induced electricity shortages.

5.3 Regional rationing mechanism and potential welfare improvement

Finally, building upon our justification for applying power rationing to industrial firms, we further explore potential improvements to reduce the welfare loss from heat-induced power rationing. Our static model suggests that enhancing industrial firm productivity can mitigate the welfare loss from power rationing, aligning with existing empirical studies (Sweeting, 2007; Ito and Reguant, 2016; Cicala, 2022). For instance, Cicala (2022) documents that introducing market mechanisms to determine power generation in the United States can significantly reduce production costs and enhance welfare. In addition to the liberalization of electricity markets, which are typically slow and contentious, regional rationing mechanisms can directly reduce the welfare loss from power rationing. Efficient regional rationing, as opposed to random rationing, can minimize social costs by prioritizing rationing in regions with lower social costs (de Nooij et al., 2007; 2009).

In Figure 7, we present the heterogeneity analysis of the impact of high temperatures on firms' electricity usage based on their total assets, return on assets (ROA), and TFP. Our findings indicate that larger, more profitable, and more productive firms do not escape power rationing. This confirms our conclusion that the price mechanisms are absent during high-temperature shocks. With market mechanisms in place, we expect the electricity usage of better-performing firms to be less affected by high temperatures, as they have a higher capability and willingness to pay to avoid power interruptions. More importantly, these results suggest that the Chinese government implements random regional rationing, which implies that the welfare loss could be mitigated through efficient regional rationing by prioritizing rationing in regions with lower social costs first.

[Insert Figure 7 about here]

6. Conclusions

Global climate change has led to more frequent heat shocks and droughts, impacting both the supply and demand sides of the electricity market and threatening social welfare. Despite its importance, there is limited empirical evidence on the impact of heat-induced power shortages and power rationing on industrial firms' performance. This paper presents the first study documenting the effects of power rationing on firms and the significant reduction in their electricity availability due to high temperatures. We further explore how the government allocates electricity resources between household and residential sectors during heat-induced power shortages and market inefficiencies.

Our study has several key implications. First, we demonstrate that the power system's response to high temperatures is a crucial mechanism affecting the industrial sector. Our research highlights the government's central role in managing the nexus of climate change, electricity supply, and firm performance. In the context of climate change and increasing resource constraints, governments must balance the welfare of residential and industrial sectors. Ignoring specific institutional backgrounds and the power system's role can significantly underestimate the welfare impacts of high temperatures and climate change.

Second, hydropower provides resilience in addressing peak load during high temperatures. Our empirical results indicate that when high temperatures coincide with decreased hydropower availability, the electricity supply is significantly restricted, leading to power shortages and rationing. High-confident climate models predict that climate change will lead to higher temperatures and increased drought conditions in Asia. In such scenarios, the energy sector may turn to technological substitutions, increasing reliance on thermal power generation and emitting more CO_2, thereby hindering energy transition and climate governance efforts. Policymakers must consider both high temperature and water availability in climate change adaptation strategies.

Lastly, our research provides insights into mitigating and adapting to the impacts of high temperatures on firms. It is often assumed that larger-scale and more profitable firms exhibit greater resilience against shocks like high temperatures. However, our findings demonstrate that firms are subject to power rationing regardless of size, profitability, and productivity, indicating random regional rationing in China. An efficient regional rationing mechanism that prioritizes regions with lower social costs may mitigate the welfare loss from heat-induced power rationing.

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Figures and Tables

Figures

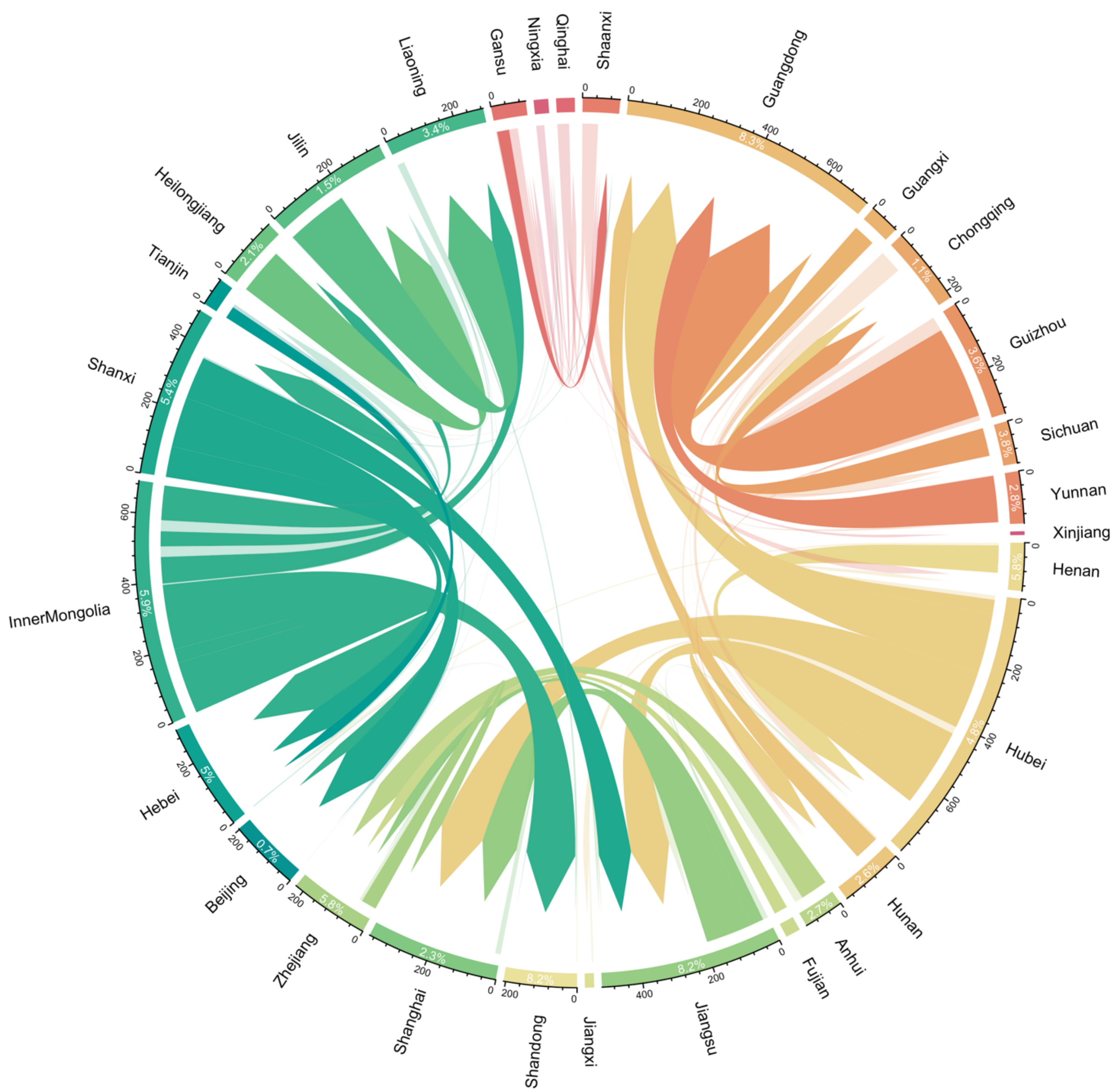

Figure 1. Interprovincial electricity transmission volume in China in 2007. Only the dispatching of electricity is depicted. The percentage indicates the proportion of provincial annual electricity generation to total national electricity generation. The grid on the axis indicates the amount of electricity imported or exported by the province (in GWh).

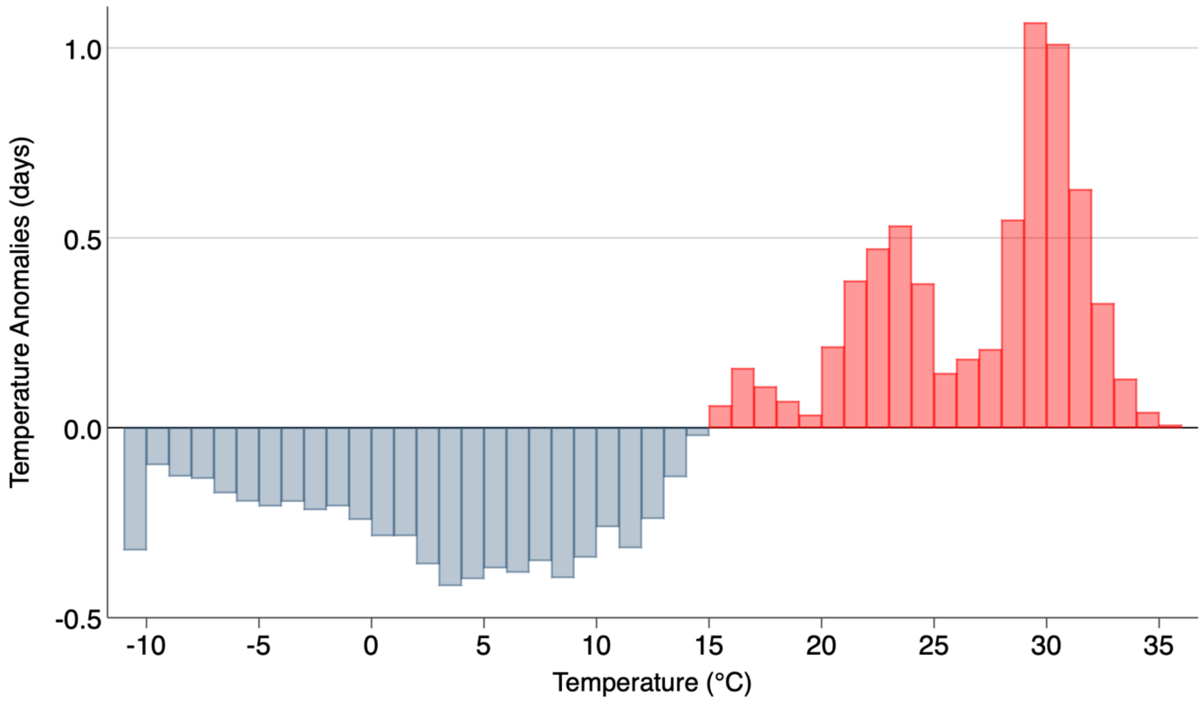

Figure 2. Mean values of temperature anomalies experienced by an average county in each 1°C interval in China from 2003 to 2020. Temperature anomalies are calculated by subtracting the average temperature bin over the average of the past ten years.

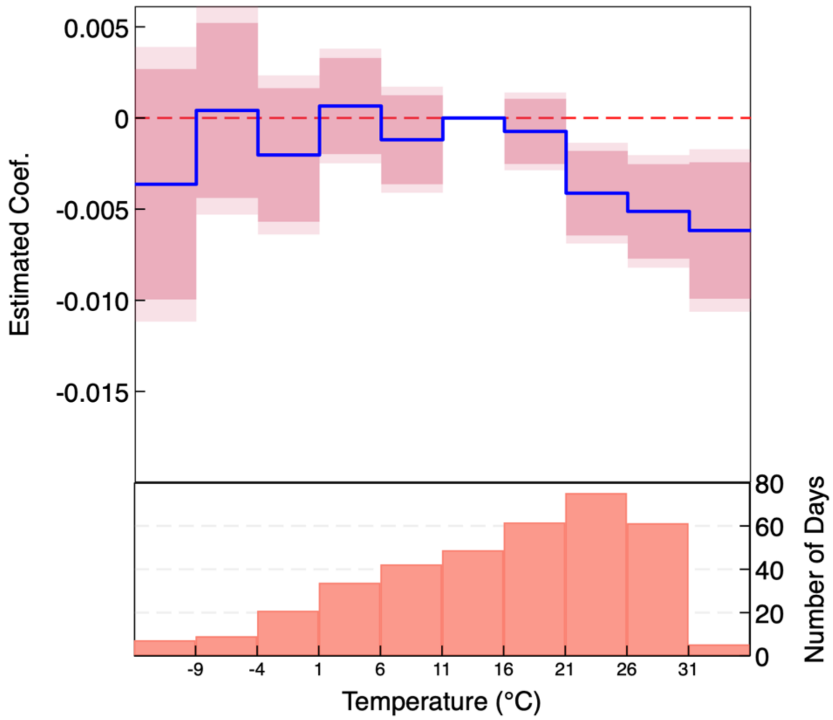

Figure 3. The impact of temperature on firms' electricity consumption using the bin approach. The solid blue line represents the point estimate for β^n, while the dark- and light-shaded areas represent the 95% and 90% confidence intervals, respectively. We control for firm, province-year, and two-digit industry-year fixed effects and employ cluster-robust standard errors at the county level. Detailed results can be found in the third column of Table 2. The lower half of the figure displays the distribution of temperature bins.

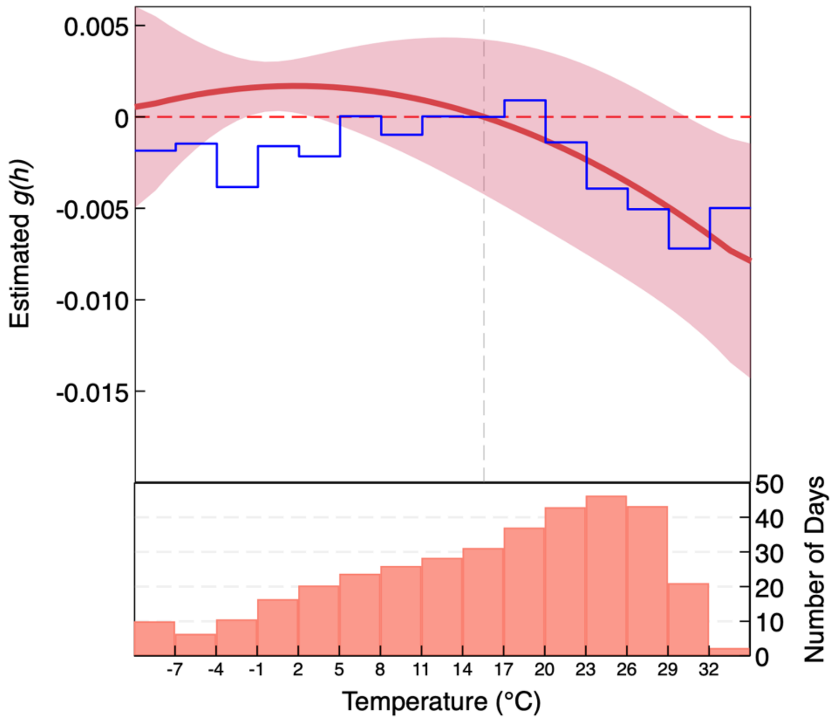

Figure 4. The effect of temperature on firm's electricity usage using 3°C interval temperature bins and Chebyshev polynomials. The blue solid line represents the estimation results of equation (1) using temperature bins with a 3°C interval, with the omission of the ninth (14°C–17°C) bin. Detailed regression results are in column (6) of Table 3. The red solid line presents the estimation results using the Chebyshev polynomials approach proposed by Schlenker and Roberts (2009), with the shaded area representing the 95% confidence interval for this estimation. Consistent with Addoum et al. (2023), we employ third-order Chebyshev polynomials, where $g(h) = \sum_{s=1}^{3} \gamma_s T_s(h)$ and $T_s(h)$ indicates the s-th order Chebyshev polynomial. $g(h)$ is defined in the Appendix B.

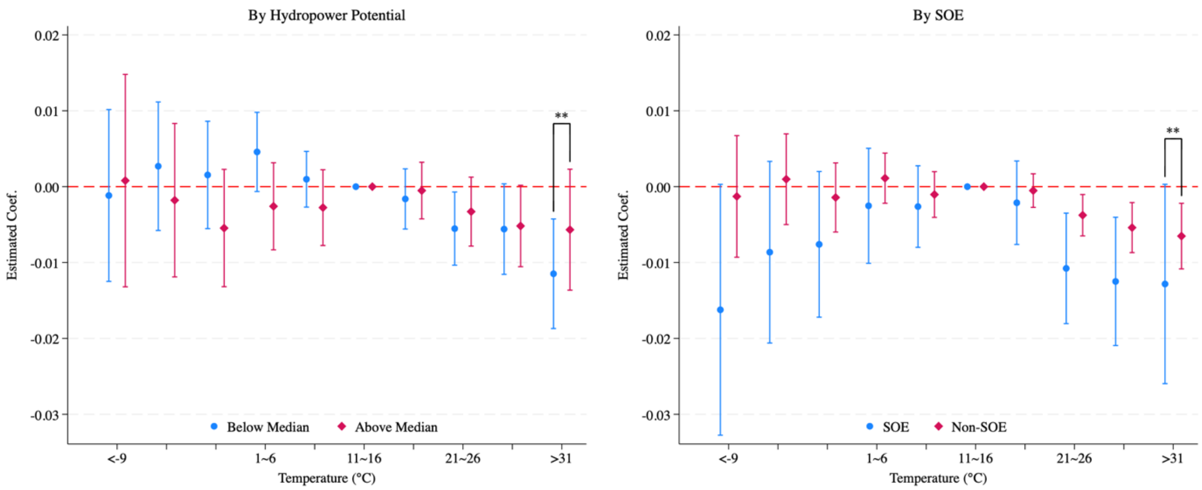

Figure 5. Heterogeneity in the effects of high temperatures on firm electricity consumption. Detailed regression results can be found in Table A2. The left panel divides the sample into two groups based on the median *HydropowerPotential*, with the blue line representing the results using the below-the-median subsample and the red line representing the results using the above-the-median subsample. The right panel presents the results of estimating equation (1) using samples for SOEs (blue line) and Non-SOEs (red line), respectively. Asterisk brackets indicate the significance of the difference between the regression coefficients of the two models. * p<0.1, ** p<0.05, *** p<0.01.

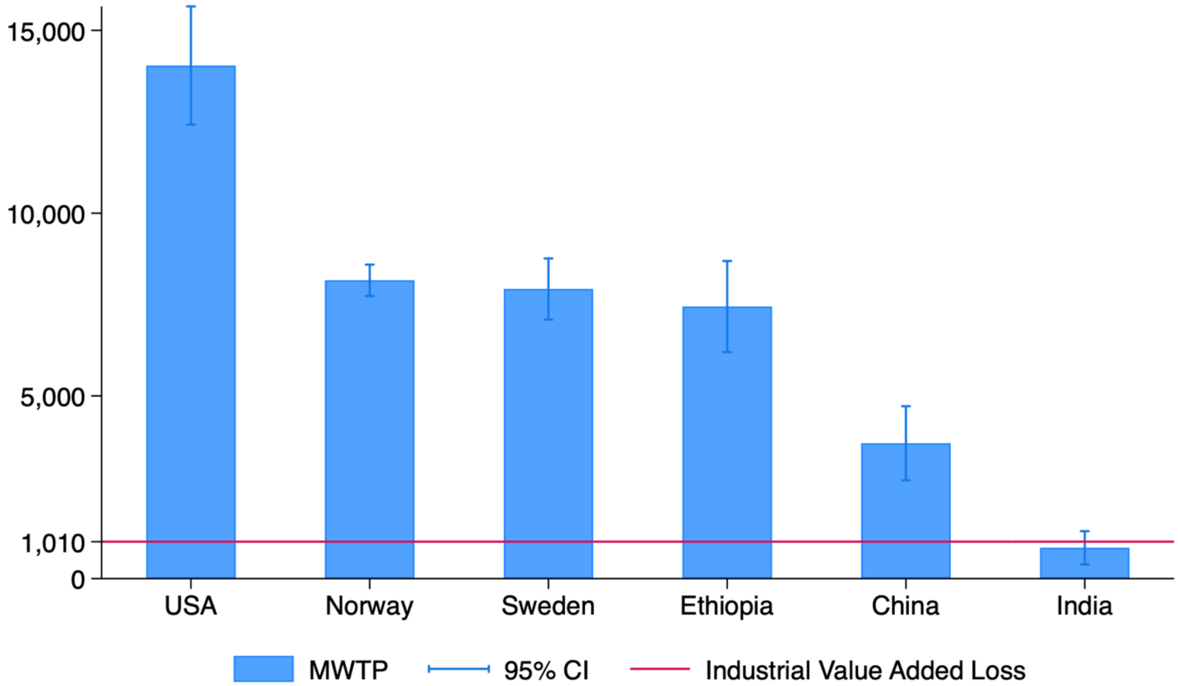

Figure 6. Comparing losses of industrial value-added (in China) and median WTP of households (across countries) avoiding power interruptions in summer. Nuances and references for the calculations can be found in Table A6. All the values are PPP adjusted to 2007 US dollars.

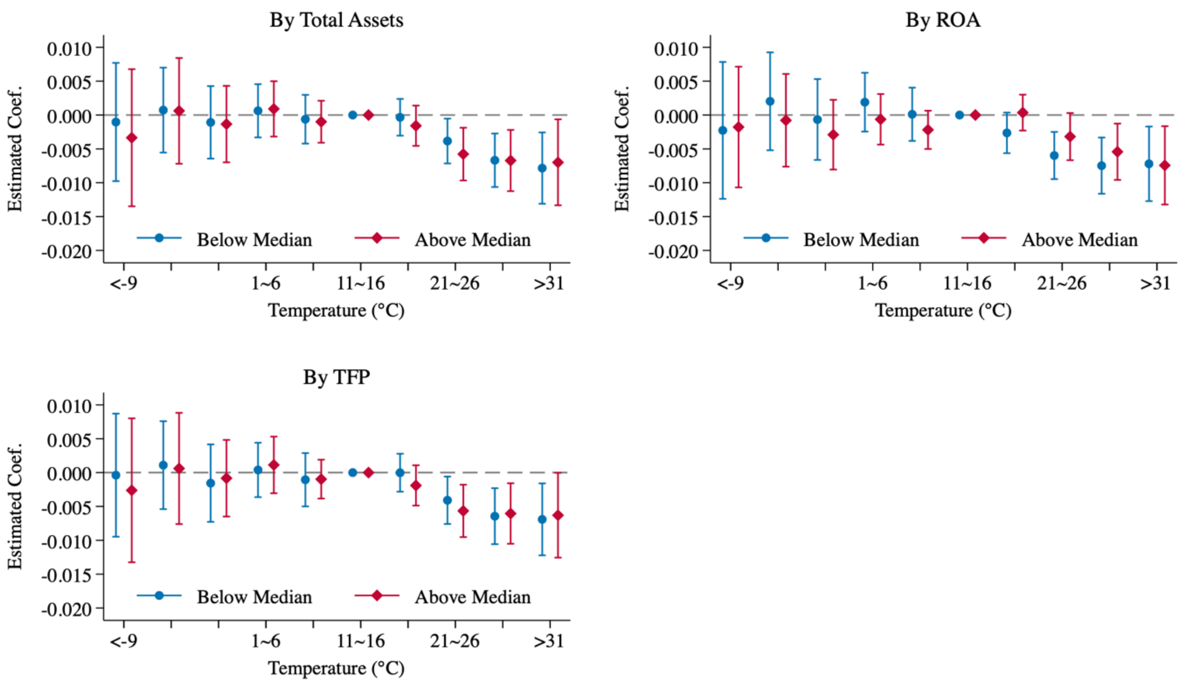

Figure 7. Heterogeneous effect of the impact of high temperatures on firm's electricity usage by total assets, ROA, and TFP. Regression results are detailed in Table A7.

Tables

Table 1. Summary statistics.

Variable	Obs.	Mean	S.D.	Min	Median	Max
Panel A: Main variables						
Ln(Output)	586,168	8.67	2.20	2.20	8.81	13.34
Ln(Electricity)	586,168	4.82	2.17	0.69	4.70	10.84
Ln(Labor)	586,168	4.86	1.33	1.61	4.84	8.02
Ln(Capital)	586,168	8.95	2.13	2.30	9.04	13.69
Ln(Assets)	586,168	10.54	1.88	5.20	10.56	14.95
ROA	586,168	0.01	0.02	-0.09	0.00	0.10
Ln(TFP-LP-E)	586,168	4.71	1.65	-4.35	4.90	11.31
Ln(TFP-LP-NE)	586,168	4.84	1.67	-3.92	5.04	11.73
Ln(TFP-OP-E)	586,168	4.70	1.65	-4.35	4.90	11.31
Ln(TFP-OP-NE)	586,168	4.83	1.67	-3.93	5.03	11.73
Temp	586,168	15.82	4.56	-4.25	16.70	26.09
Pre	586,168	1136.77	529.92	11.66	1097.96	3301.30
Rhu	586,168	69.69	7.24	30.23	71.49	90.38
Win	586,168	2.29	0.55	0.60	2.25	6.43
Sun	586,168	5.39	1.10	1.82	5.17	9.48
Panel B: Temperature bins 5°C interval						
(, -9°C]	586,168	7.23	19.73	0.00	0.00	152.00
(-9°C, -4°C]	586,168	9.08	14.49	0.00	0.00	79.00
(-4°C, 1°C]	586,168	20.86	20.44	0.00	14.00	94.00
(1°C, 6°C]	586,168	33.77	20.00	0.00	38.00	116.00
(6°C, 11°C]	586,168	42.22	17.35	0.00	44.00	125.00
(11°C, 16°C]	586,168	48.76	14.62	0.00	48.00	142.00
(16°C, 21°C]	586,168	61.62	15.42	0.00	60.00	186.00
(21°C, 26°C]	586,168	75.21	16.99	0.00	75.00	242.00
(26°C, 31°C]	586,168	61.22	41.50	0.00	59.00	226.00
(31°C,)	586,168	5.32	8.21	0.00	1.00	54.00
Panel C: Temperature bins 3°C interval						
(, -7°C)	586,168	9.98	23.76	0.00	0.00	158.00
(-7°C, -4°C]	586,168	6.34	9.82	0.00	0.00	52.00
(-4°C, 1°C]	586,168	10.54	12.68	0.00	2.00	61.00
(-1°C, 2°C]	586,168	16.36	13.04	0.00	17.00	68.00
(2°C, 5°C]	586,168	20.29	12.82	0.00	22.00	92.00
(5°C, 8°C]	586,168	23.70	12.61	0.00	25.00	88.00
(8°C, 11°C]	586,168	25.95	10.76	0.00	26.00	87.00
(11°C, 14°C]	586,168	28.31	9.86	0.00	28.00	113.00
(14°C, 17°C]	586,168	31.12	9.91	1.00	31.00	98.00
(17°C, 20°C]	586,168	37.02	10.56	0.00	35.00	126.00
(20°C, 23°C]	586,168	42.91	10.60	0.00	42.00	156.00
(23°C, 26°C]	586,168	46.23	14.26	0.00	46.00	176.00
(26°C, 29°C]	586,168	43.23	28.13	0.00	40.00	175.00
(29°C, 32°C]	586,168	21.03	18.21	0.00	20.00	89.00
(32°C,)	586,168	2.28	4.83	0.00	0.00	33.00

Table 2. The impact of temperature on firm's electricity consumption.

	(1) Ln(Electricity)	(2) Ln(Electricity)	(3) Ln(Electricity)
(31°C,)	-0.006***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
(26°C, 31°C]	-0.005***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)
(21°C, 26°C]	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
(16°C, 21°C]	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
(11°C, 16°C]			
(6°C, 11°C]	-0.001	-0.001	-0.001
	(0.001)	(0.002)	(0.001)
(1°C, 6°C]	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
(-4°C, 1°C]	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
(-9°C, -4°C]	0.000	0.001	0.001
	(0.003)	(0.003)	(0.003)
(, -9°C]	-0.004	-0.003	-0.003
	(0.004)	(0.004)	(0.004)
Pre		-0.045	-0.038
		(0.098)	(0.096)
Pre^2		0.002	-0.000
		(0.028)	(0.027)
Rhu		-2.418	-2.352
		(2.647)	(2.624)
Rhu^2		1.602	1.476
		(1.892)	(1.874)
Wind		0.173	0.152
		(0.167)	(0.163)
$Wind^2$		-0.041	-0.036
		(0.030)	(0.030)
Sun		0.178	0.188
		(0.126)	(0.124)
Sun^2		-0.015	-0.016
		(0.011)	(0.011)
Constant	5.617***	5.939***	5.960***
	(0.328)	(1.125)	(1.109)
Effect of 1 Std. Dev. Change as % of Dep. Var.:			
(31°C,)	-3.00	-3.64	-3.50
p-value	[0.007]	[0.001]	[0.001]
Obs.	586,168	586,168	586,168
R^2	0.758	0.758	0.758
Firm FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Industry-Year FE	No	No	Yes

Notes: The within-county standard deviation of the 10th temperature bin (>31°C) is 4.86. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table 3. Robustness checks.

	(1) Ln(Electricity)	(2) Ln(Electricity)	(3) Ln(Electricity)	(4) Ln(Electricity)	(5) Ln(Electricity)	(6) Ln(Electricity)	(7) Ln(Electricity)	(8) Ln(Electricity)
(31°C,)	-0.006**	-0.006***	-0.007***	-0.007**				
	(0.003)	(0.002)	(0.002)	(0.003)				
(26°C, 31°C]	-0.005**	-0.005***	-0.006***	-0.006**				
	(0.002)	(0.002)	(0.002)	(0.002)				
(21°C, 26°C]	-0.003*	-0.004***	-0.004***	-0.004*				
	(0.002)	(0.001)	(0.002)	(0.002)				
(31°C,) Anomaly					-0.007***			
					(0.002)			
(26°C, 31°C] Anomaly					-0.006***			
					(0.002)			
(21°C, 26°C] Anomaly					-0.004***			
					(0.001)			
(32°C,)						-0.005*		
						(0.003)		
(29°C, 32°C]						-0.007***		
						(0.002)		
(26°C, 29°C]						-0.005***		
						(0.002)		
(23°C, 26°C]						-0.004***		
						(0.001)		
(32°C,) Anomaly							-0.005*	
							(0.003)	
(29°C, 32°C] Anomaly							-0.008***	
							(0.002)	
(26°C, 29°C] Anomaly							-0.005***	
							(0.002)	
(23°C, 26°C] Anomaly							-0.004***	
							(0.001)	
CDD								-0.003*
								(0.002)
HDD								0.001
								(0.001)
Controls and other bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	586,168	586,168	586,168	586,168	586,168	586,168	586,168	586,168
R^2	0.758	0.758	0.758	0.758	0.758	0.758	0.758	0.758
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	County	County	Firm and Province-Year	Province	County	County	County	County

Notes: Columns (1) and (2) present the results when replacing the reference bin with the fifth (6°C–11°C) and seventh (16°C–21°C) bins, respectively. Columns (3) and (4) report the results when clustering the standard errors at *Firm + Province-Year* and *Province* (31 provinces) level, respectively. Temperature anomalies are calculated by subtracting the average temperature bin over the average of the past ten years. CDD and HDD refer to the cooling degree days and heating degree days following Guo et al. (2023), respectively. * p<0.1, ** p<0.05, *** p<0.01.

Table 4. Hydropower potential shock and firm's electricity consumption.

	(1) Ln(Electricity)	(2) Ln(Electricity)	(3) Ln(Electricity)	(4) Ln(Electricity)
HydropowerPotential	0.427***	0.490***	0.468***	0.468**
	(0.111)	(0.106)	(0.104)	(0.216)
Pre		-0.393***	-0.372***	-0.372**
		(0.092)	(0.089)	(0.175)
Pre^2		0.108***	0.104***	0.104**
		(0.027)	(0.026)	(0.042)
Rhu		0.456	0.774	0.774
		(2.186)	(2.175)	(3.047)
Rhu^2		-0.194	-0.444	-0.444
		(1.565)	(1.560)	(2.227)
Wind		0.107	0.083	0.083
		(0.167)	(0.163)	(0.268)
$Wind^2$		-0.018	-0.014	-0.014
		(0.034)	(0.033)	(0.053)
Sun		0.157*	0.160**	0.160
		(0.084)	(0.082)	(0.159)
Sun^2		-0.013	-0.013*	-0.013
		(0.008)	(0.008)	(0.014)
Constant	4.823***	4.281***	4.178***	4.178***
	(0.001)	(0.768)	(0.759)	(1.085)
Obs.	585,093	585,093	585,093	585,093
R^2	0.753	0.753	0.754	0.754
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Industry-Year FE	No	No	Yes	Yes

Notes: Standard errors in the parentheses are clustered at county the level for columns (1)–(3). In column (4), standard errors are clustered at the province level. * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Controlling productivity proxies.

	(1) Ln(Electricity)	(2) Ln(Electricity)	(3) Ln(Electricity)
(31°C,)	-0.007***	-0.007***	-0.005**
	(0.002)	(0.002)	(0.002)
(26°C, 31°C]	-0.006***	-0.006***	-0.004**
	(0.002)	(0.002)	(0.001)
(21°C, 26°C]	-0.004***	-0.004***	-0.003**
	(0.001)	(0.001)	(0.001)
Labor Productivity	0.127***	0.097***	2.905***
	(0.006)	(0.007)	(0.063)
Capital Productivity		0.031***	1.081***
		(0.006)	(0.028)
TFP			-3.920***
			(0.088)
Controls and other bins	Yes	Yes	Yes
Obs.	586,168	586,168	586,168
R^2	0.762	0.762	0.808
Firm FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: Labor productivity is measured as output per employee. Capital productivity is the ratio of output to capital. TFP is estimated using the LP method while controlling for electricity as an input factor, denoted as Ln(*TFP-LP-E*) in Table 1. Our results are independent of the method used to estimate TFP. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table 6. The impact of temperature on firm's repair and maintenance costs.

	(1) Ln(1+R&M)	(2) Ln(1+R&M)	(3) Ln(1+R&M)
(31°C,)	-0.007	-0.009**	-0.008*
	(0.004)	(0.005)	(0.005)
(26°C, 31°C]	-0.001	-0.003	-0.002
	(0.003)	(0.004)	(0.004)
(21°C, 26°C]	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)
Controls	No	Yes	Yes
Obs.	321,314	321,314	321,314
R^2	0.665	0.665	0.666
Firm FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Industry-Year FE	No	No	Yes

Notes: All temperature bins except the 6th bin are included in the regression analysis. We only report the regression coefficients for the three bins representing high temperatures for brevity. In columns (1)–(3), the dependent variables are the firm's equipment repair and maintenance expenses in log form. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table 7. The impact of high temperatures on output through electricity.

Panel A: The impact on firm's output and TFP								
	Ln(Output)				TFP			
	Not Controlling E	Controlling E	Not Controlling E	Controlling E	Not Excluding E	Excluding E	Not Excluding E	Excluding E
	(1a)	(1b)	(1c)	(1d)	(2a)	(2b)	(2c)	(2d)
(31°C,)	-0.004*	-0.003			-0.004*	-0.003		
	(0.002)	(0.002)			(0.002)	(0.002)		
(32°C,)			-0.006**	-0.005*			-0.006**	-0.006*
			(0.003)	(0.003)			(0.003)	(0.003)
Ln(Electricity)		0.159***		0.159***				
		(0.006)		(0.006)				
Controls and other bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	586,168	586,168	586,168	586,168	586,168	586,168	586,168	586,168
R^2	0.768	0.774	0.768	0.774	0.612	0.605	0.612	0.605
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
% of change of Mar. Eff.	30.13		13.41		12.07		5.46	
chi2 of Diff.	51.74		16.57		54.61		16.89	
p-value	[0.000]		[0.000]		[0.000]		[0.000]	
Panel B: The impact on firm's factor reallocation								
	Ln(Labor)		Ln(Capital)					
	(3a)	(3b)	(3c)	(3d)				
(31°C,)	0.057		0.422					
	(0.566)		(0.761)					
(32°C,)		0.176		-0.488				
		(0.700)		(1.020)				
Controls and other bins	Yes	Yes	Yes	Yes				
Obs.	586,168	586,168	586,168	586,168				
R^2	0.950	0.950	0.955	0.955				
Firm FE	Yes	Yes	Yes	Yes				
Province-Year FE	Yes	Yes	Yes	Yes				
Industry-Year FE	Yes	Yes	Yes	Yes				
Panel C: The substitution effect								
	Coal				Oil			
	D(Coal)	D(Coal)	Ln(1+Coal)	Ln(1+Coal)	D(Oil)	D(Oil)	Ln(1+Oil)	Ln(1+Oil)
	(4a)	(4b)	(4c)	(4d)	(5a)	(5b)	(5c)	(5d)
(31°C,)	0.000		-0.005*		0.001		0.001	
	(0.001)		(0.003)		(0.001)		(0.004)	
(32°C,)		-0.000		-0.008*		0.002		0.006
		(0.001)		(0.004)		(0.001)		(0.005)
Controls and other bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	586,168	586,168	434,365	434,365	586,168	586,168	474,817	474,817
R^2	0.757	0.757	0.829	0.829	0.599	0.599	0.629	0.629
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A reports the impact of high temperatures on the firm's output and TFP and compares the effect with and without controlling the electricity input. In columns (2b) and (2d), the electricity input is controlled when estimating TFP. Panel B reports high temperatures' impact on firm labor and capital. Panel C reports the impact of high temperatures on the firm's coal and oil usage for both extensive and intensive margins. D(Coal) and D(Oil) are dummy variables equal to 1 if the firm's coal (or oil) consumption is non-zero. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix A: Figures and Tables

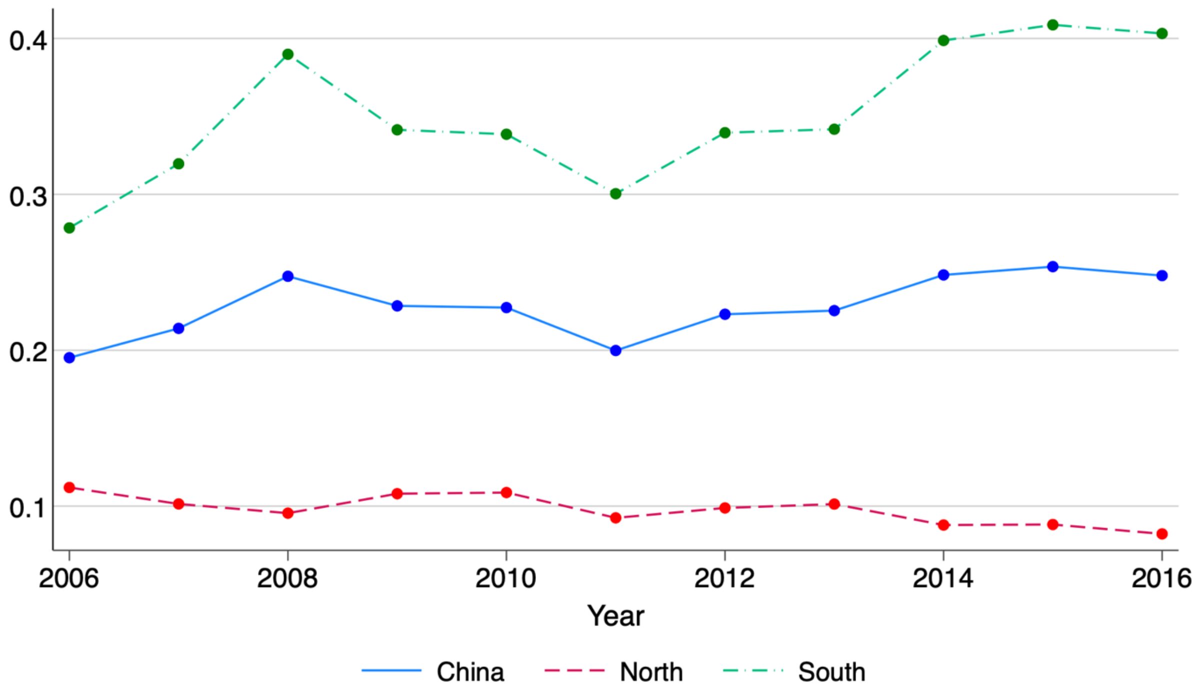

Figure A1. Temporal dynamics in the proportions of hydropower in total electricity consumption across all Chinese provinces, northern provinces, and southern provinces from 2006 to 2016. The solid, dashed, and dash-dotted lines depict the average proportions of annual hydropower consumption in total electricity consumption, calculated for all provinces in China, northern provinces, and southern provinces, respectively.

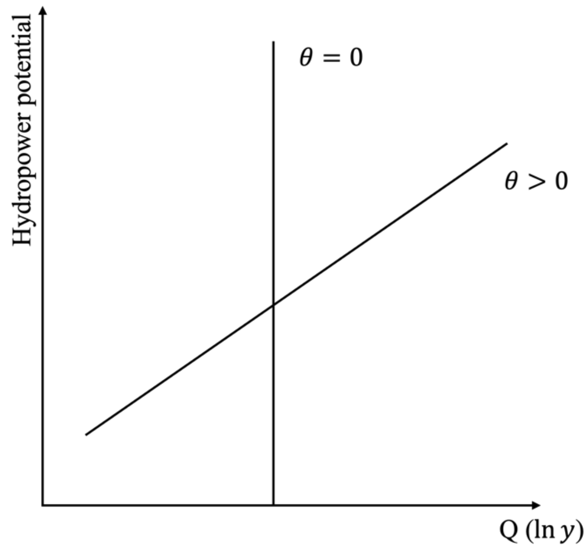

Figure A2. Illustration of different values of θ of the equation (5).

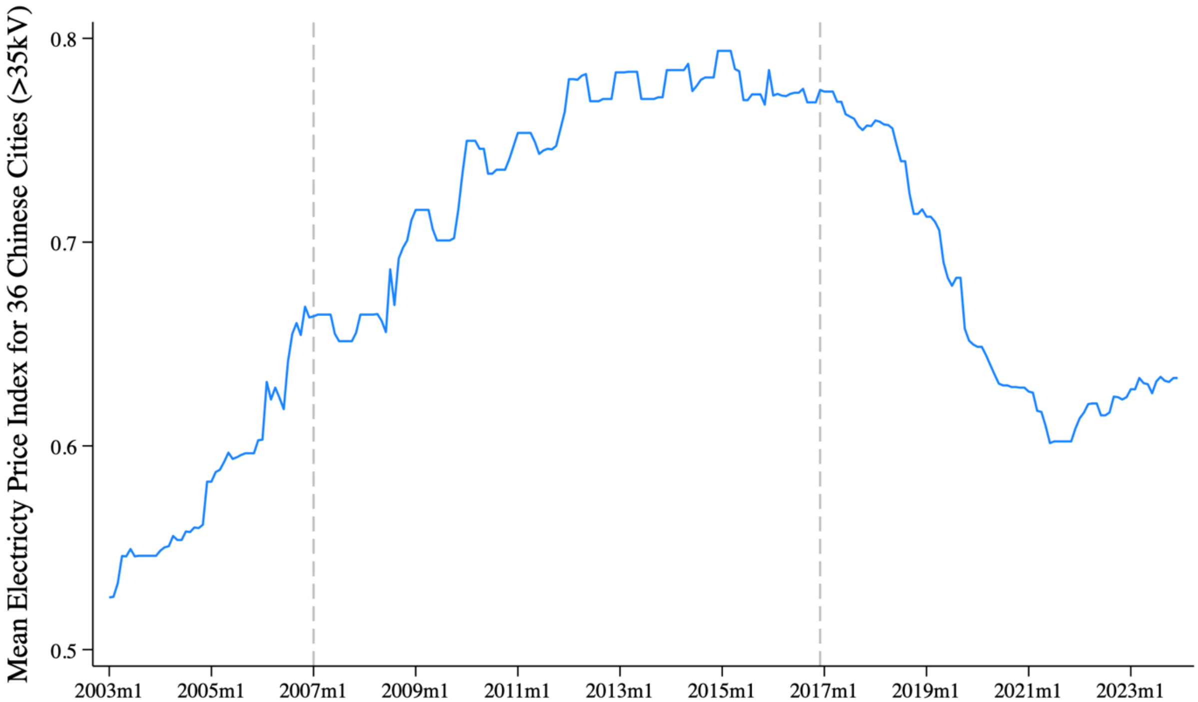

Figure A3. Dynamics of the monthly mean electricity price index for 36 Chinese cities. The interval we study is between the two vertical dotted lines.

Table A1. Falsification test.

	(1) Ln(Electricity)	(2) Ln(Electricity)	(3) Ln(Electricity)
Hydropower Potential$_{[m+2,m+3]}$	0.157	0.192	0.195
	(0.160)	(0.160)	(0.156)
Pre		-0.396***	-0.377***
		(0.091)	(0.089)
Pre^2		0.118***	0.115***
		(0.026)	(0.026)
Rhu		-0.290	0.059
		(2.219)	(2.206)
Rhu^2		0.404	0.129
		(1.586)	(1.579)
Wind		0.118	0.092
		(0.162)	(0.159)
Wind^2		-0.025	-0.021
		(0.033)	(0.032)
Sun		0.125	0.131
		(0.084)	(0.081)
Sun^2		-0.010	-0.011
		(0.008)	(0.008)
Constant	4.821***	4.600***	4.482***
	(0.001)	(0.780)	(0.770)
Obs.	585,093	585,093	585,093
R^2	0.753	0.753	0.754
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	No
Industry-Year FE	No	No	Yes

Notes: Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table A2. Heterogeneity in the effects of high temperatures on firm electricity consumption.

	(1)	(2)	(3)	(4)
	Ln(Electricity)		Ln(Electricity)	
	Hydropower Potential		SOE	
	Below Median	Above Median	SOE	Non-SOE
(31°C,)	-0.011***	-0.006	-0.013*	-0.007***
	(0.004)	(0.004)	(0.007)	(0.002)
(26°C, 31°C]	-0.006*	-0.005*	-0.012***	-0.005***
	(0.003)	(0.003)	(0.004)	(0.002)
(21°C, 26°C]	-0.006**	-0.003	-0.011***	-0.004***
	(0.002)	(0.002)	(0.004)	(0.001)
Controls and other bins	Yes	Yes	Yes	Yes
Obs.	232,553	239,781	44,166	534,602
R^2	0.804	0.789	0.753	0.758
Firm FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Coef. difference in the 10th bin (>31°C)	0.006**		0.006**	
p-value	[0.020]		[0.033]	

Notes: Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table A3. The impact of hydropower resource abundance.

	(1)	(2)	(3)
		Hydropower Resource Abundance	
	High	Middle	Low
Hydropower Potential$_{[m-3,m-2]}$	0.221	0.831***	1.648**
	(0.326)	(0.160)	(0.698)
Pre	-0.111	-0.412	-0.226
	(0.209)	(0.257)	(0.140)
Pre^2	0.064	0.085	0.089
	(0.060)	(0.065)	(0.051)
Rhu	3.735	-0.683	-0.728
	(4.246)	(3.155)	(5.049)
Rhu^2	-2.017	0.700	0.196
	(2.718)	(2.151)	(3.905)
Wind	-0.432	0.415	0.262
	(0.344)	(0.404)	(0.204)
Wind^2	0.067	-0.065	-0.048
	(0.086)	(0.064)	(0.036)
Sun	-0.034	0.099	-0.145
	(0.129)	(0.296)	(0.243)
Sun^2	0.012	-0.012	0.014
	(0.013)	(0.024)	(0.019)
Constant	3.552*	4.505***	5.467***
	(1.596)	(1.253)	(1.141)
Obs.	125,881	260,578	198,612
R^2	0.766	0.761	0.742
Firm FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Cluster	Province	Province	Province

Notes: The dependent variable in the regressions is *ln(Electricity)*. *Hydropower Resource Abundance* represents the proportion of hydropower production to total electricity generation in each province in 2007, where a higher proportion indicates richer hydropower resources. In columns (1) to (3), we regress sub-samples of the top, medium, and bottom provinces based on *Hydropower Resource Abundance* (10 provinces for each sub-sample). Tibet is not included. Standard errors in the parentheses are clustered at the province level. * p<0.1, ** p<0.05, *** p<0.01.

Table A4. Temperature and electricity price indices.

	(1) Ln(EPI)	(2) Ln(EPI)	(3) Ln(EPI)	(4) Ln(EPI)
MonthlyAverageTemp	0.002*	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\text{MonthlyAverageTemp}^2$		0.000		0.000
		(0.000)		(0.000)
Controls	Yes	Yes	Yes	Yes
Obs.	4,320	4,320	1,200	1,200
R^2	0.864	0.864	0.985	0.985
City FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	No	No
Province-Year-Month FE	No	No	Yes	Yes

Notes: Standard errors in the parentheses are clustered at the city level. * p<0.1, ** p<0.05, *** p<0.01.

Table A5. Estimation the C-D production function using 2SLS.

	(1) First Stage	(2) Second Stage
	Ln(Electricity)	Ln(Output)
Ln(Electricity)		0.065***
		(0.000)
Hydropower Potential$_{[m-3,m-2]}$	0.435***	
	(0.103)	
TFP - LP	0.082***	1.000***
	(0.007)	(0.000)
Ln(Labor)	0.413***	0.432***
	(0.009)	(0.000)
Ln(Capital)	0.140***	0.174***
	(0.006)	(0.000)
Controls	Yes	Yes
Obs.	585,093	585,093
Firm FE	Yes	Yes
Industry-Year FE	Yes	Yes
Underidentification test	25.39	23.735
	[0.000]	[0.000]
Weak identification test	17.95	102.701
	[0.000]	

Notes: For the first-stage regression results, we report the SW Chi2-statistics and its p-value for the underidentification test, as well as the SW F-statistics and its p-value for the weak identification test. As for the second-stage regression results, we present the Kleibergen-Paap RK LM statistics and its p-value for the underidentification test, as well as the Cragg-Donald Wald F-statistic for the weak identification test. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Table A6. Nuances and references for calculating the median WTPs.

Country/Region	Paper	Survey Year	Valuation Basis	Timing/Peak	Appliances	Currency	PPP Factor	CPI Factor	MWTP for 10 MWh	MWTP SE
USA	Baik et al. (2020)	2018	Per 1 KWh	-	All	USD	1	1.211	14,038	1,618
Norway	Vennemo et al. (2022)	2021	1H Outage	-	All	NOK	8.962	1.307	8,161	429
Sweden	Carlsson et al. (2021)	2017	1H Outage	January	All	SEK	8.852	1.182	7,924	836
Ethiopia	Aweke and Navrud (2022)	2018	1H Outage	-	All	USD	1	1.211	7,444	1,246
China	Zhao et al. (2022)	2020	1H Outage	Summer Peak	AC	CNY	4.174	1.248	3,702	1,014
India	Bigerna et al. (2024)	2021	1H Outage	-	All	USD	1	1.307	842	455

Notes: We assume that an average air conditioner's power is 3.5 KW, which is the type that dominates the Chinese household AC market (Lin and Rosenquist, 2008; Wu et al., 2019). All the valuations are measured based on the contingent valuation method. We derive the standard error of China's MWTP using the delta method.

Table A7. Heterogeneous impact of high temperatures on firms' electricity usage.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Electricity) Total Assets		Ln(Electricity) ROA		Ln(Electricity) TFP	
	Below Median	Above Median	Below Median	Above Median	Below Median	Above Median
(31°C,)	-0.008***	-0.007**	-0.007**	-0.007**	-0.007**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
(26°C, 31°C]	-0.007***	-0.007***	-0.007***	-0.005**	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(21°C, 26°C]	-0.004**	-0.006***	-0.006***	-0.003*	-0.004**	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Controls and other bins	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	276,397	269,452	258,939	258,035	255,728	251,468
R^2	0.735	0.661	0.775	0.772	0.796	0.740
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

Appendix B: Discussion on Estimation Strategies

Following Schlenker and Roberts (2009) and Addoum et al. (2023), we assume that the firm's production process, denoted as $g(h)$, nonlinearly depends on regional temperature exposure, h. We hypothesize that the firm's annual electricity usage y_{it} can be represented as follows

$$\ln y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)dh + \delta \boldsymbol{X}_{it} + \mu_i + \lambda_{pt} + I_{st} + \boldsymbol{\epsilon}_{it} \tag{B1}$$

where ϕ_{it} is the time distribution of heat over year t in the county of firm i. $\overline{h}$ and $\underline{h}$ are upper and lower bound of the observed temperatures. Other terms are identical to the equation (1).

The key assumption in equation (B1) is that year-to-year weather fluctuations across counties are unrelated to factors affecting firms' production given the fixed effects (Deschênes and Greenstone, 2011). Equation (B1) also implies that the effects of temperature on firms' electricity usage accumulate over time. Since *ϕ(h)* is defined based on daily temperature within a year in this paper, we assume that the marginal effect of temperature exposure on firms' electricity usage and other activities is additively separable throughout the year (Schlenker and Roberts, 2009; Blanc and Schlenker, 2017). We approximate the integral in equation (B1) with

$$\ln y_{it} = \sum_{h=\underline{h}}^{\overline{h}} g(h+2.5)[\Phi_{\mathrm{it}}(h+5) - \Phi_{it}(h)] + \delta \boldsymbol{X}_{it} + \mu_i + \lambda_{pt} + I_{st} + \boldsymbol{\epsilon}_{it} \tag{B2}$$

where $\Phi_{it}(h)$ is the cumulative distribution function of $\phi_{it}(h)$. In our baseline model, we specify *g(h)* as a step function within each 5°C temperature interval. This is identical to estimate equation (1), our baseline model.

Appendix C: Effect of high temperatures on other sectors

Panel A of Table C1 shows the change in sample size of our baseline regression dataset across cleaning steps. Panel B of Table C1 presents the cleaning steps for the all-industry sample. In Table C2, using the full industry sample, we still find that high-temperature exposure significantly reduces firms' electricity usage, albeit with a smaller coefficient. Further heterogeneity analysis reveals that the impact of high temperatures on firms' electricity usage is primarily concentrated in manufacturing firms. According to the results in Figure C1, high temperatures are also negatively correlated with electricity usage of firms in the *Mining*, *Wholesale and Retail*, and *Agriculture* industries, but not statistically significant. Furthermore, high temperatures may lead to an increase in electricity usage for firms in the *Accommodation and Food Service*, *Software*, and *Finance and Real Estate* industries. These results suggest that power rationing induced by high temperatures primarily affects manufacturing firms. In the NTS data, manufacturing firms account for 40% of the total number of firms and 69% of total electricity usage. Therefore, our main regression analysis focuses on manufacturing firms.

Table C1. Data cleaning steps.

Steps	Description	Remaning Observations.
Dataset A: Baseline sample cleaning steps		
1	Raw data (2007 to 2016)	6,706,471
2	Unify firm ID, region codes, and industry codes. Firms in the industries with less than 200 firms are dropped. Observations with missing region codes and industry codes are dropped.	6,165,740
3	Remove non-manufacturing firms.	2,294,906
4	Remove firms with electricity usage equal or smaller than 1.	1,851,731
5	Remove firms with prime operating revenue and fixed assets smaller than 1. Exclude firms with no more than four employees. Remove irregular observations that exhibit non-positive values for total assets or value-added output.	992,516
6	Remove observations with electricity usage, number of employees, output, or capital missing.	734,974
7	Remove singletons.	586,168
Dataset B: All industries		
1	Raw data (2007 to 2016)	6,706,471
2	Unify firm ID, region codes, and industry codes. Firms in the industries with less than 200 firms are dropped. Observations with missing region codes and industry codes are dropped.	6,165,740
3	Remove firms with electricity usage smaller than 0.	6,165,292
4	Remove firms with prime operating revenue and fixed assets smaller than 1. Exclude firms with no more than four employees. Remove irregular observations that exhibit non-positive values for total assets or value-added output.	2,281,924
5	Remove singletons.	1,796,084

Notes: Panel A describes the cleaning steps for the baseline dataset (Dataset A) that focus on manufacturing firms. Panel B describes the cleaning steps for the dataset (Dataset B), which includes both manufacturing and non-manufacturing firms.

Table C2. Impact of high temperatures on firm's electricity usage using all-industry samples.

	(1) Ln(1+Electricity)	(2) Ln(1+Electricity)	(3) Ln(1+Electricity)
(31°C,)	-0.006**	-0.005**	-0.004*
	(0.002)	(0.002)	(0.002)
(26°C, 31°C]	-0.004**	-0.004**	-0.004**
	(0.002)	(0.002)	(0.002)
(21°C, 26°C]	-0.003**	-0.002*	-0.002
	(0.001)	(0.001)	(0.001)
(16°C, 21°C]	-0.001	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
Other bins	Yes	Yes	Yes
Effect of 1 Std. Dev. Change as % of Dep. Var.:			
(31°C,)	-3.16	-2.54	-2.34
p-value	[0.015]	[0.050]	[0.062]
Obs.	1,796,084	1,796,084	1,796,084
R^2	0.710	0.710	0.714
Weather Controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Industry-Year FE	No	No	Yes

Notes: Results (1) to (3) are based on the dataset that includes both manufacturing and non-manufacturing firms. The within-county standard deviation of the 10th temperature bin (>31°C) is 5.53. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.

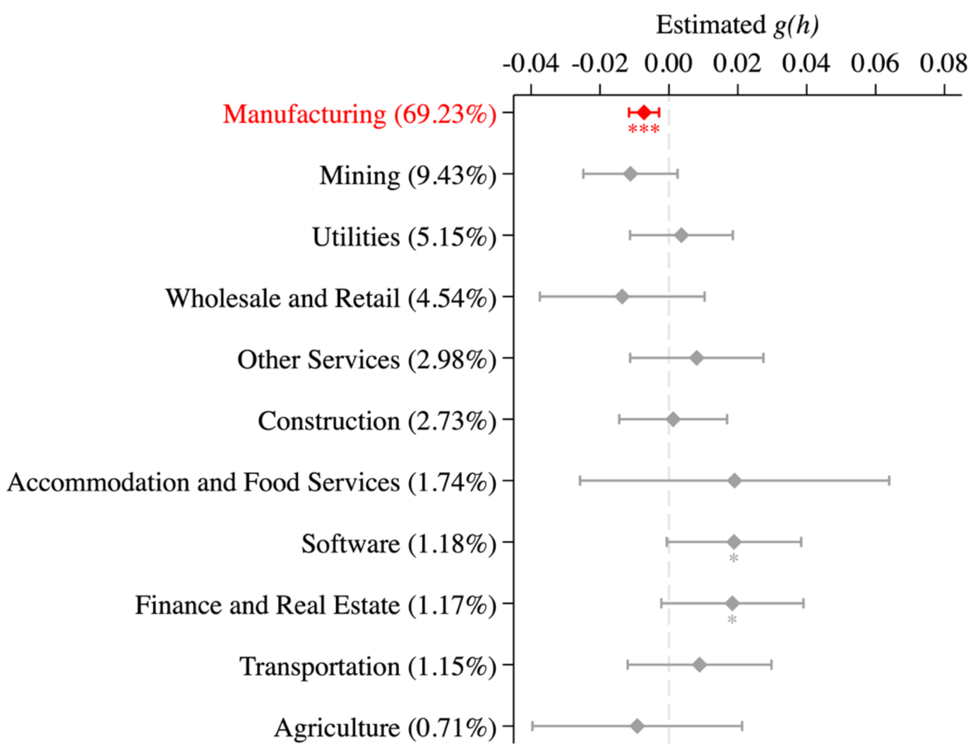

Figure C1. Estimated effects of temperatures above 31°C on firm's electricity usage for each sector. The percentage indicates the proportion of industry electricity usage to the total electricity usage of the NTS. The diamond symbols and error bars represent the regression coefficients and the 95% confidence intervals for the 10th temperature bin (>31°C). * p<0.1, ** p<0.05, *** p<0.01.

Appendix D: A Static Model of Optimal Electricity Allocation

D1. Model specification

Our objective is to construct an intuitive model to illustrate how governments should allocate electricity resources between the household and industrial sectors when the electricity supply is limited. In this simple model, we consider a representative household and two producers: the power sector and the manufacturer. The power sector employs a fraction of the labor and generates electricity, with its maximum output constrained by a constant *N*. The manufacturer produces normal goods by employing labor and consuming electricity. The welfare of the representative household is shaped by consuming both normal goods and electricity using a CES utility function. The social planner, or the government, exogenously determines the electricity price and allocates electricity resources between the household and the manufacturer. We aim to understand how a social planner should allocate electricity between the household and the manufacturer to maximize social welfare. Furthermore, we explore how electricity resources should be allocated when faced with rising household electricity demand and consumption due to transitory shocks such as high temperatures.

The utility function U of the representative household is defined as

$$U = \left[\lambda_1 Y^{\frac{s_1 - 1}{s_1}} + (1 - \lambda_1) E_H^{\frac{s_1 - 1}{s_1}}\right]^{\frac{s_1}{s_1 - 1}} \tag{D1}$$

where Y and E_H indicate the consumption of normal goods and electricity, respectively. λ_1 is the share parameter, and s_1 denotes the household's elasticity of substitution. The household's budget constrain is given by

$$pY + eE_H \leq I \tag{D2}$$

$$I = \omega L = \omega(L_E + L_I) \tag{D3}$$

where p and e indicate the price of normal goods and electricity, respectively. The income I is fixed by wage level ω and total labor supply L. L_E and L_I are the labor employed by the power sector and the manufacturer, respectively.

The total electricity output of the power sector E_S is featured by a Leontief production function so that the maximum electricity output is a constant N. A_E denotes the productivity of the power sector.

$$E_S = \min\left(A_E L_E, N\right) \tag{D4}$$

Normal good is produced by the manufacturer with the technology

$$Y = A_I \left[\lambda_2 L_I^{\frac{s_2-1}{s_2}} + (1-\lambda_2) E_I^{\frac{s_2-1}{s_2}} \right]^{\frac{s_2}{s_2-1}} \tag{D5}$$

where Y is the total normal good produced. There are no savings, and all the final normal goods are used only for consumption. So, we do not distinguish between the notation of the normal good produced and the normal good consumed. L_I and E_I represent the labor and electricity inputs, and s_2 represents the elasticity of substitution between the two composites. We assume that $s_2 < 1$, which implies the complementarity between labor and electricity (Bretschger and Jo, 2024). A_I denotes the manufacturer's productivity.

We denote

$$\frac{E_H}{E_S} = \mu, \text{ and } \frac{E_I}{E_S} = 1 - \mu \tag{D6}$$

C2. Optimal allocation of electricity

To begin with, for the power sector, the total output of electricity is constrained by a constant, featuring exogenous natural resources and unit capacity. We have

$$E_S = A_E L_E = N \text{ and } L_E = \frac{N}{A_E} \tag{D7}$$

At the social planner's equilibrium, we also have

$$\omega = \frac{eE_S}{L_E} = eA_E \tag{D8}$$

The marginal willingness to pay for labor in the power sector depends on the electricity price and productivity. In this static model, the labor market is exogenously featured as we assume that electricity price e remains constant. Thus, we do not incorporate the wage effect or reallocation effect of transitory high temperatures, which is consistent with our empirical results as we do not find the

For the social planner's problem, we solve

$$\frac{\partial U}{\partial \mu} = 0 \tag{D9}$$

$$\frac{\partial U}{\partial \mu} = U^{\frac{1}{s_1}} \lambda_1 Y^{-\frac{1}{s_1}} \frac{\partial Y}{\partial \mu} + U^{\frac{1}{s_1}} (1-\lambda_1)(E_H)^{-\frac{1}{s_1}} \frac{\partial E_H}{\partial \mu} \tag{D10}$$

So, the effect of change in μ on utilities can be decomposed into two parts. The first component refers to the change in utility resulting from a change in the consumption of product, while the second component represents the change in utility resulting from a change in the consumption of electricity. Because we always have

$$\frac{\partial Y}{\partial \mu} = \frac{-E_S A_I \left[\lambda_2 L_I^{\frac{s_2-1}{s_2}} + (1-\lambda_2)[(1-\mu)E_S]^{\frac{s_2-1}{s_2}} \right]^{\frac{1}{s_2-1}}}{[(1-\mu)E_S]^{\frac{1}{s_2}}} < 0 \tag{D11}$$

So when more electricity is assigned to the household sector (μ increases), it decrease in the firm's production due to power rationing.

Denote $r = \frac{E_I}{E_H}$ (so that $r = \frac{1-\mu}{\mu}$), we have[11]

$$\frac{\lambda_1}{1-\lambda_1} A_I^{1-\frac{1}{s_2}} Y^{\frac{1}{s_2}-\frac{1}{s_1}} = r^{\frac{1}{s_2}} E_H^{\frac{1}{s_2}-\frac{1}{s_1}} \tag{D12}$$

and

$$r = A_I^{s_2-1} \left(\frac{\lambda_1}{1-\lambda_1}\right)^{s_1} \left(\frac{e}{p}\right)^{s_1-s_2} \tag{D13}$$

We define

$$\theta = \frac{pY}{eE_H} = \left(\frac{p}{e}\right)^{1-s_1} \left(\frac{\lambda_1}{1-\lambda_1}\right)^{s_1} \tag{D14}$$

Then

$$r = A_I^{s_2-1} \left(\frac{\lambda_1}{1-\lambda_1}\right)^{s_1 \frac{1-s_2}{1-s_1}} \theta^{\frac{s_2-s_1}{1-s_1}} \tag{D15}$$

The intuition of the model results are

- As A_I increases, r decreases. Intuitively, more electricity can be allocated to the household sector if the productivity of firms improves.
- We assume that high temperatures increase household electricity demand, and the social planner always prioritizes the household sector, resulting in a decrease in θ.
- If $s_1 < s_2$, then during high temperatures, as θ decreases, r also decreases. This implies that more electricity should be allocated to the household sector during high temperatures to maximize welfare.
- If $s_2 < s_1 < 1$, then during high temperatures, as θ decreases, r increases. This indicates that more resources should be allocated to the industry sector during high temperatures to maximize welfare.

[11] From the social planner's problem we have $\frac{\lambda_1}{1-\lambda_1} A_I^{1-\frac{1}{s_2}} Y^{\frac{1}{s_2}-\frac{1}{s_1}} = \frac{E_I^{\frac{1}{s_2}}}{E_H^{\frac{1}{s_1}}}$. For the household, we have $\frac{Y}{E_H} = \left(\frac{e}{p}\right)^{s_1} \left(\frac{\lambda_1}{1-\lambda_1}\right)^{s_1}$.

The elasticity of substitution in two sectors plays a crucial role. When both s_1 and s_2 are smaller than one, it implies that electricity and other factors are, to some extent, complementary in both sectors. In other words, it is harder to change the consumption (input) proportions of different composites while keeping utility (output) unchanged. Thus, the allocation of electricity resources during high temperatures depends on the relative magnitudes of the substitution elasticities in the two sectors. The sector with a smaller substitution elasticity, indicating a stronger complementarity and a more significant utility loss for changing the proportion, should receive more electricity. In the particular case where s_1 equals s_2, the optimal proportion of electricity allocation is a constant and is featured by firms' productivity and the preferences of households.

C3. Calibration of elasticities

We estimate s_1 using the Slutsky equation and the estimation of price and income elasticity from Hu et al. (2019). The Slutsky equation indicates that

$$\eta_{EY} = \delta_Y s_1 - \delta_Y \eta_{EI} \tag{D16}$$

where $\delta_Y = \frac{pY}{I}$. η_{EY} and η_{EI} are price and income elasticity, respectively. Based on the results of Hu et al. (2019) using the household level data from 1992 to 2009 in China, $\widehat{\delta_Y} = 0.58$, uncompensated elasticity $\widehat{\eta_{EY}} = -0.043$, and $\widehat{\eta_{EI}} = 0.690$. Thus, we have $\widehat{s_1} = 0.616$.

We estimate s_2 following Bretschger and Jo (2024) using 2SLS. The results are detailed in Table D1. We show that $\widehat{s_2}$ is about 0.84–0.86, significantly larger than the $\widehat{s_1}$. Following the model implication, it indicates that the government should allocate *more* electricity to the household sector as $s_1 < s_2$.

$$log\left(\frac{E_{it}}{L_{it}}\right) = \beta_0 + s_2\, log(\frac{W_{it}}{e_{it}}) + \mu_i + \lambda_{pt} + I_{st} + \epsilon_{it} \tag{D17}$$

Table D1: Estimate the elasticity of substitution between labor and energy.

	(1)	(2)	(3)	(4)
	First Stage	Second Stage	First Stage	Second Stage
	log W/P	log E/N	log W/P	log E/N
logW/P		0.837***		0.863***
		(0.038)		(0.046)
log AvgW/AvgP	0.113***		0.117***	
	(0.006)		(0.008)	
Obs.	145,048	145,048	145,045	145,045
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No
Industry FE	Yes	Yes	No	No
Year-Industry FE	No	No	Yes	Yes
Year-Province FE	No	No	Yes	Yes
Underidentification test	292.56	288.41	216.00	211.17
	[0.000]	[0.000]	[0.000]	[0.000]
Weak identification test	292.43	593.326	215.59	430.162
	[0.000]		[0.000]	

Notes: For the first-stage regression results, we report the SW Chi2 statistic and its p-value for the underidentification test, as well as the SW F-statistic and its p-value for the weak identification test. As for the second-stage regression results, we present the Kleibergen-Paap RK LM statistic and its p-value for the underidentification test, as well as the Cragg-Donald Wald F statistic for the weak identification test. Standard errors in the parentheses are clustered at the county level. * p<0.1, ** p<0.05, *** p<0.01.