Temperature and Productivity: Evidence from Plant-level Data

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Abstract

Research in biomedical science finds that warmer temperature diminishes functioning of human brains, causes stress and anxiety, affects people's mood, and leads to higher suicide rate and various social conflicts. Using plant-level data in the U.S., we find that on average warmer temperature negatively affects plant's productivity. The average effect of temperature remains strong for plants that choose to relocate to warmer counties presumably for tax reasons, suggesting that our results are robust to self-selection concerns. Using information on establishment-level innovation, we document that warmer temperature affects the productivity of inventors and contributes to the net outflows of inventors out of the county. We estimate county-level measures of suicide rate-temperature sensitivity and hospital admissions-temperature sensitivity and find that temperature affects productivity via its negative impacts on employees' mental and physical health. Placebo test shows an insignificant effect of weekend temperature on productivity, suggesting that our results are not a spurious relation. This study contributes to the emerging climate finance literature by documenting micro-level evidence on the impact of rising temperature on plant-level productivity.

Keywords: Temperatures; Firm Performance; Plant-Level Productivity; Innovation; Mental Health; Physical Health

JEL Code: G30; G38

"Don't fall in to the trap of arguing whether climate change is real… The real debate is how much economic damage does climate change actually do."

John H. Cochrane (February 2017)
Former President of the American Finance Association

1. Introduction

Climate research documents that warming temperature has a negative impact on public health (Deschênes and Greenstone, 2011), social unrest, violence, and human conflicts (Hsiang and Burke, 2014). Recent studies (e.g., Hsiang, 2010; Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015) provide macro-level evidence that a country's economic activities significantly decline when its temperature increases. There is, however, little research on how rising temperature affects productivity at the micro (i.e., establishment) level. Addressing this question is important because business entities play a central role in driving a country's productivity and innovation. As the above quote pointed out, it also offers direct implications for corporate managers, investors, and policymakers on the degree of economic damage that warming temperature caused to businesses.

Building on research in the biomedical field, we hypothesize that temperature affects firm performance via lower productivity of workers. Scientific research suggests that productivity is lower because human bodies cannot cope with uncomfortable and hot temperature. When employees' productivity is lower, it follows that firm performance and productivity will suffer. There are at least three medical reasons for lower employees' performance as temperature is warmer.

First, warm temperature ranging from 25 to 35°C (77-95°F) will cause heart rate to be higher and heart rate variability (HRV) to be lower (Sollers et al., 2002; Wu et al., 2013), which are the conditions leading to higher stress and anxiety. The physical effect is analogous to people facing danger or harmful situations, which cause their HRV to be lower (Malik, 1996; Stauss, 2003;

Thayer et al., 2012). Low HRV is also an important determinant of bad mood, which Caplan and Jones (1975) and Laborde and Raab (2013) show to negatively affect creativity, productivity, and even decision making of people. Taken together, research in cardiology finds that higher temperature affects HRV, which, in turn, negatively affects people's mood, creativity, and cognitive ability (Davis, 2009; Laborde and Raab, 2013).

Second, warmer temperature affects the ability of the brain to dispose of waste heat. When the brain is overheated, its functions become significantly impaired. On average, the brain generates 20% of all the heat of the human body of which it needs to dispose. Since the brain's functioning is sensitive to temperature, the disposal of waste heat becomes harder when the ambient temperature rises (Schiff and Somjen, 1985; Yablonskiy et al., 2000). Schiff and Somjen (1985), for example, document that when ambient temperature ranges 29-33°C (84-91°F), there is an elevated risk of dysfunctions of brain activities.

Third, human bodies devote more energy to cool down when the ambient temperature is hotter than it does to warm up when the temperature is colder (Kilbourne, 1997; Parsons, 2003). When temperature is high, the body automatically circulates more blood near the skin to take advantage of cooling opportunities, thereby limiting the supply of blood to key organs, such as the brain and the heart. Moreover, warmer temperature makes dehydration more likely, which diminishes employees' productivity (Sawka and Montain, 2000).

Building on the above scientific evidence, we hypothesize that, by affecting employees' cognitive and physical activities, warm temperature can have a negative impact on business entities' performance and productivity. Research in health economics suggests that ambient temperature also has an impact on the productivity of office workers. Deryugina and Hsiang (2013) find that the U.S. economy has not fully implemented adaptation measures to offset the impact of warming temperature. They argue that, because the marginal cost of adaptation is sufficiently large, it is optimal for economic activities to "not fully be insulated from the environment". Indeed, while many commercial buildings are air-conditioned, the internal thermal conditions are often either not well-controlled or not adjusted as frequently as the outside temperature changes (Seppanen et al. 2006). Federspiel et al. (2004) find that temperature can affect workers' productivity because employees typically cannot set their own thermostat to a comfortable level. Zivin et al. (2015) track the performance of students in mathematics between 1979 and 1994 and find that these students perform worse on warm days (greater than 26℃ or 78°F). In their study, students are interviewed on randomly chosen days in their homes. This finding is consistent with the medical findings that high temperature can affect the functioning of human brains, thereby impairing their cognitive ability. Seppanen et al. (2006) examine the effect of temperature on productivity of call-center workers and find that higher temperature causes longer customer service time and handling time per customer call. Zivin and Neidell (2014) document that employees in the manufacturing industry allocate less time to work on days when temperature is higher. Finally, even when employees may stay indoor most of the time, they are still exposed to outdoor temperatures during their commute.

To examine the effect of temperature on business entities' productivity, we employ comprehensive plant-level data on U.S. subsidiaries, branches, and plants from the National Establishment Time Series (NETS) database over the period from 1990 to 2015. Using the information on outputs and employment levels of plants from the NETS database, we compute two alternate measures of plant-level productivity: total factor productivity (*TFP*), which captures the overall productivity of a plant in utilizing its capital and labor, and the modified TFP measure, *OP_TFP*, which is estimated using Olley and Pakes (1996) method. The latter measure corrects for the possibility that plants simultaneously choose the level of inputs as they choose their outputs. We obtain daily temperature data at the county level from the U.S. National Climatic Data Center (NCDC) and compute a yearly temperature measure in the county of a plant as the average of daily temperature over a firm's fiscal year. To maintain the convention in both the NCDC database and the vast majority of scientific studies, we measure temperature in degrees Celsius.

We find that warmer temperature causes both measures of *TFP* to be lower. The effect is strong and robust even after controlling for a battery of known plant-level and firm-level characteristics, county-level variables, as well as the inclusion of various fixed effects such as firm, county, and year fixed effects or firm-by-year and county fixed effects. The effect is also economically significant. For example, using the plant-level *TFP* as a measure of productivity, a $1°C$ $(1.8°F)$ rise in the average yearly temperature is associated with a reduction of productivity by 8.9% relative to the sample average (or equivalent to a drop from the 75^{th} percentile to the 60^{th} percentile of productivity in the cross-section of plants).[1] While the effect of temperature on productivity is broadly manifested across industries in the U.S., the relation is, expectedly, stronger for plants in agriculture and outdoor industries. At the firm level, we find that *Tobin's Q* of multi-state firms is significantly lower when temperatures in their plants' local counties are warmer.[2]

While yearly variation in temperature is arguably exogenous to firm characteristics, the location of a plant may not be random. To mitigate this concern, we take advantage of state-level tax changes and analyze the productivity of plants that relocate from a colder, higher-tax county to a hotter, lower-tax county. We contend that these plant relocations are possibly motivated by lower corporate tax rates, since Giroud and Rauh (2018) find causal evidence that a decrease in

[1] In Section 4, we replicate our main empirical results using firm-level *Tobin's Q* and find that our results do not qualitatively change.
[2] We approximate the firm-level temperature by computing the weighted average of temperatures in the plants' counties where the weight is the plant's economic weight within the firm's network.

state-level corporate tax rate leads to more new plants in the state. We conduct a difference-in-difference analysis surrounding a plant's relocation event within two years after the tax-reduction law was passed. We find that treatment plants experience a significant drop in their productivity compared to the other plants. In terms of economic magnitude, after relocating to a warmer county treatment plants experience a reduction in *TFP* by 18-23% relative to the sample mean. These results suggest that plants, which choose to relocate to a warmer county presumably for tax-motivated purposes, are also affected by warmer temperature.

We next examine whether plant's productivity is affected by warmer or colder temperatures. We do so by constructing four variables representing the number of days over the firm's fiscal year in which the daily average temperature is below 10℃ (50°F), between 10℃ (50°F) and 20℃ (68°F), between 20℃ (68°F) and 30℃ (86°F), and above 30℃ (86°F). We find an inverted U-shaped relation between temperature days and plant-level productivity. However, consistent with scientific findings, the effect of *Ln(> 30*℃ *days)* is stronger and more robust than that of colder temperatures. These results are consistent with the biomedical evidence that employees' cognitive and physical activities are significantly impaired when temperature is warmer.

A potential alternative explanation for our findings is that the effect of temperature on establishment-level productivity may be driven by lower local customer demand, rather than lower workers' productivity. To rule out this alternative explanation, we follow Agrawal and Matsa (2013) and employ data of total revenues of goods shipped to intrastate and interstate customers from the US Commodity Flow Survey, which is conducted by the U.S. Bureau of the Census and surveys plants across the U.S. We examine the effect of local temperature on productivity of a sample of plants, whose 95% of sales revenues come from out-of-state customers. We continue to find that these plants are negatively affected by their local counties' temperatures. These results indicate that demand of local customers is unlikely to be the explanation for our findings.

We perform several additional tests, which together suggest that temperature affects establishment-level productivity via its impacts on the mental and physical activities of employees. We first investigate the effect of temperature on corporate innovation (i.e., productivity of inventors). We construct establishment-level innovation measures by merging the patent information from Kogan et al. (2017) and the location of inventors of each patent from the U.S. Patent Inventor Database. We find that both the number of patents and patent citations at each establishment are lower as county's temperature rises, suggesting that temperature affects productivity via its negative impacts on the creativity and cognitive activities of inventors. We further find that the effect of temperature is more pronounced for establishments, whose overall productivity is more dependent on innovation outputs. At the aggregate county level, we show that counties experience a significant net outflow of inventors when their medium- and long-run temperatures increase.

In our next avenue of inquiry, we examine whether plant's productivity is lower in counties, whose residents' mental health is more sensitive to warmer temperature. Research in environmental and health economics finds that social conflicts are particularly responsive to changes in temperature (Hsiang, Burke, and Miguel, 2013). Burke et al. (2018) document that warm temperature leads to higher suicide rates in the U.S. and Mexico, indicating that high temperature can have a negative impact on mental health. To the extent that local temperature affects productivity via its negative impacts on the mental health of residents, we expect that plant's productivity is significantly lower in counties whose residents' mental health is more sensitive to warmer temperature. To test this conjecture, we estimate a yearly county-level measure of sensitivity of suicide rates to temperature and examine the effect of this sensitivity on plant-level productivity. Consistent with our hypothesis, we find that plant's productivity is significantly lower as county's suicide rate sensitivity to temperature increases. This finding is consistent with the notion that temperature affects firm performance by impairing mental health of workers and, in turn, their productivity.

We further examine whether plant's productivity is lower in counties, whose residents' physical health is more sensitive to temperature. Employing data on hospital admissions in California, we estimate a measure of county-level sensitivity of residents' physical health to temperature and examine the effect of this sensitivity on plant's productivity. Consistent with our hypothesis, we find that plant's productivity is significantly lower in counties with high hospital admissions-temperature sensitivity.[3]

Finally, we conduct a placebo analysis in which we test the effect of weekend temperature on plant's productivity and find that the effect is statistically insignificant. As most major business operations occur on weekdays, rather than weekends (Deryugina and Hsiang, 2014), these results suggest that the relation between temperature and firm performance documented in our study is not a spurious result. In other robustness tests, we confirm that our results do not qualitatively change when we examine the effect of long-run average temperature or when we control for other weather-related variables such as sunshine, wind speed, precipitation, and air evaporation.

Our study contributes to the existing literature in two ways. First, we employ a comprehensive plant-level dataset and provide one of the first micro-level evidence of the average effect of temperature on plant-level productivity and firm performance in the U.S. There is a dearth of empirical evidence on this important question. Burke, Hsiang, and Miguel (2015) provides macro-

[3] We use California-based hospitals because only these admissions data are available to us. We confirm that our baseline results are not driven by establishments in California.

level evidence by studying the data from 166 countries. Given that U.S. corporations have business operations in multiple states, it remains unknown whether the *average effect* of temperature across all establishments in the U.S. is consistent with the macro-level findings. Our study takes advantage of presumably random fluctuations in daily temperatures at the county level in the U.S. and document robust evidence that warm temperatures are detrimental to firm performance, establishment productivity, and innovation. Moreover, we also find that temperature affects firm performance by affecting employees' mental and physical health – consistent with findings the medical literature. As such, our study has direct implications for managers and policymakers.

This study also contributes to the emerging literature on climate finance, which is still limited in scope and chiefly examines the impact of climate change in capital markets. Hong, Li, and Xu (2018) investigate whether the market efficiently incorporates the risk of droughts in stock prices of food companies. Bansal, Kiku, and Ochoa (2016) document that virtually all U.S. equity portfolios are exposed to the risk of rising temperature. Choi, Gao, and Jiang (2018) find that stocks of carbon-intensive firms experience a lower average return than those of low-carbon firms in abnormally warm temperatures. Painter (2018) documents that counties affected by climate change incur a higher cost of debt when issuing long-term municipal bonds compared to counties unlikely to be affected by climate change. In the real estate market, Bernstein, Gustafson, and Lewis (2017) find that prices of homes on the coastal lines that will be affected by rising sea levels are sold at a discount compared to unaffected homes. Baldauf, Garlappi, and Yannelis (2018) show that differences in beliefs about climate change in a neighborhood will determine house prices in the area. Our study adds to this contemporary literature by documenting the real consequences of rising temperature on the business entities' performance and productivity.

The remainder of the paper is organized as follows. Section 2 describes the data and research design. Section 3 shows the descriptive statistics and our main findings. Section 4 reports the additional analysis and Section 5 concludes the paper.

2. Data

2.1. Plant-level and firm-level data

We obtain information on subsidiaries, branches, and plants of multi-state firms from the National Establishment Time-Series (NETS) database between 1990 and 2015, which is supplied by credit rating agency, Dun and Bradstreet (D&B), and is maintained by Walls and Associates.[4] As noted by Faccio and Hsu (2017), the NETS database contains a comprehensive record of plants in the U.S. because plants wishing to obtain lines of credit from suppliers or financial institutions have incentives to report accurate information. D&B also collects information from independent sources including phone calls to suppliers and customers, legal and bankruptcy filings, press reports, and government records (Heidi and Ljungqvist, 2015; Ljungqvist et al., 2017).

The NETS database provides us with information on the county, number of employees, and sales at each establishment, as well as their historical headquarters' names and locations. In our regression tests, we control for plant-level credit score, *Credit_Score*, which ranges from 0 to 100 and is rated by D&B using the trade credit information supplied by suppliers and customers of a plant. Following prior research (Heidi and Ljungqvist 2015; Ljungqvist et al. 2017), we match plants in the NETS database with firms in Compustat by their legal names and historical headquarters information obtained from their SEC filings. Our firm-level data are the intersection

[4] Our sample period is constrained by the availability of the NETS database. At the time of conducting this study, 2015 is the latest update of the NETS database.

of accounting data from Compustat and market data from CRSP. As standard in the literature, we do not consider financial firms (those with SIC codes 6000-6999) and non-common stocks (those with CRSP share codes different from 10 or 11).

We employ two alternate proxies for plant-level performance: total factor productivity (TFP) and the refined measure of TFP *(OP_TFP)* following the estimation method in Olley and Pakes (1996). First, TFP is a measure of overall productivity of a plant in utilizing its capital and labor (e.g., Olley and Pakes, 1996; Basu, Fernald, and Kimball 2006; Kogan et al., 2017). Since we observe number of employees and output levels at each plant but do not have information on capital and inputs, we follow Imrohoroglu and Tuzel (2014) and Kogan et al. (2017) and approximate capital and input levels using firm-level information from Compustat. Specifically, the plant-level (log) TFP of each plant is the estimated residual obtained from the following regression:

$$Ln(y_{ijt}) = \alpha_{jt} + b_{jt}\ln(K_{ijt}) + c_{jt}\ln(L_{ijt}) + d_{jt}\ln(M_{ijt}) + \varepsilon_{ijt} \quad (1)$$

where plant-level labor (L) is the number of employees at each plant and output (y) is the plant-level sales obtained from NETS. We approximate capital (K) as the plant's economic weight within its firm multiplied by the firm-level property, plant and equipment (PPE) from Compustat. A plant's economic weight within its firm is equal to $\frac{1}{2}\frac{employees_{i,p}}{employees_{i,total}} + \frac{1}{2}\frac{sales_{i,p}}{saless_{i,total}}$, where $employees_{i,p}$ and $sales_{i,p}$ are the employment and sales levels at plant p of firm i; and $employees_{i,total}$ and $saless_{i,total}$ are the total employment and sales across all plants of firm i.[5]

[5] Heidi and Ljungqvist (2015) and Ljungqvist, Zhang, and Zhang (2017) employ a similar weighting method to compute the weighted tax rate of multi-state firms. In unreported anlaysis, we confirm that our results are qualitatively unchanged when we conduct firm-level analysis (instead of plant-level), where the effect of temperatures at the firm-level is approximated by either headquarters' county or a nexus weighted average as in Heidi and Ljungqvist (2015).

Similarly, to compute plant-level input material (M), we multiply the plant's weight by the firm-level cost of goods sold.

Our second measure is *OP_TFP*, which is a modified TFP measure that corrects for the fact that plants simultaneously choose the level of inputs as they choose outputs. For example, firms tend to increase the use of inputs when they observe a positive production shock. Olley and Pakes (1996) use investment as a proxy variable, which is determined by the shock to production and existing capital stock. We approximate investment at the plant level as the plant's economic weight multiplied by the firm-level investment obtained from Compustat. Using this instrument, we follow Olley and Pakes's (1996) methodology and estimate the production function for each industry separately.

In our regression tests, we control for a set of variables, which account for the effects of other known determinants of performance. These include the natural logarithm of credit rating of each plant (*Credit_Score*), the natural logarithm of book-to-market ratio (*BM*), the natural logarithm of firm size (*ME*), leverage (*Lev*) defined as the ratio of long-term debt over equity, the natural logarithm of firm age computed as the number of years since the firm has its listed price in the CRSP database (*Age*), revenue as the natural logarithm of sales (*Sales*), interest expense (*Interest_Exp*) defined as the ratio of interest expense over sales revenue, asset tangibility (*PPE*) computed as net properties, plants and equipment scaled by total assets, and capital expenditure (*CAEX*) defined as capital expenditures divided by total assets.

We further control for firm's financial constraints (*FinConst1*) using Hoberg and Maksimovic's (2015) text-based measure, which is based on the Capitalization and Liquidity Subsection (CAPLIQ) section in a firm's 10-K report. Hoberg and Maksimovic (2015) show that firms with higher values of *FinConst1* are more similar to a set of firms known to be at risk of delaying their investments due to issues with liquidity. Since *FinConst1* may be missing for firms that do not have machine-readable CAPLIQ, we follow Hoberg and Maksimovic's advice and create a dummy variable, *FinConst2*, which takes a value of one if *FinConst1* is missing for a firm-year observation and zero otherwise.[6] Hoberg and Maksimovic (2015) find that firms that do not disclose their financial constraints in the CAPLIQ section are less constrained than disclosing firms. In addition to plant- and firm-level variables, we control for county-level macroeconomic variables such as the natural logarithm of total population (*pop*), the natural logarithm of household income (*inc*), and education levels (*edu*). Total population is the number of residents (in thousands) of the plant's local county. Household income is the average household income of local residents in a county. Level of education is the proportion of local residents above the age of 25 who have completed a bachelor's degree or higher.

We employ two alternative regression specifications. The first model includes county fixed effects as well as firm and year fixed effects, which control for unobserved time-invariant determinants of firm performance. For the second regression specification, we incorporate county fixed effects and firm-by-year fixed effects, which control for unobservable transitory economic shocks to the firm.

2.2. Temperature measures

[6] In Gerard Hoberg's data guidelines posted on his website, he advises: "if a researcher wishes to include the constraint variables in a regression where some observations are missing (and the researcher wants to not lose observations and thus control for the missing values), we recommend (A) including a dummy in the regression for observations where the given variable is missing and (B) then it is okay to set the constraint variable to zero for these missing observations." We thank Gerard Hoberg for providing the data on his website. We use delay investment score in their data.

To measure daily average temperatures, we use daily surface data from the National Climatic Data Center (NCDC). These data are measured at thousands of physical weather stations located across the U.S. We use the latitude and longitude of each weather station to identify the county in which it is located. Where there is more than one station in a county, we compute the average temperature across all stations in the same county on a given day. We further omit observations where the maximum temperature exceeds 60℃ (140°F) or the minimum temperature is lower than -80℃ (-112°F) as they are likely errors (Deryugina and Hsiang 2014). As standard in the climatology literature, the daily average temperature is then a simple average between the daily maximum and minimum temperatures. Auffhammer et al. (2013) point out that weather station data may be incomplete because of mechanical failures, political events, or financial constraints that cause the station to shut down. We follow their suggestion and remove station-year observations that do not have a complete set of daily weather temperatures (Deryugina and Hsiang, 2014). Consistent with the convention in the science literature and the U.S. NCDC database, we measure temperature in degrees Celsius in our analysis.

We compute yearly average temperature, *Tmp* (in degrees Celsius), as the average of daily temperature in each county over a firm's fiscal year. We also construct a set of four degree-days variables representing four ranges of daily temperatures. Specifically, we construct four count variables representing the number of days over a firm's fiscal year in which the daily average temperature is below 10℃ (50°F), between 10℃ (50°F) and 20℃ (68°F), between 20℃ (68°F)and 30℃ (86°F), and above 30℃ (86°F).

3. Descriptive Statistics and Main results

3.1. Variation in temperature in the U.S.

Figure 1 plots the average temperature each year between 1969 and 2015 across all U.S counties where plants in our sample are located. While plant-level data begin in 1990, we extend the sample period in these graphs to 1969, which exhibit a visible trend of rising temperature over time. The first graph shows that the country's average temperature rises every year. In 1969, the average temperature in the U.S. is about 11.7℃ (53.06°F). By the end of our sample period in 2015, the average temperature has risen to 12.6℃ (54.68°F). Consistently, we see a rise in both the average high and low temperatures across the nation. Over a shorter, more recent sample period 1990-2015, the rising trend is less visible.

Figure 1 also exhibits a feature that is preferable for our empirical analysis: there is a significant year-on-year variation in the average temperature. This variation indicates that even when a plant chooses to locate in a county of predominantly warm climate, the local average temperature can be colder in one year than another and potentially affect the mood and cognitive ability of workers as scientific studies suggest.

< Insert Figure1 around here >

Figure 2 depicts the average number of days in a year with temperatures below 10℃ (50°F), between 10℃ (50°F) and 20℃ (68°F), between 20℃ (68°F) and 30℃ (86°F), and above 30℃ (86°F). Due to the averaging method of daily max and min temperatures and the fact that the U.S. has more colder states than warmer states, the nationwide average temperature is relatively low. Figure 2 shows that the number of cold days (below 10℃) decreases from 68 days in 1969 to about 58 days in 2015. Consistently, we see a rise in the average number of hot days (above 30℃), ranging from about one day in 1969 to about two days in 2015. Consistent with Figure 1, there are also significant year-on-year variations in each of the temperature-day variables.

< Insert Figure 2 around here >

3.2. Univariate relation between temperature and plant-level productivity and summary statistics

Figure 3 plots the univariate relation between temperature and plant-level productivity (*TFP* in Panel A) and (*OP_TFP* in Panel B). We classify temperature into terciles, which, respectively, represent average temperatures below ≤ 10℃ (50°F), between 10℃ (50°F) and 25℃ (77°F), and above 25℃ (77°F).[7] We observe a non-linear univariate relation between temperature and productivity. Specifically, productivity is highest when temperature is in tercile 2 (between 10℃ and 25℃). While productivity in tercile 1 (below 10℃) is lower, it is lowest in warmer temperatures. These results provide preliminary evidence for our central hypothesis that temperature is negatively associated with plant's productivity.

< Insert Figure 3 around here >

Table 1 presents summary statistics for variables used in the main empirical analysis. Plants in our sample have an average *TFP* of 0.92 and a standard deviation of 0.19. The mean value of the modified measure of *TFP*, *OP_TFP*, is 0.770, with a standard deviation of 0.24. The average log value of plant-level credit score is 4.22 with a standard deviation of 0.01. The average temperature in our sample is 13.25℃ with a standard deviation of 4.39℃. The mean values of *Ln(< 10℃ days)*, *Ln(10℃-20℃ days)*, *Ln(20℃-30℃ days)*, and *Ln(> 30℃ days)* are 4.55, 4.79, 4.54, and 1.84,

[7] When computing the nationwide average temperature, the high temperature (above 30℃ (86°F)) in one place of the country offsets the low temperature (below 0℃ (32°F)) in another place. As such, in Figure 3 we do not have yearly average temperatures at the two extremes. However, in regression analysis where we use daily temperatures, we are able to have finer categories of temperatures.

respectively. Appendix Table A3 provides state-by-state summary statistics of average temperatures. The top 5 coldest states are North Dakota, Montana, Wyoming, Vermont, and Maine with the average temperatures ranging from 4℃ (39°F) to 6℃ (43°F). The top 5 warmest states are Florida, Arizona, Louisiana, Texas, and Mississippi with the average temperatures ranging from 18℃ (64°F) to 23℃ (73°F).

The statistics of other control variables indicate that, on average, firms have the log value of age (*Age*) of 2.95, a log value of *BM* of 0.39, a log value of firm size (*ME*) of 7.70, leverage (*LEV*) of 0.25, a delay investment score (*FinConst1*) of -0.01, interest expense ratio of 0.02, log value of sales of 1.23, asset tangibility (*PPE*) of 0.31, and capital expenditure (*CAEX*) of 0.07. Approximately 45% of our plant-year observations have missing Hoberg and Maksimovic's (2015) delay investment score. Thus, to be conservative, in addition to these text-based measures of financial constraints, we also control for interest expense ratio and plant-level credit scores in all regressions.

Appendix Table A2 presents pairwise correlations between variables used in our study. Temperature is negatively correlated with plant's *TFP* and *OP_TFP*. These productivity measures are also negatively correlated with *Ln(>30*℃ *days)*, which is the number of days above 30℃ (86°F) in a given year.

3.3. Multivariate analysis

We start our main empirical analysis by investigating the relation between temperature and plant-level productivity. Our null hypothesis is that there is no relation between temperature and performance. This null hypothesis is based on the premise that with the advances of modern technologies such as fully air-conditioned offices, possibly coupled with human body's adjustment to the surrounding environment, workers are no longer affected by presumably random variations in daily temperatures. The alternative hypothesis is derived from that the biomedical literature, which suggests that the cognitive and physical abilities of workers still do not function well in the warmer temperature. These effects, in turn, decrease workers' productivity.

Table 2 reports results of different regression models of plant-level *TFP* (Models (1)-(3)) or *OP_TFP* (Models (4)-(6)) on temperature and controls. For each alternate measure of plant-level performance, we subsequently control for industry, county, and year fixed effects (Model (1) and Model (4)), firm, year, and county fixed effects (Model (2) and Model (5)), and county, firm × year fixed effects (Model (3) and Model (6)). Since temperature is measured at the county level, we report robust *t*-statistics clustered by county and year to correct for potential serial correlation. To reduce the number of decimals in the coefficient estimate, we scale the temperature variable by 10.

In all models, the coefficient on temperature is negative and statistically significant at the 1 percent level, suggesting that plant's productivity is lower when local temperature is higher. The effect is also economically significant. For example, the coefficient on temperature of -0.825 in Model (2) indicates that when yearly local temperature increases by $1°C$ (which is less than one standard deviation of $4.4°C$), plant's *TFP* decreases by 8.9% compared to the sample mean.[8] For another perspective, this marginal effect means that the *TFP* ranking of the affected plant drops from the 75^{th} percentile of 1.089 (reported in Table 1) to roughly the 60^{th} percentile of 1.007 (not tabulated) in the cross-section of plants in the U.S. Similarly, the coefficient on temperature in

[8] Using the summary statistics in Table 1, the economic impact of temperature on *TFP* is equal to $(-\frac{0.825}{10} \times 1℃)/0.924$, where 0.924 is the sample mean of *TFP*.

Model (6) shows that a $1°C$ increase in yearly temperature results in a reduction in plant-level OP_TFP by 1.7% relative to the sample mean.

< Insert Table 2 around here >

4. Additional Analysis

4.1. Effects of temperature on plants relocating to states with warmer temperature and lower tax rates

Previous section documents a strong and robust effect of temperature on plant-level productivity. While fluctuations in temperature are random and exogenous to firms' characteristics, endogeneity issues are possible because the choice of a plant's location may not be random: firms may choose to base their plants in counties where their employees are most comfortable with the climate of those counties and hence become more productive. To mitigate these concerns, we take the advantage of plant relocation events that are likely due to state-level tax policy changes. We identify a sample of plants that moved from a colder, higher-tax county to a warmer, lower-tax county within two years after a tax-rate reduction law in the destination state was passed. We contend that these plant relocations are possibly motivated by lower corporate tax rates, since Giroud and Rauh (2018) find strong causal evidence that a decrease in state-level corporate tax rate leads to more new plants in the state.

We obtain information on state-level tax policy changes from Heider and Ljungqvist (2015). A destination county is considered warmer than the origin county if its average temperature in the past five years is one degree Celsius higher than that of the origin county. Since temperature in the destination county varies on a yearly basis and it may happen to be colder in the relocation year, we require that the average temperature in the destination county in the event year be at least 0.5

degree Celsius higher than its own temperature in the prior year. We create a *Post* dummy variable that takes a value of one to indicate the two years after the relocation of a treatment plant. We employ two sets of control plants. The first control sample contains all other plants that do not experience such relocation events. For the second control sample, we use plants that relocate to a colder, lower-tax state.

Examining these relocation events yields at least three advantages. First, firms presumably relocate their plants for economic reasons such as lower corporate tax rates (Giroud and Rauh 2018)), and variation in temperature is likely to be exogenous to this choice. Second, to the extent that firms choose to relocate their plants to a lower tax county with warmer temperature, we should no longer find a negative effect of temperature on productivity of these relocated plants because these plants may have already considered the negative impacts of warmer temperature and adopted measures to prevent potential negative impacts of hotter temperature. Thus, these events make our tests more conservative and bias against finding an effect of temperature on productivity. Third, relocations events are "staggered" at the plant level and affect plant's productivity at different points in time. As argued by Roberts and Whited (2011), Edmans, Jayaraman, and Schneemeier (2017) and others, staggered events provide researchers with a setting similar to a difference-in-difference (DiD) analysis that avoids the common challenge faced by studies using a single systematic shock, which affects all plants at the same time. At the same time, there are a number of plants that enjoy the benefit of lower corporate tax rates in counties with a colder climate. These plants are included in the potential control group in our DiD analysis, thereby helping to filter out common temporal trends between treatment and control plants (Guo and Masulis 2015).

Table 3 Panel A reports the DiD analysis using all non-event plant-years as control group. Model (1) and (2) report results for the regression of *TFP*, while Model (3) and Model (4) present results for the regression of *OP_TFP*. The coefficient on *Post* in Model (1) where firm, county and year fixed effects are included, is -0.211 with an associated *t*-statistic of -2.80, which is significant at the 1 percent level. This coefficient estimate indicates that treatment plants experience a reduction in *TFP* by 21% (or 23% relative to the sample mean) after relocating to a hotter, lower-tax county. Model (2) shows similar results when we include county and firm × year fixed effects. Consistently, Model (3) uses *OP_TFP* as the dependent variable and shows that the coefficient on *Post* is -0.142 (*t*-statistic of -2.36). In terms of economic magnitude, this reduction in performance of treatment plants represents 18% of the unconditional mean of *OP_TFP*.

< Insert Table 3 around here >

A potential concern regarding the DiD analysis is that the difference between treatment and control groups may exist prior to the real event year. We formally test the parallel trend assumption by employing "pseudo-events" that happen before the actual event. Specifically, we create a dummy variable *Pseudo_Event*, which takes a value of one for treatment firms in the two years surrounding the actual relocation event.[9] We also control for *Post*, which is the actual event dummy. If the parallel trend assumption is rejected, we should observe a significant coefficient on *Pseudo_Event*. Table 3 Panel B shows that the coefficient on *Pre_Event* is insignificant for both regressions of *TFP* and *OP_TFP*, while the coefficient on the actual *Post* event dummy remains statistically significant. This result re-assures the validity of our relocation events.

[9] In unreported analysis, we use two years before the actual relocation event as *Pseudo_Event* variable and our results do not qualitatively change.

4.2.Temperature days and plant-level performance

In this section, we examine whether plant's performance is lower in hotter years. We construct four count variables representing the number of days over a firm's fiscal year during which the daily average temperature is below 10℃ (50°F), between 10℃ (50°F) and 20℃ (68°F), between 20℃ (68°F)and 30℃ (86°F), and above 30℃ (86°F). Table 4 reports estimation results for regressions of plant-level *TFP* (Model (1) and Model (2)) and *OP_TFP* (Model (3) and Model (4)) on these four temperature days variables and controls. In Models (1) and (2), we observe an inverted U-shaped relation between temperature days and *TFP*. The coefficient on *Ln(< 10*℃ *days)* is negative -0.048, while the coefficient on *Ln(10*℃*-20*℃ *days)* is positive and statistically significant at the 1% level. As there are more warmer days in a year, *TFP* is lower with the coefficients on *Ln(20*℃*-30*℃ *days)* and *Ln(> 30*℃ *days)* being negative and statistically significant at the 1% level.

The effect of cold temperature on *TFP*, however, is not robust in Models (3) and (4), where the dependent variable is *OP_TFP*, which allows plants to change the level of inputs as productivity changes. The coefficient on *Ln(< 10*℃ *days)* in the last two columns is insignificant even at the 10% level, whereas the coefficient on *Ln(> 30*℃ *days)* remains negative and statistically significant. *Ln(10*℃*-20*℃ *days)* has a positive effect on *OP_TFP* with the coefficient being positive and significant at the 1% level, suggesting that productivity is highest in this temperature range.

< Insert Table 4 around here >

These results indicate that there is an inverted U-shaped relation between temperature and plant-level productivity. However, the effect of extremely hot temperature is stronger and more robust than that of cold temperature. Plant-level productivity is highest when the ambient temperature is between *10*℃ and *20*℃. These results are consistent with scientific findings that hot temperature has a more significant impact on workers' health and productivity than cold temperature.[10]

4.3. Customer demand versus supplier productivity

A potential confounding effect is that plant's performance may be lower due to lower demand of their products rather than productivity of workers. To rule out this alternative explanation, one would ideally need to observe the location of each customer of each plant. Unfortunately, to the best of our knowledge, such data are not publicly available. We thus follow Agrawal and Matsa (2013) and employ data from the U.S. Commodity Flow Survey, which is conducted by the U.S. Bureau of the Census and surveys plants across the U.S. on the total revenues of goods shipped to intrastate and interstate customers. Using this dataset, we examine a sample of plants, whose 95% of sales revenues come from out-of-state customers.

We regress plant-level *TFP* and *Tobin's Q* on its home county's temperature for this sample of plants, whose sales are mainly generated out of their home states. Table 5 reports regression results. Model (1) and Model (2) present the regression of *TFP*, while Model (3) and Model (4) report regression results for *OP_TFP*. In all the four models, the coefficient on local temperature is negative and statistically significant at the conventional level. These results suggest that even for plants that make most of their revenues from non-local customers are still affected by the local temperature of their counties.

< Insert Table 5 around here >

[10] Scientific research also shows that human body functions best when the ambient temperature is around 21℃ (70°F) (https://www.scientificamerican.com/article/why-people-feel-hot/)

4.4. Agriculture and outdoor industries

Our hypothesis is that temperature affects plant's performance through lower workers' productivity. This hypothesis builds on the health science literature that ambient temperature affects both indoor and outdoor workers. Nevertheless, we expect that the effect should be stronger for plants in industries that are more exposed to temperature such as agriculture and outdoor industries.

Using the SIC code of each plant from the NETS database, we construct a dummy variable, *Agriculture*, which indicates plants in the agriculture industry based on Fama and French's industry classifications (those with SIC codes 0100-0799). We also create an indicator variable, *Outdoor*, which takes a value of 1 for establishments of outdoor industries such as construction and transportation (those with SIC codes 1500-2459 and 4000-4789). We then regress plant-level *TFP* and *OP_TFP* on temperature, its interaction with each of these indicator variables, and controls. Since the SIC code does not change frequently for each firm, we cannot employ firm fixed or industry fixed effects in these regressions. Thus, we control for year and county fixed effects in this analysis.

< Insert Table 6 around here >

Table 6 reports regression results. Models (1) and (2) use *TFP* is the dependent variable, while Models (3) and (4) employ *OP_TFP* as the dependent variable. Model (1) shows that the coefficient on the interaction term between temperature and *Agriculture* is negative and statistically significant at the 1% level. In Model (2), the coefficient on the interaction term between temperature and *Outdoor* is also negative and significant at the 1% level. Model (3) and Model (4) show consistent results for *OP_TFP*. In all models, the coefficient on temperature remains significant and negative. These results indicate that while temperature affects productivity of an average firm across all industries, the effect is larger for agriculture and outdoor industries.

4.5. How does warmer temperature affect productivity? Innovation channel

If temperature affects plant's productivity via the cognitive ability of workers, then corporate innovation and patent quality, which are heavily dependent on creativity and productivity of inventors, would also be lower in regions with warmer temperature. We obtain innovation data from Kogan et al. (2017) for the period 1990-2010. Following prior studies in innovation, we assume that it takes, on average, about two years from the development stage to the application date of the patent.

To measure innovation at each plant, we identify the location of each inventor of a patent in Kogan et al.'s (2017) database using inventor-level information from the U.S. Patent Inventor Database. For each patent, the U.S. Patent Inventor Database provides a unique identifier of an inventor, location of the inventor, patent ID, and the assignee (i.e., the firm that owns the patent). We match this information with patent data of Kogan et al. (2017) together with the plant's location from NETS to obtain the innovation level at each plant.

We estimate the regression of the natural logarithm of number of patents and patent citations on local county's temperature, controlling for firm, year, and county fixed effects or firm-by-year and county fixed effects. Table 7 reports regression results. In Models (1) and (2), where the dependent variable is the natural logarithm of number of patents at each plant, *Ln(Patents)*, the coefficient on temperature is -0.627 and -0.665 with an associated *t*-statistic of -3.36 and -3.21, which are statistically significant at the 1 percent level. The magnitude of these coefficients is also economically significant. For example, the coefficient estimate on temperature in Model (1) suggests that an increase in yearly temperature by 1℃ leads to a reduction in *Ln(Patents)* by 2.6% relative to the sample mean.[11] Model (3) and Model (4) regress the natural logarithm of patent citations on temperature and controls. We observe that the coefficient on temperature remains negative and statistically significant at the 1 percent level. Consistent with the biomedical prediction, these results suggest that warmer temperature impacts productivity of inventors, causing innovation at the plant to be lower.

< Insert Table 7 around here >

In Table 7 Panel B, we examine whether our results are driven by the state of California, where many innovative firms are located. We remove establishments in California and re-estimate the innovation regression. The coefficient on temperature remains negative and significant, suggesting that our results are not driven by these California-based firms.

Since inventors are highly skilled employees, they are relatively able to migrate out of hotter counties if warm temperature impairs their cognitive ability and creativity. Such brain drain can cause plants in these counties to lose talents in the medium to long run, and as a result, innovation of these firms to be lower. To empirically test this prediction, we employ inventor-level data from the U.S. Patent Inventor Database and compute the number of inventors in each county in each year. Since inventors do not necessarily migrate out of a county immediately after temperature in a given year is warmer, we focus on examining the effect of medium- to long-term average temperature on the medium- to long-term average number of inventors (net of inflows and outflows).

[11] This is computed as $(-\frac{0.627}{10} \times 1℃)/2.39$, where 2.39 is the sample average of *Ln(Patents)*.

Results are reported in Table 7 Panel C. Model (1) regresses the natural logarithm of three-year average number of inventors in a county on three-year average temperature. Model (2) regresses the natural logarithm of five-year average number of inventors in a county on the five-year average temperature, while Model (3) uses ten-year averages. In all models, the coefficient on average temperature is negative and statistically significant at the 1 percent level, suggesting that counties lose more talents as medium- and long-term average temperatures are higher. The effect is also economically significant. For example, the coefficient on temperature in Model (1) indicates that when the three-year average temperature increases by 1℃, the talent pool in the county decreases by 1%, representing 0.23% of the sample average, which is equivalent to a net outflow of 595 inventors out of the county.[12]

Our last test of the innovation channel examines whether the negative impact of warmer temperature on innovative activities would result in lower the overall productivity and performance of a firm. To do so, we first estimate a plant's overall productivity sensitivity to innovation. Specifically, we estimate a 10-year rolling regression of a plant's *TFP* or *OP_TFP* on the natural logarithm of number of patents (*Ln(Patents)*). The annual coefficient on *Ln(Patents)*, denoted as β_{tmp}^{inno}, represents a plant's performance sensitivity to innovation. In the second stage, we regress a plant's *TFP* or *OP_TFP* on temperature, β_{tmp}^{inno}, and the interaction between these two variables, and controls. Table 7 Panel D reports regression results. The coefficient on the interaction term, $\beta_{tmp}^{inno} \times Tmp$ is negative and significant at the 1 percent level in all the four models. This suggests that the effect of temperature on a plant's productivity is larger if it is more dependent on innovation outputs of inventors.

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[12] $0.23\% = \frac{0.182/10}{7.85} \times 100$, where 7.85 is the mean of *Ln(3-year average of number of inventors in a county).*

4.6. How does rising temperature affect productivity? Mental health channel

The science and health economics literature documents that warmer temperature can cause human conflicts, bad mood, and suicide rates (Hsiang, Burke, and Miguel 2013; Burke et al. 2018). To the extent that suicide rate in a county is sensitive to warmer temperature in a given year, we expect that productivity of workers in the county is also lower in the year. To test this conjecture, we obtain suicide rates in each county from the Center for Disease Control and Prevention for the period 1999-2014.[13] For each county, we estimate ten-year rolling regressions of suicide rate on temperature and retain the time-series of the coefficient, denoted $\beta_{tmp}^{suicide}$, which is the suicide rate sensitivity to temperature of each county. In the second stage, we regress a plant's *TFP* or *OP_TFP* on temperature, $\beta_{tmp}^{suicide}$, and the interaction between these two variables, controls, and firm, year, county fixed effects as well as firm-by-year and county fixed effects.

Table 8 Panel A reports the regression results. Model (1) and Model (2) use plant-level *TFP* as the dependent variable, while the dependent variable in Model (3) and Model (4) is plant-level *OP_TFP*. The coefficient on the interaction term between temperature and $\beta_{tmp}^{suicide}$ is negative and statistically significant at the 1 percent level in all regressions. These results suggest that productivity is significantly lower for plants located in counties, where the residents' mental health is more sensitive to warmer temperature. These results provide further supporting evidence for the notion that temperature affects cognitive ability of workers in the county.

< Insert Table 8 around here >

4.7. How does rising temperature affect productivity? Physical health channel

[13] The data are obtained from https://wonder.cdc.gov/wonder/help/ucd.html, which are available since 1999.

Warm temperatures can also cause physical health issues and dehydration for employees located in the warm county. To examine whether plant's productivity is lower in counties where residents are more likely to be hospitalized due to injuries, we collect hospital admissions data in each county in California from the Center for California health and human services open data portal website for the period 2010-2014.[14] To derive a measure of physical health sensitivity to temperature, we estimate a regression of county's average number of days admitted to hospital per patient on temperature in that county using all data between 2010 and 2014 for each county in California. The physical health sensitivity to temperature of each county is the coefficient on temperature, denoted $\beta_{tmp}^{hospital}$, obtained from these regressions. In the second stage, we regress a plant's *TFP* or *OP_TFP* on temperature, $\beta_{tmp}^{hospital}$, and the interaction between these two variables, and controls.

We report results in Table 8 Panel B. In all models, the coefficient on the interaction term between temperature and $\beta_{tmp}^{hospital}$ is negative and statistically significant at the conventional level. These results suggest that productivity is significantly lower for plants located in counties where residents' physical health is more sensitive to hotter temperature.

4.8. Firm-level analysis: *Tobin's Q*

In this subsection, we examine whether our results still hold at the firm level. Since a firm may have plants in different counties, we follow Heidi and Ljungqvist (2015) and Ljungqvist, Zhang,

[14] Admissions data are publicly available for hospitals in California only. The data are obtained from https://data.chhs.ca.gov/dataset/patient-discharge-data-by-admission-type, which are available from 2010 to 2014. We manually collect information on the location of each hospital from Google searches and hospital websites.

and Zhang (2017) and compute the weighted temperature in a firm's nexus states in a fiscal year as follows:

$$Weighted\,Tmp\ = \left(0.5 \times \frac{sales_{p,i}}{total\ sales_i} + 0.5 \times \frac{employees_{p,i}}{total\ employees_i}\right) Tmp_p$$

where $sales_{p,i}$ and $employees_{p,i}$ are sales and number of employees at plant p of firm i; $total\ sales_i$ and $total\ employees_i$ are total sales and employees across all plants of the firm; and Tmp_p is the average yearly temperature in the county of plant p.

We repeat the main regression at the firm level and report estimation results in Table 9. Model (1) and Model (2) examine the effect of weighted temperature on firm-level *Tobin's Q*, while Model (3) and Model (4) regress *Tobin's Q* on weighted temperature-days variables. We alternately control for industry, county, and year fixed effects as well as firm, year, and county fixed effects. Models (1) and (2) show that the coefficient on weighted temperature is negative and statistically significant at the 1 percent level. Consistent with the plan-level results, these findings suggest that firm performance is lower when its plants are affected by warmer temperature. In Models (3) and (4), we can see that the coefficient on weighted *Ln(> 30*℃ *days)* is negative and statistically significant at the 1 percent level. While the coefficients on other temperature days are also significant in Model (3) with industry, county and year fixed effects, they become insignificant when we control for firm, county, and year fixed effects. These results show that the effect of hot temperature on firm performance is strong and robust to different research designs.

< Insert Table 9 around here >

4.9. Placebo analysis using temperature on weekend

In this subsection, we test whether the relation between temperature and plant-level productivity is a spurious result. We do so by taking advantage of the fact that a majority of economic activities occur during weekdays, rather than weekends (Deryugina and Hsiang, 2013). If our results are spurious, we expect that the effect of weekend temperature to be significant. Table 10 reports estimation results. Across all regression models, the coefficient on weekend temperature is statistically insignificant even at the 10% level and the estimate is also economically small. These results suggest that plant-level productivity is not affected by temperature on weekends and that the baseline relation documented in our study is not a spurious result.

< Insert Table 10 around here >

4.10. Controlling for other weather variables

Our next sensitivity analysis addresses a concern that temperature could be correlated with other weather variables, such as precipitation, evaporation, sunshine time, and wind speed. We thus control for these dimensions of weather, which are obtained from the NCDC database, and report results in Table 11. In general, the effects of temperature on plant-level *TFP* (Model (1) and Model (2)), *OP_TFP* (Model (3) and Model (4)), remain robust after controlling for these additional weather-related variables. Among these other weather variables, only evaporation shows a marginally significant effect on plant-level *TFP* in one model specification. These results suggest that the effect of temperature is not confounded by other weather events.

< Insert Table 11 around here >

4.11. Effects of long-run temperature on long-run productivity

Our final avenue of analysis examines whether the effect of yearly temperature translates into a long-run effect. This has implications for the cost of climate change, which refers to the long-run rising temperature. Since the impact of long-term climate trend is an aggregation of short-term effects of temperature changes over time (Schmidt, Shindell, and Tsigaridis 2014), we expect that rising long-term temperature should also have a negative impact on plant-level productivity.

To test this implication, we compute moving averages of temperature, *TFP* and *OP_TFP* over the windows of three, five, and ten years. Table 12 reports results for the regression of moving-average *TFP* and *OP_TFP* on the corresponding moving average temperature and controls. Across all models, the coefficient on the long-term temperature is negative and statistically significant at the 1 percent level. These results suggest that the long-term productivity of plants is lower as long-term temperature rises.

< Insert Table 12 around here >

5. Conclusion

Employing plant-level data for U.S. firms and data on county-level temperature, this paper provides one of the first U.S. evidence on whether, and how, temperature affects business productivity and firm performance. Findings of our paper therefore have direct implications for managers and policymakers. Our study also extends the scope of an emerging literature on climate finance, which focuses on investigating the micro-level effect of climate risk and the efficiency of capital markets in pricing the impact of climate change.

We find strong evidence that rising temperature negatively affects plant-level productivity measured by total factor productivity and firm-level performance measured by *Tobin's Q*. The effect remains robust to examining a sample of plants that choose to relocate from a colder county to a hotter county, presumably for tax-motivated reasons. This result suggests that self-selection of plants to be based in warmer counties cannot fully explain our findings.

We explore the channels through which rising temperature impedes productivity. Consistent with the science literature, which suggests that warmer temperature impairs the cognitive ability and productivity of employees, we find that the quality and quantity of inventors' innovation are lower. Moreover, the effect is stronger for plants, whose overall performance is more dependent on productivity of inventors. We also find that plant-level productivity is lower in counties where residents' mental health and physical health are more sensitive to warm temperature. Overall, our study contributes to the literature examining the cost of warming temperature. Findings in our study also fit into the existing climate finance literature as they serve as a potential mechanism for why investors should be concerned about the consequences on rising temperature in capital markets.

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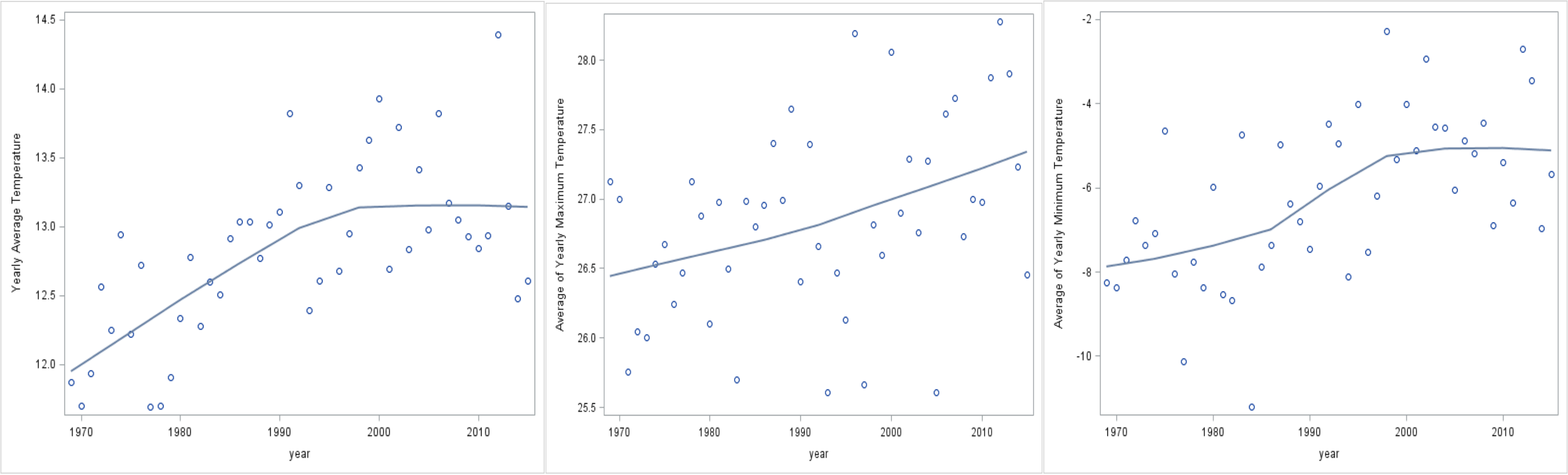

Figure 1: The figure plots the trend of average temperatures in the U.S. between 1969 and 2015. The first panel shows the trend in average temperature computed as average of daily temperatures. The middle graph depicts the trend in average maximum temperature on a yearly basis. The last panel plots the average minimum temperature on a yearly basis across the entire country. The continuous line depicts a fitted spline through the data.

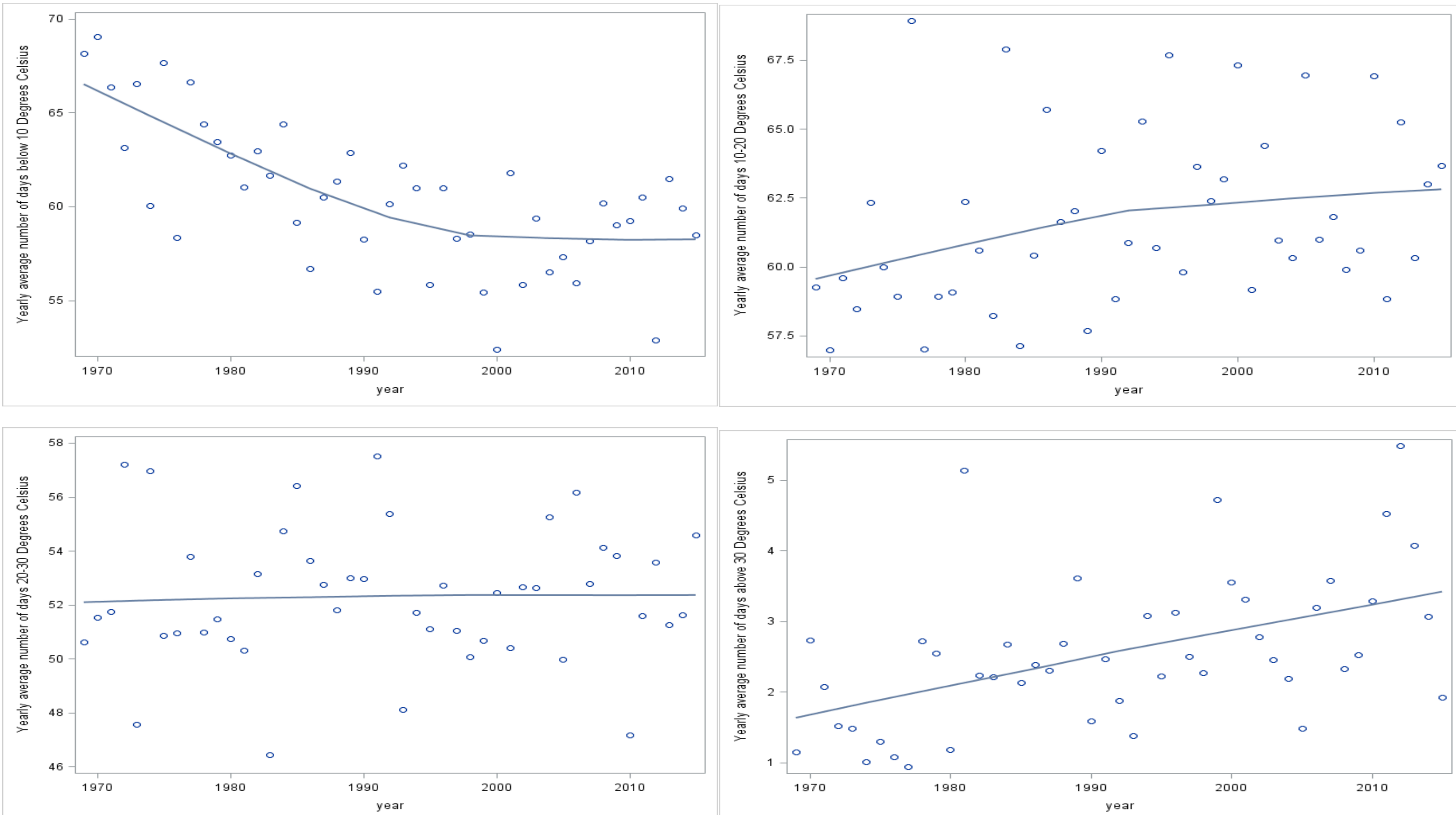

Figure 2: The figure plots the trend of temperature days at the country level between 1969 and 2015. The upper left-hand side panel shows the average number of temperature days below ≤ 10°C (50°F). The upper right-hand side panel depicts the average number of temperature days between 10°C (50°F) and 20°C (68°F). The lower left-hand side panel shows the average number of temperature days between 20°C (68°F)and 30°C (86°F). Finally, the lower right-hand side panel plots the average number of temperature days above 30°C (86°F). The continuous line depicts a fitted spline through the data. (Note: Due to the averaging method of daily max and min temperatures and the fact that the U.S. has more colder states than warmer states, the nationwide average temperature is relatively low.)

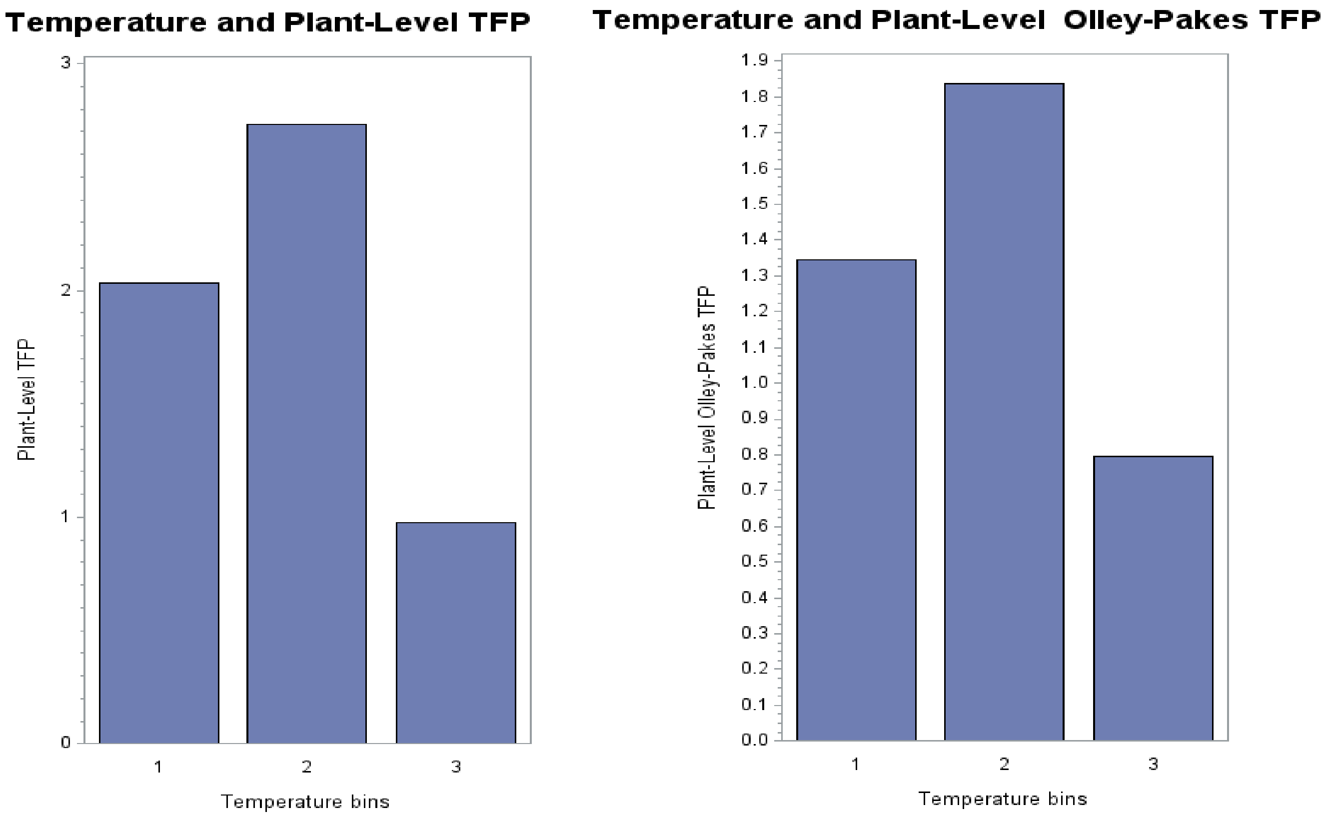

Figure 3: Univariate relations between plant-level productivity and temperature.

The figure plots average plant-level productivity across temperature terciles 1-3, which, respectively, represent average temperature below ≤ 10℃ (50°F), between 10℃ (50°F) and 25℃ (77°F), and above 25℃ (77°F). *TFP* and *OP_TFP* are defined in Appendix A1.

Table 1: Summary statistics

The table presents descriptive statistics for the variables used in regression tests over our main sample period 1990-2015. Variable definitions are presented in Table A1.

Variables	**Mean**	**SD**	**Q1**	**Median**	**Q3**
Plant-level variables					
TFP	0.924	0.190	0.754	0.918	1.089
OP_TFP	0.770	0.244	0.622	0.651	0.905
Ln(Credit_Score)	4.222	0.010	4.214	4.220	4.231
County-level variables					
Tmp /10 *(°C)*	1.325	0.447	0.987	1.210	1.630
Ln(> 30℃ *days)*	1.842	0.561	1.609	1.609	1.792
Ln(20℃*-30*℃ *days)*	4.539	0.611	4.290	4.575	4.875
Ln(10℃*-20*℃ *days)*	4.794	0.320	4.663	4.762	4.868
Ln(< 10℃ *days)*	4.552	1.115	4.407	5.043	5.187
Ln(Pop)	5.819	2.262	4.231	5.636	7.309
Ln(Inc)	3.314	0.433	2.960	3.357	3.656
Ln(Edu)	0.088	0.037	0.061	0.080	0.106
Firm-level variables					
Age	2.955	0.164	2.786	2.921	3.136
BM	0.394	0.054	0.357	0.386	0.442
ME	7.703	0.690	7.123	7.721	8.275
Lev	0.245	0.025	0.225	0.248	0.264
Interest_Exp	0.031	0.058	0.003	0.013	0.032
FinConst1	-0.008	0.006	-0.013	-0.011	0.005
FinConst2	0.453	0.350	0.180	0.262	1.000
Sales	1.496	0.075	1.457	1.502	1.547
PPE	0.351	0.029	0.328	0.344	0.372
CAEX	0.070	0.010	0.064	0.070	0.078

Table 2: Effects of temperature on plant-level productivity

The table reports results for regressions of plant-level productivity (as measured by *TFP* or *OP_TFP*) on temperature at the plant's county and controls. Variables are defined in the Appendix. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses.

Dep. Var. =	***TFP***			***OP_TFP***		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
***Tmp* /10 (°C)**	**-2.119*** **	**-0.825*** **	**-0.710*** **	**-0.163*** **	**-0.085*** **	**-0.128*** **
	(-5.23)	**(-4.39)**	**(-7.16)**	**(-3.15)**	**(-3.05)**	**(-4.82)**
Ln(Credit_Score)	1.602*	-1.795**	-0.577*	1.136***	-0.411**	-0.465**
	(1.74)	(-2.52)	(-1.94)	(4.49)	(-2.23)	(-2.56)
Ln(Pop)	0.716**	0.159	0.212**	0.310***	0.216***	0.180***
	(2.34)	(1.36)	(2.16)	(5.89)	(9.32)	(10.49)
Ln(Inc)	-1.974*	-1.818***	-0.718**	0.313**	0.086	-0.267***
	(-1.84)	(-3.43)	(-2.64)	(2.27)	(0.96)	(-4.44)
Ln(Edu)	-5.548	-3.326	-1.000	2.852***	-1.048*	0.007
	(-1.09)	(-1.31)	(-0.85)	(3.45)	(-1.85)	(0.02)
FinConst1	5.110*	0.982		6.373***	0.235	
	(1.83)	(0.50)		(12.66)	(0.99)	
FinConst2	-1.433***	-0.459		-0.342***	-0.038	
	(-3.78)	(-1.64)		(-4.00)	(-1.08)	
Interest_Exp	-68.651***	-63.381***		1.901	-9.951***	
	(-9.07)	(-7.30)		(0.95)	(-4.80)	
Age	-1.727***	-1.915***		-0.526***	-1.517***	
	(-9.23)	(-3.96)		(-9.14)	(-11.11)	
BM	-4.383***	2.707*		-6.540***	-0.981***	
	(-4.67)	(1.83)		(-32.03)	(-4.44)	
ME	-1.102***	1.544***		-1.256***	0.247***	
	(-6.24)	(4.33)		(-38.84)	(5.14)	
Lev	44.305***	39.372***		-7.714***	-0.760**	
	(7.72)	(8.03)		(-19.00)	(-2.58)	
Sales	-4.489***	4.216***		-3.264***	-0.255***	
	(-8.15)	(6.79)		(-32.04)	(-3.35)	
PPE	-17.322***	-20.898***		-2.530***	-0.429*	
	(-10.17)	(-7.60)		(-6.16)	(-1.85)	
CAEX	2.166	-17.234***		11.542***	1.715**	
	(0.49)	(-2.79)		(12.47)	(2.68)	

R^2(%)	0.034	0.511	0.582	0.117	0.540	0.619
Obs.	1,843,607	1,843,607	1,843,607	1,763,991	1,763,991	1,763,991
Firm FE	No	Yes	No	No	Yes	No
Year FE	Yes	Yes	No	Yes	Yes	No
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	Yes	No	No
Firm × Year FE	No	No	Yes	No	No	Yes

Table 3: Effects of temperature on plant-level productivity: Post-relocation to warmer a county

This table reports results for difference-in-difference analysis of the effect of temperature on plant-level productivity surrounding the relocation of a plant from a colder, higher-tax state to a warmer, lower tax county. Treatment plants are those that relocate to a warmer county within two years after a tax-rate reduction law was passed in the destination state. A destination county is deemed warmer than the origin county if its average temperature in the past five years is more than one degree Celsius higher than the past five-year average of the origin county. Since temperature in the destination county varies on a yearly basis and it may be colder in the relocation year, we additionally require that the average temperature in the destination county in the event year be at least 0.5 degree Celsius higher than its own temperature in the prior year. *Post* is a dummy variable indicating the two years after the relocation of a treatment plant. As relocation events are staggered, the coefficient on *Post* represents the difference-in-difference estimate. Panel A presents the results of DiD analysis using the sample of all plants (including non-relocating plants) as control group. Panel B repeats the analysis of Panel A and incorporates a *Pseudo_Event* dummy, which takes a value of 1 for the two years before and two years after the relocation event. Variable definitions are presented in Table A1. Fixed effects estimators are estimated using within-group transformation (Gormely and Matsa 2014) and thus reported R^2 is within-group R^2. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Difference-in-difference analysis around relocation events

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Post	**-0.211*** **	**-0.298*** **	**-0.142** **	**-0.227*** **
	(-2.80)	**(-5.27)**	**(-2.36)**	**(-4.27)**
Ln(Credit_Score)	0.096	0.074	-0.012	-0.045
	(1.37)	(1.29)	(-0.19)	(-0.76)
Ln(Pop)	0.211***	0.164***	0.225***	0.180***
	(7.74)	(8.05)	(9.29)	(9.29)
Ln(Inc)	0.045	-0.243**	0.109	-0.182***
	(0.34)	(-2.37)	(1.33)	(-3.37)
Ln(Edu)	0.520	0.607	-0.844	0.171
	(0.84)	(1.38)	(-1.52)	(0.43)
FinConst1	-0.567*		0.215	
	(-1.97)		(1.04)	
FinConst2	-0.037		-0.045	
	(-0.85)		(-1.36)	
Interest_Exp	-0.112***		-0.124**	
	(-2.81)		(-2.43)	
Age	-0.829***		-1.420***	
	(-6.87)		(-10.79)	
BM	-1.222***		-0.813***	
	(-6.77)		(-4.69)	
ME	0.063*		0.274***	
	(1.73)		(6.49)	
Lev	-1.619***		-1.172***	
	(-5.45)		(-4.87)	
Sales	0.716***		-0.180**	
	(7.70)		(-2.77)	
PPE	-4.466***		-0.221	
	(-16.14)		(-0.98)	
CAEX	-0.332		1.537**	
	(-0.64)		(2.51)	
R^2	0.558	0.10	0.528	0.592
Obs.	1,725,947	1,725,947	1,652,056	1,652,056
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Panel B: pseudo-events

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Pseudo_Event	**0.0734**	**-0.1468**	**0.009**	**-0.109**
	(0.48)	**(-1.14)**	**(0.01)**	**(-0.93)**
Post	**-0.210*****	**-0.298*****	**-0.142*****	**-0.228*****
	(-4.04)	**(-7.35)**	**(-3.13)**	**(-6.30)**
Credit_Score	0.097	0.074	-0.012	-0.045
	(1.18)	(1.08)	(-0.15)	(-0.65)
Ln(Pop)	0.211***	0.164**	0.225***	0.180***
	(2.66)	(2.44)	(3.04)	(2.88)
Ln(Inc)	0.045	-0.243	0.109	0.182
	(0.21)	(-1.56)	(0.50)	(1.10)
Ln(Edu)	0.522	0.604	-0.844	0.169
	(0.38)	(0.52)	(-0.62)	(0.14)
FinConst1	-0.567		0.215	
	(-1.27)		(0.50)	
FinConst2	-0.037		(0.045)	
	(-0.67)		(-0.86)	
Interest_Exp	-0.112***		-0.124**	
	(-2.74)		(-2.16)	
Age	-0.829***		-1.420***	
	(-5.12)		(-7.33)	
BM	-1.222***		-0.813***	
	(-5.73)		(-3.96)	
ME	0.064		0.274***	
	(0.93)		(3.74)	
Lev	-1.619***		-1.172***	
	(-4.07)		(-3.24)	
Sales	0.716***		-0.180**	
	(5.45)		(-1.96)	
PPE	-4.466***		-0.221	
	(-7.62)		(-0.46)	
CAEX	-0.332		1.537**	
	(-0.48)		(2.29)	
R^2	0.558	0.621	0.528	0.592
Obs.	1,725,947	1,725,947	1,652,056	1,652,056
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 4: Temperature days and plant-level productivity

This table presents results of regression tests of plant-level productivity on temperature days and controls. Variable definitions are presented in Table A1. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The reported R^2 is within-group R^2.

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Ln(> 30℃ days)	**-0.061***** **(-4.34)**	**-0.053***** **(-6.14)**	**-0.081***** **(-2.58)**	**-0.062**** **(-2.12)**
Ln(20℃-30℃ days)	-0.149*** (-8.26)	-0.118*** (-10.02)	-0.103** (-2.05)	-0.092* (-1.91)
Ln(10℃-20℃ days)	0.190*** (10.12)	0.167*** (10.04)	0.175*** (2.73)	0.152** (2.51)
Ln(< 10℃ days)	-0.048*** (-4.20)	-0.033*** (-3.24)	-0.039 (-1.53)	-0.032 (-1.23)
Ln(Credit_Score)	-0.089 (-0.94)	-0.088 (-1.03)	-0.190** (-2.32)	-0.206* (-1.99)
Ln(Pop)	0.067*** (5.65)	0.064*** (6.51)	0.011 (0.3)	0.015 (0.41)
Ln(Inc)	0.297*** (3.98)	0.121* (2.05)	0.362*** (2.73)	0.210* (1.91)
Ln(Edu)	0.125 (0.44)	0.359** (2.08)	0.092 (0.14)	0.439 (0.75)
FinConst1	-0.594* (-1.89)		0.231 (0.5)	
FinConst2	-0.045 (-0.98)		-0.04 (-0.72)	
Interest_Exp	-20.946*** (-9.41)		-9.920*** (-3.60)	
Age	-0.935*** (-7.24)		-1.517*** (-7.47)	
BM	-1.398*** (-6.11)		-0.982*** (-4.16)	
ME	0.047 (1.08)		0.245*** (3.08)	
Lev	-0.407 (-1.17)		-0.764* (-1.92)	
Sales	0.684*** (6.04)		-0.257** (-2.47)	
PPE	-4.827*** (-15.44)		-0.426 (-0.82)	
CAEX	-0.767 (-1.58)		1.737** (2.12)	
R^2	0.565	0.647	0.539	0.618
Obs.	1,843,305	1,843,305	1,763,694	1,763,694
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 5: Effects of temperature on plants with 95% sales to out-of-states customers

This table examine the effect of local county temperature on performance of plants that have more than 95 percent of their sales to non-local customers. *Tmp* is the yearly average temperature in the local county. Variable definitions are presented in Table A1. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Tmp	**-0.209****	**-0.156***	**-0.447****	**-0.565*****
	(-2.24)	**(-1.93)**	**(-2.75)**	**(-3.02)**
Ln(Credit_Score)	0.894	0.572	0.902	0.290
	(1.16)	(0.74)	(0.91)	(0.30)
Ln(Pop)	-0.149	-0.234**	-0.762***	-0.648***
	(-1.46)	(-2.18)	(-4.34)	(-3.22)
Ln(Inc)	-0.522***	-0.615***	0.545	0.373
	(-3.12)	(-4.06)	(1.50)	(0.74)
Ln(Edu)	0.097	0.0589	-0.635***	-0.616**
	(1.06)	(0.67)	(-2.85)	(-2.54)
FinConst1	-1.557		-8.689***	
	(-1.31)		(-3.48)	
FinConst2	2.581		0.330	
	(1.14)		(0.08)	
Interest_Exp	53.339		-3.307	
	(0.83)		(-0.03)	
Age	-6.310***		-0.280	
	(-4.91)		(-0.12)	
BM	-5.629***		-6.461***	
	(-8.48)		(-5.81)	
ME	-2.549**		-4.078*	
	(-2.06)		(-1.87)	
Lev	-54.032***		-93.850***	
	(-6.44)		(-5.14)	
Sales	-10.867***		-47.188***	
	(-3.66)		(-8.49)	
PPE	-10.125***		0.125	
	(-7.93)		(0.38)	
CAEX	7.966***		2.081***	
	(2.87)		(3.68)	
R^2	0.689	0.636	0.725	0.647
Obs.	10,367	10,367	9,810	9,810
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 6: Effects of temperature on special industries

The table reports results for regression tests of plant-level performance on temperature, indicators for agriculture and outdoor industries, interactions between temperature and the two indicators, and controls. *Agriculture* is an indicator variable equal to 1 for agricultural industries (those with SIC codes 100-799 according to Fama and French's classification). *Outdoor* is an indicator variable equal to 1 for construction and transportation industries (those with SIC codes 1500-2459 and 4000-4789 as per Fama and French's classification). Variable definitions are presented in Table A1. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Tmp	**-0.492********	**-0.500********	**-0.295********	**-0.292********
	(-7.88)	**(-8.02)**	**(-5.07)**	**(-5.00)**
Tmp* × *Agriculture	**-0.116********		**-0.041*******	
	(-4.53)		**(-2.36)**	
Tmp* × *Outdoor		**-0.205********		**-0.270********
		(-6.68)		**(-4.72)**
Agriculture	0.168***		0.153***	
	(3.00)		(7.32)	
Outdoor		0.123***		0.215***
		(4.24)		(3.63)
Ln(Credit_Score)	0.359***	0.358***	0.318***	0.317***
	(8.56)	(8.52)	(6.34)	(6.32)
Ln(Pop)	0.725***	0.718***	0.322**	0.328**
	(4.04)	(3.98)	(2.17)	(2.20)
Ln(Inc)	4.213***	4.231***	4.698***	4.687***
	(3.85)	(3.85)	(6.46)	(6.45)
Ln(Edu)	-2.367***	-2.399***	-1.309***	-1.329***
	(-6.34)	(-6.49)	(-5.09)	(-5.19)
FinConst1	6.189***	6.174***	5.247***	5.227***
	(7.83)	(7.77)	(8.16)	(8.14)
FinConst2	-0.099	-0.087	-0.261***	-0.252***
	(-0.95)	(-0.83)	(-2.95)	(-2.88)
Interest_Exp	-1.368	-1.512	1.970	1.958
	(-0.71)	(-0.78)	(0.93)	(0.92)
Age	-0.477***	-0.482***	-0.362***	-0.365***
	(-7.87)	(-7.92)	(-5.98)	(-5.96)
BM	-8.234***	-8.226***	-6.602***	-6.591***
	(-21.60)	(-21.54)	(-25.31)	(-25.04)
ME	-1.538***	-1.539***	-1.075***	-1.076***
	(-23.63)	(-23.58)	(-24.46)	(-24.37)
Lev	-8.628***	-8.625***	-7.736***	-7.756***
	(-22.37)	(-22.60)	(-18.82)	(-19.10)
Sales	-2.620***	-2.617***	-2.863***	-2.863***
	(-32.78)	(-32.85)	(-45.12)	(-44.80)
PPE	-4.691***	-4.653***	-2.511***	-2.487***
	(-15.19)	(-15.17)	(-9.19)	(-9.12)
CAEX	-1.931	-1.997	3.131***	3.120***
	(-1.53)	(-1.58)	(2.82)	(2.81)
R^2	0.083	0.083	0.075	0.075
Obs.	1,843,608	1,843,608	1,763,991	1,763,991
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Table 7: Temperature, innovation, and plant-level productivity

The table examines the effect of temperature on productivity of inventors at the establishment level. Panel A presents results for regression tests of the natural logarithm of number of patents (*Ln(Patents)*) and citation-weighted number of patents (*TCW*) on plant-level county temperature and controls. To measure innovation at each plant, we first identify the location of each inventor in a firm. We then match the patent ID of Kogan et al. (2017) with its inventor and the county of each plant from the NETS database to measure the innovation at the inventor's plant location. The sample period is 1969-2010. Variable definitions are presented in Table A1. Panel B repeats the analysis of Panel A, except that it uses the sample without establishments located in California. Panel C presents results for regression tests of the natural logarithm of the average number of inventors in a county on average temperature and county-level controls. *Tmp_3year_Avg*, *Tmp_5year_Avg*, and *Tmp_10year_Avg* are the 3-year, 5-year, and 10-year moving averages (MA) of temperature, respectively. The dependent variables in Models (1), (2), and (3) are the natural logarithm of 3-year, 5-year, 10-year moving averages of number of inventors in a county, respectively. *Education_Avg*, *Income_Avg*, and *Population_Avg* are moving averages of county-level education, income, and population, where the moving average window of each regression matches the duration of the dependent variable. Panel D reports results for regression tests of temperature on productivity of plants that are more dependent on innovative ability of inventors. To estimate a plant's performance sensitivity to innovation, we estimate a 10-year rolling regression of a plant's *TFP* or *OP_TFP* on the natural logarithm of number of patents (*Ln(Patents))*. The annual coefficient on *Ln(Patents),* denoted as β_{tmp}^{inno}, represents an plant's performance sensitivity to productivity of inventors. In the second stage, we regress a plant's *TFP* or *OP_TFP* on temperature, β_{tmp}^{inno}, interaction between the two variables, and controls and report estimation results in Panel D. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effects of temperature on establishment-level innovation

Dependent Variable =	***Ln(Patents)*** **(1)**	***Ln(Patents)*** **(2)**	***TCW*** **(3)**	***TCW*** **(4)**
Tmp	**-0.627*****	**-0.665*****	**-0.714*****	**-0.742*****
	(-3.36)	**(-3.21)**	**(-3.34)**	**(-3.17)**
Ln(Credit_Score)	-0.036	-0.065	-0.059	-0.105
	(-0.44)	(-0.73)	(-0.57)	(-1.04)
Ln(Pop)	0.153	0.202	0.186	0.246
	(0.95)	(1.11)	(1.01)	(1.23)
Ln(Inc)	0.605	0.410	0.828	0.590
	(1.07)	(0.52)	(1.23)	(0.66)
Ln(Edu)	-0.664	1.257	0.471	3.194
	(-0.18)	(0.27)	(0.11)	(0.60)
FinConst1	-0.065		-0.346	
	(-0.21)		(-0.80)	
FinConst2	0.076		0.127	
	(1.39)		(1.57)	
Interest_Exp	0.005		0.002	
	(1.58)		(0.18)	
Age	0.693***		0.473**	
	(4.29)		(2.50)	
BM	0.290*		0.124	
	(1.73)		(0.52)	
ME	0.175***		0.134*	
	(3.46)		(1.82)	
Lev	0.150		0.175	
	(0.85)		(0.58)	
Sales	-0.005		-0.016	
	(-0.17)		(-0.41)	
PPE	0.539*		0.362	
	(1.70)		(0.77)	
CAEX	-0.752		-0.484	
	(-0.94)		(-0.37)	
R^2	0.449	0.487	0.555	0.621
Obs.	101,380	101,380	98,981	98,981
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Panel B: Effects of temperature on innovation - Removing California-based establishments

Dependent Variable =	***Ln(Patents)*** **(1)**	***Ln(Patents)*** **(2)**	***TCW*** **(3)**	***TCW*** **(4)**
Tmp	**-0.440*****	**-0.465*****	**-0.510*****	**-0.511****
	(-2.88)	**(-2.66)**	**(-2.78)**	**(-2.52)**
Ln(Credit_Score)	-0.008	0.005	-0.047	-0.032
	(-0.09)	(0.05)	(-0.42)	(-0.28)
Ln(Pop)	0.186	0.216	0.220	0.268
	(1.04)	(1.08)	(1.08)	(1.20)
Ln(Inc)	1.069*	0.860	1.278*	1.073
	(1.93)	(1.29)	(1.95)	(1.33)
Ln(Edu)	-1.165	0.262	-0.121	1.859
	(-0.45)	(0.08)	(-0.04)	(0.49)
FinConst1	-0.208		-0.680	
	(-0.60)		(-1.37)	
FinConst2	0.131**		0.175*	
	(1.98)		(1.80)	
Interest_Exp	0.005*		0.000	
	(1.84)		(0.03)	
Age	0.652***		0.523**	
	(2.98)		(2.14)	
BM	0.373		0.065	
	(1.60)		(0.21)	
ME	0.180**		0.170	
	(2.13)		(1.46)	
Lev	0.066		0.335	
	(0.34)		(0.97)	
Sales	-0.026		-0.038	
	(-0.79)		(-0.91)	
PPE	0.419		0.296	
	(1.19)		(0.55)	
CAEX	-0.821		-1.005	
	(-0.66)		(-0.52)	
R^2	0.511	0.550	0.587	0.658
Obs.	76,369	76,369	74,584	74,584
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Panel C: Effects of temperature on migration of talents

Dependent Variable =	***Ln(3-year average of number of inventors in a county)*** **(1)**	***Ln(5-year average of number of inventors in a county)*** **(2)**	***Ln(10-year average of number of inventors in a county)*** **(2)**
Tmp_3year_Avg	**-0.182**		
	(-4.76)* **		
Tmp_5year_Avg		**-0.138**	
		(-3.94)* **	
Tmp_10year_Avg			**-0.106**
			(-3.30)* **
Education_Avg	-0.094	-0.010	-0.038
	(-1.72)*	(-0.17)	(-0.48)
Income_Avg	0.141	0.190	0.319
	(3.36)***	(4.12)***	(7.04)***
Population_Avg	0.097	0.085	0.110
	(8.48)***	(7.81)***	(9.40)***
R^2	80.27	75.23	64.13
Obs.	21,083	21,080	21,073
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes

Panel D: Effects of temperature on innovative firms

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Tmp	**-0.221**	**-0.148**	**-0.875**	**-0.441**
	(-2.46)**	**(-2.73)*****	**(-2.34)****	**(-3.86)*****
$\boldsymbol{\beta_{tmp}^{inno}} \times$ ***Tmp***	**-0.958**	**-0.524**	**-1.939**	**-0.532**
	(-7.14)***	**(-3.29)*****	**(-8.07)*****	**(-5.47)*****
β_{inno}	0.714	.3504	1.307	.2780
	(5.90)***	(2.07)**	(5.76)***	(2.82)***
Ln(Credit_Score)	-0.846	-.9369	-.3166	5.997
	(-0.38)	(-0.75)	(-0.06)	(2.91)***
Ln(Pop)	-0.641	-1.715	-1.729	-1.172
	(-1.27)	(-4.77)***	(-2.13)**	(-1.57)
Ln(Inc)	-1.260	-1.340	-5.883	-6.497
	(-0.28)	(-0.47)	(-0.42)	(-1.82)*
Ln(Edu)	-1.586	-3.478	9.683	9.828
	(-1.07)	(-3.08)***	(0.18)	(0.59)
FinConst1	-5.992		-3.722	
	(-2.97)***		(-1.10)	
FinConst2	3.266		2.134	
	(2.18)**		(0.45)	
Interest_Exp	-70.798		-17.890	
	(-10.16)***		(-3.35)***	
Age	-2.159		-2.473	
	(-2.40)**		(-0.94)	
BM	1.152		2.039	
	(0.91)		(1.07)	
ME	1.206		1.580	
	(3.81)***		(2.79)***	
Lev	71.7253		38.2034	
	(6.93)***		(1.88)*	
Sales	3.632		1.129	
	(5.23)***		(1.57)	
PPE	-10.096		-1.5458	
	(-10.92)***		(-0.05)	
CAEX	-0.790		0.220	
	(-0.02)		(0.39)	
R^2	0.498	0.565	0.459	0.547
Obs.	35,862	35,862	34,480	34,480
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 8: Temperature, mental health, physical health, and plant-level productivity

This table examines whether plant's productivity is more affected by temperature when the mental health of residents in the local county is more sensitive to temperature. Panel A reports results for regressions of productivity on temperature, a measure of sensitivity of suicide rate to temperature (denoted as $\beta_{tmp}^{suicide}$), the interaction term between temperature and $\beta_{tmp}^{suicide}$, and controls. To compute $\beta_{tmp}^{suicide}$ for a county in a given year, we estimate 10-year rolling window regressions of county's suicide rate on temperature in the county. $\beta_{tmp}^{suicide}$ is the annual (time-series) coefficient on temperature obtained from these rolling regressions. Panel B reports results for regressions of productivity on temperature, a measure of sensitivity of hospital admissions to temperature of each county in California (denoted as $\beta_{tmp}^{hospital}$), and controls. Since only information on hospitals in California is publicly available, the sample for Panel B is restricted to establishments in California. Moreover, since the data are available over the period 2010-2014 only, we compute $\beta_{tmp}^{hospital}$ for a county by estimating a regression of the county's average number of days admitted to hospital per patient on temperature in the county using all data between 2010 and 2014. This gives an estimate of $\beta_{tmp}^{hospital}$ for each county, which is the coefficient on temperature obtained from these county-level regressions. We assume that $\beta_{tmp}^{hospital}$ is the same over the larger sample for a county. Other variable definitions are presented in Table A1. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Sensitivity of local suicide rate to temperatures and plant-level productivity

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Tmp	**-0.105***** **(-6.81)**	**-0.092***** **(-6.42)**	**-0.079***** **(-5.96)**	**-0.072***** **(-5.68)**
$\boldsymbol{\beta_{tmp}^{suicide}} \times$ ***Tmp***	**-0.505***** **(-4.50)**	**-0.042***** **(-4.53)**	**-0.056***** **(-4.82)**	**-0.024**** **(-2.51)**
β_{tmp}	0.501*** (3.14)	0.040*** (4.03)	0.053*** (3.14)	0.016 (1.43)
Ln(Credit_Score)	-0.323** (-2.32)	-0.300** (-2.45)	-0.365*** (-3.12)	-0.391*** (-3.50)
Ln(Pop)	0.097*** (7.19)	0.083*** (7.79)	0.017* (1.98)	0.023** (2.52)
Ln(Inc)	0.393*** (5.01)	0.196*** (3.24)	0.455*** (8.95)	0.294*** (10.47)
Ln(Edu)	0.347 (1.08)	0.636*** (3.38)	0.463* (1.81)	0.798*** (5.28)
FinConst1	-0.687* (-2.05)		0.203 (0.84)	
FinConst2	-0.056 (-1.15)		-0.046 (-1.23)	
Interest_Exp	-21.700*** (-8.19)		-7.900** (-2.45)	
Age	-1.005*** (-7.28)		-1.598*** (-11.28)	
BM	-1.582*** (-6.91)		-1.191*** (-5.19)	
ME	0.083* (1.95)		0.262*** (5.09)	
Lev	-0.703* (-1.82)		-1.047*** (-3.68)	
Sales	0.695*** (6.17)		-0.319*** (-3.99)	
PPE	-5.058*** (-15.31)		-0.541** (-2.09)	
CAEX	-1.117 (-1.70)		2.306*** (3.08)	
R^2	0.561	0.632	0.532	0.602
Obs.	1,712,300	1,712,300	1,638,956	1,638,956
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Panel B: Sensitivity of local hospital admission rate to temperatures and plant-level productivity

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Tmp	**-0.796***** **(-3.24)**	**-0.634***** **(-3.03)**	**-0.713***** **(-4.16)**	**-0.699***** **(-2.65)**
$\boldsymbol{\beta_{tmp}^{hospital}} \times$ ***Tmp***	**-0.235***** **(-2.86)**	**-0.146**** **(-2.43)**	**-0.165**** **(-2.04)**	**-0.168**** **(-2.22)**
β_{tmp}	0.153** (2.35)	0.054 (1.28)	0.053 (0.72)	0.047 (0.92)
Ln(Credit_Score)	-1.608* (-1.96)	-1.959*** (-2.91)	-2.499*** (-3.84)	-3.027*** (-3.47)
Ln(Pop)	-0.019 (-0.03)	-0.177 (-0.27)	-0.082 (-0.53)	-0.086 (-0.11)
Ln(Inc)	0.305 (1.06)	0.274 (1.34)	0.396*** (5.2)	0.229 (0.97)
Ln(Edu)	-5.867 (-0.42)	-1.048 (-0.83)	-1.207** (-2.14)	-1.035 (-0.70)
FinConst1	-6.215 (-1.56)		-2.499 (-1.43)	
FinConst2	-0.112 (-0.24)		0.235 (0.71)	
Interest_Exp	-11.781*** (-3.64)		-4.478* (-2.02)	
Age	-4.564*** (-3.49)		-8.289*** (-9.24)	
BM	-6.982*** (-3.93)		-5.450*** (-3.34)	
ME	0.923 (1.57)		1.490*** (3.43)	
Lev	-0.658 (-0.20)		-4.220* (-1.78)	
Sales	3.904*** (3.99)		-1.218* (-1.99)	
PPE	-26.727*** (-5.86)		2.796* (1.81)	
CAEX	-4.192 (-0.69)		11.942** (2.34)	
R^2	0.581	0.640	0.553	0.618
Obs.	219,931	219,931	210,235	210,235
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 9: Effects of temperature on firm-level *Tobin's Q*

The table reports results for regressions of firm-level Peters and Taylor's (2017) *Tobin's Q* on plant-weighted temperature and firm-level controls. Weighted temperature variables are computed as the weighted average of temperature across the counties in which a firm has an operating plant, where the weight is computed based on the economic size of each plant within the firm. Robust *t*-statistics based on standard errors clustered by industry and year are reported in parentheses.

Dependent Variable =	**(1)**	**(2)**	**(3)**	**(4)**
Weighted_Tmp	**-0.227**	**-0.199**		
	(-2.93)***	**(-2.70)*****		
Weighted_Ln(>30 ℃ days)			**-0.070**	**-0.111**
			(-2.88)***	**(-2.55)*****
Weighted_Ln(20 ℃ - 30℃ days)			0.112	0.124
			(3.81)***	(3.37)***
Weighted_Ln(10 ℃ - 20℃ days)			0.354	0.078
			(5.97)***	(1.13)
Weighted_Ln(<10 ℃ days)			0.130	0.111
			(1.70)*	(1.21)
FinConst1	-1.346	-0.567	-1.236	-0.505
	(-7.24)***	(-3.43)***	(-10.46)***	(-2.97)***
FinConst2	0.148	0.050	0.127	0.039
	(9.26)***	(3.59)***	(12.57)***	(2.72)***
Interest_Exp	-0.895	0.142	-0.818	0.098
	(-1.40)	(0.24)	(-2.03)**	(0.15)
Age	-0.351	-0.881	-0.360	-0.877
	(-7.09)***	(-9.45)***	(-5.81)***	(-7.41)***
BM	-2.332	-1.407	-2.328	-1.407
	(-19.53)***	(-15.63)***	(-16.60)***	(-10.36)***
ME	0.123	0.346	0.124	0.347
	(18.72)***	(28.14)***	(14.99)***	(16.10)***
Lev	-1.146	-0.992	-1.101	-0.988
	(-16.51)***	(-14.79)***	(-27.26)***	(-14.14)***
Sales	-0.341	-0.088	-0.318	-0.089
	(-17.16)***	(-3.74)***	(-16.90)***	(-4.07)***
PPE	-0.953	-1.293	-0.679	-1.291
	(-13.58)***	(-15.19)***	(-25.36)***	(-16.96)***
CAEX	1.576	0.802	1.262	0.802
	(8.34)***	(4.82)***	(10.49)***	(4.45)***
R^2	0.442	0.557	0.442	0.647
Obs.	62,011	62,011	61,953	61,953
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry FE	Yes	No	Yes	No

Table 10: Placebo analysis using temperature on weekends

This table examine the effect of weekend temperature on plant-level productivity and controls. Variable definitions are presented in Table A1. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	***TFP***	***TFP***	***OP_TFP***	***OP_TFP***
	(1)	**(2)**	**(3)**	**(4)**
Weekend_Tmp	**0.064**	**-0.031**	**-0.002**	**-0.024**
	(1.24)	**(-0.87)**	**(-0.05)**	**(-0.63)**
Ln(Credit_Score)	-1.788**	-0.570*	-1.760***	-1.262***
	(-2.53)	(-1.89)	(-3.72)	(-4.71)
Ln(Pop)	0.109***	0.114***	0.042	0.047*
	(2.84)	(2.99)	(1.43)	(1.99)
Ln(Inc)	0.328	0.385	-0.062	0.118
	(0.31)	(0.57)	(-0.09)	(0.26)
Ln(Edu)	0.240	0.635***	0.760***	0.803***
	(0.80)	(3.73)	(4.08)	(7.98)
FinConst1	0.980		0.741	
	(0.50)		(0.72)	
FinConst2	-0.463		-0.171	
	(-1.66)		(-1.17)	
Interest_Exp	-63.354***		-23.108***	
	(-7.30)		(-7.54)	
Age	-1.921***		-5.012***	
	(-3.98)		(-10.49)	
BM	2.702*		4.002***	
	(1.83)		(5.241)	
ME	1.542***		2.659***	
	(4.32)		(11.414)	
Lev	39.355***		14.859***	
	(8.04)		(8.098)	
Sales	4.205***		1.601***	
	(6.79)		(4.596)	
PPE	-20.875***		-5.188***	
	(-7.59)		(-4.091)	
CAEX	-17.252***		2.279	
	(-2.80)		(0.965)	
R^2	0.511	0.582	0.537	0.531
Obs.	1,843,607	1,843,607	1,763,991	1,763,991
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 11: Controlling for other weather variables

The table presents results of regression tests of plant-level performance on temperature and additional weather variables. *Precipitation* is the yearly average level of precipitation at the county level. *Wind* is the natural logarithm of the yearly average wind speed at the county level. *Evaporation* is the yearly average evaporation at the county level. *Sun* is the natural logarithm of average duration of sunshine in a year. Definitions of other variables are presented in Table A1. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable =	***TFP*** **(1)**	***TFP*** **(2)**	***OP_TFP*** **(3)**	***OP_TFP*** **(4)**
Tmp	**-0.152******	**-0.163******	**-0.417*****	**-0.316*****
	(-4.01)	**(-5.89)**	**(-2.35)**	**(-2.37)**
Precipitation	0.000	-0.000	-0.005	-0.004
	(0.29)	(-0.26)	(-0.89)	(-1.40)
Wind	0.166*	-0.008	2.385**	0.237
	(1.72)	(-0.14)	(2.36)	(1.61)
Evaporation	-0.019***	-0.004	-0.078	-0.013
	(-4.33)	(-1.64)	(-1.65)	(-1.16)
Sun	0.011**	0.002	0.122***	-0.001
	(2.60)	(0.42)	(2.80)	(-0.08)
Ln(Credit_Score)	-0.086	-0.087	-0.409	-0.338**
	(-0.92)	(-1.03)	(-1.70)	(-2.14)
Ln(Pop)	0.211***	0.161***	0.198	0.312***
	(8.24)	(8.70)	(1.58)	(3.46)
Ln(Inc)	0.035	-0.328***	-2.407***	-0.536**
	(0.26)	(-3.02)	(-4.69)	(-2.07)
Ln(Edu)	0.133	0.461	5.076*	1.395
	(0.21)	(1.08)	(1.89)	(1.31)
FinConst1	-0.590*		0.687	
	(-1.88)		(0.67)	
FinConst2	-0.043		-0.172	
	(-0.92)		(-1.16)	
Interest_Exp	-20.957***		-23.255***	
	(-9.43)		(-7.52)	
Age	-0.935***		-5.070***	
	(-7.27)		(-10.75)	
BM	-1.401***		4.132***	
	(-6.12)		(5.39)	
ME	0.047		2.700***	
	(1.09)		(11.51)	
Lev	-0.414		15.036***	
	(-1.19)		(8.19)	
Sales	0.686***		1.624***	
	(6.07)		(4.63)	
PPE	-4.822***		-5.156***	
	(-15.42)		(-4.12)	
CAEX	-0.786		2.435	
	(-1.63)		(1.04)	
R^2	0.565	0.648	0.535	0.632
Obs.	1,842,834	1,842,834	1,762,912	1,762,912
Year FE	Yes	No	Yes	No
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Firm x Year FE	No	Yes	No	Yes

Table 12: Effects of long-run temperature on plant-level productivity

The table reports results for regressions of medium- to long-run plant-level productivity (as measured by *TFP* and *OP_TFP*) on medium- to long-run average temperature at the plant's county and firm-level controls. Dependent and independent variables are moving averages using windows of three, five, and ten years. Robust *t*-statistics based on standard errors clustered by county and year are reported in parentheses.

MA Windows = Dependent Variable =	***3-year MA*** ***TFP*** **(1)**	***5-year MA*** ***TFP*** **(2)**	***10-year MA*** ***TFP*** **(3)**	***3-year MA*** ***OP_TFP*** **(4)**	***5-year MA*** ***OP_TFP*** **(5)**	***10-year MA*** ***OP_TFP*** **(6)**
MA_Tmp	**-0.098**	**-0.109**	**-0.115**	**-0.104**	**-0.134**	**-0.175**
	(-8.13)***	**(-7.70)*****	**(-6.74)*****	**(-9.38)*****	**(-9.78)*****	**(-9.44)*****
Ln(Credit_Score)	0.010	0.016	0.015	-0.037	-0.018	-0.007
	(0.57)	(1.14)	(1.51)	(-1.95)**	(-1.12)	(-0.57)
Ln(Pop)	0.016	0.007	0.005	0.002	-0.003	0.000
	(3.20)***	(1.81)*	(2.03)**	(0.40)	(-0.69)	(0.19)
Ln(Inc)	-0.024	-0.002	-0.006	0.030	0.026	0.010
	(-1.20)	(-0.10)	(-0.52)	-1.460	(1.47)	(0.75)
Ln(Edu)	0.155	0.054	0.037	-0.037	0.010	0.080
	(1.73)*	(0.79)	(0.69)	(-0.43)	(0.14)	(1.25)
R^2	0.700	0.881	0.916	0.808	0.861	0.904
Obs.	1,830,306	1,831,028	1,831,007	1,757,550	1,753,551	1,752,557
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix

Table A1: Variable definitions

Variable	Definition
TFP	Plant-level (total factor productivity (TFP) for each individual plant is the estimated residual from the following regression: $$Ln\left(y_{ijt}\right) = \alpha_{jt} + b_{jt}\ln\left(K_{ijt}\right) + c_{jt}\ln\left(L_{ijt}\right) + d_{jt}\ln\left(M_{ijt}\right) + \varepsilon_{ijt}$$ where plant-level labor (L) is the number of employees in each plant by provided by NETS and plant-level output (y) is the plant-level sales obtained from NETS. We approximate plant-level capital (K) as the plant's economic weight multiplied by the firm-level property, plant and equipment (PPE) obtained from Compustat annual file. A plant's economic weight within a firm is equal to $\frac{1}{2}\frac{employees_{i,p,t}}{employees_{i,total,t}} + \frac{1}{2}\frac{sales_{i,p,t}}{saless_{i,total,t}}$, where $employees_{i,p,t}$ and $sales_{i,p,t}$ are the employment and sales levels at plant p of firm i. Similarly, to compute plant-level input material (M), we multiply the plant's weight by the firm-level cost of goods sold obtained from Compustat.
OP_TFP	TFP measure estimated using Olley and Pakes (1996) method, which corrects for the fact that plants simultaneously choose the level of inputs as they choose their outputs. For example, firms tend to increase the use of inputs when they observe a positive production shock. Olley and Pakes (1996) use investment as a proxy variable, which is determined by the shock to production and existing capital stock. We approximate investment at the plant level as the plant's economic weight multiplied by the firm-level investment obtained from Compustat annual file. Using this instrument, we follow Olley and Pakes (1996) and estimate the production function for each industry separately.
Tmp	Temperature (in degrees Celsius) computed as the average of daily average temperature over a firm's fiscal year at the county where the firm's headquarter locates.
Weighted_Tmp	Weighted Average temperatures (in degrees Celsius) across the counties where the firm's plant is located. The weight is equal to $0.5 \times \frac{sales_{p,i}}{total\ sales_i} + 0.5 \times \frac{employees_{p,i}}{total\ employees_i}$, where $sales_{p,i}$ and $employees_{p,i}$ are sales and number of employees at plant *p* of firm *i*; $total\ sales_i$ and $total\ employees_i$ are total sales and employees across all plants of the firm.
Ln(< 10℃ *days)*	The natural logarithm of one plus number of days over a firm's fiscal year when the daily temperature is below 10℃.
Ln(10℃*-20*℃ *days)*	The natural logarithm of one plus number of days over a firm's fiscal year when the daily temperature is between 10℃ and 20℃.
Ln(20℃*-30*℃ *days)*	The natural logarithm of one plus number of days over a firm's fiscal year when the daily temperature is between 20℃ and 30℃.
Ln(> 30℃ *days)*	The natural logarithm of one plus number of days over a firm's fiscal year when the daily temperature is above 30℃.

Ln(< 10°C days_w)	The natural logarithm of the weighted average of one plus number of days across all the plants of the firms over a firm's fiscal year when the daily temperature is below 10°C in each plant's location. The weight is equal to $0.5 \times \frac{sales_{p,i}}{total\ sales_i} + 0.5 \times \frac{employees_{p,i}}{total\ employees_i}$, where $sales_{p,i}$ and $employees_{p,i}$ are sales and number of employees at plant p of firm i; $total\ sales_i$ and $total\ employees_i$ are total sales and employees across all plants of the firm.
Ln(10°C-20°C days_w)	The natural logarithm of the weighted average of one plus number of days across all the plants of the firms over a firm's fiscal year when the daily temperature is between 10°C and 20°C in each plant's location. The weight is equal to $0.5 \times \frac{sales_{p,i}}{total\ sales_i} + 0.5 \times \frac{employees_{p,i}}{total\ employees_i}$, where $sales_{p,i}$ and $employees_{p,i}$ are sales and number of employees at plant p of firm i; $total\ sales_i$ and $total\ employees_i$ are total sales and employees across all plants of the firm.
Ln(20°C-30°C days_w)	The natural logarithm of the weighted average of one plus number of days across all the plants of the firms over a firm's fiscal year when the daily temperature is between 20°C and 30°C in each plant's location. The weight is equal to $0.5 \times \frac{sales_{p,i}}{total\ sales_i} + 0.5 \times \frac{employees_{p,i}}{total\ employees_i}$, where $sales_{p,i}$ and $employees_{p,i}$ are sales and number of employees at plant p of firm i; $total\ sales_i$ and $total\ employees_i$ are total sales and employees across all plants of the firm.
Ln(> 30°C days_w)	The natural logarithm of the weighted average of one plus number of days across all the plants of the firm over its fiscal year when the daily temperature is above 30°C in each plant's location. The weight is equal to $0.5 \times \frac{sales_{p,i}}{total\ sales_i} + 0.5 \times \frac{employees_{p,i}}{total\ employees_i}$, where $sales_{p,i}$ and $employees_{p,i}$ are sales and number of employees at plant p of firm i; $total\ sales_i$ and $total\ employees_i$ are total sales and employees across all plants of the firm.
LnPop	Natural logarithm of county-level population.
LnInc	Natural logarithm of county-level average income.
Ln(Credit_Score)	Natural logarithm of plant-level credit score, which ranges from 0 to 100 and is rated by credit rating agency Dun and Bradstreet.
CAEX	Capital expenditure defined as capital expenditures divided by total assets.
PPE	Asset tangibility computed as net properties, plants and equipment scaled by total assets.
FinConst1	Hoberg and Maksimovic's (2015) text-based financial constraints. Firms with higher values of *FinConst1* are more similar to a set of firms known to be at risk of delaying their investments due to issues with liquidity.

FinConst2	An indicator variable that takes a value of 1 for firm-year with missing *FinConst1*. According to Hoberg and Maksimovic: "if a researcher wishes to include the constraint variables in a regression where some observations are missing (and the researcher wants to not lose observations and thus control for the missing values), we recommend (A) including a dummy in the regression for observations where the given variable is missing and (B) then it is ok to set the constraint variable to zero for these missing observations."
Interest_Exp	Interest expense measured as the ratio of total interest expense over total sales.
Lev	The ratio of long-term debt over book value of equity.
Age	The natural logarithm of one plus number of years since the firm has its listed price in the CRSP database.
BM	The natural logarithm of book-to-market ratio.
ME	The natural logarithm of the firm's market equity measured at the end of the fiscal year.
Sales	The natural logarithm of net sales.

Table A2: Pairwise correlations

This table reports pairwise correlations between the variables we use in our regression analysis. Variable definitions are presented in Table A1.

	OP TFP	TFP	*Tmp*	*Ln(< 10℃ days)*	*Ln(10℃-20℃ days)*	*Ln(20℃-30℃ days)*	*Ln(> 30℃ days)*	Credit Score	LnPop	LnEdu	LnInc	Fin Con1	Fin Con2	Int. Exp	LnAge	BM	ME	Lev	sales	PPE
TFP	0.45	1.00																		
Tmp	**-0.05**	**-0.04**	1.00																	
Ln(< 10℃)	0.00	0.00	-0.87	1.00																
Ln(10℃-20℃)	0.01	0.01	0.00	0.05	1.00															
Ln(20℃-30℃)	0.00	-0.01	0.76	-0.64	-0.36	1.00														
Ln(> 30℃)	-0.01	-0.01	0.63	-0.41	-0.10	0.38	1.00													
Credit Score	0.00	0.00	-0.01	0.01	0.01	-0.01	-0.01	1.00												
LnPop	-0.01	0.01	0.25	-0.31	0.21	0.05	0.29	-0.03	1.00											
LnEdu	-0.01	0.00	-0.16	0.12	0.13	-0.17	-0.18	-0.01	0.23	1.00										
LnInc	-0.02	0.00	-0.10	0.04	0.19	-0.14	-0.10	0.02	0.25	0.64	1.00									
FinCon1	0.01	0.00	0.01	-0.01	0.00	0.00	0.01	-0.02	-0.01	-0.02	-0.03	1.00								
FinCon2	0.01	0.00	-0.02	0.01	-0.01	-0.01	0.00	-0.02	-0.02	-0.07	-0.15	0.49	1.00							
Int. Exp.	0.00	-0.01	0.02	-0.01	-0.02	0.02	0.04	-0.06	-0.01	-0.04	-0.08	0.12	0.07	1.00						
LnAge	-0.04	0.00	-0.03	0.03	-0.02	0.00	-0.02	0.04	-0.02	0.01	0.06	-0.06	0.02	-0.06	1.00					
BM	-0.04	-0.01	0.00	0.00	-0.02	0.01	0.01	-0.01	-0.01	-0.01	0.02	-0.05	-0.05	0.11	-0.10	1.00				
ME	0.03	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.05	0.10	0.07	0.08	0.01	0.38	-0.47	1.00			
Lev	-0.02	-0.01	0.02	-0.01	-0.02	0.01	0.03	-0.03	-0.04	-0.08	-0.10	0.15	0.07	0.63	-0.05	0.02	-0.01	1.00		
sales	-0.02	0.01	0.00	0.00	-0.01	0.01	-0.01	0.07	-0.05	-0.05	-0.03	-0.06	-0.06	-0.54	-0.03	0.00	-0.21	-0.22	1.00	
PPE	0.02	-0.01	0.02	0.00	-0.03	0.03	0.03	0.03	-0.08	-0.12	-0.11	0.11	0.08	0.21	0.05	-0.07	0.18	0.25	-0.05	1.00
CAEX	0.03	0.00	0.02	-0.01	0.00	0.01	0.03	0.01	-0.04	-0.08	-0.13	0.07	0.08	-0.02	-0.05	-0.20	0.11	0.01	0.07	0.63

Table A3: Summary statistics of temperatures by state

This table reports summary statistics of temperatures at the state level. Yearly temperatures are computed by averaging the daily temperature over a firm's fiscal year. The reported statistics of each state are then the average of yearly measures over the sample period. "Avg. Tmp" is the average temperature in degrees Celsius. "Avg. High Tmp" is the average maximum temperature. "Avg. Low Tmp" is the average minimum temperature. "Avg. Max >30℃ days" is the average maximum number of days in a year with temperature above 30℃. "Avg. Max <10℃ days" is the average maximum number of days in a year with temperature below 10℃. "Avg. Max 20℃-30℃ days" is the average maximum number of days in a year with temperature above 30℃.

State	Average Tmp (℃)	Average High Tmp (℃)	Average Low Tmp (℃)	Average Max >30℃ days	Average Max 20℃-30℃ days	Average Max <10℃ days
Alabama	16.51	27.85	-2.89	10.21	123.25	63.70
Arizona	21.05	33.58	5.22	95.92	81.25	110.29
Arkansas	15.35	28.42	-5.81	28.83	95.50	70.56
California	15.93	26.32	5.79	61.00	141.05	118.60
Colorado	8.28	22.96	-15.16	3.14	72.83	144.03
Connecticut	9.74	25.43	-10.28	2.31	93.33	116.33
Delaware	11.96	27.33	-7.40	3.43	95.38	98.40
Florida	22.99	29.33	8.82	17.65	209.33	35.00
Georgia	15.61	27.16	-3.52	13.00	120.78	66.00
Idaho	8.56	23.86	-11.02	3.80	68.60	132.50
Illinoi	9.13	26.97	-15.16	11.88	82.50	120.00
Indiana	10.27	26.57	-13.45	6.85	100.63	108.75
Iowa	8.53	26.63	-18.24	7.57	85.50	109.50
Kansas	12.28	28.45	-12.24	23.88	105.46	87.67
Kentucky	12.46	26.90	-10.30	10.39	101.38	89.00
Louisiana	19.42	29.23	1.43	34.35	134.00	50.63
Maine	6.14	23.18	-16.29	0.33	50.92	123.25
Maryland	12.48	27.72	-7.19	6.25	101.40	95.35
Massachusetts	8.94	25.49	-11.42	0.64	78.25	113.10
Michigan	8.28	25.60	-13.36	3.00	66.60	136.00
Minnesota	6.32	25.98	-21.48	3.92	75.82	124.33
Mississippi	17.50	28.52	-1.93	13.27	111.17	61.64
Missouri	12.26	28.07	-11.84	17.44	111.71	99.75
Montana	5.88	21.28	-18.63	0.88	43.13	129.40
Nebraska	9.54	27.38	-16.54	8.79	99.75	135.47
Nevada	13.93	27.69	-2.88	87.00	68.50	123.67
New Hampshire	7.70	24.77	-13.80	0.50	70.04	120.00
New Jersey	10.91	26.71	-8.81	3.96	100.93	108.21
New Mexico	11.69	24.93	-6.82	25.33	88.00	106.15
New York	10.58	26.43	-9.13	3.65	103.50	121.17
North Carolina	14.77	27.42	-4.19	7.40	115.20	83.91

North Dakota	4.38	25.03	-24.58	2.63	39.73	132.00
Ohio	9.87	25.84	-12.60	3.00	95.00	114.50
Oklahoma	15.09	29.51	-7.84	35.20	112.33	72.25
Oregon	10.73	23.64	-2.75	2.80	58.21	121.16
Pennsylvania	10.67	26.25	-9.60	3.36	96.42	114.00
Rhode Island	9.13	24.74	-11.09	0.44	76.41	115.25
South Carolina	15.97	27.82	-2.39	11.40	112.31	64.13
South Dakota	6.84	25.61	-20.28	5.58	55.80	115.22
Tennessee	14.21	27.16	-6.98	20.38	116.77	78.07
Texas	19.12	30.18	-0.43	62.50	139.70	75.75
Utah	7.80	22.76	-11.94	16.44	60.36	120.21
Vermont	6.03	23.76	-17.78	0.38	42.53	114.45
Virginia	12.92	27.35	-6.71	6.60	124.55	90.43
Washington	9.91	22.01	-3.95	5.22	84.89	123.33
West Virginia	11.02	25.48	-10.57	2.04	63.00	91.00
Wisconsin	7.04	25.38	-18.00	3.28	63.44	124.43
Wyoming	5.97	21.66	-18.62	30.50	37.67	133.41