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Do firms adapt to climate change? Evidence from establishment-level data

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Abstract

This paper examines firms' adaptation to long-term changes in climatic conditions. Using detailed information of establishments owned by U.S. public firms from 1990 to 2012, we show that higher abnormal temperatures over the previous five years in a county lead to a significant reduction in local employment and the number of establishments. Further tests suggest that the decline in employment and establishments is largely due to a decline in local consumer demand rather than lower labor productivity. We also find that firms more likely take adaptive actions when their managers are more likely to believe in, or are concerned about, climate change. Overall, we provide large-sample evidence on firm adaptation to climate change.

Keywords: Climate change, employment, economic establishments, adaptation, abnormal

temperatures

1. Introduction

The overwhelming majority of the scientific community agrees that climate change is having a significant economic and societal impact (Stern, 2006; Hisang et al., 2017; Intergovernmental Panel on Climate Change, 2018).[1] However, so far little systematic evidence exists on how economic agents adjust to long-run environmental changes caused by climate change. Understanding whether and to what extent agents adapt to climate change is important because it sheds light on the cost and benefit analysis central to public policies in mitigating the impact of climate change. If adjustment by private sectors is large and rapid, the resulting economic damages associated with climate change could be significantly alleviated. But if agents appear to be slow or unable to adjust on their own, overall damages from climate change could be much larger and have greater welfare implications.

In this paper, we aim to examine adaptations made by the key driver of the modern economy—that is, firms—in response to long-term changes in climatic conditions. The IPCC defines adaptation as "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." Consistent with this definition, we focus on adjustments and modifications that are being made in expectation of and in response to climate change, which in turn depends on a wide range of cognitive and behavioral attributes at the organizational and individual levels. More specifically, we empirically test to what extent exposure to long-term temperature changes affects

[1] The impact of climate change ranges from agricultural and industrial output to economic growth. At the macro level, Dell, Jones, and Olken (2012) show that being 1°C warmer in a given year reduces per capita income by 1.4%, although the effect manifests only in poor countries. However, recent studies show that rising temperatures could negatively affect U.S. economic growth (Colacito, Hoffmann, and Phan, 2019). At the micro level, higher temperature has been shown to negatively affect agricultural yields (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009), manufacturing output (Jones and Olken, 2010), labor supply and productivity (Graff-Zivin and Neidell, 2014), and firm profitability (Addoum et al., 2019b). In addition, studies show that rising temperatures and more frequent extreme weather events amplified by climate change can negatively affect human health (Deschênes and Greenstone, 2011) and civil conflicts (Burke, Hsiang, and Miguel, 2015b).

establishment-level outcomes.

To that end, we construct two measures of long-term temperature exposure using the data from the National Oceanic and Atmospheric Administration (NOAA) and PRISM Climate Group. The first measure is the average abnormal temperature experienced at each establishment location during the past five years.[2] Second, to capture exposure to high temperatures that may be masked in the average temperatures, we count the number of hot days over the previous five years when daily mean temperature exceeded 25 degrees Celsius (°C).[3] To capture firms' geographic footprints, we obtain establishment-level data from the National Establishment Time Series (NETS) database. This database provides addresses as well as information on sales and employment for millions of U.S. establishments owned by public companies over the period from 1990 to 2012.

Using these measures, we estimate panel regressions of employment and the number of establishments at a firm-county-year level on long-term temperature exposure. Our empirical specification includes firm-county fixed effects that control for unobserved, time-invariant factors in each firm-county pair, thus, allowing us to identify the time-varying impact of abnormal temperatures on establishment outcomes. We also include firm-year fixed effects, which control for unobserved firm-level investment opportunities and allow us to compare the outcomes of establishments located in different counties within the same firm in the same year.

We first find an insignificant effect on firm employment and the number of establishments when measuring abnormal temperatures over a one-year period, which is consistent with the

[2] We use temperature over the previous five years at the county level as our main measure for several reasons. First, studies have shown that rising temperatures could negatively impact labor productivity and economic output. Second, variation in local temperature within a given spatial area is plausibly random, helping us to identify the causal impacts of climate change on firms' adaptive actions. Third, observed variation in these recent temperature changes largely spans the range of projected near-term changes in temperature provided by global climate models, allowing us to extrapolate the finding to make predictions of future adaptation behaviors.
[3] Our result is robust if we use 30°C as a threshold to define hot days.

finding of Addoum, Ng, and Ortiz-Bobea (2019a). However, we find that the effect of abnormal temperature on private sectors gradually picks up over a longer time horizon and becomes statistical significant effect when we focus on temperature changes over a longer horizon (e.g., larger than four-year). Therefore, to examine whether firms are responding to longer-term temperature change, we use a five-year abnormal temperature measure. We find that an abnormally high temperature over the previous five years in a county leads to a significant decline in employment and in the number of establishments. Economically, a 1°C increase in five-year average abnormal temperature leads to a 5% standard-deviation decline in employment and a 4.9% standard-deviation decrease in the number of establishments. Further tests show that the reduction in employment and closure of establishments are largely due to a decline in sales rather than lower labor productivity in affected counties. This evidence suggests that declining local demand is the main reason why firms reduce their workforce and shut down establishments.

To further shed light on the channels through which long-term abnormal temperatures affect establishment outcomes, we explore how firms' adaptation to climate change varies across industries. First, we find that the effect of abnormally high temperatures on firm adaptation is most pronounced for non-tradable and consumer-oriented sectors, buttressing our argument that the decline in employment and closure of establishments are largely driven by a decline in local consumer demand. Second, Graff-Zivin and Neidell (2014) find that extreme temperatures negatively affect labor productivity in heat-sensitive industries. If our result is driven by lower labor productivity, it should be stronger for heat-sensitive industries. However, we find that employment and number of establishments respond similarly to abnormal temperatures across heat-sensitive and non-heat-sensitive industries, inconsistent with the labor productivity channel. These two tests collectively suggest that the effects of abnormally high temperatures on firm adaptation are mainly through a reduction in consumer demand.

Note that there is an important implicit assumption here. The managers perceive that changes in the long run climate can impose a significant threat to firm performance. If managers do not pay any attention to climate change, then we should not find any adaptive actions of firms. In other words, the adaptive actions taken by firms should be based on their managers' beliefs in long-term climate change and the resultant permanent reduction in consumer demand. Consistent with this prediction, we find that a firm is more likely to lay off employees and close establishments when the firm is headquartered in a county with a strong belief in climate change and when the firm explicitly mentions "climate change" or "global warming" in its annual reports and 8-K filings.

Our paper contributes to the literature in several ways. The paper is related to the climate economy literature that examines the impact of climate change on various economic outcomes (Dell, Jones, Olken, 2014; Burke, Hsiang, and Miguel, 2015a). These studies focus on changes in weather realizations over time within a given spatial area and demonstrate impacts on agricultural output, industrial output, labor productivity, firm profitability, health and mortality, civil conflict, economic growth, etc. Consistent with these studies, we find that abnormal temperatures over a long period negatively affects establishment sales. However, we go one step further by showing that firms respond to adverse changes in climatic conditions by reducing employment and closing establishments, thus providing direct evidence of firms' adaptation towards climate change.

Our study is a timely response to the rising demand for research on climate change adaptation (e.g., Fankhauser, 2017). Empirical evidence of adaptation to climate is sparse compared to the breadth of the problem and tends to focus on country-level adaptation or exclusively on the agricultural sector. For example, Hsiang and Narita (2012) find that countries with more intense tropical cyclone climate suffer lower losses from actual tropical cyclone events, consistent with effective adaptation to climate risk over the long run. Barreca et al. (2016) show that the impact of temperature extremes on mortality in the United States has declined substantially over the 20th century and attribute the decline to the widespread adoption of residential air conditioning technology. Burke and Emerick (2016), however, find limited evidence of farmers adapting to climate change in U.S. agriculture. To the best of our knowledge, our paper is the first in the literature to provide large-sample evidence regarding *individual firms*' adaptation to climate change.

A paper that is closely related to ours is Addoum et al. (2019a) that examine how temperature shocks during the past one-year affect firms' establishment sales and productivity. Our study deviates from theirs in the following ways. First, our main variable of interest, in addition to establishment sales and productivity, is establishment employment. In other words, we put more emphasis on the labor market implications of climate change. Second, while Addoum et al. (2019a) are interested in the effect of short-term temperature shocks, we focus on a longer-run trend of global warming. We thus use abnormal temperatures measured over a long period to capture climate change instead of a one-year measure. Third, Addoum et al. (2019a) find that short-term high temperatures do not affect firms' establishment sales and productivity, but we find a significant impact of long-term high temperatures on firms' local employment, plants, and sales. The result difference is reasonable in that a one-year temperature shock does not necessarily suggest that climate changes impose a long run threat, thus does not justify any costly or irreversible adjustment; however, if high temperatures persist in a much longer period, managers are likely to believe the trend of global warming and consequently take costly adaptations such as layoffs or plant closures.

2. Empirical Methodology

The granularity of our establishment-level data enables us to conduct the empirical analysis at the firm-county-year level. We specify the regression model, as below:

$$Y_{c,s,i,t} = \beta_0 + \beta_1 \, Climate\ Change_{c,t} + \beta_2 \, X_{c,t} + \alpha_{c,i} + \gamma_{i,t} + \varepsilon_{c,s,i,t} \,, \qquad (1)$$

where *c* represents counties, *s* represents states, *i* represents firms, and *t* represents years. *Y* stands for our main dependent variables that measure firms' adaptive activities, including the number of county-level employees scaled by the number of state-level employees (*Employees*) and the number of county-level plants scaled by the number of state-level plants for each firm-year (*Plants*). The advantage of using a ratio instead of the raw number of county-level employees is that the ratio can conveniently account for the effect of time-varying state-level economic fundamentals. Therefore, our identification comes from variations in establishment outcomes across counties located in the same state in the same year. To examine potential drivers of firms' adaptation behaviors, we also use two other dependent variables—namely, county-level sales scaled by state-level sales for each firm-year (*Sales*) and the natural logarithm of the ratio of establishment sales to the number of employees as a proxy for labor productivity (*Productivity*).[4]

We construct two measures of long-term temperature exposure (*Climate Change*) as our key explanatory variables. The first measure is the difference between the average temperature over the past five years and the historical average temperature (1961–1990) in a county (*Ab_Temperature*). Our second measure is the number of hot days, defined as the number of days with daily mean temperature greater than 25°C over the past five years (*Hot_Days*). In addition to using continuous measures of abnormal temperature and hot days, we also group *Ab_Temperature* and *Hot_Days* into quintiles in order to detect any nonlinear effect of abnormal temperatures on

[4] We do not scale county-level productivity by state-level productivity because productive is already a ratio measure and should not be related to firms' geographical unit.

firm adaptation. To replicate the result of Addoum et al. (2019a), we also construct *Ab_Temperature* and *Hot_Days* over the past one year. *X* represents a set of county-level macroeconomic variables, including the natural logarithm of the number of a county's labor force (*ln(Labor force)*), the unemployment rate (*Unemployment rate*), and the natural logarithm of average weekly wage (*ln(Weekly wage)*).

We use high-dimensional fixed effects to further account for the effect of omitted variables. $\alpha_{c,i}$ stands for firm-county fixed effects, which control for unobserved, time-invariant factors in the firm-county pair and thus allow us to identify the time-varying impact of temperature shocks on establishment outcomes. $\gamma_{i,t}$ represents firm-year fixed effects, which can control for time-varying firm investment opportunities, thus allowing us to compare the outcomes of establishments located in different counties within the same firm in the same year. Since *Productivity* is not scaled at the state level, we control for firm-county and firm-state-year fixed effects in regressions with *Productivity* as the dependent variable.

3. Data and Summary Statistics

Our establishment-level data come from the NETS Publicly Listed Database produced by Wall & Associates. This database provides addresses for every U.S. establishment owned by each public firm over the period from 1990 to 2012. In addition to locations, the database provides information on the proportion of a firm's annual sales generated at each of its establishments as well as information on the number of employees working at each establishment. We match each establishment with its parent company in Compustat by company name, and group all firms into 11 industries based on their two-digit GIC code. Some studies have shown that NETS employment data is sometimes imputed rather than actually reported by firms (Neumark, Zhang, and Wall, 2007). To address the concern about data quality, we show that our main results are robust to using actual employment information provided by the establishment.

We collect county-level monthly temperature data from NOAA (National Oceanic and Atmospheric Administration) and daily temperature data from PRISM Climate Group.[5] After matching the temperature data with each establishment based on the county's location, we have 3,738,422 establishment-year level observations. We then aggregate the establishment-level data to firm-county-year level and firm-state-year level, and compute dependent variables detailed in Section 2, including *Employees*, *Plants*, *Sales*, and *Productivity*. We collect information on county-level labor force and unemployment rate from the Local Area Unemployment Statistics (LAUS) dataset of the U.S. Bureau of Labor Statistics. County-level weekly average wage data come from the Quarterly Census of Employment and Wages (QCEW) database of the U.S. Bureau of Labor Statistics. After requiring non-missing observations for all these variables, our final sample consists of 1,921,118 firm-county-year observations for 2,934 unique counties from 1990 to 2012.

We use two proxies to measure firm managers' beliefs and concerns about climate change. *Belief* is the first principal component of quintile ranks of answers to survey questions from Yale Climate Opinion Maps 2015.[6] The survey measures the fraction of people in a county agreeing with the following four statements: 1) Global warming is happening; 2) Global warming is caused mostly by human activities; 3) Most scientists think global warming is happening; 4) Global warming is affecting the weather in the United States. We use the climate change belief of the county in which a firm is headquartered to proxy for firm managers' belief about climate change.

[5] PRISM Climate Group is the U.S. Department of Agriculture's official climatological database. The PRISM data capture the daily mean, minimum, and maximum temperature and the level of precipitation, in each of the 481,631 16-square-kilometer (i.e., 4*4km) grids covering the continental United States.
[6] This map depicts estimates of the proportion of American adults (ages 18 and over) who hold specific beliefs about global warming. The estimates were generated from a statistical model that incorporates actual survey responses and demographic data from the United States.

Concern is a dummy variable that is equal to one if "climate change" or "global warming" is mentioned in the firm's 8-K or 10-K filings in a year, and zero otherwise.

Table 1 reports the summary statistics of variables used in this study. Table 1 Panel A presents the descriptive statistics for temperature variables. The mean (median) *Ab_Temperature* is 1.148 degrees Fahrenheit (°F) (1.220°F), suggesting that the five-year moving average temperature over 1990-2012 is 1.148°F higher than the average temperature over 1961-1990. This increasing trend of county-level temperatures is consistent with Global Warming. The mean (median) *Hot_Days* is 260 days (262 days), which means that on average there are 52 days per year with mean daily temperature greater than 25°C. Table 1 Panel B presents the summary statistics of establishment-level variables. The ratios of county-level employees and sales over state-level employees and sales for an average firm are both around 0.32. The mean natural logarithm of establishment sales over the number of employees is about 11. Panel C presents the summary statistics of county-level macroeconomic variables, and Panel D presents the summary statistics of *Belief* and *Concern* used in cross-sectional tests.

[Table 1 is here]

In Figure 1, we plot the average *Ab_Temperature* across U.S. counties over 1990-2012. Darker colors represent higher average abnormal temperatures. The map visualizes the large cross-county differences in average abnormal temperatures experienced over the 1990-2012. In Figure 2, we plot the abnormal temperatures in time series, for both the abnormal temperatures measured over the past one year and over the past five years. There are several notable patterns in this graph: 1) consistent with Global Warming, the abnormal temperatures are positive in general, suggesting that the recent period (1990-2012) has experienced higher temperatures than the pre-1990 period; 2) the five-year abnormal temperature shows a rising trend, indicating a rising long-term temperature trend in the recent period; and 3) the one-year abnormal temperature is quite volatile with no clear trend, indicating that short-term temperature shocks may not be able to capture the trend of global warming.

4. Empirical Results

4.1 Firms' response to short-run abnormal temperature exposure

Addoum et al. (2019a) find that the average abnormal temperature during the past one year has no significant effect on firm sales and productivity. Before moving to our main analyses that use long-term temperature exposure, we follow Addoum et al. (2019a) and construct abnormal temperature over the past one year (*Ab_Temperature1yr*), and examine its effect on *Employment*, *Plants*, and *Sales*.[7]

We present the results in Table 2. The coefficients on *Ab_Temperature1yr* are statistically insignificant and economically small for all dependent variables. For example, column (1) shows that the coefficient on *Ab_Temperature1yr* is -0.017 and statistically insignificant for *Employment*. The coefficient magnitude suggests that a 1°C increase (1.80 × 1°F increase) leads to a 0.6% standard-deviation reduction in employment (0.017% × 1.80/5.3%), a negligible economic impact. Therefore, our finding suggests that firms do not take costly adaptive actions toward short-term temperature shocks. This finding is consistent with Addoum et al. (2019a).

[Table 2 is here]

Although our first result shows that firms do not respond to short-term abnormal temperatures, it is possible that firms will take more visible actions when facing longer-term changes in weather conditions if temperature anomalies over the longer horizon are more informative about the trend

[7] We also follow their study and use the number of hot days over the past year as an alternative measure, and consistently find insignificant results.

of global warming and more profoundly shape managers' belief in climate change. To test this possibility, we construct abnormal temperatures averaged over the past two years to past four years and re-run the regressions. Table 3 shows that the coefficient of abnormal temperatures becomes monotonically larger when we increase the horizon of abnormal temperature, and the effect becomes statistically significant when we measure abnormal temperatures over past four years. This result makes intuitive sense as the layoff of employees and shutdown of establishments are costly and potentially irreversible decisions that firms will more likely take when facing long-term change in climatic conditions rather than temporary temperature shocks.

[Table 3 is here]

4.2 Firms' response to long-run abnormal temperature exposure

We carry on our analysis by examining how firms adapt to long-run changes in climatic conditions. We measure long-run changes in climatic conditions using abnormal temperatures and number of hot days measured over the past five years in our subsequent analyses.

In Table 4, we regress *Employees* on *Ab_Temperature* (Panel A) and *Hot_Days* (Panel B), respectively. Columns (1) to (3) of Panel A report the effect of abnormal temperature on employment. Column (1) shows that the coefficient on *Ab_Temperature* is -0.145 (t = -2.18), suggesting that a higher abnormal temperature in a county during the previous five years leads to a lower level of employment for firms with establishments located in that county. The economic magnitude indicates that a 1°C increase (1.80 × 1°F increase) leads to a 5% standard-deviation reduction in employment (0.145% × 1.80/5.3%). Column (2) shows the results using the quintile rank of abnormal temperatures as the explanatory variable. The coefficient on *Ab_Temperature_Q* is significantly negative, with an estimated magnitude of -0.045 (t = -2.61). In column (3), we show the result using dummies indicating abnormal temperature quintiles. We find a strictly monotonic effect of abnormal temperatures on employment: the higher the abnormal temperatures, the larger the reduction in employment. Columns (1) to (3) of Panel B show that the results are similar when we use the number of hot days as a proxy for temperature exposure. The effect becomes much stronger when hot days become more frequent. For example, the coefficient estimate on *Hot_Days_Q5* suggests that for establishments located in counties experiencing the highest number of hot days over the previous five years, there is a 13.4% (0.712% × 1/5.3%) standard-deviation reduction in employment compared with firms located in counties with the lowest number of hot days.

We next examine whether the long-term abnormal temperatures also affect the number of establishments in a county. Columns (4) to (6) of Panel A and Panel B show the results using abnormal temperatures and the number of hot days, respectively. The results suggest that a higher abnormal temperature or a higher frequency of hot days over the previous five years leads to fewer firm establishments in the exposed county relative to other counties in the same state. Again, this effect increases monotonically with *Ab_Temperature* and *Hot_Days*. The results suggest that prolonged high temperatures in a county affect not only firms' employment decisions (intensive margin) but also firms' decision to close the entire establishment (extensive margin).

Motivated by the climate economy literature, we conjecture two channels for firms to lay off employees and close establishments when facing prolonged high temperatures. First, the decline in employment and establishments could reflect a firm's response to shrinking local demand for its products/services due to higher temperatures. Deryugina and Hsiang (2014) show that abnormally high temperatures reduce annual income in U.S. counties. Colacito et al. (2019) document that a higher summer temperature reduces annual growth in state-level output. The declining household income and deteriorating local economic conditions due to prolonged high temperatures could reduce consumer demand for local products and services. Under this channel, we expect abnormally high temperatures to negatively affect establishment sales. In columns (7) to (9) of Panel A, we show the effect of abnormal temperatures on *Sales*. The coefficient on *Ab_Temperature* (-0.138, t = -2.05) indicates that a 1°C increase (1.80 × 1°F increase) leads to a 4.7% standard-deviation reduction in establishment sales (0.138% × 1.80/5.3%). This economic magnitude is similar to the reduction in employment, suggesting that firms are likely to adjust labor inputs in response to declining local demand. The coefficients on *Ab_Temperature_Q* and the dummies of abnormal temperature quintiles suggest that the higher the abnormal temperatures, the larger the decline in sales. In Panel B, we show that using the number of hot days as a measure of abnormal temperatures generates similar inferences.

Lower labor productivity could be another channel underlying firms' adaptation to climate change. Prior studies (Graff-Zivin and Neidell, 2014; Heal and Park, 2013; Zhang et al., 2018) show that extreme temperatures can negatively affect the productivity of workers. Lower labor productivity could cause firms to lay off workers and shut down plants in the affected area. We thus use *Productivity* as the dependent variable and examine whether it is affected by abnormal temperatures (columns (10) to (12) of Panel A) and the number of hot days (columns (10) to (12) of Panel B). In general, we find limited evidence that labor productivity is negatively affected by abnormally high temperatures. The coefficient on *Ab_Temperature* is small and insignificant (-0.001, t = -0.45). The economic magnitude is negligible: A 1°C increase (1.80 × 1°F increase) leads to a 0.016% standard-deviation reduction in labor productivity (0.001% × 1.80/11%). Similarly in Panel B, we find a small and insignificant effect of the number of hot days on labor productivity.

[Table 4 is here]

Our analyses throughout the paper use all data from NETS, including both imputed observations and those reported by firms. As a robustness check, we re-run the baseline tests using the data that are reported by firms. The results using actual reported data are presented in Table 5. We find the results are similar to those in Table 4 where we use all data, in terms of both statistical significance and economic magnitude.

Taken together, the results in Table 4 and Table 5 imply that firms do adapt to climate change by reducing employment and closing establishments in counties experiencing prolonged high temperatures. Firms' adaptation is mainly driven by declining local demand rather than lower labor productivity. Since our results throughout this paper are qualitatively similar using either abnormal temperatures or the number of hot days, in the remaining analyses, we will present the results using only abnormal temperatures and put the results using the number of hot days in the online appendix.

[Table 5 is here]

4.3 Industry-level analysis

The local demand channel predicts a differential response of non-tradable versus tradable sectors across U.S. counties. Firms in non-tradable sectors rely heavily on local demand, while tradable sectors rely more broadly on national or even global demand. A direct prediction of the local demand channel is that while the change in employment of *non-tradable* sectors could be uniformly affected by higher temperatures of counties, the effect of temperatures on employment of *tradable* sectors should be much weaker.

We take these key predictions to the data by classifying industries into tradable and non-tradable sectors following the definition in Mian and Sufi (2014). We then run the baseline regressions for non-tradable and tradable sectors separately. If the observed firm response to abnormal temperatures is mainly due to declining local demand, the effect should be particularly strong for firms in the non-tradable sectors. Supporting the local demand channel, Table 6 shows that the coefficients on *Ab_Temperature* are larger and only significant for firms in the non-tradable sectors. In Online Appendix Table O1, we use *Hot_Days* as the measure for temperature exposure and find consistent results. This is consistent with the local demand channel: declining local demand due to abnormally hot temperatures mainly affects firms whose sales relying heavily on local demand, and consequently leads those firms to lay off employees and close establishments.

[Table 6 is here]

To provide further evidence on the channels of firm adaptation, we conduct an industry-level analysis to examine which industries react more strongly to climate change. We run the baseline regressions for each industry, where industry is defined at the two-digit GIC level. For the ease of comparison, in Table 7 we only report the coefficients on *Ab_Temperature*, with *Employees*, *Plants*, and *Sales* as dependent variables, respectively. The point estimates on *Ab_Temperature* are negative for seven of 11 industries when the dependent variables are *Employees* and *Plants*, suggesting that adaptation to prolonged abnormal temperatures is widespread across sectors. In terms of statistical significance and economic magnitude, we find that firms in the consumer discretionary sector have the largest decline in employment, number of establishments, and sales in response to rising temperatures. We find similar results using the number of hot days as a proxy for temperature exposure, as shown in Online Appendix Table O2. Therefore, the sectors most relying on consumer demand exhibit the strongest reactions to climate change. This is also consistent with the channel of local consumer demand.

[Table 7 is here]

To test the channel of labor productivity, we examine whether our results are stronger for establishments that are in the heat-sensitive industries. Graff-Zivin and Neidell (2014) show that the effect of high temperatures on labor productivity is concentrated in the heat-sensitive industries. Following Graff-Zivin and Neidell (2014), we use GIC codes to identify heat-sensitive industries as follows: 151050 (paper & forest products), 151040 (metals & mining), 201030 (construction & engineering), 251020 (automobile & motorcycle manufacturers), 203010−203050 (transportation), 302020−302030 (food product & tobacco producers), and 551010−551050 (utilities). We define an indicator, *Heat_Sensitive*, which equals one if the firm belongs to a heat-sensitive industry and zero otherwise. We then run our baseline regressions, adding an interaction term between *Heat_Sensitive* and the abnormal temperature variables. Table 8 shows that the coefficients on the interaction terms are mostly insignificant, suggesting that firm response to abnormal temperatures is similar across heat-sensitive and non-heat-sensitive industries. In Online Appendix Table O3, we use *Hot_Days* as a proxy for temperature exposure and continue to find insignificant coefficients on the interaction term. Overall, the cross-sectional test suggests that firm adaption to climate change is not significantly stronger in heat-sensitive industries. This is inconsistent with the channel of labor productivity.

[Table 8 is here]

4.4 Cross-sectional tests

4.4.1 Beliefs and concerns about climate change

Reducing the labor force and closing establishments are costly and potentially irreversible firm decisions. Firms would not undertake such costly adaptive actions unless their managers genuinely believe that the abnormal temperatures experienced over the past several years was not just a temporary weather pattern but instead was a manifestation of global warming trend that could result in a permanent change in weather conditions. As a result, we hypothesize that the effect of abnormal temperatures on firm adaptation should be more pronounced for firms whose decision makers strongly believe in and are concerned about climate change.[8] To test this, we use two proxies to capture firm managers' beliefs and concerns about climate change. The first measure, *Belief,* is the local climate change belief in a firm's headquarter county from the Yale Climate Opinion Maps 2015 (Howe et al., 2015). The second measure, *Concern*, is a dummy variable that equals one if "climate change" or "global warming" appears in a firm's 8-K or 10-K filings in a year. We then interact the two measures with the abnormal temperature (*Belief* × *Ab_Temperature* and *Concern* × *Ab_Temperature*) and expect the coefficients on the interaction terms to be significantly negative in the regression.

The results are presented in Table 9. Columns (1) and (3) report the results for *Belief*, and columns (2) and (4) for *Concern*. The coefficients on the interaction term *Belief* × *Ab_Temperature* and *Concern* × *Ab_Temperature* are indeed negative and significant for both *Employees* and *Plants*. The results using the number of hot days are similar (except for the coefficient on *Hot_Days* × *Concern*), as shown in Online Appendix Table O4. These findings suggest that top managers' beliefs and concerns about climate change play an important role in shaping their firms' adaptation to climate change.

[Table 9 is here]

[8] Consistent with the idea that climate change belief plays an important role in affecting agents' decision-making, recent studies show that real estate prices and mortgage lenders take into account climate risks only in areas where residents strongly believe in climate change (Baldauf, Garlappi, and Yannelis, 2018; Duan and Li, 2019).

4.4.2 Organizational structure

In addition to climate change belief, we look at whether firms' adaptation to climate change depends on their organizational structure. Hannan and Freeman (1984) suggest that organizational inertia, or resistance to change, increases with firm age and size. The underlying reason is that old and large organizations have established stable internal relationships and formalized roles, which discourages speedy change in resource reallocation that could introduce uncertainty. Therefore, adaptive actions may be constrained by the age and size of the firm (e.g., Hannan and Freeman, 1984; Kelly and Amburgey, 1991).

To test this, we use firm age and size as proxies for organizational inertia, interact them with temperature exposure measures, and include interaction terms in the regression model. Table 10 reports the results. We find that the coefficients on the interaction between organizational inertia and abnormal temperatures (*Age* × *Ab_Temperature and Size* × *Ab_Temperature*) are insignificant. However, using the number of hot days as a proxy for temperature exposure in Table O5, we find significantly positive coefficients on *Age* × *Ab_Temperature* and *Size* × *Ab_Temperature*, suggesting that older and larger firms indeed adjust to climate change more slowly. To sum up, we find some evidence supporting the notion that organizational inertia impedes firms' adaptation to climate change.

[Table 10 is here]

5. Conclusion

Quantitative estimates of the impact of climate change on various economic outcomes are an important input to climate mitigation policies such as investments in emissions reduction technologies and carbon taxes. A common issue of many impact estimates is that they do not account for long-term adjustments that economic agents might make in response to a changing climate.

In this paper, we examine firms' adaptation to long-term changes in climatic conditions. Using detailed establishment-level data of U.S. public firms from 1990 to 2012, we find that abnormally warm temperatures over the previous five years in a county lead to a significant reduction in employment and to establishment closures. The decline in employment and establishments mainly concentrates in the non-tradable sectors and consumer discretionary industries, but not in heat-sensitive industries, implying that firms' adaptation to climate change is largely due to a decline in local consumer demand rather than lower labor productivity. Further, firms are more likely to take adaptive actions when they are headquartered in counties with a strong belief in climate change and when they explicitly mention "climate change" or "global warming" in their annual reports and 8-K filings. Overall, our findings provide large-sample evidence on firm adaptation to climate change and various factors that may shape firms' climate adaption strategies.

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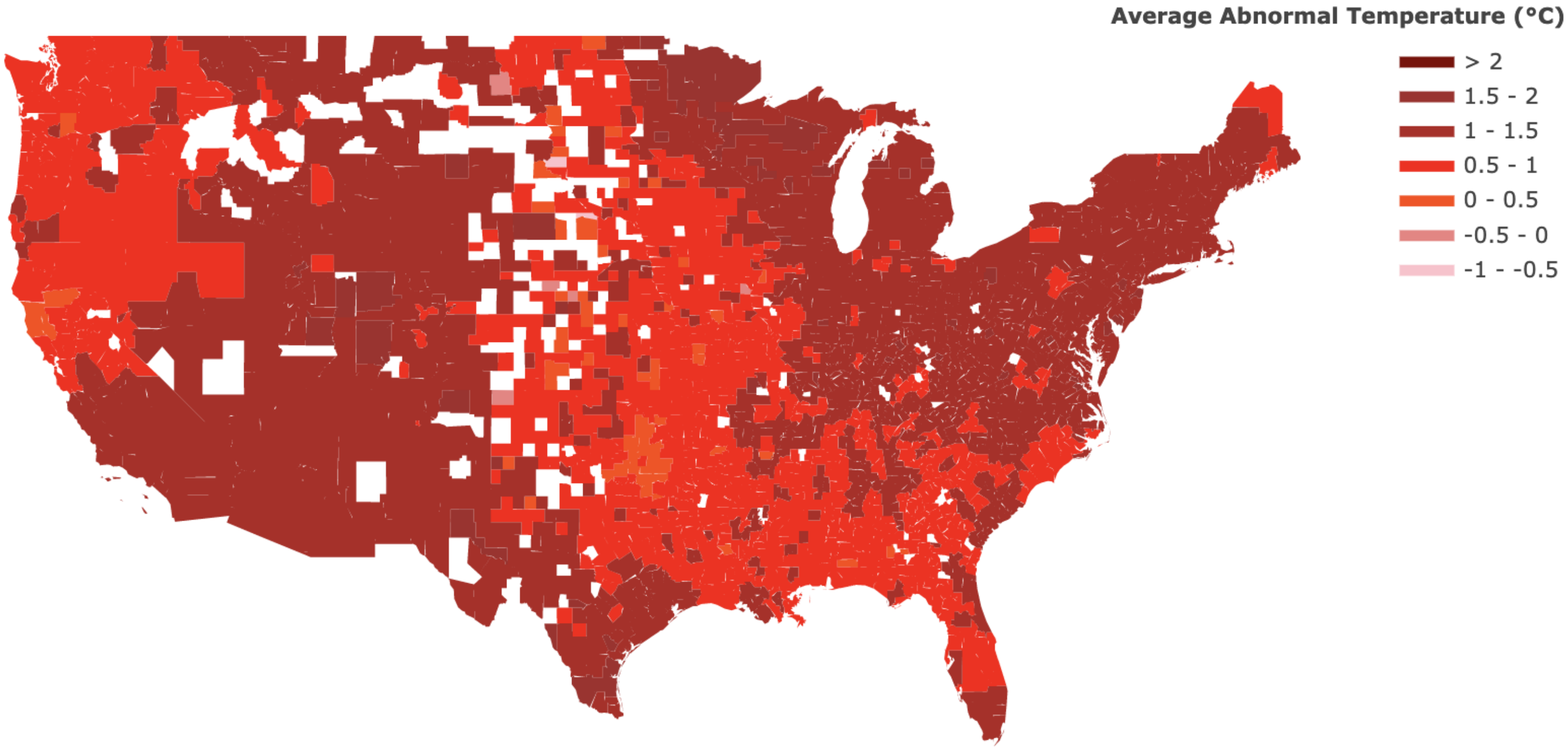
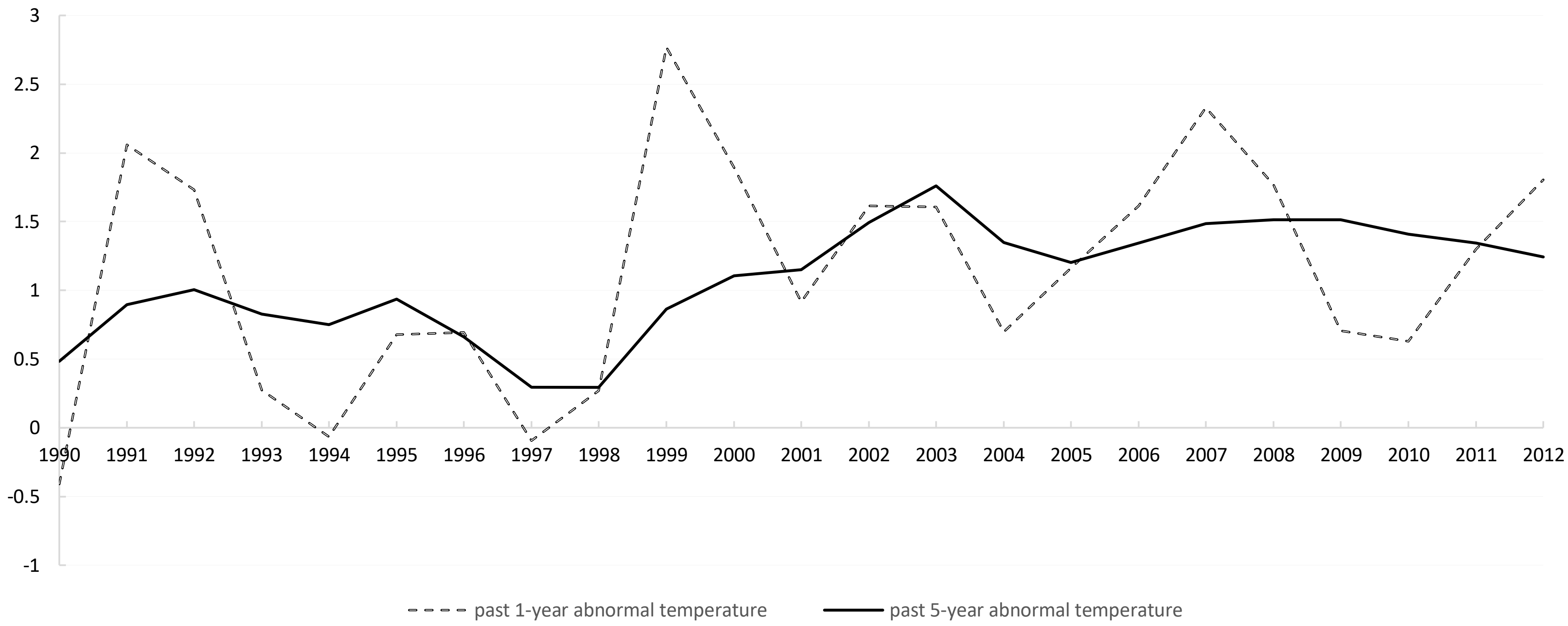
Figure 1. U.S. County Mean Abnormal Temperatures from 1990 to 2013



The figure shows the mean abnormal temperature for each county. Abnormal temperature is defined as the difference between the previous five year moving average temperature and the 30-year historical (1961–1990) average temperature.

Figure 2. U.S. abnormal temperatures from 1990 to 2012



This figure plots the time-series of the average abnormal temperature over the previous one year (dotted line) and the average abnormal temperature over the previous five years (solid line) during the period 1990-2012.

Table 1. Summary Statistics

	Mean	Standard Deviation	Min.	25th percentile	Median	75th percentile	Max.
Panel A: Temperature variables							
Ab_Temperature	1.148	0.469	0.106	0.850	1.220	1.493	1.906
Hot_Days	260.374	21.142	221.530	243.990	262.491	276.694	294.809
Panel B: Firm adaptation variables							
Employees (%)	32.272	5.310	26.437	28.677	31.103	34.482	51.513
Plants (%)	32.261	5.315	26.413	28.665	31.094	34.469	51.503
Sales (%)	32.273	5.310	26.437	28.678	31.104	34.482	51.514
Productivity	11.448	0.104	11.208	11.387	11.461	11.523	11.613
Panel C: Macroeconomics variables							
ln(Labor force)	11.766	0.078	11.602	11.712	11.777	11.830	11.875
Unemployment rate	5.801	1.849	3.426	4.425	5.388	6.681	9.832
ln(Weekly wage)	6.440	0.205	6.031	6.269	6.464	6.628	6.729
Panel D: Other variables							
Belief	3.909	2.110	-4.711	2.889	4.860	5.459	5.635
Concern	0.048	0.030	0.036	0.036	0.036	0.047	0.135

The table reports the summary statistics of variables. The sample period is 1990 to 2013. Panel A reports summary statistics of temperature variables. We first calculate the statistics at the county level and then take the average of these statistics. Panel B reports the summary statistics of firm adaptation variables. We take the average of each variable at the firm-year level, calculate the variable statistics at the firm level, and then report the mean of these statistics. Panel C reports the summary statistics of county-level macroeconomic variables. We first calculate the statistics at the county level and then report the mean of these statistics. Panel D reports the summary statistics of *Belief* and *Concern*. For *Belief*, we calculate its summary statistics using pooled data. For *Concern*, we first calculate the summary statistics at the firm level and then take the average of these statistics.

Table 2. Short-Term Temperature Exposure and Firm Adaptation

	Employees (%)	Plants (%)	Sales (%)	Productivity
Ab_Temperature1yr	-0.017	-0.013	-0.020	-0.0001
	(-0.63)	(-0.47)	(-0.73)	(-0.17)
ln(Labor force)	2.064***	1.485***	1.970***	-0.005
	(4.56)	(3.31)	(4.31)	(-0.87)
Unemployment rate	-0.050	-0.039	-0.053*	-0.0002
	(-1.70)	(-1.41)	(-1.79)	(-0.88)
ln(Weekly wage)	-0.404	-1.115	-0.419	-0.005
	(-0.55)	(-1.64)	(-0.56)	(-0.67)
Adj. *R* sq.	0.915	0.935	0.914	0.966
N	1,921,118	1,921,118	1,921,070	1,576,583
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	YES

The table reports firm adaptation to short-term temperature exposure. Short-term temperature exposure is measured by the abnormal temperature during the past one year. Dependent variables are at the firm-county-year level. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Abnormal Temperatures over Different Horizons and Firm Adaptation

	Employees (%)			Plants (%)			Sales (%)			Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ab_Temperature2yr	-0.020			-0.015			-0.023			-0.0001		
	(-0.55)			(-0.38)			(-0.63)			(-0.15)		
Ab_Temperature3yr		-0.044			-0.048			-0.044			0.0001	
		(-1.02)			(-1.05)			(-1.01)			(0.09)	
Ab_Temperature4yr			-0.101*			-0.108**			-0.098*			-0.0004
			(-1.92)			(-2.11)			(-1.85)			(-0.30)
ln(Labor force)	2.062***	2.059***	2.052***	1.484***	1.480***	1.472***	1.968***	1.966***	1.959***	-0.005	-0.005	-0.005
	(4.56)	(4.56)	(4.54)	(3.31)	(3.30)	(3.27)	(4.31)	(4.31)	(4.29)	(-0.87)	(-0.88)	(-0.86)
Unemployment rate	-0.050	-0.049	-0.048	-0.039	-0.038	-0.036	-0.053*	-0.052*	-0.051	-0.0002	-0.0002	-0.0002
	(-1.69)	(-1.67)	(-1.62)	(-1.40)	(-1.37)	(-1.32)	(-1.78)	(-1.75)	(-1.71)	(-0.88)	(-0.89)	(-0.87)
ln(Weekly wage)	-0.407	-0.419	-0.444	-1.116	-1.133	-1.160*	-0.422	-0.432	-0.456	-0.005	-0.005	-0.005
	(-0.55)	(-0.57)	(-0.61)	(-1.65)	(-1.69)	(-1.74)	(-0.56)	(-0.58)	(-0.61)	(-0.67)	(-0.67)	(-0.68)
Adj. *R* sq.	0.915	0.915	0.915	0.935	0.935	0.935	0.914	0.914	0.914	0.966	0.966	0.966
N	1,921,118	1,921,118	1,921,118	1,921,118	1,921,118	1,921,118	1,921,070	1,921,070	1,921,070	1,576,583	1,576,583	1,576,583
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES

The table reports firm adaption to abnormal temperatures measured over different horizons. *Ab_Temperature2yr*, *Ab_Temperature3yr* and *Ab_Temperature4yr* are the abnormal temperatures over past two years, three years and four years, respectively. Dependent variables are at the firm-county-year level. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Long-Term Temperature Exposure and Firm Adaptation

Panel A: Abnormal temperatures and firm adaptation

	Employees (%)			Plants (%)			Sales (%)			Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ab_Temperature	-0.145**			-0.145**			-0.138*			-0.001		
	(-2.18)			(-2.15)			(-2.05)			(-0.45)		
Ab_Temp _Q		-0.045**			-0.048**			-0.043**			0.0000	
		(-2.61)			(-2.73)			(-2.46)			(0.01)	
Ab_Temp _Q2			-0.068			-0.047			-0.058			0.002***
			(-1.25)			(-0.93)			(-1.07)			(3.00)
Ab_Temp _Q3			-0.063			-0.079			-0.061			0.001
			(-0.96)			(-1.13)			(-0.90)			(1.68)
Ab_Temp _Q4			-0.152*			-0.153*			-0.144*			0.001
			(-2.00)			(-2.00)			(-1.86)			(1.29)
Ab_Temp _Q5			-0.181**			-0.187**			-0.170**			0.001
			(-2.37)			(-2.41)			(-2.21)			(0.61)
ln(Labor force)	2.043***	2.050***	2.053***	1.464***	1.471***	1.473***	1.951***	1.958***	1.961***	-0.005	-0.005	-0.005
	(4.51)	(4.54)	(4.54)	(3.24)	(3.26)	(3.27)	(4.27)	(4.29)	(4.30)	(-0.85)	(-0.87)	(-0.88)
Unemployment rate	-0.048	-0.048	-0.048	-0.037	-0.036	-0.036	-0.051*	-0.051	-0.051*	-0.0002	-0.0002	-0.0002
	(-1.64)	(-1.63)	(-1.65)	(-1.35)	(-1.33)	(-1.34)	(-1.73)	(-1.72)	(-1.73)	(-0.86)	(-0.88)	(-0.90)
ln(Weekly wage)	-0.462	-0.454	-0.458	-1.174*	-1.170*	-1.175*	-0.472	-0.464	-0.469	-0.005	-0.005	-0.005
	(-0.63)	(-0.62)	(-0.63)	(-1.76)	(-1.75)	(-1.76)	(-0.63)	(-0.62)	(-0.63)	(-0.68)	(-0.67)	(-0.69)
Adj. *R* sq.	0.915	0.915	0.915	0.935	0.935	0.935	0.914	0.914	0.914	0.966	0.966	0.966
N	1,921,118	1,921,118	1,921,118	1,921,118	1,921,118	1,921,118	1,921,070	1,921,070	1,921,070	1,576,583	1,576,583	1,576,583
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES

Panel B: Hot days and firm adaptation

	Employees (%)			Plants (%)			Sales (%)			Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hot_Days	-0.003***			-0.004***			-0.003***			0.0000		
	(-2.94)			(-3.53)			(-2.98)			(1.06)		
Hot_Days_Q		-0.204**			-0.191**			-0.229**			-0.0000	
		(-2.54)			(-2.82)			(-2.81)			(-0.03)	
Hot_Days _Q2			-0.037			-0.075			-0.080			-0.004***
			(-0.27)			(-0.63)			(-0.59)			(-3.23)
Hot_Days _Q3			-0.360			-0.305			-0.451*			-0.003*
			(-1.67)			(-1.73)			(-2.09)			(-2.03)
Hot_Days _Q4			-0.625**			-0.552**			-0.698**			-0.003
			(-2.39)			(-2.58)			(-2.68)			(-1.24)
Hot_Days _Q5			-0.712**			-0.731**			-0.810**			0.0008
			(-2.42)			(-2.77)			(-2.65)			(0.25)
ln(Labor force)	1.880***	1.879***	1.879***	1.320***	1.319***	1.318***	1.778***	1.777***	1.778***	-0.008	-0.008	-0.008
	(4.09)	(4.07)	(4.08)	(3.14)	(3.11)	(3.11)	(3.81)	(3.79)	(3.79)	(-1.38)	(-1.38)	(-1.39)
Unemployment rate	-0.034	-0.037	-0.037	-0.021	-0.025	-0.0245	-0.037	-0.040	-0.040	-0.0002	-0.0001	-0.0001
	(-1.10)	(-1.22)	(-1.21)	(-0.76)	(-0.91)	(-0.89)	(-1.18)	(-1.30)	(-1.29)	(-0.62)	(-0.61)	(-0.58)
ln(Weekly wage)	-0.470	-0.449	-0.468	-1.012*	-0.993	-1.004	-0.373	-0.350	-0.365	-0.0000	0.0000	0.0001
	(-0.78)	(-0.74)	(-0.77)	(-1.76)	(-1.72)	(-1.74)	(-0.61)	(-0.57)	(-0.60)	(-0.00)	(0.00)	(0.01)
Adj. *R* sq.	0.923	0.923	0.923	0.942	0.942	0.942	0.922	0.922	0.922	0.968	0.968	0.968
N	1,644,465	1,644,465	1,644,465	1,644,465	1,644,465	1,644,465	1,644,417	1,644,417	1,644,417	1,358,671	1,358,671	1,358,671
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES

The table reports firm adaptation to long-term temperature exposure. Dependent variables are at the firm-county-year level. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Long-Term Temperature Exposure and Firm Adaptation (Using NETS Actual Employment Data)

Panel A: Abnormal temperatures and firm adaptation

	Employees (%)			Plants (%)			Sales (%)			Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ab_Temperature	-0.152**			-0.152**			-0.144**			-0.001		
	(-2.19)			(-2.28)			(-2.13)			(-0.77)		
Ab_Temp _Q		-0.043**			-0.045**			-0.039**			0.0001	
		(-2.24)			(-2.38)			(-2.12)			(0.29)	
Ab_Temp _Q2			-0.076			-0.050			-0.066			0.001**
			(-1.59)			(-1.04)			(-1.37)			(2.35)
Ab_Temp _Q3			-0.039			-0.069			-0.033			0.001
			(-0.65)			(-1.09)			(-0.56)			(1.28)
Ab_Temp _Q4			-0.125			-0.131			-0.112			0.001
			(-1.67)			(-1.64)			(-1.51)			(1.46)
Ab_Temp _Q5			-0.183**			-0.183**			-0.167**			0.0007
			(-2.36)			(-2.35)			(-2.21)			(0.56)
ln(Labor force)	2.033***	2.043***	2.046***	1.437***	1.447***	1.448***	1.927***	1.937***	1.939***	-0.004	-0.004	-0.004
	(4.66)	(4.69)	(4.69)	(3.31)	(3.34)	(3.34)	(4.42)	(4.45)	(4.45)	(-0.66)	(-0.70)	(-0.70)
Unemployment rate	-0.065**	-0.065**	-0.065**	-0.063**	-0.063**	-0.063**	-0.066**	-0.066**	-0.066**	-0.0001	-0.0001	-0.0001
	(-2.39)	(-2.38)	(-2.41)	(-2.54)	(-2.53)	(-2.55)	(-2.41)	(-2.40)	(-2.44)	(-0.31)	(-0.36)	(-0.36)
ln(Weekly wage)	-0.288	-0.274	-0.277	-1.205	-1.195	-1.197	-0.369	-0.355	-0.358	-0.008	-0.008	-0.008
	(-0.36)	(-0.35)	(-0.35)	(-1.64)	(-1.63)	(-1.63)	(-0.47)	(-0.45)	(-0.45)	(-1.00)	(-0.99)	(-0.99)
Adj. *R* sq.	0.906	0.906	0.906	0.927	0.927	0.927	0.905	0.905	0.905	0.965	0.965	0.965
N	1,614,834	1,614,834	1,614,834	1,614,834	1,614,834	1,614,834	1,614,834	1,614,834	1,614,834	1,316,653	1,316,653	1,316,653
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES

Panel B: Hot days and firm adaptation

	Employees (%)			Plants (%)			Sales (%)			Productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Hot_Days	-0.002*			-0.003**			-0.002*			0.0000		
	(-1.94)			(-2.75)			(-1.89)			(0.26)		
Hot_Days_Q		-0.176**			-0.191***			-0.203**			-0.0002	
		(-2.19)			(-2.92)			(-2.50)			(-0.21)	
Hot_Days _Q2			0.019			-0.035			-0.015			-0.004**
			(0.11)			(-0.23)			(-0.09)			(-2.23)
Hot_Days _Q3			-0.260			-0.258			-0.349			-0.004*
			(-1.18)			(-1.46)			(-1.60)			(-1.79)
Hot_Days _Q4			-0.580**			-0.533**			-0.681**			-0.003
			(-2.23)			(-2.58)			(-2.64)			(-1.13)
Hot_Days _Q5			-0.555*			-0.736**			-0.639*			0.0003
			(-1.77)			(-2.72)			(-2.00)			(0.09)
ln(Labor force)	1.828***	1.827***	1.824***	1.301***	1.299***	1.298***	1.714***	1.712***	1.711***	-0.006	-0.006	-0.006
	(3.99)	(3.98)	(3.98)	(3.14)	(3.11)	(3.11)	(3.72)	(3.71)	(3.71)	(-1.11)	(-1.11)	(-1.12)
Unemployment rate	-0.056*	-0.058**	-0.057**	-0.051*	-0.053**	-0.053**	-0.058**	-0.059**	-0.059**	0.0000	0.0000	0.0000
	(-2.07)	(-2.14)	(-2.12)	(-2.05)	(-2.18)	(-2.16)	(-2.12)	(-2.19)	(-2.17)	(0.03)	(0.04)	(0.05)
ln(Weekly wage)	-0.215	-0.198	-0.225	-0.973	-0.955	-0.970	-0.226	-0.206	-0.233	-0.002	-0.002	-0.002
	(-0.34)	(-0.31)	(-0.35)	(-1.51)	(-1.48)	(-1.50)	(-0.37)	(-0.33)	(-0.38)	(-0.29)	(-0.29)	(-0.28)
Adj. *R* sq.	0.913	0.913	0.913	0.934	0.934	0.934	0.912	0.912	0.912	0.968	0.968	0.968
N	1,372,889	1,372,889	1,372,889	1,372,889	1,372,889	1,372,889	1,372,889	1,372,889	1,372,889	1,126,505	1,126,505	1,126,505
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES

The table reports firm adaptation to long-term temperature exposure using actually reported data from NETS. Dependent variables are at the firm-county-year level. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Subsample Test for Non-tradable and Tradable Sectors

	Non-tradable Sectors			Tradable Sectors		
	Employees (%)	Plants (%)	Sales (%)	Employees (%)	Plants (%)	Sales (%)
Ab_Temperature	-0.304**	-0.264**	-0.285**	-0.090	-0.122	-0.064
	(-2.58)	(-2.39)	(-2.38)	(-0.65)	(-0.99)	(-0.45)
ln(Labor force)	2.542***	2.440***	2.594***	1.101	0.228	0.742
	(3.22)	(3.13)	(3.28)	(1.26)	(0.32)	(0.85)
Unemployment rate	-0.060	-0.038	-0.063	-0.068*	-0.077**	-0.071*
	(-1.22)	(-0.83)	(-1.29)	(-1.72)	(-2.21)	(-1.77)
ln(Weekly wage)	-2.140*	-1.860	-2.133*	-0.229	-1.760*	0.076
	(-1.83)	(-1.66)	(-1.82)	(-0.21)	(-1.88)	(0.07)
Adj. *R* sq.	0.889	0.903	0.887	0.905	0.926	0.905
N	532,006	532,006	532,006	535,513	535,513	535,478
Firm-county FE	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES

This table reports firm adaptation to long-term temperature exposure, separately for non-tradable and tradable sectors. We define tradable and non-tradable sectors following Main and Sufi (2014). Appendix Table 1 of Main and Sufi (2014) provides a complete list of tradable, non-tradable and other industry classification for each of 294 NAICS four-digit industries. All variables are defined in Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Industry-Level Analysis

Panel A: Industry-level analysis on *Employees*

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Communication Services	Utilities	Real Estate
Ab_Temperature	0.370	-0.036	-0.085	-0.268**	-0.059	-0.184	2.895*	-0.215	0.531	-0.122	0.094
	(0.99)	(-0.17)	(-0.60)	(-2.52)	(-0.39)	(-0.63)	(1.85)	(-0.84)	(1.07)	(-0.74)	(0.13)
Adj. *R* sq.	0.911	0.917	0.899	0.910	0.920	0.895	0.896	0.869	0.892	0.926	0.886
N	50,241	116,723	288,964	849,989	194,314	139,368	4,455	186,739	40,242	20,746	9,878
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Industry-level analysis on *Plants*

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Communication Services	Utilities	Real Estate
Ab_Temperature	0.170	-0.202	0.028	-0.282**	-0.239*	-0.064	0.690	-0.064	0.492	-0.017	0.360
	(0.52)	(-1.07)	(0.21)	(-2.48)	(-1.77)	(-0.32)	(0.68)	(-0.31)	(1.11)	(-0.13)	(0.59)
Adj. *R* sq.	0.932	0.934	0.925	0.925	0.941	0.925	0.937	0.894	0.913	0.953	0.908
N	50,241	116,723	288,964	849,989	194,314	139,368	4,455	186,739	40,242	20,746	9,878
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel C: Industry-level analysis on *Sales*

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Communication Services	Utilities	Real Estate
Ab_Temperature	0.421	-0.010	-0.063	-0.262**	-0.070	-0.187	3.151*	-0.228	0.501	-0.126	0.182
	(1.10)	(-0.05)	(-0.43)	(-2.46)	(-0.46)	(-0.67)	(1.95)	(-0.94)	(1.01)	(-0.66)	(0.24)
Adj. *R* sq.	0.909	0.914	0.900	0.909	0.919	0.895	0.896	0.869	0.889	0.921	0.885
N	50,240	116,723	288,953	849,989	194,311	139,355	4,454	186,722	40,240	20,746	9,878
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

The table reports industry-level analysis of firm adaptation to long-term temperature exposure. Industry is defined at the two-digit GIC code level. Dependent variables are at the firm-county-year level. Panels A, B, and C report the industry-level analysis on *Employees*, *Plants*, and *Sales*, respectively. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Cross-Sectional Test: Heat-Sensitive Industries

	Employees (%)	Plants (%)	Sales (%)	Productivity
Ab_Temperature	-0.158**	-0.151**	-0.150*	-0.0008
	(-2.19)	(-2.13)	(-2.05)	(-0.47)
Ab_Temperature × Heat_Sensitive	0.175	0.083	0.151	-0.0001
	(0.76)	(0.46)	(0.65)	(-0.01)
ln(Labor force)	2.043***	1.464***	1.951***	-0.005
	(4.51)	(3.24)	(4.27)	(-0.85)
Unemployment rate	-0.048	-0.037	-0.051*	-0.0002
	(-1.64)	(-1.35)	(-1.73)	(-0.86)
ln(Weekly wage)	-0.462	-1.174*	-0.473	-0.005
	(-0.63)	(-1.76)	(-0.63)	(-0.68)
Adj. *R* sq.	0.915	0.935	0.914	0.966
N	1,921,118	1,921,118	1,921,070	1,576,583
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	NO
Firm-state-year FE	NO	NO	NO	YES

The table reports the results of firm adaptation to long-term temperature exposure interacted with an indicator of heat-sensitive industries. Following Graff-Zivin and Neidell (2014), *Heat_Sensitive* is a dummy variable that equals one if a firm's six-digit GIC code is in the following categories: 151050 (paper & forest products), 151040 (metals & mining), 201030 (construction & engineering), 251020 (automobile & motorcycle manufacturers), 203010–203050 (transportation), 302020–302030 (food product & tobacco producers), and 551010–551050 (utilities). All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Cross-Sectional Tests: Climate Change Belief and Concern

	Employees (%)		Plants (%)	
Ab_Temperature	0.230*	-0.131*	0.257**	-0.147**
	(1.93)	(-1.89)	(2.26)	(-2.13)
Ab_Temperature × Belief	-0.089***		-0.093***	
	(-3.20)		(-3.71)	
Ab_Temperature × Concern		-1.025**		-0.901**
		(-2.55)		(-2.72)
ln(Labor force)	2.147***	2.317***	1.521***	1.876***
	(4.79)	(4.49)	(3.34)	(3.90)
Unemployment rate	-0.049	-0.044	-0.036	-0.035
	(-1.72)	(-1.52)	(-1.35)	(-1.28)
ln(Weekly wage)	-0.447	-1.013	-1.110	-1.473**
	(-0.62)	(-1.29)	(-1.66)	(-2.21)
Adj. *R* sq.	0.916	0.919	0.935	0.937
N	1,792,747	1,415,498	1,792,747	1,415,498
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES

The table reports the results of firms' adaptation to long-term temperature exposure interacted with firm managers' belief and concern about climate change. Dependent variables are at the firm-county-year level. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Cross-Sectional Tests: Organizational Inertia

	Employees (%)		Plants (%)	
Ab_Temperature	-0.075	-0.124	0.099	-0.046
	(-0.40)	(-1.06)	(0.52)	(-0.42)
Ab_Temperature × Age	-0.003		-0.027	
	(-0.12)		(-1.14)	
Ab_Temperature × Size		0.001		-0.002
		(0.31)		(-0.59)
ln(Labor force)	2.176***	2.206***	1.707***	1.741***
	(4.26)	(4.31)	(3.74)	(3.68)
Unemployment rate	-0.026	-0.033	-0.020	-0.026
	(-0.89)	(-1.09)	(-0.72)	(-0.93)
ln(Weekly wage)	-0.998	-1.100	-1.264*	-1.402*
	(-1.30)	(-1.39)	(-1.86)	(-2.06)
Adj. *R* sq.	0.919	0.918	0.938	0.937
N	1,519,739	1,569,839	1,519,739	1,569,839
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES

The table reports the firm adaptation to long-term temperature exposure interacted with proxies of organizational inertia. Dependent variables are at the firm-county-year level. We use *Age* and S*ize* as proxies for organizational inertia. *Age* is the log of the number of years since the firm first appeared in COMPUSTAT database. *Size* is the natural log of market capitalization at the end of each fiscal year. All other variables are defined in the Appendix A. The *t*-statistics, in parentheses, are based on two-way clustered standard errors at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A: Definitions of Variables

Variables	Definition
Climate change variables	
Ab_Temperature	Abnormal temperature is the U.S. county-level average temperature anomaly. It is the difference between the previous five-year moving average temperature and the 30-year historical (1961–1990) average temperature for each county.
Ab_Temp_Q	The rank variable for each quintile of Abnormal_Temperature. Quintile groups are built on Ab_Temperature across all counties each year. Quintile Group 5 has the largest Ab_Temperature.
Ab_Temperature _Q2	A dummy variable that equals one if Ab_Temperature belongs to the second quintile and zero otherwise.
Ab_Temperature _Q3	A dummy variable that equals one if Ab_Temperature belongs to the third quintile and zero otherwise.
Ab_Temperature _Q4	A dummy variable that equals one if Ab_Temperature belongs to the fourth quintile and zero otherwise.
Ab_Temperature _Q5	A dummy variable that equals one if Ab_Temperature belongs to the fifth quintile and zero otherwise.
Hot_Days	The number of hot days that a county experienced over the previous five years. Hot days are defined as days with daily mean temperature greater than 25 degrees Celsius.
Hot_Days _Q	The rank variable for each quintile of Hot_Days. Quintile groups are built on Hot_Days across all counties each year. Quintile Group 5 has the highest Hot_Days.
Hot_Days _Q2	A dummy variable that equals one if Hot_Days belongs to the second quintile and zero otherwise.
Hot_Days _Q3	A dummy variable that equals one if Hot_Days belongs to the third quintile and zero otherwise.
Hot_Days _Q4	A dummy variable that equals one if Hot_Days belongs to the fourth quintile and zero otherwise.
Hot_Days_Q5	A dummy variable that equals one if Hot_Days belongs to the fifth quintile and zero otherwise.
Establishment-level variables	
Employees	The number of county-level employees scaled by the number of state-level employees.
Plants	The number of county-level plants scaled by the number of state-level plants.
Sales	The county-level sales scaled by the state-level sales.
Productivity	The natural logarithm of the ratio of sales to the number of employees.
Macroeconomics variables	
Ln(Labor force)	The natural logarithm of the number of labor force in a county.
Unemployment rate	The unemployment rate of a county.
Ln(Weekly wage)	The natural logarithm of the average weekly wage of a county.
Other variables	
Belief	The first principal component of quintile ranks of four survey questions from Yale Climate Opinion Maps 2015. The survey measures the fraction of people in a county responding in agreement to the four statements: Global warming is happening; global warming is caused mostly by human activities; most scientists think global warming is happening; global warming is affecting the weather in the United States. We use the climate change belief of the county in which a firm is headquartered.
Concern	A dummy variable that equals one if "climate change" or "global warming" appears in a firm's 8-K or 10-K filings in that year.

Online Appendix

Table O1. Subsample Test for Non-tradable and Tradable Sectors (Number of Hot Days)

	Non-tradable Sectors			Tradable Sectors		
	Employees (%)	Plants (%)	Sales (%)	Employees (%)	Plants (%)	Sales (%)
Hot_Days	-0.005**	-0.006***	-0.005**	-0.001	-0.002	-0.001
	(-2.49)	(-3.00)	(-2.37)	(-0.56)	(-1.03)	(-0.57)
ln(Labor force)	2.037**	1.995**	2.089**	1.101	0.477	0.815
	(2.48)	(2.53)	(2.53)	(1.21)	(0.68)	(0.87)
Unemployment rate	-0.013	0.001	-0.016	-0.071	-0.063	-0.078*
	(-0.26)	(0.03)	(-0.32)	(-1.66)	(-1.69)	(-1.79)
ln(Weekly wage)	-1.693	-1.366	-1.582	0.125	-1.196	0.384
	(-1.60)	(-1.40)	(-1.50)	(0.14)	(-1.47)	(0.42)
Adj. *R* sq.	0.899	0.914	0.897	0.913	0.934	0.912
N	463,147	463,147	463,147	444,371	444,371	444,336
Firm-county FE	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES

This table reports firm adaptation to the number of hot days, separately for non-tradable and tradable sectors. All variables are defined in Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table O2. Industry-Level Analysis (Number of Hot Days)

Panel A: Industry-level analysis on Employees

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Communication Services	Utilities	Real Estate
Hot_Days	0.006	0.003	-0.003	-0.006***	0.002	-0.003	0.025	-0.003	-0.016*	0.002	0.0007
	(1.30)	(0.88)	(-0.97)	(-3.99)	(0.79)	(-0.68)	(1.07)	(-0.66)	(-1.93)	(0.57)	(0.06)
Adj. *R* sq.	0.920	0.924	0.907	0.919	0.926	0.906	0.901	0.876	0.901	0.936	0.895
N	42,664	95,214	242,016	743,874	161,717	121,633	3,866	156,305	35,304	16,979	8,463
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Industry-level analysis on Plants

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Communication Services	Utilities	Real Estate
Hot_Days	0.002	0.002	-0.003	-0.006***	0.002	-0.004	0.019	-0.003	-0.022**	0.003	0.005
	(0.48)	(0.47)	(-1.29)	(-3.51)	(0.86)	(-1.55)	(1.21)	(-0.96)	(-2.86)	(1.45)	(0.50)
Adj. *R* sq.	0.940	0.942	0.933	0.933	0.947	0.935	0.941	0.900	0.922	0.960	0.919
N	42,664	95,214	242,016	743,874	161,717	121,633	3,866	156,305	35,304	16,979	8,463
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel C: Industry-level analysis on Sales

	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	Information Technology	Communication Services	Utilities	Real Estate
Hot_Days	0.007	0.00183	-0.003	-0.006***	0.003	-0.003	0.032	-0.003	-0.017*	0.0007	0.002
	(1.38)	(0.49)	(-1.03)	(-3.88)	(1.16)	(-0.82)	(1.39)	(-0.82)	(-2.03)	(0.18)	(0.16)
Adj. *R* sq.	0.917	0.921	0.908	0.918	0.925	0.906	0.902	0.876	0.899	0.932	0.891
N	42,663	95,214	242,004	743,874	161,714	121,620	3,865	156,289	35,302	16,979	8,463
Firm-county FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

The table reports industry-level analysis of firm adaptation to long-term temperature exposure. Industry is defined at the level of the two-digit GIC code. Panels A, B, and C report the industry-level analysis on *Employees*, *Plants*, and *Sales*, respectively. *Labor force*, *Unemployment rate*, and *Weekly wage* are included as controls but are not reported (for brevity). All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table O3. Cross-Sectional Tests: Heat Sensitive Industries (Number of Hot Days)

	Employees (%)	Plants (%)	Sales (%)	Productivity
Hot_Days	-0.004***	-0.004***	-0.004***	0.0000
	(-3.11)	(-3.59)	(-3.18)	(0.66)
Hot_Days × Heat_Sensitive	0.004	0.003	0.004	0.0001
	(0.98)	(1.08)	(1.16)	(1.13)
ln(Labor force)	1.881***	1.321***	1.779***	-0.008
	(4.10)	(3.14)	(3.81)	(-1.38)
Unemployment rate	-0.034	-0.021	-0.037	-0.0002
	(-1.10)	(-0.76)	(-1.18)	(-0.62)
ln(Weekly wage)	-0.470	-1.012*	-0.373	-0.0000
	(-0.78)	(-1.76)	(-0.61)	(-0.00)
Adj. R sq.	0.923	0.942	0.922	0.968
N	1,644,465	1,644,465	1,644,417	1,358,671
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	NO
Firm-state-year FE	YES	YES	YES	YES

The table reports the results of firm adaptation to long-term temperature exposure interacted with a dummy indicating heat-sensitive industries. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table O4. Cross-Sectional Tests: Climate Change Belief and Concern (Number of Hot Days)

	Employees (%)		Plants (%)	
Hot_Days	0.002	-0.004***	0.003	-0.004***
	(1.02)	(-3.10)	(1.61)	(-3.69)
Hot_Days × Belief	-0.001***		-0.002***	
	(-3.27)		(-4.33)	
Hot_Days × Concern		-0.0002		0.0002
		(-0.39)		(0.38)
ln(Labor force)	1.946***	2.144***	1.317***	1.785***
	(4.16)	(4.07)	(3.09)	(3.89)
Unemployment rate	-0.035	-0.031	-0.022	-0.021
	(-1.19)	(-0.95)	(-0.84)	(-0.73)
ln(Weekly wage)	-0.470	-0.740	-0.938	-1.252*
	(-0.77)	(-1.10)	(-1.63)	(-2.09)
Adj. *R* sq.	0.923	0.925	0.942	0.943
N	1,535,416	1,212,313	1,535,416	1,212,313
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES

The table reports the cross-sectional test of firm adaptation to the number of hot days. The dependent variables are at firm-county-year level. All variables are defined in the Appendix A. The *t*-statistics, in parentheses, are two-way clustered at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table O5. Cross-Sectional Tests: Organizational Inertia (Number of Hot Days)

	Employees (%)		Plants (%)	
Hot_Days	-0.006***	-0.006***	-0.005***	-0.006***
	(-3.50)	(-3.61)	(-3.71)	(-4.71)
Hot_Days × Age	0.0003**		0.0003**	
	(2.59)		(2.29)	
Hot_Days × Size		0.0001**		0.0001***
		(2.54)		(3.42)
ln(Labor force)	2.006***	1.690***	1.595***	1.281**
	(3.88)	(3.07)	(3.57)	(2.74)
Unemployment rate	-0.013	-0.015	-0.003	-0.004
	(-0.39)	(-0.48)	(-0.11)	(-0.16)
ln(Weekly wage)	-0.733	-0.937	-1.084*	-1.352**
	(-1.12)	(-1.35)	(-1.76)	(-2.14)
Adj. *R* sq.	0.925	0.924	0.944	0.943
N	1,324,754	1,362,497	1,324,754	1,362,497
Firm-county FE	YES	YES	YES	YES
Firm-year FE	YES	YES	YES	YES

The table reports the firm adaptation to the number of hot days interacted with proxies of organizational inertia. Dependent variables are at the firm-county-year level. We use *Age* and S*ize* as proxies for organizational inertia. The *t*-statistics, in parentheses, are based on two-way clustered standard errors at the county-year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.