Labor Exposure to Climate Risk, Productivity Loss, and Capital Deepening

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Abstract

The rising frequency and severity of abnormally high temperatures pose significant threats to the health and productivity of exposed workers. This paper identifies a labor channel of corporate exposure to climate risk, measured using firms' reliance on workers exposed to high temperatures while performing job duties. Consistent with the physical risk mechanism, unexpected extreme heat significantly reduces firm-level and plant-level labor productivity, making labor less efficient than capital as a production input. Firms adapt to these disruptions by shifting toward more capital-intensive production functions, i.e., higher capital-labor ratios. Firms further respond by investing more in robotics-related human capital and developing more automation-related technology. At the macro level, climate change impedes the growth of high-exposure industries in hot areas. My findings highlight that climate change accelerates automation in occupations and firms exposed to rising temperatures.

Keywords: Climate change; High temperatures; Labor productivity; Automation; Capital-labor ratio; Employment.
JEL Codes: D22, G30, J30, J63, O30, Q54.

"..extreme heat is now the leading weather-related killer in America. Rising temperatures pose an imminent threat to millions of American workers exposed to the elements..."

- Joe Biden, Sep 2021

"High heat can be a big problem for the nation's workers, not just farmworkers and construction workers, but delivery workers, utility workers, landscaping workers, and warehouse workers."

- Steven Greenhouse, Nieman Reports, Jan 2023

1 Introduction

High temperatures precipitated by climate change pose significant health risks to workers, especially those working in environments without climate controls (e.g., Luber and McGeehin, 2008; Mora et al., 2017). For instance, Park et al. (2021) estimate that high temperatures caused approximately 360,000 additional worker injuries in California from 2001 to 2018.[1,2] Notably, such temperature threats can affect a variety of economic outcomes; existing studies have highlighted the negative impact on aggregated output and income (e.g., Dell et al., 2009, 2012; Burke et al., 2015; Behrer and Park, 2017). These findings are further corroborated by micro-level evidence demonstrating that extreme heat reduces individuals' productivity by impairing physical and cognitive abilities (e.g., Heyes and Saberian, 2019; LoPalo, 2023).

While the literature on the impact of extreme heat on economic activity is extensive, three gaps in particular remain. First, existing evidence on the impact of high temperatures on corporate performance is limited and mixed. For example, Addoum et al. (2020) find no evidence that high temperatures affect corporate sales or labor productivity. In contrast, Pankratz et al. (2023) find that high temperatures reduce firm performance. Addoum et al. (2023) further document bi-directional effects of temperatures on firm sales - some get hurt while others benefit. Second, although the above studies fre-

[1] A report by the Atlantic Council estimates that extreme heat explains around 120,000 occupational injuries per year, and this number could increase nearly fourfold to almost 450,000 without adaptation measures taken. Further, over 8,500 deaths annually are associated with average temperatures above 90°F, which is projected to increase nearly sevenfold to 59,000 by 2050. See "Extreme Heat: The Economic and Social Consequences for the United States".

[2] In Internet Appendix B, I present several pieces of evidence that underscore significant risks that high temperatures bring for field workers, sourced from regulators, nonprofit organizations, and media outlets.

quently cite labor productivity as an important channel, direct evidence examining the channel is scarce.[3] Third, while climate change brings numerous corporate challenges, little work has been done to understand firms' adaptation actions to address such challenges (Fankhauser, 2017). Answering these questions is crucial as it represents an essential step in guiding the business community's adaptation to a warmer era.

This paper aims to bridge these gaps in three steps. First, I introduce a method to quantify a labor channel of firms' exposure to climate change, utilizing firms' reliance on workers exposed to high temperatures while performing job duties. Second, through the channel, I estimate the causal effects of unexpected high temperatures on firm- and plant-level labor productivity. My analysis shows that labor productivity of high-exposure firms (at the 75^{th} percentile) drops by 1.9% following heat shocks. Third, I investigate firms' adaptation to extreme heat via automation. My reasoning is that high temperatures reduce the efficiency of workers relative to capital assets (i.e., computers, equipment, machines, robots, and sensors) as production inputs. Consequently, firms will use more automated capital assets and less labor in production, leading to higher capital-labor ratios. In line with this hypothesis, I find that high-exposure firms increase capital-labor ratios by 1.6%, invest 32.7% more in robotics-related human capital, and are 4.0% more likely to file an automation-related patents after unexpected high temperatures.

Crucial to my empirical investigations is the measurement of corporate exposure to climate risk from a labor perspective. To this end, I obtain data on occupations needed in each industry from the Occupational Employment and Wage Statistics (OEWS) and each occupation's exposure to changing climates from the Occupational Information Network (O*NET) program. The exposure is based on how often a job requires working outdoors, exposed to all weather conditions.[4] I next construct an index of climate exposure at the

[3] Addoum et al. (2023) find some support for the labor productivity channel. However, their results most strongly support a consumer demand channel, suggesting mixed evidence regarding the channels through which high temperatures can impact firm sales.

[4] The Bureau of Labor Statistics (BLS) estimates that 32.9% of U.S. workers had regular outdoor exposure in 2022. See "32.9 percent of employees had regular outdoor exposure in 2022". Based on the BLS employment data, as of Oct 2023, the U.S. has around 162 million employed civilian labor force. This suggests that 53.3 million American workers are regularly exposed to high temperatures while performing job duties.

four-digit NAICS level, calculated as the employment-weighted average of all occupations' outdoor exposures. Based on this index, I create a rank variable of labor exposure to climate risk, *Labor Exposure*, ranging from 1 to 20, with 20 indicating the highest exposure. I further aggregate the exposure measure at the firm level, utilizing plant-level data on employment across industries provided by the Your Economy Time Series (YTS).

To quantify temperature fluctuations across locations and time, I obtain daily grid-level (4×4 km) temperature data for the continental U.S. from the PRISM Climate Group, spanning 1981 to 2022. I then construct a location- and time-specific measure of *heat shocks* for each county and year following prior works (Perkins and Alexander, 2013; Addoum et al., 2020; Pankratz and Schiller, 2023). Specifically, heat shocks are defined as significant upward deviations from the county's historical temperature distributions. I further aggregate the measure at the firm level using firms' geographic footprints across counties from the YTS data. By construction, this measure captures deviations from the means of county- and month-specific historical temperatures and thus can be regarded as random draws from the distribution of temperatures within and across counties (Auffhammer et al., 2013; Dell et al., 2014). For any given firm, these shocks are plausibly exogenous.

With the measures, I first investigate the impact of high temperatures on labor productivity at firm and plant levels over the period 1999 - 2019. Labor productivity is measured as the natural logarithm of sales per employee. Consistent with Addoum et al. (2020), the population average effect of high temperatures on labor productivity is zero. However, firms and plants with substantial heat exposures through the labor channel experience significant reductions in labor productivity following heat shocks. The findings remain robust after an extensive set of fixed effects to control for firm-, county-, and industry-level heterogeneities, such as county-by-year, industry-by-year, and county-by-industry fixed effects. The effects are also economically significant; firms with labor exposure at the 75^{th} percentile experience a 1.9% drop in labor productivity following a heat shock. The evidence suggests that extreme heat reduces the productivity of exposed workers only and, consequently a subset of firms that employ these workers in the economy.

Given the negative impact of extreme heat on labor productivity, an inevitable question arises: What actions are firms taking, or planning to take, in response? One potential strategy is to limit the use of heat-exposed workers by automating their tasks, i.e., more utilization of capital assets in production,[5] assuming that capital performance is less affected by high temperatures.[6] However, the implementation of such adaptations is potentially costly, time-consuming, and challenging. For instance, firing workers displaced by automation can be onerous, while investment in capital assets demands substantial financial resources. Consequently, firms might not instantly resort to automation after a one-time heat shock. Instead, they may make gradual adjustments in production inputs over the years after sensing medium-term or long-term temperature threats. To capture this nuance, I redesign my empirical strategy to study firms' response to medium-term temperature fluctuations, i.e., heat shocks in the past three years.

To test the conjecture, I examine firms' capital utilization in production, a fundamental aspect of automation (e.g., Brozen, 1957; Acemoglu and Restrepo, 2019), measured as the natural logarithm of total capital - a firm's property, plant, and equipment plus its depreciation-adjusted past R&D expenses. Besides, I also use the employment-scaled total capital as the dependent variable, i.e., capital-labor ratio, which captures the use of capital relative to labor in the production process. I find no effects of high temperatures on the average firm's capital utilization in production. However, for high-exposure firms, the effects are positive and statistically significant and hold after including firm, county-by-year, county-by-industry, and industry-by-year fixed effects. The economic magnitudes are also large. After a heat shock, firms with temperature exposures at the 75^{th} percentile increase their capital-labor ratios by 1.6%. Overall, the evidence implies that heat shocks prompt firms to enhance automation to ensure a more robust production system.

Additionally, I explore cross-sectional heterogeneities in firms' capital utilization in response to high heat challenges. I first find that heat shocks positively affect capital-labor

[5] Notably, these capital assets are neither necessarily "green," nor do they contain climate-related technology. As long as these assets can be used to replace heat-exposed workers and function effectively under high temperatures, firms can use them as substitutes for laborers.

[6] I discuss the impact of high temperatures on capital performance and alternative adaptation strategies in Section 6.1.5 "*Robustness and Discussions*."

ratios of only high-exposure firms that operate in counties with significant projected long-term temperature increases. This evidence supports the prediction that firms respond only to temperature threats that are likely to become more severe and frequent as climate change intensifies. Second, consistent with the notion that labor unions increase firms' operating leverage (e.g., Chen et al., 2011), high-exposure firms in industries with higher unionization rates are more incentivized to increase capital utilization. Last, I examine the role of labor skills. Consistent with prior studies documenting that low-skilled tasks are easier to automate (Graetz and Michaels, 2018), I find that heat shocks significantly affect the capital-labor ratios only in firms that predominantly employ low-skilled workers. Further analysis yields consistent findings when analyzing capital investment rates.

Next, I examine firms' employment practices in response to high temperatures, given that labor reduction is both an impetus for and a consequence of increased automation. To do so, ideally I would analyze a firm's hiring and firing of workers based on temperature exposures and skill levels, as a decline in heat-exposed workers could coincide with a rise in less-exposed and skilled workers capable of managing automated systems. Unfortunately, such occupational information is unavailable in Compustat and YTS, so my analysis focuses only on total employment at the firm and plant levels. This approach comes with the caveat that net changes in total employment may be small and thus difficult to detect. Reflecting this notion, my analysis reveals a limited impact of heat shocks on firm-level or plant-level total employment, regardless of labor exposures. However, employment in small plants exhibits a strong and negative response to high temperatures. In particular, plants with heat exposure at the 75^{th} percentile experience a 0.53% reduction in employment, implying that small plants may have limited adaptation strategies beyond automation, or that firms prioritize downsizing the labor force in small plants in response to temperature threats. These findings lend partial support to my hypothesis that firms adapt to heat challenges by substituting capital for labor. Moreover, in line with my prediction regarding new hires, high-exposure firms are more likely to advertise job openings requiring robotics-related skills. This evidence complements the findings on capital utilization and provides further support for the automation hypothesis.

I further investigate firms' innovation of automation-related technology in the adaptation process, given the importance of technological advancement in shaping today's capital-intensive economy (Karabarbounis and Neiman, 2014). As climate change increasingly pushes firms toward automation, those with innovation abilities and efficiency may spend more effort innovating machines and equipment to reduce their reliance on labor. Utilizing the classification of automation-related patents from Mann and Püttmann (2023), I find that high-exposure firms are more likely to develop automation technology after heat shocks. The probability of filling an automation patent increases by 4.0% for firms with temperature exposure at the 75^{th} percentile. Taken together, the findings on capital utilization, employment practices, and automation technology provide consistent evidence supporting the hypothesis that firms adopt more capital-intensive production functions in response to escalating labor risks associated with high temperatures.

In my final analysis, I discuss the broad implications of firms' adaptations to climate change through automation. I demonstrate that firms with a higher degree of automation are more resilient to heat shocks, as evidenced by the limited impact of heat shocks on labor productivity in firms with high capital-labor ratios. This finding further supports the hypothesis that automation is an effective adaptation strategy for meeting the labor challenges posed by climate change. Moreover, I find that industries whose workers are highly exposed to high temperatures grow more slowly than their low-exposure counterparts in the same county, reinforcing the plant-level employment results finding that high temperatures contribute to job losses.

2 Related Literature

2.1 The Economic Outcomes of Climate Change

Starting from 1970s, economists have provided extensive evidence on the relation between climate change and economic outcomes (e.g., Dell et al., 2009, 2012, 2014; Burke et al., 2015). Prior studies on the impact of extreme heat on labor participation and productivity primarily focus on macro-level economic output such as income and GDP (e.g., Dell et al., 2009, 2012; Deryugina and Hsiang, 2014); firms and plants in a narrow set of industries, such as agriculture, construction, and manufacturing (e.g., Chen and Yang, 2019; Somanathan et al., 2021); and specific groups of individuals such as students and interviewers (Park et al., 2020; LoPalo, 2023). This paper both complements and extends the existing literature; rather than limiting the focus to specific sectors, I demonstrate the widespread impact of high heat on labor efficiency and productivity across the entire U.S. economy.

2.2 Climate Finance

Recent research from financial economics explores the implications of climate change for the financial market and firms, with a focus on quantifying the effects of climate risks on prices of different asset classes (e.g., Bernstein et al., 2019; Hong et al., 2020; Choi et al., 2020; Bolton and Kacperczyk, 2021; Giglio et al., 2021; Ilhan et al., 2021). However, a gap in the literature remains on how climate change, particularly high temperatures, affects firms' human capital. This paper first fills the void by proposing an approach to quantify firms' exposure to climate change from a labor perspective, which shares similar spirits with prior measures of routine tasks and labor skills (Autor and Dorn, 2013; Ghaly et al., 2017) and the climate exposure measure in Xiao (2023b). In this regard, this paper contributes to existing studies that measure firms' climate exposures from various perspectives, e.g., asset exposure to seal level rise, carbon emissions, and textual analyses of disclosures (e.g., Bernstein et al., 2019; Li et al., 2020; Sautner et al., 2023; Bolton and Kacperczyk, 2021).[7]

Then, with the measure, I investigate the physical risk mechanism by examining how high temperatures affect labor productivity at both firm and plant levels, an area in which

[7] By construction, this measure is different from the classification of heat-sensitive industries in Graff Zivin and Neidell (2014), which classifies agriculture, forestry, fishing, hunting, construction, mining, manufacturing, utilities, and transportation as heat-sensitive, following standards in the National Institute for Occupational Safety and Health (NIOSH). First, my measure primarily focuses on heat induced by climate change, while theirs includes heat generated by both weather and production processes, such as heat from industrial steel production. Second, my measure highlights large heterogeneities in workers' temperature exposures within and across sectors, allowing for more thorough analyses. See Internet Appendix C for a detailed discussion of the distribution of high-exposure occupations and industries across sectors, labor skill levels, and counties.

existing evidence is mixed. For example, Addoum et al. (2020) find no evidence that high temperatures affect sales or labor productivity of U.S. firms and plants. Their follow-up work documents bi-directional effects of temperatures - some firms get hurt while others benefit (Addoum et al., 2023). In contrast, other works show that increased exposures to high temperatures reduce firms' operating performance (Custodio et al., 2022; Pankratz et al., 2023). The negative effects also transmit along supply chains to firms' customers (Pankratz and Schiller, 2023). My study advances these discussions in two main aspects. First, my research provides evidence that extreme heat does reduce labor productivity in U.S. firms and plants, and this effect is observed only in those with significant temperature exposures through the labor channel. Second, while the above studies frequently cite labor productivity as an important channel, direct evidence identifying the channel is scarce. My findings provide direct evidence quantifying the importance of the labor channel in assessing the impact of high temperatures on labor productivity.

2.3 Adaptation to Climate Change

Another strand of literature explores adaptation strategies economic agents can use to mitigate climate risks (e.g., Fankhauser, 2017; Behrer and Park, 2017; Lai et al., 2023). Despite comprehensive discussions from the perspectives of agriculture, biology, public policy, and physiology, analyses of adaptation behavior within the business sector are limited, with a few exceptions. For instance, Somanathan et al. (2021) show that climate controls, such as air conditioning, can eliminate plant-level productivity declines triggered by high heat, while Heyes and Saberian (2019) document limited mitigation effects. However, these studies focus primarily on indoor environments in which climate controls could reasonably be implemented, as opposed to outdoor environments, in which doing so could be costly or simply not possible (Dillender, 2021). Additionally, Pankratz et al. (2023) show that firms manage temperature threats through supply chains. In contrast, I explore automation as a potential adaptation strategy for firms to mitigate temperature threats to workers, and find that firms increase automation after heat shocks. Consequently, this paper echoes the call for more research on adaptation to climate change

(Fankhauser, 2017). A contemporaneous working paper by Xiao (2023a) examines firms' disclosures of automation-related investments in response to extreme heat. My paper differs by focusing on changes in firms' production functions and related practices on capital assets, employment, and automation technology, and further investigating the broad implications for firm resilience and industry dynamics.

2.4 Labor Economics and Finance

This paper also adds to the literature on labor economics and finance that examine the micro-foundations of production functions (e.g., Brozen, 1957; Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2020; Bena et al., 2022). A fundamental question is what drives the decline of the labor share and the rise of automation over the past several decades. This paper proposes a new force driving the increase in labor costs and the shift to a capital-intensive economy: high temperatures induced by climate change. In response to temperature challenges, firms resort to automation.

3 Conceptual Framework

3.1 Climate Change, Health Risk, and Labor Efficiency in Production

Climate risks can be classified into two types - *physical* and *transition* risks (Giglio et al., 2021; Stroebel and Wurgler, 2021). Physical risk refers to economic losses resulting from the increased frequency and severity of climate-related weather events.[8] Transition risk involves the uncertain impact of shifting to a low-carbon economy, such as changes in policies (e.g., carbon taxes), technologies, and consumer preferences. High temperatures precipitated by climate change present both physical and transition risks to firms. This paper examines the physical risk aspect only and primarily focuses on the negative impact of high temperatures on labor productivity.[9]

Exposure to extreme heat can cause a range of heat-related illnesses, such as heat

[8]For instance, rising sea levels may inundate coastal communities, and wildfires may devastate residential properties and corporate warehouses.

[9]See Xiao (2024) for a discussion of temperature-induced regulations in the labor market and the implications for firms.

cramps, heat exhaustion, and heat stroke (Luber and McGeehin, 2008; Mora et al., 2017). As global warming intensifies, the frequency and severity of high temperatures will increase substantially, presenting severe threats to workers' health (Dillender, 2021; Park et al., 2021), which will limit their physical and cognitive abilities (Heyes and Saberian, 2019; Park et al., 2020). Deteriorating physical and cognitive performance will translate into reduced productivity (Chen and Yang, 2019; Somanathan et al., 2021; LoPalo, 2023). Importantly, even the world's wealthiest economy is subject to material heat-related productivity losses (Deryugina and Hsiang, 2014; Burke et al., 2015; Behrer and Park, 2017).[10]

Studies show that exposed workers reduce working hours during hot days, implying a contraction in labor supply (Graff Zivin and Neidell, 2014; Dillender, 2021; Somanathan et al., 2021). For example, Graff Zivin and Neidell (2014) find that workers in heat-exposure industries work one hour less when daily maximum temperature reaches beyond 85°F (29.4°C). Somanathan et al. (2021) find that absenteeism increases with both contemporaneous and past high temperatures. Consequently, to retain workers, firms need to provide non-wage benefits to alleviate health threats, such as such as professional workwear, cooling services, and medical care. Failure to do so would expose firms to significant litigation risks (Xiao, 2024).

The above discussions identify four channels through which high temperatures might lower labor efficiency in production: (1) lower productivity while at work, (2) lower labor supply, (3) more non-wage labor costs, and (4) higher litigation risks. While neoclassical economic frameworks posit that labor inputs are fully flexible and have little impact on firms' operations, the reality is different; firms face numerous frictions that impede their labor adjustments (Taylor, 1999). Powerful labor unions, for instance, often intervene in firms' wage and firing decisions. Various regulations on labor protection further limit firms' discretion in adjusting wages and labor forces. These rigidities increase firms' op-

[10] A report by the Atlantic Council estimates that the U.S. loses approximately $100 billion annually from heat-induced labor productivity losses, and the number will double by 2030 and quintuple by 2050 if no actions were to be taken to reduce greenhouse gas emissions. By comparison, the record-breaking U.S. hurricane season in 2020 caused an estimated $60 - $65 billion in economic losses. See "Extreme Heat: The Economic and Social Consequences for the United States".

erating leverages and decrease their market values (Chen et al., 2011). Therefore, high temperatures reduce labor efficiency and pushes up firms' *production costs per unit of output*.[11]

3.2 Adaptation to Climate Risk Through Automation

As discussed above, high temperatures significantly reduce labor efficiency in production, demonstrating that firms should enhance their production methods to establish a more resilient operating system. Furthermore, salient heat events prompt corporate managers to revise their beliefs about climate change upward and pay more attention to climate risks (e.g., Sisco et al., 2017; Choi et al., 2020), which further motivate them to prepare for future heat threats. The question now is what changes firms should make.

One potential solution is automation. In practice, engineers have been developing a variety of industrial automation equipment that can operate in extreme conditions. To date, such equipment, which effectively substitutes for workers, has been deployed across nearly all industries. For example, the manufacturing sector uses various technologies such as Computer Numerical Control (CNC) machinery and robotic arms, while the chemical and pharmaceutical industries use robots to transfer and process dangerous chemicals. By delegating tasks to fast, consistent, and resilient automated equipment, firms ensure not only increased productivity but also the well-being of their workforce in challenging conditions (e.g., Bellingham and Rajan, 2007; Gihleb et al., 2022).

Similarly, firms can use all sorts of automation equipment to address temperature threats to their production. For example, instead of using workers to inspect high-voltage power lines, electric power companies can use specialized robots that are less impacted by high temperatures.[12] Likewise, the oil industry may deploy various robots and sen-

[11] In equilibrium, both demand- and supply-side forces could drive the decrease in labor efficiency. On the demand side, workers may proactively leave an occupation, a firm, or an area, or produce less while at work if temperature-induced health risks are too high, especially when the risk-adjusted pay is below expectations or firms fail to implement sufficient protective measures. On the supply side, firms may voluntarily reduce using labor in production given increasing climate risks and related labor costs. Crucially, both sides predict a lower efficiency of using labor in production. Disentangling the two sides and identifying the contribution of each are interesting but are beyond the scope of this paper.

[12] A robot named "Expliner" was specifically developed by a Japanese company, Hibot, to inspect high-

sors to monitor the operating status of their pipelines and detect leaks, thereby reducing the need for field workers. In the service industry, logistic companies can leverage automatic sorting machines and autonomous vehicles to distribute packages more efficiently without exposing workers to excess heat.

In summary, high temperatures negatively affect the efficiency of using labor relative to capital in production processes. Firms can confront this challenge by transitioning towards more capital-intensive production functions - a higher use of capital and a lower reliance on labor. Given the escalating threat of extreme heat in coming years, we anticipate that firms will increasingly turn to capital-intensive production functions.

4 Data, Measures, and Summary Statistics

4.1 Firms

I collect data on public firms and their balance sheet information (annual and quarterly) from the Compustat/CRSP Merged database. I exclude firms from financial, utility, public administration, and unclassified industries. Firms headquartered outside of the U.S. are dropped. Information on firms' historical headquarters state, county, and industry classifications is compiled from the "Augmented 10-X Header Data" provided by Bill McDonald and "Company Headquarters" provided by Joshua A. Lee.[13]

4.2 Plants

I obtain data on plant-level locations, employment, sales, and industry classifications from Your Economy Time Series (YTS) from 1998, provided by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin.[14]

voltage power lines in 2010.

[13] I thank Bill McDonald and Joshua A. Lee for sharing the data.

[14] All establishments covered by YTS are in-business. Businesses that are created for the purpose of housing financial, real estate, and tax reporting entities, or are suspected of never actually conducting commercial activities, are not included.

4.3 Temperatures

I obtain data on daily temperatures and precipitation for 1981 - 2022 from the PRISM Climate Group maintained by Oregon State University. PRISM gathers climate observations from diverse monitoring networks and employs rigorous quality controls to develop spatial climate datasets to reveal short- and long-term climate patterns. The data covers each of 481,631 16-square-kilometer (i.e., 4×4 km) grids for the continental U.S. and includes daily mean, minimum, and maximum temperatures, as well as daily precipitation levels. I aggregate the grid-level information to the county level.

This paper aims to study how *unexpected high temperatures* affect firms' labor productivity and adaptation strategies. In line with the goal, I construct a measure of *heat shocks* following prior works (Perkins and Alexander, 2013; Addoum et al., 2020; Pankratz and Schiller, 2023). First, I calculate the 90^{th} percentile of historical temperature distributions for each county on a monthly basis, using temperature data from 1981 up to the previous year (*1981 to t-1*), with a maximum of 30 years. Second, for each day within a given county and month, I compare the *realized* daily maximum temperature with the estimated 90^{th} percentile to identify *abnormally hot days*, i.e., $\textit{Realized Temperatures} \geq 90^{\text{th}}\ \textit{Percentile}$. Third, given that subsequent empirical analyses are conducted at the year level, I aggregate the number of hot days during summer months each year to develop a measure that captures significant upward shifts in temperature distributions compared to historical data.[15,16] Specifically,

$$\mathbb{1}(Realized \gg Expected)_{c,t} = \begin{cases} 1 & \textit{No. Hot Days } [\textit{Realized Temperatures}_{c,t} \geq 90^{th}\ \textit{Percentile}^{*}_{c,t}] \geq T \\ 0 & \textit{otherwise} \end{cases} \tag{1}$$

[15]Summer months include June, July, and August, following the definition of meteorological seasons. I exclude hot temperatures in other months, as high temperatures outside the summer season, especially during winter, can be beneficial for workers. For example, McDonald's earnings announcement in 2015 stated that - "*fourth quarter comparable sales increased 5.7%, benefiting from...unseasonably mild weather*".

[16]Figure ID.1 presents the number of days with maximum temperatures above the estimated 90^{th} percentile for the average county from 1999 to 2019. It shows that, from 1999 to 2019, the average number of hot days hovers around 10, but with considerable year-to-year variability. As a comparison, the year-to-year change in average temperatures is relatively small. See Figure ID.2.

where c denotes county and t denotes year. $Realized\ Temperatures_{c,t}$ is daily maximum temperatures in county c and year t. $90^{th} Percentile^*_{c,t}$ is the estimated 90^{th} percentile of county c's past temperatures. *No. Hot Days* is the number of hot days in summer in county c and year t, based on "$Realized\ Temperatures_{c,t} \geq 90^{th}\ Percentile^*_{c,t}$". T is the threshold to identify abnormally hot summers after adjusting for seasonality and location.[17]

By construction, this method identifies hot days in a *relative* sense - comparing the current to historical temperatures in the same county and month. For a specific county, if there are no changes in temperature distributions from the past to the current year, one would anticipate approximately 10 days ($T = 10$) to be flagged as hot.[18] If a summer experiences more than 10 hot days ($T > 10$), it implies an upward shift in temperature distributions. Put differently, any additional hot days beyond the expected ten signify unexpected heat shocks. To capture a *significant* upward shift and, consequently, an unlikely overlooked heat shock, I set the threshold at $T = 15$, a 50% increase relative to the benchmark.[19] It's worth emphasizing that $T = 15$ does not simply mean 5 additional hot days in a summer. Instead, it implies a significant intensification of heat.[20,21]

To match the measure with firm-level analyses using Compustat/CRSP, I aggregate the county-level heat shocks at the firm level using the plant-level data on employment from YTS as follows:

$$1(Realized \gg Expected)_{f,t} = \begin{cases} 1 & No.\ Hot\ Days_{f,t} \geq T{=}15 \\ 0 & otherwise \end{cases} \tag{2}$$

[17] Ideally, one should incorporate humidity and wind speed into this measure. However, comprehensive and accurate data on humidity and wind is not available.

[18] The meteorological summer season comprises a total of 92 days — 30 days in June, 31 days in July, and 31 days in August. Consequently, assuming no changes in temperature distributions, a typical summer would yield around 10 hot days, i..e, 92/10=9.2 (rounded up to 10).

[19] The mean, 25^{th} percentile, median, 75^{th} percentile, and 90^{th} percentile of the number of days exceeding the 90^{th} percentile temperature threshold in a summer are 10, 3, 8, 14 and 22, respectively.

[20] Figure ID.3 shows that the average number of hot days above the 90^{th} percentile is 22 in hot scenarios ($T \geq 15$) and 6 in non-hot ones ($T < 15$). The number of days with temperatures above the 30° C is 60 and 42, respectively, indicating that the relative temperature shocks are hot at the absolute level as well. Further, the average daily maximum temperatures are 31° C and 29° C, respectively.

[21] Research indicates that labor productivity declines at temperatures above 24° C and experiences a sharp decrease beyond 29° C (e.g., Seppanen et al., 2006; Graff Zivin and Neidell, 2014).

$$No.\ Hot\ Days_{f,t} = \sum_{c=1}^{C_{f,t}} \left(\frac{Emp_{f,c,t}}{Emp_{f,t}} \times No.\ Hot\ Days\ [Realized\ Temperatures_{c,t} \geq 90^{th}\ Percentile^{*}_{c,t}] \right) \quad (3)$$

where f denotes firm, c denotes county, and t denotes year. $C_{f,t}$ is the total number of counties in which firm $f's$ plants operate. $Emp_{f,c,t}$ is firm $f's$ employment in county c and year t. $Emp_{f,t}$ is $f's$ total employment in year t. $No.\ Hot\ Days_{f,t}$ is the employment-weighted average of firm $f's$ exposure to heat shocks across counties in year t. For consistency, I still set $T = 15$.

4.4 Labor Exposure to Climate Risk

To measure a firm's exposure to climate risk through a labor channel, I first obtain industry-level data on occupations from the Occupational Employment and Wage Statistics (OEWS) provided by the U.S. Bureau of Labor Statistics (BLS). This data includes occupations needed in each industry, wage estimates for each occupation, and the number of employees working in each occupation.

Then, I collect data on each occupation's current and historical exposures to changing climates from the U.S. Department of Labor's Occupational Information Network (O*NET) program. This study uses the survey that focuses on the working context of "*Outdoors, Exposed to Weather*". Specifically, O*NET gives each occupation a score between 1 and 5 based on the following question - "*How often does this job require working outdoors, exposed to all weather conditions?*."[22] A higher score indicates a greater degree of an occupation's exposure to changing climates when performing job duties.[23]

Utilizing the OEWS and the O*NET data, I construct an index of labor exposure to

[22] A score of "1" indicates that workers in this occupation are *never* exposed to any weather conditions during the working process. "2" indicates "*once a year or more but not every month*." "3" indicates "*once a month or more but not every week*." "4" indicates "*once a week or more but not every day*." "5" indicates "*every day*." For detailed information on the underlying datasets and the rationale in selecting occupational characteristics for measure construction, refer to the Internet Appendix, Section C.1.

[23] By definition, this score captures an occupation's exposure to many climate conditions beyond high temperatures, the focus of this paper. In Internet Appendix E Table IE.5 and F Table IF.7, I discuss the impact of other climate conditions (e.g., cold temperatures, precipitation, floods, earthquakes, etc.) and show the robustness of my results after controlling for other types of climate conditions.

climate risk following prior works on routine task and labor skill (Autor and Dorn, 2013; Ghaly et al., 2017). Specifically,

$$Labor\ Exposure_{i,t} = Rank_{r=1}^{r=20}\left\{\sum_{o=1}^{O_{i,t}}\left(\frac{Emp_{i,o,t}}{Emp_{i,t}} \times Score_{o,t}\right)\right\} \tag{4}$$

where i denotes industry, o denotes occupation, and t denotes year. $O_{i,t}$ is the total number of occupations in industry i and year t. $Score_{o,t}$ is the occupational score of outdoor activity from the O*NET program for occupation o in year t. $Emp_{i,o,t}$ is the number of employees working in occupation o in industry i and year t. $Emp_{i,t}$ is the total number of employees in industry i and year t. This index thus is a weighted average of all occupations' exposures to changing climates in a four-digit NAICS industry. The weight is the percentage of employees working in a given occupation in an industry. With this index, I further create a rank variable $Labor\ Exposure_{i,t}$, ranging from 1 to 20, with 20 indicating the highest exposure. The measure is available for the period 1999 - 2022.[24]

Figure IC.1, IC.2, and IC.3 and Table IC.2 in Internet Appendix C present the distribution of the measure of labor exposure to climate risk across sectors, labor skill levels, and counties. A key takeaway is that there exist significant variations in workers' climate exposures within and across sectors, skill levels and counties. This indicates that the measure does not simply capture sector-, skill- or county-specific heterogeneities. The widespread presence of high-exposure industries suggests that high temperatures have a comprehensive impact on the entire U.S. economy. Further, in Internet Appendix C, I validate the measure of labor exposure to climate risk by showing that managers of high-exposure firms discuss more climate-related issues in earnings conference calls and 10-Ks, suggesting that relying on outdoor workers exposes firms to significant climate risks. More importantly, this labor-channel exposure can not be fully explained by other measures of climate exposures developed in the literature or by Trucost Climate Analytics. Collectively, these evidence highlights the importance of and builds the foundation

[24]The O*NET data uses the Standard Occupational Classification (SOC) taxonomy to define occupations, while the OEWS data adopted this taxonomy starting in 1999. Therefore, I exclude the OEWS data in 1997 and 1998 when matching the two datasets.

for studying corporate exposure to climate change and adaptations from a labor channel.

I further aggregate the exposure measure at the firm level using plant-level data on employment across industries from YTS as follows:

$$Labor\ Exposure_{f,t} = \sum_{i=1}^{I_{f,t}} \left(\frac{Emp_{f,i,t}}{Emp_{f,t}} \times Labor\ Exposure_{i,t} \right) \tag{5}$$

where f denotes firm, i denotes four-digit NAICS industry, and t denotes year. $I_{i,t}$ is the number of industries in which firm $f's$ plants operates. $Emp_{f,i,t}$ is firm $f's$ employment in industry i and year t. $Emp_{f,t}$ is firm $f's$ total employment in year t. $Labor\ Exposure_{i,t}$ is the industry-level labor exposure to climate risk in equation (4). The firm-level labor exposure is thus a weighted average of the industry-level measure, with the weight being the percentage of firm $f's$ employees in a NAICS4 industry. Using the same method, I construct a measure of labor skill based on job zones from the O*NET program.

4.5 Additional Data

Temperature Projections. I obtain data on county-level long-term temperature projections from the Centers for Disease Control and Prevention (CDC). The raw data is from the Localized Constructed Analogs (LOCA), derived from 32 Coupled Model Intercomparison Project (CMIP5) models that are widely used in the climate science literature. The CDC processes the raw data and aggregates it at the county level. The data gives projected differences in extreme hot days (90°F/32.2°C) between the time period selected (2016 - 2045) and the referent period (1976 – 2005).

Patents. Data on firms' patenting activities is from Kogan et al. (2017). It includes the applicant's PERMNO number, filing year, grant year, and the estimated patent value. Data on the classification of automation-related patents is from Mann and Püttmann (2023). Specifically, the authors apply a machine learning algorithm to all U.S. patents granted from 1976 to 2014 to identify automation-related patents - patents used to develop a device that carries out a process independently of human intervention. The device can be a physical machine, a combination of machines, an algorithm or a computer program.

The definition of independence means that the automation device works without human intervention, except at the start and for supervision.[25]

4.6 Sample and Summary Statistics

The final sample for empirical analyses spans the period 1999 - 2019.[26] Table 1 reports summary statistics of variables used in empirical analyses. Panel A presents firm-level variables and Panel B presents plant-level ones. The mean and median of a firm's labor productivity are 4.144 and 4.100, with a standard deviation of 0.835. The average use of capital and capital per employee is 4.914 and 4.364. Meanwhile, 18.6% of the firms are exposed to short-term temperature shocks. The average rank of labor exposure to climate risk is 8 at the NAICS4 industry level and 9 at the firm level.

One caveat should be recognized before moving to empirical analyses. While the YTS data offers an extensive overview of firms' employment and sales across counties and industries, a large portion of the data is imputed, despite its widespread use in academic and policy works (e.g., Ghent, 2021; Campello et al., 2022; Flynn and Ghent, 2022; Coyne and Johnson, 2023).[27] The imputations can introduce measurement errors and attenuation biases, which are against me finding significant results. This implies that conclusions drawn from the YTS data might underestimate the impact of high temperatures. Nevertheless, I conduct additional analyses to ensure the robustness of my results.[28]

[25] This definition excludes patents that are minor parts of an automation innovation and highly abstract patents with no obvious application. Therefore, their classification is fairly strict, as devices that require some labor involvement but are efficiency-enhancing are also desirable for reducing labor costs.

[26] I choose 1999 as the beginning year due to the availability of the measure of labor exposure to climate risk. Additionally, there were few discussions about the influence of climate change on the financial market and firms before 2000. I end my sample in 2019 to avoid any disruptions to production caused by the Covid-19 pandemic. For example, industries with significant shares of outdoor workers are likely less affected by Covid-19, considering that maintaining social distance is easier for outdoor workers.

[27] See Kunkle (2018) for a comparison of the YTS data with the BLS's Current Employment Statistics (CES) and Current Population Survey (CPS).

[28] For instance, I cross-verify YTS-based plant-level analyses on labor productivity using the firm-level data from Compustat. Also, my measures of firm-level labor exposure to climate risk and temperature shocks (Equation (2) and (5)) could be biased. To mitigate the concerns, I show that my results are robust to using the industry-level labor exposure to climate risk (Equation (4)) and heat shocks in firms' headquarters counties (Equation (1)). Further details are discussed in the empirical part.

5 Physical Climate Risk: Heat Shocks and Labor Productivity

My empirical analyses start by investigating the physical risk mechanism of high temperatures - the impact of heat shocks on firm- and plant-level labor productivity, which I expect to be negative.

5.1 Firm-level Evidence

5.1.1 Empirical Methodology

I first conduct analyses at the firm level using the quarterly Compustat/CRSP Merged database. To match with heat shocks in summer, I focus on sales in summer quarters, i.e., quarters including at least one summer month. I measure labor productivity as the natural logarithm of sales per employee. The empirical specification is as follows.

$$\begin{aligned} Y_{f,c,i,t} =& \mu_f + \tau_{c,t} + \theta_{c,i} + \pi_{i,t} + \beta_1 \mathit{1\ (Realized \gg Expected)}_{f,t} + \\ & \beta_2 \mathit{1\ (Realized \gg Expected)}_{f,t} \times \mathit{Labor\ Exposure}_{f,t} + \beta_3 \mathit{Labor\ Exposure}_{f,t} + \delta \boldsymbol{X}_{f,t} + \varepsilon_{f,c,i,t} \end{aligned} \tag{6}$$

where f denotes firm, c denotes headquarters county, i denotes industry, and t denotes year. Y is the dependent variable - the natural logarithm of firm $f's$ sales per employee (*Log(Sales/Emp)*). *1 (Realized $\gg$ Expected)* is a dummy indicating firm $f's$ exposure to heat shocks (Equation (1) and (2)). *Labor Exposure* is the measure of firm $f's$ exposure to climate risk through the labor channel (Equation (4) and (5)). $\boldsymbol{X}$ is a vector of controls including the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). μ_f is firm fixed effects that control for firm-level time-invariant characteristics. $\tau_{c,t}$ is county-by-year fixed effects that control for time-varying changes in economic conditions and policies in county c. $\theta_{c,i}$ is county-by-NAICS2 industry fixed effects that control for the importance of industry i in county c. $\pi_{i,t}$ is NAICS2 industry-by-year or NAICS4 industry-by-year fixed effects that control for time-varying growth trends of industry i.

One concern regarding using temperatures as shocks is that firms may incorporate local climate conditions into their production decisions, such as choices of production functions, product types, and operating locations. These considerations will invalidate the assumption that temperatures are exogenous shocks and, therefore, may bias my estimation. However, this concern is more relevant when using absolute temperature levels, i.e., number of days with temperatures above 30°C. By construction, this relative measure of heat shocks (*1 (Realized $\gg$ Expected)*) captures deviations from the means of county- and month-specific historical temperatures. Consequently, these temperature deviations can be regarded as random draws from the distribution of temperatures within and across counties (Auffhammer et al., 2013; Dell et al., 2014). Consistent with this notion, over time, the occurrence of relative hot days is not concentrated in a specific county in Figure 1, which presents the average number of relative hot days for each county in the continental U.S. in 2000, 2006, 2009, 2012, 2015 and 2018. Instead, unexpected high temperatures appear in different counties across years. Therefore, for any given firm, heat shocks are plausibly exogenous and randomly distributed across its operating locations. Accordingly, the firm cannot take any precautious measures *ex ante*.

5.1.2 Empirical Results

Table 2 estimates the impact of unexpected high temperatures on labor productivity using equation (6). Columns (1) - (5) report analyses using the industry-level measure of labor exposure to climate risk and columns (6) - (10) report analyses using the firm-level measure.[29] Columns (1) and (6) report the average effects of heat shocks on labor productivity. Consistent with Addoum et al. (2020), the coefficient of heat shocks is negative but is not statistically significant, indicating a limited impact of high temperatures for an average firm in the economy. I interact heat shocks with the measure of labor exposure in columns (2) and (7), and further add county-by-year fixed effects in columns (3) and (8). The coefficient of heat shocks becomes positive but is not significant, except for column (2). Importantly, the coefficient of the interaction term is negative and statistically significant, suggesting that extreme heat negatively affects labor productivity of high-exposure

[29] I present results using both industry- and firm-level measures of labor exposures to address concerns regarding quality issues of the YTS data. Results using temperature shocks in firms' headquarters counties are reported in Internet Appendix E Table IE.7, due to space limitations.

firms. Such effects are not likely driven by changes in state- or county-level characteristics, given the inclusion of state-by-year and county-by-year fixed effects. The results also hold after adding industry(NAICS2)-by-year and county-by-industry(NAICS2) fixed effects in columns (4) and (9). The results still hold after using NAICS4-by-year to replace NAICS2-by-year fixed effects in columns (5) and (10), indicating that the results are not likely driven by changes in industry conditions.[30]

At the bottom of the table, I present the average effects of heat shocks on labor productivity for firms with labor exposure at the 75^{th} percentile of the distribution (*Labor Exposure=15*) and firms with the highest exposure (*Labor Exposure=20*). Column (5) shows that firms with exposure at the 75^{th} percentile experience a loss of approximately 1.9% in labor productivity following a heat shock. Labor productivity of firms with the highest exposure is about 3% lower after a shock. Detailed estimations of the effects for firms in each exposure category (*1 to 20*) is reported in Panel A of Table IE.1 and Figure 2. As can be seen, significant heterogeneities exist in the treatment effects of heat shocks across firms with different exposures. Specifically, the effects are positive for firms with very limited exposure to climate risk (*Labor Exposure*$\leq$*6*) but are not statistically significant. The effects start becoming negative for firms with an exposure of 7 and significantly negative for firms with an exposure of 12. The economic magnitude increases from 1.3% to 3% as the exposure increases from 12 to 20.

Table IE.1 Panel B and Figure 3 present the dynamic treatment effects of heat shocks on labor productivity. Results show that labor productivity is only negatively affected by concurrent heat shocks (T). Neither past ($T-3$, $T-2$, or $T-1$) nor future ($T+1$, $T+2$, or $T+3$) shocks influence present labor productivity. This evidence supports the claim that heat shocks are exogenous from a given firm's perspective and there are no pre-existing differential trends between firms that experience the shocks and those that do not.

[30]Consistent with prior works on labor productivity, employment and capital utilization (e.g., Addoum et al., 2020; Bena et al., 2022; Pezone, 2023), adjusted R^2 in this and subsequent regressions are high. For example, in Addoum et al. (2020), the adjusted R^2 from estimating effects of temperatures on sales and labor productivity is above 90%. In Bena et al. (2022), the adjusted R^2 from estimating effects of labor protections on the utilization of capital versus labor is around 90%. In Pezone (2023), the adjusted R^2 from estimating effects of judicial trial length on employment is about 93%.

5.2 Plant-level Evidence

I also conduct analyses on labor productivity using plant-level data on employment and sales from the YTS. I aggregate the data at the firm-by-county-by-NAICS4 industry level to enhance the estimation accuracy and efficiency. Below is the empirical model.

$$\begin{aligned} Y_{f,c,i,t} = & \mu_{f,t} + \tau_{c,t} + \theta_{c,i} + \pi_{i,t} + \delta_i + \beta_1 \, \mathit{1\ (Realized \gg Expected)}_{f,c,t} \\ & + \beta_2 \, \mathit{1\ (Realized \gg Expected)}_{f,c,t} \times \mathit{Labor\ Exposure}_{f,i,t} + \beta_3 \, \mathit{Labor\ Exposure}_{f,i,t} + \varepsilon_{f,c,i,t} \end{aligned} \tag{7}$$

where f denotes firm, c denotes county of plants, i denotes industry of plants, and t denotes year. Y is the dependent variable - the natural logarithm of sales per employee (*Log(Sales/Emp)*). *1 (Realized ≫ Expected)* is a dummy indicating that firm $f's$ plants in county c are exposed to heat shocks (Equation (1)). *Labor Exposure* measures the exposure of firm $f's$ plants in industry i to climate risk (Equation (4)). $\mu_{f,t}$ is firm-by-year fixed effects. $\tau_{c,t}$ is county-by-year and $\theta_{c,i}$ is county-by-NAICS2 industry fixed effects. $\pi_{i,t}$ is NAICS2 industry-by-year and δ_i is NAICS4 industry fixed effects. In the strictest model, I use firm-by-county-by-year to replace firm-by-year and county-by-year fixed effects, and NAICS3 industry-by-year to replace NAICS2 industry-by-year fixed effects.

Table 3 presents the results. Consistent with the firm-level evidence, the population average effects of heat shocks on plant-level labor productivity is zero in columns (1) and (3). However, the coefficient estimate of the interaction term between heat shocks and labor exposures is negative and statistically significant in columns (2) and (4). The effects hold in columns (5) and (6) after adding county-by-year fixed effects to remove heterogeneities across counties and firm-by-year fixed effects to remove heterogeneities across firms. The results are also robust to using NAICS3 industry-by-year to replace NAICS2 industry-by-year fixed effects in column (7). In columns (8) and (9), I further use firm-by-county-by-year to replace firm-by-year and county-by-year fixed effects, which enables the comparison of labor productivity across plants that have heterogeneous labor exposures but are in the same firm-county pair. Put differently, this test compares plants that have the same firm-level fundamentals, experience the same heat shocks, but have different levels of heat exposures through the labor channel. The negative effects of heat shocks on labor productivity of high-exposure plants hold.

Internet Appendix Table IE.2 and Figure IE.1 present the effects of heat shocks on plant-level labor productivity in each labor exposure category. Consistent with the firm-level evidence, the negative impact of heat shocks concentrates among high-exposure plants, i.e., exposure ≥ 13. Internet Appendix Table IE.2 Panel B presents consistent dynamic effects of heat shocks, further supporting the firm-level evidence.

Notably, although both firm- and plant-level analyses show that unexpected high temperatures negatively affect labor productivity, the economic magnitude is larger at the firm level. For example, after a heat shock, firm-level labor productivity drops by 1.9% for firm with *Labor Exposure=15*, compared to a 0.13% decline at the plant level. Two potential reasons may contribute to the gap. First, the firm-level sales data is from the quarterly Compustat/CRSP, while the YTS data only contains annual sales, which can be influenced by more factors beyond summer temperatures. Put differently, the time mapping between labor productivity and heat shocks is less precise in YTS-based tests, which is against me finding a large economic magnitude, even though the YTS data provides more cross-sectional variations. Second, the gap may be attributed to the errors-in-variables problem in the YTS data. As highlighted in Section 4, the YTS data on employment, especially sales, is mostly imputed. The measurement errors could introduce attenuation bias, thereby dampening the estimated economic magnitudes.

5.3 Robustness

In Internet Appendix E, I conduct additional tests to show the robustness of my results in Table 2 and 3. First, in Table IE.3 and IE.8, I use a rolling window of the past 10 or 20 years to estimate the 90^{th} percentile threshold to measure heat shocks. I also use a fixed reference period from 1981 to 2000 (*untabulated*). Results hold. Second, I reconstruct the measure of heat shocks by further incorporating absolute temperature levels following Pankratz and Schiller (2023). Specifically, a heat shock is identified if (1) a relative heat shock happens (Equation (1) and (2)); and (2) a county or a firm experiences more than 30 days with absolute temperatures above 30° C in summer. For the alternative, I require 40 days with temperatures above 30° C. Table IE.4 and Table IE.9 report the results. Third, Internet Appendix Table IE.5 and IE.10 control for exposures to other types of climate events, such as cold temperatures, precipitation, earthquakes, floods, wildfires, and storms. Results hold. Fourth, high temperatures may also affect consumer behaviors. In Table IE.6, I show that this consumer channel does not drive my results by excluding consumer-oriented sectors. I further drop the agricultural sector and split firms into two broad categories: goods-producing and service sectors. The effects of high temperatures exist in both categories. The evidence also demonstrates that drops in crop yields do not drive the findings. More importantly, service sectors suffer larger losses in labor productivity from heat (-4.4%) relative to goods-producing sectors (2.3%), suggesting that prior studies focusing on manufacturing firms might underestimate the impact of extreme heat on labor productivity. Fifth, Table IE.7 redo the analyses by utilizing heat shocks happened in firms' headquarters counties. Results hold. Sixth, I conduct segment-level analyses using data on segment sales and assets from the Compustat segment files in Table IE.11. Segments with labor exposure at the 75^{th} percentile lose about 1.9% of asset-scaled sales following heat shocks, while segments with the highest exposure lose about 3.4%.

In summary, this section presents robust and consistent evidence demonstrating that unexpected high temperatures negatively affect labor productivity of high-exposure firms and plants. The findings support the physical risk mechanism of high temperatures and the labor channel of firms' exposures to climate risk. An inevitable question then arises: How would firms adapt to such heat threats, considering the increasing frequency and severity of high temperatures over time? I explore this question in the remaining part of this paper.

6 Adaptation Through Automation

As discussed in Section 3, firms could automate tasks performed by heat-exposed workers to mitigate the reduced efficiency of labor relative to capital in production. Given that much of automation in the economy involves an increasing use of capital and a decreasing use of labor (e.g., Brozen, 1957; Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2020), I analyze firms' utilization of capital assets (i.e., computers, machines, robots, and sensors), employment practices, and development of automation technology following heat shocks. Analyses on capital utilization and automation technology are at the firm level given that the YTS data does not provide plant-level capital information. Analyses on employment practices use both firm- and plant-level data.

6.1 Capital Utilization in Production

6.1.1 Empirical Methodology

The implementation of adaptations through automation is costly, time-consuming, and challenging. Firing workers displaced by automation can be onerous, particularly in the presence of labor unions and regulations. Investment in capital assets demands substantial financial resources, as well as the hiring and training of skilled workers who can operate new capital assets. Consequently, firms might not resort to automation immediately or fully after a one-time short-term heat shock. Instead, they make gradual adjustments in production inputs over the years after sensing medium-term or long-term temperature threats. To capture this nuance, I redesign the empirical strategy to study firms' response to changes in medium-term temperature patterns, i.e., temperature fluctuations from $t-3$ to t. Medium-term heat shocks ($1(Realized \gg Expected)(M)$) are measured in the same way as Equation (1) and (2), with two modifications. First, I calculate the total number of hot days (temperatures above the rolling 90^{th} percentile) in summers over the period from $t-3$ to t. Second, I use $T = 45$ relative to the benchmark 40 to define medium-term heat shocks - $\textit{No. Hot Days}_{t-3,t} \geq 45$[31], which is equivalent to a 12.5% average increase relative to past temperature distributions, or at least one significant short-term heat shock (i.e., 45=15+10+10+10) from $t-3$ to t. In line with this, *Labor Exposure* is recalculated as the average exposure from $t-3$ to t. The empirical model mirrors that in Equation (6).

[31] The mean, 25^{th} percentile, median, 75^{th} percentile, and 90^{th} percentile of the total number of hot days are 40, 25, 36, 49, and 67, respectively.

6.1.2 Empirical Results

Table 4 presents the results. Columns (1) - (4) use the natural logarithm of total capital (*Log(Capital)*) as the dependent variable, which is the sum of a firm's property, plant, and equipment (PPENT) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. Columns (5) - (8) use the natural logarithm of employment-scaled total capital (*Log(Capital/Emp)*) as the dependent variable, a standard measure of capital-labor ratio, which captures the use of capital relative to labor in production. A higher ratio implies a more capital-intensive production function and a higher-degree of automation (Brozen, 1957). In columns (1) and (5), the coefficient of heat shocks (*1 (Realized $\gg$ Expected) (M)*) is positive but not statistically significant, indicating that medium-term heat shocks do not affect the average firm's capital utilization in production. In columns (2), (3), (6) and (7), the coefficient of *1 (Realized $\gg$ Expected) (M)* becomes negative and significant, suggesting that firms with *zero* heat exposure even reduce capital after heat shocks. Importantly, the interaction term between heat shocks and labor exposure (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*) is positive and statistically significant. The results are not driven by firm-level time-invariant or county-level time-varying characteristics, given the inclusion of firm and county-by-year fixed effects. In columns (4) and (8), after adding county-by-NAICS2 industry and NAICS2 industry-by-year fixed effects, the significance of *1 (Realized $\gg$ Expected) (M)* disappears but the significance of (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*) remains. The economic magnitude is also large. In column (4), the post-estimation test suggests that total capital utilization increases by 2.6% for firms with heat exposure at the 75^{th} percentile and by 3.9% for firms with the highest exposure. In column (8), the capital-labor ratio increases by 1.6% for firms with heat exposure at the 75^{th} percentile and by 2.8% for firms with the highest exposure. The economic effects for firms in each exposure category (1 to 20) are reported in Table IF.1 and Figure 4. Overall, results in Table 4 imply that medium-term heat shocks prompt firms to enhance their capital utilization in the production process, as evidenced by a significant increase in both total capital and capital-labor ratios.

6.1.3 Heterogeneities

I explore cross-sectional heterogeneities in the effects of medium-term heat shocks on firms' capital utilization in production. First, I examine the impact of projected long-term temperature increases in firms' operating locations. My economic reasoning behind adaptation through automation is that firms' current production methods are not robust to abnormally high temperatures and they expect to experience more heat shocks in coming years. Consequently, firms reorganize their production process to ensure a resilient operating system. However, without future occurrences of extreme heat events, firms may not deem adaptation necessary. To test this conjecture, I divide firms into two categories: those operating in counties with projected temperature increases above the sample median, and those operating in counties with increases below the median. I then examine the effects of medium-term heat shocks on capital utilization for the two groups separately. Analysis in columns (1) - (4) of Table 5 reveals that heat shocks positively affect capital-labor ratios of firms in counties with significant projected temperature increases while having no effect on firms in other areas.

Second, I examine the impact of labor unions. Prior studies show that automation increases more in firms that have limited flexibility in workforce management, and a key driver of such inflexibility is labor unions, which significantly strengthen workers' negotiating power over firms (Chen et al., 2011). For example, labor unions can protect employees from wage cuts and layoffs, even when their performance decreases in high temperatures. Consequently, in industries with higher unionization rates, firms are more incentivized to augment capital use in response to temperature challenges. Consistent with this prediction, results in columns (5) - (8) demonstrate that heat shocks positively affect capital-labor ratios predominantly in highly unionized industries.

Third, the feasibility of enhancing automation hinges on the substitutability of exposed workers with automated capital assets. In industries where the substitution is unfeasible, firms must persist in using exposed workers despite high risks and costs. This predicts that the temperature effects should be more pronounced in industries where jobs are easy to automate. Building on prior studies that document a reduction in low-skilled workers due to automation (e.g., Graetz and Michaels, 2018), I investigate how labor skills influence the effects of heat shocks on capital utilization. Analysis in columns (9) - (12) of Table 5 shows that heat shocks only affect capital-labor ratios of firms that predominantly employ low-skilled workers, indicating that the potential for increasing automation is contingent on the skill composition of heat-exposed workers.

6.1.4 Capital Investment Rate

Additionally, I examine firms' capital investment rates in Table 6. The dependent variable is the logarithm of a firm's capital investment rate, defined as total capital expenditures divided by lagged total assets. Total capital expenditures are the sum of a firm's capital expenditures (*CAPX*) and R&D expenses. Columns (1) - (3) present analyses using the full sample. Columns (4) - (5) focus on firms operating in counties with significant long-term temperature increases. Columns (6) - (7) consider firms in highly unionized industries, while columns (8) - (9) involve firms employing a large fraction of low-skilled workers. Consistent with findings in Table 5, heat shocks positively affect firms' capital investment rates. The effects mainly hold among firms operating in counties with significant long-term temperature increases and firms with a high share of low-skilled employees. The economic magnitudes are also large. In column (5), firms with labor exposure at the 75^{th} percentile experience a 3.8% increase in capital investment rates following heat shocks.

6.1.5 Robustness and Discussions

Robustness. In Internet Appendix F, I present additional analyses demonstrating the robustness of the results in Table 4. I first show that the results are robust to using a rolling window of the past twenty years (Table IF.5), or a rolling window of the past ten years (*untabulated*), or a fixed reference window from 1981 to 2000 (*untabulated*) to estimate the 90^{th} percentile to measure medium-term heat shocks. Second, the results hold after further incorporating the number of absolute hot days (i.e., temperatures above 30° C) to construct heat shocks. Specifically, heat shocks are redefined by requiring (1) the existence of medium-term relative heat shocks (1 *(Realized* $\gg$ *Expected* (M)) and (2) at least 100 days with temperatures above 30° C in summers from $t-3$ to t (Table IF.6). The results are also robust to using an alternative of 120 days (*untabulated*). Third, the results hold after controlling for cold temperatures and precipitation (Table IF.7) and other types of disasters in FEMA (*untabulated*). Fourth, in Table IF.8, I repeat the analyses but using the firm-level measure of labor exposure to climate risk. Results hold.

Discussions. Several issues warrant further discussions. First, my economic reasoning for adaptation through automation rests on three assumptions. The first assumption is that extreme heat affects the performance of capital assets less than that of workers. While this is a reasonable assumption[32], it's crucial to recognize that high temperatures can reduce the performance of capital assets as well.[33] The second assumption is that automation serves a key strategy for firms to mitigate temperature challenges. In practice, firms may have many other adaptation strategies, such as climate controls, relocation, supply chain management, outsourcing, changing working schedules, and financial hedging. While a comprehensive analysis of all adaptation strategies is essential, this paper focuses on automation and leaves others to future works. The third assumption is that the costs of using capital assets to perform job duties must be lower than using human capital, even though high temperatures may push up the prices of capital assets.[34] Crucially, if any of the three assumptions is violated, I should not find significant effects of high temperatures on automation. Put differently, if capital assets prove unreliable or too costly in hot conditions or firms predominantly use strategies other than automation to tackle climate risks, the effects on automation should not be observable in the data.[35]

Second, these capital assets are used to replace workers as production inputs, rather

[32] Somanathan et al. (2021) show that the damage of high temperatures to labor productivity, rather than to capital efficiency, explains the vast majority of output losses.

[33] For instance, excessive heat can cause mechanical fatigue, resulting in the degradation of material or component integrity.

[34] For example, capital assets may require more maintenance and repairment during extreme heat. High temperatures may trigger more energy and electricity demand, resulting in higher oil and electricity prices. Also, a spike in the market-wide demand for specific capital assets may increase their prices.

[35] Some of the alternative adaptation strategies are also against me finding effects on labor productivity. For example, if firms have superior climate controls for outdoor workers, we should not expect their productivity to reduce under high temperatures.

than to protect them against heat threats. As discussed in Section 3, firms may invest in climate controls to protect workers against heat. However, the possibility of investing in climate controls for outdoor workers who are directly exposed to heat in open fields is low, and the costs are high. A recent work by Xiao (2024) investigates climate-induced regulations that protect workers against extreme heat - the Heat Illness Prevention Standard (HIPS). The HIPS requires employers to provide more cool water and shade, longer breaks, and better medical care to employees. Xiao (2024) show that this regulation further reduces labor efficiency and firms respond by increasing automation and changing operating strategies. So far, this regulation is only effective in California (2005) and Washington (2006). I exclude the regulation effects by examining firms and plants in other states. Results hold. Furthermore, in Internet Appendix Table IF.9, I show that the effects of high temperatures on automation primarily exist among firms with low social ratings (S). This is consistent with the notion that low-S firms care less about local communities and employee benefits and are more likely to fire workers and pay less. Collectively, these evidence supports the conjecture that firms use capital assets as substitutes for workers.

6.2 Employment Practices

I also examine firms' employment practices in response to heat shocks, given that a reduced use of labor in production is both a driver and a consequence of increased automation. To do so, ideally one would analyze a firm's hiring and firing of workers based on heat exposures and skills, as a decrease in exposed workers could coincide with an increase in less-exposed and skilled workers who are capable of operating automated capital assets. However, information on occupation heat exposures and skills is missing in the Compustat and YTS data. Therefore, my analysis focuses only on firm- and plant-level total employment, acknowledging that an increase in less-exposed and skilled workers would be against me finding effects on employment reduction following heat shocks.

Table 7 Panel A presents analyses of firm-level total employment. The empirical model is the same as Equation (6), excepting that the dependent variable is the natural logarithm of a firm's total employment (*Log(Emp)*). In columns (1) - (3), analyses using the full-sample data do not find significant effects of medium-term heat shocks on firm-level total employment. I also find no effects when focusing on firms operating in counties with significant projected long-term temperature increases (columns (4) & (5)) or firms in highly unionized industries (columns (6) & (7)). In column (8), when examining firms that predominately use low-skilled workers, I find a significant decline in employment following heat shocks. For high-exposure firms (*Labor Exposure=15*), total employment drops by around 1.6%. However, the effects disappear in column (9) when I further include NAICS2 industry-by-year fixed effects. Taken together, these findings show that medium-term heat shocks have a limited impact on firm-level total employment.

As noted earlier, the lack of evidence on firm-level total employment does not mean that firms' employment practices are not affected by temperatures. Firms could reduce heat-exposed workers while hiring more skilled and low-exposure workers to manage automation-related assets, which is against finding effects on total employment. For instance, considering the critical role of robots in advancing automation (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020), firms may seek workers proficient in operating and developing robotics. I test this conjecture in Table 7 Panel B. Specifically, I investigate firms' investments in robotics-related human capital following heat shocks, measured using the fraction of robotics-related job postings, provided by Babina et al. (2024). I find that the coefficient of the interaction term between *1 (Realized* $\gg$ *Expected) (M)* and *Labor Exposure* is positive and statistically significant, indicating that high-exposure firms are more likely to advertise job openings demanding robotics-related skills. For firms with labor exposure at the 75^{th} percentile, the demand for robotics-related human capital increases by 32.7%. Detailed economic effects by labor exposure category is presented in Figure 5 (A) and Internet Appendix Table IF.2. These evidence complements the findings in Table 4 and 6 and provides further support to the automation hypothesis.

I further examine changes in plant-level employment following heat shocks in Table 7 Panel C. Consistent with the firm-level evidence, columns (1) - (4) find no effects of high temperatures on employment in the full sample, regardless of heat exposures. In columns (5) – (8), I focus on small plants - those with 50 employees or fewer. On the one hand, small plants may have limited alternatives to automation to adapt. On the other hand, firms might prioritize downsizing the workforce in small plants to address heat threats. Supporting this conjecture, I find negative and statistically significant effects of high temperatures on employment of small plants with high exposures. For small plants with labor exposure at the 75^{th} percentile, total employment drops by 0.53% following heat shocks. Plants with the highest exposure cut 0.88% of their workforce. Figure 5 (B) and Table IF.3 present the treatment effects of heat shocks in each exposure category. It shows that high temperatures only negatively affect the employment of small plants with above-median labor exposures.[36] In addition, consistent with Table 5, the employment effects mainly hold for small plants: (1) located in counties with significant projected long-term temperature increases; (2) in highly unionized industries; and (3) in industries that predominately employ low-skilled workers.

In summary, results in Table 7 show that firms downsize their workforce in small and exposed plants in response to unexpected high temperatures. Meanwhile, high-exposure firms recruit additional workers skilled in robotics to promote automation. These evidence lends further support to the hypothesis that firms address temperature-induced challenges by increasing automation.

6.3 Automation Technology

To delve deeper into the investigation, I study firms' innovation of automation technology in the adaptation process, considering the importance of technological advancement in shaping today's capital-intensive economy (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2020). For example, Karabarbounis and Neiman (2014) show that the declining labor share since the early 1980s is mostly driven by the decrease in the relative price of investment goods, often attributed to advances in information tech-

[36] In Section 7 and Internet Appendix Table IG.2, I discuss the effects of heat shocks on employment at the county-by-NAICS4 level using the Quarterly Census of Employment and Wages (QCEW) data. I find that the plant-level effects can add up to an economically important magnitude that leads to an industry-wide employment contraction: high-exposure industries have much lower employment levels and slower growth rates in hot areas.

nology and the computer age. To promote automation, firms with innovation ability and efficiency may spend more effort innovating machines and equipment or new production methods to reduce reliance on labor.[37] To test this conjecture, I utilize the classification of automation-related patents from Mann and Püttmann (2023), which are used to develop devices that carry out a process independently of human intervention.

Table 8 presents the results. The dependent variable is a dummy indicating that the firm files at least one automation-related patent (*Automation Patent*). Consistent with prior results, heat shocks do not affect the average firm's filings of automation-related patents. In contrast, the coefficient estimate of the interaction term *1 (Realized $\gg$ Expected) (M)* $\times$ *Labor Exposure* is positive and statistically significant, suggesting that high-exposure firms are more likely to develop automation technology after heat shocks.[38] The economic magnitudes are also large. In column (9), the probability of filling an automation patent increases by 4.0% for firms with temperature exposure at the 75^{th} percentile and by 6.1% for firms with the highest exposure. Detailed estimations of the economic effects for firms in each exposure category are reported in Table IF.4 and Figure IF.1.

To conclude, this section provide consistent and robust evidence supporting the hypothesis that firms adopt more capital-intensive production functions in response to the escalating risks associated with high temperatures affecting their labor force.

7 Implications

In the last step of my analysis, I explore the broad implications of firms' adaptation to climate change through automation, with a focus on firms' resilience to temperature threats and the macro-level consequences for industry dynamics.

[37] Firms don't always innovate independently to progress in automation. If the machines and equipment a firm needs are readily available in the market and purchasing them are more cost-effective than in-house innovation, the firm could simply acquire them and pay the prices. Nevertheless, there exist scenarios wherein firms choose to undertake internal innovation, which occur when (1) firms have highly specific production processes and automation needs and they can not find the automated assets in the market; (2) the prevailing market prices for machinery and equipment are exorbitant.

[38] I use a more relaxed set of fixed effects relative to the analyses in Table 4 due to the scarcity of automation-related patents across firms.

7.1 Firm Resilience

An alternative approach to testing the hypothesis that firms utilize automation to address temperature challenges is examining their resilience to heat shocks, taking into account the capital intensity of their existing production functions. Put differently, firms with a higher degree of automation should exhibit greater resilience to unexpected high temperatures, assuming that automation effectively mitigates labor-related heat challenges. I test this conjecture in Internet Appendix Section G Table IG.1. I divided firms into two subsamples: those with capital-labor ratios below the sample median and those with capital-labor ratios above the median. Supporting my prediction, I find that that the negative effects of heat shocks on labor productivity manifest only among firms with below-median capital-labor ratios. This evidence demonstrates that automation is an effective adaptation strategy to mitigate labor-related climate threats.

7.2 Industry Dynamics

While the negative effects of high temperatures on employment mainly concentrate in small plants, the impact may add up to an economically important magnitude that leads to industry-wide employment contraction. Put differently, industries that are highly susceptible to heat in hot areas might experience slower growth. I test this conjecture on industry dynamics using the Quarterly Census of Employment and Wages (QCEW) data on employment and wages at the county-by-industry level. Internet Appendix Table IG.2 presents the results. I use total employment to proxy for the size of a NAICS4 industry in a county in Panel A and total wages in Panel B. In both panels, I observe a negative and statistically significant coefficient for the interaction term *1 (Realized* $\gg$ *Expected) (M)* $\times$ *Labor Exposure*, implying that, within a county, high-exposure industries exhibit considerably slower growth compared to their low-exposure counterparts following heat shocks. The results are more pronounced when focusing on smaller industries, i.e., employment size smaller than 800 or 400.[39] The employment level is about 0.06% lower for a one-unit

[39] The mean, median, and 75^{th} percentile of industry-level employment in a county are 1008, 336, and 804, respectively.

increase in labor exposure after heat shocks in Panel A column (1). Total wages drop by 0.1% for a one-unit increase in labor exposure, equivalent to 1% when moving from industries with labor exposure at the 25^{th} percentile to industries with labor exposure at the 75^{th} percentile. These findings suggest that climate change leads to the contraction of high-exposure industries in hot areas, further supporting the hypothesis on automation.

8 Conclusions

Climate change has constantly been pushing up global temperatures, creating enormous challenges to human and economic activities. Outdoor workers are among those who are most affected. Not only their health but also their lives are under significant threats. Considering that human capital is key to firms' production, not paying enough attention to the threats causes material risks to firms. This paper looks into these risks and calls for more attention to the health issues of outdoor workers in the transition to a warmer era.

How do high temperatures affect the productivity of exposed workers and corporate performance? To answer this question, I utilize information on each occupation's exposure to extreme heat and construct a measure reflecting firms' exposure to climate risk through a labor channel. Consistent with the physical risk mechanism of high temperatures, both firm-level and plant-level evidence show that unexpected extreme heat significantly reduces labor productivity through the labor channel. On average, labor productivity of firms with labor exposure at the 75^{th} percentile drops by 1.9% following heat shocks.

Given the reduction in the efficiency of labor relative to capital in production during high temperatures, how should firms cope? I argue that firms could resort to automation, i.e., replacing labor with automated capital assets such as computers, equipment, machines, and robots. To implement this strategy, firms will shift towards more capital-intensive production functions, i.e., reducing the use of labor and increasing the use of capital in production. Consistent with this conjecture, I find that following high heat shocks, firms increase capital utilization in production, reduce employment in small plants, invest more in robotics-related human capital, and develop more automation-related technology. These findings indicate that climate change promotes automation and speeds up our entering into a capital-intensive economy.

An important implication of my findings is that climate change leads to significant job and income losses for exposed workers. This is further confirmed in the industry-wide evidence that exposure to climate change through the labor channel negatively affects the size and growth of high-exposure industries in hot areas, echoing various scientific reports predicting increasing economic losses as global warming intensifies. The evidence also reveals unexpected negative effects of firms' adaptation to climate change on workers and local communities. Future works could further explore broad implications of the labor channel for other economic agents, such as banks, entrepreneurs, households, and institutional investors.

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Figures

Figure 1. Distribution of Heat Shocks in the Continental U.S.

These figures present the annual number of days with heat shocks (max temperatures exceed the 90^{th} percentile threshold during summer) for each county in the continental U.S. in 2000, 2006, 2009, 2012, 2015 and 2018.

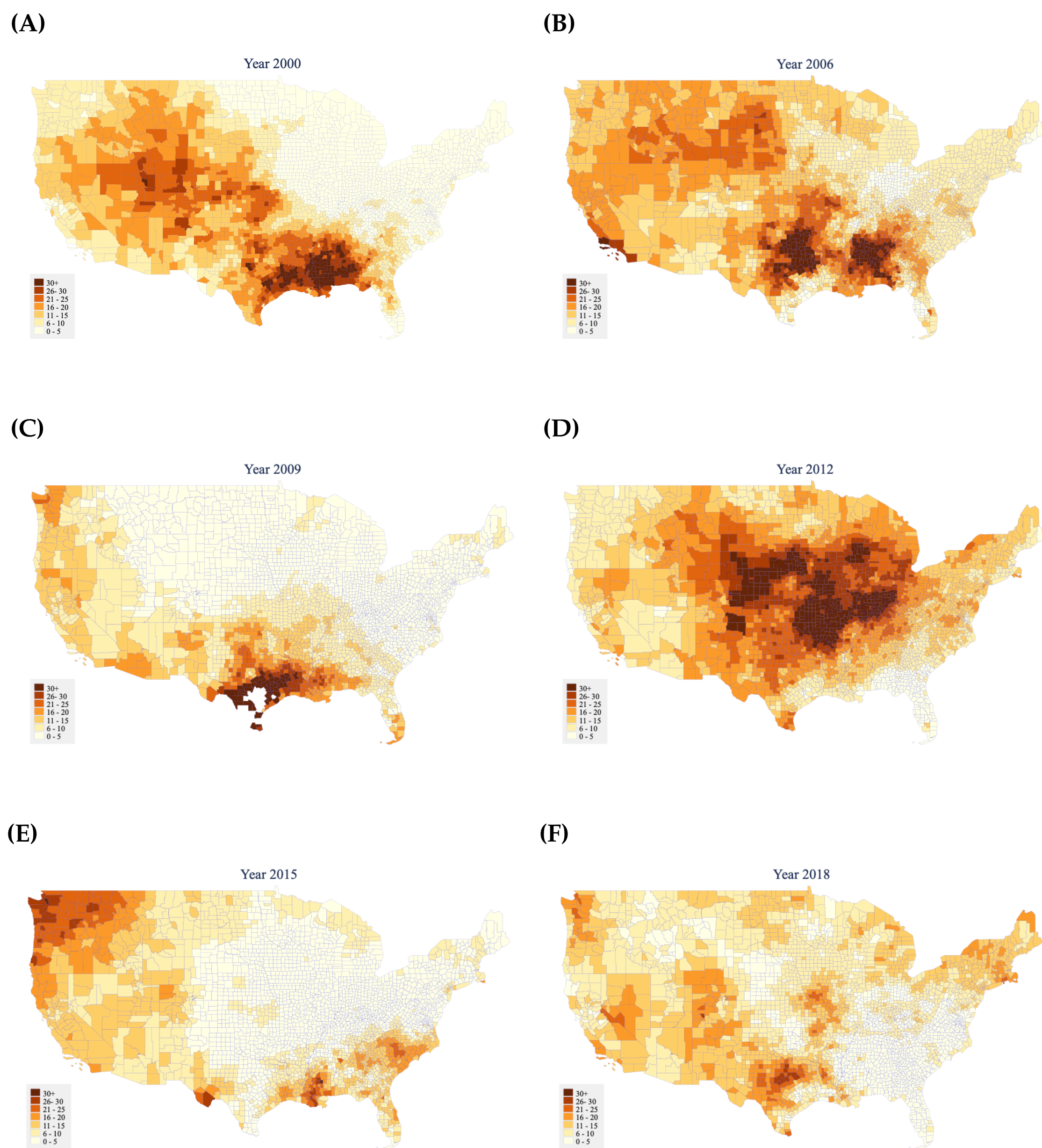


Figure 2. Treatment Effects of Heat Shocks on Labor Productivity

This figure presents the treatment effects of short-term heat shocks on firm-level labor productivity by labor exposure category, based on the estimation in column (5) of Table 2 and Table IE.1.

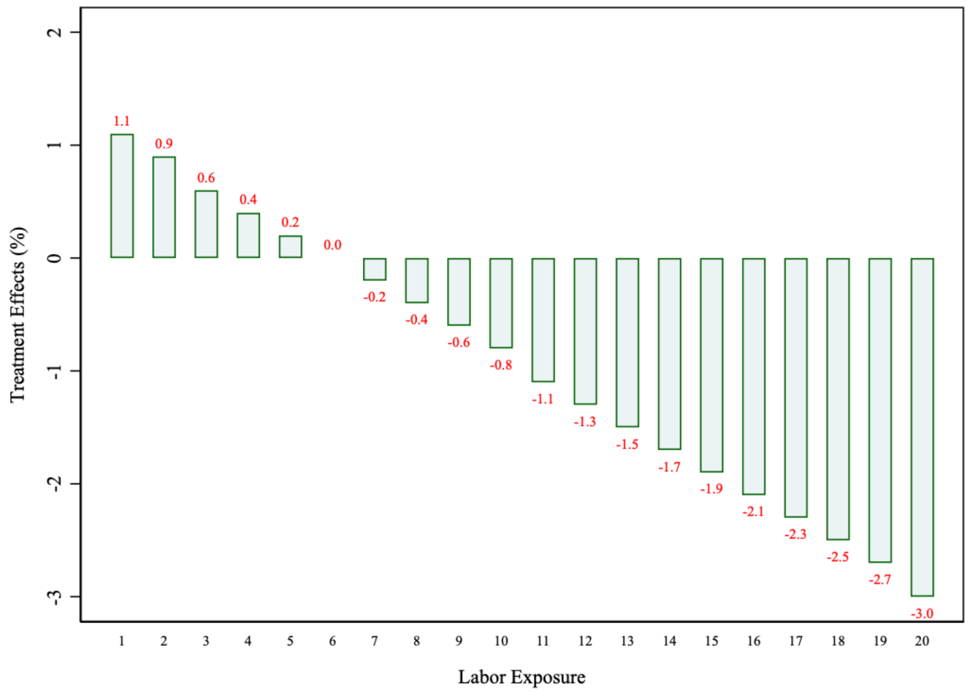


Figure 3. Dynamic Treatment Effects of Heat Shocks on Labor Productivity

This figure presents the dynamic treatment effects of short-term heat shocks on firm-level labor productivity, based on the estimation in Table IE.1 Panel B.

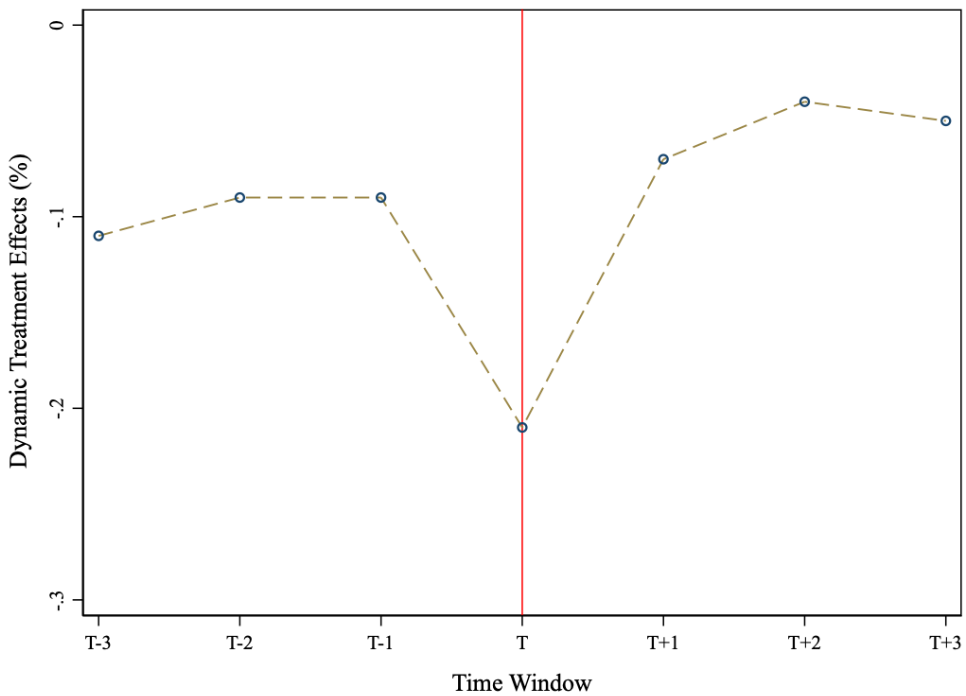
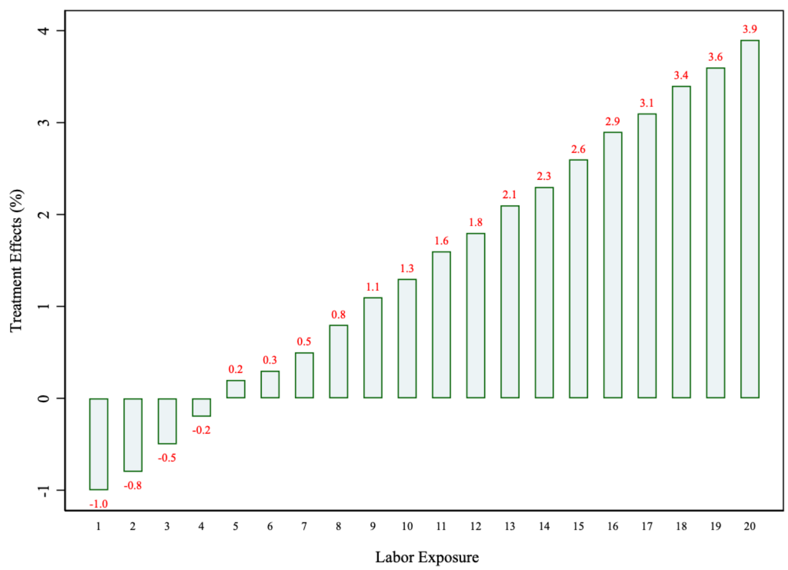


Figure 4. Treatment Effects of Heat Shocks on Capital Utilization in Production

This figure presents the treatment effects of medium-term heat shocks on capital utilization in production by labor exposure category. Figure (A) presents the estimate on total capital and Figure (B) presents the estimate on total capital per employee. These figures are based on estimations in Table 4 columns (4) and (8) and Table IF.1.

(A) Capital Stock - Log(Capital)



(B) Capital-labor Ratio - Log(Capital/Emp)

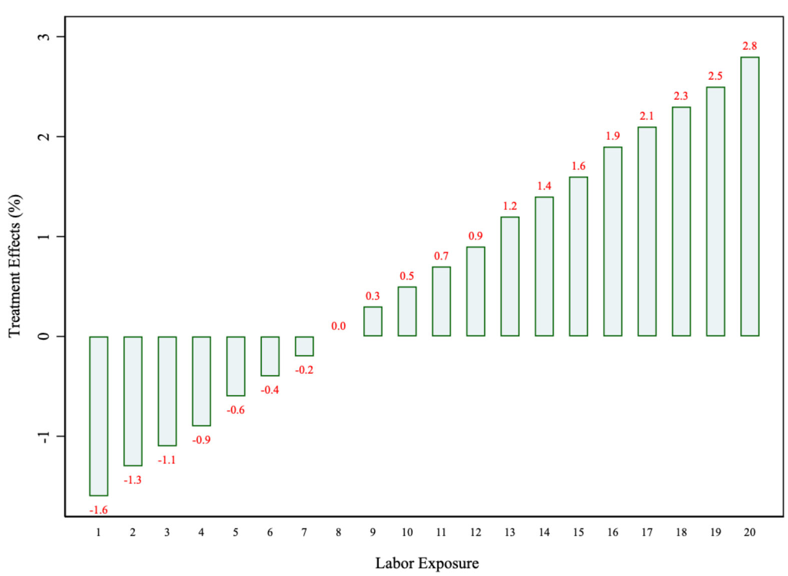
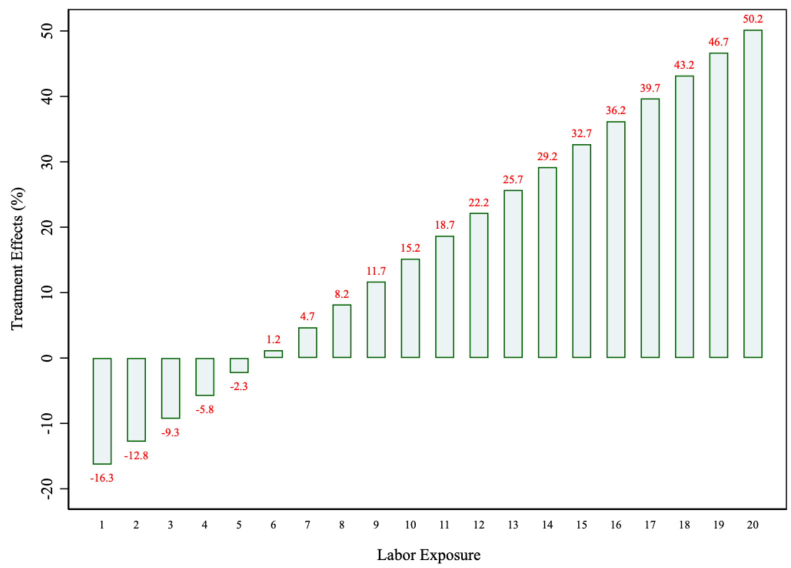


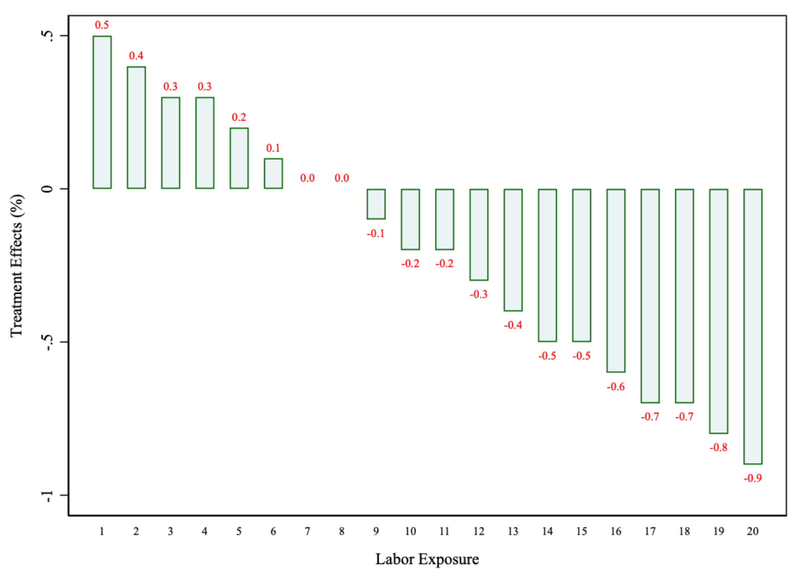
Figure 5. Treatment Effects of Heat Shocks on Employment Practices

This figure presents the treatment effects of medium-term heat shocks on firms' employment practices by labor exposure category. Figure (A) examines firms' investments in robotics-related human capital, based on the estimation in Table 7 Panel B column (2) and Table IF.2. Figure (B) examines changes in total employment of small plants, based on the estimation in Table 7 Panel C column (7) and Table IF.3.

(A) Investments in Robotics-related Human Capital



(B) Employment of Small Plants



Tables

Table 1. Summary Statistics

This table presents summary statistics of variables used in empirical analyses. Panel A presents firm-level statistics and Panel B presents plant-level statistics. See Internet Appendix A for definitions of variables. The sample period is from 1999 to 2019, except that "*Automation Patents*" is available for 1999 - 2014 and "*Human Capital - Robotics*" is available for 2010 - 2018.

	N	Mean	P5	Median	P95	SD
Panel A. Firm Level						
Log(Sale/Emp)	60,129	4.144	2.627	4.100	5.879	0.835
Log(Capital)	60,384	4.914	1.692	4.827	8.538	1.902
Log(Capital/Emp)	60,384	4.364	2.080	4.294	7.007	1.311
Log(Capital Investment Rate)	57,185	-2.627	-4.312	-2.564	-1.111	1.001
Log(Emp)	61,478	0.508	-2.313	0.432	3.829	1.787
Human Capital - Robotics	10,349	0.132	0	0	0.990	.409
Automation Patent	44,793	0.232	0.000	0.000	1.000	0.422
1 (Realized $\gg$ Expected)	60,129	0.186	0.000	0.000	1.000	0.389
1 (Realized $\gg$ Expected) (M)	61,478	0.274	0.000	0.000	1.000	0.446
Labor Exposure (Industry)	61,478	7.833	1.000	6.000	18.000	5.533
Labor Exposure (Firm)	61,478	8.550	1.000	8.000	18.000	5.183
Size	61,478	6.244	3.275	6.160	9.630	1.802
M/B	61,173	1.645	0.497	1.241	4.863	1.153
Book Leverage	61,217	0.232	0.000	0.199	0.672	0.207
Cash	61,476	0.189	0.004	0.109	0.678	0.200
Dividend Payer	61,478	0.393	0.000	0.000	1.000	0.488
Panel B. Plant Level						
Log(Sale/Emp)	2,788,930	5.104	3.774	5.100	6.888	0.901
Log(Emp)	2,788,930	4.333	2.996	4.127	6.397	1.027
1 (Realized $\gg$ Expected)	2,788,930	0.225	0.000	0.000	1.000	0.418
1 (Realized $\gg$ Expected) (M)	2,788,930	0.299	0.000	0.000	1.000	0.458
Labor Exposure (Industry)	2,788,930	10.169	2.000	9.000	19.000	5.082

Table 2. Heat Shocks and Firm-level Labor Productivity

This table presents the treatment effects of short-term heat shocks on firm-level labor productivity. Columns (1) - (5) use the industry-level measure of labor exposure to climate risk (Equation 4) and columns (6) - (10) use the firm-level measure (Equation 5). The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating short-term heat shocks (*1 (Realized* $\gg$ *Expected)*), and an interaction term of the two (*1 (Realized* $\gg$ *Expected)* $\times$ *Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level in columns (1) - (5) and the firm level in columns (6) - (10). ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log(Sales/Emp)									
	Industry-level Labor Exposure					Firm-level Labor Exposure				
1 (Realized $\gg$ Expected)	-0.002	0.015*	0.016	0.012	0.013	-0.002	0.013	0.015	0.012	0.014
	(0.006)	(0.009)	(0.010)	(0.010)	(0.011)	(0.005)	(0.009)	(0.010)	(0.009)	(0.010)
Labor Exposure		0.007**	0.007***	0.001			0.004***	0.004***	0.002	0.003**
		(0.003)	(0.003)	(0.002)			(0.001)	(0.001)	(0.001)	(0.001)
1 (Realized $\gg$ Expected) x Labor Exposure		-0.002***	-0.002***	-0.002**	-0.002**		-0.002**	-0.002**	-0.002*	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Observations	58,711	58,711	54,489	54,399	53,494	59,548	59,548	55,313	55,226	54,298
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.876	0.856	0.856	0.857	0.868	0.873

Treatment Effect for *1 (Realized* $\gg$ *Expected)* $\times$ *Labor Exposure*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Labor Exposure=15		-0.016**	-0.020**	-0.015*	-0.019**		-0.012*	-0.016**	-0.012*	-0.016**
		(0.007)	(0.008)	(0.008)	(0.008)		(0.007)	(0.008)	(0.007)	(0.008)
Labor Exposure=20		-0.027***	-0.032***	-0.023**	-0.030***		-0.021**	-0.026**	-0.019*	-0.026**
		(0.009)	(0.010)	(0.010)	(0.011)		(0.009)	(0.011)	(0.010)	(0.011)

Table 3. Heat Shocks and Plant-level Labor Productivity

This table presents the treatment effects of short-term heat shocks on plant-level labor productivity. This sample is at the firm-by-county-by-NAICS4-by-year level using the YTS data. The dependent variable is the natural logarithm of sales per employee (*Log(Sales/Emp)*). The key independent variables are a plant's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) $\times$ Labor Exposure*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and the county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Sales/Emp)								
1(Realized $\gg$ Expected)	-0.0001	0.0037***	-0.0002	0.0022**					
	(0.0005)	(0.0013)	(0.0004)	(0.0011)					
Labor Exposure		0.0007		0.0003	0.0007	0.0003	0.0012	0.0013	0.0036*
		(0.0008)		(0.0011)	(0.0008)	(0.0011)	(0.0017)	(0.0011)	(0.0020)
1 (Realized $\gg$ Expected) x Labor Exposure		-0.0004***		-0.0002**	-0.0004***	-0.0002**	-0.0003***	-0.0012***	-0.0012***
		(0.0001)		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0003)
Observations	2,786,839	2,786,839	2,773,205	2,773,205	2,782,878	2,769,222	2,769,217	560,898	560,864
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	No
County x NAICS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	Yes	No	No	No	No
Firm x Year FE	No	No	Yes	Yes	No	Yes	Yes	No	No
County x Year FE	No	No	No	No	Yes	Yes	Yes	No	No
NAICS3 x Year FE	No	No	No	No	No	No	Yes	No	Yes
Firm x County x Year FE	No	No	No	No	No	No	No	Yes	Yes
Adjusted R^2	0.929	0.929	0.933	0.933	0.928	0.932	0.933	0.885	0.886

Treatment Effect for 1 (Realized $\gg$ Expected) $\times$ Labor Exposure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Labor Exposure=15		-0.0018**		-0.0013**					
		(0.0009)		(0.0006)					
Labor Exposure=20		-0.0037**		-0.0025**					
		(0.0015)		(0.0010)					

Table 4. Heat Shocks and Capital Utilization in Production

This table presents the treatment effects of medium-term heat shocks on firm-level capital utilization in production. The dependent variables are the natural logarithm of total capital *Log(Capital)* in columns (1) - (4) and the natural logarithm of total capital per employee *Log(Capital/Emp)* in columns (5) - (8). Total capital is the sum of a firm's property, plant, and equipment (*PPENT*) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are the industry-level measure of a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating medium-term heat shocks (*1 (Realized ≫ Expected) (M)*), and an interaction term of the two (*1 (Realized ≫ Expected) (M) × Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Capital)				Log(Capital/Emp)			
1 (Realized ≫ Expected) (M)	0.006	-0.013	-0.019**	-0.013	0.002	-0.025**	-0.030***	-0.018*
	(0.006)	(0.008)	(0.009)	(0.009)	(0.007)	(0.010)	(0.010)	(0.010)
Labor Exposure		-0.001	-0.002	-0.004		0.003	0.004	-0.005*
		(0.002)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.003***	0.003***	0.003***		0.004***	0.004***	0.002**
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Observations	59,082	59,082	54,887	54,787	59,082	59,082	54,887	54,787
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	Yes	Yes	No	No
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	No	No	No	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.971	0.971	0.971	0.973	0.935	0.935	0.937	0.943
Treatment Effect for 1 (Realized ≫ Expected) (M) × Labor Exposure								
Labor Exposure=15		0.026***	0.027***	0.026***		0.029***	0.026**	0.016*
		(0.009)	(0.010)	(0.010)		(0.009)	(0.010)	(0.009)
Labor Exposure=20		0.038***	0.043***	0.039***		0.047***	0.044***	0.028**
		(0.012)	(0.014)	(0.014)		(0.013)	(0.014)	(0.013)

Table 5. Heat Shocks and Capital Utilization in Production: Heterogeneities

This table presents cross-sectional heterogeneities in the treatment effects of medium-term heat shocks on firm-level capital utilization in production. Column (1) - (4) examine long-term temperature projections, columns (5) - (8) examine labor unions, and columns (9) - (12) examine labor skills. '*High*' and '*Low*' denote high and low levels in each of the above dimensions, respectively. The dependent variable is the natural logarithm of total capital per employee, *Log(Capital/Emp)*. Total capital is the sum of a firm's property, plant, and equipment (*PPENT*) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating medium-term heat shocks (*1 (Realized ≫ Expected) (M)*), and an interaction term of the two (*1 (Realized ≫ Expected) (M) × Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log(Capital/Emp)											
	Temperature projections				Labor Union				Labor Skill			
	High		Low		High		Low		High		Low	
1 (Realized ≫ Expected) (M)	-0.035**	-0.031*	-0.027	-0.022	-0.022	-0.017	-0.008	0.002	-0.025	-0.023	-0.036**	-0.020
	(0.017)	(0.017)	(0.022)	(0.020)	(0.017)	(0.017)	(0.019)	(0.019)	(0.017)	(0.017)	(0.017)	(0.016)
Labor Exposure	0.003	-0.001	0.002	-0.004	0.003	-0.001	0.002	-0.004	-0.002	-0.014***	0.006	0.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)	(0.004)
1 (Realized ≫ Expected) (M) x Labor Exposure	0.004***	0.004**	0.003	0.002	0.004**	0.003**	0.002	0.000	0.002	0.002	0.004***	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	19,488	19,470	20,003	19,983	21,367	21,351	21,884	21,797	23,017	23,009	29,703	29,703
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.949	0.952	0.928	0.930	0.937	0.939	0.948	0.952	0.936	0.938	0.941	0.944
Treatment Effect for 1 (Realized ≫ Expected) (M) × Labor Exposure												
Labor Exposure=15	0.031**	0.024*			0.035**	0.027**					0.31**	0.021
	(0.013)	(0.014)			(0.014)	(0.013)					(0.014)	(0.013)
Labor Exposure=20	0.053***	0.042**			0.054**	0.042**					0.053***	0.035*
	(0.019)	(0.020)			(0.021)	(0.019)					(0.019)	(0.018)

Table 6. Heat Shocks and Capital Investment Rate

This table presents the treatment effects of medium-term heat shocks on firms' capital investment rate. Columns (1) - (3) use the full sample data. Columns (4) - (5) focus on firms that operate in counties with significant projected long-term temperature increases. Columns (6) - (7) focus on firms in highly unionized industries. Columns (8) - (9) focus on firms that employ large fractions of low-skilled workers. The dependent variable is the logarithm of a firm's capital investment rate defined as total capital expenditures divided by lagged total assets. Total capital expenditures is the sum of a firm's capital expenditures (*CAPX*) and R&D expenses. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized ≫ Expected) (M)*), and an interaction term of the two (*1 (Realized ≫ Expected) (M) × Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Capital Investment Rate)								
	Full Sample			CDC		Labor Union		Labor Skill	
1 (Realized ≫ Expected) (M)	-0.009	-0.034**	-0.019	-0.029	-0.018	-0.046**	-0.053***	-0.073**	-0.049**
	(0.008)	(0.016)	(0.013)	(0.023)	(0.020)	(0.018)	(0.019)	(0.029)	(0.021)
Labor Exposure		0.003	0.003	0.003	0.003	0.001	0.006	0.007*	0.008*
		(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.003**	0.002	0.004**	0.004*	0.003	0.004*	0.006***	0.004**
		(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	55,844	55,844	55,844	28,347	28,345	23,240	23,212	32,698	32,698
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	No	No	No	No	No	Yes	No	Yes
Adjusted R^2	0.810	0.810	0.818	0.781	0.791	0.737	0.747	0.784	0.793
Treatment Effect for 1 (Realized ≫ Expected) (M) × Labor Exposure									
Labor Exposure=15		0.014		0.032**	0.038**		0.003	0.015	0.018
		(0.013)		(0.016)	(0.018)		(0.019)	(0.014)	(0.015)
Labor Exposure=20		0.031		0.053**	0.056**		0.022	0.044**	0.040*
		(0.019)		(0.024)	(0.026)		(0.029)	(0.022)	(0.023)

Table 7. Heat Shocks and Employment Practices

This table presents the treatment effects of medium-term heat shocks on employment practices. Panel A presents analyses of firm-level total employment. Panel B presents analyses of firm-level investments in robotics-related human capital, measured using job postings that require robotics-related skills. Panel C presents analyses of plant-level total employment. Columns labeled with *"Full Sample"* represent analyses using the full-sample data. Columns labeled with *"EMP $\leq$ 50* represent analyses using plants with 50 employees or fewer. Columns labeled with *"Temperature Projections"* represents analyses using firms operated in counties with significant projected long-term temperature increases. Columns labeled with *"Labor Union"* represent analyses using firms in highly unionized industries. Columns labeled with *"Labor Skill"* represent analyses using firms that predominately employ low-skilled workers. In Panel A and C, the dependent variable is the natural logarithm of total employment (*Log(Emp)*). In Panel B, the dependent variable is fraction of a firm's robotics-related job postings, provided by (Babina et al., 2024). The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Controls in Panel A and B include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). Panel C controls for *Log(Emp)* at $t-3$ as a proxy for plant size. The sample period is from 1999 to 2019 in Panel A and C, and from 2010 to 2018 in Panel B. Numbers in parentheses are standard errors. In Panel A and B, standard errors are clustered at the NAICS4 level. In Panel C, standard errors are double clustered at the NAICS4 and county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Firm-level Total Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Emp)								
	Full Sample			Temperature Projections		Labor Union		Labor Skill	
1 (Realized $\gg$ Expected) (M)	0.000	0.006	0.003	0.002	-0.012	0.009	-0.001	0.016	0.010
	(0.006)	(0.009)	(0.009)	(0.016)	(0.015)	(0.012)	(0.011)	(0.015)	(0.014)
Labor Exposure		-0.005**	0.001	-0.003	0.001	-0.001	0.000	-0.007**	-0.004
		(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		-0.001	-0.000	-0.001	0.001	-0.002	-0.000	-0.002*	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	60,167	60,167	60,167	22,314	22,296	24,647	24,619	34,758	34,758
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.975	0.975	0.976	0.977	0.979	0.979	0.980	0.976	0.977
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure									
Labor Exposure=15								-0.016*	
								(0.009)	
Labor Exposure=20								-0.027**	
								(0.013)	

Panel B.Firm-level Investments in Robotics-related Human Capital

	(1)	(2)	(3)	(4)
	Human Capital - Robotics			
1 (Realized ≫ Expected) (M)	0.005	-0.026	-0.020	-0.021
	(0.013)	(0.016)	(0.016)	(0.017)
Labor Exposure		-0.002	0.001	0.000
		(0.004)	(0.005)	(0.006)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.005***	0.004**	0.004**
		(0.001)	(0.002)	(0.002)
Observations	9,870	9,870	9,917	9,870
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	Yes
NAICS2 x Year FE	No	No	Yes	Yes
Adjusted R^2	0.523	0.524	0.520	0.521
Treatment Effect for 1 (Realized ≫ Expected) (M) × Labor Exposure				
Labor Exposure=15		0.043**	0.036**	0.035*
		(0.017)	(0.018)	(0.020)
Labor Exposure=20		0.066***	0.055**	0.054**
		(0.023)	(0.025)	(0.027)

Panel C. Plant-level Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Log(Emp)										
	Full Sample				Emp $\leq$ 50				Emp $\leq$ 50		
									Temperature Projections	Labor Union	Labor Skill
1(Realized $\gg$ Expected) (M)	-0.0042***	-0.0042	-0.0017		-0.0013	0.0057**	0.0054**		0.0067	0.0025	0.0050
	(0.0016)	(0.0034)	(0.0033)		(0.0014)	(0.0023)	(0.0027)		(0.0051)	(0.0048)	(0.0041)
Labor Exposure		0.0001	0.0052	0.0017		-0.0008	0.0020	-0.0009	-0.0008	-0.0023	0.0028*
		(0.0020)	(0.0041)	(0.0024)		(0.0007)	(0.0014)	(0.0007)	(0.0017)	(0.0018)	(0.0016)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		-0.0000	-0.0003	-0.0000		-0.0007***	-0.0007***	-0.0008***	-0.0008**	-0.0006*	-0.0006*
		(0.0004)	(0.0004)	(0.0004)		(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0003)
Observations	1,195,249	1,195,249	1,185,130	1,190,612	453,586	453,586	446,026	446,530	219,307	147,626	366,881
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	No	No
Firm x Year FE	No	No	Yes	No	No	No	Yes	No	Yes	Yes	Yes
County x Year FE	No	No	No	Yes	No	No	No	Yes	No	No	No
Adjusted R^2	0.855	0.855	0.867	0.854	0.373	0.373	0.386	0.353	0.408	0.328	0.417
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure											
Labor Exposure=15						-0.0051***	-0.0053***		-0.0052**	-0.0066***	-0.0044***
						(0.0015)	(0.0015)		(0.0026)	(0.0020)	(0.0016)
Labor Exposure=20						-0.0088***	-0.0088***		-0.0091**	-0.0096***	-0.0076**
						(0.0024)	(0.0025)		(0.0039)	(0.0032)	(0.0031)

Table 8. Heat Shocks and Automation Technology

This table presents the treatment effects of medium-term heat shocks on firms' development of automation-related technology. Columns (1) - (3) use the medium-term heat shocks (*1 (Realized $\gg$ Expected) (M)*). Columns (4) - (6) further require at least 100 absolute hot days (i.e., temperatures above 30° C). Columns (7) - (9) further require at least 120 absolute hot days (i.e., temperatures above 30° C). The key independent variable is a dummy indicating that a firm files at least one automation-related patent (*Automation Patent*). The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating medium-term heat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2014. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Automation Patent								
	1 (Realized $\gg$ Expected)			1 (Realized $\gg$ Expected) & Days 30°C $\geq$ 100			1 (Realized $\gg$ Expected) & Days 30°C $\geq$ 120		
1 (Realized $\gg$ Expected) (M)	0.002	-0.005	-0.005	0.003	-0.006	-0.006	0.001	-0.012	-0.010
	(0.004)	(0.005)	(0.006)	(0.004)	(0.007)	(0.008)	(0.004)	(0.008)	(0.008)
Labor Exposure		-0.001	0.000		-0.001	-0.000		-0.001	-0.000
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.001**	0.001		0.001**	0.001		0.002***	0.001*
		(0.000)	(0.000)		(0.001)	(0.001)		(0.001)	(0.001)
Observations	43,692	43,692	43,692	43,692	43,692	43,692	43,692	43,692	43,692
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
NAICS2 x Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.641	0.641	0.648	0.641	0.641	0.648	0.641	0.641	0.648
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure									
Labor Exposure=15		0.009**	0.005		0.011**	0.006		0.012**	0.008*
		(0.005)	(0.004)		(0.005)	(0.004)		(0.005)	(0.005)
Labor Exposure=20		0.014**	0.008		0.017**	0.010		0.021**	0.014**
		(0.006)	(0.006)		(0.007)	(0.006)		(0.007)	(0.007)

Internet Appendix to

“Labor Exposure to Climate Risk, Productivity Loss, and Capital Deepening"

Jan 2024

A Variable Definitions

Variables	Description
Dependent Variables	
Log(Sales/Emp)	The natural logarithm of sales per employee. The firm-level variable uses sales from the quarterly Compustat/CRSP Merged data and employment from the annual Compustat/CRSP Merged data. The plant-level variable uses annual sales and employment from the YTS data at the firm-by-county-by-NAICS4 level.
Log(Capital)	The natural logarithm of total capital. Total capital is the sum of a firm's property, plant, and equipment (*PPENT*) and its R&D stock. R&D stock is the sum of a firm's historical R&D expenses, assuming a 20% depreciation rate.
Log(Capital/Emp)	The natural logarithm of total capital scaled by the number of employees.
Log(Capital Investment Rate)	The natural logarithm of total capital expenditures divided by lagged total assets. Total capital expenditures is the sum of a firm's capital expenditures (*CAPX*) and R&D expenses.
Log(Emp)	The natural logarithm of the number of employees. The firm-level variable uses employment from the annual Compustat/CRSP Merged data. The plant-level variable uses employment from the YTS data at the firm-by-county-by-NAICS4 level.
Human Capital - Robotics	The fraction of a firm's robotics-related job postings, provided by Babina et al. (2024).
Automation Patent	A dummy indicating that a firm files at least one automation patent. The classification of automation-related patents is from Mann and Püttmann (2023).
Key Independent Variables	
1 (Realized $\gg$ Expected)	A dummy indicating a short-term heat shock at the county or the firm level. The county-level measure is defined in Equation (1). Heat shock is measured using temperatures at t relative to the $0th$ percentile of historical temperatures in the same county and month from 1981 to $t-1$, with a maximum of 30 years. The identification threshold is 15 days, relative to the benchmark (expectation) 10 days. The firm-level measure is the employment-weighted average of the county-level measure, defined in Equation (2). The employment data is from the YTS.
1 (Realized $\gg$ Expected) (M)	A dummy indicating a medium-term heat shock at the county or the firm level. The medium-term heat shock is measured in the same way as *1 (Realized $\gg$ Expected)* but using temperatures from $t-3$ to t. The identification threshold is 45 days, relative to the benchmark (expectation) 40.

Variables	Description
Key Independent Variables	
Labor Exposure	A rank variable of labor exposure to climate risk from 1 to 20, with 20 indicating the highest exposure, at the NAICS4 industry or the firm level. The industry-level measure is a weighted average of all occupations' exposure to changing climates in a four-digit NAICS industry, defined in Equation (4). The occupational exposure score is from the O*NET program. The weight is the percentage of employees working in a given occupation in an industry from the OEWS data. The firm-level measure is weighted average of the industry-level measure, defined in Equation (5). The weight is the percentage of a firm's employees working in a NAICS4 industry from the YTS data.
Other Independent Variables	
Size	The logarithm of a firm's total assets (AT).
MB	The market value of assets (prcc_f $\times$ csho + dlc + dltt) divided by the book value of assets (AT).
Book Leverage	The book value of long-term debt (DLTT) plus debt in current liabilities (DLC) divided by total assets (AT).
Cash	Cash and short-term investments (CHE) divided by total assets (AT).
Dividend Payer	A dummy indicating that a firm pays dividends (DVC & DVP).

B Anecdotal Evidence of Temperature Threats to Exposed Workers

In this section, I present several pieces of anecdotal evidence from multiple sources that underscore considerable heat risks filed workers face due to climate change.

[1] Extreme Heat and Unprotected Workers
Public Citizen, 2018

[2] Extreme Heat: The Economic and Social Consequences for the United States
Adrienne Arsht – Rockefeller Foundation Resilience Center, 2021

[3] FACT SHEET: Biden Administration Mobilizes to Protect Workers and Communities from Extreme Heat
The White House, 2021

[4] Heat Is Killing Workers in the U.S. — And There Are No Federal Rules to Protect Them
Julia Shipley, Brian Edwards, David Nickerson, Robert Benincasa, Stella M. Chávez, Cheryl W. Thompson, NPR News, 2021.

[5] Too Hot To Work: Assessing The Threats Climate Change Poses to Outdoor Workers
Kristina Dahl and Rachel Licker, *Union of Concerned Scientists*, 2021

[6] Too Hot To Work: The Dire Impact of Extreme Heat on Outdoor US Jobs
Aliya Uteuova and Andrew Witherspoon, *The Guardian*, 2021

[7] How Rising Temperatures Are Becoming a Labor Story
Steven Greenhouse, *Nieman Reports*, 2023.

[8] Extreme Heat Is Endangering America's Workers—and Its Economy
Aryn Baker, *Time*, 2023

[9] Workers Exposed to Extreme Heat Have Few Protections
Noah Weiland, *The New York Times*, 2023

[10] When Is It Too Hot to Work Outside?
Adolfo Flores and Dan Frosch, *The Wall Street Journal*, 2023

[11] What happens when it is too hot to work?
The Economist, 2023

C Labor Exposure to Climate Risk

C.1 Data and Measure Construction

This section provides an overview of the raw datasets used for constructing the measure of labor exposure to climate risk. Table IC.1 reports the versions and release dates of the Occupational Employment and Wage Statistics (OEWS) and the Occupational Information Network (O*NET) datasets used. The OEWS and the O*NET data are matched using the SOC occupation code for 1999 - 2022.

C.1.1 Occupational Employment and Wage Statistics (OEWS)

The Bureau of Labor Statistics's (BLS) Occupational Employment and Wage Statistics (OEWS) produces employment and wage estimates for approximately 830 occupations based on a survey of almost all industries from about 200,000 establishments in the U.S. every six months. The survey covers wage and salary workers in nonfarm establishments and does not include the self-employed, owners and partners in unincorporated firms, household workers, or unpaid family workers. The publicly available OEWS datasets include cross-industry occupational employment and wage estimates for the nation and over 580 areas (e.g., states and MSAs) and national industry-specific estimates.

Several points are worth noting. First, the OEWS data is available starting from 1988. However, before 1997, the data were collected over three-year survey cycles. Annual updates become available starting from 1997 with a May reference date. Second, occupational classifications rely on the Dictionary of Occupational Titles (DOT) pre 1999 and transition to the Standard Occupational Classification (SOC) system afterward. Third, industry classifications are based on the SIC code before 2002 and the NAICS code from 2002 onwards.

C.1.2 The Occupational Information Network (O*NET) Program

The Occupational Information Network (O*NET) is a comprehensive database of worker attributes and job characteristics, including workers' abilities, skills, knowledge and experience, work values, work styles, work activities, etc. The O*NET Program replaces the Dictionary of Occupational Titles (DOT) and is currently the primary source of U.S.

occupational information. Data in O*NET is collected by surveying job incumbents using questionnaires in a two-stage design in which (a) a statistically random sample of businesses expected to employ workers in the targeted occupations will be identified and (b) a random sample of workers in those occupations within those businesses will be selected. In addition, abilities and skills information is developed by occupational analysts using the updated information from incumbent workers.

O*NET has been continuously updating occupational characteristics quarterly/semi-annually since 2003 through ongoing surveys - "*O*NET 5.0*" to the latest version "*O*NET 28.0*". These updates allow researchers to track changes in a specific occupation's characteristics over time. In addition, O*NET also has a transitional database including "*O*NET 4.0 (June 2002)*", "*O*NET 3.1 (June 2001)*", "*O*NET 3.0 (August 2000)*", and "*O*NET 98 (December 1998)*". These datasets are not built on the current multi-method data collection methodology featuring job incumbents, occupational experts, big data, and other sources. Rather, O*NET 98 to O*NET 4.0 are populated using data supplied by occupational analysts. Specifically, occupational analysts evaluate and refine the existing Dictionary of Occupational Titles (DOT) data (e.g., the revised 4^{th} edition) and then extrapolate these data to the O*NET Content Model. I use the latest analyst estimates, O*NET 4.0, for analyses before 2003 (1999 - 2002).

C.1.3 Occupational Exposure to High Temperatures

In the section on work context, O*NET has five elements that help capture workers' temperature exposures while performing job tasks. The first element is "*Outdoors, Exposed to Weather*," based on the survey question "*How often does this job require working outdoors, exposed to all weather conditions*?" The second is "*Outdoors, Under Cover*," associated with the question "*How often does this job require working outdoors, under cover (e.g., structure with roof but no walls)*?" The third is "*Indoors, Environmentally Controlled*" with the question "*How often does this job require working indoors in environmentally controlled conditions*?" The fourth is "*Indoors, Not Environmentally Controlled*" with the question "*How often does this job require working indoors in non-controlled environmental conditions (e.g., warehouse without heat)*?" The last one is “*Very Hot or Cold Temperatures*" with the question “*How often does this job require working in very hot (above 90°F degrees) or very cold (below 32°F degrees) temperatures*?"

In this study, I only use the first element (“*Outdoors, Exposed to Weather*") to quantify labor exposure to changing climates. The reason is that this study focuses on workers' exposure to naturally generated heat induced by climate change. This study does not consider workers' exposure to heat generated during the production process, such as steel making, as this production-induced heat is not caused by climate change and is endogenous to firms' operating activities. In line with this, I exclude the element “*Very Hot or Cold Temperatures*."

Additionally, I exclude the element “*Indoors, Environmentally Controlled*" because of limited data on onsite climate controls and mixed evidence on how high temperatures affect labor productivity in climate-controlled environments. For example, some studies document that indoor workers in climate-controlled environments are well protected by cooling machines like air conditioners. Consequently, high temperatures do not harm these workers' productivity (Somanathan et al., 2021). However, other studies show that even with high-quality climate-controls available, high temperatures still affect individuals' decision consistency and quality (Heyes and Saberian, 2019).

Further, I exclude “*Outdoors, Under Cover*" and “*Indoors, Not Environmentally Controlled*" for three reasons. First, outdoor workers under cover are protected by the cover and thus are less affected by changing climates relative to outdoor workers who are directly exposed to all weather conditions. Second, the survey question for “*Indoors, Not Environmentally Controlled*" tilts toward indoor non-hot conditions even without climate controls - *warehouse without heat* in the survey question. Therefore, including this element may bias my measure. Third, neither survey question was available until 2006. I drop them to ensure the consistency in measure construction. Nevertheless, in additional robustness checks, I reconstruct the measure of labor exposure by incorporating the three survey questions - “*Outdoors, Exposed to Weather*", “*Outdoors, Under Cover*" and “*Indoors, Not Environmentally Controlled*." Results (*untabulated*) hold.

C.2 Distribution of Labor Exposure to Climate Risk

C.2.1 Across Sectors

Figure IC.1 presents the distribution of industry-level labor exposure to climate risk across different sectors. The x-axis represents NAICS2 sectors and the y-axis represents the measure of labor exposure to climate risk. The dots denote the minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum of labor exposure across NAICS4 industries in each sector. In line with common experience, agriculture, mining, construction, transportation and warehousing, and real estate and rental and leasing have large fractions of workers exposed to climate risks. In contrast, sectors like management of companies and enterprises and educational services have small fractions. Additionally, the figure yields three noteworthy observations. First, while the manufacturing sector is widely explored in estimating the effects of high temperatures on economic activities in prior studies, it's not among those most exposed, implying that prior focus on manufacturing firms might underestimate the impact of climate change on labor productivity. This is consistent with a recent report by Romanello et al. (2022) showing that heat-induced labor productivity loss in manufacturing sectors is smaller than that in construction and service sectors. Second, industries in wholesale trade and service sectors (i.e., *arts, entertainment, and recreation; administrative and support and waste management and remediation services; other services (except public administration)*) also have significant fractions of workers exposed to climate threats, which indicates a broad impact of high temperatures on the whole U.S. economy. Third, even within each sector, there are significant variations of labor exposures across NAICS4 industries, suggesting that the measure does not simply capture sector-specific characteristics. This also highlights the importance of a more refined measure to quantify the labor channel and the improvement relative to the sector-level measure in Graff Zivin and Neidell (2014).

Table IC.2 provides examples of industries with high, medium, or low exposures to climate risk based on the value of *Labor Exposure* in 2015. As expected, high-exposure industries are those that need the most outdoor workers, including logging, retail transportation, basic chemical manufacturing, postal service, etc. Medium-exposure industries include furniture stores, amusement parks and arcades, employment services, steel manufacturing, and plastic product manufacturing, etc. At the lower end of the spectrum, examples are advertising, accommodation, grocery stores, footwear manufacturing, business support services, and personal care services. Furthermore, consistent with patterns in Figure IC.1, within each exposure category — high, medium, or low — there is a diverse distribution of sectors. For example, the high-exposure category spans various major sectors, including agriculture, forestry, fishing, and hunting (NAICS2 11), mining, quarrying, and oil and gas extraction (NAICS2 21), construction (NAICS2 23), manufacturing (NAICS 31-33), wholesale trade (NAICS 42), transportation and warehousing (NAICS 48-49), administrative and support and waste management and remediation services (NAICS 56), health care and social assistance (NAICS2 62), and other services (except public administration) (NAICS2 81). This wide distribution of high-exposure industries across sectors underscores the extensive impact of high temperatures on the entire economic landscape.

C.2.2 Across Labor Skill Levels

Figure IC.2 presents the distribution of the industry-level measure of labor exposure to climate risk by labor skill levels. The x-axis represents labor skill levels ranging from 1 to 20, with 20 representing the most skilled workers. The dots represent the minimum, 25^{th} percentile, median, 75^{th} percentile, and maximum of labor exposure to climate risk across NAICS4 industries in each skill level. Consistent with expectation, there is a negative correlation between labor exposure to climate risk and labor skill, indicated by a correlation of -0.35. However, significant heterogeneities exist in labor exposures across NAICS4 industries in each labor skill skill, especially for skill levels below 16. The patterns indicate that, although lower-skilled workers generally face higher exposure to climate risks, a substantial number of higher-skilled workers are also impacted.

C.2.3 Across Counties

Figure IC.3 presents the degree of labor exposure to climate risk for each U.S. county in 2000, 2006, 2012, and 2018. The county-level exposure variable is calculated as the employment-weighted average of the industry-level measure of labor exposure. The weight is the number of employees working in a NAICS4 industry and a county from the Quarterly Census of Employment and Wages (QCEW) data. Counties in white denote those for which the QCEW data is not available. The figures indicate a relatively uniform distribution of high-exposure workers and industries across the U.S., with a moderate concentration in the central region. The extensive geographic spread of high-exposure industries, together with the widespread and unpredictable distribution of temperature fluctuations (Figure 1), further suggests that high temperatures have a comprehensive impact on the U.S. economy, rather than an impact confined to specific areas.

C.3 Measure Validation

Prior studies have developed several measures of corporate exposures to climate conditions by analyzing textual information in firm disclosures, i.e., annual reports (10-K) and earnings conference calls. Notably, these measures are constructed in a comprehensive way by incorporating all climate-related information in disclosures. In contrast, my measure utilizes occupational working contexts and thus focuses on exposures to changing climates from a labor perspective. On this point, my measure captures a unique labor channel of firms' exposure to climate change and, consequently, better explains firms' choices of production inputs from the labor aspect. Importantly, if the use of outdoor workers in production significantly increases firms' exposure to climate risk, managers should discuss more issues related to climate change in earnings conference calls and 10-Ks. Therefore, I expect a positive relation between my measure of labor exposure to climate risk and exposure measures developed in the literature.

To validate my measure of labor exposure to climate risk, I first obtain data on firms' exposure to weather from Nagar and Schoenfeld (2022). It gives the frequency count of the term *weather* in firms' 10-Ks. Instances where the word *weather* appears out-of-context as a verb are excluded. Figure IC.4 (A) presents the correlation between my measure of labor exposure to climate risk and the natural logarithm of one plus the frequency count of the term *weather*, after controlling firm size and time-invariant firm characteristics. As expected, it shows a strong positive relation between the two measures, suggesting that firms that employ more outdoor workers discuss more about weather in 10-Ks. More importantly, in Figure IC.4 (B), the positive correlation between the labor exposure measure and firms' capital utilization in production (*Log(Capital/Emp)*) holds after controlling for firm-level characteristics and the *weather* variable, suggesting that the labor exposure measure has significant additional power in explaining firms' choices of labor and capital in production.

Additionally, I obtain data on managers' discussion of climate change in earnings conference calls from Sautner et al. (2023). I use two measures developed in the paper - *Climate Change Exposure* and *Climate Change Risk*. The exposure measure captures the relative frequency of managers' mention of climate change in earnings conference calls. The risk measure captures the relative frequency of managers' mention of climate change together with the words "*risk*" or "*uncertainty*" (or synonyms thereof). I scale the two measures by multiplying them by 1,000. It shows that the labor exposure measure has a positive correlation with both *Climate Change Exposure* (Figure IC.5 (A)) and *Climate Change Risk* (Figure IC.6 (A)), the former of which displays a greater magnitude of correlation compared to the latter. More importantly, the positive correlation between the labor exposure measure and firms' capital utilization in production can not be fully explained by *Climate Change Exposure* (Figure IC.5 (B)) or *Climate Change Risk* (Figure IC.5 (B)).

Furthermore, I compare the correlations between my labor exposure measure and corporate exposure to extreme heat developed by Trucost, part of the S&P Global. Specifically, Trucost first models location-specific (100x100km to 200x200km) heat risk scores (1 to 100) and then aggregate the scores at the firm level based on the firm's asset locations. In the absence of sufficient asset-level data, physical risk is estimated based on firms' headquarters locations (weighted at 20%), firm revenue shares by country, and the average physical risk level in each country (weighted at 80%). The measures are available starting from August 2018. Essentially, the asset-based measure assumes that all of the firm's physical assets are exposed to and affected by extreme heat in the same magnitude if local temperatures are abnormally hot, despite significant heterogeneities in these asset types. The revenue-based measure assumes that the firm's revenues are affected in a country if the country experiences a heat wave, which may not affect firms' production processes at all. Consequently, Trucost's measures are fundamentally different from mine by construction and do not capture any heat exposure from a labor perspective. Consistent with this conjecture, Figure IC.7 (A) and IC.8 (A) show that the correlations between my measure of labor exposure and Trucost's measures of heat exposure are almost zero.[40] More importantly, Figure IC.7 (B) and IC.8 (B) show that the significant power of labor exposure in explaining firms' choices of labor and capital in production remains after controlling the asset-based or revenue-based heat exposures from Trucost.

Overall, these results show that reliance on outdoor workers in production exposes firms to significant climate risks. Such exposure can not be fully explained by other measures of climate exposures developed in the literature or by Trucost. These evidence builds the foundation for studying corporate exposure to climate change and adaptation actions from a labor channel.

[40]The correlations between heat exposures from Trucost and exposure measures from Sautner et al. (2023) and Nagar and Schoenfeld (2022) are also very low. For instance, the asset-based heat exposure measure has a correlation of -0.079 with *Climate Change Exposure* and a correlation of -0.064 with *Climate Change Risk*. The revenue-based heat exposure measure has a correlation of -0.012 with *Climate Change Exposure* and a correlation of -0.039 with *Climate Change Risk*.

Figure IC.1. Distribution of Labor Exposure to Climate Risk Across Sectors

This figure presents the distribution of the industry-level measure of labor exposure to climate risk (Equation (4)) across NAICS2 sectors.

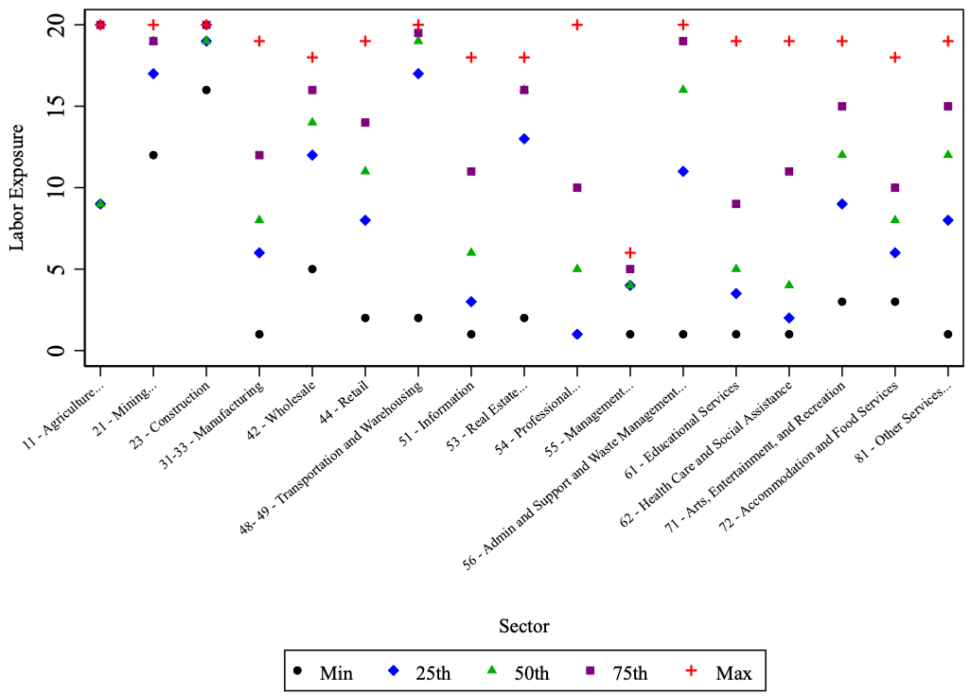


Figure IC.2. Distribution of Labor Exposure to Climate Risk Across Skill Levels

This figure presents the distribution of the industry-level measure of labor exposure to climate risk (Equation (4)) across skill levels.

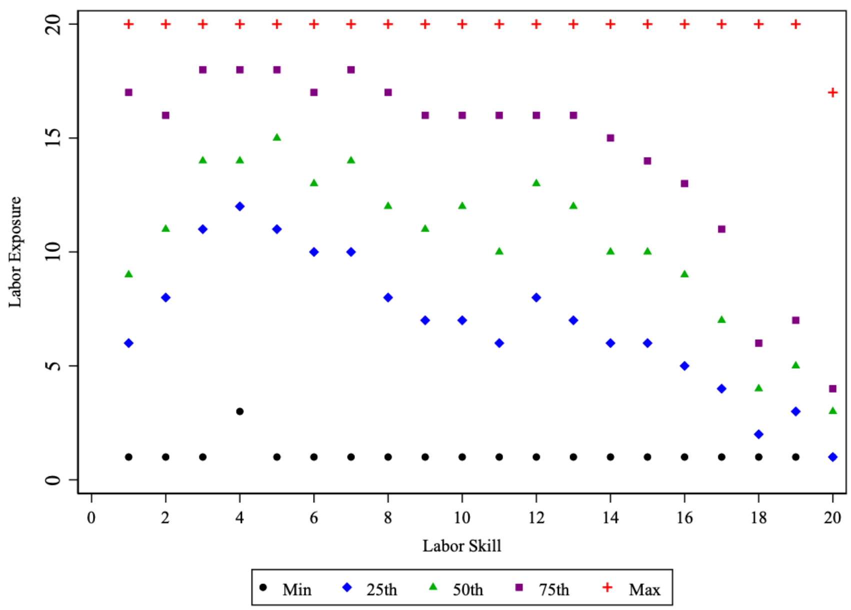
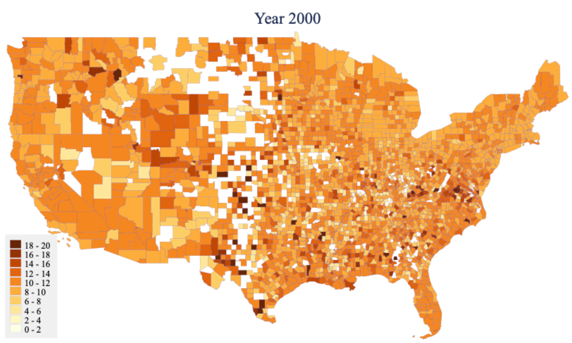


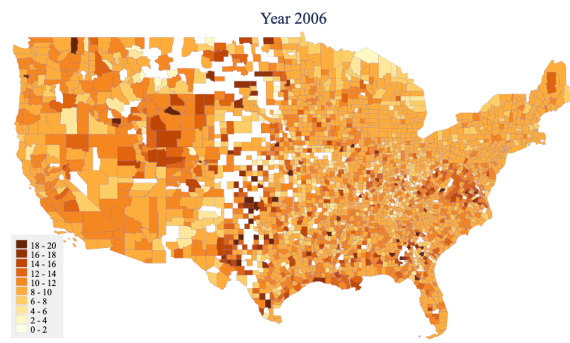
Figure IC.3. Distribution of Labor Exposure to Climate Risk Across Counties

These figures present the level of labor exposure to climate risk for each U.S. county in 2000, 2006, 2012, and 2018. The county-level labor exposure is calculated using the weighted average of each NAICS4 industry's labor exposure. The weight is the number of employees working in a NAICS4 industry and a county from the Quarterly Census of Employment and Wages (QCEW) data. Counties in white denote those for which the QCEW data is not available.

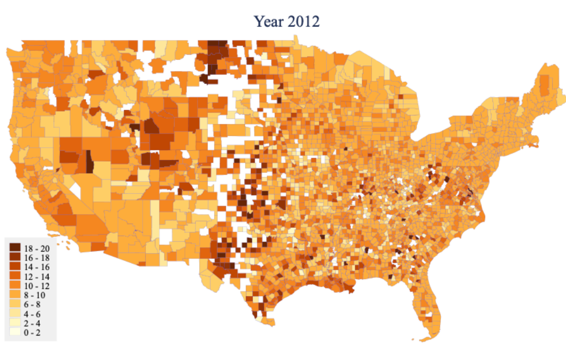
(A)



(B)



(C)



(D)

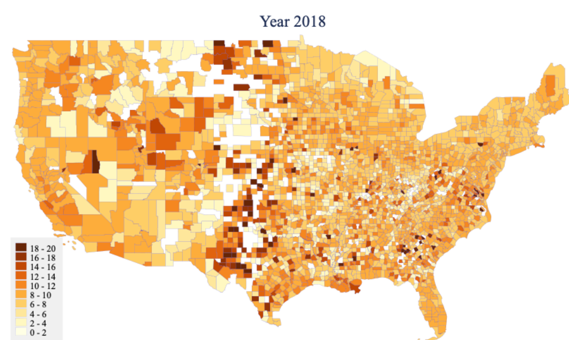
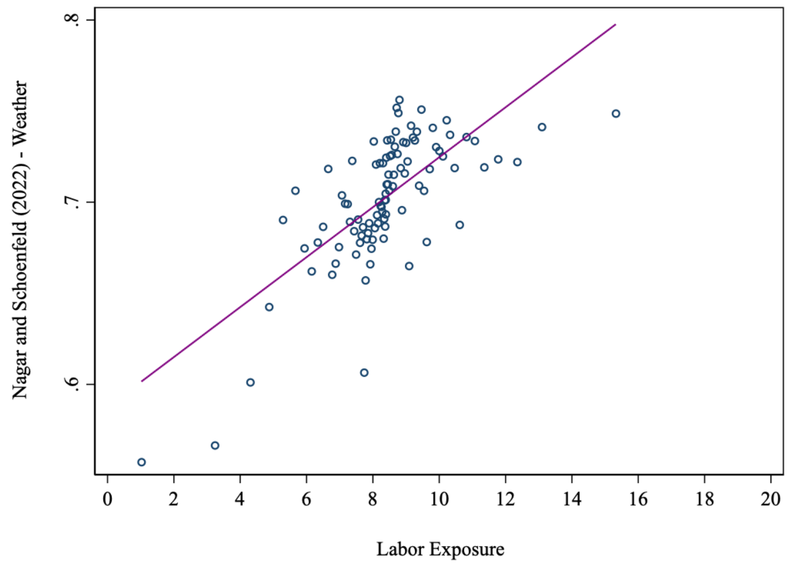


Figure IC.4. Labor Exposure to Climate Risk and Firms' Discussion of Weather in 10-Ks

Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' discussion of weather in 10-Ks from Nagar and Schoenfeld (2022) after controlling firm size and time-invariant firm characteristics. Figure (B) presents the correlation between the measure of labor exposure to climate risk and firms' capital utilization in production (*Log(Capital/Emp)*) after controlling for firm-level characteristics and firms' discussion of weather in 10-Ks. The sample period is from 1999 to 2018.

(A) Weather



(B) Capital-labor Ratio - Log(Capital/Emp)

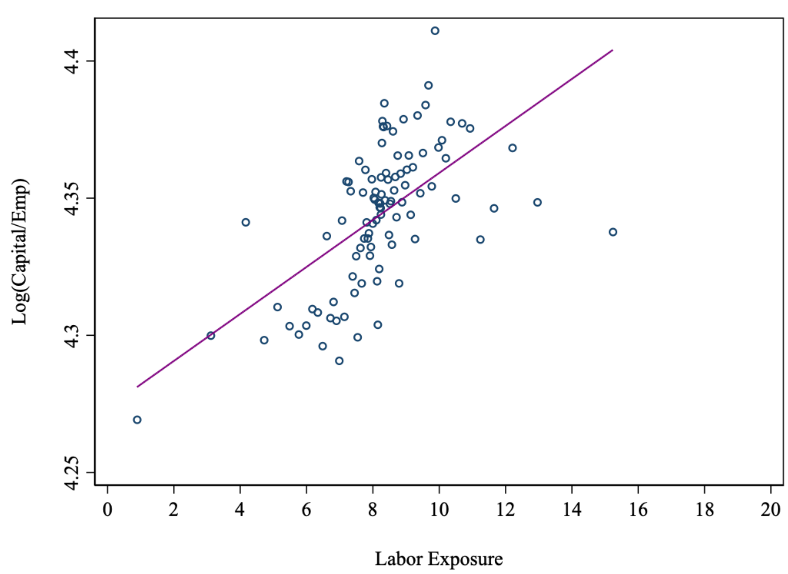
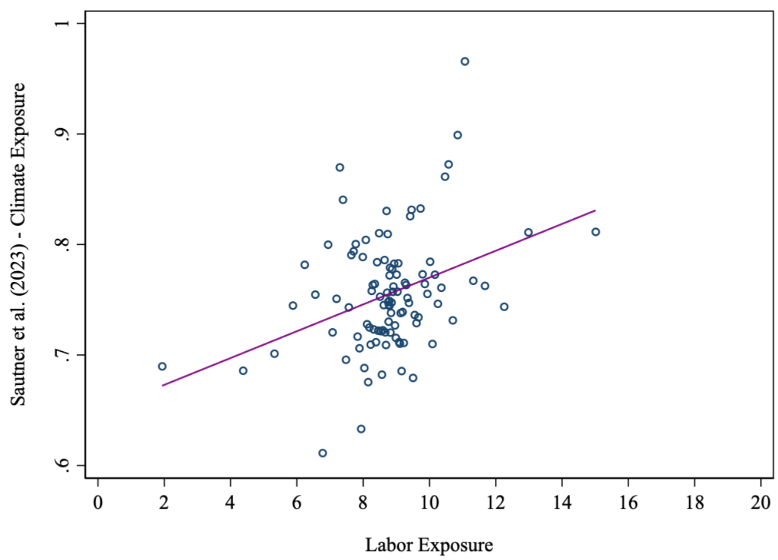


Figure IC.5. Labor Exposure to Climate Risk and Firms' Discussion of Climate Change in Earnings Conference Calls

Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' discussion of climate change in earnings conference calls (*Climate Change Exposure*) from Sautner et al. (2023) after controlling firm size and time-invariant firm characteristics. Figure (B) presents the correlation between the labor exposure measure and firms' capital utilization in production (*Log(Capital/Emp)*) after controlling for firm-level characteristics and the *Climate Change Exposure* measure. The sample period is from 1999 to 2019.

(A) Climate Change Exposure



(B) Capital-labor Ratio - Log(Capital/Emp)

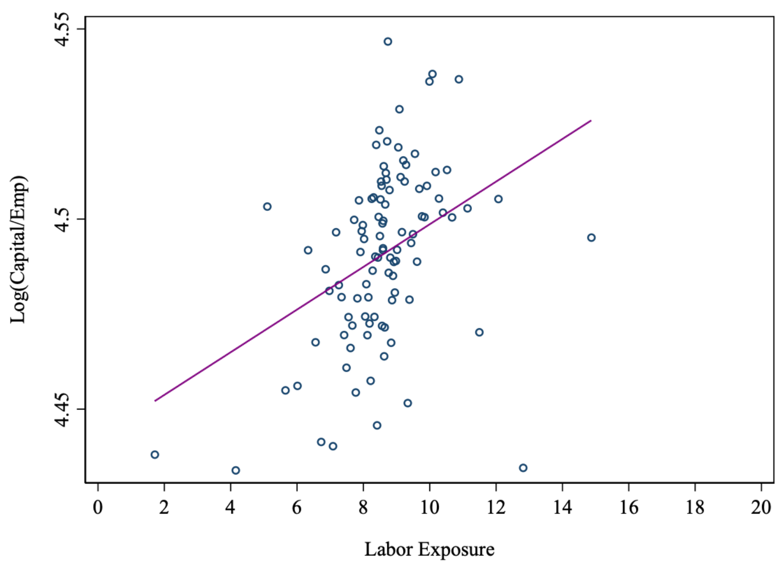
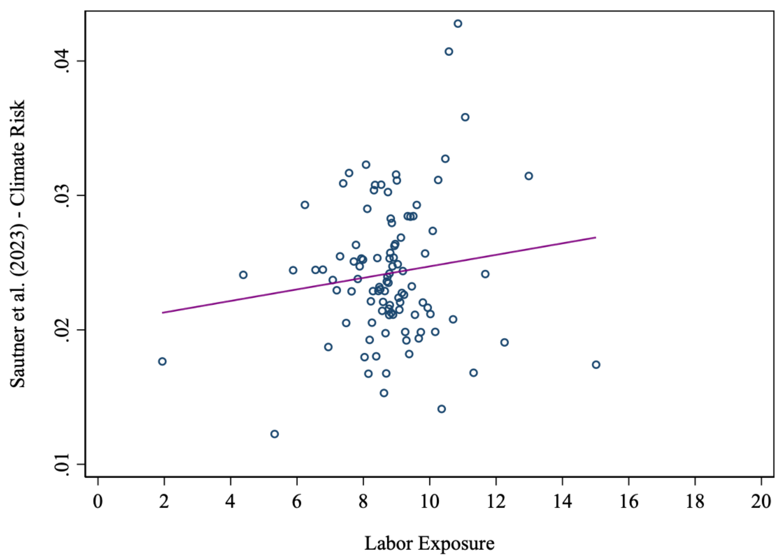


Figure IC.6. Labor Exposure to Climate Risk and Firms' Discussion of Climate Risk in Earnings Conference Calls

Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' discussion of climate risk in earnings conference calls (*Climate Change Risk*) from Sautner et al. (2023) after controlling firm size and time-invariant firm characteristics. Figure (B) presents the correlation between the labor exposure measure and firms' capital utilization in production (*Log(Capital/Emp)*) after controlling for firm-level characteristics and the *Climate Change Risk* measure. The sample period is from 1999 to 2019.

(A) Climate Change Risk



(B) Capital-labor Ratio - Log(Capital/Emp)

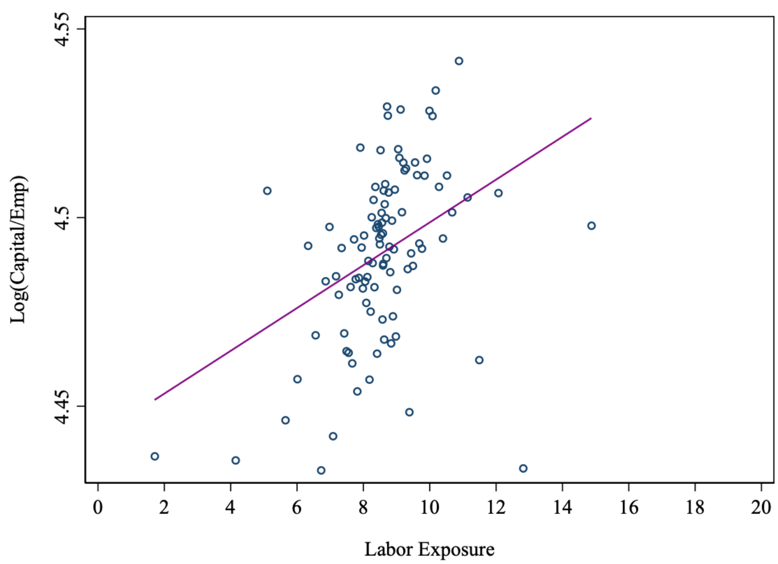
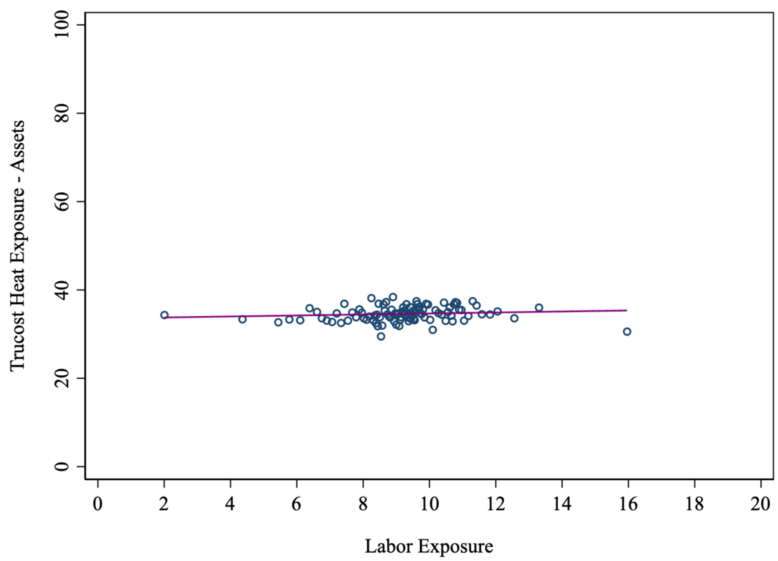


Figure IC.7. Labor Exposure to Climate Risk and Asset-based Heat Exposure from Trucost Climate Analytics

Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' asset exposure to extreme heat provided by Trucost Climate Analytics, after controlling firm size and time-invariant industry characteristics. Figure (B) presents the correlation between the labor exposure measure and firms' capital utilization in production (*Log(Capital/Emp)*) after controlling for firm-level characteristics and the Trucost asset-based measure of heat exposure.

(A) Trucost Asset-based Exposure to Extreme Heat



(B) Capital-labor Ratio - Log(Capital/Emp)

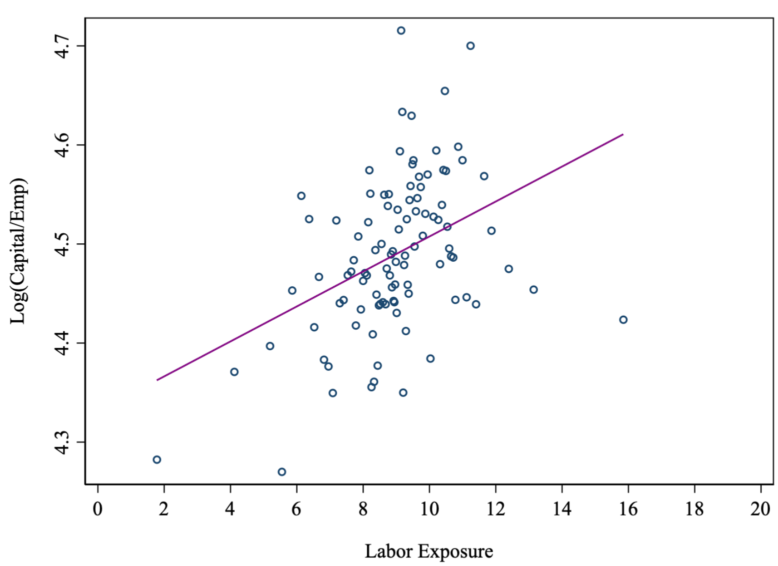
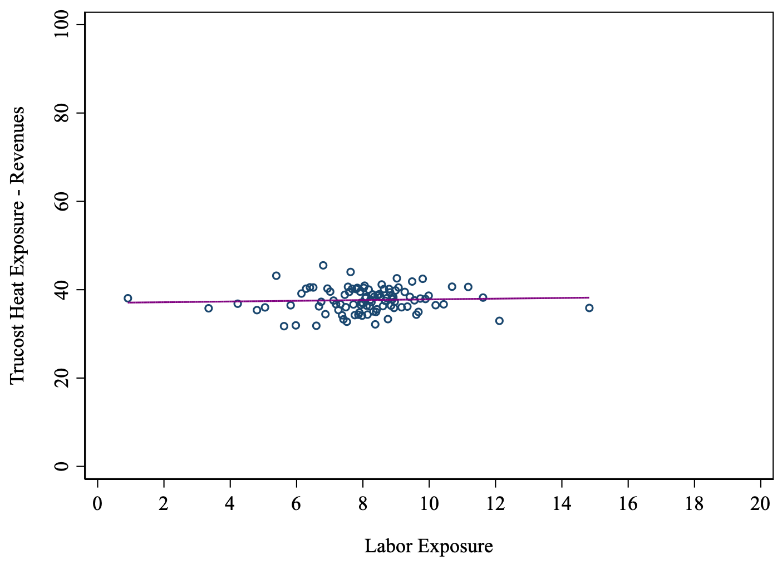


Figure IC.8. Labor Exposure to Climate Risk and Revenue-based Heat Exposure from Trucost Climate Analytics

Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' revenue exposure to extreme heat provided by Trucost Climate Analytics, after controlling firm size and time-invariant industry characteristics. Figure (B) presents the correlation between the labor exposure measure and firms' capital utilization in production (*Log(Capital/Emp)*) after controlling for firm-level characteristics and the Trucost revenue-based measure of heat exposure.

(A) Trucost Revenue-based Exposure to Extreme Heat



(B) Capital-labor Ratio - Log(Capital/Emp)

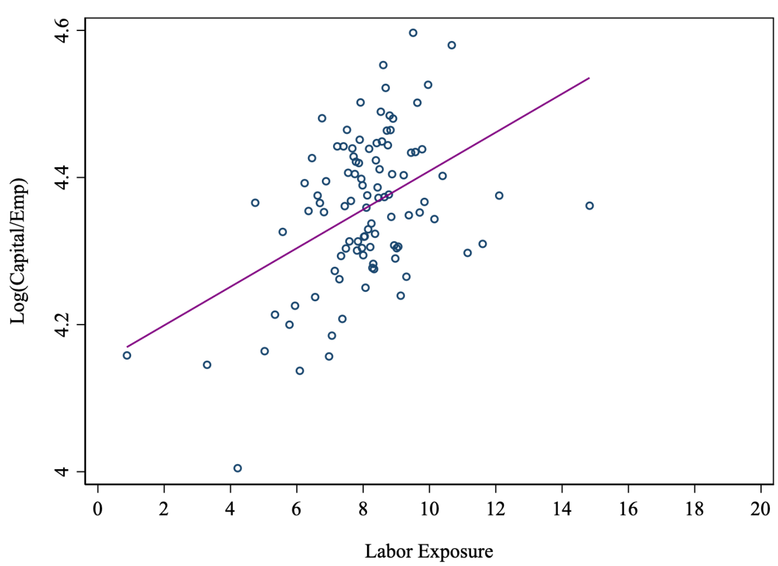


Table IC.1. Occupational Employment and Wage Statistics (OEWS) and the Occupational Information Network (O*NET) Program

This table reports the versions and release dates of the Occupational Employment and Wage Statistics (OEWS) and the Occupational Information Network (O*NET) Program datasets used for constructing the measure of labor exposure to climate risk.

Year	**O*NET Data**		**OEWS Data**	
	Version	**Release Date**	**Release Date**	**Industry Code**
1999	Work Context_4_0	June, 2002	1999	SIC
2000	Work Context_4_0	June, 2002	2000	SIC
2001	Work Context_4_0	June, 2002	2001	SIC
2002	Work Context_4_0	June, 2002	2002	NAICS
2003	Work Context_5_1	November, 2003	May, 2003	NAICS
2004	Work Context_7_0	December, 2004	May, 2004	NAICS
2005	Work Context_9_0	December, 2005	May, 2005	NAICS
2006	Work Context_11_0	December, 2006	May, 2006	NAICS
2007	Work Context_12_0	June, 2007	May, 2007	NAICS
2008	Work Context_13_0	June, 2008	May, 2008	NAICS
2009	Work Context_14_0	June, 2009	May, 2009	NAICS
2010	Work Context_15_1	February, 2011	May, 2010	NAICS
2011	Work Context_16_0	July, 2011	May, 2011	NAICS
2012	Work Context_17_0	July, 2012	May, 2012	NAICS
2013	Work Context_18_0	July, 2013	May, 2013	NAICS
2014	Work Context_19_0	July, 2014	May, 2014	NAICS
2015	Work Context_20_1	October, 2015	May, 2015	NAICS
2016	Work Context_21_1	November, 2016	May, 2016	NAICS
2017	Work Context_22_1	October, 2017	May, 2017	NAICS
2018	Work Context_23_1	November, 2018	May, 2018	NAICS
2019	Work Context_24_1	November, 2019	May, 2019	NAICS
2020	Work Context_25_1	November, 2020	May, 2020	NAICS
2021	Work Context_26_1	November, 2021	May, 2021	NAICS
2022	Work Context_27_1	November, 2022	May, 2022	NAICS

Table IC.2. Examples of Industries with Heterogeneous Labor Exposures to Climate Risk

This table presents examples of industries with high, medium or low exposure to climate risk through the labor channel, based on the measure of *Labor Exposure* in 2015 (Equation (4)).

NAICS4 Code	NAICS4 Title	Labor Exposure
High Exposure		
1133	Logging	20
5621	Waste Collection	20
4821	Rail Transportation	20
2121	Coal Mining	19
2362	Nonresidential Building Construction	19
4911	Postal Service	19
4244	Grocery and Related Product Merchant Wholesalers	17
3251	Basic Chemical Manufacturing	16
8113	Commercial and Industrial Machinery and Equipment (except Automotive and Electronic) Repair and Maintenance	16
6244	Child Day Care Services	16
Medium Exposure		
4421	Furniture Stores	14
7131	Amusement Parks and Arcades	12
5613	Employment Services	12
8112	Electronic and Precision Equipment Repair and Maintenance	11
3272	Glass and Glass Product Manufacturing	11
3312	Steel Product Manufacturing from Purchased Steel	10
5151	Radio and Television Broadcasting	10
6243	Vocational Rehabilitation Services	9
3261	Plastics Product Manufacturing	8
3353	Electrical Equipment Manufacturing	7
Low Exposure		
5418	Advertising, Public Relations, and Related Services	5
7211	Traveler Accommodation	5
4451	Grocery Stores	4
3341	Computer and Peripheral Equipment Manufacturing	3
5182	Data Processing, Hosting, and Related Services	2
3162	Footwear Manufacturing	2
5614	Business Support Services	1
5412	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	1
6215	Medical and Diagnostic Laboratories	1
8121	Personal Care Services	1

D Temperatures

Figure ID.1 presents the annual number of abnormally hot days (daily maximum temperatures above the estimated 90^{th} percentile threshold in summer) for the average county from 1999 to 2019. It shows that, from 1999 to 2019, the average number of hot days hovers around 10, but with considerable year-to-year variability. Due to the occurrence of two significant North American heatwaves, 2011 and 2012 stand out with more hot days — 22 and 18, respectively — compared to the rest of the period.

Figure ID.2 presents the average summer temperatures (daily mean and maximum) in the continental U.S. from 1999 to 2019. The year-to-year fluctuations in average temperatures are modest compared with variations in relative temperature shocks presented in Figure ID.1.

Figure ID.3 presents differences in temperatures under hot and non-hot scenarios. Hot scenarios refer to counties and years with relative heat shocks defined in Equation (1). The figure shows that the average number of days with temperatures above the rolling 90^{th} percentile threshold in summer is 22 in hot scenarios ($T \geq 15$) and 6 in non-hot ones ($T < 15$). The number of days with temperatures above the 30° C in summer is 60 and 42, respectively. And the average daily maximum temperature in summer is 31° C and 29° C, respectively. These evidence suggests that summer temperatures classified as hot by Equation (1) are significantly hotter than those in other summers.

Figure ID.1. Time-Series Abnormally High Temperatures in the Continental U.S.

This figure presents the annual number of abnormally hot days (daily maximum temperatures above the estimated 90^{th} percentile threshold in summer) for the average county from 1999 to 2019.

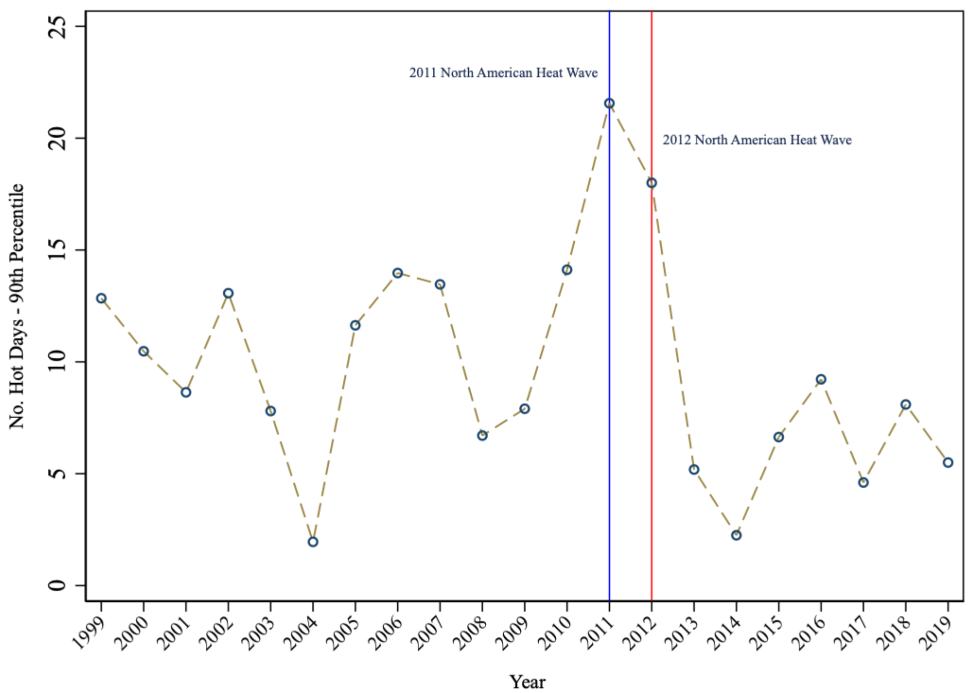


Figure ID.2. Time-Series Average Temperatures in the Continental U.S.

This figure presents the average summer temperatures (daily mean and maximum) in the continental U.S. from 1999 to 2019.

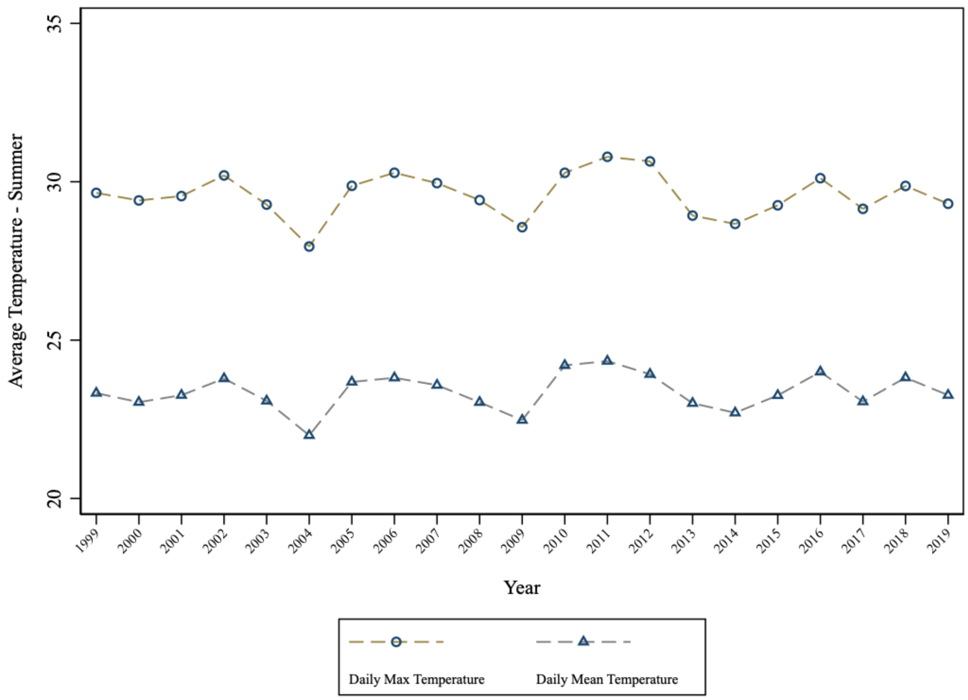
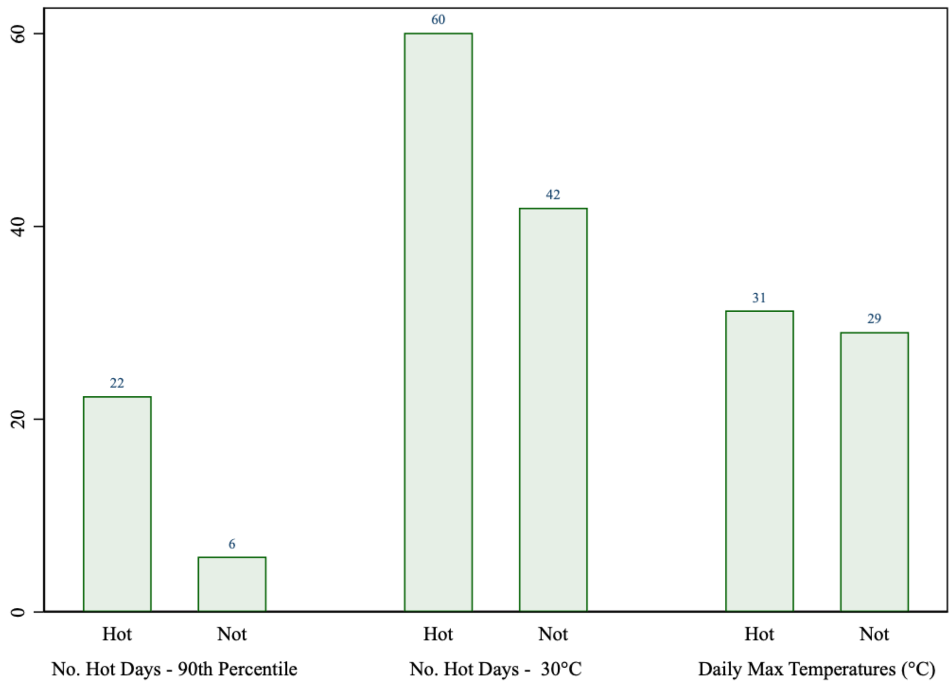


Figure ID.3. Temperature Variations: Hot vs. Non-Hot Scenarios

This figure presents differences in temperatures under hot and non-hot scenarios. Hot scenarios refer to counties and years with relative heat shocks defined in Equation (1). The first two bars present the average number of days in summer with temperatures above the rolling 90^{th} percentile threshold. The second two bars present the number of days with summer temperatures above the $30°$ C. The third two bars present the average daily maximum temperature in summer.



E Labor Productivity

In this section, I first present additional figures and tables that are complementary to analyses in Table 2 and 3. I then present additional analyses to demonstrate the robustness of the results in Table 2 and 3.

E.1 Additional Analyses - Table 2 and 3

Panel (A) of Table IE.1 presents the treatment effects of heat shocks on firm-level labor productivity for firms in each exposure category (1 to 20), based on the estimation in column (5) of Table 2. Panel B of Table IE.1 presents the dynamic treatment effects. Panel (A) of Table IE.2 and Figure IE.1 presents the treatment effects of heat shocks on plant-level labor productivity for plants in each exposure category (1 to 20), based on the estimation in column (4) of Table 3. Panel B of Table IE.2 presents the dynamic treatment effects.

E.2 Robustness of Table 2 and 3

Alternative Measures of Heat Shocks. In Equation (1) and (2), I use historical temperatures from 1981 to the previous year (*1981 to t*) to estimate the 90^{th} percentile threshold and identify heat shocks, with a maximum of 30 years. By construction, the number of reference years varies, increasing from 18 in 1999 to a maximum of 30 for 2011 - 2019 period. To address the concern that variations in the reference period would bias my estimation, I conduct additional analyses using a rolling window of the past 10 or 20 years, or a fixed reference period 1981 - 2000 to estimate the 90^{th} percentile threshold. Table IE.3 and Table IE.8 present results using temperatures in the past 10 or 20 years. Results hold. I also reconstruct the measure of heat shocks by incorporating absolute temperature levels following Pankratz and Schiller (2023). Specifically, I measure heat shocks if (1) a relative short-term heat shock happens (Equation (1) and (2); and (2) a county or a firm experiences more than 30 days with absolute temperatures above 30° C in a summer. For the alternative, I require 40 days with temperatures above 30° C. Table IE.4 and Table IE.9 report the results.

Controlling for Other Climate Events. In addition to high temperatures, my measure of labor exposure also captures workers' and firms' exposures to other climate events, such as cold temperatures, precipitation, earthquakes, hurricanes, floods, wildfires, and storms. Some of these climate events affect both indoor and outdoor workers (e.g., floods, hurricanes, wildfires, storms), and some affect indoor workers more (e.g., earthquakes). These events could introduce biases against my analyses, making it harder to find significant effects of heat shocks. However, climate events like cold temperatures and precipitation primarily affect outdoor workers and thus may bias my estimation. To address this concern, in Internet Appendix Table IE.5 and IE.10, I add interaction terms of labor exposure with other climate events, including cold temperatures, precipitation, and all climate disasters reported to Federal Emergency Management Agency (FEMA). Overall, I find no effects of non-heat climate events on firm-level or plant-level labor productivity. The fact that cold temperature shocks do not affect labor productivity in summer also serves as a falsification test, further supporting my hypothesis. More importantly, after adding these controls, high temperatures still negatively affect labor productivity, and economic magnitudes are similar.

Excluding A Consumption Channel and Sector Breakdowns. High temperatures may drive consumers toward indoor activities, thereby keeping them away from stores and restaurants and leading to lower firm sales (Addoum et al., 2023). Consequently, one may argue that my findings could be influenced by consumer demand. To mitigate the concern, I redo the analyses after excluding consumer-oriented sectors in Table IE.6 columns (1) - (3). The results hold and economic effects are similar, indicating that demand-side forces do not likely drive my findings. Additionally, I further drop the agricultural sector and split firms into two broad categories: goods-producing (columns (4) - (6)) and service sectors (columns (7) - (9)). Consistent with my expectation that the outdoor workforce is a critical production input in the whole economy, I find that the effects of extreme heat exist in both categories. The evidence also demonstrates that drops in crop yields do not drive my results. More importantly, service sectors suffer larger heat-related losses in labor productivity (-4.4% at the 75^{th} percentile) relative to goods-producing sectors (2.3%), indicating that prior studies focusing on manufacturing firms might underestimate the impact of extreme heat on labor productivity.

Heat Shocks in Firm Headquarters County. Table IE.7 presents the treatment effects of short-term heat shocks that happen in firms' headquarters counties on firm-level labor productivity. Columns (1) - (5) use short-term heat shocks that happen in firms' headquarters counties, measured in Equation (1). Columns (6) - (8) further require at least at least 30 summer days with temperatures $\geq 30°C$. Columns (9) - (11) further require at least at least 40 summer days with temperatures $\geq 30°C$. Results hold.

Segment Sales. Table IE.11 presents the treatment effects of heat shocks on segment-level sales. I obtain the segment-level data on sales and assets from the Compustat segment files. The dependent variable is a segment's sales scaled by its assets, *Log(Segment Sales/Segment AT)*. I do not calculate labor productivity using the segment-level number of employees because this information is missing for most observations. Nevertheless, my analysis shows that heat shocks significantly reduce segment-level sales. The economic magnitude is also large. Segments with labor exposure at the 75^{th} percentile lose about 1.9% of sales scaled by assets following heat shocks, while segments with the highest exposure lose about 3.4%. This evidence lends further support to the results in Table 2 and 3 that unexpected high temperatures hurt corporate sales and labor productivity.

Figure IE.1. Treatment Effects of Heat Shocks on Plant-level Labor Productivity: Table 3

This figure presents the treatment effects of heat shocks on plant-level labor productivity by labor exposure category, based on the estimation in column (4) of Table 3.

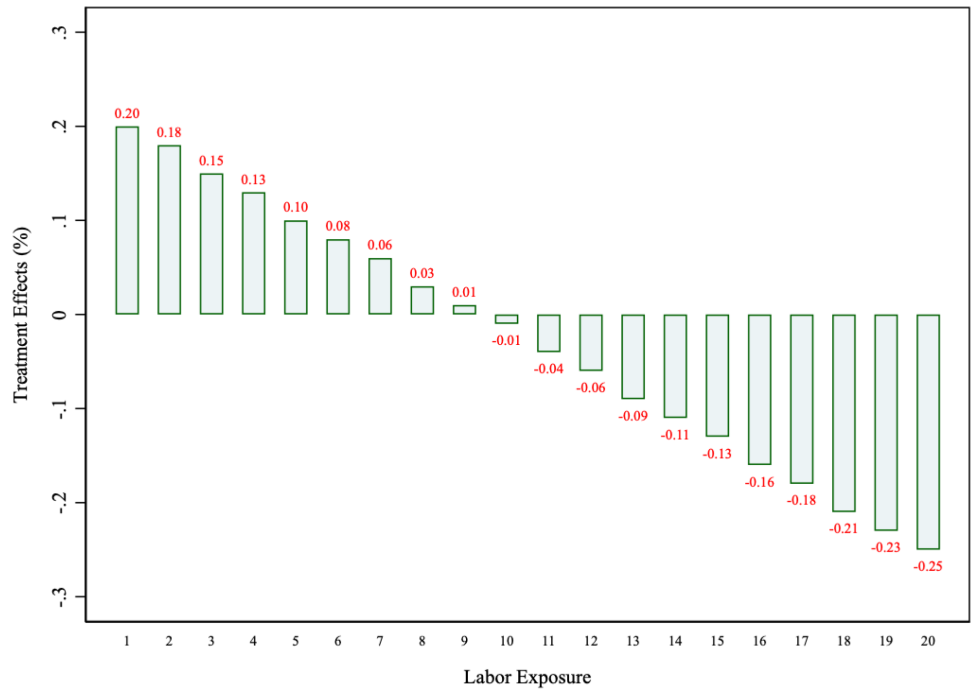


Table IE.1. Heat Shocks and Firm-level Labor Productivity: Table 2

This table presents additional tests in the setting of Table 2. Panel A presents the treatment effects of heat shocks on labor productivity by labor exposure category, based on the estimation in Table 2 column (5). Panel B presents the dynamic treatment effects.

Panel A. Treatment Effects by Labor Exposure

Labor Exposure	Treatment Effect (%)	Std. Error
1	1.1	(0.011)
2	0.9	(0.010)
3	0.6	(0.009)
4	0.4	(0.009)
5	0.2	(0.008)
6	0.0	(0.008)
7	-0.2	(0.008)
8	-0.4	(0.007)
9	-0.6	(0.007)
10	-0.8	(0.007)
11	-1.1	(0.007)
12	-1.3*	(0.007)
13	-1.5**	(0.007)
14	-1.7**	(0.008)
15	-1.9**	(0.008)
16	-2.1**	(0.009)
17	-2.3**	(0.009)
18	-2.5**	(0.010)
19	-2.7***	(0.010)
20	-3.0***	(0.011)

Panel B. Dynamic Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(Sales/Emp)						
1 (Realized ≫ Expected) (T-3) x Labor Exposure	-0.0011						
	(0.0011)						
1 (Realized ≫ Expected) (T-2) x Labor Exposure		-0.0009					
		(0.0011)					
1 (Realized ≫ Expected) (T-1) x Labor Exposure			-0.0009				
			(0.0009)				
1 (Realized ≫ Expected) (T) x Labor Exposure				-0.0021**			
				(0.0009)			
1 (Realized ≫ Expected) (T+1) x Labor Exposure					-0.0007		
					(0.0010)		
1 (Realized ≫ Expected) (T+2) x Labor Exposure						-0.0004	
						(0.0010)	
1 (Realized ≫ Expected) (T+3) x Labor Exposure							-0.0005
							(0.0010)
Observations	35,032	40,059	45,951	53,494	45,993	40,056	35,031
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.903	0.898	0.890	0.876	0.883	0.886	0.888

Table IE.2. Heat Shocks and Plant-level Labor Productivity: Table 3

This table presents additional tests in the setting of Table 3. Panel A presents the treatment effects of heat shocks on plant-level labor productivity by labor exposure category, based on the estimation in Table 3 column (4). Panel B presents the dynamic treatment effects.

Panel A. Treatment Effects by Labor Exposure

Labor Exposure	Treatment Effect (%)	Std. Error
1	0.20**	(0.010)
2	0.18*	(0.009)
3	0.15*	(0.008)
4	0.13*	(0.007)
5	0.10	(0.007)
6	0.08	(0.006)
7	0.06	(0.005)
8	0.03	(0.005)
9	0.01	(0.004)
10	-0.01	(0.004)
11	-0.04	(0.004)
12	-0.06	(0.004)
13	-0.09*	(0.005)
14	-0.11**	(0.005)
15	-0.13**	(0.006)
16	-0.16**	(0.007)
17	-0.18**	(0.007)
18	-0.21**	(0.008)
19	-0.23**	(0.009)
20	-0.25**	(0.010)

Panel B. Dynamic Treatment Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(Sales/Emp)						
1 (Realized ≫ Expected) (T-3) x Labor Exposure	-0.0001						
	(0.0001)						
1 (Realized ≫ Expected) (T-2) x Labor Exposure		-0.0000					
		(0.0001)					
1 (Realized ≫ Expected) (T-1) x Labor Exposure			-0.0001				
			(0.0001)				
1 (Realized ≫ Expected) (T) x Labor Exposure				-0.0002**			
				(0.0001)			
1 (Realized ≫ Expected) (T+1) x Labor Exposure					-0.0001		
					(0.0001)		
1 (Realized ≫ Expected) (T+2) x Labor Exposure						0.0000	
						(0.0001)	
1 (Realized ≫ Expected) (T+3) x Labor Exposure							-0.0001
							(0.0001)
Observations	1,653,870	1,939,820	2,307,504	2,769,222	2,307,470	1,939,865	1,653,878
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No
Firm x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	No	No	No	No	No	No
NAICS3 x Year FE	No	No	No	No	No	No	No
Firm x County x Year FE	No	No	No	No	No	No	No
Adjusted R^2	0.943	0.940	0.936	0.932	0.935	0.938	0.940

Table IE.3. Heat Shocks and Firm-level Labor Productivity: Rolling Windows of Past 10 or 20 Years

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity, using rolling windows of past 10 or 20 years to calculate the 90^{th} percentile threshold for each county and month. The dependent variable is the natural logarithm of a firm's sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized* $\gg$ *Expected)*), and an interaction term of the two (*1 (Realized* $\gg$ *Expected)* $\times$ *Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log(Sales/Emp)									
	10 Years					20 Years				
1 (Realized $\gg$ Expected)	-0.003	0.019**	0.020**	0.009	0.007	0.002	0.021**	0.024**	0.017*	0.018
	(0.005)	(0.009)	(0.009)	(0.008)	(0.009)	(0.006)	(0.009)	(0.010)	(0.010)	(0.011)
Labor Exposure		0.007***	0.007***	0.001			0.007***	0.007***	0.001	
		(0.003)	(0.003)	(0.002)			(0.003)	(0.003)	(0.002)	
1 (Realized $\gg$ Expected) x Labor Exposure		-0.003***	-0.003***	-0.001**	-0.002**		-0.002***	-0.003***	-0.002**	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Observations	58,711	58,711	54,489	54,399	53,494	58,711	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.876	0.858	0.858	0.859	0.871	0.876
Treatment Effect for 1 (Realized $\gg$ *Expected)* $\times$ *Labor Exposure*										
Labor Exposure=15		-0.020***	-0.020**	-0.013*	-0.018**		-0.014**	-0.015*	-0.010	-0.014*
		(0.007)	(0.008)	(0.007)	(0.007)		(0.007)	(0.008)	(0.008)	(0.008)
Labor Exposure=20		-0.032***	-0.033***	-0.020**	-0.027**		-0.025***	-0.029***	-0.018*	-0.025**
		(0.009)	(0.011)	(0.010)	(0.011)		(0.009)	(0.011)	(0.010)	(0.012)

Table IE.4. Heat Shocks and Firm-level Labor Productivity: Number of Days with Temperatures $\geq 30°C$

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity by incorporating the number of days with temperature $\geq 30°C$. Columns (1) - (5) define temperature shocks by requiring (1) the existence of a relative heat shock defined before (*1 (Realized $\gg$ Expected)*, and (2) at least 30 summer days with temperatures $\geq 30°C$. Columns (6) - (10) differs by requiring at least 40 summer days with temperatures $\geq 30°C$. The dependent variable is the natural logarithm of a firm's sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log(Sales/Emp)									
	1 (Realized $\gg$ Expected) & Days (30°C) $\geq$ 30					1 (Realized $\gg$ Expected) & Days (30°C) $\geq$ 40				
1 (Realized $\gg$ Expected)	-0.008	0.012	0.014	0.008	0.010	-0.007	0.012	0.016	0.010	0.011
	(0.006)	(0.010)	(0.012)	(0.011)	(0.012)	(0.006)	(0.011)	(0.012)	(0.011)	(0.012)
Labor Exposure		0.007**	0.007***	0.001			0.007**	0.007***	0.001	
		(0.003)	(0.003)	(0.002)			(0.003)	(0.003)	(0.002)	
1 (Realized $\gg$ Expected) x Labor Exposure		-0.002***	-0.003***	-0.002*	-0.002**		-0.002***	-0.003***	-0.002**	-0.002**
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Observations	58,711	58,711	54,489	54,399	53,494	58,711	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.876	0.858	0.858	0.859	0.871	0.876
Treatment Effect for 1 (Realized $\gg$ Expected) $\times$ Labor Exposure										
Labor Exposure=15		-0.022***	-0.026***	-0.018**	-0.022**		-0.020***	-0.026***	-0.020**	-0.026***
		(0.007)	(0.009)	(0.008)	(0.009)		(0.007)	(0.009)	(0.008)	(0.009)
Labor Exposure=20		-0.034***	-0.040***	-0.026**	-0.032***		-0.031***	-0.040***	-0.030***	-0.038***
		(0.009)	(0.011)	(0.011)	(0.012)		(0.009)	(0.012)	(0.011)	(0.013)

Table IE.5. Heat Shocks and Firm-level Labor Productivity: Controlling for Other Climate Events

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity, by controlling other climate events. Columns (1) - (3) controls for cold temperature shocks. Columns (4) - (6) controls for precipitation shocks. Columns (7) - (9) controls for all disasters reported to the FEMA. The dependent variable is the natural logarithm of a firm's sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a firm's labor exposure to other climate events (*Other Climate Events*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), and the interaction terms. Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Sales/Emp)								
	Cold Temperatures			Precipitation			FEMA Disasters		
1 (Realized » Expected)	0.016	0.011	0.013	0.016	0.012	0.013	0.016	0.012	0.013
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
Labor Exposure	0.007***	0.001		0.007***	0.001		0.008***	0.001	
	(0.003)	(0.002)		(0.003)	(0.002)		(0.003)	(0.002)	
1 (Realized $\gg$ Expected) x Labor Exposure	-0.002***	-0.002**	-0.002**	-0.002***	-0.002**	-0.002**	-0.002***	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Other Climate Events	-0.014	-0.008	-0.000	-0.007	0.003	0.002	0.002	-0.001	-0.001
	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.005)
Other Climate Events x Labor Exposure	0.002*	0.001	-0.000	0.001	0.000	-0.000	-0.001**	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	54,489	54,399	53,494	54,489	54,399	53,494	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	No	No	No	No	No	No	No	No
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
NAICS2 x Year FE	No	Yes	No	No	Yes	No	No	Yes	No
NAICS4 x Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.859	0.871	0.876	0.859	0.871	0.876	54,489	54,399	53,494
Treatment Effect for 1 (Realized $\gg$ Expected) $\times$ Labor Exposure									
Labor Exposure=15	-0.020**	-0.015*	-0.019**	-0.019**	-0.014*	-0.019**	-0.020**	-0.014*	-0.019**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Labor Exposure=20	-0.032***	-0.023**	-0.029***	-0.031***	-0.023**	-0.030***	-0.032***	-0.023**	-0.029***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)

Table IE.6. Heat Shocks and Firm-level Labor Productivity: Sector Breakdowns

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity using sector-based subsamples. Columns (1) - (3) exclude consumer-oriented sectors (*NAICS2 44, 45, 61, 62, 71, & 72*). Columns (4) - (6) focus on non-consumer-oriented good-producing sectors (*NAICS2 21, 23, 31-33, 42, 48 - 49*). Columns (7) - (9) focus on non-consumer-oriented service sectors (*NAICS2 51, 53, 54, 56, 81*). The dependent variable is the natural logarithm of a firm's sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a firm's labor exposure to other climate events (*Other Climate Events*), a dummy indicating heat shocks (*1 (Realized ≫ Expected)*), and the interaction terms. Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Sales/Emp)								
	Non-consumer-oriented Sectors			Goods-producing Sectors			Service Sectors		
1 (Realized ≫ Expected)	0.021*	0.010	0.012	0.033**	0.020	0.022	0.014	-0.000	-0.001
	(0.011)	(0.011)	(0.013)	(0.016)	(0.016)	(0.017)	(0.013)	(0.013)	(0.014)
Labor Exposure	0.006**	0.001		0.010**	0.006*		0.002	-0.000	
	(0.003)	(0.002)		(0.004)	(0.003)		(0.003)	(0.003)	
1 (Realized ≫ Expected) x Labor Exposure	-0.003***	-0.002**	-0.002**	-0.004***	-0.003**	-0.003**	-0.003***	-0.002	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	46,785	46,728	46,083	31,906	31,876	31,385	13,056	13,044	12,936
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	No	No	No	No	No	No	No	No
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
NAICS2 x Year FE	No	Yes	No	No	Yes	No	No	Yes	No
NAICS4 x Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.841	0.850	0.857	0.832	0.837	0.843	0.872	0.876	0.885
Treatment Effect for 1 (Realized ≫ Expected) $\times$ *LaborExposure*									
Labor Exposure=15	-0.019**	-0.016*	-0.023**	-0.023***	-0.021**	-0.023**	-0.036*		-0.044**
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	(0.021)		(0.021)
Labor Exposure=20	-0.032***	-0.025**	-0.034***	-0.041***	-0.034***	-0.039***	-0.053**		-0.058**
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.014)	(0.025)		(0.026)

Table IE.7. Heat Shocks and Firm-level Labor Productivity: Heat Shocks in Firm Headquarters County

This table presents the treatment effects of short-term heat shocks happened in firms' headquarters counties on firm-level labor productivity. Columns (1) - (5) use short-term heat shocks that happen in firms' headquarters counties, measured in Equation 1. Columns (6) - (8) further require at least at least 30 summer days with temperatures $\geq 30°C$. Columns (9) - (11) further require at least at least 40 summer days with temperatures $\geq 30°C$. The dependent variable is the natural logarithm of sales per employee (*Log(Sales/Emp)*). The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and the county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Log(Sales/Emp)										
	1 (Realized $\gg$ Expected)					1 (Realized $\gg$ Expected) & Days (30°C) $\geq$ 30			1 (Realized $\gg$ Expected) & Days (30°C) $\geq$ 40		
1 (Realized $\gg$ Expected)	-0.004	0.014				0.005			0.010		
	(0.007)	(0.012)				(0.013)			(0.013)		
Labor Exposure		0.007**	0.007***	0.001		0.007**	0.007***	0.001	0.007**	0.007***	0.001
		(0.003)	(0.003)	(0.002)		(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
1 (Realized $\gg$ Expected) x Labor Exposure		-0.002**	-0.003**	-0.002**	-0.002**	-0.002**	-0.003**	-0.002*	-0.002*	-0.003**	-0.002*
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	58,711	58,711	54,489	54,399	53,494	58,711	54,489	54,399	58,711	54,489	54,399
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No	Yes	No	No	Yes	No	No
County x Year FE	No	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes	No	No	Yes	No	No	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes	No	No	Yes
NAICS4 x Year FE	No	No	No	No	Yes	No	No	No	No	No	No
Adjusted R^2	0.858	0.858	0.859	0.867	0.872	0.858	0.859	0.867	0.858	0.859	0.867

Treatment Effect for 1 (Realized $\gg$ Expected) $\times$ Labor Exposure	(2)	(6)	(9)
Labor Exposure=15	-0.016**	-0.027***	-0.021***
	(0.007)	(0.007)	(0.006)
Labor Exposure=20	-0.026***	-0.038***	-0.031***
	(0.010)	(0.010)	(0.011)

Table IE.8. Heat Shocks and Plant-level Labor Productivity: Rolling Windows of Past 10 or 20 Years

This table presents robustness checks of the treatment effects of short-term heat shocks on plant-level labor productivity, using rolling windows of past 10 or 20 years to calculate the 90^{th} percentile thresholds for each county and month. This sample is at the firm by county by NAICS4 by year level using the YTS data. The dependent variable is the natural logarithm of sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) $\times$ Labor Exposure*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and the county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Sales/Emp)							
	10 Years				20 Years			
1(Realized $\gg$ Expected)	0.0033**	0.0018*			0.0036***	0.0023**		
	(0.0014)	(0.0011)			(0.0013)	(0.0011)		
Labor Exposure	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003
	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0008)	(0.0011)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.0003*	-0.0002*	-0.0003**	-0.0002**	-0.0003***	-0.0002**	-0.0004***	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,786,839	2,773,205	2,782,878	2,769,222	2,786,839	2,773,205	2,782,878	2,769,222
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Firm x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.929	0.933	0.928	0.932	0.929	0.933	0.928	0.932
Treatment Effect for 1 (Realized $\gg$ Expected) $\times$ Labor Exposure								
Labor Exposure=15	-0.0009	-0.0010*			-0.0017*	-0.0010*		
	(0.0010)	(0.0006)			(0.0009)	(0.0006)		
Labor Exposure=20	-0.0023	-0.0019*			-0.0034**	-0.0021**		
	(0.0017)	(0.0011)			(0.0015)	(0.0010)		

Table IE.9. Heat Shocks and Plant-level Labor Productivity: Number of Days with Temperatures $\geq$ 30°C

This table presents robustness checks of the treatment effects of short-term heat shocks on plant-level labor productivity by incorporating the number of days with temperature $\geq$ 30°C. This sample is constructed at the firm by county by NAICS4 by year level using the YTS data. Columns (1) - (4) define temperature shocks by requiring (1) the existence of a relative heat shock defined before (*1 (Realized $\gg$ Expected)* , and (2) at least 30 summer days with temperatures $\geq$ 30°C. Columns (5) - (8) differs by requiring at least 40 summer days with temperatures $\geq$ 30°C. The dependent variable is the natural logarithm of sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) $\times$ Labor Exposure*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and the county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Sales/Emp)							
	1 (Realized $\gg$ Expected) & Days (30°C) $\geq$ 30				1 (Realized $\gg$ Expected) & Days (30°C) $\geq$ 40			
1(Realized $\gg$ Expected)	0.0039***	0.0021*			0.0038***	0.0020*		
	(0.0013)	(0.0011)			(0.0014)	(0.0012)		
Labor Exposure	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003
	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0008)	(0.0011)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.0004***	-0.0002**	-0.0004***	-0.0002**	-0.0004***	-0.0002**	-0.0004***	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,786,839	2,773,205	2,782,878	2,769,222	2,786,839	2,773,205	2,782,878	2,769,222
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Firm x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.929	0.933	0.928	0.932	0.929	0.933	0.928	0.932
Treatment Effect for 1 (Realized $\gg$ Expected) $\times$ Labor Exposure								
Labor Exposure=15	-0.0021**	-0.0013**			-0.0023***	-0.0016**		
	(0.0008)	(0.0006)			(0.0008)	(0.0007)		
Labor Exposure=20	-0.0041***	-0.0025**			-0.0044***	-0.0028**		
	(0.0014)	(0.0010)			(0.0014)	(0.0012)		

Table IE.10. Heat Shocks and Plant-level Labor Productivity: Controlling for Other Climate Events

This table presents robustness checks of the treatment effects of heat shocks on plant-level labor productivity by controlling other climate events. Columns (1) - (4) controls cold temperature shocks. Columns (5) - (8) controls precipitation shocks. The dependent variable is the natural logarithm of sales per employee *Log(Sales/Emp)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a firm's labor exposure to other climate events (*Other Climate Events*), a dummy indicating heat shocks (*1 (Realized* $\gg$ *Expected)*), and an interaction term of the two (*1 (Realized* $\gg$ *Expected)* $\times$ *Labor Exposure*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and the county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Sales/Emp)							
	Cold Temperatures				Precipitation			
1 (Realized $\gg$ Expected)	0.0036***	0.0023**			0.0039***	0.0025**		
	(0.0013)	(0.0011)			(0.0013)	(0.0011)		
Labor Exposure	0.0007	0.0003	0.0007	0.0003	0.0008	0.0004	0.0008	0.0004
	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0008)	(0.0011)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.0003***	-0.0002**	-0.0004***	-0.0002**	-0.0004***	-0.0002**	-0.0004***	-0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Other Climate Events	-0.0009	-0.0019	0.0000	0.0000	0.0022	0.0018	0.0000	0.0000
	(0.0011)	(0.0012)	(0.0000)	(0.0000)	(0.0017)	(0.0015)	(0.0000)	(0.0000)
Other Climate Events x Labor Exposure	0.0000	0.0001	0.0000	0.0001	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Observations	2,786,839	2,773,205	2,782,878	2,769,222	2,786,839	2,773,205	2,782,878	2,769,222
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Firm x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.929	0.933	0.928	0.932	0.929	0.933	0.928	0.932
Treatment Effect for 1 (Realized $\gg$ *Expected)* $\times$ *Labor Exposure*								
Labor Exposure=15	-0.0016*	-0.0010*			-0.0017*	-0.0011*		
	(0.0009)	(0.0006)			(0.0009)	(0.0006)		
Labor Exposure=20	-0.0034**	-0.0021**			-0.0036**	-0.0023**		
	(0.0015)	(0.0010)			(0.0015)	(0.0010)		

Table IE.11. Heat Shocks and Segment-level Sales

This table presents the treatment effects of heat shocks on segment-level sales scaled by assets. The dependent variable is the natural logarithm of a segment's sales scaled by its assets, *Log(Segment Sales/Segment AT)*. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), and the interaction terms. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(Segment Sales/Segment AT)				
1 (Realized $\gg$ Expected)	-0.006	0.014	0.010	0.023**	0.019
	(0.006)	(0.010)	(0.010)	(0.011)	(0.011)
Labor Exposure		0.002	0.001	0.001	0.000
		(0.004)	(0.004)	(0.004)	(0.004)
1 (Realized $\gg$ Expected) x Labor Exposure		-0.002**	-0.002*	-0.003**	-0.002*
		(0.001)	(0.001)	(0.001)	(0.001)
Observations	71,250	71,250	71,250	68,632	68,632
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	No	No
NAICS2 x Year FE	No	No	Yes	No	Yes
County x Year FE	No	No	No	Yes	Yes
Adjusted R^2	0.646	0.646	0.673	0.633	0.663
Treatment Effect for 1 (Realized $\gg$ Expected) $\times LaborExposure$					
Labor Exposure=15		-0.022**	-0.020**	-0.019*	-0.015
		(0.010)	(0.010)	(0.011)	(0.011)
Labor Exposure=20		-0.035**	-0.030**	-0.034**	-0.026*
		(0.015)	(0.015)	(0.015)	(0.015)

F Automation

In this section, I first present additional figures and tables that are complementary to analyses in Table 4, 7, and 8. I then conduct supplementary analyses to demonstrate the robustness and heterogeneities of the results in Table 4.

F.1 Additional Analyses - Table 4, 7, and 8

Table IF.1 presents the treatment effects of medium-term heat shocks on firms' capital utilization in production by labor exposure category, based the estimation in columns (4) and (8) of Table 4.

Table IF.2 presents the treatment effects of medium-term heat shocks on firms' investments in robotics-related human capital by labor exposure category, based on the estimation in column (2) of Table 7 Panel B. "*Coefficients*" represents the regression estimation of coefficients for firms in each exposure category. "*Treatment Effect (%)*" represents the economic effects relative to the sample mean. The table shows that, for firms with exposure at the 75^{th} percentile, the demand for robotics-related human capital increases by 33.6% following heat shocks. Firms with the highest exposure increase the demand by 50.2%.

Table IF.3 presents the treatment effects of heat shocks on plant-level employment by labor exposure category, based on the estimation in column (7) of Table 7 Panel B.

Figure IF.1 and Table IF.4 presents the treatment effects of heat shocks on firms' development of automation-related technology by labor exposure category, based on the estimation in column (9) of Table 8.

F.2 Robustness of Table 4

Alternative Measures of Heat Shocks. Consistent with Internet Appendix E, I use a rolling window of past 20 years to estimate estimate the 90^{th} percentile threshold to measure medium-term heat shocks and present the results in Table IF.5. Results (*untabulated*) also hold if I use a rolling window of past 10 years or a fixed reference period 1981 - 2000. I also reconstruct the measure of heat shocks by incorporating absolute temperature levels. Specifically, I measure medium-term heat shocks if (1) a relative medium-term heat shock happens; and (2) a county or a firm experiences more than 100 days with absolute temperatures above 30° C in summer from $t-3$ to t. Table IF.6 reports the results. For the alternative, I require 120 days with temperatures above 30° C in summer. Results (*untabulated*) continue to hold.

Controlling for Other Climate Disasters. I also follow the estimates in Internet Appendix E and control for other types of climate events and report the results in Table IF.7. Consistent with the evidence in Table IE.5, I do not find that other types of climate disasters significantly affect firms' capital utilization in production.

Firm-level Measure of Labor Exposure to Climate Risk. In Table IF.8, I repeat the analyses in Table 4 but using the firm-level measure of labor exposure to climate risk (Equation (5)). Results hold.

F.3 Heterogeneity - Social Ratings

Table IF.9 presents the impact of firms' social ratings (S) on the treatment effects of medium-term heat shocks on their capital utilization in production. The data on social ratings is from the Refinitiv Environmental, Social, and Governance (ESG) database. The results show that the positive effects of heat shocks on capital-labor ratios mainly exist among firms with low social ratings. For firms that have ratings above the sample median, the effects are not statistically significant. The evidence is consistent with the notion that high-S firms care more about local communities and employee welfare and are less likely to cut workers and wages relative to low-S firms. Two things to note. First, the sample size is much smaller due to the availability of ESG ratings from the Refinitiv database. Second, medium-term heat shocks are defined as those in Table IF.6: the existence of a relative medium-term heat shock *(1 (Realized $\gg$ Expected) (M)* and at least 100 days with temperatures $\geq 30^{\circ}$C in summer from $t-3$ to t. The results are weaker if focusing relative heat shocks only (without requiring at least 100 days with temperatures $\geq 30^{\circ}$C). I use a stricter definition to increase the statistical power, considering a smaller sample size.

Figure IF.1. Treatment Effects of Heat Shocks on Automation Technology

This figure presents the treatment effects of medium-term heat shocks on firms' development of automation-related technology by labor exposure category, based on the estimation in Table 8 column (9) and Table IF.4.

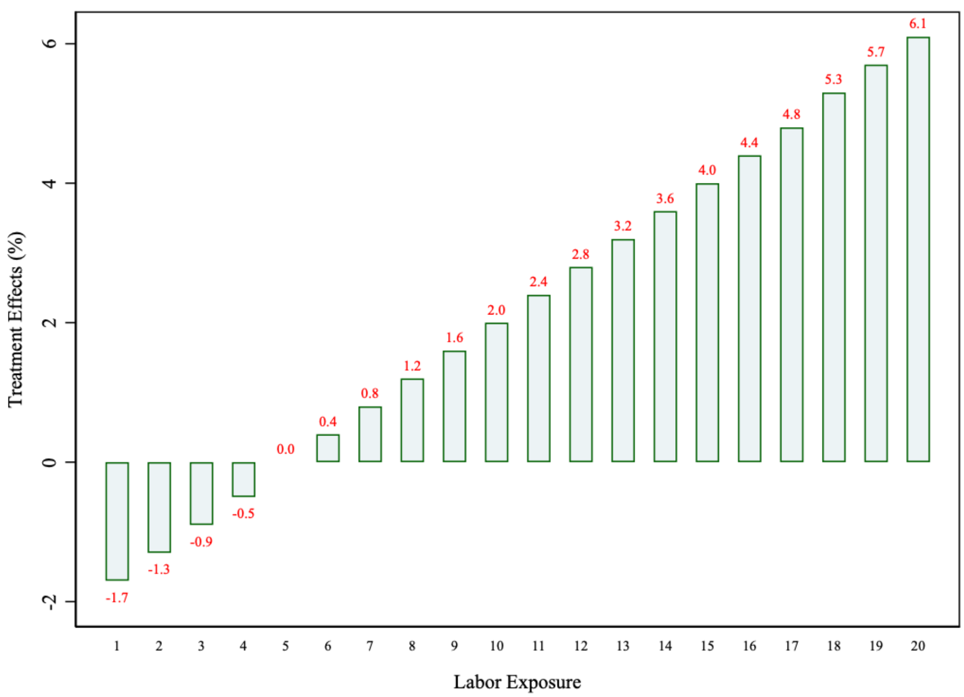


Table IF.1. Heat Shocks and Capital Utilization: Table 4

This table presents the treatment effects of medium-term heat shocks on firm-level capital utilization in production by labor exposure category, based on the estimation in column (4) and (8) of Table 4.

Labor Exposure	Log(Capital)		Log(Capital/Emp)	
	Treatment Effect (%)	Std. Error	Treatment Effect (%)	Std. Error
1	-1.0	(0.009)	-1.6*	(0.009)
2	-0.8	(0.008)	-1.3	(0.009)
3	-0.5	(0.008)	-1.1	(0.008)
4	-0.2	(0.007)	-0.9	(0.007)
5	0.2	(0.007)	-0.6	(0.007)
6	0.3	(0.007)	-0.4	(0.007)
7	0.5	(0.006)	-0.2	(0.006)
8	0.8	(0.007)	0.0	(0.006)
9	1.1	(0.007)	0.3	(0.006)
10	1.3*	(0.007)	0.5	(0.007)
11	1.6**	(0.007)	0.7	(0.007)
12	1.8**	(0.008)	0.9	(0.008)
13	2.1**	(0.008)	1.2	(0.008)
14	2.3**	(0.009)	1.4	(0.009)
15	2.6***	(0.010)	1.6*	(0.009)
16	2.9***	(0.010)	1.9*	(0.010)
17	3.1***	(0.011)	2.1*	(0.011)
18	3.4***	(0.012)	2.3**	(0.012)
19	3.6***	(0.013)	2.5**	(0.013)
20	3.9***	(0.014)	2.8**	(0.013)

Table IF.2. Heat Shocks and Investments in Robotics-related Human Capital: Table 7 Panel B

This table presents the treatment effects of medium-term heat shocks on firms' investments in robotics-related human capital by labor exposure category, based on the estimation in column (2) of Table 7 Panel B. "*Coefficient Estimation*" represents the regression estimation of coefficients for firms in each exposure category. "*Treatment Effect (%)*" represents the economic effects relative to the sample mean.

Labor Exposure	Coefficient Estimation	Treatment Effect (%)
1	-0.022	-16.3
2	-0.017	-12.8
3	-0.012	-9.3
4	-0.008	-5.8
5	-0.003	-2.3
6	0.002	1.2
7	0.006	4.7
8	0.011	8.2
9	0.015	11.7
10	0.020	15.2
11	0.025*	18.7*
12	0.029**	22.2**
13	0.034**	25.7**
14	0.038**	29.2**
15	0.043**	32.7**
16	0.048***	36.2***
17	0.052***	39.7***
18	0.057***	43.2***
19	0.062***	46.7***
20	0.066***	50.2***

Table IF.3. Heat Shocks and Plant-level Employment: Table 7 Panel C

This table presents the treatment effects of heat shocks on plant-level employment by labor exposure category, based on the estimation in column (7) of Table 7 Panel C.

Labor Exposure	Treatment Effect (%)	Std. Error
1	0.47*	(0.002)
2	0.40*	(0.002)
3	0.33	(0.002)
4	0.25	(0.002)
5	0.18	(0.002)
6	0.11	(0.001)
7	0.04	(0.001)
8	-0.03	(0.001)
9	-0.10	(0.001)
10	-0.17	(0.001)
11	-0.24**	(0.001)
12	-0.31***	(0.001)
13	-0.39***	(0.001)
14	-0.46***	(0.001)
15	-0.53***	(0.002)
16	-0.60***	(0.002)
17	-0.67***	(0.002)
18	-0.74***	(0.002)
19	-0.81***	(0.002)
20	-0.88***	(0.002)

Table IF.4. Heat Shocks and Automation Technology: Table 8

This table presents the treatment effects of medium-term heat shocks on firms' development of automation-related technology by labor exposure category, based on the estimation in column (9) of Table 8. "*Coefficient Estimation*" represents the regression estimation of coefficients for firms in each exposure category. "*Treatment Effect (%)*" represents the economic effects relative to the sample mean.

Labor Exposure	Coefficient Estimation	Treatment Effect (%)
1	-0.004	-1.7
2	-0.003	-1.3
3	-0.002	-0.9
4	-0.001	-0.5
5	0.000	0.0
6	0.001	0.4
7	0.002	0.8
8	0.003	1.2
9	0.004	1.6
10	0.005	2.0
11	0.006	2.4
12	0.007*	2.8*
13	0.007*	3.2*
14	0.008**	3.6**
15	0.009**	4.0**
16	0.010**	4.4**
17	0.011**	4.8**
18	0.012**	5.3**
19	0.013**	5.7**
20	0.014**	6.1**

Table IF.5. Heat Shocks and Capital Utilization in Production: A Rolling Window of Past 20 Years

This table presents robustness checks of the treatment effects of medium-term heat shocks on firm-level capital utilization in production, using a rolling window of past 20 years to estimate the 90^{th} percentile for each county and month. The dependent variable is the natural logarithm of total capital (*Log(Capital)*) in columns (1) - (4) and is the natural logarithm of total capital per employee (*Log(Capital/Emp)*). Total capital is the sum of a firm's property, plant, and equipment (PPENT) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized* $\gg$ *Expected) (M)*), and an interaction term of the two (*1 (Realized* $\gg$ *Expected) (M)* $\times$ *Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Capital)				Log(Capital/Emp)			
1 (Realized $\gg$ Expected) (M)	0.009	-0.011	-0.018*	-0.011	0.006	-0.020*	-0.023**	-0.011
	(0.006)	(0.008)	(0.010)	(0.010)	(0.007)	(0.010)	(0.011)	(0.011)
Labor Exposure		-0.001	-0.002	-0.004		0.003	0.004	-0.005*
		(0.002)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.003***	0.003***	0.003***		0.003***	0.004***	0.002**
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Observations	59,082	59,082	54,887	54,787	59,082	59,082	54,887	54,787
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	Yes	Yes	No	No
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	No	No	No	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.971	0.971	0.971	0.973	0.935	0.935	0.937	0.943
Treatment Effect for 1 (Realized $\gg$ *Expected) (M)* $\times$ *Labor Exposure*								
Labor Exposure=15		0.029***	0.032***	0.032***		0.032***	0.030***	0.020**
		(0.010)	(0.011)	(0.012)		(0.010)	(0.011)	(0.009)
Labor Exposure=20		0.042***	0.048***	0.046***		0.049***	0.048***	0.031**
		(0.013)	(0.016)	(0.016)		(0.014)	(0.015)	(0.013)

Table IF.6. Heat Shocks and Capital Utilization in Production: Number of Days with Temperatures $\geq$ 30°C

This table presents robustness checks of the treatment effects of medium-term heat shocks on firm-level capital utilization in production by incorporating the number of days with temperatures $\geq$ 30°C. Temperature shocks are redefined by requiring the existence of a relative medium-term temperature shock (*1 (Realized $\gg$ Expected) (M)* and at least 100 days with temperatures $\geq$ 30°C in summer from $t-3$ to t. The dependent variable is the natural logarithm of total capital (*Log(Capital)*) in columns (1) - (4) and is the natural logarithm of total capital per employee (*Log(Capital/Emp)*). Total capital is the sum of a firm's property, plant, and equipment (PPENT) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Capital)				Log(Capital/Emp)			
1 (Realized $\gg$ Expected) (M)	-0.000	-0.026**	-0.029***	-0.021*	-0.005	-0.040***	-0.047***	-0.030***
	(0.006)	(0.010)	(0.011)	(0.012)	(0.007)	(0.010)	(0.010)	(0.010)
Labor Exposure		-0.001	-0.002	-0.004		0.003	0.004	-0.006**
		(0.002)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.003***	0.004***	0.003***		0.005***	0.005***	0.003***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Observations	59,082	59,082	54,887	54,787	59,082	59,082	54,887	54,787
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	Yes	Yes	No	No
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	No	No	No	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.971	0.971	0.971	0.973	0.935	0.935	0.937	0.943
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure								
Labor Exposure=15		0.024***	0.028***	0.027***		0.028***	0.026**	0.019*
		(0.009)	(0.010)	(0.011)		(0.010)	(0.011)	(0.010)
Labor Exposure=20		0.041***	0.047***	0.043***		0.051***	0.050***	0.035**
		(0.013)	(0.015)	(0.015)		(0.014)	(0.014)	(0.014)

Table IF.7. Heat Shocks and Capital Utilization in Production: Controlling for Other Climate Events

This table presents robustness checks of the treatment effects of medium-term heat shocks on firm-level capital utilization in production by controlling other climate events. Columns (1) - (4) controls cold temperatures and Columns (5) - (8) controls precipitation. The dependent variable is the natural logarithm of total capital (*Log(Capital)*) in columns (1), (2), (5) and (6). The dependent variable is the natural logarithm of total capital per employee (*Log(Capital/Emp)*) in columns (3), (4), (7) and (8). Total capital is the sum of a firm's property, plant, and equipment (PPENT) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating hheat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Capital)		Log(Capital/Emp)		Log(Capital)		Log(Capital/Emp)	
	Cold Temperatures				Precipitation			
1 (Realized $\gg$ Expected) (M)	-0.018*	-0.012	-0.029***	-0.017*	-0.020**	-0.013	-0.031***	-0.018*
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
Labor Exposure	-0.002	-0.004	0.004	-0.005*	-0.002	-0.004	0.003	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
1 (Realized $\gg$ Expected) (M) x Labor Exposure	0.003***	0.003***	0.004***	0.002**	0.003***	0.003***	0.004***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Other Climate Events	-0.027**	-0.016	-0.033**	-0.015	-0.013	-0.009	-0.015	-0.005
	(0.013)	(0.014)	(0.013)	(0.014)	(0.019)	(0.018)	(0.014)	(0.014)
Other Climate Events x Labor Exposure	0.001	-0.000	0.003**	0.000	0.001	-0.000	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	54,887	54,787	54,887	54,787	54,887	54,787	54,887	54,787
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	No	No	No	No	No	No	No
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
NAICS2 x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.971	0.973	0.937	0.943	0.971	0.973	0.937	0.943
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure								
Labor Exposure=15	0.028***	0.027***	0.025**	0.017*	0.027***	0.025***	0.028***	0.018*
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)
Labor Exposure=20	0.043***	0.040***	0.043***	0.028**	0.043***	0.038***	0.048***	0.029**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)

Table IF.8. Heat Shocks and Capital Utilization in Production: Firm-level Measure of Labor Exposure to Climate Risk

This table presents robustness checks of the treatment effects of medium-term heat shocks on firm-level capital utilization in production by using the firm-level measure of labor exposure to climate risk. The dependent variables are the natural logarithm of total capital *Log(Capital)* in columns (1) - (4) and the natural logarithm of total capital per employee *Log(Capital/Emp)* in columns (5) - (8). Total capital is the sum of a firm's property, plant, and equipment (*PPENT*) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are the firm-level measure of labor exposure to climate risk (*Labor Exposure*), a dummy indicating medium-term heat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the firm level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Capital)				Log(Capital/Emp)			
1 (Realized $\gg$ Expected) (M)	0.006	-0.012	-0.020*	-0.008	0.002	-0.025**	-0.033***	-0.018
	(0.006)	(0.010)	(0.012)	(0.012)	(0.006)	(0.010)	(0.011)	(0.011)
Labor Exposure		-0.001	-0.000	0.000		0.003*	0.003**	0.002
		(0.001)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.002**	0.003***	0.002*		0.003***	0.004***	0.002*
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Observations	59,082	59,082	54,887	54,787	59,082	59,082	54,887	54,787
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	Yes	Yes	No	No
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	No	No	No	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.971	0.971	0.971	0.973	0.935	0.935	0.937	0.943
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure								
Labor Exposure=15		0.019**	0.023***	0.019**		0.023***	0.022**	0.012
		(0.008)	(0.009)	(0.009)		(0.009)	(0.010)	(0.009)
Labor Exposure=20		0.030***	0.037***	0.028**		0.039***	0.041***	0.022*
		(0.011)	(0.013)	(0.013)		(0.013)	(0.014)	(0.014)

Table IF.9. Heat Shocks and Capital Utilization in Production: Social Ratings

This table presents the impact of firms' social ratings on the treatment effects of medium-term heat shocks on their capital utilization in production. Data on social ratings is from the Refinitiv ESG database. 'High' and 'Low' denote high and low social ratings, respectively. The dependent variable is the natural logarithm of total capital per employee (*Log(Capital/Emp)*). Total capital is the sum of a firm's property, plant, and equipment (PPENT) and its R&D stock. R&D stock is the sum of a firm's past R&D expenses, assuming a 20% depreciation rate. The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating heat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). Note that medium-term temperature shocks are defined as those in Table IF.6. The sample period is from 2002 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Capital/Emp)							
	High				Low			
1 (Realized $\gg$ Expected) (M)	-0.032*	-0.019	-0.013	-0.003	-0.074**	-0.050*	-0.072*	-0.079**
	(0.018)	(0.016)	(0.022)	(0.026)	(0.034)	(0.029)	(0.041)	(0.038)
Labor Exposure	-0.007	-0.001	-0.009	-0.003	-0.007	0.002	-0.007	0.011
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.008)	(0.010)
1 (Realized $\gg$ Expected) (M) x Labor Exposure	0.002	0.002	-0.000	-0.000	0.010**	0.008**	0.012**	0.014***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)
Observations	6,380	6,345	5,109	5,052	6,603	6,571	5,228	5,176
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	Yes	Yes	No	No
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
NAICS2 x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.977	0.979	0.978	0.980	0.974	0.977	0.975	0.977
Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure								
Labor Exposure=15					0.076	0.066*	0.103**	0.125**
					(0.049)	(0.038)	(0.052)	(0.054)
Labor Exposure=20					0.126*	0.104*	0.161**	0.193**
					(0.073)	(0.056)	(0.076)	(0.078)

G Implications

In this section, I present additional results that demonstrate the broad implications of firms' adaptation to climate change through automation, with a focus on firms' resilience to short-term temperature threats and the macro-level consequences for industry dynamics. Detailed descriptions of the results in Table IG.1 and IG.2 are presented in Section 7. Data on industry dynamics (employment and wages) for each U.S. county is from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW) database. The QCEW program publishes a quarterly count of employment and wages covering more than 95 percent of all jobs in the U.S., available at the county, MSA, state, and national levels by industry. For this study, I use the QCEW data that covers all six-digit NAICS industries for more than 3,000 counties at the annual frequency from 1990 to 2022.

Table IG.1. Heat Shocks and Firm Resilience

This table presents results on firms' resilience to short-term heat shocks, conditional on capital utilization in production. Columns (1) - (4) focus on a subsample of firms with capital-labor ratios (*Log(Capital/Emp)*) below the industry median, and columns (5) - (8) focus on a subsample of firms with capital-labor ratio above the industry median. The dependent variable is the natural logarithm of sales per employee (*Log(Sales/Emp)*). The key independent variables are a firm's labor exposure to climate risk (*Labor Exposure*), a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) $\times$ Labor Exposure*). Controls include the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), and a dummy indicating that a firm pays dividends (*Dividend Payer*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Sales/Emp)							
	Low Capital Utilization				High Capital Utilization			
	0.026**	0.028**	0.034**	0.026*	0.003	0.010	0.008	0.005
1 (Realized $\gg$ Expected) (M)	(0.010)	(0.012)	(0.015)	(0.015)	(0.011)	(0.014)	(0.016)	(0.016)
	0.005**	0.006**	0.004	-0.000	0.007*	0.007*	0.008**	-0.002
Labor Exposure	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
	-0.003***	-0.003***	-0.004***	-0.003**	-0.001	-0.001	-0.001	-0.001
1 (Realized $\gg$ Expected) (M) x Labor Exposure	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	26,005	25,931	22,857	22,760	28,333	28,255	25,336	25,241
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	Yes	No	No	No
State x Year FE	No	Yes	No	No	No	Yes	No	No
County x Year FE	No	No	Yes	Yes	No	No	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	No	No	No	Yes
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.889	0.890	0.891	0.903	0.848	0.850	0.853	0.863

Treatment Effect for 1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure				
Labor Exposure=15	-0.015*	-0.016*	-0.023*	-0.020
	(0.008)	(0.009)	(0.012)	(0.013)
Labor Exposure=20	-0.028**	-0.030**	-0.042***	-0.036**
	(0.011)	(0.013)	(0.016)	(0.018)

Table IG.2. Heat Shocks and Industry Dynamics

This table presents the treatment effects of medium-term heat shocks on industry dynamics. The size of a NAICS4 industry in a county is measured using either total employment or total wages from the QCEW data. Panel A presents the summary statistics. In Panel B, the dependent variables are the natural logarithm of total employment (*Log(Emp)*), the annual change in the natural logarithm of total employment (Δ *Log(Emp)*), and the employment share (*(Emp Share)*). In Panel C, the dependent variables are the natural logarithm of total wages (*Log(Wages)*), the annual change in the natural logarithm of total wages (Δ *Log(Wages)*), and the wage share (*Wage Share*). The key independent variables are an industry's labor exposure to climate risk (*Labor Exposure*), a dummy indicating medium heat shocks (*1 (Realized $\gg$ Expected) (M)*), and an interaction term of the two (*1 (Realized $\gg$ Expected) (M) $\times$ Labor Exposure*). Panel A columns (1) - (3) controls *Log(Emp)* at $t-3$ and Panel B columns (1) - (3) controls *Log(Wages)* at $t-3$, as a proxy for industry size. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and the county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Summary Statistics

Variables	**N**	**Mean**	**P5**	**Median**	**P95**	**SD**
Log(Emp)	1,756,215	6.033	4.710	5.817	8.199	1.059
Δ Log(Emp)	1,626,173	0.007	-0.197	0.008	0.207	0.112
Emp Share	1,756,215	2.458	0.086	0.849	12.292	4.345
Log(Wages)	1,756,215	16.404	14.624	16.212	18.853	1.240
Δ Log(Wages)	1,626,173	0.037	-0.197	0.036	0.270	0.129
Wage Share	1,756,215	2.388	0.069	0.805	11.752	4.205
1 (Realized $\geq$ Expected) (M)	1,756,215	0.294	0.000	0.000	1.000	0.456
Labor Exposure	1,756,215	10.520	1.000	11.000	20.000	5.925

Panel B. Total Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Emp)			Δ Log(Emp)			Emp Share		
	Full Sample	EMP≤800	EMP≤400	Full Sample	EMP≤800	EMP≤400	Full Sample	EMP≤800	EMP≤400
1 (Realized ≫ Expected) (M) x Labor Exposure	-0.0006**	-0.0006**	-0.0007***	-0.0003***	-0.0003***	-0.0003***	-0.0004	-0.0010	-0.0012*
	(0.0003)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0008)	(0.0007)	(0.0007)
Observations	1,379,550	1,009,246	730,540	1,614,263	1,196,530	880,603	1,741,911	1,300,556	966,013
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.962	0.877	0.781	0.0606	0.0486	0.0429	0.972	0.975	0.980

Panel C. Total Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Wages)			Δ Log(Wages)			Wage Share		
	Full Sample	EMP$\leq$800	EMP$\leq$400	Full Sample	EMP$\leq$800	EMP$\leq$400	Full Sample	EMP$\leq$800	EMP$\leq$400
1 (Realized $\gg$ Expected) (M) x Labor Exposure	-0.0010***	-0.0011***	-0.0013***	-0.0004***	-0.0005***	-0.0004***	-0.0015*	-0.0023***	-0.0026***
	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0008)	(0.0008)
Observations	1,379,550	1,009,246	730,540	1,614,263	1,196,530	880,603	1,741,911	1,300,556	966,013
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.965	0.918	0.896	0.0678	0.0567	0.0516	0.960	0.965	0.970

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