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

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Abstract

I find that exposed firms address heat challenges by shifting toward more capital-intensive production functions, increasing capital expenditures and R&D expenses, acquiring robotics-related human capital, and developing automation-related technologies. These effects are concentrated among firms facing large long-run temperature increases and among financially unconstrained firms. I further show that reduced labor efficiency relative to capital is one important mechanism underlying capital deepening and related automation investments. Finally, these capital responses mitigate heat-induced productivity losses, and investors appear to value firms' adaptation capacity.

Keywords: Climate Change; Adaptation; Capital Deepening; Automation; Labor Productivity.
JEL Codes: D22, G30, J30, J63, O30, Q54.

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"*...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

I Introduction

High temperatures induced 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, Pankratz, and Behrer (2021) estimate that high temperatures caused approximately 360,000 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, Jones, and Olken (2009), Burke, Hsiang, and Miguel (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., LoPalo (2023)).

Despite extensive research on heat risk and economic activity, three gaps remain. First, while climate change brings numerous challenges, less is known about how firms adapt to these risks (Fankhauser (2017)). Understanding firms' adaptation strategies is essential for guiding the business community's response to a warmer climate. Second,

[1] A report by the Atlantic Council estimates that extreme heat explains around 120,000 occupational injuries in the U.S. per year, and this number could increase nearly fourfold to 450,000 without adaptation measures taken. Further, over 8,500 deaths annually are associated with average temperatures above 32°C, 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 A, I present several pieces of evidence that underscore significant heat risk in the workplace, sourced from regulators, nonprofit organizations, and media outlets.

existing evidence on the impact of heat risk on corporate performance is limited and mixed. For example, Addoum, Ng, and Ortiz-Bobea (2020) find no evidence that high temperatures affect corporate sales or labor productivity. In contrast, Pankratz and Schiller (2024) and Custodio et al. (2026) find that high temperatures reduce firm performance along supply chains. Addoum, Ng, and Ortiz-Bobea (2023) further document bidirectional effects of temperature on sales, with some firms experiencing losses and others benefiting. Third, although existing studies frequently cite labor productivity as an important channel, direct firm-level evidence examining this channel is scarce. For instance, Addoum et al. (2023) find strong support for a consumer demand channel but limited evidence for a labor productivity channel.

This paper bridges these gaps in three steps. First, I introduce a novel method to quantify a labor channel of corporate exposure to climate risk, based on firms' reliance on workers exposed to high temperatures while performing job duties. Second, through this channel, I examine firms' adaptation to heat risk through capital deepening and automation. My reasoning is that high temperatures reduce the efficiency of workers relative to capital assets, such as algorithms, computers, machines, robots, and sensors, as production inputs. Consequently, firms may use more automated capital assets and less labor in production, leading to more capital-intensive production functions. Supporting this hypothesis, I find that high-exposure firms, defined as firms with labor exposure at the 75^{th} percentile,[3] increase capital-labor ratios by 1.6%, increase capital expenditures and R&D expenses by 3.8%, invest 27.6% more in robotics-related human

[3]For simplicity, hereafter, I use "*high-exposure firms*" to refer to firms with labor exposure at the 75^{th} percentile when discussing economic significance.

capital, and are 4.4% more likely to file automation patents after heat shocks. Third, I provide direct firm-level evidence that unexpected high temperatures reduce labor productivity, with high-exposure firms experiencing a 1.9% decline following heat shocks.

Capital deepening can serve as an adaptation strategy because it allows firms to reduce reliance on workers whose productivity is exposed to high temperatures. Automated capital assets can perform tasks that would otherwise require heat-exposed labor, thereby limiting operational disruptions when extreme heat reduces worker efficiency. Unlike some adaptation strategies, such as relocation or supply chain restructuring, automation can directly alter the input mix within firms' existing production processes. Therefore, if heat risk makes labor less efficient relative to capital, firms have incentives to substitute capital for labor and adopt more capital-intensive production functions.

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 data on each occupation's exposure to changing climates from the Occupational Information Network (O*NET) program. The exposure measure is based on how often a job requires working outdoors to fulfill duties.[4] I next construct an index of labor exposure at the four-digit NAICS (NAICS4) level, calculated as the employment-weighted average of all occupations' outdoor exposures. Based on this

[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, about 53 million U.S workers were regularly exposed to high temperatures while performing job duties in 2023.

index, I create a rank variable of labor exposure to climate risk, ranging from 1 to 20, with 20 indicating the highest exposure. I further aggregate the exposure measure to the firm level using plant-level employment and industry classification data from Your Economy Time Series (YTS).

For temperature fluctuations, I obtain daily grid-level U.S. temperature data from the PRISM Climate Group. I construct a location- and time-specific measure of *heat shocks* for each county and year, defined as significant upward deviations from the county's historical temperature distributions. I aggregate this measure to the firm level using firms' geographic footprints across counties from YTS. By construction, the measure captures deviations from county- and time-specific historical temperature distributions and thus can be regarded as random draws from the distribution of temperatures within and across counties (Auffhammer et al. (2013), Dell, Jones, and Olken (2014)). Therefore, for any given firm, these shocks are plausibly exogenous.

To test the hypothesis of adaptation through capital deepening, I first 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—property, plant, and equipment plus depreciation-adjusted R&D expenses. I also use the employment-scaled total capital as the dependent variable, i.e., capital-labor ratio, which captures the use of capital assets relative to labor in the production process. My analysis reveals no effect of heat shocks on the average firm's capital utilization. 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 findings also hold after accounting for exposure to non-heat climate events and are not driven by declines in crop yields, and persist under alternative measures of capital and heat shocks. The economic magnitude is significant. Following heat shocks, high-exposure firms increase their total capital utilization by 2.6% and capital-labor ratios by 1.6%. This evidence indicates that heat risk prompts exposed firms to adopt more capital-intensive production functions to ensure a resilient production system.

Additionally, I explore cross-sectional heterogeneity in firms' capital deepening responses to heat challenges. I first find that heat shocks increase capital-labor ratios only among high-exposure firms operating in counties with significant projected long-term temperature increases. This evidence supports the prediction that firms respond primarily to heat threats that increasingly jeopardize their operations as climate change intensifies. Second, consistent with the notion that labor unions increase workers' bargaining power and limit firms' flexibility in workforce management, exposed firms increase capital intensity after heat shocks only in highly unionized industries. Third, the positive effects of heat shocks on capital-labor ratios arise only among high-exposure firms with low social ratings, suggesting that these firms may place less weight on employee welfare and are thus more likely to substitute capital for labor. Fourth, consistent with prior research showing that low-skilled tasks are easier to automate (Graetz and Michaels (2018)), heat shocks significantly affect capital-labor ratios only among exposed firms that predominantly employ low-skilled workers. Fifth, capital deepening after heat shocks occurs primarily among less complex exposed firms, as they are more agile in changing production inputs. Finally, the positive effects of heat shocks on capital utilization are concentrated among exposed firms with low financial constraints.

Moreover, to better understand how firms shift toward capital-intensive production functions, I examine their investments in physical capital assets and automation-related human capital. My analysis reveals that high-exposure firms increase capital expenditures and R&D expenses by 3.8% and post 27.6% more robotics-related jobs following heat shocks. Furthermore, I investigate firms' innovation in automation-related technologies as part of the automation process. Using the classification of automation-related patents from Mann and Püttmann (2023), I find that the probability of filing at least one automation patent within three years after heat shocks increases by 4.4% for high-exposure firms.

As additional evidence, I examine firms' disclosures of automation-related initiatives in 10-K filings. I find that heat-exposed firms discuss automation more frequently after heat shocks, particularly in contexts related to adaptation and risk mitigation. This evidence further supports the interpretation that firms use automation as an adaptation strategy to address heat-related challenges. Taken together, the findings on production functions, capital expenditures and R&D expenses, robotics-related human capital, automation technology, and automation disclosures provide consistent evidence that firms resort to automation to address escalating labor risks associated with high temperatures.

I further study labor productivity as one possible mechanism underlying firms' automation responses. If heat risk reduces the efficiency of exposed workers, high-exposure firms should experience larger productivity losses following heat shocks, creating incentives to substitute capital for labor. Consistent with Addoum et al. (2020), the population average effect of high temperatures on labor productivity is zero. However, firms with substantial heat exposure through the labor channel experience significant reductions in labor productivity following heat shocks. The findings remain robust after including an extensive set of fixed effects that control for firm-, county-, and industry-level heterogeneity. The results also hold after accounting for non-heat climate events and are not driven by consumer demand or declines in crop yields. The results further hold under alternative measures of heat shocks and in plant-level and segment-level analyses. The effects are economically significant as well: high-exposure firms experience a 1.9% decline in labor productivity after heat shocks. This evidence suggests that extreme heat reduces the productivity of exposed workers and, consequently, affects the subset of firms that rely on these workers for production and operating activities.

Finally, I turn to whether capital deepening mitigates the adverse effects of heat risk and whether investors value firms' adaptation efforts. If capital deepening helps firms address heat-related production disruptions, firms with more capital-intensive production functions should be less adversely affected by unexpected high temperatures. Consistent with this prediction, I find that the negative effects of heat shocks on labor productivity appear only among firms with below-median capital-labor ratios, while firms with above-median ratios do not experience significant declines, indicating greater operational resilience. I further find that heat shocks reduce the stock returns of exposed firms, but the effect is significantly weaker for firms with higher capital-labor ratios. These findings suggest that capital deepening can serve as an effective adaptation strategy and that investors appear to value firms' adaptation capacity.

II Related Literature

A Adaptation to Climate Change

This paper relates to research on adaptation strategies adopted by economic agents to mitigate climate risks (e.g., Fankhauser (2017), Behrer and Park (2017), Lai et al. (2023)). Despite extensive discussion in other fields, research on adaptation behavior in the business sector remains limited, with a few exceptions. Somanathan et al. (2021) show that climate controls can eliminate plant-level productivity declines caused by high heat in India, while Heyes and Saberian (2019) document limited effects. However, these studies focus on indoor environments where climate controls, such as air conditioning, can be implemented, rather than outdoor settings, where doing so is costly or impossible (Dillender (2021)). In addition, Pankratz and Schiller (2024) show that firms mitigate heat risk through supply chain management, while Acharya, Bhardwaj, and Tomunen (2024) document workforce reallocation as a response to heat. In contrast, I show that firms increase capital deepening and automation as adaptation strategies to mitigate heat risk, thereby reducing labor productivity losses and increasing firm value. Consequently, this paper responds to the call for more research on adaptation to climate change (Fankhauser (2017)).

Xiao (2023) shows that firms increase announcements of automation-related investments following high temperatures. This study differs by (i) focusing exclusively on outdoor heat and excluding production-generated heat unrelated to climate change; (ii) using comprehensive grid-level daily temperature data to identify abnormal heat based on past temperature distributions; (iii) examining firms' adaptation through changes in capital-labor intensity, capital expenditures and R&D investments, robotics-related human capital, automation technologies, and automation disclosures in 10-K filings; and (iv) studying the implications of these adaptations for firm resilience and market value.

B Climate Change, Heat Risk, and Labor Productivity

This paper also contributes to the growing climate finance literature by deepening our understanding of how climate change, particularly high temperatures, affects firms' production activities. It develops a novel measure of firms' climate exposure from a labor perspective, enabling firm- and plant-level analyses of how heat risk affects labor productivity, an area in which existing evidence remains mixed. For example, Addoum et al. (2020) find no evidence that high temperatures affect the sales or labor productivity of U.S. firms and plants. Other studies show that increased temperatures reduce firms' operating performance (Pankratz, Bauer, and Derwall (2023)) and that these effects transmit along supply chains (Pankratz and Schiller (2024), Custodio et al. (2026)). In addition, while existing studies frequently cite labor productivity as an important channel, direct firm-level evidence on this channel is scarce. My study provides evidence that heat risk reduces labor productivity in U.S. firms and plants, but only among those with significant temperature exposure through the labor channel. This evidence supports reduced labor efficiency relative to capital as one potential mechanism underlying firms' capital deepening and related automation investments in response to heat challenges.

III Conceptual Framework

A Climate Change, Workplace Safety, and Labor Efficiency in Production

Heat exposure can cause a variety of heat-related illnesses, such as heat cramps and heat stroke (Luber and McGeehin (2008), Mora et al. (2017)). As global warming intensifies, rising temperatures will increasingly threaten workers' health (Dillender (2021), Park et al. (2021)), impairing their physical and cognitive abilities (Heyes and Saberian (2019), Park et al. (2020)), and ultimately their productivity (Chen and Yang (2019), LoPalo (2023)). 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)).

Studies also show that exposed workers reduce working time during hot days, implying a contraction in labor supply (Graff Zivin and Neidell (2014), Dillender (2021), Somanathan et al. (2021)). To attract and retain workers, firms must offer either more pecuniary compensation or non-pecuniary benefits, such as cooling services, to alleviate heat risks. Failure to do so would expose firms to significant reputational damage and litigation risks if workers suffer injuries or fatalities (Ortiz-Molina, Xiao, and Zheng (2026)).

These findings identify four channels through which heat risk may reduce the efficiency of labor as a production input: (i) lower productivity at work, (ii) reduced labor supply, (iii) higher non-wage labor costs, and (iv) greater reputational and litigation risks. While the neoclassical economic framework posits that labor inputs are fully flexible and have little impact on firms' operations, the reality is different; firms face frictions that impede their labor adjustments. Labor unions, for instance, often intervene in firms' wage and firing decisions. Regulations on labor protection further limit firms' discretion in adjusting wages and workforce. These rigidities increase firms' operating leverages and decrease their values. Therefore, high temperatures reduce labor efficiency in production and push up firms' *production costs per unit of output*.

B Adaptation to Climate Change Through Capital Deepening and Automation

Heat-induced reductions in labor efficiency create incentives for firms to adjust production processes and build more resilient operations. Moreover, salient heat events lead managers to update their beliefs about climate change and pay greater attention to climate risks (e.g., Sisco, Bosetti, and Weber (2017), Choi, Gao, and Jiang (2020)), further motivating adaptation. This raises the question of how firms adjust their production strategies in response.

Automation offers one potential solution, as firms across industries have developed equipment that can operate in extreme conditions. For instance, manufacturers use Computer Numerical Control (CNC) machinery and robotic arms, while chemical and pharmaceutical firms use robots to transfer and process hazardous materials. By delegating tasks to resilient automated equipment, firms can increase productivity while protecting workers in challenging conditions (e.g., Bellingham and Rajan (2007), Gihleb et al. (2022)). Similarly, firms can deploy automation assets to address heat-related threats to production. These assets need not be "green" or climate-specific; as long as they can replace heat-exposed workers and operate effectively under high temperatures, firms can use them as substitutes for labor.[5]

[5]For example, instead of using workers to inspect high-voltage power lines, power companies can use specialized robots that are less affected by high temperatures. A robot named "Expliner" was developed by a Japanese company, Hibot, to inspect high-voltage power lines in 2010. In additional, the oil industry

Notably, the feasibility of adaptation through automation rests on three assumptions. The first is that extreme heat impacts the performance of capital assets less than that of workers.[6] The second is that automation serves as a key strategy for firms to mitigate temperature challenges.[7] The third is that the costs of using capital assets in production are lower than those of using exposed labor.[8] Crucially, if any of the assumptions is violated, I should not find significant effects of heat risk on automation. Put differently, if capital assets prove unreliable or too costly in hot conditions, or if firms predominantly use strategies other than automation to address heat risks, the effects on automation should not be observable in the data.

In summary, heat risk reduces labor efficiency relative to capital in production. Firms can address this challenge by shifting toward more capital-intensive production functions. As extreme heat becomes more frequent and severe, heat-exposed firms are expected to further enhance automation.[9]

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may deploy robots and sensors to monitor the operating status of their pipelines and detect leaks, thereby reducing the need for field workers. Logistics companies can leverage automatic sorting machines and autonomous vehicles to distribute packages more efficiently without exposing workers to excess heat.

[6] Somanathan et al. (2021) show that heat-related damage to labor productivity, rather than capital efficiency, explains most output losses. Nevertheless, direct disruptions to capital assets may also incentivize firms to invest in new capital. For example, firms may upgrade to more energy-efficient capital in response to higher energy costs, replace equipment that deteriorates more quickly under extreme heat, or invest in heat-resistant equipment to mitigate downtime and maintenance costs. These channels, however, are unlikely to operate through the labor channel, which is the primary focus of this paper.

[7] In practice, firms may use other adaptation strategies, such as climate controls, relocation, supply chain management, outsourcing, or modified work schedules. While these approaches are also important, this paper focuses on automation and leaves other adaptation strategies for future research.

[8] However, high temperatures may also increase capital costs. Capital assets may require more maintenance and repair during high-temperature periods. Extreme heat may also raise energy demand, increasing oil and electricity prices. In addition, market-wide demand for specific capital assets may increase their prices.

[9] In equilibrium, both demand- and supply-side forces could drive the progress toward automation. 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 falls below expectations or firms fail to implement sufficient protective measures. On the supply side, firms may voluntarily reduce the use of exposed workers due to rising climate risks and labor costs. Disentangling the two sides and identifying the contribution of each are interesting but are beyond the scope of this paper.

IV Data, Measures, and Sample

A 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 also excluded. 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.

B Plants

Data on the distribution of a firm's plants across locations come from the Your Economy Time Series (YTS) database, provided by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin. YTS provides detailed establishment-level information, including plant location (e.g., county and ZIP code), industry classification (e.g., NAICS code), place type (e.g., headquarters, subsidiary, or independent), employment, sales, and parent company identifiers. The dataset is constructed from Data Axle (formerly Infogroup) business records and links establishments over time using unique identifiers (American Business Identifiers, ABIs) to create a longitudinal panel.[10] The data are available annually from 1997 and have been widely used in academic research and policy analysis, including Ghent (2021), Campello et al. (2022), Flynn and Ghent (2022), Coyne and Johnson (2023), and Arefeva

[10] YTS focuses on establishments verified to be operating or intending to conduct business activities, excluding entities such as paper companies and other organizations that do not represent active economic operations, including entities created solely for financial, real estate, or tax reporting purposes. The database also incorporates additional information from external sources and applies further verification procedures to improve the consistency of employment, industry, and establishment relationship variables.

et al. (2025).[11]

In this study, YTS is used to identify the geographic locations, industry classifications, and employment levels of firms' plants. Because the underlying Data Axle records rely on verified business addresses and the analysis uses county-level geographic information rather than finer spatial measures, the location information is generally reliable. Data Axle assigns industry classifications based on Yellow Pages headings and verifies businesses through telephone interviews to confirm their accuracy, and YTS further refines these classifications. In addition, plant employment is used primarily as a size weight when aggregating county-level heat risk to the firm level; therefore, moderate measurement error in employment is unlikely to materially affect the estimation results.[12]

C Labor Exposure to Climate Risk

To quantify corporate exposure to climate risk through a labor channel, I first obtain data on occupations from the Occupational Employment and Wage Statistics (OEWS). This data includes occupations needed in each industry and the number of employees working in each occupation. Then, I collect data on each occupation's current and historical exposures to climate conditions from the Department of Labor's Occupational Information Network (O*NET) program. This study uses the survey that

[11]The data and detailed documentation are available at https://youreconomy.org/yts-database.html. More studies using YTS data can be found at https://youreconomy.org/download/recentpubs.pdf. In addition, Kunkle (2018) compares YTS with government employment datasets, including the Current Employment Statistics (CES) and the Current Population Survey (CPS), and finds that YTS produces employment levels that closely match CPS aggregates while capturing employment dynamics during economic downturns in a manner similar to CES.

[12]It is important to note that more than half of the employment figures in YTS are estimated. In addition, YTS employment counts include all individuals working at an establishment, including both full-time and part-time employees.

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?*" A higher score indicates greater exposure to climate conditions while performing job duties.[13]

Using these two datasets, I construct a labor exposure to climate risk index as follows:

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

where i denotes industry, o denotes occupation, and t denotes year. $O_{i,t}$ is the total number of occupations industry i has in year t. $Score_{o,t}$ is the occupational score of outdoor activity. $Emp_{i,o,t}$ is the number of employees working in occupation o in industry i in year t. $Emp_{i,t}$ is the total number of employees in industry i in year t. This index is therefore the employment-weighted average outdoor exposure across occupations within a NAICS4 industry. I then create a rank variable $Labor\ Exposure_{i,t}$, ranging from 1 to 20, with 20 indicating the highest exposure.

In Internet Appendix B, Figures IB.1, IB.2, and IB.3, and Table IB.2 present distributions of the exposure measure across sectors, labor skills, and counties. A key takeaway is that significant variations exist in workers' climate exposures within and across sectors, skill levels, and counties, indicating that this measure does not simply capture sector-, skill-, or county-specific heterogeneities. The widespread presence of high-exposure occupations and industries suggests that high temperatures have a

[13] 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 more details on the underlying datasets, the selection of occupational characteristics, and the construction and validation of the measures, refer to Internet Appendix Section B.

comprehensive impact on the entire economy. Further, in Internet Appendix Section C (Figures IB.4, IB.5, IB.6, IB.7, and IB.8), I validate the labor exposure measure by showing that managers of high-exposure firms discuss more climate issues in earnings conference calls and 10-K filings, suggesting that dependence on outdoor workers exposes firms to significant climate risks. Additionally, this labor channel can not be fully explained by other measures of climate exposures developed in the literature or by Trucost Climate Analytics. This evidence highlights the importance of, and lays the foundation for, studying corporate exposure to climate change and adaptation through a labor channel.

YTS assigns each plant an industry classification based on its business operations. I aggregate labor exposure to the firm level using plant-level employment and NAICS4 codes from YTS as follows:

$$Labor\ Exposure_{f,t} = \sum_{i=1}^{I_{f,t}} \left(\frac{Emp_{f,i,t}}{Emp_{f,t}} \times Labor\ Exposure_{i,t} \right) \tag{2}$$

where f denotes firm, i denotes NAICS4 industry, and t denotes year. $I_{i,t}$ is the number of industries in which firm $f's$ plants operate. $Emp_{f,i,t}$ is firm $f's$ employment in industry i. $Emp_{f,t}$ is firm $f's$ total employment. $Labor\ Exposure_{i,t}$ is the industry-level labor exposure measure in Equation (1). The firm-level labor exposure is therefore the employment-weighted average of industry-level exposure across a firm's NAICS4 industries. I also construct a labor skill measure based on O*NET job zones using the same method.

D Heat Shocks

I obtain data on daily temperatures and precipitation for 1981—2022 from the PRISM Climate Group. 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 precipitation levels. I aggregate the grid-level information to the county level.[14]

This paper examines how *unexpected high temperatures* affect firms' labor productivity and adaptation strategies conditional on their labor exposures. To do so, I construct a measure of *heat shocks*, conceptually similar to the abnormal heat measure in Addoum et al. (2020) and the abnormal snow measure in Brown, Gustafson, and Ivanov (2021). This approach improves upon the use of temperature levels by accounting for firms' dynamic adaptations to local climate conditions, such as adjustments in production processes and locations.[15]

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, 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., *Realized Temperatures* $\geq 90^{\text{th}}$ *Percentile*. Third, since the subsequent empirical analyses are conducted at the yearly level, I aggregate the number of hot days during summer months each year to create a measure that captures significant upward shifts in temperature distributions compared to historical data.[16]

[14] I use the county as the geographic unit of analysis due to the broad distribution of firms' production and operational locations, particularly in outdoor-dependent industries. For instance, workers at logistics firms may travel tens to hundreds of kilometers while performing their duties.

[15] Jones et al. (2026) show that empirical approaches based on temperature levels or discrete temperature bins can generate spurious findings. This occurs because global warming induces systematic trends in extreme temperatures that are mechanically correlated with a location's baseline climate. If outcome variables also trend with baseline temperature for unrelated reasons, estimates based on temperature levels or bins may be substantially biased.

[16] 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. Nevertheless, the results remain robust after controlling for abnor-

Specifically,

$$(3) \qquad 1(Realized \gg Expected)_{c,t} = \begin{cases} 1 & \textit{No. Hot Days } [Realized\ Temperatures_{c,t} \geq 90^{th}\ Percentile_{c,t}] \geq T \\ 0 & Otherwise \end{cases}$$

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.

This method identifies hot days in a *relative* sense by comparing current temperatures to historical temperatures in the same county-month. For each 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.[17] 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 10 signify unexpected heat risk.[18] 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 10 days, which identifies the top-quartile cases with

mally high temperatures outside the summer season.

[17] 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).

[18] Internet Appendix Figure IC.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 in Figure IC.2.

severe relative heat shocks.[19]

[Insert Figure 1 here]

Figure 1 presents the average number of relative hot days for each county in the continental U.S. across years. The occurrence of relative hot days is not concentrated in any specific county but instead occurs in different counties over time. Therefore, for any given firm, heat shocks are plausibly exogenous and randomly distributed across its operating locations, making it difficult for firms to take precautionary actions *ex ante*.[20]

I aggregate county-level heat shocks to the firm level using plant-level employment and location data from YTS as follows:

$$1(Realized \gg Expected)_{f,t} = \begin{cases} 1 & \textit{No. Hot Days}_{f,t} \geq T\text{=}15 \\ 0 & \textit{Otherwise} \end{cases} \tag{4}$$

$$\textit{No. Hot Days}_{f,t} = \sum_{c=1}^{C_{f,t}} \left(\frac{Emp_{f,c,t}}{Emp_{f,t}} \times \textit{No. Hot Days}\left[\textit{Realized Temperatures}_{c,t} \geq 90^{th}\ \textit{Percentile}_{c,t}\right] \right) \tag{5}$$

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

[19] The mean, the 25^{th} percentile, the median, the 75^{th} percentile, and the 90^{th} percentile of the number of days exceeding the 90^{th} percentile temperature threshold are 10, 3, 8, 14 and 22, respectively. Although this choice of T may seem arbitrary, in the empirical analysis, I use temperature bins and alternative threshold choices to demonstrate that the heat effects on labor productivity become significant around this threshold. In addition, it's worth emphasizing that setting $T = 15$ does not simply mean 5 additional hot days in a summer. Instead, it implies significant heat intensification.

[20] These relative heat shocks also capture high summer temperatures in an absolute sense. For example, Figure IC.3 shows that the average number of days above the county-month-specific 90^{th} percentile is 22 in relative hot summers (T $\geq$ 15) and 6 in non-hot summers (T $<$ 15). The number of days with temperatures above the 30°C is 60 and 42, respectively, indicating that relative heat shocks correspond to high absolute temperatures as well. Furthermore, the average daily maximum temperatures are 31°C and 29°C, respectively. Prior research suggests that labor productivity declines at temperatures above 24°C and declines sharply beyond 29°C (e.g., Seppanen, Fisk, and Lei (2006), Graff Zivin and Neidell (2014)). Additionally, in the empirical part, I combine relative temperature shocks with absolute temperature levels (30°C) to refine the analysis and show the robustness of the findings.

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 $T = 15$ to define heat shocks at the firm level.

Additionally, I construct a county-level measure of cumulative medium-term heat shocks, *1(Realized* $\gg$ *Expected)(M)*, following Equations (3) and (4), with two modifications, in order to capture the gradual intensification of unexpected heat risk over time that may trigger adaptation responses. First, I calculate the total number of relatively hot days in summers over the period from $t - 3$ to t. Second, I set the threshold at $T = 45$, relative to the benchmark of 40, to define medium-term heat shocks, i.e., *No. Hot Days*$_{t-3,t} \geq 45$.[21] This threshold corresponds to approximately a 12.5% increase relative to historical temperature distributions, or at least one significant short-term heat shock over the period, i.e., $45 = 15 + 10 + 10 + 10$.

E Additional Data

Temperature Projections. County-level long-term temperature projections are sourced from the Centers for Disease Control and Prevention (CDC). 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), which applies a machine learning algorithm to all U.S. patents granted from 1976

[21] The mean, 25th percentile, median, 75th percentile, and 90th percentile of the total number of relatively hot days are 40, 25, 38, 46, and 67, respectively. Thus, the threshold captures the top quartile of severe relative heat shocks, consistent with setting $T = 15$ for short-term heat shocks.

to 2014 to identify automation-related patents, i.e., 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.

F Sample and Summary Statistics

The final empirical sample spans the period 1999—2019.[22] Table 1 reports summary statistics for key variables used in empirical analyses. The average use of capital and capital per employee are 4.914 and 4.364, respectively. The mean and median of firm labor productivity are 4.144 and 4.100, with a standard deviation of 0.835. Meanwhile, 18.6% of firms are exposed to short-term temperature shocks, while 27.4% are exposed to medium-term ones. The average rank of labor exposure to climate risk is 8 at the NAICS4 industry level.

[Insert Table 1 here]

V Adaptation Through Capital Deepening and Automation

Section III discusses the rationale underlying firms' adaptation to heat risk through automating tasks performed by heat-exposed workers. Because automation requires greater use of capital and therefore raises capital intensity in production (e.g., Brozen (1957), Karabarbounis and Neiman (2014), Acemoglu and Restrepo (2019), Acemoglu and Restrepo (2020)), I examine firms' use of capital assets—such as algorithms, computers, equipment, machines, robots, and sensors—as well as related investments, including capital expenditures, R&D, the acquisition of robotics-related

[22] I choose 1999 as the starting year due to the availability of the labor exposure measure and the limited discussion of climate change in financial markets and firms prior to 2000. The sample ends in 2019 to avoid potential production disruptions caused by the COVID-19 pandemic. For example, industries with larger shares of outdoor workers may have been less affected by COVID-19 because maintaining social distance is easier for outdoor workers.

human capital, and the development of automation-related technologies. I also examine firms' disclosures of automation initiatives following heat shocks.

A Empirical Methodology

Adaptation through automation can be costly, time-consuming, and challenging. For example, dismissing workers displaced by automation can be onerous, particularly in the presence of labor unions and regulations. Adopting new capital assets requires substantial financial resources and the hiring and training of skilled workers capable of operating them. Consequently, firms might not resort to automation immediately or fully after a one-time short-term heat shock. Instead, they adjust production inputs gradually over time as they perceive persistent medium- or long-term temperature risks. To capture this gradual adjustment, I examine firms' automation responses to medium-term heat shocks using the following empirical specification.

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

where f denotes firm, c denotes headquarters county, i denotes two-digit NAICS (NAICS2) industry code, and t denotes year. Y is the dependent variable measuring a firm's automation progress. *1 (Realized ≫ Expected) (M)* is a dummy indicating firm $f's$ exposure to medium-term heat shocks. *Labor Exposure* measures firm f's average exposure to climate risk through the labor channel, as defined in Equations (1) and (2), over the period from $t-3$ to t. $\boldsymbol{X}$ 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 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 fixed effects that control for time-varying growth trends of industry i.

B Capital Utilization in Production

1 Main Results

Table 2 examines how firms adjust their use of capital in production following heat shocks. Columns 1–4 use the natural logarithm of total capital, *Log(Capital)*, as the dependent variable. Total capital is defined as 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, capturing the accumulation of intangible research capital that supports automation.[23] Columns 5–8 use the natural logarithm of employment-scaled total capital, *Log(Capital/Emp)*, as the dependent variable. This measure captures the capital-labor ratio, reflecting firms' use of capital relative to labor in production. A higher ratio indicates a more capital-intensive production function and a higher degree of automation (Brozen (1957)).

[Insert Table 2 here]

In columns 1 and 5, the estimated coefficient on heat shocks, *1 (Realized* $\gg$ *Expected) (M)*, is positive but statistically insignificant, indicating that heat shocks do not

[23] This is consistent with the evidence in Table 6, which shows that firms generate more automation patents during the adaptation process. The results also hold when R&D capital is excluded, as shown in Internet Appendix Table ID.2.

affect capital utilization for the average firm. In columns 2, 3, 6, and 7, the coefficient on *1 (Realized $\gg$ Expected) (M)* becomes negative and significant, suggesting that *a hypothetical firm with zero exposure* reduces capital utilization after heat shocks.[24]

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) $\times$ Labor Exposure* remains. The economic magnitude is 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 are reported in Internet Appendix Table ID.1. Overall, these findings demonstrate that past heat shocks prompt exposed firms to enhance their capital utilization in production processes, as evidenced by a significant increase in total capital and capital-labor ratios.

2 Robustness Checks and Ruling Out Alternative Explanations

Internet Appendix Section D presents additional analyses to demonstrate the robustness of the capital utilization results in Table 2 and to rule out alternative explanations. I

[24] Firms with *Labor Exposure = 1*, the minimum observed exposure level, either do not change capital utilization or only marginally decrease their capital-labor ratios. See Internet Appendix Table ID.1 for more detailed estimates. The marginal negative effects on capital utilization for firms with *Labor Exposure =1* may be driven by the rescheduling of work activities discussed in Footnote 30, which enhances the efficiency of labor in production during high temperatures and reduces the need for capital upgrades.

briefly discuss these results below.

Measurement of Capital Excluding R&D Capital. In Table ID.2, I reconstruct the measures of total capital utilization and capital-labor ratios using PPENT only, excluding depreciation-adjusted R&D expenses. The results remain consistent.

Accounting for Temperature Levels. In Table ID.3, I reconstruct the measure of heat shocks by incorporating absolute temperature levels, i.e., number of summer days above 30°C from $t-3$ to t. The results hold, and the economic magnitudes are larger.

An Alternative Rolling Window to Define Heat Shocks. In Table ID.4, I use a 20-year rolling window, instead of a 30-year window, to estimate the 90^{th} percentile threshold for measuring heat shocks. The results remain consistent, with larger economic magnitudes.

Heat Shocks in Firm Headquarters County. Table ID.5 focuses on headquarters-county heat shocks and the results are largely consistent.

Controlling for Other Climate Events. In Table ID.6, I repeat the analysis by controlling for other types of climate events. In Panel A, I control for cold temperature shocks and total precipitation, while in Panel B, I account for heat shocks occurring outside the summer season and all disasters reported by FEMA. I find no significant effects of these non-heat climate events on firms' capital utilization in production. The effects of heat shocks on capital utilization remain robust, with similar economic magnitudes.

Sector Breakdowns and Excluding A Consumer Demand Channel. I exclude agricultural and consumer-oriented industries in Table ID.7 and non-tradable industries in Table ID.8. The results continue to hold, with similar economic magnitudes, suggesting that the findings on heat-induced capital deepening are not driven by the consumer demand channel or by declines in crop yields.

Alternative Measures of Labor Exposure. Table ID.9 repeats the analysis using the firm-level measure of labor exposure defined in Equation (2), and Table ID.10 reports robustness checks using a continuous measure of labor exposure instead of the rank-based measure. The results hold in both analyses.

3 Heterogeneity

I further explore cross-sectional heterogeneity in the effects of heat shocks on firms' capital utilization in production to better understand the underlying economic mechanisms.

[Insert Table 3 here]

First, I examine the role of projected long-term temperature increases in firms' operating locations. The capital response should be concentrated in locations with large projected temperature increases, where current heat shocks are more likely to signal persistent and worsening future heat risk. In these areas, firms have stronger incentives to reorganize production processes and invest in automated capital assets to improve operational resilience. By contrast, when projected temperature increases are limited, firms may view current heat shocks as less informative about future operating conditions and therefore have weaker incentives to adapt. To test this conjecture, I categorize firms into two groups based on whether projected temperature increases in their operating counties are above or below the sample median. I then examine the effects of heat shocks on capital utilization separately for each group. The analysis in columns 1 and 2 of Panel A of Table 3 shows that the interaction term between heat shocks and labor exposure is positive and statistically significant only for firms in counties with large projected temperature increases, whereas the estimate is insignificant for firms in counties with small projected increases.

Second, I examine the impact of labor unions. Prior studies show that automation increases more in firms with limited flexibility in workforce management, often driven by labor unions that strengthen workers' bargaining power. For example, labor unions can protect employees from wage cuts and layoffs, even when their performance decreases during high temperatures. Consequently, in industries with high unionization rates, firms are incentivized to augment capital utilization in response to heat challenges. Table 3 Panel A columns 3 and 4 show that heat shocks positively affect the capital-labor ratios of exposed firms only in highly unionized industries.[25]

Third, I examine the impact of firms' social ratings (S). I hypothesize that the incentive for capital deepening is stronger in low-S firms, which care less about local communities and employee welfare and are thus more likely to cut workers and replace them with capital assets. I obtain data on social ratings from the Refinitiv Environmental, Social, and Governance (ESG) database. Results in Table 3 Panel A columns 5 and 6 show that the positive effects of heat shocks on capital-labor ratios exist only in exposed firms with low social ratings. This evidence further suggests that these capital assets are used to replace workers as production inputs rather than to protect them from heat threats.[26]

[25] While unions may resist firms' automation efforts, the findings suggest that firms' bargaining power and incentives outweigh union influence. Nonetheless, unions may advocate for a portion of capital investments to be allocated toward labor protection.

[26] Two things to note. First, the sample size is much smaller due to the limited availability of social ratings from the Refinitiv database, particularly in earlier years of the sample. Second, medium-term heat shocks are defined as those in robustness checks in Table ID.3: a relative medium-term heat shock happens, and a

Fourth, the feasibility of automation hinges on the substitutability of heat-exposed workers with automated capital assets. In industries where the substitution is unfeasible, firms may continue using exposed workers despite high risks and costs. This predicts that the heat effects should be concentrated 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 the role of labor skills in the adaptation process. The analysis in columns 7 and 8 of Table 3 Panel A shows that heat shocks affect capital-labor ratios only among exposed firms that predominantly employ low-skilled workers, suggesting that the scope for capital deepening depends on the skill composition of heat-exposed workers.

Fifth, the progress towards capital-intensive production functions should be easier for firms with less complex operating structures, as they are more agile in making changes in production inputs to meet heat challenges. I test this prediction using a 10-K text-based measure of firm complexity proposed by Loughran and McDonald (2023). Columns 9 and 10 of Panel A show that capital deepening following heat shocks primarily occurs in low-complexity firms.

Sixth, adaptation through capital deepening is costly because it requires substantial investment in automated capital assets and skilled workers to operate them. Therefore, I expect the heat effects to be concentrated among exposed firms with greater financial resources. Panel B of Table 3 presents the analysis. In columns 1–6, I use the 10-K text-based measures of financial constraints proposed by Hoberg and Maksimovic

county or a firm experiences more than 120 days with absolute temperatures above 30°C in summers from $t-3$ to t. I use a stricter definition to enhance statistical power, given the smaller sample size.

(2015). I find that the effects of heat shocks on capital utilization are evident only among financially unconstrained firms. In columns 7–8, I measure financial constraints using cash holdings and classify firms with above-median cash as financially unconstrained. In columns 9–10, I consider both cash holdings and financial leverage and classify firms with above-median cash and below-median leverage as financially unconstrained. The results further show that the heat effects mainly arise among unconstrained firms.

To summarize, this section shows that heat-exposed firms increase capital utilization and capital-labor ratios following heat shocks. These effects are concentrated among firms operating in counties with high expected heat risk, firms in highly unionized industries, firms with low social ratings, firms employing large shares of low-skilled workers, firms with low-complexity operating structures, and firms with low financial constraints.

4 Temperature Variations

The analysis so far focuses on heat shocks, which capture temperature realizations that exceed decision-makers' expectations based on local past temperature distributions. Beyond the level of realized heat risk, variation in past heat risk may also shape firms' adaptation decisions. Greater variation in the positive deviations of relatively hot days indicates more frequent movements of temperatures toward extreme-heat conditions, increasing firms' perceived exposure to future heat risk. Such variation may prompt firms to adjust their production processes toward greater resilience, particularly when they rely more heavily on heat-exposed labor. To examine this possibility, I construct *Temperature Variation*, defined as the standard deviation of the positive deviation in the number of relatively hot days over the preceding 30 years. The positive deviation is defined as the number of days above the county-month-specific 90^{th} percentile temperature threshold minus 10 (the benchmark), bounded below by zero.

[Insert Table 4 here]

Results in Table 4 support this conjecture. The coefficient estimate on *Temperature Variation* $\times$ *Labor Exposure* is positive and statistically significant in columns 1 and 2, indicating that firms are more likely to shift toward capital-intensive production functions when variation in positive deviations from historical temperature distributions is high. Moreover, the analysis in columns 3 and 4 shows that such variation becomes particularly relevant when heat shocks occur. In columns 5 and 6, the effect of temperature variation is concentrated among firms located in counties with high projected long-term temperature increases, where such variation is more likely to translate into future heat shocks. Overall, these findings provide additional support that heat risk prompts firms to adopt more capital-intensive production functions.

C Capital and R&D Investments and Robotics-related Human Capital

To better understand firms' shift toward capital-intensive production functions, I investigate their capital expenditures and R&D expenses in columns 1–6 of Table 5. The dependent variable is the natural logarithm of capital investment rate, defined as total capital investment divided by lagged assets. Total capital investment is the sum of a firm's capital expenditures (CAPX) and R&D expenses. "*H*" (columns 1—3) and "*L*" (columns 4—6) denote firms operating in areas with high and low expected heat risk, respectively. The results show that heat-exposed firms significantly increase their capital investment rate after heat shocks, particularly those anticipating more frequent and severe heat threats in the future. In economic terms, firms with heat exposure at the 75^{th} percentile increase CAPX and R&D expenses by 3.8%.

[Insert Table 5 here]

Additionally, I investigate firms' investment in robotics-related human capital in columns 7—12 of Table 5, considering the critical role of robotics in advancing automation (Graetz and Michaels (2018), Acemoglu and Restrepo (2020)) and the need for workers to develop and operate robotics. The dependent variable is firms' investments in robotics-related human capital, measured using the fraction of robotics-related job postings, provided by Babina et al. (2024). I find that heat-exposed firms are more likely to advertise job openings demanding robotics-related skills following heat shocks. Consistent with the evidence on capital investment, the effects primarily concentrate in firms operating in areas with large expected heat risk. For firms with heat exposure at the 75^{th} percentile, demand in robotics-related human capital increases by 27.6%.

Taken together, these results show that, following heat shocks, firms significantly increase capital expenditures and R&D expenses and acquire more robotics-related human capital to deepen capital intensity.

D Automation Technology

To investigate further, I study firms' innovation in automation-related technologies in the adaptation process, given the importance of technological advancement in shaping today's capital-intensive economy. For instance, Karabarbounis and Neiman (2014) show that the declining labor share since 1980s is mostly driven by advances in information technology. Therefore, I conjecture that heat-exposed firms with greater innovation capabilities may devote more effort to developing machines, equipment, or new production methods that reduce reliance on heat-exposed labor. It is important to note, however, that heat-exposed firms do not always innovate internally to advance automation. If the required automation assets are readily available and more cost-effective to purchase than to develop in-house, firms may choose to acquire them at market prices. Nevertheless, firms may pursue internal innovation when they have highly specific production processes or automation needs that cannot be met by available market assets, or when prevailing market prices for automation assets are prohibitively high.

[Insert Table 6 here]

To test this conjecture, I utilize the classification of automation-related patents from Mann and Püttmann (2023), which identifies patents for developing devices that operate independently of human intervention. Table 6 presents the results. The dependent variable is a dummy indicating that a firm files at least one automation-related patent within a given period. Columns 1—3 examine filings of automation-related patents in year t,[27] columns 4—6 examine filings from year t to $t+3$, and columns 7—9 examine filings from year t to $t+5$. The analysis reveals that heat-exposed firms file more automation-related patents following heat shocks, implying that they develop more automation technology to advance their automation

[27] Note that heat shocks are measured from $t-3$ to t, allowing firms time to respond and begin filing automation patents in year t.

efforts. The economic impact is also significant. In column 6, the probability of filing at least one automation-related patent within three years after heat shocks increases by 4.4% for firms at the 75th percentile of heat exposure and by 6.6% for firms with the highest exposure.

E Automation Disclosure

As additional evidence, I examine firms' disclosures of automation-related initiatives in their 10-K filings in Table 7. In columns 1–4, the dependent variables capture both the number and the share of sentences related to automation.[28] The coefficient estimate on the interaction term between heat shocks and labor exposure is positive and statistically significant, except in column 2. This evidence suggests that, following heat shocks, heat-exposed firms are more likely than their counterparts to discuss automation-related activities in their 10-K filings. In columns 5–8, the dependent variables capture firms' automation initiatives related to adaptation or risk mitigation. The coefficient estimate on the interaction term is again positive and statistically significant, suggesting that firms use automation as an adaptation strategy to address heat-related risks. Overall, these findings reinforce the interpretation that automation constitutes an important adaptation response to heat risk.[29]

[Insert Table 7 here]

F Employment

In Internet Appendix Section F, I examine changes in employment in response to heat shocks, considering that decreased reliance on labor in production both drives and

[28] See Internet Appendix Section E for details on the construction of these measures.

[29] One caveat is that these 10-K-based measures are noisy and reflect automation-related discussion rather than realized automation investment.

results from increased automation. At the firm level (Table IF.1), there is no significant overall decline in employment following heat shocks. This non-result may be attributed to offsetting changes in firms' hiring and dismissal practices, whereby firms dismiss more heat-exposed workers while hiring more automation-related workers, a pattern that may not be fully captured by firm-level total employment data. Consistent with this view, Table 5 shows that firms exposed to heat shocks increase their demand for robotics-related human capital, which runs counter to the expectation of employment reductions following the shocks. In addition, the limited effect on employment may reflect firms' prioritization of capital investment over workforce reductions, consistent with capital deepening. That said, Table IF.1 also shows significant employment reductions after heat shocks among firms that predominantly employ low-skilled workers and have high cash reserves.

At the plant level (Table IF.2), I find that heat shocks reduce employment only in exposed small plants, defined as those with 50 or fewer employees. Consistent with Table 3, these effects are concentrated among plants facing higher long-run heat risk, plants in highly unionized industries, and plants that primarily employ low-skilled workers. The findings are broadly consistent with Ponticelli, Xu, and Zeume (2023), which reports no significant effects of long-run temperature changes on total employment but finds negative and significant effects on employment in small plants. They also align with Xiao (2026), which shows that heat shocks reduce industry-wide firm and job creation, particularly in high-exposure industries.

VI Economic Mechanism: Reduced Labor Efficiency Under High Temperatures

Section III discusses reduced labor productivity under high temperatures as one possible channel through which heat risk lowers labor efficiency in production and incentivizes firms to enhance automation. This section provides direct evidence on this channel in light of the mixed evidence in the literature on how heat risk affects corporate performance.

A Main Results

I conduct analyses at the firm level using the quarterly Compustat/CRSP Merged data. To match with heat shocks in summer, I focus on sales in summer quarters, i.e., quarters including at least one summer month. The empirical specification is as follows:

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

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 ≫ Expected)* is a dummy indicating firm $f's$ exposure to heat shocks (Equations (3) and (4)). *Labor Exposure* measures firm $f's$ exposure to climate risk through the labor channel (Equations (1) and (2)). $\boldsymbol{X}$ is a vector of controls including *Size*, *M/B*, *Book Leverage*, *Cash*, and *Dividend Payer*. μ_f is firm fixed effects, $\tau_{c,t}$ is county-by-year fixed effects, $\theta_{c,i}$ is county-by-NAICS2 industry fixed effects, and $\pi_{i,t}$ is NAICS2 industry-by-year fixed effects.

[Insert Table 8 here]

Table 8 presents the results. Column 1 reports the average effects of heat shocks on labor productivity. Consistent with Addoum et al. (2020), the estimated coefficient on heat shocks is negative but statistically insignificant, indicating that high temperatures have a limited effect on the average firm in the economy. In column 2, I interact heat shocks with the labor exposure measure and further add county-by-year fixed effects in column 3. The estimated coefficient on heat shocks becomes positive but remains statistically insignificant. Importantly, the coefficient on the interaction term is negative and statistically significant, suggesting that heat risk reduces labor productivity only among high-exposure firms. Such effects are not likely driven by differences in state- or county-level characteristics, given the inclusion of state-by-year and county-by-year fixed effects. The result holds after adding industry (NAICS2)-by-year and county-by-industry (NAICS2) fixed effects in column 4. The results also hold when replacing NAICS2-by-year fixed effects with NAICS4-by-year fixed effects in column 5, indicating that the findings are unlikely to be driven by changes in industry conditions.

In terms of economic magnitudes, column 5 shows that firms with exposure at the 75^{th} percentile experience an approximately 1.9% decline in labor productivity following heat shocks. Firms with the highest exposure experience a decline of about 3%. Detailed estimates for firms in each exposure category, ranging from 1 to 20, are reported in Panel A of Internet Appendix Table IG.1. As shown, the effects of heat shocks vary substantially across firms with different levels of labor exposure. Specifically, the effects are positive for firms with very limited exposure (*Labor Exposure*$\leq$*6*) but are not statistically significant.[30] The effects become negative for firms with an exposure of 7

[30] Although the effects are not statistically significant, one possible explanation for the positive estimates is

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.

Panel B of Table IG.1 and Figure 2 present the dynamic treatment effects of heat shocks. The results show that labor productivity is affected only by contemporaneous heat shocks (T). Neither past shocks ($T-3$, $T-2$, or $T-1$) nor future shocks ($T+1$, $T+2$, or $T+3$) affect current labor productivity. This evidence suggests the absence of pre-existing differential trends between firms that experience heat shocks and those that do not, supporting the assumption that heat shocks are exogenous from a given firm's perspective. These findings help mitigate endogeneity concerns, particularly those related to omitted variable bias and reverse causality.

[Insert Figure 2 here]

B Robustness Checks and Ruling Out Alternative Explanations

In Internet Appendix G, I conduct additional analyses to demonstrate the robustness of the results in Table 8 and to rule out alternative explanations.

Alternative Measures of Heat Shocks. In Internet Appendix Table IG.2, I conduct several tests to validate the definition of heat shocks and assess the robustness of the labor productivity results. The results show that the negative effects of heat shocks on labor productivity emerge only when the number of relatively hot days exceeds a sufficiently high threshold, supporting the use of $T = 15$ in the main analyses. The results also hold when heat shocks are defined using both relative and absolute

that workers in industries with very limited heat exposure may adjust their work schedules during abnormally hot periods, increasing working time and productivity and taking more breaks, particularly for outdoor leisure, when temperatures cool down. This interpretation is consistent with Xiao (2026), which finds that a few industries with very low heat exposure exhibit significant positive responses in firm and job creation following heat shocks.

temperature criteria, and the economic magnitudes increase with the number of absolute hot days, consistent with the view that relative heat shocks in hotter areas are more damaging to labor productivity.

An Alternative Rolling Window to Define Heat Shocks. Table IG.4 uses an alternative 20-year rolling window to define heat shocks. The results continue to hold.

Heat Shocks in Firm Headquarters County. Table IG.5 shows robust results using heat shocks occurring in firms' headquarters counties, which do not require YTS data.

Controlling for Other Climate Events. To address concerns that other non-heat climate events may bias the estimates, Table IG.6 includes interaction terms between labor exposure and cold temperature shocks, precipitation, and climate disasters reported by FEMA. The results show no significant effects of non-heat climate events on labor productivity. Importantly, after including these controls, heat shocks continue to negatively affect labor productivity, with similar economic magnitudes.

Sector Breakdowns and Excluding A Consumer Demand Channel. High temperatures may shift consumers toward indoor activities, reducing foot traffic to stores and restaurants and potentially lowering firm sales (Addoum et al. (2023)). To rule out this consumer demand channel, Table IG.7 shows that the results remain robust, with similar economic magnitudes, after excluding consumer-oriented sectors. Table IG.8 further excludes the agricultural sector and separates firms into goods-producing and service sectors. The effects of high temperatures are present in both groups.

Alternative Measures of Labor Exposure. Tables IG.9 and IG.10 present robustness checks using a firm-level measure of labor exposure and a continuous measure of labor exposure.

Segment-level Analysis. Table IG.11 validates the results using data on segment sales, assets, and industry classifications from the Compustat segment files and find that heat shocks significantly reduce segment-level sales scaled by assets.

Plant-level Analysis. Finally, I conduct analyses using plant-level employment and sales data from YTS in Table IG.12. Both cross-firm and within-firm analyses show significant negative effects of heat risk on plant-level labor productivity.

In summary, this section presents robust and consistent evidence that unexpected high temperatures negatively affect labor productivity among high-exposure firms and plants. The findings support the physical risk mechanism of extreme heat and the labor channel of corporate exposure to climate change.

VII Effectiveness of Adaptation Through Capital Deepening

The results thus far suggest that labor productivity losses are one important mechanism underlying firms' capital responses. A crucial remaining question is whether capital deepening effectively mitigates the adverse effects of heat on firms' production. If so, firms with greater capital intensity should be less adversely affected by unexpected high temperatures and exhibit greater operational resilience. I test this conjecture in Table 9. Specifically, I divide firms into two groups: those with capital-labor ratios below the industry median (L in columns 1 and 3) and those with capital-labor ratios above the industry median (H in columns 2 and 4). Supporting my conjecture, I find that the negative effects of heat shocks on labor productivity appear only among firms with below-median capital-labor ratios. In contrast, firms with above-median capital-labor ratios do not experience significant declines in labor productivity following heat shocks. The decline in sales further translates into lower operating income, indicating reduced profitability. This evidence suggests that adopting more capital-intensive production methods can serve as an effective adaptation strategy and further supports the hypothesis that firms use capital upgrades to address heat-related challenges.

[Insert Table 9 here]

VIII Value Implications of Adaptation Through Capital Deepening

Building on the evidence that capital deepening enhances firms' resilience to heat shocks, I examine the valuation implications of such adaptation efforts. If investors recognize heat risk and value firms' adaptation capacity, heat-exposed firms with greater capital intensity should have higher market valuations than those with lower capital intensity when facing heat-induced disruptions. I test this prediction in Table 10. The dependent variable is the annual buy-and-hold return (*Return (%)*) of a firm's stock. The coefficient estimate on the interaction term *1 (Realized* $\gg$ *Expected)* $\times$ *Labor Exposure* is negative and statistically significant, indicating that heat shocks reduce the returns of exposed firms. Importantly, the coefficient estimate on the triple interaction term with firms' existing capital-labor ratios, *1 (Realized* $\gg$ *Expected)* $\times$ *Labor Exposure* $\times$ *Log(Capital/Emp)*, is positive and statistically significant. This implies that heat-exposed firms with higher existing capital-labor ratios experience smaller reductions in returns following heat shocks and, consequently, receive relatively higher market valuations than firms with lower capital intensity. For instance, the annual buy-and-hold return of heat-exposed firms (*Labor Exposure=15*) with capital-labor ratios at the 75^{th} percentile is

4.4 percentage points higher than that of heat-exposed firms with capital-labor ratios at the 25^{th} percentile, and this difference is statistically significant. Collectively, these findings are consistent with investors recognizing firms' capacity to adapt to heat risk and placing higher valuations on heat-exposed firms that are better positioned to maintain resilience following heat-induced disruptions.

[Insert Table 10 here]

IX Conclusions

Climate change has steadily increased global temperatures, creating substantial workplace safety concerns and exposing firms to new production risks. This paper investigates these issues by identifying a labor channel of corporate exposure to heat risk and examining how firms adapt to this risk through capital deepening and automation.

Using granular U.S. temperature data and a novel measure of labor exposure to climate risk, I show that exposed firms respond to heat shocks by shifting toward more capital-intensive production functions. Specifically, following heat shocks, exposed firms increase capital utilization in production, raise capital expenditures and R&D expenses, acquire more robotics-related human capital, develop more automation-related technologies, and discuss more automation initiatives in 10-K filings. Collectively, these findings indicate that climate change prompts exposed firms to enhance automation and accelerates the shift toward more capital-intensive production.

I then show reduced labor efficiency as one important mechanism underlying firms' automation responses. Consistent with the physical risk mechanism of high temperatures, labor productivity declines by 1.9% for firms with labor exposure at the

75^{th} percentile following heat shocks, while firms with the highest exposure experience a 3% decline. These findings indicate that high temperatures reduce the efficiency of heat-exposed labor relative to capital, thereby creating incentives for firms to automate exposed tasks.

Additionally, I examine whether capital deepening effectively mitigates heat-related disruptions and find that firms with higher capital intensity are less adversely affected by heat risk and exhibit greater operational resilience. The return evidence is also consistent with investors recognizing this adaptation capacity, as exposed firms with higher capital intensity experience smaller declines in stock returns following heat shocks.

This paper's findings on adaptation to climate change may have distributional consequences for workers. While automation can improve firms' resilience to heat risk, it may also reduce demand for heat-exposed workers, particularly those performing tasks that are easier to automate. This highlights a potential trade-off between strengthening firms' resilience to climate threats and safeguarding employee welfare. Future research could examine policy frameworks that balance these objectives. More broadly, future studies could explore the implications of this labor channel of climate exposure for other economic agents, including banks, entrepreneurs, households, and institutional investors.

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Appendix A: Variable Definitions

Variables	Definition
Dependent Variables	
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.
Capital Investment Rate	The natural logarithm of investment rate, defined as total investment divided by lagged assets. Total investment is the sum of a firm's capital expenditures (CAPX) and R&D expenses.
Robotics-related Human Capital	The fraction of a firm's robotics-related job postings, provided by Babina et al. (2024).
Automation Technology	A dummy indicating that a firm files at least one automation-related patent within a given period. The classification of automation-related patents is from Mann and Püttmann (2023).
Automation Count	The number of sentences related to automation, scaled by 100.
Automation Share	The proportion of sentences related to automation, scaled by 1,000,000.
Automation+Adaptation Count	The number of sentences related jointly to automation and adaptation, scaled by 100.
Automation+Adaptation Share	The proportion of sentences related jointly to automation and adaptation, scaled by 1,000,000.
Log(Sales/Emp)	The natural logarithm of sales per employee.
OIBDP/Emp	Operating income per employee.
Return (%)	The annual buy-and-hold return of a firm's stock.
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 (3). Heat shocks are measured using temperatures at t relative to the $90th$ 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 (4). The county-level employment data for a firm is from YTS.

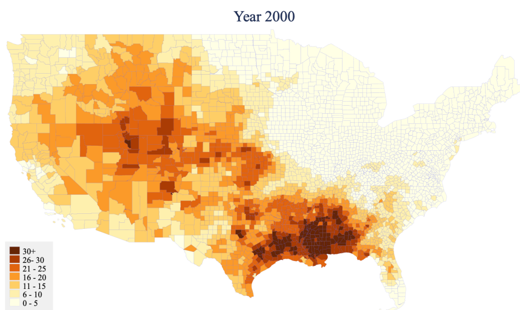
Variables	Definition
Key Independent Variables	
1 (Realized $\gg$ Expected) (M)	A dummy indicating a medium-term heat shock at the county or the firm level. The medium-term heat shock is measured in the same way as *1 (Realized $\gg$ Expected)* but using temperatures from $t-3$ to t. The identification threshold is 45 days, relative to the benchmark (expectation) 40 days.
Temperature Variation	The standard deviation of the positive deviation in the number of relatively hot days over the preceding 30 years. The positive deviation is defined as the number of days above the county-month-specific 90^{th} percentile temperature threshold minus 10 (the benchmark), bounded below by zero.
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 within a NAICS4 industry, defined in Equation (1). The occupational exposure score is from the O*NET program. The weight is the percentage of employees working in a given occupation in a NAICS4 industry from the OEWS data. The firm-level measure is a weighted average of the industry-level measure, defined in Equation (2). The weight is the percentage of a firm's employees working in a NAICS4 industry from YTS.
Other Independent Variables	
Size	The logarithm of a firm's total assets (AT).
M/B	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).
Log(1+No. Patents)	The natural logarithm of one plus the total number of patents a firm has in the past ten years.
Return Volatility	The average volatility of a firm's stock returns over the preceding 12 months.
CAPM Beta	The average CAPM beta of a firm's stock, calculated using a rolling window of the past 36 months.

Figures

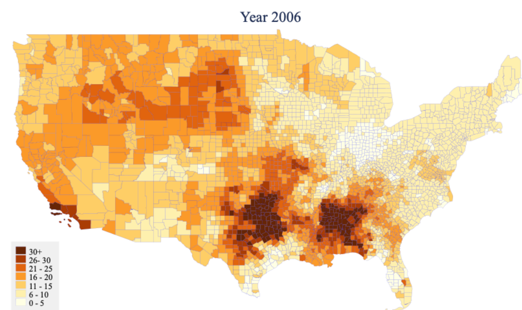
Figure 1. Geographic Distribution of Heat Shocks Across Counties in the Continental U.S.

These figures present the number of summer days with relative heat shocks (Equation (3)) for each county in the continental U.S. in the years 2000, 2006, 2009, 2012, 2015, and 2018.

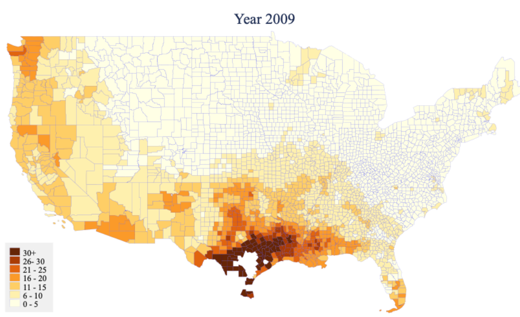
(A) Year 2000



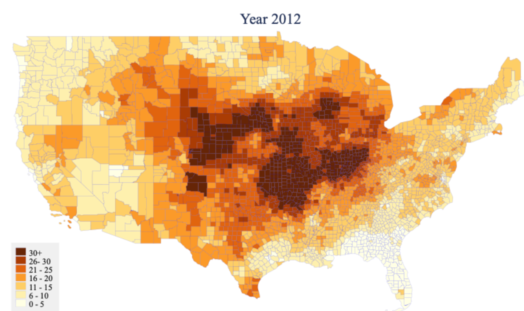
(B) Year 2006



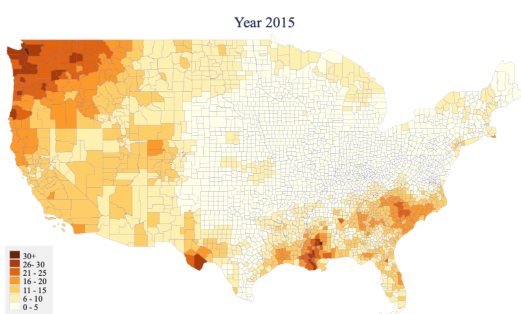
(C) Year 2009



(D) Year 2012



(E) Year 2015



(F) Year 2018

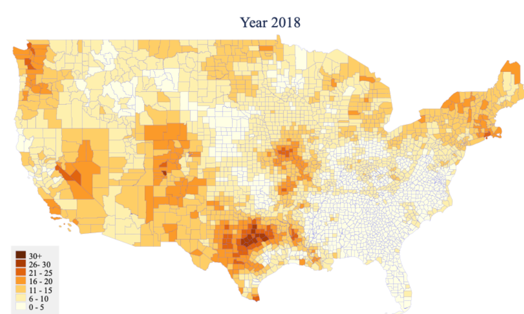
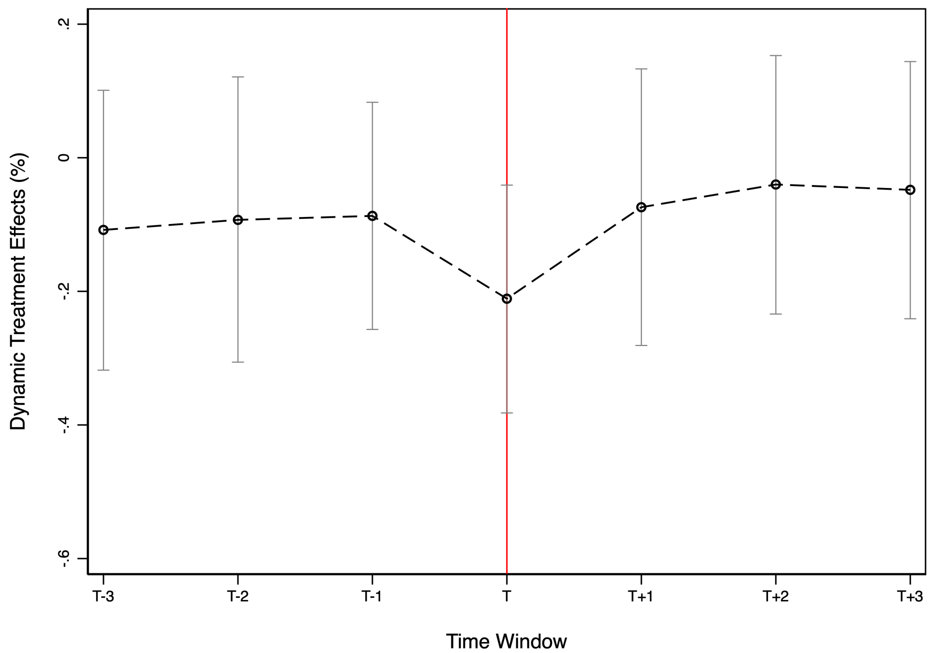


Figure 2. Dynamic Treatment Effects of Heat Shocks on Labor Productivity

This figure presents the dynamic treatment effects of heat shocks on firm-level labor productivity conditional on labor exposures, based on the estimation in Panel B of Internet Appendix Table IG.1. *T-3*, *T-2*, *T-1*, *T*, *T+1*, *T+2*, *T+3* denote heat shocks occurring in the years *T-3*, *T-2*, *T-1*, *T*, *T+1*, *T+2*, *T+3*, respectively.



Tables

Table 1. Summary Statistics

This table presents summary statistics of key variables used in empirical analyses. See "*Appendix A: Variable Definitions*" for detailed variable definitions. The sample period spans 1999–2019, except that "*Automation Technology*" is available for 1999–2013 and "*Robotics-related Human Capital*" is available for 2007 and 2010—2018.

	N	Mean	P5	Median	P95	SD
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
Capital Investment Rate	57,179	-2.627	-4.312	-2.565	-1.111	1.001
Robotics-related Human Capital	11,322	0.087	0.000	0.000	0.743	0.274
Automation Technology	42,443	0.242	0.000	0.000	1.000	0.428
Automation Count	49,117	224	0	100	1,300	355
Automation Share	49,117	885	0	201	5,338	1,448
Automation+Adaptation Count	49,117	22	0	0	200	55
Automation+Adaptation Share	49,117	81	0	0	787	212
Log(Sale/Emp)	60,129	4.144	2.627	4.100	5.879	0.835
OIBDP/Emp	56,851	15.115	-24.622	6.071	66.790	93.347
Return (%)	55,839	8.088	-57.506	3.674	92.107	45.302
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
Temperature Variation	61,478	6.323	2.853	5.909	11.771	2.727
Labor Exposure	61,478	7.833	1.000	6.000	18.000	5.533
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
Log(1+No. Patents)	42,443	2.001	0	0	8.825	3.316
Return Volatility	55,839	11.209	5.119	11.073	17.817	3.869
CAPM Beta	53,259	1.049	0.106	1.016	2.136	0.609

Table 2. Heat Shocks and Capital Utilization in Production

This table presents the treatment effects of 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, both multiplied by 100. 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.604	-1.320	-1.916**	-1.271	0.200	-2.481**	-3.003***	-1.777*
	(0.557)	(0.824)	(0.925)	(0.925)	(0.672)	(0.992)	(1.017)	(1.003)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.258***	0.311***	0.258***		0.358***	0.371***	0.227**
		(0.083)	(0.093)	(0.093)		(0.091)	(0.094)	(0.098)
Labor Exposure		-0.135	-0.156	-0.396		0.318	0.389	-0.534*
		(0.241)	(0.252)	(0.265)		(0.312)	(0.303)	(0.279)
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 Effects								
Labor Exposure=15		2.551***	2.742***	2.600***		2.888***	2.564**	1.623*
		(0.855)	(0.995)	(0.977)		(0.946)	(1.018)	(0.944)
Labor Exposure=20		3.841***	4.295***	3.890***		4.677***	4.420***	2.757**
		(1.200)	(1.376)	(1.360)		(1.299)	(1.384)	(1.344)

Table 3. Heat Shocks and Capital Utilization in Production: Heterogeneity

This table presents cross-sectional heterogeneity in the treatment effects of heat shocks on firm-level capital utilization in production. In Panel A, columns 1—2 examine long-term temperature projections, columns 3—4 examine labor union, columns 5—6 examine social ratings, columns 7—8 examine labor skill, and columns 9—10 examine firm complexity. "*H*" and "*L*" denote high and low levels in each of the above dimensions, respectively. Panel B examine financial constraints using different measures. Columns 1—6 use 10-K text-based measures developed by Hoberg and Maksimovic (2015). Columns 1—2 focus on equity financing constraints, columns 3—4 focus on private placement financing constraints, and columns 5—6 focus on debt financing constraints. Columns 7—8 focus on cash holdings, and columns 9 —10 focus on cash holdings and financial leverage. "*U*" and "*C*" denote financially unconstrained and constrained firms, respectively. The dependent variable is the natural logarithm of total capital per employee, *Log(Capital/Emp)*, multiplied by 100. 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 reported are a dummy indicating medium-term heat shocks (*1 (Realized $\gg$ Expected) (M)*) and its interaction term with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 2002 to 2019 for Panel A columns 5—6, from 1999 to 2015 for Panel B columns 1—6, and from 1999 to 2019 for all other columns. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Expected Heat Risk, Incentives, and Operating Constraints

	1	2	3	4	5	6	7	8	9	10
	Log(Capital/Emp) x 100									
	Temperature Projections		Labor Union		Social Ratings		Labor Skill		Firm Complexity	
	H	L	H	L	H	L	H	L	H	L
1(Realized $\gg$ Expected) (M)	-4.175***	-0.091	-2.183	1.266	-1.542	-3.286	-1.594	-1.945	-1.033	-2.302
	(1.437)	(1.478)	(1.516)	(1.729)	(1.773)	(2.568)	(1.411)	(1.636)	(1.341)	(1.461)
1 (Realized $\gg$ Expected) (M) x Labor Exposure	0.470***	0.029	0.315**	-0.088	0.208	0.583*	0.141	0.288**	0.105	0.315**
	(0.118)	(0.151)	(0.132)	(0.151)	(0.178)	(0.300)	(0.187)	(0.138)	(0.137)	(0.150)
Observations	29,528	29,044	24,597	23,812	6,345	6,571	24,804	33,667	25,554	25,546
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.952	0.926	0.937	0.949	0.979	0.977	0.938	0.942	0.947	0.942

Treatment Effects										
Labor Exposure=15	2.881***		2.543**			5.464*		2.382**		2.419*
	(1.050)		(1.087)			(2.878)		(1.104)		(1.390)
Labor Exposure=20	5.233***		4.118**			8.381**		3.825**		3.993**
	(1.478)		(1.598)			(4.222)		(1.626)		(2.026)

Panel B. Financial Constraints

	1	2	3	4	5	6	7	8	9	10
	Log(Capital/Emp) x 100									
	Text-based Measures of Financial Constraints						Cash		Cash + Leverage	
	Equity		Private Placement		Debt					
	U	C	U	C	U	C	U	C	U	C
1(Realized $\gg$ Expected) (M)	-0.945	-2.608	-0.965	-2.329	-3.198**	0.368	-2.612*	-2.157*	-3.684*	-1.070
	(1.388)	(1.865)	(1.429)	(1.885)	(1.577)	(1.352)	(1.387)	(1.255)	(2.124)	(1.211)
1 (Realized $\gg$ Expected) (M) x Labor Exposure	0.263**	0.228	0.281**	0.174	0.321*	0.127	0.437***	0.273***	0.578***	0.176*
	(0.132)	(0.158)	(0.131)	(0.173)	(0.190)	(0.121)	(0.166)	(0.102)	(0.216)	(0.101)
Observations	19,354	19,261	19,447	19,185	19,112	19,213	29,306	28,577	20,827	37,112
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.944	0.947	0.951	0.941	0.935	0.956	0.927	0.958	0.928	0.952

Treatment Effects										
Labor Exposure=15	2.994**		3.245**		1.618		3.950**	1.932**	4.984**	1.576*
	(1.389)		(1.268)		(2.115)		(1.608)	(0.971)	(2.027)	(0.937)
Labor Exposure=20	4.307**		4.648***		3.223		6.137***	3.294**	7.873***	2.457*
	(1.915)		(1.781)		(2.960)		(2.359)	(1.333)	(2.938)	(1.302)

Table 4. Temperature Variations and Capital Utilization in Production

This table presents the treatment effects of past temperature variations on firm-level capital utilization in production. The dependent variable is the natural logarithm of total capital per employee (*Log(Capital/Emp)*), multiplied by 100. 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 reported are the measure of variation in past temperatures (*Temperature Variation*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). *Temperature Variation* is the standard deviation of the positive deviation in the number of relatively hot days over the preceding 30 years. The positive deviation is defined as the number of days above the county-month-specific 90^{th} percentile temperature threshold minus 10, bounded below by zero. "*Y*" in column 3 and "*N*" in column 4 denote firms operating in counties with and without heat shocks, respectively. "*H*" in column 5 and "*L*" in column 6 denote firms operating in counties with high and low expected long-run heat risk, respectively. Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6
	Log(Capital/Emp) x 100					
	Full Sample		Heat Shocks		Temperature Projections	
			Y	N	H	L
Temperature Variation	-0.932	-0.468	-1.976	-0.221	-1.600	-2.153
	(0.990)	(0.968)	(1.459)	(1.121)	(1.490)	(1.814)
Temperature Variation x Labor Exposure	0.149***	0.097*	0.153*	0.083	0.189***	-0.108
	(0.054)	(0.052)	(0.080)	(0.060)	(0.072)	(0.088)
Observations	59,082	59,082	15,543	41,948	24,927	33,950
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.935	0.938	0.955	0.937	0.951	0.930

Table 5. Heat Shocks and Investments: Capital Expenditures and R&D Expenses, and Robotics-related Human Capital

This table presents the treatment effects of heat shocks on firms' capital expenditures and R&D expenses and acquisition of robotics-related human capital. The dependent variable in columns 1—6 is the natural logarithm of the capital investment rate, multiplied by 100, defined as total capital investment divided by lagged assets. Total capital investment is the sum of a firm's capital expenditures (CAPX) and R&D expenses. The dependent variable in columns 7—12 is the fraction of a firm's robotics-related job postings, multiplied by 100, provided by Babina et al. (2024). "*H*" (columns 1—3 and 7—9) and "*L*" (columns 4—6 and 10—12) denote firms operating in counties with high and low expected long-run heat risk, respectively. The key independent variables reported are a dummy indicating medium-term heat shocks (*1 (Realized* $\gg$ *Expected) (M)*) and its interaction term with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 1999–2019 for columns 1—6 and 2007 and 2010–2018 for columns 7—12. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9	10	11	12
	Capital Investment Rate x 100						Robotics-related Human Capital x 100					
	H			L			H			L		
1(Realized $\gg$ Expected) (M)	0.785	-2.932	-1.770	-0.552	-0.502	-0.315	1.228	-0.692	-0.677	0.439	-0.814	0.124
	(1.205)	(2.321)	(2.046)	(1.261)	(1.684)	(1.780)	(1.235)	(1.474)	(1.667)	(1.377)	(2.044)	(2.071)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.412**	0.369*		-0.009	0.001		0.213**	0.205*		0.190	0.028
		(0.204)	(0.201)		(0.201)	(0.222)		(0.091)	(0.115)		(0.206)	(0.204)
Observations	28,347	28,347	28,345	27,044	27,044	27,025	5,381	5,381	5,381	5,261	5,261	5,239
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.781	0.781	0.791	0.838	0.838	0.845	0.584	0.584	0.582	0.419	0.419	0.408
Treatment Effects												
Labor Exposure=15		3.244**	3.764**					2.499*	2.393*			
		(1.589)	(1.757)					(1.374)	(1.398)			
Labor Exposure=20		5.303**	5.609**					3.562**	3.416**			
		(2.390)	(2.601)					(1.622)	(1.734)			

Table 6. Heat Shocks and Automation Technology

This table presents the treatment effects of heat shocks on firms' development of automation-related technologies. The dependent variable is a dummy indicating that a firm files at least one automation-related patent within a given period (*Automation Technology*), multiplied by 100. Columns 1—3 examine filings of automation-related patents in year t, columns 4—6 examine filings from year t to $t+3$, and columns 7—9 examine filings from year t to $t+5$. The key independent variables reported are a dummy indicating medium-term heat shocks (*1 (Realized $\gg$ Expected) (M)*) and its interaction term with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), a dummy indicating that a firm pays dividends (*Dividend Payer*), and the natural logarithm of one plus the total number of patents a firm has in the past ten years (*Log(1+No. Patents)*). The sample period is from 1999 to 2013. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9
	Automation-related Patent x 100								
	T			T to T+3			T to T+5		
1 (Realized $\gg$ Expected) (M)	0.250	-0.964***	-0.576	0.494*	-1.140***	-0.561	0.438*	-1.208***	-0.630
	(0.244)	(0.358)	(0.371)	(0.256)	(0.383)	(0.388)	(0.258)	(0.390)	(0.411)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.162***	0.083**		0.219***	0.113**		0.220***	0.112**
		(0.037)	(0.037)		(0.043)	(0.045)		(0.044)	(0.046)
Observations	41,370	41,370	41,370	41,370	41,370	41,370	41,370	41,370	41,370
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	0.783	0.783	0.785	0.819	0.820	0.823	0.824	0.825	0.828
Treatment Effects									
Labor Exposure=15		1.472***	0.671*		2.138***	1.137**		2.093***	1.045**
		(0.414)	(0.373)		(0.481)	(0.467)		(0.483)	(0.468)
Labor Exposure=20		2.284***	1.087**		3.231***	1.704**		3.193***	1.603**
		(0.571)	(0.524)		(0.664)	(0.666)		(0.672)	(0.665)

Table 7. Heat Shocks and Automation Disclosures

This table presents the treatment effects of heat shocks on firms' disclosures of automation initiatives in 10-K filings. In columns 1 and 2, the dependent variable is *Automation Count*, the number of sentences related to automation, scaled by 100. In columns 3 and 4, the dependent variable is *Automation Share*, the proportion of sentences related to automation, scaled by 1,000,000. In columns 5 and 6, the dependent variable is *Automation+Adaptation Count*, the number of sentences related jointly to automation and adaptation, scaled by 100. In columns 3 and 4, the dependent variable is *Automation+Adaptation Share*, the proportion of sentences related jointly to automation and adaptation, scaled by 1,000,000. The key independent variables reported are a dummy indicating medium-term heat shocks (*1 (Realized $\gg$ Expected) (M)*) and its interaction term with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Automation Count		Automation Share		Automation+Adaptation Count		Automation+Adaptation Share	
1 (Realized $\gg$ Expected) (M)	-13.794**	-13.204**	-51.193**	-59.830***	-2.479**	-2.382**	-11.216***	-10.760***
	(6.260)	(6.391)	(21.121)	(21.182)	(1.004)	(0.964)	(3.824)	(3.782)
1 (Realized $\gg$ Expected) (M) x Labor Exposure	0.852*	0.760	3.671*	3.974*	0.212**	0.214**	0.736**	0.674*
	(0.501)	(0.552)	(1.922)	(2.019)	(0.092)	(0.089)	(0.365)	(0.360)
Observations	47,951	47,950	47,951	47,950	47,951	47,950	47,951	47,950
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	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.747	0.748	0.749	0.750	0.526	0.526	0.529	0.529
Treatment Effects								
Labor Exposure=15	-1.010		3.874	-0.214	0.698	0.826	-0.180	-0.655
	(4.042)		(16.747)	(17.823)	(0.928)	(0.935)	(3.376)	(3.433)
Labor Exposure=20	3.251		22.230	19.658	1.757	1.896	3.499	2.713
	(5.819)		(24.384)	(26.109)	(1.291)	(1.286)	(4.863)	(4.886)

Table 8. Heat Shocks and Firm-level Labor Productivity

This table presents the treatment effects of heat shocks on firm-level labor productivity. The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*), multiplied by 100. The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Sales/Emp) x 100				
1 (Realized $\gg$ Expected)	-0.240	1.538*	1.632	1.160	1.273
	(0.601)	(0.899)	(1.036)	(0.987)	(1.121)
1 (Realized $\gg$ Expected) x Labor Exposure		-0.210***	-0.243***	-0.175**	-0.211**
		(0.069)	(0.077)	(0.076)	(0.087)
Observations	58,711	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.875
Treatment Effects					
Labor Exposure=15		-1.604**	-2.006**	-1.462*	-1.897**
		(0.698)	(0.803)	(0.790)	(0.827)
Labor Exposure=20		-2.652***	-3.218***	-2.336**	-2.953***
		(0.924)	(1.047)	(1.039)	(1.115)

Table 9. Effectiveness of Adaptation Through Capital Deepening

This table presents results examining the effectiveness of climate change adaptation through capital deepening, focusing on firm resilience to short-term heat shocks conditional on existing capital intensity. Columns 1 and 3 focus on firms with capital-labor ratios (*Log(Capital/Emp)*) below the industry median, while columns 2 and 4 focus on firms with capital-labor ratios above the industry median. The dependent variables are the natural logarithm of sales per employee (*Log(Sales/Emp)*) in columns 1—2, and operating income per employee (*OIBDP/Emp*) in columns 3—4. The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction term with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4
	Log(Sales/Emp) x 100		OIBDP/Emp	
	L	H	L	H
1 (Realized ≫ Expected)	2.960*	0.523	0.568	-0.402
	(1.510)	(1.646)	(0.356)	(0.600)
1 (Realized ≫ Expected) x Labor Exposure	-0.387***	-0.063	-0.064*	0.023
	(0.131)	(0.111)	(0.034)	(0.058)
Observations	21,810	25,241	20,665	24,368
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes
County x NAICS2 FE	Yes	Yes	Yes	Yes
NAICS2 x Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.887	0.863	0.751	0.771

Table 10. Value Implications of Adaptation Through Capital Deepening

This table presents the value implications of adapting to climate change through capital deepening. The dependent variable is the annual buy-and-hold stock return (*Return (%)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*), its interaction term with a firm's labor exposure to climate risk (*Labor Exposure*), and the triple interaction term with a firm's capital-labor ratio —*1 (Realized $\gg$ Expected) $\times$ Labor Exposure $\times$ Log(Capital/Emp)*. Controls include *Labor Exposure*, *Log(Capital/Emp)*, other two-way interaction terms, the logarithm of total assets (*Size*), market-to-book ratio (*M/B*), book leverage (*Book Leverage*), cash holdings (*Cash*), a dummy indicating that a firm pays dividends (*Dividend Payer*), a firm's return volatility over the preceding 12 months (*Return Volatility*), and a firm's CAPM beta (*CAPM Beta*). The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3
	Return (%)		
1 (Realized $\gg$ Expected)	5.097	5.769	5.492
	(3.693)	(3.523)	(3.386)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.883**	-0.786**	-0.657*
	(0.344)	(0.334)	(0.392)
1 (Realized $\gg$ Expected) x Labor Exposure x Log(Capital/Emp)	0.231***	0.195**	0.163*
	(0.075)	(0.076)	(0.092)
Observations	51,161	51,114	51,114
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	No	No
State x Year FE	No	Yes	Yes
NAICS2 x Year FE	No	No	Yes
Adjusted R^2	0.276	0.292	0.318

Internet Appendix to

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

June 2026

A Anecdotal Evidence on Heat Threats to Exposed Workers

In this section, I present several pieces of anecdotal evidence from multiple sources that highlight the significant heat risks faced by field workers as a result of 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

B Labor Exposure to Climate Risk: Measure Construction, Distribution, and Validation

A 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 IB.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 Standard Occupational Classification (SOC) occupation code for 1999 - 2022.

1 Occupational Employment and Wage Statistics (OEWS)

The Bureau of Labor Statistics's (BLS) 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) prior to 1999 and transition to the SOC system afterward. Third, industry classifications are based on the SIC code before 2002 and the NAICS code from 2002 onwards.

2 The Occupational Information Network (O*NET) Program

The O*NET program 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).

3 Occupational Exposure to High Temperatures

In the section on work context, O*NET has five elements that help capture workers' heat 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 heat risks. The reason is that this study focuses on workers' exposure to nature heat induced by climate change. This study does not consider workers' exposure to heat generated during production processes, 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 negatively 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 temperatures 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 construction and estimation. Third, neither survey question was available until 2006. I drop them to ensure the consistency in measure construction.

B Distribution of Labor Exposure to Climate Risk

1 Across Sectors

Figure IB.1 presents the distribution of the 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, the 25th percentile, the median, the 75th percentile, and the maximum of labor exposures across NAICS4 industries in each sector. This figure yields four noteworthy observations. First, 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. Second, 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. Third, 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. Fourth, 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 a significant improvement relative to the sector-level measure in Graff Zivin and Neidell (2014).

Table IB.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 IB.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.

2 Across Labor Skill Levels

Figure IB.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, the 25^{th} percentile, the median, the 75^{th} percentile, and the maximum of labor exposure to climate risk across NAICS4 industries for each skill level. Consistent with expectation, there is a negative correlation between labor exposure to climate risk and labor skill, as indicated by a correlation of -0.35. However, within each labor skill category, there exist significant heterogeneities in labor exposures across NAICS4 industries. These patterns indicate that, although lower-skilled workers generally face higher exposures to climate risks, a substantial number of higher-skilled workers are also impacted.

3 Across Counties

Figure IB.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 Measure Validation

Prior studies have developed several measures of corporate exposures to climate conditions by analyzing textual information in firm disclosures, such as 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 only. 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 perspective. 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), which 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 IB.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 IB.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 IB.5 (A)) and *Climate Change Risk* (Figure IB.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 IB.5 (B)) or *Climate Change Risk* (Figure IB.6 (B)).

Furthermore, I compare the correlations between my labor exposure measure and the heat exposure measures developed by Trucost, part of the S&P Global. Specifically, Trucost first models location-specific (100 x 100km to 200 x 200km) 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 (20% weight), revenue shares by country, and the average physical risk level in each country (80% weight). Trucost's heat exposure measures are available starting from August 2018. Essentially, the asset-based measure assumes that all of a firm's physical assets are exposed to and affected by extreme heat in the same magnitude, despite significant heterogeneities in these asset types. The revenue-based measure assumes that a firm's revenues are affected in a country if the country experiences a heat wave, even if the heat wave does not affect the firm's production processes. Consequently, Trucost's measures are fundamentally different from mine by construction and do not capture any heat exposures from a labor perspective. Consistent with this conjecture, Figure IB.7 (A) and IB.8 (A) show that the correlations between my measure of labor exposure and Trucost's measures of heat exposure are almost zero.[31] More importantly, Figure IB.7 (B) and IB.8 (B) show that the significant explanatory power of my labor exposure measure for firms' choices of labor and capital inputs remains even after controlling for the asset-based or revenue-based heat exposures from Trucost.

Overall, these analyses demonstrate that reliance on outdoor workers in production exposes firms to significant climate risks. This labor-channel exposure to climate risk can not be fully explained by other measures of climate exposures developed in the literature or by Trucost. This evidence lays the foundation for studying corporate exposure to climate change and adaptation actions through a labor channel.

[31] 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 IB.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 (1)) across NAICS2 sectors.

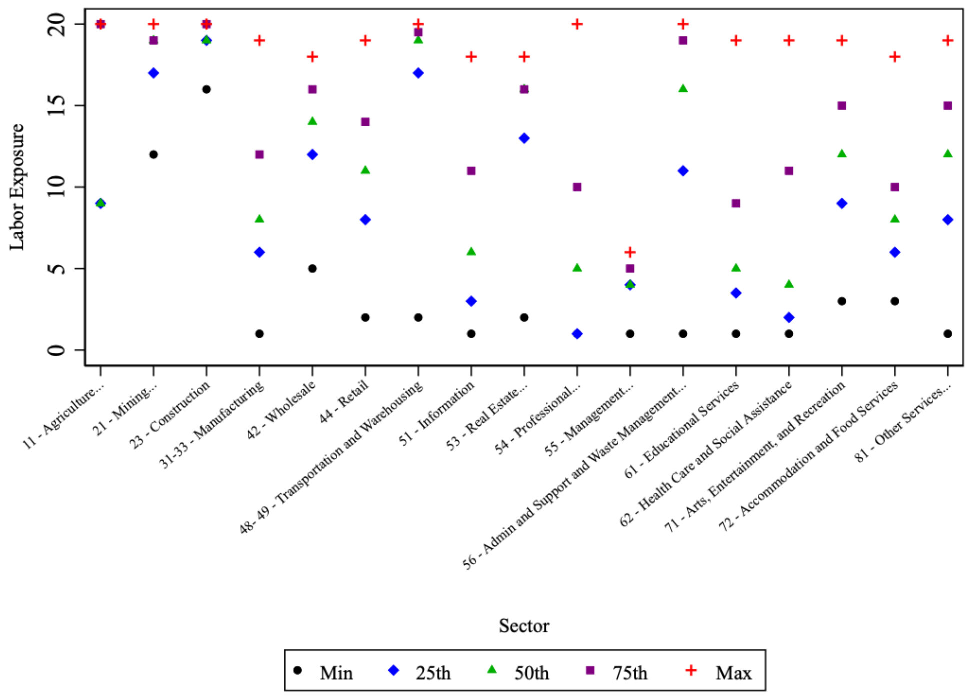


Figure IB.2. Distribution of Labor Exposure to Climate Risk Across Labor Skill Levels

This figure presents the distribution of the industry-level measure of labor exposure to climate risk (Equation (1)) across labor skill levels.

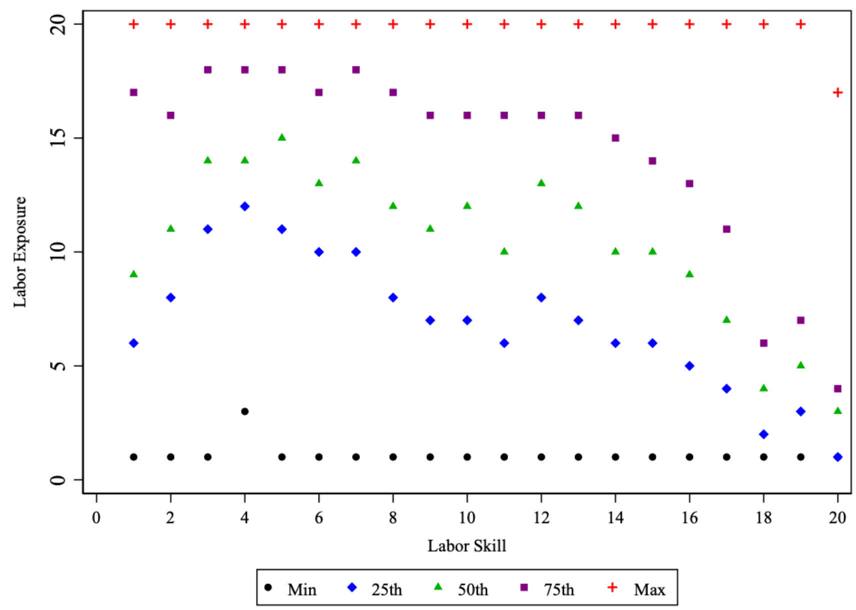
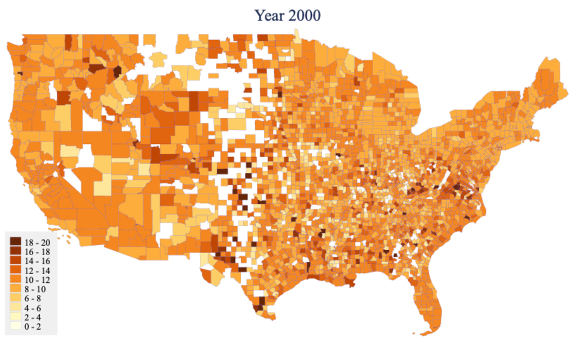


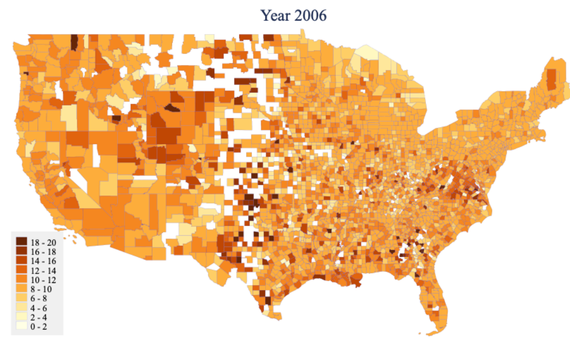
Figure IB.3. Distribution of Labor Exposure to Climate Risk Across Counties

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.

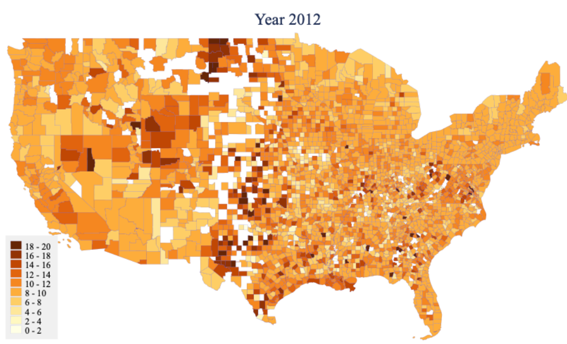
(A) Year 2000



(B) Year 2006



(C) Year 2012



(D) Year 2018

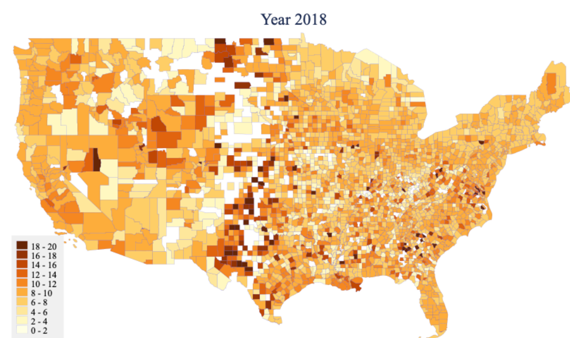
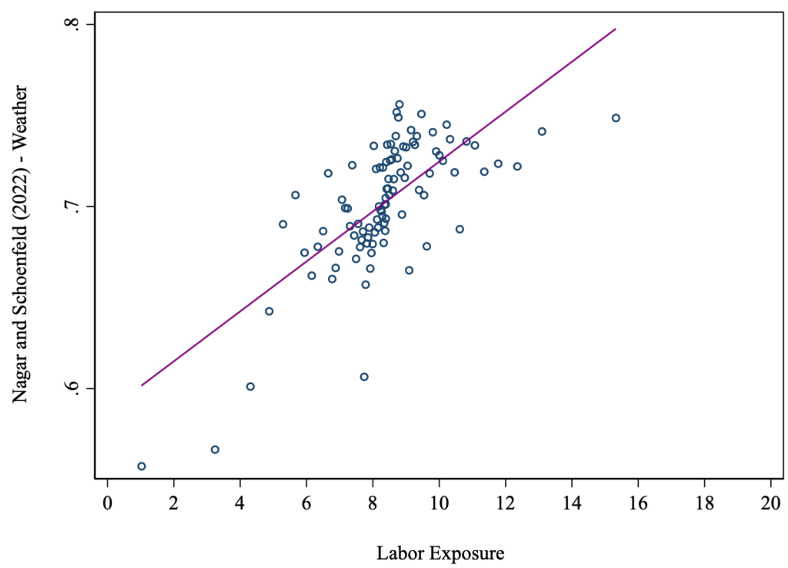


Figure IB.4. Labor Exposure to Climate Risk and Firms' Discussion of Weather in 10-Ks

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)

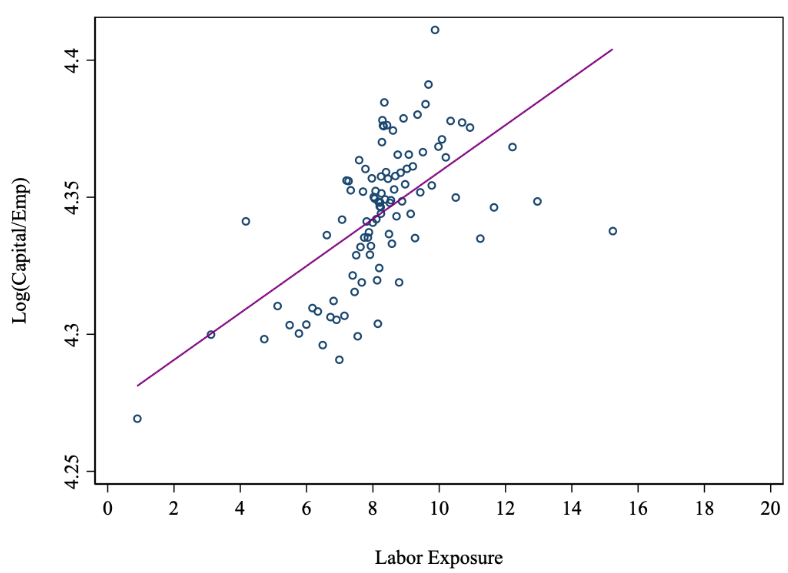
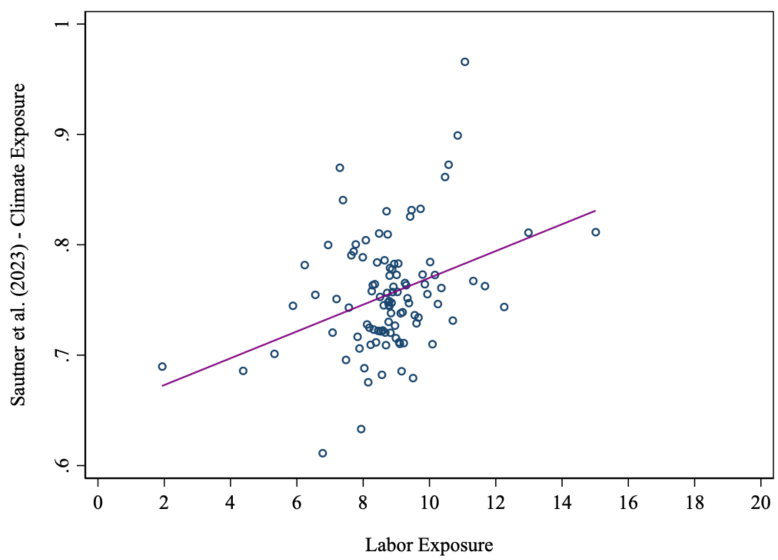


Figure IB.5. Labor Exposure to Climate Risk and Firms' Discussion of Climate Change in Earnings Conference Calls

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)

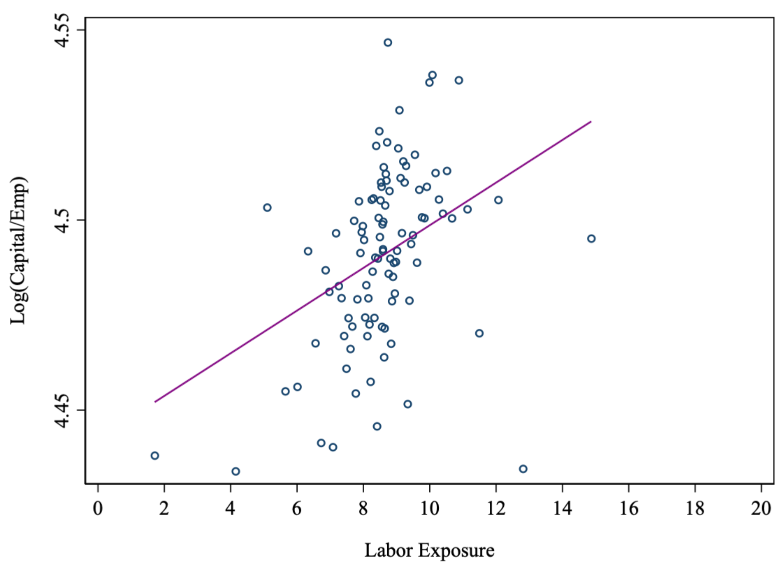
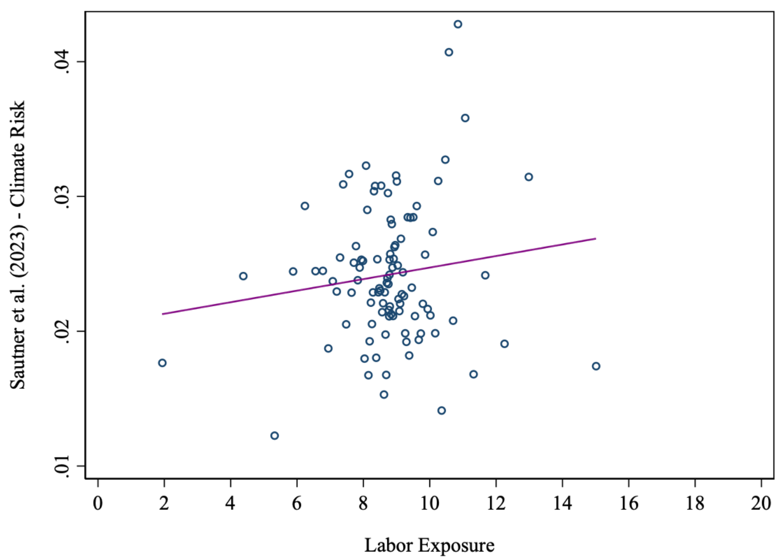


Figure IB.6. Labor Exposure to Climate Risk and Firms' Discussion of Climate Risk in Earnings Conference Calls
Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' discussion of climate risk in earnings conference calls (*Climate Change Risk*) from Sautner 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)

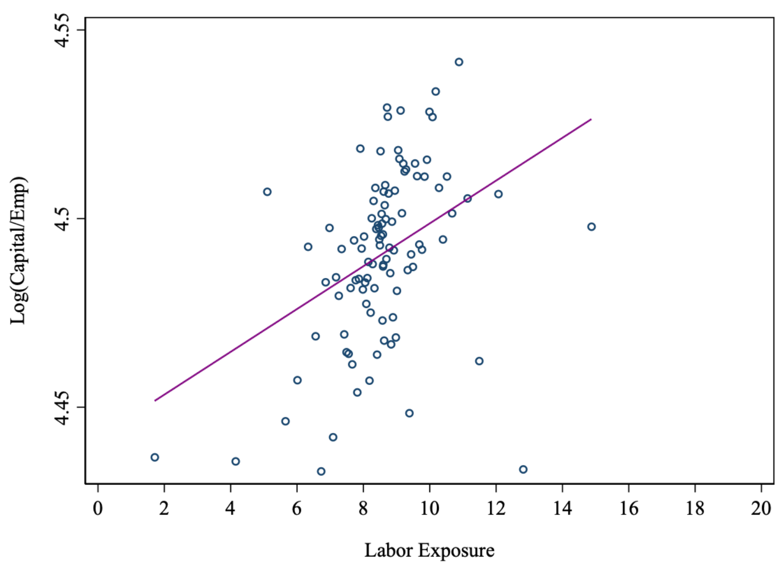
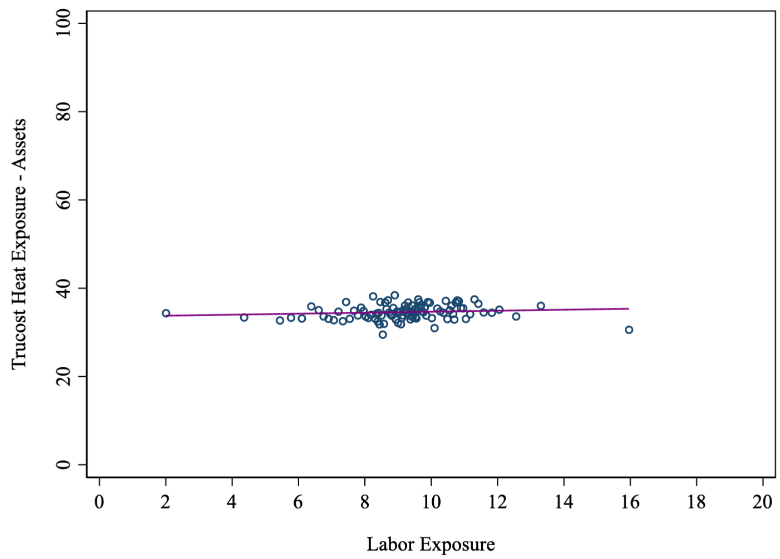


Figure IB.7. Labor Exposure to Climate Risk and Asset-based Heat Exposure from Trucost Climate Analytics

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)

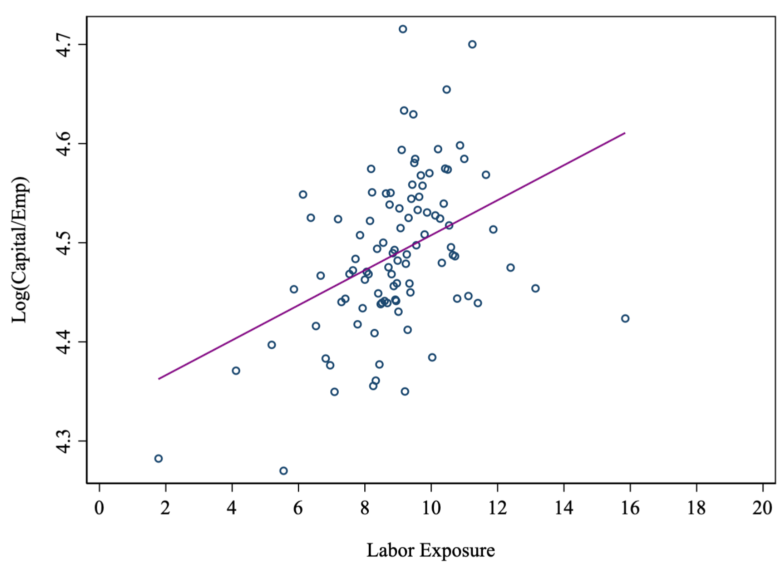
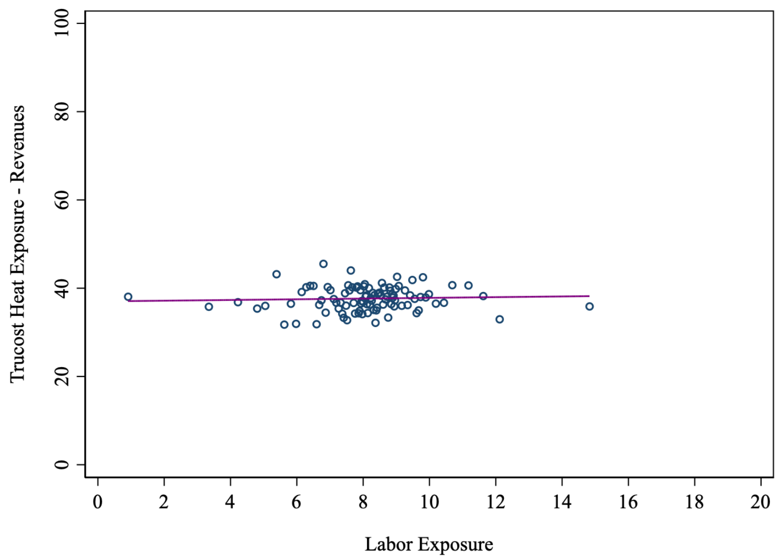


Figure IB.8. Labor Exposure to Climate Risk and Revenue-based Heat Exposure from Trucost Climate Analytics
Figure (A) presents the correlation between the measure of labor exposure to climate risk and firms' revenue exposure to extreme heat provided by Trucost Climate Analytics, after controlling firm 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)

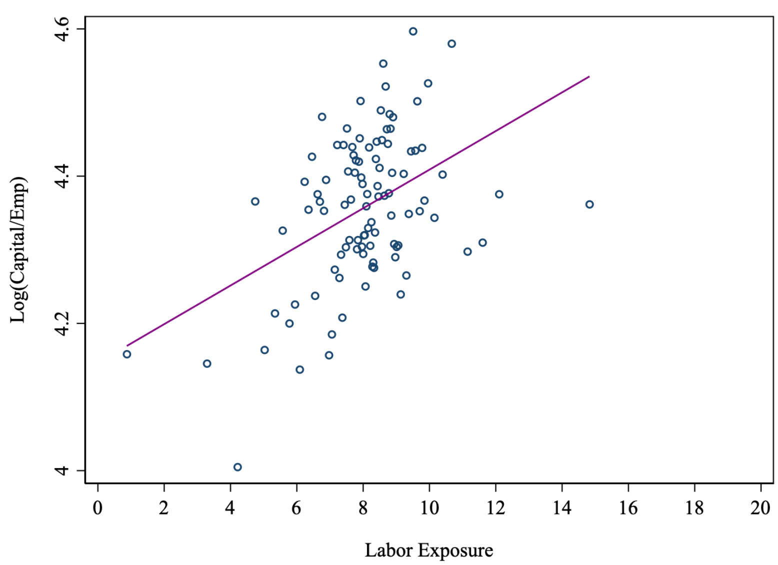


Table IB.1. Occupational Employment and Wage Statistics (OEWS) and the Occupational Information Network (O*NET) Program

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 IB.2. Examples of Industries with Heterogeneous Labor Exposure 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 (1)).

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

C Temperature Patterns

Figure IC.1 presents the annual number of abnormally hot days (daily maximum temperatures exceeding 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 and widespread North American heatwaves, 2011 and 2012 stand out with more hot days — 22 and 18, respectively — compared to the rest of the period.

Figure IC.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 the variations in relative high temperatures presented in Figure IC.1.

Figure IC.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 (3). 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. This figure suggests that summer temperatures classified as heat shocks by Equation (3) are significantly higher than those in other summers, and these relative heat shocks are also hot in an absolute sense.

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

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

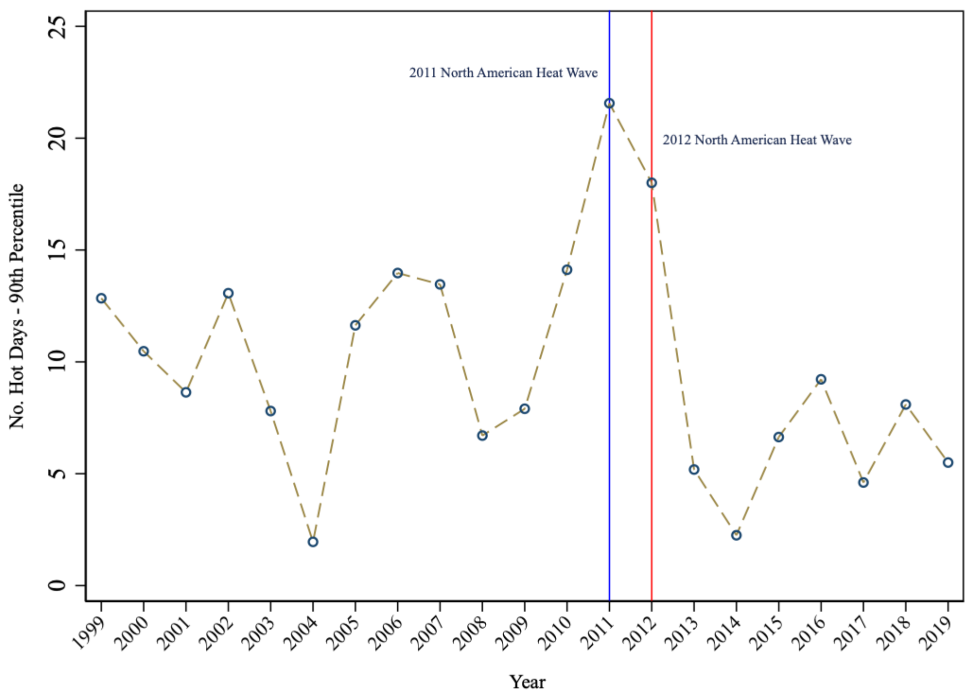


Figure IC.2. Time-Series Average Temperatures in the Continental U.S.

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

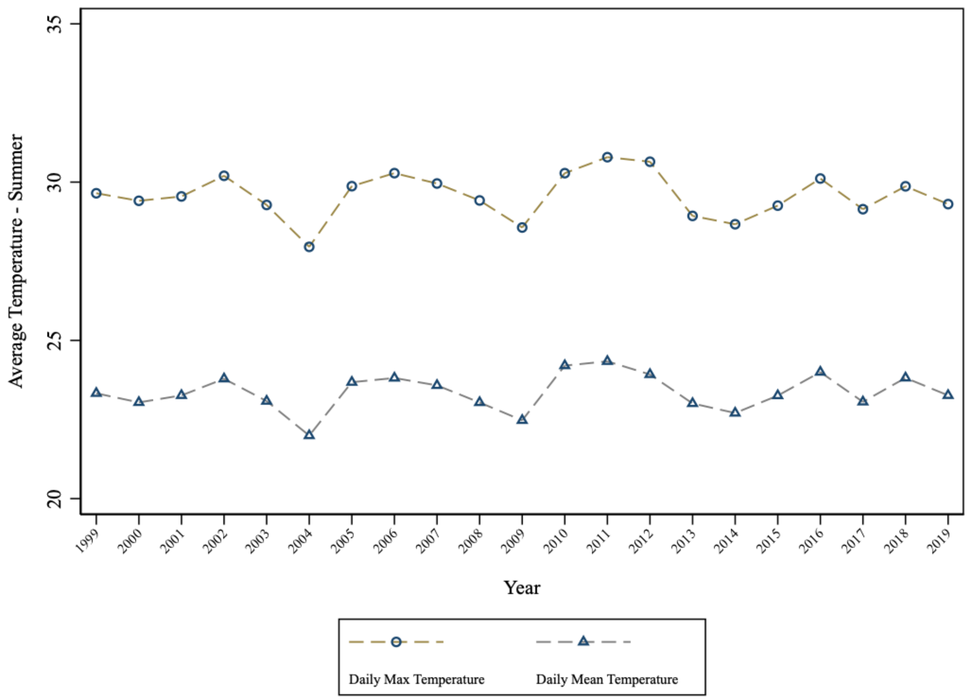
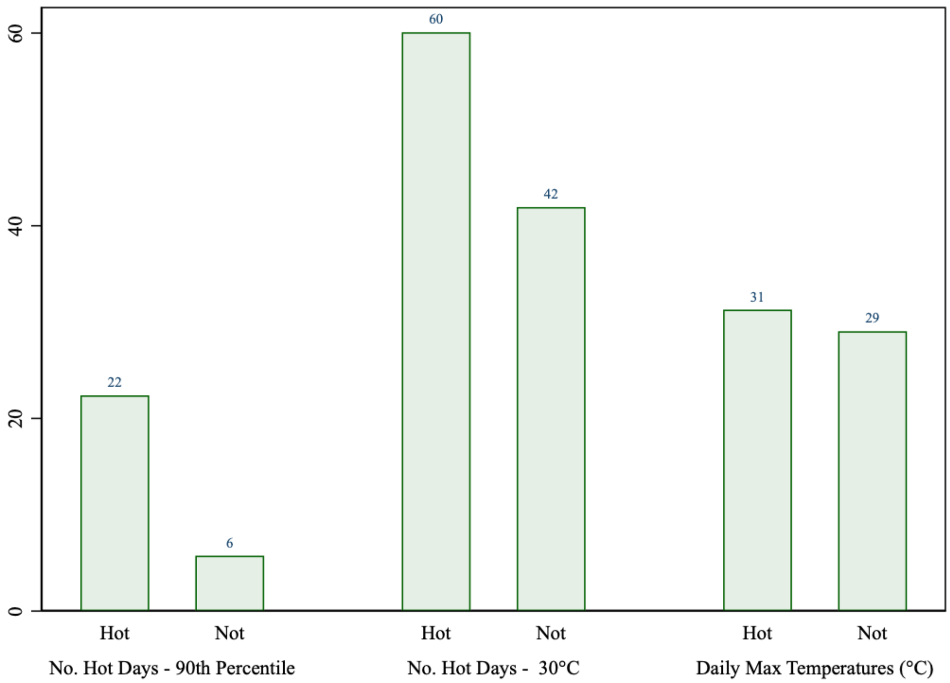


Figure IC.3. Temperature Differences: Hot vs. Non-Hot Scenarios

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 (3). 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.



D Additional Results on Heat Shocks and Capital Utilization in Production

In this section, I first present additional results that complement the analyses in Table 2. I then report further robustness analyses based on Table 2.

A Additional Results

Table ID.1 presents the treatment effects of medium-term heat shocks on firms' capital utilization in production by labor exposure category (1 to 20), based the estimation in columns 4 and 8 of Table 2.

B Robustness Checks

1 Measurement of Capital Excluding R&D Capital

By construction, the measures of total capital and capital-labor ratios in main analyses also capture firms' accumulation of intangible research capital that supports automation, which is consistent with the empirical evidence showing that firms generate more automation patents in response to heat risk in Table 6. In Table ID.2, I reconstruct the measures of total capital utilization and capital-labor ratios using PPENT only, excluding depreciation-adjusted R&D expenses. The results remain consistent.

2 Accounting for Temperature Levels

In Table ID.3, I reconstruct the measure of heat shocks by incorporating absolute temperature levels, i.e., number of summer days above 30°C from $t-3$ to t. Specifically, I measure medium-term heat shocks if (i) a relative medium-term heat shock happens, and (ii) a county or a firm experiences more than 120 days with absolute temperatures above 30°C in summers from $t-3$ to t. The results hold, and the economic magnitudes are larger. This evidence is consistent with subsequent results in Table IG.2 Panel C that relative heat shocks in hot areas are more damaging to labor productivity. Consequently, firms in already hot regions have stronger incentives to pursue capital deepening.

3 An Alternative Rolling Window to Define Heat Shocks

Instead of using a rolling window of 30 years, I use a 20-year rolling window to estimate the 90^{th} percentile threshold for measuring heat shocks and report the results in Table ID.4. The results remain consistent, with larger economic magnitudes.

4 Heat Shocks in Firm Headquarters County

Table ID.5 presents robustness checks using heat shocks occurring only in firms' headquarters counties and therefore does not rely on YTS data to aggregate heat shocks across operating locations to the firm level. The results are largely consistent.

5 Controlling for Other Climate Events

In addition to high temperatures, the 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 noises to 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, I repeat the analysis in Table 2 by controlling for other types of climate events and report the results in Table ID.6. Specifically, in Panel A, I control for cold temperature shocks and total precipitation, while in Panel B, I account for heat shocks occurring outside the summer season and all disasters reported by Federal Emergency Management Agency (FEMA). Consistent with the subsequent evidence presented in Table IG.6, I find no significant effects of these non-heat climate events on firms' capital utilization in production. More importantly, the effects of heat shocks on capital deepening remain robust, with similar economic magnitudes. In addition, the absence of significant effects from heat shocks outside the summer season suggests that these events have limited effects on firms' production decisions, further supporting my focus on summer heat shocks in the main analyses.

6 Sector Breakdowns and Excluding A Consumer Demand Channel

High temperatures may shift consumers toward indoor activities, thereby reducing visits to stores and restaurants and lowering firm sales (Addoum et al. (2023)). High temperatures may also directly reduce crop yields. Consequently, one may argue that my findings could be influenced by consumer demand or agricultural productivity. To mitigate these concerns, I repeat the analysis by excluding agricultural and consumer-oriented industries in Table ID.7 and by excluding non-tradable industries in Table ID.8. The results continue to hold, with similar economic magnitudes. These findings indicate that the results on heat-induced automation are not driven by the consumer demand channel or by declines in crop yields. They are also consistent with the subsequent analyses in Tables IG.7 and IG.8 on labor productivity.

7 Alternative Measures of Labor Exposure to Climate Risk

In Table ID.9, I repeat the analysis using the firm-level measure of labor exposure to climate risk, as defined in Equation (2). In Table ID.10, I conduct robustness checks using a continuous measure of labor exposure from Equation (1), rather than the rank-based measure. The results remain consistent.

Table ID.1. Heat Shocks and Capital Utilization in Production: Table 2

This table presents the treatment effects of heat shocks on firm-level capital utilization in production by labor exposure category (1 to 20), based on the estimation in column 4 and 8 of Table 2.

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	0.0	(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 ID.2. Heat Shocks and Capital Utilization in Production: Measurement of Capital Excluding R&D Capital

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by excluding R&D capital from the measurement of capital. 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, both multiplied by 100. Total capital is a firm's property, plant, and equipment (PPENT). 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.775	-0.987	-2.088**	-1.884*	0.396	-2.116**	-2.999***	-2.181**
	(0.644)	(0.878)	(1.013)	(1.103)	(0.654)	(0.990)	(1.056)	(1.026)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.236***	0.328***	0.300***		0.335***	0.382***	0.267***
		(0.087)	(0.101)	(0.101)		(0.095)	(0.099)	(0.096)
Labor Exposure		-0.093	-0.137	-0.200		0.361	0.398*	-0.275
		(0.244)	(0.249)	(0.310)		(0.246)	(0.235)	(0.306)
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	0.974	0.974	0.973	0.976	0.916	0.916	0.917	0.924
Treatment Effects								
Labor Exposure=15		2.557***	2.838***	2.613**		2.913***	2.734***	1.822*
		(0.988)	(1.080)	(1.018)		(1.002)	(1.045)	(0.981)
Labor Exposure=20		3.739***	4.480***	4.112***		4.589***	4.645***	3.156**
		(1.344)	(1.494)	(1.413)		(1.386)	(1.438)	(1.359)

Table ID.3. Heat Shocks and Capital Utilization in Production: Accounting for Temperature Levels

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by accounting for temperature levels. Heat shocks are redefined by requiring the existence of a relative medium-term heat shock (*1 (Realized ≫ Expected) (M)* and at least 120 days with temperatures $\geq 30°C$ in summer from $t-3$ to t. 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, both multiplied by 100. 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 ≫ 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.504	-2.019*	-1.962*	-0.889	-0.563	-4.553***	-4.451***	-2.620**
	(0.625)	(1.062)	(1.148)	(1.166)	(0.721)	(1.050)	(1.064)	(1.129)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.315***	0.345***	0.253**		0.499***	0.490***	0.311***
		(0.102)	(0.111)	(0.111)		(0.099)	(0.096)	(0.104)
Labor Exposure		-0.137	-0.151	-0.383		0.301	0.377	-0.546*
		(0.242)	(0.253)	(0.264)		(0.312)	(0.304)	(0.280)
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 Effects								
Labor Exposure=15		2.708***	3.209***	2.910***		2.930***	2.895***	2.040*
		(0.949)	(1.134)	(1.103)		(1.057)	(1.125)	(1.046)
Labor Exposure=20		4.283***	4.932***	4.176***		5.425***	5.343***	3.593**
		(1.369)	(1.582)	(1.547)		(1.448)	(1.496)	(1.452)

Table ID.4. Heat Shocks and Capital Utilization in Production: A Rolling Window of Past 20 Years

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by using a rolling window of past 20 years to estimate the 90^{th} percentile to identify heat shocks. 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, both multiplied by 100. 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 ≫ 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.882	-1.090	-1.762*	-1.090	0.603	-1.960*	-2.330**	-1.100
	(0.630)	(0.840)	(0.950)	(0.994)	(0.711)	(1.000)	(1.071)	(1.056)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.263***	0.330***	0.284***		0.343***	0.354***	0.210**
		(0.087)	(0.098)	(0.101)		(0.095)	(0.095)	(0.097)
Labor Exposure		-0.133	-0.158	-0.399		0.326	0.398	-0.526*
		(0.240)	(0.251)	(0.266)		(0.310)	(0.301)	(0.280)
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 Effects								
Labor Exposure=15		2.860***	3.184***	3.169***		3.185***	2.985***	2.044**
		(0.957)	(1.149)	(1.158)		(1.033)	(1.091)	(0.947)
Labor Exposure=20		4.177***	4.833***	4.589***		4.900***	4.757***	3.092**
		(1.321)	(1.553)	(1.576)		(1.408)	(1.451)	(1.327)

Table ID.5. Heat Shocks and Capital Utilization in Production: Heat Shocks in Firm Headquarters County

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by using heat shocks occurring in firms' headquarters counties. 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, both multiplied by 100. 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized $\gg$ Expected) (M)	0.589	-1.028			-0.265	-2.036*		
	(0.792)	(1.087)			(0.810)	(1.124)		
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.215**	0.313***	0.242**		0.243**	0.263**	0.104
		(0.093)	(0.118)	(0.122)		(0.097)	(0.106)	(0.099)
Labor Exposure		-0.121	-0.157	-0.394		0.351	0.419	-0.500*
		(0.241)	(0.254)	(0.266)		(0.315)	(0.309)	(0.283)
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 Effects								
Labor Exposure=15		2.200**	4.691***	3.623**		1.607	3.941**	
		(1.026)	(1.776)	(1.825)		(1.083)	(1.589)	
Labor Exposure=20		3.276**	6.254***	4.830**		2.822*	5.255**	
		(1.371)	(2.369)	(2.433)		(1.446)	(2.118)	

Table ID.6. Heat Shocks and Capital Utilization in Production: Controlling for Other Climate Events

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by controlling for other climate events. In Panel A, columns 1—4 control for cold temperature shocks and columns 5—8 control for total precipitation. In Panel B, columns 1—4 control for heat shocks outside the summer season and 5—8 control for all disasters reported by the FEMA. In both panels, the dependent variable is the natural logarithm of total capital (*Log(Capital)*) in columns 1, 2, 5, and 6, and 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 heat shocks (*1 (Realized ≫ Expected) (M)*), existence of other climate disasters, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Cold Temperature Shocks and Precipitation

	1	2	3	4	5	6	7	8
	Log(Capital) x 100		Log(Capital/Emp) x 100		Log(Capital) x 100		Log(Capital/Emp) x 100	
	Cold Shocks				Precipitation			
1 (Realized ≫ Expected) (M)	-1.837*	-1.231	-2.871***	-1.736*	-1.994**	-1.319	-3.134***	-1.821*
	(0.937)	(0.939)	(1.017)	(1.005)	(0.929)	(0.923)	(0.992)	(0.990)
1 (Realized ≫ Expected) (M) x Labor Exposure	0.309***	0.261***	0.357***	0.227**	0.315***	0.256***	0.396***	0.238**
	(0.095)	(0.094)	(0.094)	(0.098)	(0.095)	(0.093)	(0.092)	(0.097)
Other Climate Events (M)	-2.731**	-1.594	-3.342**	-1.463	-1.290	-0.909	-1.468	-0.516
	(1.335)	(1.417)	(1.328)	(1.365)	(1.890)	(1.816)	(1.395)	(1.429)
Other Climate Events (M) x Labor Exposure	0.108	-0.001	0.270**	0.032	0.057	-0.027	0.295*	0.155
	(0.131)	(0.127)	(0.129)	(0.126)	(0.165)	(0.162)	(0.155)	(0.168)
Labor Exposure	-0.168	-0.396	0.362	-0.537*	-0.169	-0.391	0.315	-0.569**
	(0.251)	(0.265)	(0.301)	(0.279)	(0.259)	(0.271)	(0.291)	(0.275)
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 Effects								
Labor Exposure=15	2.801***	2.688***	2.483**	1.673*	2.728***	2.520***	2.812***	1.754*
	(1.013)	(0.982)	(1.020)	(0.949)	(1.001)	(0.968)	(1.012)	(0.938)
Labor Exposure=20	4.347***	3.995***	4.268***	2.809**	4.302***	3.800***	4.795***	2.945**
	(1.405)	(1.367)	(1.388)	(1.350)	(1.396)	(1.353)	(1.375)	(1.334)

Panel B. Heat Shocks Outside the Summer Season and Disasters Reported by the FEMA

	1	2	3	4	5	6	7	8
	Log(Capital) x 100		Log(Capital/Emp) x 100		Log(Capital) x 100		Log(Capital/Emp) x 100	
	Heat Shocks Outside the Summer Season				FEMA Disasters			
1 (Realized ≫ Expected) (M)	-2.454***	-1.902**	-3.135***	-1.851*	-1.980**	-1.324	-3.012***	-1.777*
	(0.944)	(0.929)	(1.049)	(1.036)	(0.915)	(0.913)	(1.014)	(1.002)
1 (Realized ≫ Expected) (M) x Labor Exposure	0.346***	0.308***	0.380***	0.243**	0.310***	0.256***	0.371***	0.226**
	(0.093)	(0.093)	(0.098)	(0.099)	(0.092)	(0.092)	(0.094)	(0.098)
Other Climate Events (M)	14.084***	15.168***	3.430	1.194	0.551	0.580	-0.008	-0.029
	(5.277)	(5.757)	(6.053)	(6.214)	(0.404)	(0.455)	(0.436)	(0.476)
Other Climate Events (M) x Labor Exposure	-0.887**	-1.083**	-0.220	-0.386	0.046	0.029	0.024	0.020
	(0.367)	(0.454)	(0.387)	(0.471)	(0.044)	(0.053)	(0.047)	(0.054)
Labor Exposure	4.119**	4.821**	1.449	1.323	-0.210	-0.430	0.360	-0.560*
	(1.770)	(2.195)	(1.924)	(2.304)	(0.263)	(0.264)	(0.318)	(0.294)
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 Effects								
Labor Exposure=15	2.732***	2.714***	2.564**	1.801*	2.663***	2.521***	2.548**	1.606*
	(1.004)	(0.980)	(1.086)	(0.969)	(0.990)	(0.971)	(1.015)	(0.939)
Labor Exposure=20	4.461***	4.253***	4.464***	3.019**	4.211***	3.802***	4.402***	2.733**
	(1.382)	(1.362)	(1.474)	(1.367)	(1.368)	(1.352)	(1.381)	(1.339)

Table ID.7. Heat Shocks and Capital Utilization in Production: Excluding Agricultural and Consumer-Oriented Industries

This table presents robustness checks of the treatment effects of hocks on firm-level capital utilization in production by excluding agricultural and consumer-oriented industries (*NAICS2 11, 44, 45, 61, 62, 71, & 72*). 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, both multiplied by 100. 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 ≫ 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.806	-1.234	-1.601*	-0.737	0.571	-2.167**	-2.235**	-1.060
	(0.603)	(0.874)	(0.937)	(0.942)	(0.697)	(1.011)	(1.053)	(1.007)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.276***	0.317***	0.235**		0.373***	0.357***	0.200**
		(0.094)	(0.101)	(0.102)		(0.094)	(0.098)	(0.100)
Labor Exposure		-0.150	-0.111	-0.312		0.290	0.421	-0.418
		(0.286)	(0.288)	(0.295)		(0.331)	(0.310)	(0.308)
Observations	50,834	50,834	47,038	46,975	50,834	50,834	47,038	46,975
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	0.970	0.970	0.970	0.972	0.933	0.933	0.935	0.940

Treatment Effects								
Labor Exposure=15		2.902***	3.156**	2.785**		3.424***	3.119***	1.938**
		(0.973)	(1.118)	(1.105)		(0.956)	(1.005)	(0.983)
Labor Exposure=20		4.281***	4.742***	3.959**		5.288***	4.903***	2.938**
		(1.375)	(1.550)	(1.537)		(1.325)	(1.393)	(1.398)

Table ID.8. Heat Shocks and Capital Utilization in Production: Excluding Non-Tradable Industries

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by excluding non-tradable industries. The classification method of tradable and non-tradable industries is from Mian and Sufi (2014). 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, both multiplied by 100. 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 ≫ 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.804	-1.248	-1.548	-0.967	0.538	-2.226**	-2.324**	-1.269
	(0.604)	(0.871)	(0.950)	(0.957)	(0.706)	(1.044)	(1.047)	(1.055)
1 (Realized ≫ Expected) (M) x Labor Exposure		0.280***	0.312***	0.244**		0.378***	0.348***	0.203**
		(0.091)	(0.099)	(0.102)		(0.096)	(0.094)	(0.102)
Labor Exposure		0.068	0.103	-0.127		0.615*	0.772**	-0.121
		(0.272)	(0.288)	(0.313)		(0.320)	(0.314)	(0.314)
Observations	53,337	53,337	49,390	49,288	53,337	53,337	49,390	49,288
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	0.970	0.970	0.970	0.973	0.933	0.933	0.935	0.941
Treatment Effects								
Labor Exposure=15		2.945***	3.135***	2.698**		3.442***	2.891***	1.774*
		(0.955)	(1.103)	(1.103)		(0.966)	(1.024)	(1.006)
Labor Exposure=20		4.342***	4.696***	3.919**		5.331***	4.629***	2.788*
		(1.340)	(1.519)	(1.532)		(1.342)	(1.388)	(1.421)

Table ID.9. Heat Shocks and Capital Utilization in Production: A Firm-level Measure of Labor Exposure

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by using the firm-level measure of labor exposure to climate risk defined in Equation (2). 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, both multiplied by 100. 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 firm level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized $\gg$ Expected) (M)	0.604	-1.055	-1.973*	-1.360	0.200	-2.429**	-3.324***	-2.206*
	(0.557)	(1.017)	(1.118)	(1.145)	(0.672)	(1.146)	(1.156)	(1.142)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		0.199**	0.282***	0.222**		0.312***	0.366***	0.230**
		(0.093)	(0.104)	(0.106)		(0.102)	(0.109)	(0.112)
Labor Exposure		-0.061	-0.038	-0.087		0.313	0.347*	0.133
		(0.193)	(0.203)	(0.227)		(0.199)	(0.205)	(0.197)
Observations	59,082	59,082	54,887	54,887	59,082	59,082	54,887	54,887
Controls	Yes	Yes	s	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
NAICS2 x Year FE	No	No	No	Yes	No	No	No	Yes
Adjusted R^2	0.971	0.971	0.971	0.971	0.935	0.935	0.937	0.939
Treatment Effects								
Labor Exposure=15		1.927**	2.255**	1.971**		2.257**	2.168**	1.250
		(0.773)	(0.930)	(0.905)		(0.899)	(1.015)	(0.957)
Labor Exposure=20		2.922**	3.664***	3.081**		3.819***	3.998***	2.403*
		(1.147)	(1.348)	(1.333)		(1.298)	(1.455)	(1.431)

Table ID.10. Heat Shocks and Capital Utilization in Production: A Continuous Measure of Labor Exposure

This table presents robustness checks of the treatment effects of heat shocks on firm-level capital utilization in production by using a continuous measure of labor exposure from Equation (1), rather than a rank variable. 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, both multiplied by 100. 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 ≫ 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 firm level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8
	Log(Capital) x 100				Log(Capital/Emp) x 100			
1 (Realized ≫ Expected) (M)	0.604	-4.829***	-5.631***	-3.953**	0.200	-7.028***	-7.453***	-4.293**
	(0.557)	(1.696)	(1.933)	(1.913)	(0.672)	(2.017)	(2.028)	(2.120)
1 (Realized ≫ Expected) (M) x Labor Exposure		2.733***	3.035***	2.325**		3.624***	3.625***	2.125**
		(0.827)	(0.942)	(0.917)		(0.941)	(0.945)	(0.987)
Labor Exposure		0.707	0.084	-3.456		6.989**	6.873**	-4.980
		(2.706)	(2.824)	(3.158)		(3.459)	(3.170)	(3.442)
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

E Measuring Automation Disclosures

I construct the disclosure measures from the full text of firms' annual 10-K filings. After converting each filing into plain text, I split the filing into sentences and classify each sentence using keyword dictionaries. A sentence is classified as an automation sentence if it contains at least one term from an automation dictionary, which includes *automation, automate, automated, automating, robot, robots, robotic, robotics, industrial robot, industrial robots, process automation, industrial automation, manufacturing automation, automated system, automated systems, automated production, automated manufacturing, automated equipment, automation technology, automation technologies, machine vision, machine vision systems, process control, process controller, process controllers, statistical process control, computer integrated manufacturing, programmable manufacturing devices, autonomous manufacturing systems, material handling robots, integrated sensors, sensor-based systems, remote monitoring, predictive maintenance, smart manufacturing, advanced manufacturing, automatic device control, robot motion control, industrial control systems, production automation, plant automation, and facility automation*. I then aggregate these sentence-level classifications to construct *Automation Count*, defined as the number of automation-related sentences in a filing (scaled by 100), and *Automation Share*, defined as the number of automation-related sentences divided by the total number of sentences in the filing (scaled by 1,000,000).

To capture automation discussed in an adaptation context, I combine the automation dictionary with a second dictionary containing heat-, climate-, and adaptation-related terms, including *heat, temperature, weather, climate, extreme heat, hot* *weather, physical risk, disruption, operational disruption, downtime, business continuity, continuity, contingency, contingency planning, resilience, resilient, business resilience, adaptation, adapt, adaptive, mitigation, mitigate, mitigating, response, respond, responding, preparedness, prepare, prepared, protection, safeguard, recovery, recovery planning, worker safety, labor shortage, labor shortages, labor constraint, labor constraints, facility stress, system stress, operational risk, risk mitigation, mitigate risk, adjustment, adjustments, operational adjustment, and operational adjustments*. An automation sentence is classified as an automation-and-adaptation sentence if either that sentence or one of the immediately adjacent sentences contains at least one adaptation-related term. Based on this classification, I construct *Automation+Adaptation Count*, defined as the number of automation sentences linked to adaptation-related discussion (scaled by 100), and *Automation+Adaptation Share*, defined as this count divided by the total number of sentences in the filing (scaled by 1,000,000).

F Heat Shocks and Employment

As an additional analysis, I examine changes in firms' employment in response to heat shocks, considering that decreased reliance on labor in production both drives and results from increased automation.

Ideally, the investigation would examine a firm's hiring and firing practices in relation to heat exposures and worker skills, as a decrease in exposed workers may coincide with an increase in less-exposed, skilled workers capable of operating automated capital assets. However, information on occupational heat exposures and skills is missing in Compustat and YTS. 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 finding effects on employment reduction following heat shocks.

A Firm-level Employment

Table IF.1 presents analyses of firm-level total employment. The empirical model is the same as Equation (7), except that the dependent variable is the natural logarithm of a firm's total employment (*Log(Emp)*) and heat shocks are measured over the medium term ($t-3$ to t). In columns 1—3, analyses using the full-sample data do not find significant effects of heat shocks on firm-level total employment, regardless of heat exposures. Similarly, no effects are found when focusing on firms operating in counties with significant projected long-term temperature increases (columns 4 & 5) or on firms in highly unionized industries (columns 6 & 7). In column 8, when examining firms that predominately employ low-skilled workers, I find a significant decline in employment following heat shocks. For high-exposure firms (*Labor Exposure=15*), total employment decreases by around 1.6%, suggesting that these firms primarily reduce their low-skilled workforce. Further analysis in columns 10 and 11 shows that the result is concentrated among firms with high cash reserves, consistent with the finding in Table 3 Panel B, which demonstrates that cash-unconstrained firms are more aggressive in enhancing automation to mitigate temperature-related labor risks.

Overall, the findings suggest that heat shocks have limited effects on firms' total employment. This non-result may be attributed to simultaneous changes in firms' hiring and firing practices, which are not fully captured by firm-level total employment data. For instance, Table 5 indicates that firms exposed to heat shocks exhibit a significant increase in demand for robotics-related human capital, which would contradict expectations of employment reductions following such shocks. Additionally, the limited effect on employment may stem from firms prioritizing capital investment over workforce reductions after experiencing heat shocks.

B Plant-level Employment

Table IF.2 presents analyses of plant-level total employment. Consistent with the firm-level evidence, columns 1—4 find no effects of high temperatures on total employment in the full sample, regardless of heat exposures. In columns 5—8, I focus on small plants (i.e., those with 50 or fewer employees), where I expect to observe stronger effects. Small plants may have fewer alternatives to automation for adaptation, making them more vulnerable. Additionally, firms might prioritize downsizing the workforce in small plants to mitigate the impact of heat threats (Ponticelli et al. (2023)). Supporting this conjecture, I find that high temperatures have negative and statistically significant effects on employment in small and high-exposure plants. For small plants at the 75^{th} percentile of heat exposure, total employment drops by 0.53% following heat shocks, while plants with the highest exposure reduce their workforce by 0.88%. Additional analyses in columns 9—11 show that the effects are more pronounced among small plants located in counties with high expected long-run heat risks, small plants in industries with high unionization rates, and small plants employing large fractions of low-skilled workers, consistent with the finding in Table 3. I repeat the analysis for large plants (i.e., those with more than 50 employees) but do not find any significant effects.

In summary, these results indicate that firms downsize their workforce in small and heat-exposed plants in response to unexpected high temperatures, supporting the hypothesis that firms address temperature-induced labor challenges by increasing automation. However, the overall impact on total employment remains limited.[32] The findings are generally consistent with Ponticelli et al. (2023), which report no significant effects of long-run temperature changes on total employment but find negative and significant effects on employment in small plants. The findings are also consistent with Xiao (2026), which documents that the negative effects of heat shocks, through the labor exposure channel, can accumulate to an economically significant magnitude, leading to a contraction in industry-wide entrepreneurial activities and employment.

[32]The results should be interpreted with caution, given that the plant-level employment data in YTS is mostly estimated. See more discussion on the data issue in Section 8.

Table IF.1. Heat Shocks and Firm-level total Employment

This table presents the treatment effects of medium-term heat shocks on firm-level total employment. Columns 1—3 labeled with *"Full Sample"* represent analyses using the full-sample data. Columns 4—5 labeled with *"Temperature Projections - H"* represent analyses using firms operated in counties with significant projected long-term temperature increases. Columns 6—7 labeled with *"Labor Union - H"* represent analyses using firms in industries with high unionization rates. Columns 8—9 labeled with *"Labor Skill - L"* represent analyses using firms that predominately employ low-skilled workers. Columns 10—11 labeled with *"Labor Skill - L & Cash - H"* represent analyses using firms that predominately employ low-skilled workers and have high cash holdings. The dependent variable is the natural logarithm of total employment (*Log(Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9	10	11
	Log(Emp) x 100										
	Full Sample			Temperature Projections - H		Labor Union - H		Labor Skill - L		Labor Skill - L & Cash - L	
1 (Realized $\gg$ Expected) (M)	0.039	0.588	0.316	0.168	-1.177	0.876	-0.057	1.614	1.028	3.782*	3.355
	(0.596)	(0.939)	(0.916)	(1.612)	(1.489)	(1.178)	(1.142)	(1.509)	(1.405)	(2.012)	(2.045)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		-0.071	-0.024	-0.073	0.095	-0.159	-0.032	-0.214*	-0.140	-0.434***	-0.384**
		(0.095)	(0.090)	(0.140)	(0.130)	(0.128)	(0.120)	(0.119)	(0.109)	(0.149)	(0.171)
Observations	60,167	60,167	60,167	22,314	22,296	24,647	24,619	34,758	34,758	16,801	16,794
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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS2 x Year FE	No	No	Yes	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	0.978	0.979
Treatment Effects											
Labor Exposure=15								-1.591*		-2.733**	-2.403*
								(0.851)		(1.359)	(1.375)
Labor Exposure=20								-2.659**		-4.904***	-4.322**
								(1.270)		(1.824)	(2.013)

Table IF.2. Heat Shocks and Plant-level Total Employment

This table presents the treatment effects of medium-term heat shocks on plant-level total employment. This sample is constructed at the firm-by-county-by-NAICS4 industry-by-year level using the YTS data. Columns 1—4 labeled with *"Full Sample"* represent analyses using the full-sample data. Columns 5—11 labeled with *"EMP $\leq$ 50"* represent analyses using plants with 50 or fewer employees. Columns 9 labeled with *"Temperature Projections - H"* represent analyses using firms and plants operated in counties with significant projected long-term temperature increases. Columns 10 labeled with *"Labor Union - H"* represent analyses using firms and plants in industries with high unionization rates. Columns 11 labeled with *"Labor Skill - L"* represent analyses using firms and plants that predominately employ low-skilled workers. The dependent variable is the natural logarithm of total employment (*Log(Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*) and its interaction with a plant's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure* and *Log(Emp)* at $t-3$ as a proxy for plant size. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are double clustered at the NAICS4 and county levels. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9	10	11
	Log(Emp) x 100										
	Full Sample				Emp<=50				Emp<=50		
									Temperature Projections - H	Labor Union - H	Labor Skill - L
1(Realized $\gg$ Expected) (M)	-0.425***	-0.423	-0.173		-0.133	0.571**	0.540**		0.666	0.249	0.479
	(0.155)	(0.337)	(0.334)		(0.000)	(0.232)	(0.266)		(0.506)	(0.484)	(0.315)
1 (Realized $\gg$ Expected) (M) x Labor Exposure		-0.000	-0.027	-0.001		-0.072***	-0.071***	-0.082***	-0.079**	-0.060*	-0.065**
		(0.037)	(0.036)	(0.036)		(0.021)	(0.023)	(0.023)	(0.039)	(0.036)	(0.027)
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	398,915
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	0.405
Treatment Effects											
Labor Exposure=15						-0.514***	-0.528***		-0.516**	-0.656***	-0.490***
						(0.154)	(0.154)		(0.263)	(0.201)	(0.155)
Labor Exposure=20						-0.875***	-0.884***		-0.910**	-0.957***	-0.813***
						(0.239)	(0.250)		(0.393)	(0.324)	(0.263)

G Additional Results on Heat Shocks and Labor Productivity

In this section, I first present additional results that complement the analyses in Table 8. I then report further robustness analyses based on Table 8.

A Additional Results

Panel (A) of Table IG.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 8. Panel B of Table IG.1 presents the regression results on the dynamic treatment effects behind Figure 2.

B Robustness Checks

1 Alternative Measures of Heat Shocks

To address concerns that defining heat shocks with $T = 15$ seems arbitrary and to provide additional support for this choice, in Table IG.2 Panel A, I use temperature bins to define three heat categories: 1 *0 $\leq$ number of relative hot days in a summer $<$ 10*, (2) *10 $\leq$ number of relative hot days in a summer $<$ 15*, and (3) *number of relative hot days in a summer $\geq$ 15*. The first category (0 $\leq$ number of relative hot days in a summer $<$ 10) signifies no upward shift in temperature distributions relative to historical records and, therefore, does not represent heat shocks. In regression, this category will be used as an benchmark and thus omitted. In all four columns, the analysis shows that the effects of heat on labor productivity become significant only when the number of relative hot days exceeds 15, as evidenced by the coefficient of $1(\textit{No. Relative Hot Days} > 15) \times \textit{Labor Exposure}$. This evidence strongly supports the choice of using $T = 15$ to define heat shocks.

In Panel B, I use alternative thresholds ($T = 10, 12, 14$, or 16) to define heat shocks and find that the significant negative effects of heat shocks on labor productivity emerge when $T = 14$ and become more pronounced as the threshold increases. This evidence further supports the temperature-bin-based results and the choice of $T = 15$ in the main analyses.

Furthermore, I do not find significant effects when using a continuous measure of the number of relatively hot days in Table IG.3. This suggests that firms actively adapt to local temperature conditions, and that only substantial deviations from historical temperatures that exceed their tolerance thresholds harm labor productivity and trigger additional adaptation.

Internet Appendix Figure IC.3 demonstrates that relative heat shocks also capture high temperatures in an absolute sense. To further show the effects of absolute temperatures, I reconstruct the measure of heat shocks by incorporating absolute temperature levels. Specifically, in Table IG.2 Panel C, columns 1—2 define heat shocks by requiring (i) the existence of a relative heat shock (*1 (Realized* $\gg$ *Expected)*) in Equation (3), and (ii) at least 10 summer days with temperatures $\geq 30°$C. Columns 3–4, columns 5—6, and column 7—8 differ by requiring at least 20, 30, and 40 summer days with temperatures $\geq 30°$C, respectively. The results hold across all measures, and the economic magnitudes generally increase as the number of absolute hot days rises from columns 1 to 8. This finding is consistent with the idea that relative heat shocks in hot areas are more damaging to labor productivity.

2 An Alternative Rolling Window to Define Heat Shocks

In Equations (3) and (4), I use historical temperatures from 1981 to the previous year (*1981 to* $t-1$) to estimate the 90^{th} percentile threshold used to identify heat shocks, with a maximum window of 30 years. By construction, the number of reference years varies, increasing from 18 in 1999 to a maximum of 30 during the 2011–2019 period. To assess robustness to this rolling-window choice, I conduct additional analyses using a rolling window of the past 20 years to estimate the 90^{th} percentile threshold. The results in Table IG.4 are consistent.

3 Heat Shocks in Firm Headquarters County

Table IG.5 presents the treatment effects of short-term heat shocks that happen in firms' headquarters counties on firm-level labor productivity. This methodology does not require YTS data on plant-level employment to aggregate county-level heat shocks (Equation (3)) to the firm level. The results hold.

4 Controlling for Other Climate Events

In Table IG.6, I add interaction terms of labor exposure with other climate events, including cold temperature shocks, 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 absence of an effect from cold temperature shocks on summer labor productivity also serves as a falsification test, given that the regression sample focuses on firm sales in summer quarters. More importantly, after including these controls, high temperatures continue to negatively affect labor productivity, with similar economic magnitudes.

5 Sector Breakdowns and Excluding A Consumer Demand Channel

Table IG.7 columns 1—3 conduct robustness checks by excluding consumer-oriented sectors. The results hold and economic effects are similar, indicating that demand-side forces do not likely drive the findings. Additionally, I drop the agricultural sector and split firms into two broad categories: non-consumer-oriented goods-producing (columns 4—6) and service sectors (columns 7—9). Consistent with the fact that the outdoor workforce is a critical production input for the whole economy, I find that the negative effects of heat risk exist in both categories. The evidence also demonstrates that drops in crop yields do not drive the 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 may underestimate the impact of extreme heat on labor productivity.

In addition, to provide further evidence ruling out the consumer demand channel, I repeat the analysis in Table 8 by excluding non-tradable industries. Columns 1—3 of Table IG.8 present the results. The results hold, with similar economic magnitudes. In columns 4—6, I exclude both non-tradable and construction industries and find consistent results, suggesting that the negative effects of heat shocks are not confined to the construction sector. Finally, in columns 7—9, I limit the sample to firms in tradable industries and obtain consistent results.

6 Alternative Measures of Labor Exposure to Climate Risk

In Table IG.9, I repeat the analysis using the firm-level measure of labor exposure to climate risk, as defined in Equation (2). In Table IG.10, I present robustness checks using a continuous measure of labor exposure, rather than a rank variable. The results remain consistent.

7 Segment-level Analysis

Table IG.11 presents the treatment effects of heat shocks on segment-level sales. The segment-level data on sales, assets, and industry classifications are obtained from the Compustat segment files. The dependent variable is the 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. The labor exposure of each segment is determined by its own industry classification rather than by the firm's classification. My analysis shows that heat shocks significantly reduce segment-level sales. The economic magnitude is also significant. 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 8 that unexpected high temperatures reduce corporate performance.

8 Plant-level Analysis

I also conduct analyses on labor productivity using plant-level data on employment and sales from YTS. In YTS, each plant is assigned an industry classification that represents the nature of its business operations, which may differ from the parent company's primary industry classification. To improve estimation accuracy and efficiency and to align with the industry-level labor exposure measure, I aggregate the data to the firm-by-county-by-NAICS4 industry level. I measure each plant's labor exposure by matching it with the industry-level measure based on its classification. Table IG.12 Panel A presents the summary statistics. Below is the empirical model.

$$
\begin{aligned}
Y_{f,c,i,t} = & \mu_{f,t} + \tau_{c,t} + \theta_{c,i} + \pi_{i,t} + \delta_i + \beta_1 \mathit{1\ (Realized \gg Expected)}_{f,c,t} \\
& + \beta_2 \mathit{1\ (Realized \gg Expected)}_{f,c,t} \times \mathit{Labor\ Exposure}_{f,i,t} + \beta_3 \mathit{Labor\ Exposure}_{f,i,t} + \varepsilon_{f,c,i,t}
\end{aligned} \tag{8}
$$

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* $\gg$ *Expected)* is a dummy indicating that firm $f's$ plants in county c are exposed to heat shocks (Equation (3)). *Labor Exposure* measures the exposure of firm $f's$ plants in industry i to climate risks (Equation (1)). $\mu_{f,t}$ 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 IG.12 Panel B 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 results hold.

Additionally, Table IG.12 Panel C presents the effects of heat shocks for plants in each labor exposure category (1 to 20). As can be seen, the negative impact of heat shocks concentrates among high-exposure plants, i.e., labor exposure ≥ 13. Table IG.12 Panel D presents consistent dynamic effects of heat shocks at the plant level, further supporting the firm-level evidence.

However, although both firm- and plant-level analyses show that heat shocks negatively affect labor productivity, the economic magnitude is larger at the firm level. For example, after a heat shock, the firm-level labor productivity drops by 1.9% for firm with *Labor Exposure=15*, while the plant-level labor productivity drops by 0.13%. Two potential factors may contribute to the gap. First, the firm-level analysis uses data on summer sales from the quarterly Compustat/CRSP, while the YTS data only contains annual sales, which can be influenced by more variables beyond summer temperatures. Put differently, the time mapping between labor productivity and heat shocks is less precise in the YTS-based test, which is against me finding a large economic magnitude. Second, the gap may be attributed to the errors-in-variables problem in YTS. 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. The imputation introduces measurement errors and attenuation biases that are against finding significant results, implying that conclusions drawn from the YTS data might underestimate the impact of temperatures on corporate activities.

Table IG.1. Heat Shocks and Firm-level Labor Productivity: Table 8

This table presents additional results in the setting of Table 8. Panel A presents the treatment effects of heat shocks on firm-level labor productivity by labor exposure category (1 to 20), based on the estimation in Table 8 column 5. Panel B presents the regression results on the dynamic treatment effects behind Figure 2.

Panel A. Treatment Effects by Labor Exposure

Labor Exposure	Treatment Effect (%)	Std. Error
1	1.1	(1.053)
2	0.9	(0.990)
3	0.6	(0.931)
4	0.4	(0.877)
5	0.2	(0.828)
6	0.0	(0.786)
7	-0.2	(0.752)
8	-0.4	(0.726)
9	-0.6	(0.710)
10	-0.8	(0.704)
11	-1.1	(0.709)
12	-1.3*	(0.724)
13	-1.5**	(0.749)
14	-1.7**	(0.783)
15	-1.9**	(0.824)
16	-2.1**	(0.872)
17	-2.3**	(0.926)
18	-2.5**	(0.984)
19	-2.7***	(1.045)
20	-3.0***	(1.112)

Panel B. Dynamic Treatment Effects

	1	2	3	4	5	6	7
	Log(Sales/Emp) x 100						
1 (Realized $\gg$ Expected) (T-3) x Labor Exposure	-0.108						
	(0.106)						
1 (Realized $\gg$ Expected) (T-2) x Labor Exposure		-0.093					
		(0.108)					
1 (Realized $\gg$ Expected) (T-1) x Labor Exposure			-0.087				
			(0.086)				
1 (Realized $\gg$ Expected) (T) x Labor Exposure				-0.211**			
				(0.086)			
1 (Realized $\gg$ Expected) (T+1) x Labor Exposure					-0.074		
					(0.105)		
1 (Realized $\gg$ Expected) (T+2) x Labor Exposure						-0.040	
						(0.098)	
1 (Realized $\gg$ Expected) (T+3) x Labor Exposure							-0.048
							(0.098)
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 IG.2. Heat Shocks and Firm-level Labor Productivity: Alternative Measures of Heat Shocks

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity, using alternative measures of heat shocks. The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). Panel A uses temperature bins to define three heat categories: (1) $0 \leq$ number of relative hot days in a summer < 10, (2) $10 \leq$ number of relative hot days in a summer < 15, and (3) number of relative hot days in a summer ≥ 15. The first category ($0 \leq$ number of relative hot days in a summer < 10) indicates no upward shift in temperature distributions relative to historical records and thus is used as an benchmark and omitted in regression. Specifically, $1(10 <= \textit{No. Relative Hot Days} < 15)$ is a dummy indicating a county or a firm experiences at least 10 relative hot days but less than 15 in a summer. $1(\textit{No. Relative Hot Days} > 15)$ is a dummy indicating that a county or a firm experiences at least 15 relative hot days in a summer. A relative hot day is identified by comparing daily maximum temperatures relative to the $90th$ percentile of historical temperatures in the same county and month from 1981 to $t-1$, with a maximum of 30 years. The key independent variables reported are $1(10 <= \textit{No. Relative Hot Days} < 15)$, $1(\textit{No. Relative Hot Days} > 15)$, and their interaction terms with a firm's labor exposure to climate risk (*Labor Exposure*). Panel B uses alternative thresholds (T) to identify heat shocks. Columns 1—2 define heat shocks by setting $T = 10$. Column 3—4, columns 5—6, and columns 7—8 set $T = 12$, $T = 14$, and $T = 16$, respectively. The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Panel C combines relative hot temperatures with absolute temperature levels. Specifically, columns 1—2 define heat shocks by requiring (1) the existence of a relative heat shock (*1 (Realized ≫ Expected)* in Equation (3) and $T = 15$, and (2) at least 10 summer days with temperatures $\geq 30°$C. Columns 3—4, columns 5—6, and column 7—8 differ by requiring at least 20, 30, and 40 summer days with temperatures $\geq 30°$C, respectively. The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Temperature Bins

	1	2	3	4
	Log(Sales/Emp) x 100			
1(10 <= No. Relative Hot Days < 15)	-1.889***	-0.327	-0.947	-0.503
	(0.724)	(0.859)	(0.796)	(0.920)
1(No. Relative Hot Days > 15)	0.579	1.514	0.793	0.975
	(0.978)	(1.019)	(0.861)	(1.125)
1(10 <= No. Relative Hot Days < 15) x Labor Exposure	0.105	0.035	0.111	0.026
	(0.070)	(0.081)	(0.078)	(0.084)
1(No. Relative Hot Days > 15) x Labor Exposure	-0.177**	-0.231***	-0.132*	-0.200**
	(0.075)	(0.081)	(0.075)	(0.095)
Observations	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
State x Year FE	Yes	No	No	No
County x Year FE	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	Yes	Yes
NAICS2 x Year FE	No	No	Yes	No
NAICS4 x Year FE	No	No	No	Yes
Adjusted R^2	0.858	0.859	0.871	0.875

Panel B. Alternative Thresholds (T) to Identify Heat Shocks

	1	2	3	4	5	6	7	8
	Log(Sales/Emp) x 100							
	T=10		T=12		T=14		T=16	
1 (Realized $\gg$ Expected)	0.493	0.078	0.774	0.355	1.927**	1.596*	1.538	1.008
	(0.712)	(0.792)	(0.848)	(0.794)	(0.791)	(0.838)	(0.936)	(1.038)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.071	-0.052	-0.113	-0.073	-0.228***	-0.181**	-0.219***	-0.196**
	(0.065)	(0.074)	(0.073)	(0.081)	(0.068)	(0.079)	(0.078)	(0.086)
Observations	54,489	53,494	54,489	53,494	54,489	53,494	54,489	53,494
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
NAICS4 x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.859	0.876	0.859	0.876	0.859	0.876	0.859	0.876

Treatment Effects								
Labor Exposure=15					-1.495*	-1.115	-1.743**	-1.936**
					(0.803)	(0.786)	(0.876)	(0.861)
Labor Exposure=20					-2.635**	-2.018*	-2.837**	-2.917**
					(1.057)	(1.105)	(1.160)	(1.171)

Panel C. Incorporating Absolute Temperature Levels

	1	2	3	4	5	6	7	8
	Log(Sales/Emp) x 100							
	Days (30C) >= 10		Days (30C) >= 20		Days (30C) >= 30		Days (30C) >= 40	
1 (Realized $\gg$ Expected)	1.357	0.935	1.525	1.063	1.437	1.034	1.631	1.149
	(1.015)	(1.072)	(1.029)	(1.092)	(1.163)	(1.220)	(1.179)	(1.232)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.231***	-0.194**	-0.231***	-0.185**	-0.271***	-0.214**	-0.284***	-0.248**
	(0.079)	(0.087)	(0.079)	(0.088)	(0.086)	(0.098)	(0.092)	(0.101)
Observations	54,489	53,494	54,489	53,494	54,489	53,494	54,489	53,494
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County x NAICS2 FE	No	Yes	No	Yes	No	Yes	No	Yes
NAICS4 x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.859	0.876	0.859	0.876	0.859	0.876	0.859	0.876

Treatment Effects								
Labor Exposure=15	-2.109**	-1.977**	-1.945**	-1.708**	-2.627***	-2.170**	-2.625***	-2.563***
	(0.822)	(0.843)	(0.825)	(0.865)	(0.865)	(0.893)	(0.858)	(0.911)
Labor Exposure=20	-3.265***	-2.947**	-3.102***	-2.631**	-3.982***	-3.238***	4.043***	3.801***
	(1.083)	(1.151)	(1.089)	(1.153)	(1.133)	(1.237)	(1.167)	(1.269)

Table IG.3. Heat Shocks and Firm-level Labor Productivity: Number of Relative Hot Days

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity using the number of relative hot days. The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). The key independent variables reported are *No. Relative Hot Days* and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). *No. Relative Hot Days* is the number of relative hot days in a summer. Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Sales/Emp) x 100				
No. Relative Hot Days	-0.027	-0.012	0.090	0.025	0.053
	(0.034)	(0.052)	(0.055)	(0.048)	(0.051)
No. Relative Hot Days x Labor Exposure		-0.001	-0.005	-0.000	-0.004
		(0.005)	(0.005)	(0.004)	(0.005)
Observations	58,711	58,711	54,489	54,399	53,494
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.875

Table IG.4. Heat Shocks and Firm-level Labor Productivity: A Rolling Window of Past 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 20 years to calculate the 90^{th} percentile threshold to identify heat shocks. The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Sales/Emp) x 100				
1 (Realized $\gg$ Expected)	0.167	2.080**	2.394**	1.702*	1.810
	(0.578)	(0.870)	(1.029)	(0.984)	(1.102)
1 (Realized $\gg$ Expected) x Labor Exposure		-0.229***	-0.262***	-0.177**	-0.214**
		(0.068)	(0.078)	(0.078)	(0.091)
Observations	58,711	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.876
Treatment Effects					
Labor Exposure=15		-1.353**	-1.540*	-0.959	-1.396*
		(0.680)	(0.846)	(0.775)	(0.840)
Labor Exposure=20		-2.498***	-2.852***	-1.845*	-2.464**
		(0.910)	(1.102)	(1.040)	(1.170)

Table IG.5. Heat Shocks and Firm-level Labor Productivity: Heat Shocks in Firm Headquarters County

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity, using heat shocks occurring in firms' headquarters counties. The dependent variable is the natural logarithm of sales per employee (*Log(Sales/Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized $\gg$ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Sales/Emp) x 100				
1 (Realized $\gg$ Expected)	-0.376	1.411			
	(0.738)	(1.089)			
1 (Realized $\gg$ Expected) x Labor Exposure		-0.203***	-0.251***	-0.174**	-0.180**
		(0.070)	(0.081)	(0.073)	(0.082)
Observations	58,711	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.875
Treatment Effects					
Labor Exposure=15		-1.633**			
		(0.685)			
Labor Exposure=20		-2.648***			
		(0.851)			

Table IG.6. 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 for other climate events. Columns 1—3 control for cold temperature shocks. Columns 4—6 control for precipitation. Columns 7—9 control for all disasters reported by 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 dummy indicating heat shocks (*1 (Realized $\gg$ Expected)*), existence of other climate disasters, and the interaction terms. Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9
	Log(Sales/Emp) x 100								
	Cold Temperatures			Precipitation			FEMA Disasters		
1 (Realized $\gg$ Expected)	1.578	1.141	1.273	1.551	1.173	1.291	1.624	1.170	1.287
	(1.041)	(0.991)	(1.119)	(1.026)	(0.998)	(1.121)	(1.032)	(0.988)	(1.119)
1 (Realized $\gg$ Expected) x Labor Exposure	-0.237***	-0.173**	-0.211**	-0.230***	-0.174**	-0.215**	-0.239***	-0.174**	-0.211**
	(0.078)	(0.076)	(0.086)	(0.077)	(0.076)	(0.086)	(0.077)	(0.076)	(0.087)
Other Climate Events	-1.439	-0.772	-0.028	-0.684	0.261	0.202	0.174	-0.070	-0.140
	(1.012)	(0.897)	(0.969)	(0.900)	(0.922)	(0.949)	(0.395)	(0.432)	(0.463)
Other Climate Events x Labor Exposure	0.155*	0.072	-0.028	0.101	0.002	-0.040	-0.070**	-0.044	-0.042
	(0.085)	(0.074)	(0.086)	(0.084)	(0.075)	(0.075)	(0.033)	(0.037)	(0.039)
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	0.859	0.871	0.876
Treatment Effects									
Labor Exposure=15	-1.981**	-1.457*	-1.892**	-1.903**	-1.442*	-1.928**	-1.963**	-1.441*	-1.880**
	(0.804)	(0.791)	(0.824)	(0.824)	(0.805)	(0.837)	(0.802)	(0.790)	(0.823)
Labor Exposure=20	-3.167***	-2.323**	-2.947***	-3.054***	-2.314**	-3.000***	-3.159***	-2.311**	-2.935***
	(1.050)	(1.041)	(1.111)	(1.068)	(1.056)	(1.123)	(1.046)	(1.039)	(1.112)

Table IG.7. Heat Shocks and Firm-level Labor Productivity: Sector Breakdowns and Excluding Consumer-oriented Sectors

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*), while columns 7—9 focus on 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 reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9
	Log(Sales/Emp) x 100								
	Non-consumer-oriented Sectors			Goods-producing Sector			Service Sector		
1 (Realized ≫ Expected)	2.092*	0.968	1.185	3.253**	2.039	2.167	1.439	-0.028	-0.114
	(1.137)	(1.139)	(1.279)	(1.585)	(1.633)	(1.705)	(1.303)	(1.347)	(1.422)
1 (Realized ≫ Expected) x Labor Exposure	-0.263***	-0.174**	-0.232**	-0.370***	-0.274**	-0.301**	-0.337***	-0.196	-0.285**
	(0.085)	(0.085)	(0.095)	(0.121)	(0.124)	(0.129)	(0.114)	(0.143)	(0.123)
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 Effects									
Labor Exposure=15	-1.857**	-1.635*	-2.290**	-2.293***	-2.067**	-2.348**	-3.617*		-4.390**
	(0.827)	(0.873)	(0.904)	(0.849)	(0.898)	(0.970)	(2.064)		(2.122)
Labor Exposure=20	-3.173***	-2.503**	-3.449***	-4.142***	-3.435***	-3.853***	-5.303**		-5.815**
	(1.094)	(1.143)	(1.205)	(1.260)	(1.312)	(1.394)	(2.533)		(2.618)

Table IG.8. Heat Shocks and Firm-level Labor Productivity: Excluding Non-Tradable and Construction Industries

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity by excluding non-tradable and construction industries. Specifically, columns 1—3 exclude non-tradable industries. Columns 4—6 exclude non-tradable and construction industries. Columns 7—9 keep tradable industries only. The classification method of tradable and non-tradable industries is from Mian and Sufi (2014). The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5	6	7	8	9
	Log(Sales/Emp) x 100								
	Excluding Non-tradable Industries			Excluding Non-tradable and Construction Industries			Tradable Industries Only		
1 (Realized ≫ Expected)	2.161**	1.201	1.208	1.624	1.241	1.277	3.170*	1.918	2.140
	(1.015)	(1.054)	(1.191)	(1.050)	(1.106)	(1.254)	(1.706)	(1.653)	(1.632)
1 (Realized ≫ Expected) x Labor Exposure	-0.277***	-0.202**	-0.242***	-0.236***	-0.204**	-0.258***	-0.402***	-0.271**	-0.329***
	(0.076)	(0.079)	(0.090)	(0.087)	(0.084)	(0.096)	(0.146)	(0.133)	(0.120)
Observations	48,895	48,798	48,123	45,515	45,425	44,808	28,740	28,725	28,548
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.849	0.860	0.865	0.839	0.849	0.853	0.811	0.816	0.822
Treatment Effects									
Labor Exposure=15	-1.999**	-1.830**	-2.427***	-1.909**	-1.823**	-2.585***	-2.859**	-2.146**	-2.788**
	(0.846)	(0.849)	(0.891)	(0.879)	(0.855)	(0.925)	(1.132)	(1.073)	(1.094)
Labor Exposure=20	-3.385***	-2.840**	-3.639***	-3.087***	-2.845**	-3.873***	-4.869***	-3.500**	-4.430***
	(1.091)	(1.101)	(1.178)	(1.195)	(1.127)	(1.243)	(1.692)	(1.550)	(1.466)

Table IG.9. Heat Shocks and Firm-level Labor Productivity: A Firm-level Measure of Labor Exposure to Climate Risk

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity by using the firm-level measure of labor exposure to climate risk defined in Equation (2). The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Sales/Emp) x 100				
1 (Realized ≫ Expected)	-0.227	1.318	1.505	1.177	1.403
	(0.528)	(0.854)	(0.973)	(0.948)	(0.981)
1 (Realized ≫ Expected) x Labor Exposure		-0.170**	-0.207**	-0.155*	-0.200**
		(0.072)	(0.081)	(0.081)	(0.083)
Observations	59,548	59,548	55,313	55,226	54,298
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes
Adjusted R^2	0.856	0.856	0.857	0.868	0.873
Treatment Effects					
Labor Exposure=15		-1.228*	-1.598**	-1.153	-1.597**
		(0.671)	(0.761)	(0.744)	(0.764)
Labor Exposure=20		-2.076**	-2.632**	-1.929*	-2.597**
		(0.939)	(1.053)	(1.045)	(1.069)

Table IG.10. Heat Shocks and Firm-level Labor Productivity: A Continuous Measure of Labor Exposure

This table presents robustness checks of the treatment effects of short-term heat shocks on firm-level labor productivity by using a continuous measure of labor exposure from Equation (1), rather than a rank variable. The dependent variable is the natural logarithm of a firm's sales per employee (*Log(Sales/Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a firm's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, 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 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Sales/Emp) x 100				
1 (Realized ≫ Expected)	-0.240	3.890**	4.299**	2.790	3.469*
	(0.601)	(1.637)	(1.819)	(1.731)	(2.060)
1 (Realized ≫ Expected) x Labor Exposure		-2.028***	-2.318***	-1.522**	-1.950**
		(0.694)	(0.777)	(0.753)	(0.898)
Observations	58,711	58,711	54,489	54,399	53,494
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	No	No	No
County x Year FE	No	No	Yes	Yes	Yes
County x NAICS2 FE	No	No	No	Yes	Yes
NAICS2 x Year FE	No	No	No	Yes	No
NAICS4 x Year FE	No	No	No	No	Yes
Adjusted R^2	0.858	0.858	0.859	0.871	0.875

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

This table presents robustness checks of the treatment effects of short-term heat shocks on labor productivity using segment-level data. The dependent variable is the natural logarithm of a segment's sales scaled by its assets, *Log(Segment Sales/Segment AT)*. The labor exposure of each segment is determined by its own industry classification rather than by the firm's classification. The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized ≫ Expected)*) and its interaction with a segment's labor exposure to climate risk (*Labor Exposure*). Controls include *Labor Exposure*, the natural logarithm of segment assets. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	1	2	3	4	5
	Log(Segment Sales/Segment AT) x 100				
1 (Realized ≫ Expected)	-0.556	1.391	0.968	2.314**	1.826
	(0.557)	(1.010)	(1.004)	(1.126)	(1.138)
1 (Realized ≫ Expected) x Labor Exposure		-0.241**	-0.196*	-0.283**	-0.221*
		(0.108)	(0.108)	(0.113)	(0.115)
Observations	71,250	71,250	71,250	68,632	68,632
Controls	Yes	Yes	Yes	Yes	Yes
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 Effects					
Labor Exposure=15		-2.225**	-1.977**	-1.925*	-1.482
		(0.983)	(0.992)	(1.077)	(1.062)
Labor Exposure=20		-3.431**	-2.958**	-3.339**	-2.584*
		(1.452)	(1.463)	(1.549)	(1.549)

Table IG.12. Heat Shocks and Plant-level Labor Productivity

This table presents robustness checks of the treatment effects of short-term heat shocks on labor productivity using plant-level data. This sample is constructed at the firm-by-county-by-NAICS4 industry-by-year level using the YTS data. Panel A presents summary statistics of the variables. Panel B present the main regression results. Panel C presents the treatment effects of heat shocks on plant-level labor productivity by labor exposure category (1 to 20), based on the estimation in column 4. Panel D presents the regression results on the dynamic treatment effects. The dependent variable is the natural logarithm of a plant's sales per employee (*Log(Sales/Emp)*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized* $\gg$ *Expected)*) and its interaction with a plant's labor exposure to climate risk (*Labor Exposure*). The key independent variables reported are a dummy indicating short-term heat shocks (*1 (Realized* $\gg$ *Expected)*) and its interaction with a plant's labor exposure to climate risk (*Labor Exposure*). Controls includes *Labor Exposure*. The sample period is from 1999 to 2019. Numbers in parentheses are standard errors. Standard errors are clustered at the NAICS4 industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Summary Statistics

	N	Mean	P5	Median	P95	SD
Log(Sale/Emp)	2,788,930	5.104	3.774	5.100	6.888	0.901
1 (Realized $\gg$ Expected)	2,788,930	0.225	0.000	0.000	1.000	0.418
Labor Exposure (Industry)	2,788,930	10.169	2.000	9.000	19.000	5.082

Panel B. Main Results

	1	2	3	4	5	6	7	8	9
	Log(Sales/Emp) x 100								
1 (Realized ≫ Expected)	-0.006	0.372***	-0.021	0.224**					
	(0.047)	(0.132)	(0.039)	(0.112)					
1 (Realized ≫ Expected) x Labor Exposure		-0.037***		-0.024**	-0.039***	-0.025**	-0.027***	-0.116***	-0.122***
		(0.013)		(0.010)	(0.013)	(0.010)	(0.010)	(0.041)	(0.038)
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
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.886	0.888

Treatment Effects	1	2	3	4	5	6	7	8	9
Labor Exposure=15		-0.183**		-0.134**					
		(0.088)		(0.056)					
Labor Exposure=20		-0.368**		-0.253***					
		(0.149)		(0.096)					

Panel C. Treatment Effects by Labor Exposure

Labor Exposure	Treatment Effect (%)	Std. Error
1	0.20*	(0.010)
2	0.18*	(0.009)
3	0.15*	(0.009)
4	0.13*	(0.008)
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*	(0.004)
14	-0.11**	(0.005)
15	-0.13**	(0.006)
16	-0.16**	(0.006)
17	-0.18**	(0.007)
18	-0.21***	(0.008)
19	-0.23***	(0.009)
20	-0.25***	(0.009)

Panel D. Dynamic Treatment Effects

	1	2	3	4	5	6	7
	Log(Sales/Emp) x 100						
1 (Realized ≫ Expected) (T-3) x Labor Exposure	-0.012						
	(0.010)						
1 (Realized ≫ Expected) (T-2) x Labor Exposure		-0.003					
		(0.009)					
1 (Realized ≫ Expected) (T-1) x Labor Exposure			-0.008				
			(0.009)				
1 (Realized ≫ Expected) (T) x Labor Exposure				-0.024**			
				(0.010)			
1 (Realized ≫ Expected) (T+1) x Labor Exposure					-0.011		
					(0.010)		
1 (Realized ≫ Expected) (T+2) x Labor Exposure						0.003	
						(0.010)	
1 (Realized ≫ Expected) (T+3) x Labor Exposure							-0.004
							(0.012)
Observations	1,658,040	1,944,055	2,311,728	2,773,205	2,311,694	1,944,090	1,658,033
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 x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.944	0.941	0.937	0.933	0.936	0.939	0.941

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