Spring 4-14-2023

Climate-Induced Labor Risk and Corporate Finance Implications

Jiqiu Rachel Xiao
Georgia State University

Climate-Induced Labor Risk and Corporate Finance Implications

BY

Jiqiu (Rachel) Xiao

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Doctor of Philosophy

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY
ROBINSON COLLEGE OF BUSINESS
2023

ACCEPTANCE

This dissertation was prepared under the direction of the Jiqiu (Rachel) Xiao Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

Richard Phillips, Dean

DISSERTATION COMMITTEE

Dr. Omesh Kini (Chair)
Dr. Mark A. Chen
Dr. Harley E. "Chip" Ryan, Jr.
Dr. Stephen H. Shore (External – Department of Risk Management and Insurance)
Dr. Vincent Yao (External – Department of Real Estate)

ACKNOWLEDGEMENTS

This dissertation and PhD would not have been completed without the help of many people. I am grateful to my dissertation committee of Omesh Kini, Mark Chen, Chip Ryan, Stephen Shore and Vincent Yao. I give special thanks to Omesh Kini for being the best advisor, mentor, and friend anyone could ask for. I am also indebted to Vincent Yao for his guidance throughout my Ph.D. journey, and numerous conversations about research and life. I thank Mark Chen for admitting me to the program six years ago. I thank Chip Ryan for his insightful feedback that significantly sharpens my understanding of finance. I am grateful to Wei Jiang and Yuehua Tang for their support and valuable advice. I appreciate all faculty members in the finance department and my fellow Ph.D. students for their care and help.

I thank my two cats for keeping me company by sleeping on my workstation every day. I also thank my friends for their help during the most challenging times. I greatly appreciate my family, especially my mother, for their unending support and faith in me throughout the years. Lastly, I dedicate this dissertation to my husband Shen for his love, support, inspiration and encouragement. Thanks for always being there; you made this work possible.

ABSTRACT

Climate-Induced Labor Risk and Corporate Finance Implications

BY

Jiqiu (Rachel) Xiao

April 14, 2023

Committee Chair: Dr. Omesh Kini

Major Academic Unit: Department of Finance

Essay 1: Climate-Induced Labor Risk: Labor Market Consequences, Firm Labor Adaptation Strategies, and Firm Performance

Abstract: This paper studies how physical climate risk affects corporations through the labor channel. By quantifying occupational climate exposure, I document that climate-exposed jobs have shorter working hours, lower productivity, and higher employment (especially of part-time workers) as workforce supplements. Firms with more climate-exposed workers adapt to unfavorable climate trends by retaining more employees, increasing insurance, and expanding offshore inputs. However, these firms have more workplace injuries and worse performance during climate surprises, indicating limitations of adaptation. I also explore various incentives and constraints for firms' labor adaptation strategies and make further causal inferences by studying the implementation of the California Heat Standard.

Essay 2: Climate-Induced Labor Risk and Firm Investments in Automation

Abstract: This paper studies whether and how firms adapt to climate-induced labor risks through automation investments. Using textual analysis, I construct a measure of automation investment intensity at the firm-year level based on material news and events. I find that firms with more climate-exposed employees invest more in automation when they face adverse long-term climate conditions and are not financially constrained. The automation news of these firms is associated with higher stock returns during the announcement period. Moreover, after adopting automation, climate-exposed firms retain fewer employees, incur smaller employee insurance expenditures and decrease offshore inputs. These firms also exhibit better operating performance under short-term temperature shocks. Overall, these results imply that automation is a selective adaptation strategy that effectively helps mitigate climate-induced labor risk.

Climate-Induced Labor Risk: Labor Market Consequences, Firm Labor Adaptation Strategies, and Firm Performance

Rachel Jiqiu Xiao*

First Draft: June 2021

Latest Draft: April 2023

Abstract

This paper studies how physical climate risk affects corporations through the labor channel. By quantifying occupational climate exposure, I document that climate-exposed jobs have shorter working hours, lower productivity, and higher employment (especially of part-time workers) as workforce supplements. Firms with more climate-exposed workers adapt to unfavorable climate trends by retaining more employees, increasing insurance, and expanding offshore inputs. However, these firms have more workplace injuries and worse performance during climate surprises, indicating limitations of adaptation. I also explore various incentives and constraints for firms' labor adaptation strategies and make further causal inferences by studying the implementation of the California Heat Standard.

JEL classification: G30; G32; J20; J28; J30; L25; Q50
Keywords: climate finance, labor finance, employee welfare, labor adaptation, firm performance

---

*Rachel Jiqiu Xiao is with J. Mack Robinson College of Business, Georgia State University. Email: jxiao4@gsu.edu.
I thank my dissertation committee members: Mark Chen, Omesh Kini (Chair), Harley (Chip) Ryan, Stephen Shore and Vincent Yao. I also benefited from the discussions with Vikas Agarwal, Ashwini Agrawal, James Barth, Sris Chatterjee, N. K. Chidambaran, Darwin Choi, Andrey Ermolov, Iftekhar Hasan, Chong Huang, Umit Gurun, Wei Jiang, Kai Li, Paige Ouimet, Mo Shen, Jinfei Sheng, YoungJun Song, Elena Simintzi, Jared Smith, Yi Tang, Yuahua Tang, Chi-Yang (Ben) Tsou, Yaoyi Xi, Han Xia, An Yan, Mark Walker, Shen Zhang, and seminar participants at Cal Poly Pomona, Fordham University, Georgia State University, and Miami University. All errors are my own.

"During summer heat waves, Amazon arranged to have paramedics parked in ambulances outside, ready to treat any (warehouse) workers who dehydrated or suffered other forms of heat stress."

-- Morning Call News (2015) [1]

Introduction

Climate change imposes substantial costs on the economy. Deloitte (2022) estimates that economic losses could grow up to $14.5 trillion by 2070 without sufficient actions. Among the projected negative economic impacts of climate change, the top two are labor-related costs including mortality and labor productivity (US Government Accountability Office, 2017). For example, extreme temperatures reduce workers' working hours (Graff Zivin and Neidell, 2014), decrease productivity (Somanathan et al., 2021), and can even induce illness and mortality (Deschênes and Greenstone, 2011). As climate change increases the likelihood and intensity of severe weather events, these climate-induced labor costs are expected to increase.

In this paper, I explore how firms are affected by and respond to climate risk through the labor channel. While neoclassical theory assumes fully flexible labor input, in reality, labor market frictions can impose substantial adjustment costs on firms (e.g., Simintzi, Vig, and Volpin, 2015; Matsa, 2018; Ouimet, Simintzi, and Ye, 2019). In the context of climate change, firms may face direct labor costs including additional hiring, wages, employee health care costs and injury compensation, and indirect costs such as losses in working hours and labor productivity, regulatory compliance, and changes in production process allocations. These increasing labor costs will incentivize firms to take action (Kahn, 2016). Moreover, compared to workers whose adaptation ability is limited (Dillender, 2019), firms have more resources to adapt (Lin et al., 2019; Pankratz and Schiller, 2019; Bartram, Hou and Kim, 2022). Therefore, their labor-related adaptation actions can potentially affect firm performance and employee welfare.

This paper provides the first systematic empirical examination of firms' labor adaptation strategies concerning climate-induced labor risk, and their impact on firm performance. The empirical analysis

[1] https://www.mcall.com/news/watchdog/mc-allentown-amazon-complaints-20110917-story.html. Latest accessed on 10/15/2022.

consists of three parts. In the first part, I construct a time-varying measure of climate exposure for each occupation based on working contexts and study its labor market consequences. Second, I aggregate the occupational climate exposure measure to the firm level according to firms' workforce composition and examine its impact on firms' labor adaptation strategies and performance. Lastly, I explore various incentives and constraints that influence firms' labor adaptation decisions and address endogeneity concerns.

One empirical challenge facing this study is to quantify climate exposure of firms' workforce, which varies according to two factors: the climate exposure of each worker and the firm's workforce mix. These two factors create two obstacles when measuring workforce climate exposure. The first one is that working conditions – a key determinant of workers' climate exposure – show significant variations cross-sectionally and over time. Across industries, over 30% of the environment-related injuries and deaths in the U.S. in 2019 are from industries with substantial outdoor work like agriculture and mining.[2] Within the industry or firm, the effects of climate differ across occupations. For instance, an accountant usually spends much less time outdoors than a truck driver in the same firm. Even indoor workers can be unequally affected. U.S. warehouse workers reported 1,970 environment-related workplace injuries in 2019, 66 times that of industrial production managers.[3] Technology advancements are also shaping an occupation's job tasks and working environment over time (Autor and Dorn, 2013; Barreca et al., 2016; Acemoglu and Restrepo, 2019). Take industrial production managers as an example: the green economy transition brings in new tasks linked to generating renewable energy, which increases their outdoor activities and exposure to heat generated in production.[4] To quantify climate exposure of workers, I exploit the occupation-level

[2] There are 36,840 nonfatal injuries and illnesses and 642 deaths attributed to harmful substances or environments in the U.S in 2019, and the information, finance and education industries account for less than 3% of these cases. (Source: *BLS*, https://www.*BLS*.gov/iif/oshcdnew2019.htm, accessed on 03/10/2022.)
[3] After considering the employment level, the incidence rate of laborers and material movers is 4.2, while that number is 1.5 for industrial production managers. The incidence rate is defined as nonfatal occupational injuries and illnesses per 10,000 full-time workers. (Source: *BLS*, https://www.*BLS*.gov/iif/oshcdnew2019.htm, accessed on 03/10/2022.)
[4] As the significance of these new tasks related to new energy production increase, *O*NET* finally added six new sub-occupations under industrial production managers in 2013, including quality control systems managers, geothermal production managers, biofuels production managers, biomass power plant managers, methane and methane and landfill gas collection system operators, and hydroelectric production managers. These new job components and tasks involve more outdoor work and increase the climate exposure of industrial production managers.

working context panel data from the *Occupational Information Network* (*O*NET*). The second challenge to measuring firms' workforce climate exposure is that firms, even those within the same industry or location, have their unique workforce composition. I accommodate this firm-level heterogeneity by using variations in the workforce composition at the establishment (local branch) level and then aggregating to the parent firm level based on establishment employment.[5]

For each occupation, I construct exposure to physical climate risk using its time allocation to various *O*NET* working contexts (e.g., indoor with air-conditioning; outdoors with shelter; outdoors without shelter) and how exposed this working context is to climate. The underlying mechanism is intuitive: outdoor work is more exposed to the weather than indoor work; Moreover, indoor work with air conditioning is the least sensitive, whereas outdoor work without shelters is the most exposed.[6] Leveraging the historical datasets of *O*NET*, I create an annual proxy for *occupational climate exposure* (*OCE*), the ex-ante sensitivity to the environment and weather, for 759 occupations at the six-digit *O*NET Standard Occupation Code* (*SOC*) level in the US from 2000-2018.

As validation, I examine the correlation between *OCE* and fatal occupational injuries related to the environment reported by the *U.S. Bureau of Labor Statistics* (*BLS*).[7] I show that fatal environment-related injuries surge sharply at the higher end of *OCE*. I uncover a similar pattern in job-related injury compensations. These results suggest that *OCE* captures climate-related physical risk in the workplace at the occupation level. *OCE* varies significantly among individuals, industries, and states. Specifically, I find that less-educated and lower-paid male workers are most sensitive to climate. Industries such as agriculture, construction, mining, transportation and warehousing, and utilities are the most climate-exposed, consistent with the notion that these industries are heat-sensitive (Graff Zivin and Neidell, 2014; Addoum, Ng, and Ortiz-Bobea, 2020). At the other extreme are industries such as education, business and management services, finance and insurance, and health care. Likewise, labor in financial, technological, educational

[5] The construction of workforce climate exposure at the occupation, establishment, and firm level is presented in Section 4 and corresponding examples are in Internet Appendix Table IA1 – IA3.
[6] The construction of occupation-level climate exposure is described in Section 3.1.2.
[7] Source: *BLS*, https://www.BLS.gov/iif/oshcfoi1.htm, accessed on 03/10/2022.

and medical hubs is less sensitive, while those in states dependent on fracking and agriculture are more exposed. The demographic, industry, and geographic distributions provide additional validation for *OCE* as a measure of different occupations' exposure to climate.

Having provided evidence validating *OCE* as a measure of climate-induced labor risk at the occupation level, I study its labor market implications by linking *OCE* to outcomes including employment, working hours, and wages generated from the *Integrated Public Use Microdata Series* (*IPUMS*) at the occupation × county × industry × year level. Earlier studies show that climate-related factors negatively affect working hours, productivity, and safety (Dell, Jones, and Olken, 2009; Graff Zivin and Neidell, 2014; Park, Pankratz, and Behrer, 2021). I add to these studies by incorporating occupational climate exposure into the analysis and testing the following hypotheses (detailed arguments to support all hypotheses are provided in Section 2). First, as climate-exposed occupations are more sensitive to climate conditions, the documented climate impact should be more pronounced for them, leading to shorter working hours and lower productivity. To meet their production demands, employers may seek to hire more employees and/or switch to cost-effective labor, such as part-time and temporary workers, as workforce supplements (Miles, 2000; Autor, 2003; Almeida et al., 2021),[8] or they can replace climate-exposed workers with capital investments like automation (e.g., Koeniger and Leonardi 2007; Acemoglu and Restrepo, 2018). These two adaptation strategies lead to opposite predictions of the employment of climate-exposed occupations. Moreover, as actual negative climate events have greater impacts on climate-exposed workers, I expect they will magnify the relation between *OCE* and labor market outcomes.

My findings are as follows. More climate-exposed occupations have shorter working hours, a proxy for short-term labor supply (Graff Zivin and Neidell, 2014), and lower productivity measured by hourly wages. I also document that these occupations maintain a greater level of employment, especially of part-time workers who are less expensive and more flexible, to supplement losses in working hours and

[8] Part-time workers have significantly less access to employer-sponseored medical care benefits (BLS (https://www.*BLS*.gov/news.release/ebs2.nr0.htm.); Almeida et al., 2021) and temporary workers help reduce employers' risk and costs of terminating permanent workers (Miles, 2000; Autor, 2003).

productivity of individual workers. This employment result is consistent with my labor adaptation hypothesis, and findings in Xiao (2023) that, on average, firms with more climate-exposed workforces do not see increased capital investment because of the scale of investment expenditure and firms' financial constraints. It also implies the mechanism underlying employers' choice between labor and capital adaptation. As shown by Bena and Simintzi (2015), the availability of low-cost labor contributes to employers' preference for labor over capital. Further, these labor market effects are more pronounced when adverse climate events (such as rising temperatures and natural disasters like hurricanes and wildfires) occur, suggesting that the labor market outcomes of *OCE* are causal.

Two potential concerns may confound my analysis: first, climate-exposed occupations may ex ante relocate to areas with better climate conditions to avoid negative climate impacts; second, these results may be driven by changes in local consumer demand (instead of labor supply) resulting from adverse climate events. To alleviate the first concern, I include county × industry × year fixed effects to force inferences to be drawn from the spatial difference between occupations in the same location-industry-year. My time-varying occupational measure allows for occupation fixed effects to control for time-invariant occupational characteristics like skill requirements. To address the second concern, I use various exogenous climate events such as natural disasters as shocks to the local labor market. I also conduct a subsample test focused on tradable sectors (e.g., manufacturing and information) that are less dependent on local demand compared to non-tradable sectors (e.g., retail and hospitality). I show that the findings hold in tradable sectors, suggesting that the results documented are not driven by local demand (Mian and Sufi, 2014).

Next, I explore whether and how the labor market outcomes of climate-exposed workers spill over to their employers. I first construct a proxy for *establishment-level workforce climate exposure* (*EWCE*) by aggregating *OCE* to the establishment level.[9] I then compute the weighted average of each establishment's *EWCE* (with weights based on establishment employment) across all the firm's establishments, and use it

[9] *EWCE* is defined as the employment weighted-average *OWCE* of the same county and industry of the establishment (as described in Section 3.3).

as the measure of *firm-level workforce climate exposure* (*FWCE*).[10] While climate-exposed workers face losses in working hours, productivity, and safety, it is not clear whether and how firms respond to this labor risk and how effective are their adaptation strategies.

I draw three testable hypotheses on firm adaptation from my labor market analysis and other previous studies. First, similar to the occupation-level analysis, I predict that firms with more climate-exposed workers will retain more employees as workforce supplements. Moreover, climate-exposed workers bear greater workplace safety risk (Park et al., 2021), increasing firms' demand for health care, especially for employer-sponsored health insurance to reduce costly claims to workers' compensation (*WC*).[11] Hence, I hypothesize that climate-exposed firms will pay more for their employee insurance policies. Lastly, as firms can not only find cost-effective employees in the domestic market (Autor 2003; Almeida et al., 2019), but also offshore (Jena and Simintzi, 2019; Grossman and Rossi-Hansberg, 2008; Blinder, 2009), I expect that firms may shift some tasks of climate-exposed workers overseas.

Regarding firm performance, I have two alternative hypotheses. If firms' labor adaptation actions, namely employment, insurance, and offshoring, are perfectly effective, firm performance will be immunized from workforce climate exposure. If not, the workplace safety risk associated with *FWCE* should still lead to more environment-related workplace injuries and higher injury compensations, and all the losses in working hours, productivity, and safety of employees can potentially result in worse operating performance.

Consistent with the labor adaptation hypothesis, I find that climate-exposed firms have more employees and higher employee health and life insurance premiums per participant. Regarding firm performance, they have more workplace injuries, pay higher injury compensation, and exhibit worse operating performance. In terms of economic significance, a one-standard-deviation increase in *FWCE* (0.32) leads to an annual loss of $35.9 million in 2018 dollars. These findings confirm that labor is a direct

[10] The construction of firm-level climate exposure is described in Section 3.3.
[11] WC is a state-regulated insurance program in which the treatment is usually more expensive (e.g., Leigh and Ward, 1997; Card and McCall, 2016).

channel through which climate risk can affect firms' operations and performance, and suggest limitations of firms' labor adaptation strategies. Nevertheless, climate-exposed firms do not, on average, purchase more overseas input, likely for two reasons. First, it may still be more practical and cost-effective to hire domestically than shift production abroad. Second, not all job tasks are suitable for offshoring (Blinder, 2009; Firpo, Fortin, and Lemieux, 2011). For instance, tasks with limited offshoring potentials are those requiring face-to-face interactions (e.g., drivers) or physical access to work sites (e.g., mine workers and security guards).[12] As many climate-exposed jobs like mining and construction fall into this category, firms' capacity to engage in offshoring endeavors is constrained.

Climate-induced labor risk of firms has two components: 1) *FWCE* (the sensitivity of a firm's workforce to climate conditions) and 2) actual climate conditions (which will magnify losses of a climate-exposed workforce). To investigate the joint effect of these two factors, I interact *FWCE* with the proxy for firm-level actual climate conditions. Interestingly, when experiencing rising temperatures, climate-exposed firms see incremental increases in employment, insurance, and offshore input buffers, but no significant changes in the number of environment-related workplace injury cases, injury compensations, or return on assets (*ROA*). One explanation could be that endogenous labor adaptation actions immunize climate-exposed firms from the harms of actual climate conditions.

I investigate this possibility by following Choi, Jiang and Gao (2020) to decompose annual temperatures into two components: predictable long-term trends (20-year moving average) and abnormal short-term surprises. The long-term trend speaks to climate-exposed firms' adaptation to predictable climate-induced labor risk, supported by earlier studies that learning and expectations of risk determine climate mitigation decisions (Dillender, 2019; Kahn, 2016; Barreca et al.; 2016; Heutel, Miller, and Molitor, 2021). My prediction is that if climate-exposed firms have adapted based on their climate projection, their performance would be less responsive or unresponsive to predictable climate trends. The short-term temperature surprises serve as exogenous shocks on firm performance because firms are unable to hedge

[12] While jobs that can be easily offshored including telemarketers, manicurists and pedicurists, and travel agents, etc.

against climate surprises (Kahn, 2016). Choi et al. (2020) find that investors update their beliefs of climate risk when experiencing abnormal temperatures, suggesting that abnormal climate components are hardly endogenized ex-ante.

I document that climate-exposed firms in traditionally hot areas maintain additional employees, greater employee insurance expenses, and more offshore input to hedge against potential labor disruptions. Meanwhile, their workplace safety and operating performance are unresponsive to long-term climate trends, indicating that firms effectively adapt to their projection of climate-induced labor risk and improve employee welfare through increased workplace safety. However, when experiencing temperature surprises, climate-exposed firms experience more environment-related workplace injuries and perform worse, while their employment, employee insurance, and offshoring input do not show timely adjustments. Holding *FWCE* constant, a 1°F (0.56 °C) increase in abnormal temperatures leads to an annual loss equivalent to $11.1 million. This finding provides causal evidence of the real impact of climate-induced labor costs on firms' operating performance and suggests the limitation of firms' adaptation strategies. With global warming, long-term temperatures will increase the likelihood and intensity of abnormal temperatures and natural disasters and, consequently, it will become costlier and harder for firms to hedge against climate-related labor risk.

In addition to operating performance, I examine the valuation implications of *FWCE* by studying monthly stock market performance. I find that firms with greater *FWCE* have significantly decreased stock returns when hit with temperature surprises. Holding *FWCE* constant, a 1 °F (0.56 °C) increase in abnormal monthly temperatures leads to a decrease of 4.5 and 6.0 basis points in monthly raw return and Fama-French three-factor adjusted return, respectively. Two potential channels can explain these findings. First, the operations of climate-exposed firms may be disrupted by abnormal temperature shocks. Second, under climate shocks, investors revise their beliefs about climate change as well as the valuation of firms (Choi et al., 2020; Pastor, Stambaugh, and Taylor, 2021). I also find the impact of *FWCE* on stock performance shows strong seasonality: It is more salient in summer (hot days) than in winter (cold days), consistent with the previous studies that heat stress has greater negative effects on labor compared to cold weather (e.g., Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Somanathan et al., 2021).

Kahn (2016) discusses a model in which different types of investors consider climate-related investments based on perceived benefits and costs. Similarly, I conduct a cost-benefit analysis of firms' labor adaptation strategies regarding climate-induced labor risk, including employment, insurance, and offshoring. The first question I explore is the firms' incentive for adaptation given its costs and limits. My previous analysis indicates that protecting firm performance from predictable climate components is one reason for adaptation. By comparing the operating performances of industry peers with different labor adaptation intensities, I find evidence of another benefit of adaptation: firms maintaining more employment/insurance/offshoring buffers ex-ante have higher *ROA* under temperature surprises.

I also examine factors that potentially constrain firms' choice of adaptation strategies. First, I study how the local labor supply and the dependency on full-time-full-year (*FTFY*) workers affect firm employment. Firms can hire more only when the local labor supply is not tight, and firms will have to maintain greater employment buffers ex-ante if they have less flexibility (more *FTFY* employees) to adjust their workforce. Second, I study the impact of the dependency on *FTFY* workers and union coverage on firms' employee insurance because *FTFY* and unionized workers get more medical care benefits.[13] Regarding offshoring adaptation, I expect firms can only offshore jobs with higher offshoring potentials to countries with lower labor costs.[14] My subsample tests find results consistent with the above predictions.

Lastly, I study the role of regulatory climate risk in firms' adaptation decisions and provide additional support for causal inferences about the impact of *FCWE*. Specifically, I conduct an event study on the passage of the *California Heat Illness Prevention Standard* in 2005 (*CA Standard*), the first heat safety mandate in the US. It requires employers to take actions, such as providing paid rest breaks, shade

[13] 99% full-time workers had medical care benefits, while the percentage of part-time workers with medical care benefits is 24% in 2022 (https://www.*BLS*.gov/news.release/ebs2.nr0.htm). Unions fight for employee benefits and protections like insurances for workers (Freeman and Medoff, 1984).
[14] See Blinder (2009); Firpo et al. (2011); Blinder and Krueger (2013); Hoberg and Moon (2017).

structures, and employee training, to reduce heat-related safety risks.[15] Similar to abnormal temperatures which magnify physical climate risk, *CA Standard* increases the regulatory climate risk of climate-exposed firms that bear higher heat-related safety risk. As a result, these firms will see increased incentives for labor adaptation to comply with the regulation. Moreover, *CA Standard* was put into effect as an emergency measure, thereby providing a clean natural experiment to examine the impact of workforce climate exposure.

I find negative cumulative abnormal returns upon the announcement of *CA Standard* for treated firms that have both greater *FWCE* and more affected employees, suggesting that investors anticipate that *CA Standard* will impose incremental costs on affected firms. Using a difference-in-differences methodology, I uncover that *CA Standard* provides better protection to climate-exposed workers by reducing working hours and increasing employment, hourly wages, and the share of part-time workers. I also find that compared to control firms, treatment firms pay less for workplace injury compensation and hire more employees to supplement the workforce after the shock. These findings confirm that climate-exposed firms take labor adaptation actions in response to increasing regulatory climate risk and support causal inferences of the impact of *FWCE* on firm adaptation strategies.

This paper is directly related to two strands of literature. Methodologically, I build on studies on occupational exposure and labor market outcomes.[16] Regarding substance, I contribute to the literature on climate economics and finance. While much attention is paid to climate-induced damages in national and industrial output and asset value,[17] a growing literature focuses on labor-related damages such as health, labor supply, and productivity (e.g., Graff Zivin and Neidell, 2014; Park et al., 2021; Somanathan et al., 2021). I extend this strain of literature by quantifying workforce climate exposure over time and exploring

[15] The Division of Occupational Safety and Health (CA/OSHA), https://www.dir.ca.gov/title8/3395.html, accessed on 03/10/2022.
[16] For example, Autor and Dorn (2013) explore the labor market impact of routine tasks of a given occupation; Lewandowski (2020) constructs an occupational exposure to Covid-19 based on how much human contact and what kind of working environment a given occupation has; Webb (2019) examines the employment and wage impact of occupational exposure to AI technologies, software, and industrial robots.
[17] See, Deschênes and Greenstone (2007); Deryugina and Hsiang (2014); Hsiang el al. (2017); Bernstein, Gustafson, and Lewis (2019); Engle et al. (2020); Krueger et al. (2020); Painter (2020); Giglio et al. (2021).

its implications for the labor market and firms. With more frequent and intense climate shocks due to climate change, the disruptive effects on labor and firms I document will only become larger.

Moreover, this paper adds significantly to the literature on climate change adaptation. Though identifying human health-related adaptation opportunities is recognized as a global research priority of the 21st century (World Health Organization, 2009; National Institute of Environmental Health Sciences, 2010), little is known about firms' roles in this regard. While two contemptuous papers (Xiao, 2023; Xiao, 2022), study how firms react to workers' climate risk based on a text-based proxy for firm automation investments and capital intensity, respectively, I diverge from these studies in both methodology and economic questions. Regarding methodology, Xiao (2022) relies on the cross-sectional variation in workers' outdoor activities, whereas I quantify workers' climate exposure over time based on various working contexts, including both indoor and outdoor work and the level of environment control. In terms of economic questions, I study firms' labor adaptation actions that have direct implications on employee welfare, rather than the capital substitution effects examined by Xiao (2023) and Xiao (2022). To the best of my knowledge, this paper presents the first evidence of firms' labor adaptation actions including employment, employee insurance and offshoring input, the incentives and constraints underlying the choice of different adaptation strategies, and the implications of firms' adaptation on employee welfare (healthcare benefits and workplace safety), in the context of climate-induced labor risk. In this regard, it also relates to the literature on firms' labor strategies when faced with changes in labor costs (Autor, 2003; Bena and Simintzi, 2019; Almeida et al. 2021).

This study also highlights the labor channel through which climate can affect firms' performance. It is still debated whether and how climate-related risks impact firm output. For example, Addoum et al. (2020) show no relation between temperatures and firm sales and productivity in the U.S., while several studies, based on international data, find that temperatures affect firm sales, profits, employment, and productivity.[18] To understand firm-level climate risks, Li et al. (2020b) and Sautner et al. (2023) quantify

[18] Pankratz, Bauer, and Derwall (2019); Pankratz and Schiller (2019), Somanathan et al. (2021) and Addoum et al. (2020).

firms' exposure to climate change based on textual information in earning calls. Their method captures the total effect of climate risk on firms including supply chain distortions, changes in consumer demand and regulations, and so on. In contrast, I pin down a specific labor channel through which climate can affect firms' workplace safety as well as operating and stock market performance. I also provide evidence that firms' performance depends on the effectiveness of their adaptation strategies. Thus, this paper fills the gap in the literature on climate's impact on aggregate output and firm-level outcomes. While many indirect costs are hard to quantify, I present a conservative estimate of labor costs imposed on firms by climate risk.

Lastly, this paper contributes to studies on the impact of labor risks on corporate policies. Labor market frictions have been documented to impact financial leverage.[19] Other corporate outcomes include cash reserve (Ghaly, Anh Dang, and Stathopoulos, 2017), firm growth (Mueller, Ouimet, and Simintzi, 2017), firm value (Shen, 2021), innovations (Jiang et al., 2021), executive compensation (Kini, Williams and Yin, 2021), M&A (Tate and Yang, 2015; Ma, Ouimet, and Simintzi, 2016; Ouimet and Zarutskie, 2020), and investments (Ouimet et al., 2019). My paper uncovers that firms' labor adaptation actions regarding climate-induced labor risk affect firms' employment, employee insurance, and offshoring policies.

The remainder of the paper is organized as follows. Section 2 discusses hypothesis development. Section 3 describes the data, construction of variables and samples. Section 4 presents the labor market implications. Section 5 displays the firm-level analysis of firms' labor adaptation actions and firm performance. Section 6 discusses the incentives and constraints of firms' adaptation strategies and addresses endogeneity concerns through an event study of the *California Heat Illness Prevention Standard*. Section 7 concludes the paper.

[19] Labor market frictions include human costs of bankruptcy (Berk, Stanton, and Zechner, 2010; Ellul and Pagano, 2019), labor unions (Matsa, 2010), unemployment risk (Agrawal and Matsa, 2013), firing cost (Simintzi et al., 2015; Serfling, 2016), outside employment opportunities (Kale and Shahrur, 2007) and labor market size (Kim, 2020).

2. Hypothesis

2.1. Labor Market Hypothesis

Using insights from climate economics research, I make predictions about the labor market implications of occupational climate exposure. Specifically, I consider the negative effects that actual climate factors (such as temperature) have on working hours, productivity, and mortality. These effects have been documented by studies such as Deschenes and Moretti (2009), Graff-Zivin and Neidell (2014), and Somanathan et al. (2021), and they vary across different industries, demographics, and occupations (Park et al., 2021). Building upon this literature, I examine how occupational climate exposure affects labor market outcomes. *OCE* captures the extent to which different occupations are exposed to climate-related hazards, such as extreme temperatures, floods, and storms, that constrain workers' ability to work and productivity. Hence, I hypothesize that the documented negative impact of climate on labor will be more pronounced in occupations with greater *OCE*, resulting in lower levels of working hours and productivity measured by hourly wages. [20]

Previous studies suggest two ways that employers can meet their production demands when they face losses in working hours and decreased productivity of workers. The longstanding literature on production factors suggests that the high relative price of a particular factor creates an incentive for firms to substitute, or efficiently use the expensive factors (e.g., Jones, 2005; Karabarbounis and Neiman, 2014). Therefore, the scarcity of labor and/or increased labor costs associated with *OCE* may motivate employers to invest in new technologies or automation to reduce labor demand (e.g., Blanchard, 1997; Koeniger and Leonardi, 2007; Acemoglu and Restrepo, 2018). Alternatively, employers may seek to hire more low-cost

[20] I use working hours to measure short-term labor supply following Graff-Zivin and Neidell (2014). According to *BLS*, labor productivity is a measure of economic performance that compares the amount of goods and services produced with the number of hours worked to produce those goods and services. Neoclassical economics suggests that the marginal revenue product of labor is equal to the wage rate in a perfectly competitive market, I use hourly wages to measure for labor productivity. Note that hourly wage rate is determined by two factors: how many marginal products are produced (productivity) and the price of the product (determined by demand and supply). I try to control for the impact of product price by controlling for local demand using fixed effects, but still the interpretation of hourly wage rate as a proxy for labor productivity requires caution.

labor (Miles, 2000; Autor, 2003), and the availability of cost-effective labor encourages employers to prioritize labor over capital (Bena and Simintzi, 2019). For example, Almeida et al. (2021) document that firms substitute full-time employees with part-time workers in response to increased healthcare costs. In the first scenario (capital adaptation), we should see decreased employment in climate-exposed occupations, while in the second situation (labor adaptation), occupations with greater *OCE* will have greater employment, especially of part-time workers who do not require employer-sponsored insurance and offer more labor adjustment flexibility. Moreover, as actual climate events have a greater impact on climate-exposed occupations, they will magnify the relation between *OCE* and labor market outcomes discussed above. The exogenous climate shocks also provide natural experiments to build causal inferences about climate exposure's impact on labor outcomes.

Hypothesis 1: *Occupations with greater OCE have shorter working hours and lower hourly wages.*

Hypothesis 2a *(labor adaptation)*: *Occupations with greater OCE have greater employment, especially of part-time workers.*

Hypothesis 2b *(capital adaptation)*:***:*** *Occupations with greater OCE have smaller employment.*

Hypothesis 3: *The relation between OCE and labor market outcomes is more pronounced when negative climate events happen.*

2.2. Firm Hypothesis

Although labor input is considered fully flexible in a neoclassical framework, in actuality, firms can experience costly labor adjustments caused by labor market frictions, such as mobility and unionization. (Agrawal and Matsa, 2013; Simintzi et al., 2015; Matsa, 2018). As a result, the impact of climate exposure on corporate labor can potentially spill over to the firm through direct labor costs like injury compensations and indirect costs like losses in productivity. Then a natural question is whether and how firms can adapt to climate exposure resulting from their workforce. The Intergovernmental Panel on Climate Change [IPCC] (2014) defines adaptation as "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." Dillender

(2019) finds that workers have limited adaptation potential, and avoiding outdoor activities during extreme temperatures seems to be the main avoidance behavior. In contrast, firms have more resources to adapt. For example, firms can react to temperatures or climate policies by relocating their plants or their supply chain components (Lin et al., 2019; Pankratz and Schiller, 2019; Bartram et al., 2022).

I draw three predictions of firms' adaptation actions built on my labor market hypothesis. *Hypothesis 1* suggests that a workforce comprised primarily of climate-exposed workers offers fewer working hours and lower productivity per worker. Similar to *Hypothesis 2* at the occupation level, firms can employ labor adaptation versus capital adaptation (e.g., Jones, 2005; Acemoglu and Restrepo, 2018). If climate-exposed firms choose the labor adaptation strategy, they will retain more employees as workforce buffers. Second, I expect firms with greater *FWCE* may pay higher employee health and life insurance premiums for two reasons. First, climate-exposed workers bear greater workplace safety risk (Park et al., 2021), increasing firms' demand for health care. Second, firms have incentives to decrease costly claims to workers' compensation (WC), a state-regulated insurance program under which treating an injury is typically more expensive, by providing health insurance (Leigh and Ward, 1997; Card and McCall, 2016). Lastly, firms do not have to only hire domestically but can also benefit from low-cost labor overseas. Jena and Simintzi (2019) show that firms' ability to source labor cheaply overseas substitutes for investments in cost-reducing production technologies. Consequently, I predict that firms with greater *FWCE* may shift more components (or tasks) of their workers offshore to hedge against domestic climate risk (Hoberg and Moon, 2017) and/or to lower labor costs (Grossman and Rossi-Hansberg, 2008; Blinder, 2009).

In contrast, if firms adapt through capital adjustments, such as replacing climate-exposed workers with investments in automation or in new technologies (e.g., Acemoglu and Restrepo, 2018; Ouimet et al, 2019), firms with greater *FWCE* should see decreases in employment (Blanchard, 1997; Koeniger and Leonardi, 2007). Along with the reduced demand for climate-exposed workers, these firms require less employee insurance coverage and fewer offshoring buffers (Jena and Simintzi, 2019).

Hypothesis 4a *(labor adaptation): Firms with greater FWCE have more employees, greater employee insurance expenditures, and more purchases of offshore inputs as labor-related adaptation.*

Hypothesis 4b *(capital adaptation)*: *Firms with greater FWCE have fewer employees, smaller employee insurance expenditures,and fewer purchases of offshore inputs as capital-related adaptation.*

The performance of climate-exposed firms depends on the effectiveness of their adaptation strategies. If a firm's adaptation actions effectively mitigate the climate risk of their workforce, firm performance will be unresponsive to their workforce climate exposure. If not, the greater safety risk borne by climate-exposed workers may still make firms with greater *FWCE* see more environment-related workplace injuries and pay higher injury compensation (e.g., Deschenes and Moretti, 2009; Dillender, 2019; Park et al., 2021). The losses in working hours, productivity, and safety of employees can potentially contribute to worse operating performance.

Hypothesis 5a*: Firms with greater FWCE do not have more environment-related workplace injuries, higher injury compensations, and worse operating performance.*

Hypothesis 5b*: Firms with greater FWCE have more environment-related workplace injuries, higher injury compensations, and worse operating performance.*

The climate-induced labor risk of firms is determined by two components: one is the sensitivity of a firm’s workforce to climate conditions, while the other is actual climate conditions that will magnify the negative impact of climate on exposed workers. Therefore, I expect climate-exposed firms to take more adaptation actions to mitigate the increasing labor risk caused by negative climate conditions. Again, if their adaptation strategies are effective, the performance of climate-exposed firms will not be affected by actual climate conditions; Otherwise, climate-exposed firms may still see more *environment-related* workplace injuries and worse operating performance when actual climate events occur.

Hypothesis 6*: Firms with greater FWCE adapt more when experiencing negative climate events.*

Hypothesis 7a*: The relation between FWCE and firm performance is not more pronounced under negative climate conditions.*

Hypothesis 7b*: The relation between FWCE and firm performance is more pronounced under negative climate conditions.*

When looking into the role of different climate components in adaptation, Dillender (2019) and Kahn (2016) show that climate mitigation decisions are influenced by learning and expectations. For example, hot days are less deadly in warm places, largely because the historical weather has led to adaptation in these places (Barreca et al., 2016; Heutel et al., 2021). Therefore, I predict climate-exposed firms react to long-term climate trends through more adaptation actions because of the expected long-lasting benefits. However, even rational expectations cannot address the uncertainty associated with climate change and help avoid climate surprises (Kahn, 2016). Choi et al. (2020) document that investors update their beliefs about climate change when experiencing abnormal temperature shocks. The evidence suggests that abnormal climate components are less likely to be adapted, which in turn, indicates that the performance of climate-exposed firms should be more sensitive to climate surprises.

Hypothesis 8a*: The adaptation actions of firms with greater FWCE are more responsive to predictable climate trends than climate surprises.*

Hypothesis 8b*: The performance of firms with greater FWCE is more responsive to climate surprises than predictable climate trends.*

Kahn (2016) discusses a model in which all three types of investors—myopic, rational expectations, and worst-case scenario—will take climate-related investments if the expected benefits exceed costs. In the context of climate adaptation, firms can benefit if adaptation effectively helps mitigate their climate-induced labor risk, outperform their competitors, and comply with climate regulations. Potential costs or constraints associated with adaptation include local labor supply, firms' workforce flexibility, union coverage, offshoring potentials of the workforce and offshoring costs, etc. Similarly, I expect firms will take more adaptation actions to hedge against climate-induced risk when the expected benefits of adaptation increase, and/or when the costs (constraints) of adaptation decline.

Hypothesis 9*: Firms with greater FWCE will take more adaptation actions when the expected benefits of adaptation increase, and/or when the costs (constraints) of adaptation decrease*.

3. Data, Variables and Sample

The empirical analysis in this paper requires data from multiple sources. I obtain occupation-level work contexts from *O*NET*, labor market outcomes from *IPUMS*, establishment location and employment from *National Establishment Time-Series* (*NETS*), workplace injuries and illnesses from *Occupational Safety and Health Administration (OSHA)*, firm-level employee benefits from Form 5500, firm external input data from Hoberg and Moon (2017), firm financial data from CRSP and Compustat, and weather observations from *National Oceanic & Atmospheric Administration* (*NOAA*). Table A1 in Appendix explains the construction of all variables in detail. If not specified, variables in all samples are winsorized at the 1% and 99% levels and all dollar-denominated variables are expressed in 2018 dollars.

3.1. Occupational Working Context Data and Variables

*3.1.1 O*NET Data*

I use work context variables from *O*NET* to investigate climate exposure of all occupations. *O*NET* collects data such as tasks, job requirements, and working context directly from incumbent workers nationwide.[21] Each occupation is identified with a unique *SOC* code. There are 967 eight-digit *SOC* code occupations in total, which can be aggregated to 759 six-digit *SOC* code occupations with the working context information. I focus on the work context because it contains physical and social factors including physical work conditions, work attire and setting, and job hazards that are potentially related to climate risk.

3.1.2 Construction of Occupational Climate Exposure

To measure climate exposure at the occupation level, I extract working contexts variables related to climate/weather/environment from *O*NET* including, for example, whether the job is exposed to very hot or cold temperatures, whether the worker performs outdoor tasks, and whether the working environment is environmentally controlled. I rank these variables based on the extent to which a worker is exposed to

[21] Source: U.S. Department of Labor, https://www.dol.gov/agencies/eta/onet/data-collection#:~:text=Data%20are%20collected%20directly%20from,%2D%20or%20web%2Dbased%20forms, accessed on 03/10/2022.

climate conditions when working in a given context, where a rank of 5 indicates the most exposed and a rank of "1" means the least exposed. Table 1 Panel A lists all the *O*NET* working context variables that I include in Equation (4) and their climate exposure rank assigned by me.

[Insert Table 1]

*O*NET* categorizes each context variable into five frequency groups to reflect the importance of performing the job in this context.[22] Then I measure climate exposure at the occupation level following the specification below:

$$OCE_{ot} = \frac{\sum_{k \in K_t} FREQ_{okt} \times RANK_k}{\sum_{k \in K_t} RANK_k} \quad (1)$$

wherein K_t is a set of working context variables k in year t, $FREQ_{okt}$ is the frequency, ranging from 1 to 5, of the working context k of occupation o in year t, and $RANK_k$ is the level that the working context k is exposed to climate conditions. I scale this number by the total rank of work context variables. As a result, OCE falls within a range of 1 to 5. Based on Equation (1), *OCE* is an increasing function of (i) the sensitivity to climate of a given working context ($RANK_k$), and (ii) the necessity to perform the job in a climate-sensitive working context ($FREQ_{okt}$). To match with the *SOC* code reported by the *IPUMS* data, I construct *OCE* for 759 six-digit *SOC* occupations with non-missing working context data from 2000-2018.[23]

Table 1 Panel B lists the top five, middle five, and bottom five occupations based on their climate exposure in 2018. Among the most exposed occupations are farmers, mining workers, utility workers, and maintenance workers, while the least exposed include medical workers, travel agents, and data workers. In general, the scoring system mostly confirms casual observations. In Table IA4 in the Internet Appendix, I present the time variation of climate exposure for industrial production managers whose *OCE* changes along with changes in job and task components. [24]

[22] The five categories of frequency are: 1) never, 2) once a year or more but not every month, 3) once a month or more but not every week, 4) once a week or more but not every day, and 5) every day.
[23] Table IA2 presents the construction of *OCE* for construction managers in 2018 as an example. Figure IA1 in Internet Appendix presents the distribution of occupational climate exposure scores in 2018.
[24] The climate exposure of industrial production managers grows from 1.248 (46th percentile) to 3.151 (82nd percentile) from 2000 to 2018 because the duty of industrial production managers is expanded to include new tasks

[Insert Table 2]

The summary statistics of *OCE* are presented in Table 2 Panel A. The mean *OCE* is 2.14 and 75% of observations have an *OCE* below 2.73, suggesting the majority of occupations are not highly exposed.

3.1.3. Relation between Occupational Climate Exposure and Other Occupational Exposure

To ensure *OCE* is not capturing other well-documented occupational exposures in the literature, I examine the correlation between *OCE* in 2018 and occupational exposure to: 1) offshorability (proposed by Firpo et al. (2011) and standardized by Autor and Dorn (2013)), 2) AI, software and robot (data from Webb (2019)), 3) routine task intensity (RTI) (created by Autor and Dorn (2013)), and 4) fintech (constructed by Jiang et al. (2021)).[25] Figure 1 shows that *OCE* remains flat as the AI exposure, fintech exposure, and routine task intensity increase, while it has a positive correlation with software and robot exposure and a mildly negative correlation with offshorability.

[Insert Figure 1]

3.1.4. Validation of Occupational Climate Exposure

I validate *OCE* by comparing it to actual workplace safety incidents and injury compensations. The results are presented in Figure 2 Panel A and B, respectively. The results indicate that climate-exposed occupations experience more environment-related injuries and higher job-related injury or illness compensations, confirming that *OCE* captures the workplace safety risk associated with climate at the occupation level.

[Insert Figure 2]

3.1.5. Distributions of Occupational Climate Exposure across Demographics, Industry and Geography

Panel C to F in Figure 2 present the demographics of workers by *OCE:* lower-paid, male, and less-educated workers have the greatest climate exposure. Table 3 summarizes the industry distributions of *OCE* at the NAICS two-digit level based on 2018 *IPUMS* employment data. The industry climate exposure is defined

---

related to renewable energy production. These new job components and tasks involve more outdoor work and increase the climate exposure of industrial production managers.

[25] All these occupational exposure measures used in Figure 1 are time-invariant except for *OWCE*.

as the employment-weighted average of *OCE* within the industry. Industries with the greatest climate exposure include agriculture, construction, transportation and warehousing, mining, and utilities, with exposures well above the 60th percentile, consistent with the notion of heat-sensitive industries in the literature (Graff Zivin and Neidell, 2014; Addoum, Ng, and Ortiz-Bobea, 2020). Conversely, education, management of companies, professional services, finance and insurance, health care, and social assistance with climate exposure percentiles below the 40th percentile.

[Insert Table 3]

Figure 3 plots the average *OCE*, weighted by employment, at the state level in 2018, showing an uneven geographic distribution. Workers in traditional financial, technology, education, and medical hubs such as the New York (e.g., NY, NJ, and CT), Boston (MA), and the Washington D.C. area (e.g., MD and VA) metropolitan areas are less exposed to climate while states more dependent on fracking and agriculture (AR, ID, ND, NE, OK, SD, TX, WY and WV) are more exposed. The demographic, industry, and geographic distributions confirm casual observations and provide additional validation for *OCE*.

[Insert Figure 3]

3.2. Labor Market Data, Variables and Sample

To gauge regional labor market conditions, I draw from two large and representative household data provided by *IPUMS*: the *American Community Survey* (*ACS*) and the *Annual Social and Economic Supplement* (*ASEC*) of the *Current Population Survey* (*CPS*).[26] *ACS* samples about 150 million employed individuals aged between 16 and 64 with information on age, gender, location, education, occupation (six-digit *SOC*), industry, and employment.[27] Acemoglu and Autor (2011) find that *ACS* provides larger samples than *CPS* and is more helpful for studying occupational employment patterns.

However, *ACS* has limitations, especially regarding earnings due to a timing mismatch. *ACS* surveys are rolled out throughout the year and ask about earnings and hours worked per week during the

[26] The ASEC of *CPS* is also known as March *CPS*.
[27] ACS samples approximately 0.35% of the US population from 2001 to 2004, and 1% of the population since 2005. I do not include the 2001-2004 sample because it does not contain the county identifier.

past 12 months rather than in the previous calendar year; this creates noisy proxies for the calendar-year estimations.[28] In contrast, *ASEC* surveys in March and asks about labor force status and earnings in the previous calendar year. These data provide more reasonable measures of the prior year's earnings, weeks worked, and hours worked per week (Acemoglu and Autor, 2011). Thus, I use *ASEC* surveys to retrieve data on weekly working hours, part-time or full-time employment status, and hourly wages.

I collapse individual-level information from *IPUMS* into occupation × county × 1990 Census Bureau industry × year level, with weights commensurate with those in the *IPUMS* surveys. The labor market outcome variables include employment from *ACS*, individual working hours (weekly), total working hours (employment times individual working hours), hourly wages constructed following Autor and Dorn (2013) and Webb (2019), and full-time or part-time status of *CPS*.[29]

Table 2 Panel A presents summary statistics of the occupation sample variables at the occupation × county × 1990 Census Bureau industry × year level, with about six million *ACS* employment cohorts, 1.5 million *CPS* labor market participation and earnings cohorts, and 759 unique occupations.

3.3. Firm-Level Data, Variables and Sample

3.3.1. Establishment-Level Data

The *NETS* data covers 29 annual snapshots taken every January of the Duns Marketing Information (*DMI*) file that followed over 71 million establishments (local branches) between January 1990 and January 2019. It reports plant and headquarters information including locations, industry, employment, and sales.[30] To match with *O*NET* and *IPUMS* data, I include the *NETS* sample during the years 2000 - 2018. I also collect

[28] For example, 2008 ACS estimates collected data between January 1, 2008 and December 31, 2008. If ACS surveyed a worker in June 2008, then the worker's estimation of annual earnings and usual weekly working hours was based on his/her status from July 2007-June 2008.

[29] 1990 Census Bureau industry is the major industry classification of Census surveys in labor economics studies (Acemoglu and Autor, 2011; Webb, 2019). The hourly wage is defined as the average hourly wages in 2018 dollars for full-time-full-year (FTFY, more than 35 hours/week and 40 weeks/year) workers in a given occupation × county × 1990 Census Bureau industry × year cell.

[30] According to Neumark, Zhang, and Wall (2007), *NETS* shows significant discrepancies in small establishments compared to the *Quarterly Census of Employment and Wages (QCEW)* and the *Current Employment Statistics (payroll) survey (CES)*. Thus, I drop establishments with less than 15 employees from the sample.

establishment workplace injury and illness data from *OSHA*. *OSHA* collected work-related injury and illness cases from private-sector establishments with more than 10 employees over the period 2002-2011.[31] I identify workplace injuries and illnesses as climate-related if *OSHA* labels them to be related to natural disasters or adverse weather conditions. For every establishment, the data contain the name, address, industry, and number of injury cases, etc.

3.3.2. Construction of Workforce Climate Exposure at the Firm Level

I take two steps to obtain the firm-level workforce climate exposure, *FWCE*. I first calculate workforce climate exposure at the establishment level (*EWCE*) by assigning the employment-weighted average *OCE* of the same county-industry-year to establishments in the same cohort in the spirit of prior studies (e.g., Donangelo, 2014; Belo et al., 2017; Ghaly et al., 2017; and Ma et al., 2021).[32]

$$EWCE_{et} = \sum_{o=1}^{759} \left(\frac{OCC\_EMP_{ocjt}}{COHORT\_EMP_{cjt}} \times OWCE_{ot}\right) \tag{2}$$

where e indexes establishment, c indexes the county that the establishment e locates, j indexes the industry of establishment e, and *o* indexes occupation in year t. OCC_EMP_{ocjt} is the employment of occupation *o* in county *c* and industry *j* in year *t*; $COHORT\_EMP_{ocjt}$ is the total employment in county *c* and industry *j* in year *t*. The employment information of occupations in a given county-industry cohort is from *ACS* and the establishment-level information including industry, county and employment, is from *NETS*.

Then I aggregate *EWCE* to the firm level based on establishment employment following the specification below.

$$FWCE_{it} = \sum_{e=1}^{n} \left(\frac{EST\_EMP_{et}}{FIRM\_EMP_{it}} \times EWCE_{et}\right) \tag{3}$$

---

[31]Some industries are exempt from reporting because of their low injury rate. Table IA5 in Internet Appendix A lists industries exempt from the ODI work-related injury and illnesses surveys from 2001-2014. I exclude these industries from the sample when conducting analyses on work-related injury and illness.

[32] The commonly used industry system in *IPUMS* is the 1990 Census Bureau industry code. Thus, industry in the *IPUSM* sample refers to is the 1990 Census Bureau industry code and later it refers to NAICS industry system. Using the crosswalk file provided by U.S. Census Bureau, I uniquely match the 1990 Census Bureau industry code in the *IPUMS* labor market datasets to the six-digit NAICS code in *NETS* data. The crosswalk files can be found at https://www.cdc.gov/niosh/topics/coding/more.html#:~:text=Census%20Crosswalks,system%20for%20a%20different%20year.

where EST_EMP_{et} is the employment of establishment e and $FIRM\_EMP_{it}$ is the total employment of the parent firm *i* based on *NETS* in year t.[33]

By taking these two steps to construct *FWCE,* I accommodate firm-level heterogeneity in *FWCE* by allowing variations in the workforce composition at the establishment level and variations in the establishment distribution at the firm level. The summary statistics of *FWCE* are presented in Table 1 Panel C. Table IA7 in the Internet Appendix lists the top 10 public firms with the highest and the bottom 10 with the lowest climate exposure in 2018. The most exposed firms are concentrated in the mining and manufacturing industries, while the less exposed are mostly in the healthcare, art, and retail industries.

3.3.3. Firm-Level Data and Sample

The financial data of public firms from 2000 -2018 is obtained from CRSP and Compustat. I discard financial firms (NAICS codes 52) and those with book assets and sales below zero.

I collect employee benefits from Form 5500. The *Employee Retirement Income Security Act of 1974* (*ERISA*) requires firms with more than 100 participants on their welfare and pension benefits plan to file a Form 5500 annually. I focus on Schedule A attached to Form 5500, "Insurance Information", available from 1999. Schedule A reports insurance plan information for each insurance company a firm hires, including insurance type (e.g., health, dental, prescription drugs, and life), number of persons covered, coverage period and the plan premium. Since the workforce climate exposure increases workplace injuries and illnesses, I retain plans for health and life benefits and drop plans with dental and vision insurance only.

Next, I aggregate Form 5500 information to the firm level and merge it with Compustat using the employer identification number (*EIN*). As firms may have separate *EIN*s for subsidiaries when filing Form 5500, I also match Compustat and Form 5500 by company name, industry, and address. I repeat the matching procedures using the information on the subsidiary of US public firms obtained from *NETS*. The final sample covers 37,181 firm-year observations, representing 5,128 unique firms from 2000 to 2018. I calculate the insurance expense scaled by the number of plan participants.

---

[33] Table IA2 - IA3 in the Internet Appendix list an example of the construction of *EWCE* and *FWCE*, respectively.

Regarding other firm-level variables, the offshore external input at the firm-country-year level is defined as the number of mentions in 10-K filings of purchasing inputs from a nation while not mentioning owning assets (Hoberg and Moon, 2017).[34] I measure the climate-related workplace safety risk using the number of workplace injuries related to weather or natural disasters reported to *OSHA* by a given firm in a given year. To estimate firm total workplace injury compensation, I first calculate establishment-level compensation per person using employment-weighted averages of the county-industry cohort that a given establishment belongs to based on *CPS* data. Then, I estimate the firm total compensation by multiplying firm employment with the establishment-level variable defined in step 1. To test potential factors that affect firms' labor adaptation actions, I quantify the local labor supply of firms as the average county-level labor supply from *ACS* data weighted by establishment employment provided by *NETS*; I measure the share of *FTFY* workers, union coverage, and the offshoring potential of firms' workforce at the firm level similarly. Specifically, I first calculate an establishment-level corresponding variable using employment-weighted averages at the county-industry level based on *CPS* data; then I aggregate this establishment-level variable to the firm-level using establishment employment as weights. The occupational offshoring potential index is constructed using the procedure created by Firpo et al. (2011) and standardized by Autor and Dorn (2013).

All variables are in 2018 dollars and described in Table A1 in Appendix A. Table 2 Panel C presents the summary statistics for the firm variables. The average premium per participant is $1,041, comparable to the number reported by Almeida et al. (2021). Firms have 0.27 environment-related safety accidents, 0.25 mentions of offshore external input in a given country in a 10-K filing, 94.2% of *FTFY* workers and 11.40% of workers are covered by unions. A mean value of 56.98 for workforce offshoring exposure suggests a neutral to positive offshoring potential given the variable ranges from 1 to 100.

[34] http://faculty.marshall.usc.edu/Gerard-Hoberg/HobergMoonDataSite/index.html.

3.4. Climate Data and Variables

The historical weather data are obtained from the *National Centers for Environmental Information* (*NCEI*), operated by *NOAA*.[35] This file contains daily weather observations, such as temperature and wind speed, from roughly 8,000 weather stations throughout the US. I collect the daily records in the US from 1980 to 2018 to generate both contemporaneous and long-term climate trend proxies. I also obtain each major natural disaster from *NOAA*'s *National Weather Service* (*NWS*).[36] This dataset records 48 types of significant weather events such as blizzards, heat events, and hurricanes since 1996.[37] For each event, the database provides information on the start date, the end date, the Federal Information Processing Standards (*FIPS*) county code, property damage, injuries, and fatalities.

I use temperatures to measure climate conditions in the main analysis following the literature (Dell et al., 2009; Graff Zivin and Neidell, 2014; Choi et al., 2020) I match weather stations with counties and calculate the mean daily temperature within the county. The temperature measure, $TEMP_{ct}$, is the annual average temperature for county c in year t.[38] I also create a variable *DISASTER*, the number of labor injuries and deaths resulting from disasters that cause over $1 million in economic damages in a given year, to quantify the impact of disasters on labor.[39]

To understand climate adaptation and address the endogeneity concern, I decompose annual temperature into predictable and abnormal patterns as follows in the spirit of Choi et al. (2020):

$$TEMP = LT\_TEMP_{ct} + AB\_TEMP_{ct} \tag{4}$$

where LT_TEMP_{ct} is the average temperature in county c over the 20 years before t, capturing the long-term/predictable trend; AB_TEMP_{ct} represents the abnormal annual temperatures.

[35] Source: *NOAA*, https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.ncdc%3AC00532, accessed on 03/10/2022.
[36] Source: *NOAA*, https://www.ncdc.noaa.gov/stormevents/details.jsp, accessed on 03/10/2022.
[37] Table IA6 in the Internet Appendix A lists weather event types defined in NWS Directive 10-1605.
[38] As robustness checks, I create an alternative temperature proxy, *HOT*, which is the number of days with the maximum temperature over 90°F (32.2 °C) in a year, and a dummy variable, *Heatwave*, which equals one if a given county reported human injuries or deaths related to heatwaves in a given year, and zero otherwise.
[39] This variable is not winsorized because of the scarcity of natural disasters.

Firm-level temperature measures are defined as the average county-year temperatures weighted by the lagged firm employment in that county as follows.

$$FIRM\_TEMP_{it} = \sum_{p=1}^{n} \left(\frac{EST\_EMP_{et-1}}{FIRM\_EMP_{it-1}} \times TEMP_{ct}\right) \tag{5}$$

where EST_EMP_{et} is the employment of establishment e located in county c and $FIRM\_EMP_{it}$ is the total employment of the parent firm *i* based on *NETS* in year *t*.

For stock market tests, I substitute annual temperatures with monthly temperature measures. I start by constructing $TEMP\_M_{cmt}$ as the monthly average temperature for county c in the month m of year t. Then I follow Choi et al. (2020) and define:

$$TEMP\_M_{ctm} = LT\_TEMP\_M_{ctm} + MON\_TEMP\_M_{ctm} + AB\_TEMP\_M_{ctm} \tag{6}$$

where $LT\_TEMP\_M_{cmt}$ is the average monthly temperature in county c over the 240 months before year t month *m* which captures the long-term trend; $MON\_TEMP\_M_{cmt}$ is the average deviation of this month's temperature from the long-term trend, that is, the average temperature in county c in the same calendar month m over the last 240 months minus $LT\_TEMP\_M_{cmt}$. $MON\_TEMP\_M_{cmt}$ captures the seasonality in the local temperature; $AB\_TEMP\_M_{cmt}$ is the abnormal monthly temperature.

Table 1 Panel B and C present summary statistics for the climate variables at the county level and the firm level, respectively. The mean of *FIRM_AB_TEMP* (0.3°F) is of a larger magnitude compared to that at the county level *AB_TEMP* (0.07°F). That is, firm branches locate in areas where temperatures are increasing in an accelerated way, suggesting that firms are facing more severe challenges of global warming.

4. Workforce Climate Exposure and Labor Market Outcomes

4.1. Empirical Specification

To assess the impact of climate exposure on the labor market outcome of occupations, I estimate panel regressions of the following form at the occupation × county × industry × year:

$$Y_{ocjt} = \alpha_o + \lambda_{cjt} + \beta OCE_{ot-1} + \varepsilon_{ocjt} \tag{7}$$

where Y_{ocjt} denotes labor market outcomes including 100 times the natural logarithm of employment, individual weekly working hours, total weekly working hours (employment times individual weekly working hours), hourly wages in 2018 dollars, and the percentage of part-time workers in occupation o in county c in the 1990 Census Bureau industry j in year t; OCE_{ot} denotes the time-varying climate exposure of occupation o in year t. I control for occupation fixed effects α_o to rule out the impact of time-invariant occupation characteristics. I also control for the county × industry × year fixed effects λ_{cjt} to absorb time-varying conditions at the location-industry level. Following Hershbein and Kahn (2018), I weight regressions using the lagged county-level employment to reduce the impact of outliers because the coverage of *IPUMS* surveys depends on the county population.[40] Standard errors are clustered by county.

[Insert Table 4]

Panel A of Table 4 presents the baseline results. The coefficient of *OCE* is 2.261 and 0.248 in the regressions of employment in column (1) and the share of part-time workers in column (5), respectively, both significant at the 1% level. In contrast, *OCE* is negatively associated with weekly working hours per employee in column (2), and with hourly wages in column (4). With a one-standard deviation (0.83) increase in *OCE*, employment increase by 1.88% (2.261%× 0.83) at the occupation× county× industry level, equivalent to 7 workers (1.88% ×362); the share of part-time workers see an increase of 20.6 basis points (equivalent to 0.00206 × 362=0.76 workers).[41] With the same increase in *OCE*, weekly working and hourly wages hours per employee decline by approximately 8 basis points (0.097%× 0.83) and 76.6 basis points (0.957%× 0.83), respectively, at the cohort level. Given an occupation on average has employment in 117 industries and 268 counties, these numbers imply 219,492 additional workers (7× 117× 268), 23,831 part-time workers, a loss of 364,136 weekly working hours (0.0008×40.1× 362×117× 268), and a $226 million (0.00766 × $28.7 × 40.1× 362×117× 268) loss in weekly wages, at the occupation

[40] https://www.census.gov/data/developers/data-sets/acs-1year.html.

[41] The average employment and the share of part-time workers is 362 and 15.9%, respectively. The change in the number of part-time workers is calculated based on the assumption that the employment is fixed to the sample mean.

level.[42] The coefficient of *OCE* is insignificant in column (3) in which the dependent variable is the total working hours. Overall, these results are consistent with *Hypothesis 1* and *Hypothesis 2a (labor adaptation)*: Climate-exposed occupations have fewer working hours and lower productivity, and employers hire additional employees, especially part-time workers, to satisfy the same production demand and keep the same total weekly working hours.

4.2. Interaction with Climate Conditions

To test the joint effect of workforce climate exposure and actual climate conditions, I extend Equation (7) by adding the interaction of *OCE* and county × year-level climate proxy, *TEMP* as an additional explanatory variable. Results are reported in Table 4 Panel B. Similar to Table 4 Panel A, I find a positive coefficient (significant at 5% level) of *OCE* × *TEMP* in the regression of employment and the percentage of part-time workers in columns (1) and (5), respectively. I also document a significantly negative coefficient of *OCE* × *TEMP* in columns (2) in which the dependent variable is the individual weekly working hours, consistent with Graff Zivin and Neidell (2014) and Dillender (2019) that avoiding working outdoor during extreme temperatures seems the main avoidance behavior of workers. The negative relation between *OCE* and hourly wages suggested by the negative coefficient in column (4) provides evidence of Somanathan et al. (2021) about the impact of temperatures on labor productivity. Holding *OCE* constant, a one-standard-deviation increase in local temperature (9.2°F) results in 1.07% (0.117% × 9.2) and 19 basis point increase in employment and the share of part-time workers; It also leads to a 23-basis point loss of individual working hours and 54.3 basis points decline in hourly wages. These numbers imply 121,454 additional workers, 21,575 more part-time workers, a loss of 1,044,281 weekly working hours, and a $70.92 million loss in weekly wages at the occupation level. Column (3) presents an insignificant coefficient of *OCE* × *TEMP* in the regression of total working hours, as employers can hire additional workers, especially part-

[42] The average individual working hours and hourly wages is 40.1 and $28.7, respectively. Thus, a one-standard deviation in *OCE* decreases working hours and hourly wage by 0.032 hours (40.1 × 0.008) and $2 (0.00766 × $28.7) per worker.

time workers, to keep the same total working hours during hot days. These results are consistent with *Hypothesis 3* that actual climate events magnify the impact of *OCE* on labor market outcomes.

The impact of temperatures may be symmetric: the deviation from the optimal temperature range adversely affects climate-exposed workers. To allow for a nonlinear relation between temperature and labor market outcomes, I replace *TEMP* with a set of indicator variables for every 5°F temperature increment. This allows differential shifts in labor market responses for each temperature bin. The coefficients of the interaction between *OCE* and each temperature bin indicator are displayed in Figure 4. I use the interaction of *OCE* and the 50°F–55°F bin as the benchmark, so the estimates are the change in labor market outcomes within a certain temperature range relative to 50°F–55°F, holding *OCE* constant.

[Insert Figure 4]

For employment in Plot A, I find little response to temperatures below 65°F but monotonic increases afterward, significant at the 5% level. Holding the *OCE* constant, employment increases by 2.11% at daily temperatures over 65°F, as compared to 50°F–55°F. Plot B shows that with constant *OCE* constant, individual working hours decrease significantly over 65°F compared to 50°F–55°F, and Plot D presents a similar pattern in hourly wages. Plot E differs from other plots in that relative to 50°F–55°F, the share of part-time workers increases significantly over 70°F instead of 65°F. Consistent with Table 4 Panel B, total working hours in Plot C do not respond to temperature changes significantly. Overall, I find an asymmetric effect of daily temperatures: Workers appear to be significantly affected by hot rather than cold weather, consistent with the notion in the previous literature that compared to cold weather, heat stress has greater effects on labor supply, labor productivity, and health (Graff Zivin and Neidell, 2014; Park et al, 2019; Somanathan et al., 2021). As robustness checks, I repeat the tests using a monthly sample generated from monthly *CPS* surveys and find the effects documented previously are more driven by summer rather than winter (Appendix A Table A2). I also find robust evidence using alternative temperature proxies including the annual number of hot days (over 90°F) and a heat wave dummy (the results are reported in Appendix A Table A3). Based on these findings, I focus on the high end of the temperature spectrum in all the following analyses.

To extend my analysis scope, I define a proxy for all kinds of natural disasters, *DISASTER*, using the number of injuries and deaths caused by disasters in a given county year. The results are reported in Table 4 Panel C. I find disasters similarly affect climate-exposed workers as temperatures. The only difference is that employers fail to hire more employees during disasters, potentially because the more hazardous disasters tighten the labor supply much more than temperatures. These results suggest my previous findings of the labor market outcomes are robust to different proxies for climate conditions, and *OCE* captures the physical risks associated with various climate events that are not limited to temperatures.

4.3. Local Demand Versus. Local Supply

Labor market outcomes depend on labor supply and demand. Even though I control for local demand by including the county × industry × year fixed effects, it is still possible that climate events reduce consumer demand, leading to decreased working hours and wages in climate-exposed occupations. However, this does not explain why employment increases. To further rule out this possibility, I conduct a subsample test based on tradable sectors that include all industries except for the retail trade industry (NAICS 44-45) and the accommodation and food services industry (NAICS 72). The goods and services of tradable sectors can be transported and consumed nationally or globally, so they are less affected by local demand compared to non-tradable sectors (Mian and Sufi, 2014). Li et al. (2020a) find high temperatures reduce employment and establishments only in the non-tradable sectors, confirming temperatures' impact on local demand. Thus, if climate events impact occupations through the labor supply channel instead of the local demand channel, the impact in *Hypothesis 1-3* should not be limited to non-tradable sectors. Appendix A Table A4 suggests that the results in Table 4 hold for tradable sectors, ruling out changes in local consumer demand as the driving factor of my previous findings.

5. Workforce Climate Exposure and Firm Outcomes

5.1. Baseline Results

To assess the impact of workforce climate exposure on firms, I calculate firm climate exposure (*FWCE*) as the employment-weighted *EWCE* and then estimate the panel regressions of the following form:

$$Y_{ijt} = \alpha_i + \lambda_{jt} + \beta X_{ijt-1} + \theta FWCE_{ijt-1} + \varepsilon_{ijt} \qquad (8)$$

where i is the firm and j is the three-digit NAICS industry. Y_{ijt} includes outcomes of firm i in year t and industry j; X_{ijt-1} is a set of lagged firm-level controls; $FWCE_{ijt-1}$ is the lagged climate exposure of firm i. If not specified, firm fixed effects α_i and industry×year fixed effects λ_{jt} are included, and standard errors are clustered by firm.

[Insert Table 5]

Results are reported in Table 5. The first three columns examine firms' adaptation strategies from 2000-2018. The dependent variable in column (1)–(2), is 100 times the natural logarithm of firm employment and employee health and life insurance per participant at the firm-year level respectively, and is 100 times offshore external output at the firm-country-year level in column (3). The last three columns test firm outcomes. Following Caskey and Ozel (2017), I estimate a Poisson regression to count the number of environment-related workplace injuries reported to *OSHA* at the firm-year level from 2002-2011 in column (4). I report OLS regression results using firm-year observations in 2000-2018 in column (5)-(6), and the dependent variable is workplace injury compensations (millions) estimated from *CPS* (column (5)) and *ROA* in percentage (column (6)), respectively. Following Chen, Harford, and Kamara (2018), I control for the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses, and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage and cash flow volatility, payout scaled by assets, and net working capital over assets in all regressions. The natural logarithm of employment and staff expenses are additionally controlled in the regression of offshore input, the number of environment-related workplace injuries, injury compensations and *ROA*. I also control for the employee over assets and the natural logarithm of sales per employee in the employment regressions in the spirit of Chen, Kacperczyk, and Ortiz-Molina (2010). The definition of all variables is described in Appendix Table A1. The Poisson regression of injury counts in column (4) only includes year-fixed effects. The offshore input regression in column (3) includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects, and standard errors clustered by firm and foreign country. All other columns include standard fixed effects and clusters in Equation (8).

The results in column (1), (2), (4), and (5) of Table 5 show that *FWCE* has a significantly positive relation with employment, employee insurance, environment-related workplace injuries, and injury compensations. Column (6) reports a coefficient of -1.411 on *FWCE* in the *ROA* regression (significant at 5% level), suggesting that *FWCE* adversely affects firm operating performance. A one-standard-deviation increase in *FWCE* (0.32) will increase firm employment by 0.73% (2.272%×0.32) and insurance costs per person by 4.5%; It also leads to a 0.47 increase in environment-related injuries (1.74 times the sample mean of 0.27), a $0.044 million increase in workplace injury compensations (14.7% of the sample mean), and a decline of 0.452% (1.411%×0.32) in *ROA*. These numbers are equivalent to 92 additional employees (0.73%×12,737) and additional $10.34 million in staff expenses (92× $112,537), and an increase of $0.90 million (4.5%× $1041×19,229 participants) in total employee health insurance.[43] Assuming the average assets of $5,452 million are constant, this reduction in *ROA* means a loss of $24.6 million (0.47%× $5,452) in operating profits.

The insignificant positive coefficient in column (3) indicates that climate-exposed firms, on average, do not purchase more input overseas. There are two possible explanations for this finding. First, it could be more cost-effective to hire more workers rather than relocate production overseas. Second, certain job duties are not suitable for offshoring, as evidenced in studies by Blinder (2009) and Firpo et al. (2011). If

[43] The average staff expenses per employee at the two-digit NAICS industry level is $112,537 based on Compustat which provides staff expenses for about 10% firms. The Compustat staff expenses represents salaries, wages, pension costs, profit sharing and incentive compensation, payroll taxes and other employee benefits.

climate-exposed workers fall into this category, firms' ability to engage in offshoring efforts will be constrained. I test this possibility by regressing firm-level workforce offshoring potentials on *FWCE* and the results reported in Internet Appendix Table IA8. The significantly negative coefficients on *FWCE* confirm the difficulty in offshoring climate-exposed workers like miners and guards. Overall, these results are consistent with *Hypothesis 4a* that climate-exposed firms take labor-related adaptation actions and findings in Xiao (2023) that firms do not choose capital adaptation on average because of the scale of investment expenditures and their financial constraints. It is also consistent with *Hypothesis 5b* that adaptation cannot fully mitigate the negative effect of climate-induced labor risk on firm performance. These findings support the labor cost channel through which workforce climate exposure can affect firms' operations and performance.[44]

5.2. Firm Responses to Actual Climate Conditions

Similar to the labor market analysis, I extend Equation (8) by adding an interaction item of *FWCE* and the firm-level temperature (*FIRM_TEMP*). Table 6 Panel A presents the regression results with the same setup as Table 5.

[Insert Table 6]

The dependent variable is 100 times the natural logarithm of firm employment and employee health and life insurance per participant in column (1) –(2), respectively, 100 times the offshore external output in column (3), the number of environment-related workplace injuries in column (4), workplace injury compensations in millions in column (5) and *ROA* in percentage in column (6). The variable of interest is *FWCE* × *FIRM_TEMP*. In column (1), I find a significantly positive coefficient on the interaction item. Consistent with the labor market analysis, climate-exposed firms hire more workers possibly to supplement the workforce when experiencing rising temperatures. Column (2) shows that these firms also pay a greater insurance premium for their employees in response to higher temperatures, possibly to hedge against

[44]To validate the construction of *FWCE* and explore firm outcome at granular level, I also conduct tests at the establishment level using *EWCE* in Appendix B. I find establishments with greater *EWCE* suffer more environment-related workplace safety accidents, maintain larger employment base, and have worse performance.

increased injuries/illnesses. Different from the baseline test, I find a marginally positive coefficient in column (3). Firms with a more climate-exposed workforce shift more input production overseas when experiencing high temperatures. This may be due to the rising labor costs that make offshoring a more viable option.[45] Holding *FWCE* constant, a one-standard-deviation increase in *FIRM_TEMP* (6.28°F) leads to a 1.43% (0.227%× 6.28) increase in firm employment (182 employees and a $20.5 million increase in staff expenses), a 7.77% (1.238%× 6.28) increase in insurance per participant (equal to $1.56 million in total employee health insurance), and 0.85 more mentions of country-level offshoring external input, 3.4 times of the sample mean (0.25). These findings are consistent with *Hypothesis 6* that firms with greater *FWCE* adapt more when experiencing negative climate conditions. The insignificant coefficients of the interaction term in columns (4)-(6) show that these firms do not see more environment-related workplace injuries, pay more injury compensation, or have lower *ROA* during higher temperatures, suggesting that firms' labor adaptation actions seem to efficiently mitigate the climate-induced labor risk. These results are consistent with *Hypothesis 7a* that the relation between *FWCE* and firm performance is not more pronounced under negative climate conditions, but contradict the previous findings that climate-exposed firms, on average, perform worse.

5.3. Adaptation, Temperature Surprises, and Operating Performance

Hypothesis 8 suggests that examining the impact of different climate components on adaptation may help explain the contradictory findings in firm performance. I decompose county-year temperatures as shown by Equation (1) and aggregate different components to the firm level to obtain the long-term trend (*FIRM_LT_TEMP*) and the short-term surprise (*FIRM_AB_TEMP*). I then add the interaction of *FWCE* with these two proxies to Equation (8). The coefficient on *FWCE* × *FIRM_LT_TEMP* captures firms'

[45] As robustness check, I repeat the analysis using alternative proxies for offshore input including offshore internal input and offshore total input. Results are reported in Internet Appendix Table IA9. I do not find similar patterns using alternative proxies, consistent with the finding in Hoberg and Moon (2017) that firms value the operational hedging provided by offshore external input.

adaptation actions to predictable climate risk, while *FWCE* × *FIRM_AB_TEMP* examines the causality between *FWCE* and firm outcomes.

Table 6 Panel B presents the results in the same setup as Table 5. I find results consistent with *Hypothesis 8a:* The positive coefficients on *FWCE×FIRM_LT_TEMP* in columns (1)-(3) suggest that firms in traditionally hot areas have more employees, higher insurance costs, and more offshoring input, confirming that they incorporate their workforce climate exposure and foreseeable climate patterns into adaptation decisions; Columns (6)-(8) show that these firms do not simultaneously experience more environment-related injuries, increased injury compensations, or a decline in *ROA*, implying that their adaptation helps mitigate predictable climate-induced labor risk and increase employee welfare by providing a safe workplace. Holding *FWCE* constant, a one-standard-deviation increase in *FIRM_LT_TEMP* (6.26°F) leads to a 1.50% (0.24%×6.26) increase in firm employment, equivalent to 191 employees and a $21.49 million increase in staff expenses. It also causes a 7.6% increase in insurance per participant (a $1.52 million increase in total health insurance expenditures) and 0.94 more mentions of country-level offshoring external input (3.8 times the sample mean). Coefficients on *FWCE×FIRM_AB_TEMP* are insignificant in all columns except for column (6) and (8), which present a negative coefficient in the environment-related workplace injuries and *ROA* regressions, respectively. That is, climate-exposed firms experience losses in workplace safety and operating performance due to their inability to make timely adjustments to their employment, insurance, and offshoring activities in response to temperature surprises, consistent with *Hypothesis 8b*. Holding *FWCE* constant, a one-standard-deviation increase in *FIRM_AB_TEMP* (1.47°F) lead to a 0.381 increase in the number of environment-related injuries, and a decrease of 0.003 (0.212%×1.47) in *ROA*, which is equivalent to a $17.0 million decrease in operating profits.[46] Taken together, these findings imply that, though firms endogenize climate exposure

[46] The dollar losses in operating profit is calculated based on the in-sample mean of total assets ($5,452 million).

and long-term climate trends in their operation policies to some extent, their operating performance is not perfectly immune to short-term climate surprises.[47]

5.4. Temperature Surprises and Stock Market Responses

Having shown that unexpected temperature shocks disrupt climate-exposed firms' operating performance, I assess the valuation implications of *FWCE* by studying stock market performance following Choi et al. (2020) and estimate the panel regressions at the firm-year-month level of the following form:

$$Y_{ijmt} = \alpha_i + \lambda_{jt} + \gamma_{mt} + \beta X_{ijmt-1} + \mu FWCE_{ijt-1} + \theta FWCE_{ijt-1} \times FIRM\_AB\_TEMP\_M_{ijmt} + \eta FIRM\_AB\_TEMP\_M_{ijmt} + \varepsilon_{ijmt} \quad (9)$$

where i is firm and j is the industry. Y_{ijmt} is either the raw return or Fama-French three-factor alpha of firm i in month m in year t and industry j;[48] X_{ijt-1} is firm-level controls that contain the contemptuous long-term monthly temperatures ($FIRM\_LT\_TEMP\_M$) and monthly seasonality ($FIRM\_MON\_TEMP\_M$), and the natural logarithm of firm sales and Tobin's Q in the prior year; $FWCE_{ijt-1}$ is the lagged one-year climate exposure; $FIRM\_AB\_TEMP\_M_{ijmt}$ is the abnormal temperature at the firm-year-month level as defined in Section 3.4. I control for firm fixed effects α_i, industry × year fixed effects λ_{jt} and year-month fixed effects γ_{mt}.

[Insert Table 7]

Table 7 reports the regression results. The dependent variable is the raw return in the first five columns and is the Fama-French three-factor alpha in the last five columns. The coefficient on *FWCE* ×

---

[47] As robustness checks, I also replace county-year average temperatures (*TEMP*) using the long-term (*LT_TEMP*) and short-term temperatures (*AB_TEMP*) and repeat the occupation-level and establishment-level tests in Table A5 Panel D and Table B2, respectively. In general, I document similar adaptation patterns in the labor market and establishments. At the occupation level, climate-exposed workers reduce working hours and accept lower wages for the lower productivity with the projection of high temperatures. In this equilibrium, employers can still hire additional workers, especially part-time workers, to maintain total working hours. However, when abnormal heat catches workers off guard, the labor market suddenly becomes too tight for additional hiring. Thus, despite the lower productivity, employers have to raise wages to motivate the current workforce. At the establishment level, climate-exposed establishments adapt to the long-term climate trends by carrying employment buffer. However, these establishments are not able to supplement the workforce and experience more workplace safety accidents and a lower PayDex score when hit by abnormally high temperatures.

[48] I estimate the monthly abnormal return using the Fama-French three-factor model. The estimation period is the previous 12 months and I require firms to have at least 6 monthly observations in the estimation period.

FIRM_AB_TEMP_M in Table 7 columns (1) and (6) is -0.045 and -0.06, respectively, both significant the 5% level, implying that climate-exposed firms experience declined stock returns under heat surprises, consistent with previous studies.[49] Equivalently, holding *FWCE* constant, a one-standard-deviation increase in monthly *FIRM_AB_TEMP_M* (2.68°F) relates to a decrease of 12.1 and 16.1 basis point in the monthly raw return and Fama-French three-factor monthly alpha, respectively. This effect can occur through two potential channels. First, abnormal weather events may disrupt the operation of climate-exposed. Second, investors may revise their beliefs about climate change and, in turn, the valuation of firms under climate-related shocks (Choi et al., 2020; Pastor et al., 2021).

This monthly specification also allows me to better investigate the non-linear relation between temperatures and firm performance by releasing the concern about annual specifications that hot days (summer) and cold days (winter) may cancel out each other. I first create two dummies: A *SUMMER* dummy equals one from June-August, and zero otherwise. A *WINTER* dummy equals one in December, January and February, and zero otherwise.[50] Then I interact these dummies with *FWCE* × *FIRM_AB_TEMP_M* accordingly. The negative coefficient on *FWCE* × *FIRM_AB_TEMP_M* × *SUMMER* in column (2) and (7) confirm that abnormally hot summers destroy firm value of climate-exposed firms. The positive coefficient on *FWCE* × *FIRM_AB_TEMP_M* ×*WINTER* is not significant in column (3) but, in column (8), provides some evidence of the benefits of an unusually warm winter resulting from better working conditions for workers and firms. Alternatively, I also interact *FWCE* with a proxy of firm-level abnormal hot days (maximum temperature over 90°F/ 32.2°C) in a given year-month (*FIRM_AB_HOT_M)* and report results consistent with findings based on the *SUMMER* dummy in column (4) and (9). Interestingly, when interacting *FWCE* with the firm-level abnormal cold days (minimum temperature below 32°F/ 0°C), I find an insignificantly negative coefficient in column (5) and (10), suggesting an abnormally cold winter does not adversely impact firms, consistent with the labor market analysis in Section 5.

[49] See Choi et al. (2020) and Pastor et al. (2021).
[50] https://www.noaa.gov/education/resource-collections/climate/changing-seasons.

6. Economics of Labor Adaptation

6.1. Firm Performance Post Labor Adaptation

A follow-up question is why firms adapt given the cost and limitations of labor adaptation discussed in Section 5. According to *Hypothesis 9*, climate-exposed firms will have more incentive to adapt if the expected benefits of adaptation increase. Section 5.3 suggests that labor adaptation effectively hedges against the predictable climate-induced labor risk. Another potential benefit is that climate-exposed firms can better survive abnormal temperatures and gain relative competitive advantages compared to peers that do not adapt. To test this hypothesis, I split my sample based on labor adaptation strategies including employment, employee insurance expenses per person, and offshoring external input accordingly. For each adaptation variable, I classify firms as *High Group* if their lagged corresponding variable falls above the median cutoff within the same industry, and the remaining firms into the *Low Group*. I then repeat the *ROA* regression in Table 6 Panel B separately for each subsample and report the results in Table 8. Subsamples are defined based on firm employment in columns (1)-(2), employee insurance expenses per person in columns (3)-(4) and offshoring external input in columns (5)-(6). The first column of each pair shows results for the *High Group* and the second column is based on the *Low Group*.

[Insert Table 8]

Table 8 column (1), (3), and (5) present regression results from the *High Group.* The insignificant coefficient on *FWCE*× *FIRM_AB_TEMP* in these columns indicates that climate surprises have no impact on the operating performance of firms that take ex-ante employment/insurance/offshoring adaptation actions. In contrast, I find a negative coefficient on *FWCE*× *FIRM_AB_TEMP*, significant at 5% level, in firms with fewer employees (column (2)) and lower employee insurance spending (column(4)), respectively, and they are larger in magnitude and stronger in significance compared to the full-sample coefficient (-0.212%) reported by Table 6 Panel B. Take column (2) as an example: holding *FWCE* constant, a one-standard-deviation increase in *FIRM_AB_TEMP* (1.47°F) decreases *ROA* by 50.1 basis point (0.341% ×1.47). Column (6) shows a negative coefficient on *FWCE*× *FIRM_AB_TEMP* (-0.227%) based on the subsample of firms with less offshore input. Though insignificant, this coefficient has more than doubled that reported by column (5) based on the *High Group*. Overall, Table 8 suggests labor adaptation, especially employment and insurance adaptation, helps firms smooth unexpected climate-induced labor disruptions and outperform peers that do not adapt. These findings also provide evidence of the incentive and effectiveness of firm labor adaptation, consistent with *Hypothesis 9* about the benefit incentives of adaptation.

6.2. Potential Driving Factors of Labor Adaptation

Given the results in the previous section, a puzzle that arises is why not all firms take actions to adapt to climate-induced labor risk. To answer this question, I next investigate the cost (constraint) incentives of *Hypothesis 8* by exploring factors that potentially affect firms' ability and/or preference to engage in certain adaptation activities. To begin, I examine the influence of local labor supply and the proportion of *FTFY* workers on firms' employment practices. Firms in areas with greater labor supply can hire more easily, while firms with a higher proportion of *FTFY* workers will have to keep a large workforce because of the lack of flexibility in labor adjustments. The share of *FTFY* workers can also affect firms' employee insurance policies, with almost all full-time workers having access to medical care benefits compared to only a quarter of part-time workers in 2022. [51] Additionally, unions typically advocate for employee benefits and safety measures (Freeman and Medoff, 1984). As a result, I expect that firms with more *FTFY* and unionized workers will have more employee insurance expenses. Lastly, concerning offshoring adaptation, I hypothesize that firms can only offshore jobs with high offshoring potentials to low-income countries that offer lower labor costs. [52]

To test these predictions, I separately sort firms based either on the firm-level characteristics including local labor supply, the share of *FTFY* workers, the share of unionized workers, workforce offshoring exposure, and country-level labor costs measured by GDP per capital. For each of the above five

---

[51] https://www.*BLS*.gov/news.release/ebs2.nr0.htm.
[52] See Blinder (2009); Firpo et al. (2011); Blinder and Krueger (2013); Hoberg and Moon (2017).

factors, I classify firms as *High Group* if their given factor is above the median cutoff in the same industry-year, while the remaining firms fall into the *Low Group*. Then I repeat the first three columns regarding labor adaptation actions in Table 6 Panel B using subsamples.

[Insert Table 9]

The results are displayed in Table 9. The dependent variable in Panel A is 100 times the natural logarithm of firm employment and the factor used to define subsamples is local labor supply in column (1)-(2), the share of *FTFY* workers in column (3)-(4). Similarly, I examine insurance adaptation in Panel B, where the dependent variable is 100 times the natural logarithm of employee insurance per person, and subsamples are split based on the share of *FTFY* workers in column (1)-(2) and the share of unionized workers column (3)-(4). In Panel C, I repeat offshoring external input regression in column (3) of Table 6 Panel B based on subsamples broken by workforce offshoring exposure in column (1)-(2) and labor costs in foreign countries in column (3)-(4). The first column in each pair presents regression results based on the *High Group* subsample, while the second column is based on the *Low Group* subsample.

I find significantly positive coefficients on *FWCE*× *FIRM_LT_TEMP* in Panel A column (1) and (3). Holding *FWCE* constant, a one-standard-deviation increase in *FIRM_LT_TEMP* (6.26°F) increases firm employment by 2.36% (301 employees) in firms with more local labor supply and by 2.74% (377 employees) in firms with more *FTFY* workers. The magnitudes are 4.4 times and 9.9 times the insignificant numbers found in the peer firms with a tighter labor market and fewer *FTFY* workers, respectively. These findings provide evidence that the local labor market and firm workforce flexibility impact firms' employment adaptation decisions. Panel B shows that only a subsample of firms that have more *FTFY* workers (column (2)), or more unionized workers (column (3)) will increase employee insurance expenditures. Finally, I report subsample tests of firm purchase of offshoring inputs in Panel C. The coefficient on *FWCE*× *FIRM_LT_TEMP* in the subsample of firms with high offshoring potentials in column (1) is about twice that found in the *Low Group* in column (2). Moreover, by comparing column (3) and (4), I find that holding *FWCE* constant, firms react to an identical increase in *FIRM_LT_TEMP* by purchasing 9 times more offshoring input from countries with lower labor costs than from richer countries.

Panel C documents evidence that the offshoring potential of jobs and the labor cost of offshoring play a role in firms' offshoring adaptation decisions.

6.3. Impact of Regulatory Climate Risk

6.3.1. Background of the California Heat Illness Prevention Standard in 2005

Having examined the impact of physical climate risk, I expand this study to examine how regulatory climate risk affects firm adaptation and performance and, in the process, provide additional evidence to make causal inferences. Specifically, I exploit the passage of the California Heat Illness Prevention Standard (*CA Standard*) imposed in 2005 by the state government. *CA Standard* requires employers to take actions to reduce heat-related safety risks for outdoor workplaces, such as providing shade structures and paid rest breaks every hour.[53] It was filed on August 8th, 2005, as an emergency measure to be implemented within 17 days and, subsequently, was passed by the State Assembly on July 7th, 2006.[54] Because firms with more climate-exposed workers also bear higher heat-related safety risks, the increased regulatory climate risk creates incentives for them to take labor adaptation actions (the benefit incentives of *Hypothesis 8*). Moreover, *CA Standard* was put into effect as an emergency measure, which makes it a clean natural experiment because pre-emptive actions and market anticipation are less likely to happen.

6.3.2. The Market Announcement Effect of the CA Standard

I start by analyzing the cumulative abnormal stock returns during the three days around the announcement of *CA Standard* in 2005 for firms affected by this regulatory shock. I estimate daily abnormal returns using the Fama-French three-factor model. The estimation period starts 280 days before each event and ends 30 days before the event day, with at least 50 return observations. I define *TREATED_EMP* as a proxy for the extent to which the firm is affected by *CA Standard*. Specifically, it is the percentage of the firm's employees in California counties where the long-term temperature is in the top tercile within the state, because *CA*

---

[53] Additional details regarding the policy are provided in Internet Appendix B.
[54] Emergency measure in California can be filed in "a situation that calls for immediate action to avoid serious harm to the public peace, health, safety, or general welfare." As soon as it is filed, it is effective for 180 days and can be readopted for two 90-day periods.

Standard solely mitigates the impact of temperature on injury claims that occur towards the upper range of the temperature spectrum (Park et al., 2019). I then regress three-day cumulative abnormal returns, *CAR [-1,1]* on the lagged *FWCE*. Controls include lagged firm sales, Tobin's Q, and three-digit NAICS industry fixed effects. Standard errors are clustered by industry.

[Insert Table 10]

Table 10 presents the results. The dependent variable is the raw return in the first two columns and the Fama-French three-factor alpha in the last two columns. Columns (1) and (3) show that *CA Standard* has, on average, no price impact on climate-exposed firms, likely because the *CA Standard* is not binding for firms operating out of California or not experiencing heat stress in California. In columns (2) and (4), I further include an interaction term between *FWCE* and *TREATED_EMP* to capture the extent to which the firms are affected by the *CA Standard* and report regression on raw return and abnormal return, respectively. The coefficients of *FWCE ×TREATED_EMP* are significantly negative in both columns, suggesting that investors anticipate *CA Standard* to impose additional costs on firms whose workforce is more climate-exposed and more affected by the regulation.

6.3.3. Real Impacts of the CA Standard on Climate-Exposed Firms

CA Standard requires employers to provide paid breaks to reduce workers' heat-related safety risks. Therefore, I expect shorter working hours in climate-exposed workers after the implementation of *CA Standard*. The employment and hourly wages of workers may increase because of firms' increasing labor demand to supplement the workforce. To examine this hypothesis, I first conduct analyses at the occupation level. Table A5 in Appendix A presents the results consistent with the hypothesis. Occupations with greater *OCE* in the treated counties where long-term temperatures are in the top tercile within the state, experience significant reductions in working hours but increases in employment, hourly wages and the share of part-time workers following the implementation of *CA Standard*.

After validating the labor market impact of *CA Standard*, I employ a triple difference-in-difference methodology using a subsample of firm-year observations in 2003-2007 to examine the impact of *CA*

Standard on firms. The treated firms are those whose workforce is more climate-exposed and more affected by the shock, and the control group includes remaining firms in a given year; The post period is years since 2006, as Park et al. (2019) find enforcement of *CA Standard* increases significantly since then. The specification is represented as follows:

$$Y_{ijt} = \alpha_i + \lambda_{jt} + \beta X_{ijt-1} + \theta FWCE_{ijt-1} \times TREATED\_EMP_{ijt-1} \times POST2005$$
$$+ \gamma FWCE_{ijt-1} \times POST2005 + \eta TREATED_{EMP\,ijt-1} \times POST2005$$
$$+ \delta FWCE_{ijt-1} + \mu TREATED\_EMP_{ijt-1} + \varepsilon_{ijt} \tag{10}$$

where i is firm and j is the three-digit NAICS industry. Y_{ijt} is operating outcomes of firm i in year t and industry j; X_{ijt-1} is a set of firm-level controls in Equation (7); $FWCE_{ijt-1}$ is the lagged climate exposure of firm i; $POST2005$ dummy equals one for years after 2005 and zero otherwise. I also include firm fixed effects α_i, and industry × year fixed effects λ_{jt}.[55] Standard errors are clustered by firm.

[Insert Table 11]

Table 11 presents the regression results in the same setup as Table 5. The dependent variables are as follows: 100 times the natural logarithm of firm employment and employee health and life insurance per participant in column (1) –(2), respectively; 100 times offshore external output in column (3); the number of environment-related workplace injuries in column (4); workplace injury compensations in column (5); 100 times *ROA* in percentage in column (6). The variable of interest is the triple interaction term, *FWCE ×POST2005 ×TREATED_EMP*, which captures the changes in treated firms pre- and post-shock relative to the control firms. I find a positive coefficient of 0.284 in column (1) and a negative coefficient of -0.011 in column (5). That is, post policy implementation, treated firms hire more workers to supplement the workforce and reduce heat-related safety risk, resulting in declined injury compensation. Holding the constant *FWCE*, a 1% increase in the share of employees affected by the policy will lead to 36 additional employees (0.284%×12,737) and a reduction of $11,000 in injury compensation (4% of the sample mean), after the shock. The evidence is consistent with the notion that extreme temperature-sensitivity of injury

[55] Definition of firm attributes is described in Appendix A Table A1.

claims declines following the the adoption of *CA Standard* (Park et al., 2021). I fail to find a significant change in the number of environment-related injuries and employee insurance. Together with the finding that injury compensation declines in the post period, it may suggest that *CA Standard* does not reduce the occurrence of workplace injuries, but does reduce the severity of these accidents. The offshore external input does not change significantly after the shock. Overall, these results confirm that climate-exposed firms adapt to regulatory climate risk through employment buffers, which effectively reduces heat-related safety risk for employees, and provide casual inferences of the impact of workforce climate exposure on labor and firms.

7. Conclusions

This paper aims to inform the ongoing debate on whether and how climate change has a real impact on the economy by exploring the effect on the labor market and firms. In this paper, I first quantify the time-varying exposure of labor to climate based on the working context of each occupation. Building on this measure, I find that more climate-exposed occupations have shorter working hours and lower productivity; they also have a larger employment base and more part-time workers, likely because employers aim to smooth labor disruptions using employment buffers. These effects are more pronounced when various adverse climate events happen and are not driven by changes in local consumer demand.

Subsequently, I examine how climate-induced labor risks resulting from the workforce affect firms' adaptation and performance. I find firms adapt to their workforce climate exposure by maintaining additional employees and increasing employee health and life insurance. However, these firms experience more environment-related workplace injuries, pay higher workplace injury compensation, and have lower *ROA*, suggesting the limitation of firms' labor adaptation and confirming that the labor cost is a channel through which climate risk can affect firm output. Additionally, climate-exposed firms adapt to adverse climate trends by retaining more employees, increasing employee insurance, and purchasing more offshore input, indicating that firms endogenize their projection of climate-induced labor risk in adaptation decisions.

The finding that the operating performance of climate-exposed firms is affected only by abnormally high temperatures, not by predictable long-term trends, supports causal inferences about the impact of climate-induced labor risk on firm performance. These results together speak to the implication of global warming on firm operations and the limitation of firms' labor adaptation actions. Additionally, by studying monthly stock market responses, I document that stock returns of climate-exposed firms are significantly lower during temperature shocks, suggesting investors' awareness of the damages of climate-induced labor risk.

Next, I explore the incentives and constraints of firms' labor adaptation strategies. After comparing the operating performance of firms with different labor adaptation intensities within the same industry, I find evidence of the effectiveness of adaptation: Firms with more employment/insurance/offshoring buffers ex-ante perform better under temperature surprises compared to their peers that do not adapt. I also examine factors that potentially constrain firms' adaptation decisions and find that local labor supply, dependency on *FTFY* workers, union coverage, offshoring potentials of jobs, and labor costs of offshoring all impact firms' adaptation actions.

Lastly, I conduct an event study on the California Heat Standard in 2005 to study the role of regulatory risk in firms' labor adaptation and provide additional evidence to support causal inferences. I document negative cumulative abnormal returns upon the announcement of *CA Standard* for firms that have both greater climate exposure and more employees affected by the policy, indicating that investors anticipate this policy to negatively impact affected firms. Using a triple difference-in-difference methodology, I find evidence of firms' employment adaptation regarding regulatory climate risk: post policy adoption, firms hire more workers to supplement the workforce, which effectively reduces heat-related safety risk and results in declined injury compensation.

This study mainly contributes to studies on climate finance and labor finance. It extends the burgeoning climate finance literature by constructing a time-varying measure of occupational exposure to climate based on a rich set of working contexts and quantifying its impact on the U.S. labor market and firms. It sheds light on the labor adaptation strategies of firms and the cost and benefits associated with climate adaptation at the individual and firm level, respectively. It also adds to the debate on whether and how climate risks impact corporation output by showing that the labor cost is a specific channel and firms' adaptation actions influence firm performance. More broadly, this paper contributes to the literature on the impact of labor risks on corporate policies by exploiting firms' climate risk resulting from their workforce.

References

Acemoglu, D., and D. Autor. 2011. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* Eds. O. Ashenfelter and D. Card. Elsevier.

Acemoglu, D., and P. Restrepo. 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108: 1488-542.

———. 2019. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives* 33: 3-30.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea. 2020. Temperature shocks and establishment sales. *Review of Financial Studies* 33: 1331-66.

Agrawal, A. K., and D. A. Matsa. 2013. Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics* 108: 449-70.

Almeida, H., R. Huang, P. Liu, and Y. Xuan. 2021. The impact of obamacare on firm employment and performance. SSRN Working Paper3073378.

Autor, D. H. 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics* 21: 1-42.

Autor, D. H., and D. Dorn. 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103: 1553-97.

Autor, D. H., W. R. Kerr, and A. D. Kugler. 2007. Does employment protection reduce productivity? Evidence from us states. *The Economic Journal* 117: F189-F217.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro. 2016. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy* 124: 105-59.

Bartram, S. M., K. Hou, and S. Kim. 2022. Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics* 143: 668-96.

Bena, J., and E. Simintzi. 2015. Labor-induced technical change: Evidence from doing business in China. SSRN Working Paper 2613248.

Berk, J. B., R. Stanton, and J. Zechner. 2010. Human capital, bankruptcy, and capital structure. Journal of Finance 65: 891-926.

Bernstein, A., M. T. Gustafson, and R. Lewis. 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics* 134: 253-72.

Blanchard, O. J., W. D. Nordhaus, and E. S. Phelps. 1997. The medium run. *Brookings Papers on Economic Activity* 1997.

Blinder, A. S. 2009. How many us jobs might be offshorable? *World Economics* 10: 41-78.

Blinder, A. S., and A. B. Krueger. 2013. Alternative measures of offshorability: A survey app*ROA*ch. *Journal of Labor Economics* 31: S97-S128.

Card, D., and B. P. McCall. 2016. Is workers' compensation covering uninsured medical costs? Evidence from the “Monday effect”. *ILR Review* 49: 690-706.

Caskey, J., and N. B. Ozel. 2017. Earnings expectations and employee safety. *Journal of Accounting and Economics* 63: 121-41.

Chen, H. J., M. Kacperczyk, and H. Ortiz-Molina. 2010. Labor unions, operating flexibility, and the cost of equity. *Journal of Financial and Quantitative Analysis* 46: 25-58.

Chen, Z., J. Harford, and A. Kamara. 2018. Operating leverage, profitability, and capital structure. *Journal of Financial and Quantitative Analysis* 54: 369-92.

Choi, D., W. Jiang, ad Z. Gao. 2020. Attention to global warming. *Review of Financial Studies* 33: 1112-45.

Dell, M., B. F. Jones, and B. A. Olken. 2009. Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review* 99: 198-204.

Deloitte. 2022. The turning point: A new economic climate in the United States.
Deryugina, T., and S. Hsiang. 2014. Does the environment still matter? Daily temperature and income in the united states. NBER Working Paper No. 20750.
Deschênes, O., and M. Greenstone. 2007. The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review* 97: 354-85.
———. 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics* 3: 152-85.
Dillender, M. 2019. Climate change and occupational health: Are there limits to our ability to adapt? *Journal of Human Resources* 56: 184-224.
Ellul, A., and M. Pagano. 2019. Corporate leverage and employees' rights in bankruptcy. *Journal of Financial Economics* 133: 685-707.
Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel. 2020. Hedging climate change news. *Review of Financial Studies* 33: 1184-216.
Firpo, S., N. Fortin, and T. Lemieux. 2011. Occupational tasks and changes in the wage structure. IZA Discussion Paper 5542.
Ghaly, M., V. Anh Dang, and K. Stathopoulos. 2017. Cash holdings and labor heterogeneity: The role of skilled labor. *Review of Financial Studies* 30: 3636-68.
Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber. 2021. Climate change and long-run discount rates: Evidence from real estate. *Review of Financial Studies* 34: 3527-71.
Graff Zivin, J., S. M. Hsiang, and M. Neidell. 2018. Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists* 5: 77-105.
Graff Zivin, J., and M. Neidell. 2013. Environment, health, and human capital. *Journal of Economic Literature* 51: 689-730.
———. 2014. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics* 32: 1-26.
Grossman, G. M., and E. Rossi-Hansberg. 2008. Trading tasks: A simple theory of offshoring. *American Economic Review* 98: 1978-97.
Hershbein, B., and L. B. Kahn. 2018. Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *American Economic Review* 108: 1737-72.
Heutel, G., N. H. Miller, and D. Molitor. 2021. Adaptation and the mortality effects of temperature across u.S. Climate regions. *Review of Economics and Statistics* 103: 740-53.
Hoberg, G., and S. K. Moon. 2017. Offshore activities and financial vs operational hedging. *Journal of Financial Economics* 125: 217-44.
Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, and T. Houser. 2017. Estimating economic damage from climate change in the united states. *Science* 356: 1362-69.
Jiang, W., Y. Tang, R. J. Xiao, and V. Yao. 2021. Surviving the fintech disruption. NBER Working Paper 28668.
Jones, C. I. 2005. The shape of production functions and the direction of technical change. *Quarterly Journal of Economics* 120: 517-49.
Kahn, M. E. 2016. The climate change adaptation literature. *Review of Environmental Economics and Policy* 10: 166-78.
Kale, J. R., and H. Shahrur. 2007. Corporate capital structure and the characteristics of suppliers and customers. *Journal of Financial Economics* 83: 321-65.
Karabarbounis, L., and B. Neiman. 2014. The global decline of the labor share. *Quarterly Journal of Economics* 129: 61-103.

Kim, H. 2020. How does labor market size affect firm capital structure? Evidence from large plant openings. *Journal of Financial Economics* 138: 277-94.

Kini, O., R. Williams, and S. Yin. 2021. Ceo noncompete agreements, job risk, and compensation. *Review of Financial Studies* 34: 4701-44.

Koeniger, W., and M. Leonardi. 2007. Capital deepening and wage differentials: Germany versus US. *Economic Policy* 22: 72-116.

Krueger, P., Z. Sautner, and L. T. Starks. 2020. The importance of climate risks for institutional investors. *Review of Financial Studies* 33: 1067-111.

Leigh, J. P., and M. M. Ward. 1997. Medical costs in workers' compensation insurance: Comment. *Journal of Health Economics* 16: 619-22.

Lewandowski, P. 2020. Occupational exposure to contagion and the spread of covid-19 in Europe. IZA Discussion Paper 13227.

Li, F. W., Y. Lin, Z. Jin, and Z. Zhang. 2020. Do firms adapt to climate change? Evidence from establishment-level data. SSRN Working Paper 3573260.

Li, Q., H. Shan, Y. Tang, and V. Yao. 2020. Corporate climate risk: Measurements and responses. SSRN Working Paper 3508497.

Lin, C., T. Schmid, and M. Weisbach. 2019. Climate change, operating flexibility and corporate investment decisions. NBER Working Paper 26441.

Ma, W., P. P. Ouimet, and E. Simintzi. 2016. Mergers and acquisitions, technological change and inequality. ECGI - Finance Working Paper 485.

Matsa, D. A. 2010. Capital structure as a strategic variable: Evidence from collective bargaining. *Journal of Finance* 65: 1197-232.

Matsa, D. A. 2018. Capital structure and a firm's workforce. *Annual Review of Financial Economics, Vol 10* 10: 387-412.

Mian, A., and A. Sufi. 2014. What explains the 2007-2009 drop in employment? *Econometrica* 82: 2197-223.

Miles, T. 2000. Common law exceptions to employment at will and u.S. Labor markets. *Journal of Law, Economics, and Organization* 16: 74-101.

Mueller, H. M., P. P. Ouimet, and E. Simintzi. 2017. Wage inequality and firm growth. *American Economic Review* 107: 379-83.

National Institute of Environmental Health Sciences. 2010. A Human Health Perspective on Climate Change.

Ouimet, P., E. Simintzi, and K. Ye. 2019. The impact of the opioid crisis on firm value and investment. SSRN Working Paper 3338083.

Ouimet, P., and R. Zarutskie. 2020. Acquiring labor. Quarterly Journal of Finance 10.

Painter, M. 2020. An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics* 135: 468-82.

Pankratz, N. M. C., R. Bauer, and J. Derwall. 2019. Climate change, firm performance, and investor surprises. SSRN Working Paper 3443146.

Pankratz, N. M. C., and C. Schiller. 2019. Climate change and adaptation in global supply-chain networks. SSRN Working Paper 3475416.

Park, R. J., N. Pankratz, and A. Behrer. 2021. Temperature, workplace safety, and labor market inequality. IZA Discussion Paper 14560.

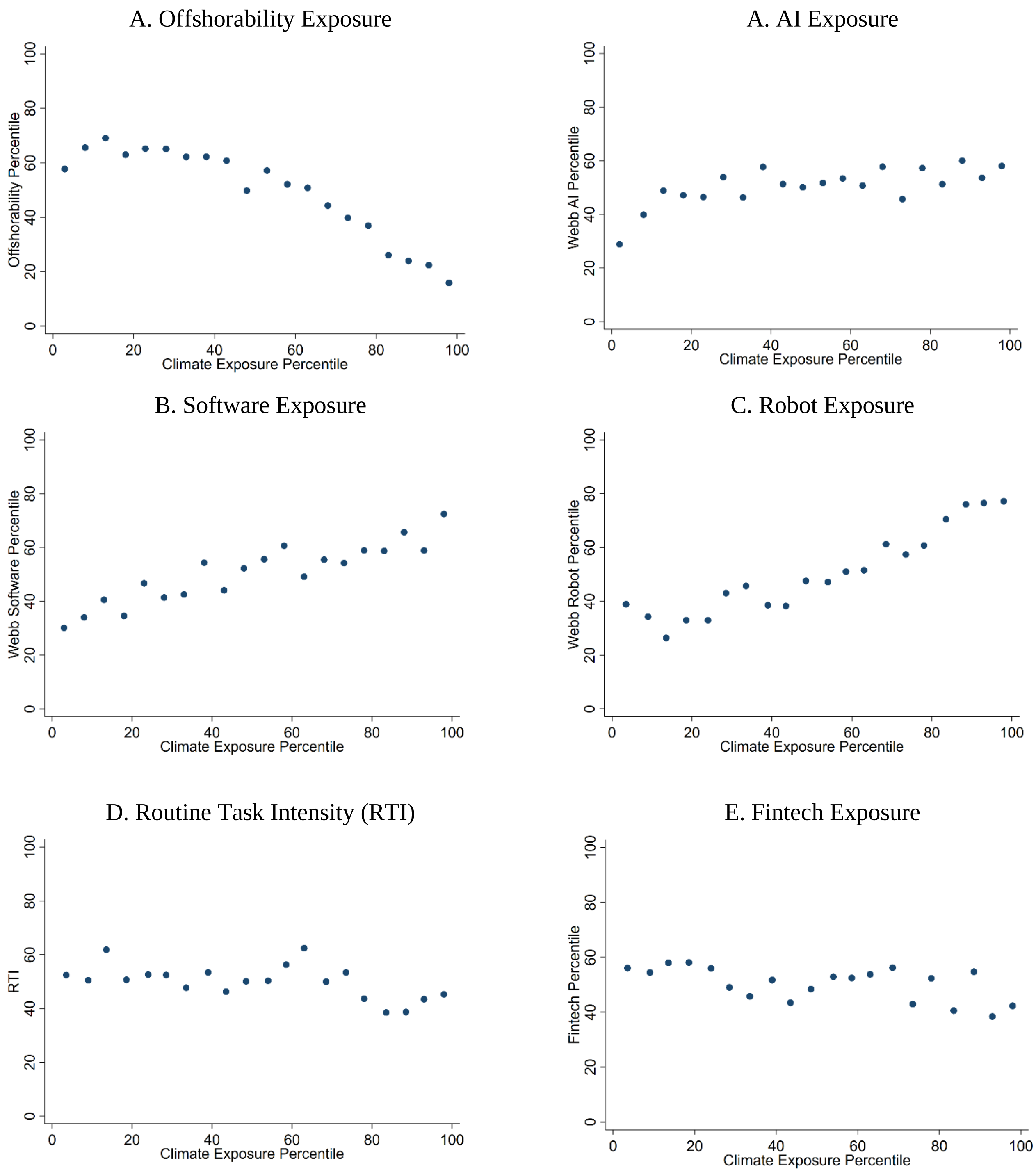
Pastor, L., R. Stambaugh, and L. Taylor. 2021. Dissecting green returns. NBER Working Paper 28940.

Sautner, Z., L. V. Lent, G. Vilkov, and R. Zhang. 2023. Firm-level climate change exposure. *Journal of Finance* 686.

Serfling, M. 2016. Firing costs and capital structure decisions. *Journal of Finance* 71: 2239-86.

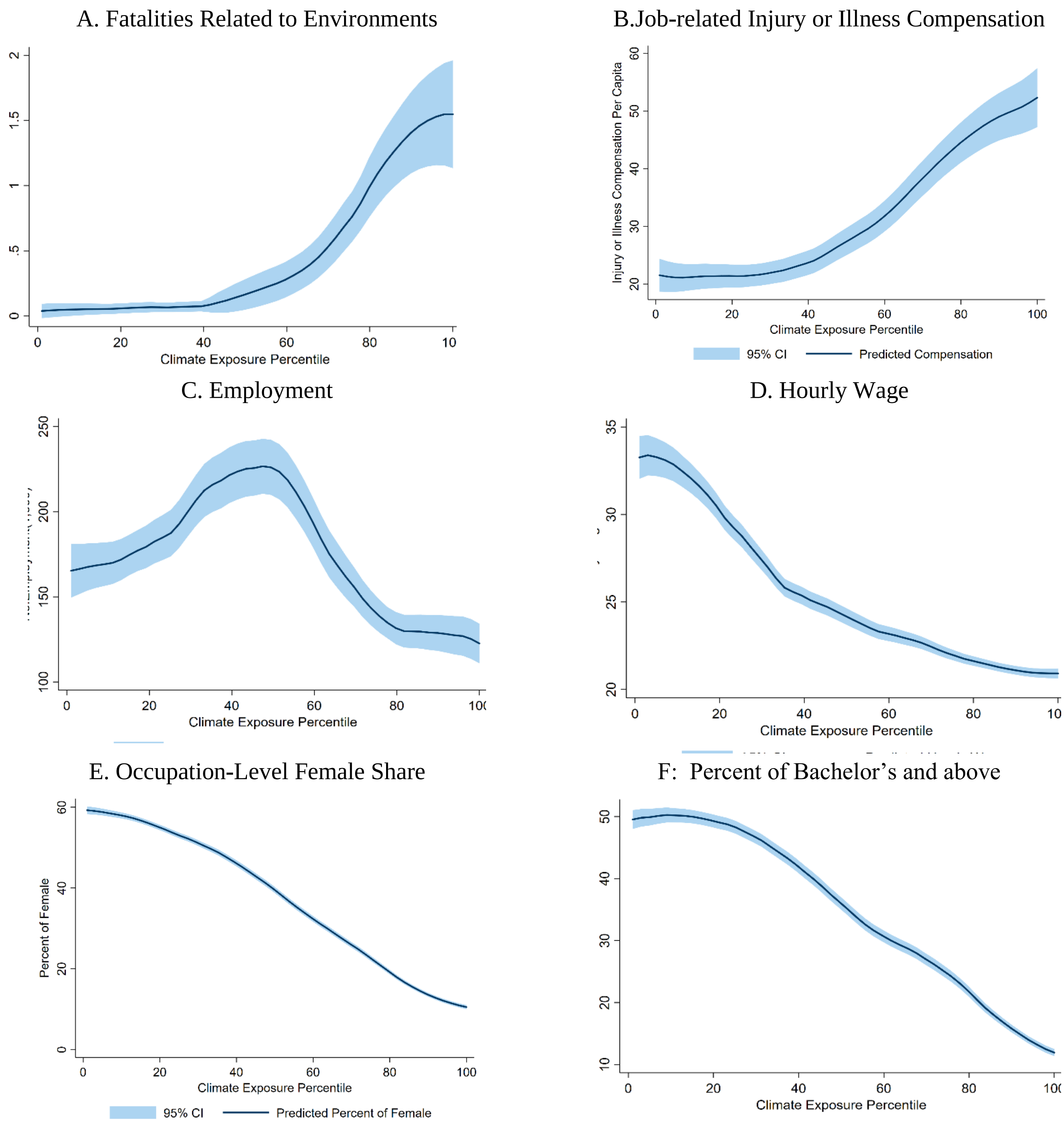
Shen, M. 2021. Skilled labor mobility and firm value: Evidence from green card allocations. *Review of Financial Studies* 34: 4663-700.
Simintzi, E., V. Vig, and P. Volpin. 2015. Labor protection and leverage. *Review of Financial Studies* 28: 561-91.
Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari. 2021. The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy* 129: 1797-827.
Tate, G. A., and L. Yang. 2015. The human factor in acquisitions: Cross-industry labor mobility and corporate diversification. US Census Bureau Center for Economic Studies Paper No. CES-WP-11-32.
US Government Accountability Office [USGAO]. 2017. Information on potential economic effects could help guide federal efforts to reduce fiscal exposure.
Webb, M. 2019. The impact of artificial intelligence on the labor market. SSRN Working Paper 3482150.
World Health Organization. 2009. Protecting Health from Climate Change. Edited by D. Campbell-Lendrum and Roberto Bertollini. Geneva: World Health Org.
Xiao, R. J. 2023. Climate-induced labor risk and firm investments in automation. SSRN Working Paper 4158049.
Xiao, Z. 2022. Labor exposure to climate change and capital deepening. The University of British Columbia Working Paper.

Figure 1: Correlation with Other Occupational Exposure Measures



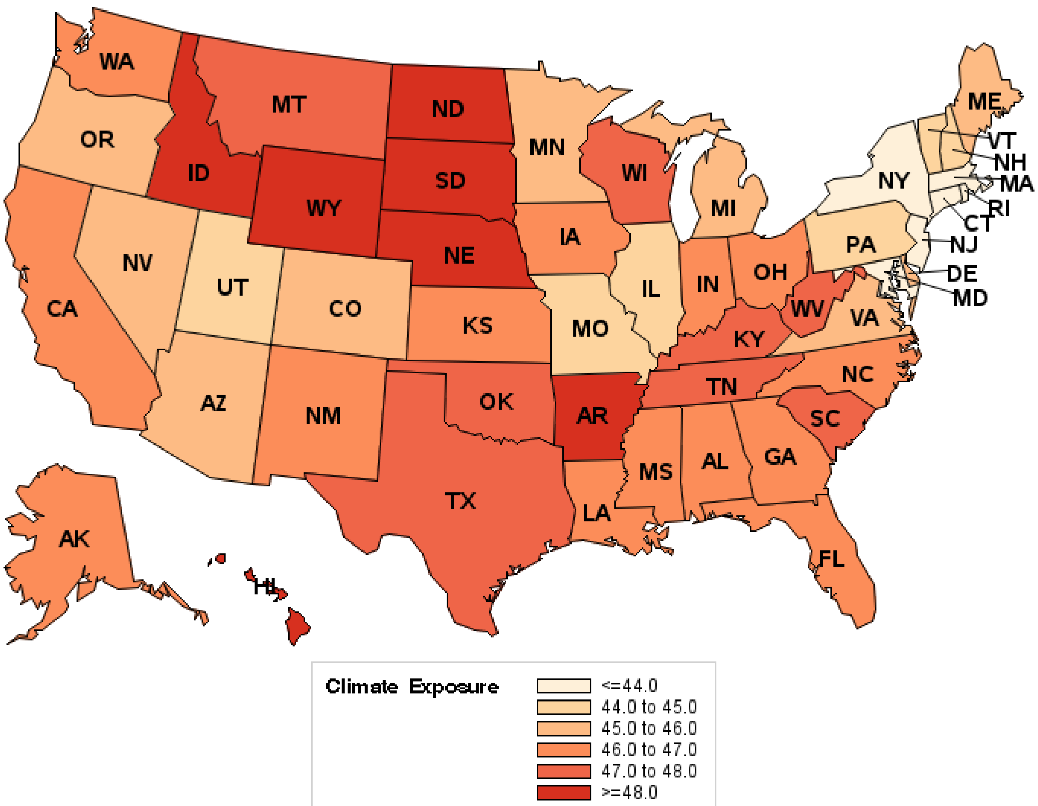
Note: The figure presents the correlation between occupational climate exposure in 2018 and occupational exposure including offshorability developed by Firpo et al. (2011) and standardized by Autor and Dorn (2013), AI, software and industrial robots from Webb (2019), routine task intensity (*RTI*) from Autor and Dorn (2013) and fintech from Jiang et al. (2021). I transform the occupational exposure scores to percentiles at the 6-digit *SOC* level. The climate exposure measure is constructed by the author.

Figure 2: Occupational Climate Exposure by Demographic Characteristics



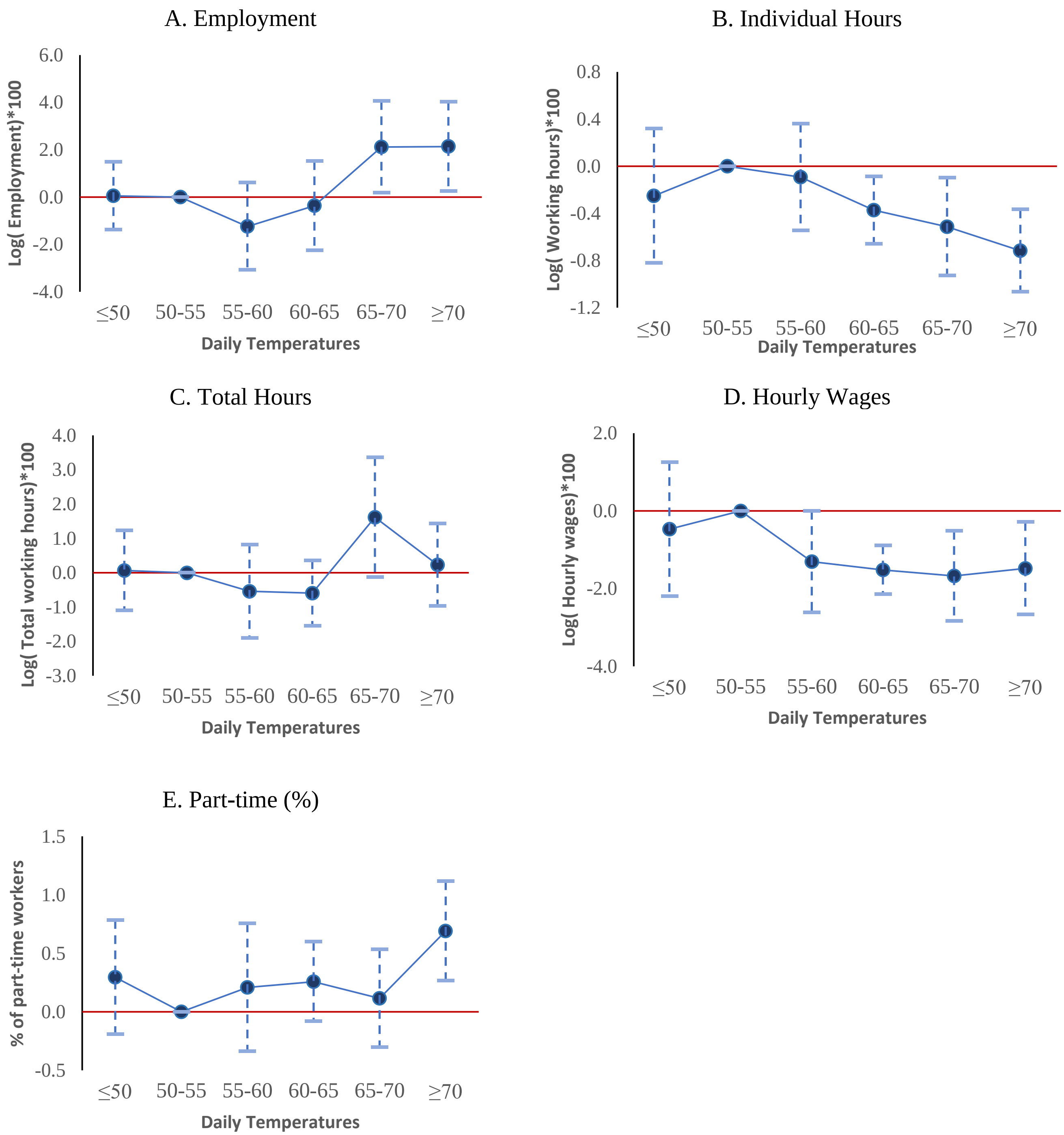
Note: The figure plots characteristics of occupations with different climate exposure using local polynomial smooth regressions with a bandwidth of 0.8 with 100 observations. Panel A shows the fractional-polynomial prediction of the average occupational fatalities related to exposure to harmful substances or environments in 2003-2018 from *BLS* by occupational climate exposure percentiles. Panel B plots the average job-related injury or illness compensation ($) from *CPS* 2000-2018 averaged across climate exposure percentiles. Panel C plots the average employment (1,000) from *OES* while Panel D plots the occupational hourly wage from *OES* averaged across climate exposure percentiles, respectively. The y-axis in Panel E and F is the percentage of female workers and the percent of workers with a bachelor's degree and above in each occupation in *IPUMS ACS* Surveys 2000, 2005-2018, respectively.

Figure 3: Geographic Distribution of Occupational Climate Exposure



Note: The figure plots the state-level average of occupational climate exposure percentiles weighted by employment in 2018. The climate exposure measure is constructed by the author and employment data is from *IPUMS ACS*.

Figure 4: Occupational Climate Exposure, Temperatures and Labor Market Outcomes



Note: This figure displays coefficients from the regression of labor market outcomes on the interaction of temperature indicators and occupational climate exposure (*OCE*) at the occupation (*SOC* 6-digit) × county × the 1990 Census Bureau industry × year level based on Equation (9). The sample of Figure A is *IPUMS ACS* data in 2000, and 2005-2018 and the dependent variable is the natural logarithm of employment; The sample of Figure B-E is *IPUMS CPS* data in 2000-2018 and the dependent variable is the natural logarithm of individual weekly working hours, total weekly working hours defined as employment times average individual weekly working hours, average hourly wages in 2018 dollars and the percentage of part-time workers, respectively. The omitted indicator is the interaction of lagged *OCE* and the indicator which equals one if the annual average of daily temperatures is between 50-55°F in a given county. All models are weighted by the lagged county-level total employment and include occupation fixed effects and county-industry-year fixed effects. Standard errors are clustered at the county level. Bars denote 95% confidence intervals.

Table 1: Working Context Variables and Occupations with the Highest, Middle and Lowest Climate Exposure

Panel A: Working Context Variables and Climate Exposure Ranking

*O*NET Working Context Before 2006*	*Climate Exposure Rank*	*O*NET Working Context After 2006*	*Climate Exposure Rank*
Indoors, Environmentally Controlled	1	Indoors, Environmentally Controlled	1
Outdoors, exposed to all weather conditions	2	Indoors, Not Environmentally Controlled	2
Very Hot or Cold Temperatures	3	In an Enclosed Vehicle or Equipment	3
		Outdoors, Under Cover	4
		In an Open Vehicle or Equipment	5
		Outdoors, exposed to all weather conditions	6
		Very Hot or Cold Temperatures	7

Panel B: Occupations with the Highest, Middle and Lowest Climate Exposure

SOC Code	Occupation Name	Climate Score	Climate Pct	Offshoring Pct	AI Pct	Software Pct	Robot Pct	RTI Pct	Fintech Pct
	Top 5 Climate Exposed								
45-2091	Agricultural Equipment Operators	4.30	100	18	99	100	99	39	53
49-9099	Installation, Maintenance, and Repair Workers…	4.16	100	9	86	99	91	54	87
49-3051	Motorboat Mechanics and Service Technicians	4.12	100	16	80	90	80	70	37
47-5013	Service Unit Operators, Oil, Gas, and Mining	4.09	100	2	85	80	79	53	39
53-7071	Gas Compressor and Gas Pumping Station Operators	4.08	100	12	80	96	79	38	12
	Middle 5 Climate Exposed								
11-1021	General and Operations Managers	1.90	50	26	33	49	47	17	67
13-1051	Cost Estimators	1.90	50	89	74	54	38	17	62
51-2022	Electrical and Electronic Equipment Assemblers	1.9	50	56	55	39	76	87	57
27-2012	Producers and Directors	1.90	50	64	53	48	37	5	36
33-3011	Bailiffs	1.90	50	13	6	14	25	33	17
	Bottom 5 Climate Exposed								
41-9041	Telemarketers	1.13	1	99	5	6	1	69	94
31-9092	Medical Assistants	1.13	1	18	20	30	31	33	40
29-9092	Genetic Counselors	1.13	1	89	26	34	18	50	87
39-5092	Manicurists and Pedicurists	1.12	1	87	12	11	50	85	49
41-3041	Travel Agents	1.12	1	82	49	20	51	80	100

Note: Panel A reports the working context variables from the *O*NET* historical database and the climate exposure rank of each variable created by the author. Panel B lists the top 5, middle 5 and bottom 5 occupations based on the climate exposure in 2018 constructed by the author. Occupational exposure including offshorability developed by Firpo et al. (2011) and standardized by Autor and Dorn (2013), AI, software and industrial robots from Webb (2019), routine task intensity (*RTI*) from Autor and Dorn (2013) and fintech from Jiang et al. (2021). I transform the occupational exposure scores to percentiles at 6-digit *SOC* level.

Table 2: Summary Statistics

Panel A: Occupation-Level Sample								
VARIABLES	N	Mean	Std	P25	P50	P75	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Occupation-Year Level Variables				
OCE	15,385	2.14	0.83	1.46	1.94	2.73	0.67	4.17
				Occupation-County-Industry-Year Level Variables				
Employment	5,982,000	362.00	637.70	80.00	145.00	320.00	17.00	4,113.00
Individual Hours (Weekly)	1,540,000	40.13	10.46	40.00	40.00	45.00	8.00	72.03
Total Hours (Weekly)	1,540,000	104,321.00	102,919.00	48,446.00	74,920.00	126,144.00	5,525.00	1,207,000.00
Hourly Wage	1,540,000	28.71	25.01	13.26	22.43	36.46	0.00	194.30
Part-time (%)	1,540,000	15.87	34.61	0.00	0.00	0.00	0.00	100.00

Panel B: County-Level Climate Sample								
VARIABLES	N	Mean	Std	P25	P50	P75	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TEMP	22,424	54.65	9.20	47.96	53.76	61.77	23.59	76.67
LT_TEMP	22,424	54.53	9.21	47.97	53.62	61.69	19.68	75.84
AB_TEMP	22,424	0.07	2.63	-1.29	0.04	1.34	-14.28	25.31
DISASTER	22,424	0.08	2.21	0.00	0.00	0.00	0.00	220.00

Panel C: Firm-Level Sample								
VARIABLES	N	Mean	Std	P25	P50	P75	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Firm-Year Level Variables				
FWCE	37,181	2.12	0.32	1.91	2.10	2.31	1.42	3.30
FIRM_ TEMP	37,181	59.40	6.28	54.80	59.24	63.20	43.73	78.23
FIRM_ LT_TEMP	37,181	59.11	6.26	54.38	59.12	62.96	40.93	75.77
FIRM_ AB_TEMP	37,181	0.30	1.47	-0.61	0.25	1.10	-4.23	11.62
No. Insurance Participants	37,181	19,229.00	50,158.00	876.00	3,888.00	14,051.00	0.00	535,859.00
No. Environment-Related Injuries	16,129	0.27	4.25	0.00	0.00	0.00	0.00	294.00
Workplace Injury Compensation (Million)	29,621	0.30	1.69	0.00	0.00	0.00	0.00	22.95
Share of *FTFY* Workers (%)	34,089	94.19	13.98	95.00	98.80	99.98	0.00	100.00
Share of Unionized Workers (%)	30,298	11.40	10.34	11.26	12.31	1.51	7.31	18.12

Workforce Offshoring Exposure	37,181	56.98	50.2	56.51	63.49	10.09	27.49	81.84
Sales	37,173	748.95	7.24	199.54	862.51	3086.14	0.00	108,011.26
Employment	36,843	12,737.00	29,834.00	600.00	2,800.00	9,800.00	0.00	250,000.00
Tobin's Q	34,593	1.95	2.44	1.11	1.46	2.14	0.45	93.67
ROA×100	37,119	2.70	25.89	1.65	6.81	11.52	-743.60	36.47
RD Dummy	37,181	0.48	0.50	0.00	0.00	1.00	0.00	1.00
RD/Assets	37,181	0.05	0.11	0.00	0.00	0.04	0.00	1.42
Capex/Assets	36,823	0.05	0.05	0.02	0.03	0.06	0.00	0.35
Cash/Assets	37,179	0.18	0.20	0.03	0.10	0.25	0.00	0.97
Cash Flow Volatility	36,686	0.09	0.19	0.02	0.03	0.08	0.00	5.18
Book Leverage	37,026	0.24	0.27	0.04	0.20	0.36	0.00	5.32
Log (Sales/Employment)	36,660	12.57	1.12	12.14	12.60	13.09	0.00	15.36
Net Working Capital/Assets	35,990	0.04	0.37	-0.04	0.04	0.15	-14.87	0.53
Payout/Assets	37,127	0.03	0.06	0.00	0.01	0.04	0.00	0.50
Staff Expense/Assets	36,212	0.46	0.64	0.15	0.30	0.54	0.00	8.34
TREATED_EMP (%)	10,075	5.90	18.31	0.00	0.00	2.17	0.00	100.00
Firm-Country-Year Level Variables								
Offshore External Input	148,010	0.25	0.74	0.00	0.00	0.00	0.00	5.00
Foreign Country GDP per capita	92,768	25,816	20,491	6,724	31,830	40,368	284.7	163,012
Firm- Year-Month Level Variables								
Raw Return (%)	398,893	0.91	13.59	-5.97	0.55	7.03	-69.63	157.20
Fama-French 3-Factor Alpha (%)	398,893	0.00	17.44	-7.94	-0.18	7.52	-165.40	137.10
FIRM_ AB_TEMP_M	398,893	0.08	2.68	-1.51	0.07	1.64	-13.19	15.23
FIRM_ LT_TEMP_M	398,893	59.09	6.28	54.35	59.09	62.98	40.93	75.28
FIRM_ AB_HOT_M	398,893	0.25	2.16	-0.19	0.00	0.25	-13.10	17.85
FIRM_ AB_COLD_M	398,893	0.17	2.09	-0.17	0.00	0.32	-14.68	12.19

Note: This table presents summary statistics for variables. Panel A summarizes occupation-level variables. The workforce climate exposure (*OCE*) at the occupation-year level from 2000-2018 is constructed by the author. The labor market sample at occupation (*SOC* 6-digit) × county × the 1990 Census Bureau industry × year level is aggregated from *IPUMS* individual data including employment (*ACS* data 2000, 2005-2018), the average individual weekly working hours, total weekly working hours (employment times individual weekly working hours), average hourly wage (2018 dollars) and the percentage of part-time workers from *CPS* data in 2000-2018.

Panel B summarizes the county-year variables based on *NOAA* data. *TEMP* is the annual temperature. *LT_TEMP* is the 20-year moving average of *TEMP* while *AB_TEMP* is abnormal temperatures defined as the difference between *TEMP* and *LT_TEMP*. *DISASTER is* the annual number of labor injuries and deaths caused by heat waves.

Panel C summarizes the firm-level variables. The main sample is at the firm × year level from 2000-2018. *FWCE* is the firm-level workforce climate exposure constructed by the author. *FIRM_ LT_TEMP* is the firm-level long-term temperatures while *FIRM_ AB_TEMP* measures firm-level abnormal temperatures. *FIRM_ LT_TEMP_M and FIRM_ AB_TEMP_M* are defined similarly at the firm-year-month level. Offshore external input is the firm-nation-year level purchase of input without owning production assets provided by Hoberg and Moon (2017). Insurance premium per person is the health and life insurance expenses per participant of a given firm estimated from Form 5500. No. Environment-Related Injuries is the number of workplace injury and illness cases related to weather or natural disasters reported by a given firm based on *OSHA* data in 2002-2011. Local labor supply is the county-level labor supply average across establishments of a given firm. Workplace injury compensation is the firm-level workplace injury compensation estimated based on *CPS* and *NETS* data. The share of *FTFY* workers (%) and the share of unionized workers (%) are constructed similar to Workplace injury compensation. Workforce offshoring exposure is the offshoring potential of a firm's workforce constructed based on the occupational offshorability index created by Firpo et al. (2011) and standardized by Autor and Dorn (2013). *TREATED_EMP (%)* is the percentage of the firm's employment potentially affected by the California Heat Standard from 2003-2007. A detailed explanation of all variables is presented in Appendix A Table A1.

Table 3: Industry Distribution of Climate Exposure

NAICS Code	Industry Name	Employment (1,000)	Climate Exposure	Offshoring Exposure
11	Agriculture	1,979	86.16	54.60
23	Construction	11,469	76.42	34.54
21	Mining	816	70.14	42.37
48-49	Transportation and Warehousing	7,700	70.15	36.12
22	Utilities	1,271	60.90	45.64
56	Administrative and Support Services	7,164	57.36	58.32
53	Real Estate Rental and Leasing	2,855	59.47	53.39
31-33	Manufacturing	15,356	55.78	46.17
42	Wholesale	3,957	56.19	55.48
92	Public Administration	7,713	50.83	72.76
81	Other Services	7,274	45.75	56.13
71	Arts, Entertainment, and Recreation	3,604	46.35	65.68
44-45	Retail Trade	16,739	45.99	60.15
51	Information	2,965	41.80	53.83
72	Accommodation and Food Services	12,256	42.76	64.69
61	Educational Services	14,891	39.57	45.58
55	Management of Companies and Enterprises	234	35.81	57.82
54	Services	11,537	33.66	62.65
52	Finance and Insurance	7,175	30.47	48.60
62	Health Care and Social Assistance	21,620	27.96	52.00

Note: This table reports the industry distribution of climate exposure and other occupation-level exposure measures. Climate exposure is the industry average of occupational climate exposure weighted by employment in 2018 from *IPUMS ACS*. The occupation-level climate exposure measure is constructed by the author. Occupational exposure including offshorability developed by Firpo et al. (2011) and standardized by Autor and Dorn (2013), AI, software and industrial robots from Webb (2019), routine task intensity (RTI) from Autor and Dorn (2013) and fintech from Jiang et al. (2021). I transform the occupational exposure scores to percentiles at the 6-digit *SOC* level.

Table 4: Occupational Climate Exposure and Labor Market Outcomes

Panel A: Baseline Results

	Log (Outcome) × 100				
Dependent Variable	Employment (1)	Individual Hours (2)	Total Hours (3)	Hourly Wages (5)	Part-time (%) (6)
OCE	2.261***	-0.097**	0.468	-0.957***	0.248***
	(11.27)	(-2.28)	(1.55)	(-6.12)	(3.28)
Occupation FE	√	√	√	√	√
Year × County × Industry FE	√	√	√	√	√
Observations	5,830,469	1,460,904	1,460,904	1,127,430	1,460,904
Adjusted R^2	0.229	0.476	0.538	0.624	0.449

Panel B: Occupational Climate Exposure, Temperatures and Labor Market Outcomes

	Log (Outcome) × 100				
Dependent Variable	Employment (1)	Individual Hours (2)	Total Hours (3)	Hourly Wages (5)	Part-time (%) (6)
OCE	-4.969	1.486***	-2.729	2.790	-1.064
	(-1.32)	(2.81)	(-1.18)	(1.42)	(-1.51)
× *TEMP*	0.117**	-0.025***	0.050	-0.059*	0.021**
	(2.01)	(-2.81)	(1.30)	(-1.84)	(1.99)
Occupation FE	√	√	√	√	√
Year × County × Industry FE	√	√	√	√	√
Observations	5,830,469	1,460,904	1,460,904	1,127,430	1,460,904
Adjusted R^2	0.229	0.470	0.538	0.624	0.449

Panel C: Occupational Climate Exposure, Natural Disasters and Labor Market Outcomes

	Log (Outcome) × 100				
Dependent Variable	Employment (1)	Individual Hours (2)	Total Hours (3)	Hourly Wages (4)	Part-time (%) (5)
OCE	2.257***	-0.093**	0.454*	-0.960***	0.264**
	(11.32)	(-2.21)	(1.81)	(-6.15)	(2.27)
× *DISASTER*	0.370	-0.070**	-0.122*	0.067	0.067*
	(0.92)	(-2.17)	(-1.81)	(1.07)	(1.79)
Occupation FE	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√
Observations	5,830,469	1,404,911	1,404,911	1,127,430	1,404,911
Adjusted R^2	0.229	0.476	0.545	0.624	0.454

Notes: The table reports the regressions that estimate the effect of occupational climate exposure on labor market outcomes at occupation (*SOC* 6-digit) × county × the 1990 Census Bureau industry × year level. Column (1) is based on *IPUMS ACS* data from 2000, and 2005-2018 while Column (2)-(6) are based on *IPUMS CPS* data in 2000-2018. The dependent variable is the natural logarithm of employment, individual weekly working hours, total weekly working hours defined as employment times average individual weekly working hours, average hourly wages in 2018 dollars and the percentage of part-time workers. The main explanatory variable is lagged *OCE*, the occupational climate exposure score that varies over time. *TEMP* is the annual average daily temperature in a given county. *DISASTER* is the number of labor injuries and deaths resulting from major disasters in a year. All models are weighted by the lagged county-level employment and include occupation fixed effects, year× county× industry fixed effects. Standard errors are clustered at county level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 5: Workforce Climate Exposure and Firm Operation

	Labor Adaptation Strategies			Firm Outcomes		
	Log (Outcome) × 100					
Dependent Variable	Employment	Employee Insurance/ Participants	Offshore External Input × 100	No. Environment-Related Injuries	Workplace Injury Compensation	*ROA*× 100
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	2.272*	14.160*	0.336	1.473***	0.139**	-1.411**
	(1.91)	(1.95)	(0.40)	(3.24)	(2.21)	(-2.29)
Model	OLS	OLS	OLS	Poisson	OLS	OLS
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	×	√	√
Year FE	×	×	×	√	×	×
Year×Industry FE	√	√	×	×	√	√
Year×Industry×Country FE	×	×	√	×	×	×
Observations	31,574	32,021	248,882	15,768	24,779	31,222
Adjusted R^2	0.983	0.677	0.286	0.240	0.236	0.767

Note: This table studies the relation between workforce climate exposure and firm operation performance at the firm level. The dependent variable is specified in the second row. Column (1)(2)(5)(6) report OLS regression results using firm-year observations in 2000-2018. The dependent variable is firm employment in Compustat in column (1), employee insurance per participant defined as the firm-year health and life insurance expenses aggregated from Form 5500 scaled by the number of participants in column (2), workplace injury compensation generated from *CPS* compensation data in column (5) and *ROA* times 100 in column (4). Column (3) report OLS regression results based on firm-country-year observations in 2000-2018 and the dependent variable is the firm's purchase of oversea inputs without the ownership of producing assets in a given county constructed by Hoberg and Moon (2017). Column (4) presents Poisson regression results using *OSHA* work-related injury and illness data in 2002-2011 and the dependent variable is the number of workplace injury and illness cases related to weather or natural disasters reported by the firm in a given year. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.3). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, and net working capital over assets in all regressions. I also control for the natural logarithm of employment and staff expenses in column (3)-(6), and the employee over assets and the natural logarithm of sales per employee in column (1). All variables are described in Appendix A Table A1. Column (1)(2)(5)(6) include firm fixed effects and three-digit NAICS industry × year fixed effects. Column (4) only includes year fixed effects. Column (3) includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects, and standard errors clustered by firm and foreign country. Standard errors in all other columns clustered by firm. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 6: Workforce Climate Exposure, Actual Climate Conditions and Firm Operation

Panel A: Workforce Climate Exposure, Temperatures and Firm Operation

	Labor Adaptation Strategies				Firm Outcomes	
	Log (Outcome) × 100					
Dependent Variable	Employment	Employee Insurance/ Participants	Offshore External Input×100	No. Environment-Related Injuries	Workplace Injury Compensation	*ROA*× 100
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	-11.084**	-58.889	-7.593*	-0.333	0.234	2.390
	(-2.09)	(-1.53)	(-1.94)	(-0.15)	(0.73)	(0.97)
× *TEMP*	0.227**	1.238*	0.135**	0.030	-0.002	-0.064
	(2.52)	(1.91)	(2.03)	(0.88)	(-0.30)	(-1.41)
TEMP	-0.433**	-2.194	-0.102	-0.036	0.003	0.103
	(-2.04)	(-1.45)	(-0.64)	(-0.45)	(0.22)	(0.97)
Model	OLS	OLS	OLS	Poisson	OLS	OLS
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	×	√	√
Year FE	×	×	×	√	×	×
Year×Industry FE	√	√	×	×	√	√
Year×Industry×Country FE	×	×	√	×	×	×
Observations	31,574	32,021	272,788	15,768	24,779	31,222
Adjusted R^2	0.983	0.677	0.253	0.243	0.236	0.767

Panel B: Predictable Long-Term Temperature Trends V.S. Short-Term Temperature Surprises

	Labor Adaptation Strategies				Firm Outcomes	
	Log (Outcome) × 100					
Dependent Variable	Employment	Employee Insurance/ Participants	Offshore External Input×100	Environment-Related Injury Dummy× 100	Workplace Injury Compensation	*ROA*× 100
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	-11.778**	-56.925	-8.432**	0.067	0.226	2.247
	(-2.23)	(-1.49)	(-2.07)	(0.03)	(0.70)	(0.91)
× *FIRM_LT_TEMP*	0.240***	1.215*	0.150**	0.023	-0.002	-0.061
	(2.66)	(1.89)	(2.14)	(0.67)	(-0.29)	(-1.33)
× *FIRM_AB_TEMP*	-0.181	-1.722	0.111	0.381**	0.020	-0.212*
	(-0.61)	(-0.80)	(0.40)	(2.16)	(1.33)	(-1.72)
FIRM_LT_TEMP	-0.441**	-1.943	-0.121	-0.023	0.002	0.096
	(-2.06)	(-1.27)	(-0.75)	(-0.29)	(0.20)	(0.90)
FIRM_AB_TEMP	0.196	1.766	-0.174	-0.740**	-0.040	0.421
	(0.31)	(0.39)	(-0.31)	(-2.00)	(-1.33)	(1.63)
Model	OLS	OLS	OLS	Poisson	OLS	OLS
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	×	√	√
Year FE	×	×	×	√	×	×
Year×Industry FE	√	√	×	×	√	√
Year×Industry×Country FE	×	×	√	×	×	×

Observations	31,574	32,021	263,675	15,768	24,779	31,222
Adjusted R^2	0.983	0.677	0.252	0.246	0.236	0.767

Note: This table studies the relation between workforce climate exposure, actual climate conditions and firm operation performance at the firm level. The dependent variable is specified in the second row. Column (1)(2)(5)(6) report OLS regression results using firm-year observations in 2000-2018. The dependent variable is firm employment in Compustat in column (1), employee insurance per participant defined as the firm-year health and life insurance expenses aggregated from Form 5500 scaled by the number of participants in column (2), workplace injury compensation generated from *CPS* compensation data in column (5) and *ROA* times 100 in column (4). Column (3) report OLS regression results based on firm-country-year observations in 2000-2018 and the dependent variable is a given firm's purchase of oversea inputs without the ownership of producing assets (external input) in a given country constructed by Hoberg and Moon (2017). Column (4) presents Poisson regression results using *OSHA* work-related injury and illness data in 2002-2011 and the dependent variable is the number of workplace injury and illness cases related to weather or natural disasters reported by the firm in a given year. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.3). *FIRM_TEMP* is the firm-level annual average daily temperature. *FIRM_LT_TEMP* is the firm-level 20-year moving average of daily temperature while *FIRM_AB_TEMP* is firm-level abnormal temperatures (as defined in 2.4.2). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, and net working capital over assets in all regressions. I also control for the natural logarithm of employment and staff expenses in column (3)-(6), and the employee over assets and the natural logarithm of sales per employee in column (1). All variables are described in Appendix A Table A1. Column (1)(2)(5)(6) include firm fixed effects and three-digit NAICS industry × year fixed effects. Column (4) only includes year fixed effects. Column (3) includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects and standard errors clustered by firm and foreign country. Standard errors in all other columns clustered by firm. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 7: Workforce Climate Exposure and Stock Market Performance

Dependent Variable	Monthly Stock Return (%)				
	(1)	(2)	(3)	(4)	(5)
FWCE	0.242**	0.270**	0.223*	0.255**	0.247**
	(2.09)	(2.21)	(1.84)	(2.20)	(2.13)
× *FIRM_AB_TEMP_M*	-0.045**	-0.018	-0.062**		
	(-2.00)	(-0.76)	(-2.07)		
× *FIRM_AB_TEMP_M* × *SUMMER*		-0.219***			
		(-3.45)			
× *FIRM_AB_TEMP_M* × *WINTER*			0.040		
			(0.91)		
× *FIRM_AB_HOT_M*				-0.098**	
				(-2.86)	
× *FIRM_AB_COLD_M*					-0.023
					(-0.85)
Firm Controls	√	√	√	√	√
Firm FE	√	√	√	√	√
Year × Month FE	√	√	√	√	√
Year × Industry FE	√	√	√	√	√
Observations	398,333	398,333	398,333	398,328	398,328
Adjusted R^2	0.191	0.191	0.191	0.192	0.192

Dependent Variable	FF 3-Factor Alpha (%)				
	(6)	(7)	(8)	(9)	(10)
FWCE	0.260	0.402**	0.307	0.274	0.256
	(1.45)	(2.12)	(1.61)	(1.52)	(1.42)
× *FIRM_AB_TEMP_M*	-0.060**	-0.040	-0.116***		
	(-2.02)	(-1.24)	(-2.67)		
× *FIRM_AB_TEMP_M* × *SUMMER*		-0.171*			
		(-1.81)			
× *FIRM_AB_TEMP_M* × *WINTER*			0.126**		
			(2.04)		
× *FIRM_AB_HOT_M*				-0.181***	
				(-3.43)	
× *FIRM_AB_COLD_M*					-0.015
					(-0.41)
Firm Controls	√	√	√	√	√
Firm FE	√	√	√	√	√
Year × Month FE	√	√	√	√	√
Year × Industry FE	√	√	√	√	√
Observations	398,333	398,333	398,333	398,328	398,328
Adjusted R^2	0.018	0.018	0.018	0.018	0.018

Note: The table examines stock market performance from 2000-2018 at the firm-year-month level. The first raw specifies the dependent variable. *FWCE* is lagged workforce climate exposure. *FIRM_AB_TEMP_M, FIRM_AB_HOT_M* and *FIRM_AB_COLD_M* measure firms' monthly abnormal temperatures, the number of hot days and cold days, respectively. The *SUMMER* dummy equals one from June-August and *the WINTER* dummy equals one in December, January and February. Models include firms' monthly long-term temperatures and seasonality, lagged firm sales and Tobin's Q, firm fixed effects, year-month fixed effects, and year × three-digit NAICS industry fixed effects. Standard errors clustered by stock. Asterisks denote significance levels (***=1%, **=5%, *=10).

Table 8: Labor Adaptation and Operating Outcomes Under Temperature Surprises

Dependent Variable	*ROA*×100					
Characteristics	Employment		Employee Insurance/ Participants		Offshore External Input× 100	
Subsample	*High Group* (1)	*Low Group* (2)	*High Group* (3)	*Low Group* (4)	*High Group* (5)	*Low Group* (6)
FWCE	-3.233	3.155	2.406	4.554	0.686	0.044
	(-1.47)	(0.90)	(0.91)	(1.16)	(0.21)	(0.02)
× *FIRM_AB_TEMP*	0.222	-0.341**	0.076	-0.444**	-0.089	-0.227
	(1.23)	(-1.96)	(0.48)	(-2.35)	(-0.41)	(-1.47)
FIRM_AB_TEMP	-0.391	0.657*	-0.246	0.950**	0.271	0.364
	(-1.04)	(1.80)	(-0.75)	(2.40)	(0.60)	(1.14)
Firm controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Year × Industry FE	√	√	√	√	√	√
Observations	15,705	14,984	15,195	15,055	10,029	20,306
Adjusted R^2	0.698	0.758	0.735	0.779	0.725	0.777

Note: This table displays OLS regression results that examine operating outcomes of climate-exposed firms after making labor adaptation. The tests are based on firm-year observations in 2000-2018. Characteristics used to define subsamples are specified in the second row and subsamples used in each column are specified in the third row. The characteristics is firm employment in Compustat in column (1)-(2), employee insurance per participant defined as the firm-year health and life insurance expenses aggregated from Form 5500 scaled by the number of participants in column (3)-(4), and a given firm's total purchase of oversea inputs without the ownership of producing assets (external input) in a given year constructed by Hoberg and Moon (2017) in column (5)-(6). Firms belong to the *High Group* if the lagged characteristics is above the median cutoff in the same industry-year while the remaining firms fall in the *Low Group*. The dependent variable is 100 times *ROA*. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.3). *FIRM_AB_TEMP* is firm-level abnormal temperatures (as defined in Section 3.4). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, an R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, net working capital over asset and the natural logarithm of employment and staff expenses. All variables are described in Appendix A Table A1. All models include firm fixed effects and three-digit NAICS industry × year fixed effects. Standard errors in all other columns clustered by firm. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 9: Potential Factors of Labor Adaptation

Panel A: Employment Adaptation

Dependent Variable	Log (Employment) × 100			
Characteristics	Local Labor Supply		Share of *FTFY* Workers	
Subsample	*High Group*	*Low Group*	*High Group*	*Low Group*
	(1)	(2)	(3)	(4)
FWCE	-20.498**	-1.279	-28.067***	-1.147
	(-2.42)	(-0.18)	(-3.74)	(-0.11)
× *FIRM_LT_TEMP*	0.377***	0.086	0.473***	0.048
	(2.71)	(0.68)	(3.84)	(0.29)
FIRM_LT_TEMP	-0.606*	-0.162	-1.025***	-0.022
	(-1.89)	(-0.53)	(-3.78)	(-0.05)
Firm Controls	√	√	√	√
Firm FE	√	√	√	√
Year × Industry FE	√	√	√	√
Observations	15,143	15,596	12,347	11,506
Adjusted R^2	0.985	0.984	0.983	0.984

Panel B: Employee Insurance Adaptation

Dependent Variable	Log (Employee Insurance/Participant) × 100			
Characteristics	Share of *FTFY* Workers		Union Coverage	
Subsample	*High Group*	*Low Group*	*High Group*	*Low Group*
	(1)	(2)	(3)	(4)
FWCE	-117.111*	41.574	-172.445**	6.881
	(-1.79)	(0.51)	(-2.30)	(0.10)
× *FIRM_LT_TEMP*	2.335**	-0.880	3.070**	0.144
	(2.08)	(-0.65)	(2.44)	(0.12)
FIRM_LT_TEMP	-4.892*	4.577	-5.000*	0.678
	(-1.94)	(1.52)	(-1.82)	(0.26)
Firm Controls	√	√	√	√
Firm FE	√	√	√	√
Year × Industry FE	√	√	√	√
Observations	12,398	11,544	12,505	12,004
Adjusted R^2	0.695	0.677	0.688	0.673

Panel C: Offshoring Adaptation

Dependent Variable	Offshore External Input × 100			
Characteristics	Workforce Offshoring Exposure		Foreign Country GDP Per Capita	
Subsample	*High Group*	*Low Group*	*High Group*	*Low Group*
	(1)	(2)	(3)	(4)
FWCE	-11.448**	-7.278	-9.606	0.000
	(-2.32)	(-1.13)	(-1.45)	(0.00)
× *FIRM_LT_TEMP*	0.200**	0.124	0.163*	0.015
	(2.36)	(1.17)	(1.72)	(0.19)
FIRM_LT_TEMP	-0.262	0.012	0.008	-0.121
	(-1.37)	(0.05)	(0.04)	(-0.55)
Firm Controls	√	√	√	√
Firm FE	√	√	√	√
Year × Industry× Country FE	√	√	√	√
Observations	105,359	120,986	75,457	72,466
Adjusted R^2	0.289	0.292	0.365	0.322

Note: This table studies the factors that potentially affect climate-exposed firms' labor adaptation strategies of at the firm level. Panel A and B report OLS regression results using firm-year observations in 2000-2018. The dependent variable is firm employment in Compustat in Panel A and the employee insurance per participant defined as the firm-year health and life insurance expenses aggregated from Form 5500 scaled by the number of participants in Panel B. Panel C displays OLS regression results based on firm-country-year observations in 2000-2018 and the dependent variable is a given firm's purchase of oversea inputs without the ownership of producing assets (external input) in a given country constructed by Hoberg and Moon (2017). Characteristics used to define subsamples are specified in the second row and subsamples used in each column are specified in the third row. The characteristics is local labor supply measured by the county-year labor supply averaged across the firm and weighted by the firm employment in that county in Panel A column (1)(2), the share of *FTFY* workers in a given firm based on *IPUMS CPS* data in Panel A column (3)(4) and Panel B column (1)(2), union coverage defined as the county-level union coverage (%) averaged across the firm and weighted by firm employment in that county in Panel B column (3)(4), the workforce offshoring exposure defined as the employment-weighted average of occupational offshorability index constructed by Firpo et al. (2011) and standardized by Autor and Dorn (2013). in Panel C column (1)(2) and foreign country GDP per capita provided by World Bank in Panel C column (3)(4). Firms belong to the *High Group* if the given factor is above the median cutoff in the same industry-year while the remaining firms fall in the *Low Group*. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.3). *TEMP* is the annual average daily temperature in a given county. *FIRM_LT_TEMP* is the firm-level 20-year moving average of daily temperature (as defined in Section 3.4). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, and net working capital over assets in all regressions. Additional control include the employee over assets and the natural logarithm of sales per employee in column Panel A and the natural logarithm of employment and staff expenses in Panel C. All variables are described in Appendix A Table A1. All models in Panel A and Panel B include firm fixed effects and three-digit NAICS industry × year fixed effects and standard errors in all columns clustered by firm. Panel C includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects and standard errors clustered by firm and foreign country. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 10: The Stock Market Responses to the 2005 California Heat Illness Prevention Standard

Dependent Variable	*CAR [-1,1]*			
	Raw Return×100		Fama-French 3-Factor Alpha ×100	
	(1)	(2)	(3)	(4)
FWCE	-0.254	-0.027	-0.197	0.028
	(-0.43)	(-0.04)	(-0.34)	(0.05)
× *TREATED_EMP*		-0.065*		-0.064*
		(-1.87)		(-1.85)
TREATED_EMP		0.148*		0.144*
		(1.87)		(1.85)
Firm Controls	√	√	√	√
Industry FE	√	√	√	√
Observations	2,050	2,050	2,050	2,050
Adjusted R^2	0.030	0.031	0.048	0.049

Note: This table studies the stock market responses round the announcement of the California Heat Illness Prevention Standard on August 8th, 2005. The dependent variables are the three-day accumulative raw return or Fama-French 3-factor adjusted returns centered on the announcement date. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm. *TREATED_EMP* is the lagged firm-level percentage of employees affected by *CA Standard* defined as the percentage of a firm's employment in California counties where the long-term temperatures in the top tercile within the state. All models include lagged firm sales in 2018 dollars, Tobin's Q, and three-digit NAICS industry fixed effects. Standard errors clustered by three-digit NAICS industry. Asterisks denote significance levels (***=1%, **=5%, *=10).

Table 11: California Heat Illness Prevention Standard and Firm Operation

	Labor Adaptation Strategies			Firm Outcomes		
	Log (Outcome) × 100					
Dependent Variable	Employment	Employee Insurance/ Participants	Offshore External Input × 100	No. Environment-Related Injuries	Workplace Injury Compensation	*ROA*× 100
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	10.374**	36.348	-7.206*	1.868**	0.024	-2.153
	(2.06)	(1.27)	(-1.71)	(2.19)	(0.10)	(-1.53)
× *POST2005*	-7.999*	-8.207	6.817*	-1.257	0.364	1.164
	(-1.66)	(-0.28)	(1.90)	(-1.45)	(1.37)	(0.96)
× *TREATED_EMP* × *POST2005*	0.284*	1.987	-0.122	0.168	-0.011*	-0.060
	(1.86)	(1.05)	(-0.81)	(1.39)	(-1.92)	(-0.80)
Model	OLS	OLS	OLS	Poisson	OLS	OLS
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	×	√	√
Year FE	×	×	×	√	×	×
Year × Industry FE	√	√	×	×	√	√
Year × Industry× Country FE	×	×	√	×	×	×
Observations	10,929	11,116	93,292	8,386	8,457	10,769
Adjusted R^2	0.987	0.757	0.245	0.256	0.199	0.813

Note: This table reports changes in firm operation performance around 2005 the California Heat Illness Prevention Standard using DID regressions. The test is based on observations from 2003-2007. The dependent variable is specified in the second row. Column (1)(2)(5)(6) in each Panel report OLS regression results using firm-year observations. The dependent variable is firm employment in Compustat in column (1), employee insurance per participant defined as the firm-year health and life insurance expenses aggregated from Form 5500 scaled by the number of participants in column (2), workplace injury compensation generated from *CPS* workplace compensation data in column (5) and *ROA* times 100 in column (4). Column (3) report OLS regression results based on firm-country-year observations in 2003-2007 whose lagged workforce offshoring exposure is above the median cutoff in the same industry-year. The dependent variable in column (3) is the firm's purchase of oversea inputs without the ownership of producing assets (external input) in a given county constructed by Hoberg and Moon (2017). Column (4) presents Poisson regression results using *OSHA* work-related injury and illness data in 2002-2011 and the dependent variable is the number of workplace injury and illness cases related to weather or natural disasters reported by the firm in a given year. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.3). *TREATED_EMP* is the lagged firm-level percentage of employees affected by CA Standard defined as the percentage of a firm's employment in California counties where the long-term temperatures in the top tercile within the state. *POST2005* is an indicator variable set to one for the years after 2005. Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, and net working capital over assets in all regressions. I also control for the natural logarithm of employment and staff expenses in column (3)-(6), and the employee over assets and the natural logarithm of sales per employee in column (1). All variables are described in Appendix A Table A1. Column (1), (2), (5), and (6) include firm fixed effects and three-digit NAICS industry × year fixed effects. Column (4) only includes year fixed effects. Column (3) includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects and standard errors clustered by firm and foreign country. Standard errors in all other columns clustered by firm. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix A

Table A1: Definition of Variables

Variable	**Definition**
	Occupation-Level Variables
OCE	Occupation-level climate exposure is based on the working context and captures the sensitivity to the climate/environment conditions in the workplace of each occupation (details in Section 3.1).
Employment	The average employment of each occupation-county-industry-year cohort from *IPUMS ACS* data.
Individual Hours	The average working hours per week of each occupation-county-industry-year cohort from *CPS*.
Total Hours	Total weekly working hours of each occupation-county-industry-year cohort: employment times average individual weekly working hours.
Hourly Wages	The average hourly wages in 2018 dollars for full-time-full-year (*FTFY*, more than 35 hours/week and 40 weeks/year) workers in a given occupation-county-industry-year cohort.
Part-time (%)	The percentage of part-time workers of each occupation-county-industry-year cohort.
County-Level Variables	
TEMP	The annual average daily temperature in a given county.
LT_ TEMP	The 20-year moving average of annual temperature (*TEMP*) in a given county.
AB_ TEMP	The county-level abnormal temperature is defined as the difference between *TEMP* and *LT_TEMP*.
HOT	The number of days with the maximum temperature over 90°F in a given county in a given year.
HEATWAVE	A dummy that equals one if a given county reported human injuries or deaths related to heatwaves in a given year and zero otherwise.
DISASTER	The number of injuries and deaths caused by disasters in a given county in a given year.
TEMP_M	The monthly average temperature for a given county in a given year-month.
LT_ TEMP_M	The average monthly temperature in a given county over the 240 months before a given year-month.
MON_ TEMP_M	Seasonality at the county-year-month level: the difference between the average temperatures in the same calendar month over the last 240 months and the long-term monthly temperatures.
AB_ TEMP_M	The monthly abnormal temperature: the difference between monthly temperatures (*TEMP_M)* and the long-term temperatures (*LT_ TEMP_M)* and the monthly seasonality (*MON_ TEMP_M)*.
Firm-Level Variables	
EWCE	Establishment-level workforce climate exposure: the employment-weighted average *OCE* of the same county and same industry of the establishment (as described in Section 3.3).
FWCE	Firm-level workforce climate exposure: the establishment employment-weighted average of *EWCE* (as described in Section 3.3).
FIRM_ TEMP	Firm-level temperature (annual): temperatures at the county-year level (*TEMP*) averaged across the firm and weighted by firm employment in that county in the prior year (as described in Section 3.4).
FIRM_ LT_ TEMP	Firm-level long-term temperatures (annual): *LT_TEMP* averaged across the firm and weighted by firm employment in that county in the prior year (as described in Section 3.4).
FIRM_ AB_ TEMP	Firm-level abnormal temperatures (annual): *AB_TEMP* averaged across the firm and weighted by the firm employment in that county in the prior year (as described in Section 3.4).
FIRM_ TEMP_M	Firm-level temperature (monthly): *TEMP_M* averaged across the firm and weighted by firm employment in that county in the prior year (as described in Section 3.4).
FIRM_ LT_ TEMP_M	Firm-level long-term temperature (monthly): *LT_TEMP_M* averaged across the firm and weighted by firm employment in that county in the prior year.
FIRM_ MON_ TEMP_M	Firm-level monthly seasonality: *MON_TEMP_M* averaged across the firm and weighted by firm employment in that county in the prior year (as described in Section 3.4).
FIRM_ AB_ TEMP_M	Firm-level abnormal temperature (monthly): *AB_TEMP_M* averaged across the firm and weighted by the firm employment in that county in the prior year.

FIRM_ AB_ HOT_M	Firm-level abnormally hot days (monthly): the county-year-month level abnormally hot days (maximum temperature over 90°F) averaged across the firm and weighted by the lagged firm employment in that county.
FIRM_ AB_ COLD_M	Firm-level abnormally cold days (monthly): the county-year-month level abnormally cold days (minimum temperature below 32°F) averaged across the firm and weighted by the lagged firm employment in that county.
Monthly Fama-French 3-Factor Alpha	The estimation period is the previous 12 months and firms are required to have at least 6 monthly observations in the estimation period.
Insurance Costs per Participant	Insurance costs per participant are the firm-year health and life insurance expenses aggregated from Form 5500 and scaled by the number of participants.
Offshore External Input	The number of mentions of the firm purchasing inputs from the given nation when the firm does not also mention owning assets there in 10K (Hoberg and Moon, 2017).
Workforce Offshoring Exposure	The average establishment-level offshorability index weighted by lagged establishment employment. Establishment-level offshorability index is constructed similarly to *EWCE* using the occupational offshorability index constructed by the author following the procedures proposed by Firpo et al. (2011) standardized by Autor and Dorn (2013).
Country GDP Per Capita	Provided by World Bank.
No. Environment-Related Injuries	The number of workplace injury and illness cases related to weather or natural disasters reported to *OSHA* in a given year by the firm.
Workplace Injury Compensation	Firm total workplace injury compensation is the product of firm employment and the workplace injury compensation per person (the employment-weighted average of the corresponding variable at the establishment level). The *establishment-level workplace injury compensation per person* is defined as the employment-weighted average of *workplace injury compensation per person* of the *CPS* county-industry-year cohort to which a *NETS* establishment belongs.
Local Labor Supply	The average county-level labor supply generated from *ACS* data weighted by establishment employment of the firm in that county.
Share of *FTFY* Workers	The number of full-time-full-year (*FTFY*, more than 35 hours/week and 40 weeks/year) workers of a given firm scaled by Compustat firm employment. The number of FTFY workers of a given firm is the sum of *establishment-level FTFY workers* that is defined as similar to *establishment-level workplace injury compensation per person* using the county-industry-year level average of the corresponding variable generated from *CPS* data.
Union Coverage	Employment-weighted average of *establishment-level union coverage* (%) which is defined similarly to *establishment-level workplace injury compensation per person* using the county-industry-year average of the corresponding variable generated from *CPS* data.
CAR [-1,1]	Three-day accumulative abnormal returns around the implementation of California Heat Standard on August 8th, 2005. The estimation period starts 280 days before each event and ends 30 days before the event day with at least 50 return observations in the estimation period.
TREATED_EMP (%)	The percentage of the firm's employees in California counties where the long-term temperature is in the top tercile within the state.
Employment	Firm-level employment from Compustat.
Return on Asset (*ROA*)	Operating profit/total assets.
Assets	Total assets in 2018 dollars.
Capex	Capital Expenditure /beginning-of-year assets.
Log (Sales)	Log (1+ sales in 2018 dollars)
Tobin's Q	(Market capitalization + total assets - common equity)/ total assets
Cash/Assets	Cash & short-term/total assets
Cash Flow Volatility	Standard deviation of cash flow to assets for the previous five years
Operating Leverage	(COGS+SGA expense)/Total assets
Book Leverage	(Long-term debt + Short-term debt) /Total assets
RD Dummy	Equals one if a firm has any R&D expenses and zero otherwise
RD/Assets	R&D expenses/total assets

Assets/Employment	Total assets in 2018 dollars/ Compustat employment
Sales/Employment	Sales in 2018 dollars/ Compustat employment

Note: Data sources include *O*NET*, *IPUMS*, *NETS*, *NOAA*, Form 5500, *OSHA*, Compustat and CRSP.

Table A2: Summer vs. Winter Effects on Labor Market Outcomes

Dependent Variable	Log (Outcome) × 100				Part-time (%)	Log (Outcome) × 100				Part-time (%)
	Employment	Individual Hours	Total Hours	Hourly Wage		Employment	Individual Hours	Total Hours	Hourly Wage	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
OCE	-1.421	-0.545*	-2.040	1.113**	0.531	-2.647**	-0.506	-3.616**	0.813	-0.059
	(-1.25)	(-1.88)	(-1.36)	(2.20)	(1.64)	(-2.05)	(-1.10)	(-2.18)	(1.36)	(-0.14)
× *TEMP_M*	0.025	0.006	0.033	-0.019**	-0.003	0.041**	0.006	0.055**	-0.015*	0.005
	(1.34)	(1.45)	(1.32)	(-2.09)	(-0.66)	(2.20)	(0.92)	(2.27)	(-1.70)	(0.93)
× *TEMP_M* × *SUMMER*	0.061*	-0.032***	0.064*	-0.030	0.034***					
	(1.91)	(-3.41)	(1.71)	(-1.08)	(2.89)					
× *TEMP_M* × *WINTER*						-0.012	0.000	-0.021	0.046***	-0.009
						(-0.68)	(0.01)	(-0.91)	(2.83)	(-1.60)
× *SUMMER*	-4.867*	2.533***	-4.860	2.455	-2.631***					
	(-1.84)	(3.43)	(-1.59)	(1.18)	(-2.88)					
× *WINTER*						1.362*	0.007	1.846*	-1.535*	0.700**
						(1.84)	(0.02)	(1.85)	(-1.89)	(2.16)
Occupation FE	√	√	√	√	√	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√	√	√	√	√	√
Observations	8,519,413	8,037,697	8,037,697	2,379,506	8,519,413	8,519,413	8,037,697	8,037,697	2,379,506	8,519,413
Adjusted R^2	0.680	0.545	0.638	0.787	0.524	0.680	0.545	0.638	0.787	0.524

Notes: The table presents the regressions that estimate the effect of occupational climate exposure on labor market outcomes in different seasons at the occupation (*SOC* 6-digit) × county × the 1990 Census Bureau industry × year-month level based on *IPUMS Monthly CPS* data in 2000-2018. The dependent variable is the natural logarithm of employment, average individual weekly working hours, total weekly working hours defined as employment times average individual weekly working hours, and average hourly wage in 2018 dollars. The main explanatory variable is lagged *OCEW*, the occupational climate exposure score that varies over time, and its interaction with *TEMP*, the annual average daily temperature in a given county. The *SUMMER* dummy equals one from June-August and zero otherwise. The *WINTER* dummy equals one in December, January and February and zero otherwise. All models are weighted by the lagged county-level total employment and include occupation fixed effects, year × county × industry fixed effects. Standard errors are clustered at county level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A3: Robustness Tests of Labor Market Outcomes using Alternative Climate Proxies

Panel A: Alternative Measure of Temperatures - Hot Days					
	Log (Outcome) × 100				
Dependent Variable	Employment	Individual Hours	Total Hours	Hourly Wages	Part-time (%)
	(1)	(2)	(3)	(4)	(5)
OCE	1.846***	0.053	0.160	-1.002***	0.099
	(7.33)	(0.84)	(0.44)	(-4.37)	(0.75)
× *HOT*	0.019***	-0.003***	0.005	-0.002	0.005***
	(3.74)	(-3.83)	(1.02)	(-0.54)	(4.78)
Occupation FE	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√
Observations	5,821,839	1,460,904	1,460,904	1,127,430	1,460,904
Adjusted R^2	0.239	0.470	0.538	0.624	0.449

Panel B: Alternative Measure of Temperatures - Heatwaves					
	Log (Outcome) × 100				
Dependent Variable	Employment	Individual Hours	Total Hours	Hourly Wages	Part-time (%)
	(1)	(2)	(3)	(4)	(5)
OCE	2.365***	-0.048	0.537**	-1.192***	0.226*
	(10.66)	(-0.90)	(1.97)	(-6.71)	(1.87)
× *HEATWAVE*	-0.608	-0.398*	-0.723	1.908***	0.332
	(-0.91)	(-1.68)	(-1.16)	(4.39)	(1.32)
Occupation FE	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√
Observations	5,830,469	1,404,911	1,404,911	1,127,430	1,404,911
Adjusted R^2	0.229	0.476	0.545	0.624	0.454

Panel C: Predictable Long-term Temperature Trends V.S. Short-term Temperature Shocks					
	Log (Outcome) × 100				
DV	Employment	Individual Hours	Total Hours	Hourly Wages	Part-time (%)
	(1)	(2)	(3)	(5)	(6)
OCE	-4.976	1.714***	-1.733	2.218	-1.373**
	(-1.41)	(4.13)	(-1.09)	(1.26)	(-2.47)
× *LT_TEMP*	0.117**	-0.030***	0.029	-0.047*	0.027***
	(2.15)	(-4.58)	(1.19)	(-1.67)	(3.38)
× *AB_TEMP*	0.115	0.073	0.485*	-0.312	-0.114**
	(0.63)	(1.31)	(1.70)	(-1.38)	(-2.16)
Occupation FE	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√
Observations	5,825,863	1,460,904	1,460,904	1,127,430	1,460,904
Adjusted R^2	0.229	0.470	0.538	0.624	0.449

Notes: The table studies labor market outcomes at occupation (*SOC* 6-digit) ×county × the 1990 Census Bureau industry × year level. Column (1) of each panel uses *ACS* data in 2000, 2005-2018 while column (2)-(5) are based on *CPS* from 2000-2018. The dependent variable is 100 times the natural logarithm of employment, individual weekly working hours, total weekly working hours (employment times individual weekly working hours), average hourly wages in 2018 dollars and the percentage of part-time workers. The main explanatory variable is the interaction of lagged *OCEW*, occupational climate exposure, and county-year-level climate proxies. The *HOT* variable is the number of hot days (max temperature over 90°F). *HEATWAVES* dummy equals one if a county had heatwave-related injuries or deaths and zero otherwise. *LT_TEMP* is the 20-year moving average of temperature while *AB_TEMP* is abnormal temperatures defined as the difference between the annual average and *LT_TEMP*. All models are weighted by the lagged county-level employment and include occupation fixed effects, year × county × industry fixed effects. Standard errors are clustered at county level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A4: Robustness Tests of Labor Market Outcomes in Tradable Sectors

Panel A: Baseline Results

Dependent Variable	Log (Outcome) × 100 Employment	Individual Hours	Total Hours	Hourly Wage	Part-time (%)
	(1)	(2)	(3)	(4)	(5)
OCE	2.799***	-0.109**	0.253	-0.605***	0.321***
	(11.33)	(-2.32)	(0.89)	(-4.22)	(2.90)
Occupation FE	√	√	√	√	√
Year × County FE	√	√	√	√	√
Observations	5,121,676	1,227,923	1,227,923	1,008,612	1,227,923
Adjusted R^2	0.232	0.471	0.560	0.624	0.447

Panel B: Occupational Climate Exposure, Temperatures and Labor Market Outcomes

Dependent Variable	Log (Outcome) × 100 Employment	Individual Hours	Total Hours	Hourly Wage	Part-time (%)
	(1)	(2)	(3)	(4)	(5)
OCE	1.411**	-3.186	3.140	-1.145	-0.622**
	(2.01)	(-1.20)	(1.59)	(-1.32)	(-2.02)
× *TEMP*	0.078*	-0.024**	0.054	-0.059*	0.023*
	(1.96)	(-2.11)	(1.22)	(-1.85)	(1.86)
Occupation FE	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√
Observations	5,121,676	1,227,923	1,227,923	1,008,612	1,227,923
Adjusted R^2	0.631	0.523	0.603	0.662	0.501

Notes: The table presents the regressions that estimate the effect of occupational climate exposure on labor market outcomes in tradable sectors at occupation (*SOC* 6-digit) × county × the 1990 Census Bureau industry × year level. The sample used in column (1) is *IPUMS ACS* data in 2000, and 2005-2018, while the sample used in column (2)-(6), is *IPUMS CPS* data in 2000-2018. The dependent variable is the natural logarithm of employment, average individual weekly working hours, total weekly working hours defined as employment times average individual weekly working hours, and average hourly wage in 2018 dollars. The main explanatory variable is lagged *OCEW*, the occupational climate exposure score that varies over time, and its interaction with *TEMP*, the annual average daily temperature in a given county. All models are weighted by the lagged county-level total employment and include occupation fixed effects, year × county × industry fixed effects. Standard errors are clustered at county level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table A5: California Heat Illness Prevention Standard and Labor Market Consequences

Dependent Variable	Log (Outcome)*100								Part-time (%)	
	Employment		Individual Hours		Total Hours		Hourly Wages			
	Treated	Control	Treated	Control	Treated	Control	Treated	Control	Treated	Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OCE	-1.102	1.885***	2.133**	0.021	0.790	1.987**	-5.005**	0.102	-2.724**	1.092***
	(-0.42)	(3.59)	(2.94)	(0.06)	(0.24)	(2.38)	(-3.29)	(0.23)	(-2.99)	(4.39)
× *POST2005*	5.904**	-0.852***	-1.955***	-0.610	3.917	-1.589***	2.830*	0.038	1.240*	-0.417
	(2.52)	(-3.05)	(-5.70)	(-1.41)	(1.46)	(-6.94)	(2.07)	(0.17)	(1.80)	(-1.30)
Occupation FE	√	√	√	√	√	√	√	√	√	√
Year × County× Industry FE	√	√	√	√	√	√	√	√	√	√
Observations	19,731	49,847	19,731	49,847	19,731	49,847	15,175	37,889	19,731	49,847
Adjusted R^2	0.552	0.361	0.500	0.376	0.504	0.341	0.651	0.542	0.481	0.375

Notes: The table examines the effect of 2005 the California Heat Illness Prevention Standard on labor market outcomes at occupation (*SOC* 6-digit) × county × the 1990 Census Bureau industry × year level based on *IPUMS CPS* data in 2003-2007. The treated sample used in column (1)(3)(5)(7)(9) is a subsample of counties in California with long-term temperatures above the top tercile cutoff within the state while the control sample used in column (2)(4)(6)(8)(10) includes all remaining counties in California. The dependent variable is the natural logarithm of employment, average individual weekly working hours, total weekly working hours defined as employment times average individual weekly working hours, and average hourly wage in 2018 dollars. The main explanatory variable is lagged *OCEW*, the occupational climate exposure score that varies over time. *POST2005* is an indicator variable set to one for the years after 2005. All models are weighted by the lagged county-level total employment and include occupation fixed effects, year× county× industry fixed effects. Standard errors are clustered at county level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix B: Workforce Climate Exposure Establishment-level Operating Outcomes

B.1. Establishment-Level Sample

The establishment sample contains about 1.5 million establishment-year observations from 2000-2018. The main explanatory variable is the establishment-level workforce climate exposure (*EWCE*) as described in Section 3.3. Outcomes include employment and PayDex score, a proxy for operating performance, from the *NETS* data. PayDex is a 100-point indexing system defined by D&B to measure bill payment promptness and a high score implies timelier payments. [57] I create two proxies for workplace safety based on *OSHA* data 2002-2011: *No. Workplace Injuries* is the number of all workplace injuries and illnesses reported by the establishment; *No. Workplace Injuries – Environment Related* only includes injuries related to weather or natural disasters. [58] Table B1 Panel A reports summary statistics.

[Insert Table B1]

B.2. Baseline Results

To test the relation between *EWCE* and establishment-level outcomes, I estimate regressions in the form of:

$$Y_{eict} = \alpha_{ct} + \lambda_{it} + \theta \, EWCE_{eict-1} + \varepsilon_{eict} \quad (1)$$

where e denotes the establishment of the firm i, c denotes the county where establishment e is located. In the first set of regressions, I estimate Poisson regressions following Caskey and Ozel (2017) where Y_{eict} denotes the number of all workplace injuries and environment-related workplace injuries reported by establishment e in county c and firm i in year t from 2002-2011, respectively. In the second set of regressions, I estimate OLS regressions in which Y_{eict} is either 100 times the natural logarithm of the establishment employment or the PayDex score from 2000-2018. $EWCE_{eict-1}$ is the lagged *EWCE* of

[57] PayDex score is a 100-point indexing system that represents trade experiences reported to D&B, compares payment to terms of sale, and scores the overall manner of payment. I do not use sales information provided by NETS, because *NETS* estimates all branch-level sales except for stand-alone firms. *NETS* multiplies the firm annual (total sales/total employee) by the employment at every branch to estimate sales for branches.

[58] The workplace safety variables are not winsorized because only 1% of establishments in the *NETS* and *OSHA* combined sample reported workplace safety cases related to weather or natural disasters.

establishment p . I include county × year fixed effects α_{ct} to absorb location conditions and the parent firm× year fixed effects λ_{it} to control for the labor and capital reallocation within the firm. Standard errors are clustered by establishment.

Table B2 Panel B presents the results. The dependent variable is the number of workplace injuries, all types in column (1) and environment-related in column (3), respectively. The insignificant coefficient on *EWCE* in column (1) and (3) implies that establishments with higher *EWCE* do not suffer more workplace injuries, likely thanks to firms' adaptation actions. Column (5) reports the regression results of the establishment employment. The coefficient on *EWCE* is 4.512, significant at 1% level, which implies that a one-standard-deviation increase in *EWCE* (0.45) is associated with a 2.0% increase in establishment employment. Consistent with the labor market findings, this evidence indicates that climate-exposed establishments hire more employees to supplement the workforce. However, the significantly negative coefficient on *EWCE* in the regression of the PayDex score in column (7) suggests that additional labor costs cause worse operating performance in climate-exposed establishments. These results are consistent with firm-level findings.

B.3. Establishment Responses to Climate Events

Like the firm-level analysis in Section 5, I test the effect of climate events on climate-exposed establishments by adding the interaction of *EWCE* and county-year temperatures (*LT_TEMP* and *AB_TEMP*) to Equation (1) and report results in Table B2 Panel B. Coefficients on *EWCE* × *LT_TEMP* imply adapt strategies of climate-exposed establishments to predictable climate conditions. The dependent variable is the number of workplace safety cases, all types in column (2) and environment-related in column (4), respectively and the insignificant coefficient on *EWCE* × *LT_TEMP* in column (2) and (4) shows that climate-exposed establishments adapt to predictable climate trends and successfully reduces workplace injuries. The positive coefficient on *EWCE* × *LT_TEMP* in the employment regression in column (6), significant at 5% level, shows that they adapt by hiring more employees and a one-standard-deviation increase in long-term temperatures (9.2°F) leads to a 1.2% increase in establishment employment, holding

EWCE constant. However, the coefficient on *EWCE* × *LT_TEMP* in the regression of the PayDex score in column (8) is significantly negative, suggesting that adaptation is costly.

The coefficients on *EWCE* × *AB_TEMP* in these regressions present how establishments with a climate-exposed workforce react to short-term climate surprises. The coefficient on *EWCE* × *AB_TEMP* is not significant in column (2) but significant and negative in column (4), implying that climate surprises increase environment-related injuries in climate-exposed establishments. Holding *EWCE* constant, a one-standard-deviation increase in *AB_TEMP* (2.63°F) causes 0.94 additional environment-related workplace injuries. These results also validate that workforce climate exposure captures climate-specific labor risk. However, this coefficient is insignificant in the employment regression in column (6), suggesting the rigidity of employment during temperature surprises. Moreover, a significantly negative coefficient on the interaction in column (8) suggests that more climate-exposed establishments fail to pay their bill promptly during usually hot days, signaling their operational difficulties. These findings indicate that when abnormally high temperatures occur, climate-exposed establishments cannot immediately supplement the workforce, leading to more workplace injuries and worse operating performance. Overall, employment adaptation strategies cannot fully mitigate the climate risk faced by workers and establishments.

Table B1: Establishment-Level Analysis

Panel A: Summary Statistics of Establishment-Level Sample

VARIABLES	N	Mean	Std	P25	P50	P75	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EWCE	1,473,000	1.95	0.45	1.62	1.92	2.20	0.83	3.49
Employment	1,473,000	85.93	116.40	20.00	38.00	100.00	15.00	700.00
No. Environment-Related Workplace Injuries	794,614	0.01	2.11	0.00	0.00	0.00	0.00	1,794.00
PayDex	808,001	67.26	12.30	61.00	70.00	78.00	18.00	80.00

Panel B: Workforce Climate Exposure and Establishment Operation

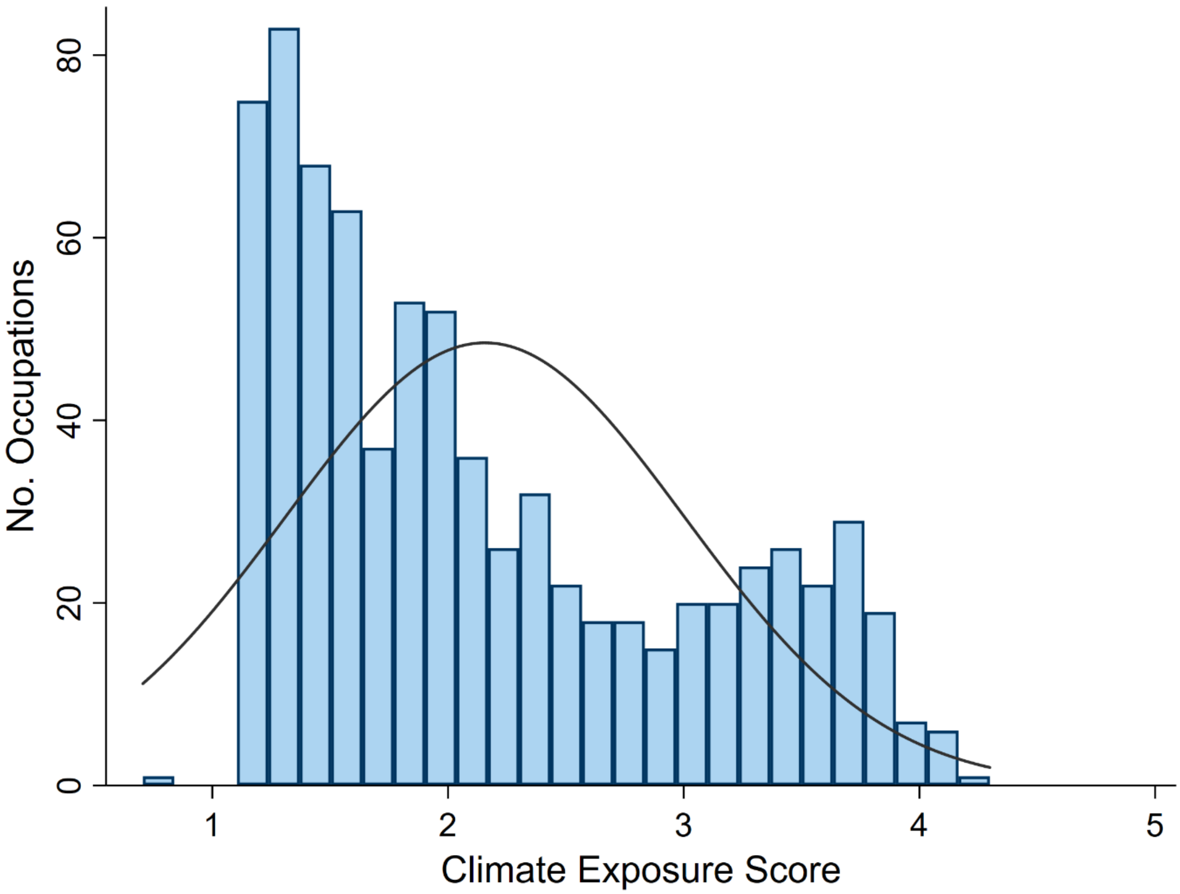
Dependent Variable	No. Workplace Injuries							
	All		Environment-Related		Log(Employment) × 100		PayDex	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EWCE	0.161	-0.801	-1.901	-17.671*	4.512***	-3.410	-0.608***	0.752*
	(1.43)	(-1.17)	(-1.27)	(-1.69)	(6.94)	(-0.98)	(-8.53)	(1.78)
× *LT_TEMP*		0.017		0.260		0.134**		-0.022***
		(1.46)		(1.64)		(2.32)		(-3.17)
× *AB_TEMP*		-0.008		0.904*		-0.167		-0.091***
		(-0.19)		(1.78)		(-0.88)		(-3.29)
Model	Poisson	Poisson	Poisson	Poisson	OLS	OLS	OLS	OLS
Year × County FE	√	√	√	√	√	√	√	√
Year × Parent Firm FE	√	√	√	√	√	√	√	√
Observations	212,207	212,207	788	788	1,456,593	1,456,593	796,914	789,705
Adjusted R^2	0.415	0.415	0.591	0.605	0.417	0.417	0.129	0.128

Note: This table summarizes the sample and regression results at the establishment × year level. Panel A summarizes the *NETS* establishment sample from 2000-2018, except for the number of workplace illness and injury cases reported by *OSHA* from 2002-2011. *EWCE* is the establishment-level climate exposure defined the employment weighted average *OCE* of the same county and same industry of the establishment (as described in Section 3.3). Employment is the establishment-year-level employment and PayDex score is a 100-point indexing system defined by D&B to measure how promptly an establishment pays its bills and a high score implies a prompt manner.

Panel B reports the regressions that estimate the effect of workforce climate exposure and operation performances at establishment × year level based on Poisson regressions in column (1)-(4) and OLS regression in column (5)-(8), respectively. The main explanatory variable is lagged establishment-level workforce climate exposure (*EWCE*). *LT_TEMP* is the 20-year moving average of daily temperature in a given county while *AB_TEMP* is local abnormal temperatures defined as the difference between the annual average temperatures and *LT_TEMP* (as described in Section 3.4). All models include county × year fixed effects and parent firm × year fixed effects. Standard errors are clustered at establishment level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Internet Appendix A

Figure IA1: Distribution of Occupational Climate Exposure



Note: The figure displays the distribution across six-digit SOC occupations of climate exposure scores in 2018.

Table IA1: Example of the Construction of OWCE - Construction Managers

***O*NET* Working Context**	**Rank**	**Frequency**
Indoors, Environmentally Controlled	1	4.00
Indoors, Not Environmentally Controlled	2	2.76
In an Enclosed Vehicle or Equipment	3	2.96
Outdoors, Under Cover	4	2.52
In an Open Vehicle or Equipment	5	1.68
Outdoors, Exposed to Weather	6	3.28
Very Hot or Cold Temperatures	7	2.80

$$OWCE_{2018} = \frac{(1*4.00+2*2.76+3*2.96+4*2.52+5*1.68+6*3.28+7*2.80)}{(1+2+3+4+5+6+7)} = 2.72$$

Note*: OWCE* is the climate exposure of construction managers in 2018 constructed by the author. The working context variables and the frequency of each working context to the occupation are from the O*NET historical database. The climate exposure rank of each variable is created by the author.

Table IA2: Example of the Construction of EWCE

Establishment	SOC Code	Occupation Name	County	Industry	*OWCE*	Employment
e	37-3011	Landscaping and Groundskeeping Workers	*c*	*j*	2.12	OCC_EMP_{ocj}
e	47-1011	First-Line Supervisors of Construction Trades and Extraction Workers	*c*	*j*	3.39	OCC_EMP_{ocj}
e	47-2131	Insulation Workers, Floor, Ceiling, and Wall	*c*	*j*	3.33	OCC_EMP_{ocj}
e	47-4099	Construction and Related Workers, All Other	*c*	*j*	3.39	OCC_EMP_{ocj}
e	…	…	*c*	*j*	…	…
e	…	…	*c*	*j*	…	…
e	53-7121	Tank Car, Truck, and Ship Loaders	*c*	*j*	3.66	OCC_EMP_{ocj}

$$EWCE_{e,2018} = \frac{\sum_{o=1}^{759} (OCC\_EMP_{ocj,2018} * OWCE_{o},2018)}{\sum_{o=1}^{759} (OCC\_EMP_{ocj,2018})}$$

Note: *EWCE* is the climate exposure of an establishment *e* located in county *c* and industry *j* in 2018 constructed by the author. *OWCE* is the climate exposure of each occupation in 2018 created by the author. OCC_EMP_{ocj} is the employment of occupation *o* in county *c* and industry *j* in 2018 from IPUMS.

Table IA3: Example of the Construction of FWCE

Firm	Establishment	Workforce Climate Exposure	Employment
i	E_1	$EWCE_1$	EST_EMP_1
i	E_2	$EWCE_2$	EST_EMP_2
i	E_3	$EWCE_3$	EST_EMP_3
i	E_4	$EWCE_4$	EST_EMP_4
i	..	$\dots$	..
i	$\dots$	$\dots$	$\dots$
i	E_n	$EWCE_n$	EST_EMP_n

$FWCE_{i,2018} = \sum_{e=1}^{n} \left(\frac{EST\_EMP_{e},2018}{FIRM\_EMP_{i},2018} * \ EWCE_{e,2018}\right)$

Note*:* *FWCE* is the workforce climate exposure of firm *i* in 2018 and *EWCE* is the climate exposure of each establishment within firm *i* in 2018*,* both constructed by the author. The employment of each establishment in 2018 is from NETS.

Table IA4: An Example of Time-Varying Occupational Climate Exposure

SOC Code	Occupation Name	Year	Climate Score	Climate Percentile
11-3051	Industrial Production Managers	2000	1.248	46
11-3051	Industrial Production Managers	2001	1.248	46
11-3051	Industrial Production Managers	2002	2.250	47
11-3051	Industrial Production Managers	2003	2.428	55
11-3051	Industrial Production Managers	2004	2.428	54
11-3051	Industrial Production Managers	2005	2.428	55
11-3051	Industrial Production Managers	2006	2.128	68
11-3051	Industrial Production Managers	2007	2.128	60
11-3051	Industrial Production Managers	2008	2.435	67
11-3051	Industrial Production Managers	2009	2.435	68
11-3051	Industrial Production Managers	2010	2.435	68
11-3051	Industrial Production Managers	2011	2.930	77
11-3051	Industrial Production Managers	2012	3.078	80
11-3051	Industrial Production Managers	2013	3.021	79
11-3051	Industrial Production Managers	2014	3.021	79
11-3051	Industrial Production Managers	2015	3.021	80
11-3051	Industrial Production Managers	2016	3.151	82
11-3051	Industrial Production Managers	2017	3.151	82
11-3051	Industrial Production Managers	2018	3.151	82

Note: Climate percentile is the percentile rank based on the occupational climate exposure measure developed by the author.

Table IA5: Industries Exempt from the ODI Work-related Injury and Illnesses Surveys 2001-2014

SIC	Industry
525	Hardware Stores
542	Meat and Fish Markets
544	Candy, Nut, and Confectionery Stores
545	Dairy Products Stores
546	Retail Bakeries
549	Miscellaneous Food Stores
551	New and Used Car Dealers
552	Used Car Dealers
554	Gasoline Service Stations
557	Motorcycle Dealers
56	Apparel and Accessory Stores
573	Radio, Television, & Computer Stores
58	Eating and Drinking Places
591	Drug Stores and Proprietary Stores
592	Liquor Stores
594	Miscellaneous Shopping Goods Stores
599	Retail Stores, Not Elsewhere Classified
60	Depository Institutions (banks & & savings institutions)
61	Nondepository Credit Institutions
62	Security and Commodity Brokers
63	Insurance Carriers
64	Insurance Agents, Brokers & Services
653	Real Estate Agents and Managers
654	Title Abstract Offices
67	Holding and Other Investment Offices
722	Photographic Studios, Portrait
723	Beauty Shops
724	Barber Shops
725	Shoe Repair and Shoeshine Parlors
726	Funeral Service and Crematories
729	Miscellaneous Personal Services
731	Advertising Services
732	Credit Reporting and Collection Services
733	Mailing, Reproduction, & Stenographic Services
737	Computer and Data Processing Services
738	Miscellaneous Business Services
764	Reupholstery and Furniture Repair
78	Motion Picture
791	Dance Studios, Schools, and Halls
792	Producers, Orchestras, Entertainers
793	Bowling Centers
801	Offices & Clinics Of Medical Doctors
802	Offices and Clinics Of Dentists
803	Offices Of Osteopathic
804	Offices Of Other Health Practitioners
807	Medical and Dental Laboratories
809	Health and Allied Services, Not Elsewhere Classified
81	Legal Services
82	Educational Services

832	Individual and Family Services
835	Child Day Care Services
839	Social Services, Not Elsewhere Classified
841	Museums and Art Galleries
86	Membership Organizations
87	Engineering, Accounting, Research, Management, and Related Services
899	Services, not elsewhere classified

Table IA6: Significant Weather Events Identified by NWS Directive 10-1605

Event Name	Designator	Event Name	Designator
Astronomical Low Tide	Z	Hurricane (Typhoon)	Z
Avalanche	Z	Ice Storm	Z
Blizzard	Z	Lake-Effect Snow	Z
Coastal Flood	Z	Lakeshore Flood	Z
Cold/Wind Chill	Z	Lightning	C
Debris Flow	C	Marine Hail	M
Dense Fog	Z	Marine High Wind	M
Dense Smoke	Z	Marine Strong Wind	M
Drought	Z	Marine Thunderstorm Wind	M
Dust Devil	C	Rip Current	Z
Dust Storm	Z	Seiche	Z
Excessive Heat	Z	Sleet	Z
Extreme Cold/Wind Chill	Z	Storm Surge/Tide	Z
Flash Flood	C	Strong Wind	Z
Flood	C	Thunderstorm Wind	C
Freezing Fog	Z	Tornado	C
Frost/Freeze	Z	Tropical Depression	Z
Funnel Cloud	C	Tropical Storm	Z
Hail	C	Tsunami	Z
Heat	Z	Volcanic Ash	Z
Heavy Rain	C	Waterspout	M
Heavy Snow	Z	Wildfire	Z
High Surf	Z	Winter Storm	Z
High Wind	Z	Winter Weather	Z

Note: Designator indicates whether the event happened in a (C) County/Parish, (Z) NWS Public Forecast Zone or (M) Marine.

Table IA7: The Most and Least Climate-Exposed Firms

Company	Headquarter	NAICS	Industry Name	Firm Climate Score	Firm Climate Percentile	Employment	Sale (million)
			Top 10 Climate-Exposed				
Davey Tree Expert Co	OH	56	Administrative and Support Services	3.40	86.89	8,900	1,024.79
American Holding Corp	OH	33	Manufacturing	3.40	87.67	79	43.15
Fitlife Brands Inc	NE	32	Manufacturing	3.40	87.67	26	17.08
Air Transport Services Group	OH	48	Transportation and Warehousing	3.35	86.50	3,830	892.35
Nobility Homes Inc	FL	32	Manufacturing	3.32	85.56	149	42.81
Hallador Energy Co	IN	21	Mining	3.31	85.48	848	291.78
S&W Seed Co	CO	11	Agriculture	3.28	82.41	84	64.09
Willamette Valley Vineyards	OR	31	Manufacturing	3.27	85.13	225	23.08
Limoneira Co	CA	11	Agriculture	3.26	81.83	286	129.39
Alabama Gas Corp	AL	22	Utilities	3.25	83.98	861	500.70
			Bottom 10 Climate-Exposed				
Teladoc Health Inc	NY	62	Health Care and Social Assistance	1.43	22.00	2,242	418
Aspira Womens Health Inc	TX	32	Manufacturing	1.42	21.33	43	3
Village Super Market	NJ	44	Retail Trade	1.42	20.27	6,742	1,612
Bluelinx Holdings Inc	GA	42	Wholesale	1.42	22.02	2,400	2,863
Davita Inc	CO	62	Health Care and Social Assistance	1.41	19.33	77,700	11,405
Doughertys Pharmacy Inc	TX	44	Retail Trade	1.41	21.88	99	36
Dover Downs Gaming & Entmt	DE	71	Arts, Entertainment, and Recreation	1.36	20.67	1,388	180
Dover Motorsports Inc	DE	71	Arts, Entertainment, and Recreation	1.36	20.67	54	47
Regis Corp	MN	81	Other Services	1.30	11.41	27,000	1,212
Midstates Petroleum Co Inc	OK	21	Mining	1.30	15.00	85	209

Note: This table lists the firms with the top 10 and bottom 10 climate exposure in 2018. The construction of firm climate exposure score and percentiles is described in Section 3. The information on firm employment and sales is from Compustat.

Table IA8: Relation between Workforce Climate Exposure and Offshoring Exposure

DV	Workforce Offshore Exposure (t)		Workforce Robot Exposure (t)	
	Raw score	Percentile	Raw score	Percentile
	(1)	(2)	(3)	(4)
FWCE	-0.365***	-2.231***	0.074***	4.196***
	(-5.35)	(-5.15)	(9.75)	(9.26)
Firm Controls	√	√	√	√
Firm FE	√	√	√	√
Year × Industry FE	√	√	√	√
Observations	31,912	31,912	31,912	31,912
Adjusted R^2	0.658	0.653	0.665	0.655

Note: This table displays OLS regression results that estimate the relation between workforce climate exposure and offshoring exposure and automation exposure based on firm-year observations in 2000-2018. The dependent variable is 100 times ROA. The dependent variable is firm-level workforce offshoring exposure defined as employment-weighted average of occupational offshoring exposure from Firpo et al. (2011) in column (1)(2) and automation exposure defined in the same way using occupational industrial robotic exposure constructed by Webb (2019) in column (3)(4), respectively. In each pair, I use raw exposure scores and The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.2). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by lagged assets, cash holdings scaled by assets, book leverage and cash flow volatility. All variables are described in Appendix A Table A1. All models include firm fixed effects and three-digit NAICS industry × year fixed effects. Standard errors clustered by firm. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table IA9: Alternative Offshoring Strategies

DV	Offshore Input*100					
	Total Input			Internal Input		
	(1)	(2)	(3)	(1)	(2)	(3)
FWCE	2.940	-25.605	-21.568	2.840	-12.741	-8.605
	(0.43)	(-0.84)	(-0.73)	(0.69)	(-0.62)	(-0.43)
× *FIRM_ TEMP*		0.484			0.264	
		(0.97)			(0.78)	
× *FIRM_LT_TEMP*			0.417			0.194
			(0.86)			(0.59)
× *FIRM_AB_TEMP*			0.153			-0.105
			(0.10)			(-0.08)
FIRM_ TEMP		-0.253			-0.064	
		(-0.23)			(-0.08)	
FIRM_LT_TEMP			-0.254			0.071
			(-0.23)			(0.09)
FIRM_AB_TEMP			0.520			0.608
			(0.17)			(0.25)
Model	OLS	OLS	OLS	OLS	OLS	OLS
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Year × Industry × Country FE	√	√	√	√	√	√
Observations	246,522	246,522	246,522	246,522	246,522	246,522
Adjusted R^2	0.290	0.290	0.290	0.274	0.274	0.274

Note: This table reports OLS regression results that study the relation between workforce climate exposure, actual climate conditions and firm offshoring input at the firm-country-year from 2000-2018. The dependent variable is alternative proxies for offshore input from a given country constructed by Hoberg and Moon (2017). The dependent variable is the firm's purchase of oversea inputs with the ownership of producing assets in a given county (internal input) in column (1)-(3) and is the firm's total input purchase (internal and external input) from a given country in column (4)-(6). The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.2). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, an R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by lagged assets, cash holdings scaled by assets, book leverage and cash flow volatility in all regressions and the natural logarithm of assets per employee. All variables are described in Appendix A Table A1. All models include firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects. Standard errors clustered by firm and foreign country. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Internet Appendix B: Details of the 2005 California Heat Illness Prevention Standard

The California Heat Illness Prevention (HIP) standard (Cal/OSHA subchapter 7, group 2, article 10, section 3395) was filed on August 8th, 2005 (Park et al, 2021). The full context is as below.[1]

§3395. Heat Illness Prevention in Outdoor Places of Employment.

(a) Title, Scope, and Application.

(1) This section shall be known and may be cited as the Maria Isabel Vasquez Jimenez heat illness standard, and shall apply to all outdoor places of employment.

EXCEPTION: If an industry is not listed in subsection (a)(2), employers in that industry are not required to comply with subsection (e), High-heat procedures.

(2) List of industries subject to all provisions of this standard, including subsection (e):

(A) Agriculture

(B) Construction

(C) Landscaping

(D) Oil and gas extraction

(E) Transportation or delivery of agricultural products, construction materials or other heavy materials (e.g. furniture, lumber, freight, cargo, cabinets, industrial or commercial materials), except for employment that consists of operating an air-conditioned vehicle and does not include loading or unloading.

(3) This section applies to the control of risk of occurrence of heat illness. This is not intended to exclude the application of other sections of Title 8, including, but not necessarily limited to, sections 1512, 1524, 3203, 3363, 3400, 3439, 3457, 6251, 6512, 6969, 6975, 8420 and 8602(e).

NOTE NO. 1: The measures required here may be integrated into the employer's written Injury and Illness Program required by section 3203, or maintained in a separate document.

NOTE NO. 2: This standard is enforceable by the Division of Occupational Safety and Health pursuant to Labor Code sections 6308 and 6317 and any other statutes conferring enforcement powers upon the Division. It is a violation of Labor Code sections 6310, 6311, and 6312 to discharge or discriminate in any other manner against employees for exercising their rights under this or any other provision offering occupational safety and health protection to employees.

(b) Definitions.

“Acclimatization” means temporary adaptation of the body to work in the heat that occurs gradually when a person is exposed to it. Acclimatization peaks in most people within four to fourteen days of regular work for at least two hours per day in the heat.

“Heat Illness” means a serious medical condition resulting from the body's inability to cope with a particular heat load, and includes heat cramps, heat exhaustion, heat syncope and heat stroke.

“Environmental risk factors for heat illness” means working conditions that create the possibility that heat illness could occur, including air temperature, relative humidity, radiant heat from the sun and other sources, conductive heat

[1] https://www.dir.ca.gov/title8/3395.html.

sources such as the ground, air movement, workload severity and duration, protective clothing and personal protective equipment worn by employees.

“Landscaping” means providing landscape care and maintenance services and/or installing trees, shrubs, plants, lawns, or gardens, or providing these services in conjunction with the design of landscape plans and/or the construction (i.e., installation) of walkways, retaining walls, decks, fences, ponds, and similar structures, except for employment by an employer who operates a fixed establishment where the work is to be performed and where drinking water is plumbed.

“Oil and gas extraction” means operating and/or developing oil and gas field properties, exploring for crude petroleum or natural gas, mining or extracting of oil or gas or recovering liquid hydrocarbons from oil or gas field gases.

“Personal risk factors for heat illness” means factors such as an individual's age, degree of acclimatization, health, water consumption, alcohol consumption, caffeine consumption, and use of prescription medications that affect the body's water retention or other physiological responses to heat.

“Shade” means blockage of direct sunlight. One indicator that blockage is sufficient is when objects do not cast a shadow in the area of blocked sunlight. Shade is not adequate when heat in the area of shade defeats the purpose of shade, which is to allow the body to cool. For example, a car sitting in the sun does not provide acceptable shade to a person inside it, unless the car is running with air conditioning. Shade may be provided by any natural or artificial means that does not expose employees to unsafe or unhealthy conditions and that does not deter or discourage access or use.

“Temperature” means the dry bulb temperature in degrees Fahrenheit obtainable by using a thermometer to measure the outdoor temperature in an area where there is no shade. While the temperature measurement must be taken in an area with full sunlight, the bulb or sensor of the thermometer should be shielded while taking the measurement, e.g., with the hand or some other object, from direct contact by sunlight.

(c) Provision of water. Employees shall have access to potable drinking water meeting the requirements of Sections 1524, 3363, and 3457, as applicable, including but not limited to the requirements that it be fresh, pure, suitably cool, and provided to employees free of charge. The water shall be located as close as practicable to the areas where employees are working. Where drinking water is not plumbed or otherwise continuously supplied, it shall be provided in sufficient quantity at the beginning of the work shift to provide one quart per employee per hour for drinking for the entire shift. Employers may begin the shift with smaller quantities of water if they have effective procedures for replenishment during the shift as needed to allow employees to drink one quart or more per hour. The frequent drinking of water, as described in subsection (h)(1)(C), shall be encouraged.

(d) Access to shade.

(1) Shade shall be present when the temperature exceeds 80 degrees Fahrenheit. When the outdoor temperature in the work area exceeds 80 degrees Fahrenheit, the employer shall have and maintain one or more areas with shade at all times while employees are present that are either open to the air or provided with ventilation or cooling. The amount of shade present shall be at least enough to accommodate the number of employees on recovery or rest periods, so that they can sit in a normal posture fully in the shade without having to be in physical contact with each other. The shade shall be located as close as practicable to the areas where employees are working. Subject to the same specifications, the amount of shade present during meal periods shall be at least enough to accommodate the number of employees on the meal period who remain onsite.

(2) Shade shall be available when the temperature does not exceed 80 degrees Fahrenheit. When the outdoor temperature in the work area does not exceed 80 degrees Fahrenheit employers shall either provide shade as per subsection (d)(1) or provide timely access to shade upon an employee's request.

(3) Employees shall be allowed and encouraged to take a preventative cool-down rest in the shade when they feel the need to do so to protect themselves from overheating. Such access to shade shall be permitted at all times. An individual employee who takes a preventative cool-down rest (A) shall be monitored and asked if he or she is experiencing symptoms of heat illness; (B) shall be encouraged to remain in the shade; and (C) shall not be ordered back to work until any signs or symptoms of heat illness have abated, but in no event less than 5 minutes in addition to the time needed to access the shade.

(4) If an employee exhibits signs or reports symptoms of heat illness while taking a preventative cool-down rest or during a preventative cool-down rest period, the employer shall provide appropriate first aid or emergency response according to subsection (f) of this section.

Exceptions to subsections (d)(1) and (d)(2):

(1) Where the employer can demonstrate that it is infeasible or unsafe to have a shade structure, or otherwise to have shade present on a continuous basis, the employer may utilize alternative procedures for providing access to shade if the alternative procedures provide equivalent protection.

(2) Except for employers in the agricultural industry, cooling measures other than shade (e.g., use of misting machines) may be provided in lieu of shade if the employer can demonstrate that these measures are at least as effective as shade in allowing employees to cool.

(e) High-heat procedures. The employer shall implement high-heat procedures when the temperature equals or exceeds 95 degrees Fahrenheit. These procedures shall include the following to the extent practicable:

(1) Ensuring that effective communication by voice, observation, or electronic means is maintained so that employees at the work site can contact a supervisor when necessary. An electronic device, such as a cell phone or text messaging device, may be used for this purpose only if reception in the area is reliable.

(2) Observing employees for alertness and signs or symptoms of heat illness. The employer shall ensure effective employee observation/monitoring by implementing one or more of the following:

(A) Supervisor or designee observation of 20 or fewer employees, or

(B) Mandatory buddy system, or

(C) Regular communication with sole employee such as by radio or cellular phone, or

(D) Other effective means of observation.

(3) Designating one or more employees on each worksite as authorized to call for emergency medical services, and allowing other employees to call for emergency services when no designated employee is available.

(4) Reminding employees throughout the work shift to drink plenty of water.

(5) Pre-shift meetings before the commencement of work to review the high heat procedures, encourage employees to drink plenty of water, and remind employees of their right to take a cool-down rest when necessary.

(6) For employees employed in agriculture, the following shall also apply:

When temperatures reach 95 degrees or above, the employer shall ensure that the employee takes a minimum ten minute net preventative cool-down rest period every two hours. The preventative cool-down rest period required by this paragraph may be provided concurrently with any other meal or rest period required by Industrial Welfare Commission Order No. 14 (8 CCR 11140) if the timing of the preventative cool-down rest period coincides with a required meal or rest period thus resulting in no additional preventative cool-down rest period required in an eight hour workday. If the workday will extend beyond eight hours, then an additional preventative cool-down rest period will be required at the conclusion of the eighth hour of work; and if the workday extends beyond ten hours, then another preventative cool-down rest period will be required at the conclusion of the tenth hour and so on. For purposes of this section, preventative cool-down rest period has the same meaning as “recovery period” in Labor Code Section 226.7(a).

(f) Emergency Response Procedures. The Employer shall implement effective emergency response procedures including:

(1) Ensuring that effective communication by voice, observation, or electronic means is maintained so that employees at the work site can contact a supervisor or emergency medical services when necessary. An electronic device, such as a cell phone or text messaging device, may be used for this purpose only if reception in the area is reliable. If an electronic device will not furnish reliable communication in the work area, the employer will ensure a means of summoning emergency medical services.

(2) Responding to signs and symptoms of possible heat illness, including but not limited to first aid measures and how emergency medical services will be provided.

(A) If a supervisor observes, or any employee reports, any signs or symptoms of heat illness in any employee, the supervisor shall take immediate action commensurate with the severity of the illness.

(B) If the signs or symptoms are indicators of severe heat illness (such as, but not limited to, decreased level of consciousness, staggering, vomiting, disorientation, irrational behavior or convulsions), the employer must implement emergency response procedures.

(C) An employee exhibiting signs or symptoms of heat illness shall be monitored and shall not be left alone or sent home without being offered onsite first aid and/or being provided with emergency medical services in accordance with the employer's procedures.

(3) Contacting emergency medical services and, if necessary, transporting employees to a place where they can be reached by an emergency medical provider.

(4) Ensuring that, in the event of an emergency, clear and precise directions to the work site can and will be provided as needed to emergency responders.

(g) Acclimatization.

(1) All employees shall be closely observed by a supervisor or designee during a heat wave. For purposes of this section only, “heat wave” means any day in which the predicted high temperature for the day will be at least 80 degrees Fahrenheit and at least ten degrees Fahrenheit higher than the average high daily temperature in the preceding five days.

(2) An employee who has been newly assigned to a high heat area shall be closely observed by a supervisor or designee for the first 14 days of the employee's employment.

(h) Training.

(1) Employee training. Effective training in the following topics shall be provided to each supervisory and non-supervisory employee before the employee begins work that should reasonably be anticipated to result in exposure to the risk of heat illness:

(A) The environmental and personal risk factors for heat illness, as well as the added burden of heat load on the body caused by exertion, clothing, and personal protective equipment.

(B) The employer's procedures for complying with the requirements of this standard, including, but not limited to, the employer's responsibility to provide water, shade, cool-down rests, and access to first aid as well as the employees' right to exercise their rights under this standard without retaliation.

(C) The importance of frequent consumption of small quantities of water, up to 4 cups per hour, when the work environment is hot and employees are likely to be sweating more than usual in the performance of their duties.

(D) The concept, importance, and methods of acclimatization pursuant to the employer's procedures under subsection (i)(4).

(E) The different types of heat illness, the common signs and symptoms of heat illness, and appropriate first aid and/or emergency responses to the different types of heat illness, and in addition, that heat illness may progress quickly from mild symptoms and signs to serious and life threatening illness.

(F) The importance to employees of immediately reporting to the employer, directly or through the employee's supervisor, symptoms or signs of heat illness in themselves, or in co-workers.

(G) The employer's procedures for responding to signs or symptoms of possible heat illness, including how emergency medical services will be provided should they become necessary.

(H) The employer's procedures for contacting emergency medical services, and if necessary, for transporting employees to a point where they can be reached by an emergency medical service provider.

(I) The employer's procedures for ensuring that, in the event of an emergency, clear and precise directions to the work site can and will be provided as needed to emergency responders. These procedures shall include designating a person to be available to ensure that emergency procedures are invoked when appropriate.

(2) Supervisor training. Prior to supervising employees performing work that should reasonably be anticipated to result in exposure to the risk of heat illness effective training on the following topics shall be provided to the supervisor:

(A) The information required to be provided by section (h)(1) above.

(B) The procedures the supervisor is to follow to implement the applicable provisions in this section.

(C) The procedures the supervisor is to follow when an employee exhibits signs or reports symptoms consistent with possible heat illness, including emergency response procedures.

(D) How to monitor weather reports and how to respond to hot weather advisories.

(i) Heat Illness Prevention Plan. The employer shall establish, implement, and maintain, an effective heat illness prevention plan. The plan shall be in writing in both English and the language understood by the majority of the employees and shall be made available at the worksite to employees and to representatives of the Division upon request. The Heat Illness Prevention Plan may be included as part of the employer's Illness and Injury Prevention Program required by section 3203, and shall, at a minimum, contain:

(1) Procedures for the provision of water and access to shade.

(2) The high heat procedures referred to in subsection (e).

(3) Emergency Response Procedures in accordance with subsection (f).

(4) Acclimatization methods and procedures in accordance with subsection (g).

Note: Authority cited: Section 142.3, Labor Code. Reference: Sections 142.3 and 6721, Labor Code.

Climate-Induced Labor Risk and Firm Investments in Automation

Rachel Jiqiu Xiao*

First Draft: March 2022

Latest Draft: April 2023

Abstract

This paper studies whether and how firms adapt to climate-induced labor risks through automation investments. Using textual analysis, I construct a measure of automation investment intensity at the firm-year level based on material news and events. I find that firms with more climate-exposed employees invest more in automation when they face adverse long-term climate conditions and are not financially constrained. The automation news of these firms is associated with higher stock returns during the announcement period. Moreover, after adopting automation, climate-exposed firms retain fewer employees, incur smaller employee insurance expenditures and decrease offshore inputs. These firms also exhibit better operating performance under short-term temperature shocks. Overall, these results imply that automation is a selective adaptation strategy that effectively helps mitigate climate-induced labor risk.

JEL classification: G30; G31; J20; J28; J30; O33; Q50

Keywords: climate finance, labor finance, climate adaptation, automation investments, textual analysis

---

*Rachel Jiqiu Xiao is with J. Mack Robinson College of Business, Georgia State University. Email: jxiao4@gsu.edu.
I thank my dissertation committee members: Mark Chen, Omesh Kini (Chair), Harley (Chip) Ryan, Stephen Shore and Vincent Yao. I also thank Junyoung Park for numerous helpful discussions. I benefited from the discussions with Vikas Agarwal, Ashwini Agrawal, Sris Chatterjee, N. K. Chidambaran, Andrey Ermolov, Iftekhar Hasan, Gerard Hoberg, Chong Huang, Wei Jiang, Kai Li, Stefano Manfredonia, Paige Ouimet, Mo Shen, Jinfei Sheng, Elena Simintzi, Yi Tang, Yuahua Tang, Chi-Yang (Ben) Tsou, Han Xia, An Yan, Shen Zhang and seminar participants at AFA 2023 PhD Poster Session. All errors are my own.

Introduction

Climate change imposes considerable costs on workers and businesses. With higher temperatures and intensity of natural disaster events, workers will suffer more losses in working hours, become less productive, and face more workplace injuries (e.g., Graff-Zivin and Neidell, 2014; Somanathan et al., 2021; Park et al., 2021). Since businesses, irrespective of size, location, and sector, depend on labor for their operations, this adverse effect is passed on to employers through higher labor costs and potentially contributes to worse operating performance if firms fail to take sufficient adaptation actions (Xiao, 2023).

Despite its substantial impact on firms, little attention has been paid to firms' adaptation strategies aimed at mitigating this climate-induced labor risk. Understanding whether and how firms react to climate-induced labor risk is imperative, especially at a time when business leaders and policymakers are drafting strategies to build a climate-resilient community (United States Agency for International Development [USAID], 2022).[1] This paper aims to focus on how firms adapt to climate-induced labor risk through investment rather than labor adaptation strategies. In addition, instead of focusing on capital investments, I examine firms' automation investments that are well documented to directly substitute for labor (e.g., Autor et al., 2003; Webb, 2019; Acemoglu and Restrepo, 2020) and, therefore, may effectively help mitigate labor risk in the context of climate exposure.

From a theoretical perspective, the effect of climate-induced labor risk on firm investments is ambiguous. On the one hand, incremental labor costs induced by climate could lead to greater capital investments by making firms replace the relatively more expensive factor (human capital) with the cheaper substitute (physical capital) (e.g., Blanchard 1997; Caballero and Hammour, 1998; Koeniger and Leonardi, 2007). On the other hand, greater labor costs raise operating leverage, which crowds out financial leverage (eg., Agrawal and Matsa, 2013; Simintzi, Vig, and Volpin, 2015; Serfling, 2016) and increases the cost of equity (Chen, Kacperczyk and Ortiz-Molina, 2010). As a result, firms' ability to finance capital investments

[1] https://www.usaid.gov/sites/default/files/2022-11/USAID-Climate-Strategy-2022-2030.pdf.

may be limited. In addition, facing increased labor costs, the ability to switch to more cost-effective labor domestically or overseas may encourage firms to prioritize labor over capital (Autor, 2003; Bena and Simintzi, 2019; Almeida et al. 2021).

These two channels generate different predictions regarding how a firm's investments react to labor risk resulting from climate. However, there are two challenges to empirically testing them. The first empirical challenge is the need for an ex-ante measure of the sensitivity of the firm's workforce to climate conditions, which is jointly determined by the climate exposure of individual employees and the firm's unique workforce composition. Following Xiao (2023), I take two steps to quantify the *workforce climate exposure at the firm level* (*FWCE)*. First, I measure the *occupation-level climate exposure* (*OCE*) based on the working contexts (e.g. indoor with air-conditioning; outdoors without shelter) of each occupation. *OCE* is constructed as an increasing function of (i) the sensitivity to climate events of a given working context, and (ii) the necessity of an occupation to perform job tasks in a climate-sensitive working context. *OCE* captures the extent to which different occupations are exposed to climate-related hazards, such as extreme temperatures, floods, and storms, that constrain workers' ability to work and hinder their productivity.[2] Second, I quantify *establishment-level workforce climate exposure* (*EWCE*) by aggregating *OCE* to the establishment level, and define the weighted average of *EWCE* (with weights based on establishment employment) across all the establishments of a given firm as the measure of *FWCE*.[3]

The second empirical obstacle faced by this study is the lack of data on firm-level automation expenditures. To overcome this challenge, I resort to textual information embedded in firm disclosures provided by *S&P Global KeyDevelopments* (*KD*). Firms disclose material news and events, mandatorily or voluntarily, to inform stakeholders of their strategic investments and actions (Sabherwal et al., 2019). Thus, I construct a novel proxy for *firm-level automation investment intensity* (*AUTO_INV*) by assessing investments publicly announced by a firm using textual analysis algorithms. Specifically, I generate two

[2] More details and validation of *OCE* can be found in Xiao (2023).
[3] *EWCE* is defined as the employment weighted average of *OCE* of the same county and industry of the establishment as described in Section 3.1. The construction of *FWCE* climate exposure is described in Section 3.1.

dictionaries for investment keywords and automation keywords using machine learning, respectively, and then search these keywords in each disclosure item from the *KD* database. I then construct *AUTO_INV* by aggregating the automation investment information of all disclosure items to the firm-year level.[4]

I adopt two approaches to validate this measure. First, I aggregate *AUTO_INV* to the industry level based on firm employment and compare it with the industry-level adoption of robots in 2017 provided by the *International Federation of Robotics (IFR)*. Previous studies leverage the industry-level robot shipment provided by *IFR* to study labor market implications of industrial robots.[5] The textual-based proxy for automation investments, instead of capital expenditure (*CAPEX*) provided by Compustat, shows a high correlation with actual robot density from *IFR*, suggesting that *AUTO_INV* reflects actual and specific investments in automation. Second, I validate *AUTO_INV* by testing the relation between *AUTO_INV* and *CAPEX*. *AUTO_INV* shows a significantly positive relation but does not fully overlap with *CAPEX*, implying that *AUTO_INV* captures some part of the information in the firm's capital investments.[6] I repeat these tests using various alternative text-based proxies for automation investments and the results are robust. Overall, these findings provide evidence of the effectiveness of my method in capturing general capital-investment information and specific automation-investment information from *KD* items.

Having examined the validity of the textual-based proxy for firm automation investments, I empirically examine the relation between workforce climate exposure (*FWCE*) and automation investments at the firm level (*AUTO_INV*). I do not find a significant impact of *FWCE* on firms' automation investments. There are two possible reasons for this finding. The first is that the required automation investment expenditures dominate the benefit from labor cost savings (*cost-benefit hypothesis*), supported by the model

[4] The detailed methodology for the construction *AUTO_INV* and other alternative measures of automation investments is provided in Section 2.1.

[5] Based on IFR data, Graetz and Michaels (2018) find that robot use increases labor productivity and total factor productivity while lowers output prices and the employment share of low-skilled workers; Acemoglu and Restrepo (2020) document robust negative effects of robots on employment and wages. One exemption is Benmelech and Zator (2022) that utilize an administrative survey from Germany to study firm-level automation adaptions in 2016, 2017 and 2019. *IFR* can be accessed at https://ifr.org/.

[6] As robustness checks, I construct textual-based proxies for general investment (*INV*) in a similar method to *AUTO_INV* and regress *INV* on *CAPEX*. I find *INV* also has a positive relation with *CAPEX*, but the magnitude is slightly greater than that of *AUTO_INV*, suggesting that my textual-based method effectively capture investment-related information.

in Kahn (2016) in which investors consider climate-related investments based on perceived benefits and costs. The second reason is a firm's ability to invest may be limited by its financial constraints despite its willingness or need to invest (*financial constraint hypothesis*) (e.g, Fazzari et al., 1988; Rauh, 2006; Lemmon and Roberts, 2010).

To test the *cost-benefit hypothesis*, I exploit a setting that introduces variations in the projection of climate-induced labor costs faced by firms with different *FWCE.* Especially, I explore the heterogeneity in long-term climate conditions faced by climate-exposed firms. Earlier studies document that learning and expectations of risk determine climate mitigation decisions (Dillender, 2019; Kahn, 2016; Barreca et al.; 2016; Heutel, Miller, and Molitor, 2021). As negative climate conditions will magnify the negative impact of climate on firms (Xiao, 2013), holding *FWCE* constant*,* firms experiencing increasing temperatures are expected to see greater increases in labor costs, creating incentives for firms to adapt. Thus, I predict that firms with greater *FWCE* will adapt to adverse long-term climate trends through more automation investments because the expected long-lasting benefits from labor cost savings will offset the short-term automation investment expenditures. To ease empirical analysis, I measure firm-level climate conditions using daily temperatures provided by the *National Centers for Environmental Information (NCEI)* and establishment-level employment from the *National Establishment Time-Series (NETS) Database*. The long-term temperature at the firm level (*FIRM_LT_TEMP*) is defined as the 240-month moving average of county-level temperatures weighted by firm employment in a given county. I then study the joint effects of workforce climate exposure and the actual climate trends by including the interaction of *FWCE* and *FIRM_LT_TEMP* in the regression of automation investments.

I find that climate-exposed firms adapt to long-term negative climate trends through more automation investments, suggesting the long-term benefits of investment offset the short-term expenditures in this case. Quantitatively, holding *FCWE* constant, a 1°F (0.56 °C) increase in *FIRM_LT_TEMP* leads to 0.004 increases in *AUTO_INV*, equivalent to 77 basis points relative to the average value of *AUTO_INV* (0.52). To allow for a nonlinear relation between temperatures and the firm's adaptation investments, I replace *FIRM_LT_TEMP* with a set of temperature quintile dummies. I find that holding *FWCE* constant, automation investments increase along with increases in temperatures, especially at the higher end. This finding is consistent with the notion in previous literature that extremely hot temperatures significantly harm labor supply, productivity, and health, which encourages firms to take adaptation actions.[7] Taken together, these results provide evidence in support of the *cost-benefit hypothesis* and help understand firms' demand for automation adaption regarding climate-induced labor risk.

I provide additional support to the *cost-benefit hypothesis* by studying stock market responses to the announcement of firms' automation investments. I find higher three-day cumulative abnormal returns (*CAR*) upon automation investment news of firms expecting increasing climate-induced labor risk in the long run (defined by the interaction of *FWCE* and *FIRM_LT_TEMP).* This finding is economically significant: holding *FWCE* constant, a 1°F (0.56 °C) increase in *FIRM_LT_TEMP* is associated with a 0.145% increase in Fama-French three factors adjusted returns. That is, investors expect automation investments to create more value for climate-exposed firms experiencing higher temperatures in the long run, consistent with the *cost-benefit hypothesis*.

Next, I investigate the *financial constraint hypothesis*. I use three proxies for financial constraints including the Kaplan-Zingales Index (Kaplan and Zingales, 1997; Lamont, Polk and Saa-Requejo, 2001), payouts (e.g., DeAngelo and DeAngelo, 1990; Kumar and Vergara-Alert, 2018) and a 10-K text-based financial constraints measure (Hoberg and Maksimovic, 2015). Firms are defined as financially unconstrained if they meet any of the following conditions: 1) the lagged Kaplan-Zingales Index is in the bottom quarter within the industry; 2) have payouts in the previous year; 3) do not have 10-K text-based financial constraints. The remaining firms fall into the constrained group. By exploring heterogeneity in automation investments by firms' financial constraints, I find the interacted effect of *FWCE* and *FIRM_LT_TEMP* on automation investments only in the subsample of unconstrained firms, consistent with

[7] See Deryugina and Hsiang (2014); Graff Zivin and Neidell (2014); Pankratz, Bauer and Derwall (2019); Li et al. (2020a).

the *financial constraints hypothesis* that financially constrained firms cannot afford to finance automation adaptation. These findings highlight the importance and potential role of the capital market in climate adaptation plans through financing firms' adaptation investments. Together with Xiao (2023) and Bena and Simintzi (2015) that suggest the availability of cost-effective labor contributes to firms' preference for labor adaptation over capital adaptation, these findings shed light on the mechanism underlying firms' choice among different adaptation strategies.

One potential concern with my analysis may arise from the possibility that firms endogenize their workforce climate exposure ex-ante. For example, automation investment decisions and workforce climate exposure may be jointly determined by industry or firm characteristics. To alleviate this concern, in all my empirical models, I employ a battery of fixed effects at the firm level and industry-year level, respectively, to control for the time-invariant firm characteristics as well as the time-varying conditions of a given industry-year. I further address this concern by exploiting a quasi-natural experiment tied to the implementation of *the California Heat Illness Prevention Standard* (*CA Standard*) in 2005. *CA Standard* requires employers to reduce heat stress in the workplace through actions such as providing paid rests and sheltering structures. As a result, firms with greater *FWCE* will have to bear incremental labor costs to comply with the regulation, creating incentives to substitute climate-exposed workers with automation. A firm potentially affected by *CA Standard* should meet two requirements: 1) climate risk faced by the workforce is high; 2) it operates in California around the implementation of the standard. Thus, I proxy for the extent to which *CA Standard* is binding for a given firm using the interaction of *FWCE* and the percentage of firm employment in California (*AFF_EMP*). Using a difference-in-differences methodology, I compare changes in automation investments of firms constrained by *CA Standard* (treatment) with the less affected firms (control) around policy adoption. I uncover significant increases in firm investments in automation following the implementation of *CA Standard* in treated firms that have more workers exposed to both climate and the *CA Standard*. Holding *FWCE* constant, a one-standard-deviation increase in *AFF_EMP* (25%) causes a 0.075 ($0.003\times 25\%$) increase in *AUTO_INV*, which is equivalent to 14.4% of the sample mean (0.52). These findings suggest that climate-exposed invest more in automation in response to greater increases in labor costs resulting from climate policies, providing causal inference for the impact of the workforce climate exposure on firms' automation investments and highlighting the importance of regulatory compliance costs in firms' adaptation decisions.

So far, my findings provide evidence that firms with the adaptation demand and adaptation capacity react to climate-induced labor risk by investing in automation. Alternatively, firms can also resort to labor adaptation, such as carrying more employees, increasing employee insurance, and purchasing more input overseas, to hedge against potential losses (Xiao, 2023). A natural question is whether labor adaptation and investment adaptation act as substitutes or complements. Thus, I divide firms into two groups based on firms' automation investments (*AUTO_INV*) in the previous year and compare the differences in their labor adaptation policies. I find some evidence of the substitute effect of automation adaptation on labor adaptation: Holding *FWCE* constant, firms that have made greater investments in automation tend to retain fewer employees, spend less on employee insurance, and make fewer purchases overseas along with increases in long-term temperatures.

The last question I explore is about the effectiveness of automation adaptation in mitigating climate-induced labor risk. The *cost-benefit hypothesis* indicates that climate-exposed firms will have more incentive to adapt if the expected benefits of adaptation increase. Hence, the effectiveness of automation adaptation also speaks to firms' incentives for adaptation. The previous literature demonstrates challenges in adapting to climate surprises (Kahn, 2016; Xiao, 2023). Thus, I examine the effectiveness of automation adaptation by comparing the operating performance of firms with different automation intensities in response to abnormal temperatures. I find that climate-exposed firms benefit from automation by suffering fewer workplace injuries and earning significantly higher *ROA* under short-term temperature surprises, compared to their industry peers who do not invest in automation. The findings suggest that automation investments assist firms in managing the most difficult adaptation challenges and effectively reducing climate-related risks. Additionally, they illustrate the incentives for companies to implement adaptive automation.

This paper contributes to the literature that examines the impact of climate change on corporate outcomes including sales, profits, employment, productivity, and operating performance (eg., Pankratz et al., 2019; Addoum et al., 2020; Li et al, 2020b; Somanathan et al., 2021). For example, Sautner et al. (2020) find that climate change exposure based on earnings calls predicts firms' efforts in transiting to the low-carbon economy measured by green job hiring and green patents; Lin, Schmid and Weisbach (2019) document that electricity-producing firms respond to electricity demand fluctuations caused by extreme weather by investing more in regions with extreme temperatures. My paper contributes by showing that firms can react to climate-induced labor risk through adjustments in automation investments, and their automation adaptation effectively protects firms' operating performance from temperature surprises. Therefore, this paper also speaks to the long-term implications of climate adaptation strategies (Lin et al., 2019; Pankratz and Schiller, 2019; Bartram, Hou and Kim, 2022).

In this regard, this paper adds to two contemporaneous papers Xiao (2023) and Xiao (2022) that study how firms adapt to workers' climate risk. While Xiao (2023) examines firms' labor adaptation including employment, insurance, and offshoring, this paper sheds light on an alternative adaptation strategy through automation. Regarding the proxy for labor's exposure to climate risk, Xiao (2022) relies on the cross-sectional variation in outdoor activities of their workforce, whereas I diverge from this paper by considering workers' climate exposure cross-sectionally and over time based on various working contexts including both indoor and outdoor work and the level of environment control. In terms of substance, Xiao (2022) examines variations in firms' capital intensity, while I focus on the specific and direct investments in automation and document that automation adaptation is affected by the perceived benefits of adaptation and financial constraints faced by firms. I also provide evidence that automation adaptation is a more selective strategy compared to labor adaptation in certain situations, adding to the literature studying the relation between capital and labor (e.g., Jones, 2005; Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2018; Bena and Simintzi, 2019). Further, this paper emphasizes the importance and potential role of the capital market in climate adaptation, as alleviating financial constraints will allow climate-exposed firms to take automation adaptation actions.

This study also relates to the literature on corporate investment (e.g., Fazzari et al., 1988; Rauh, 2006). Previous studies explain corporate investments through labor-related factors such as minimum wages (Gustafson and Kotter, 2018), labor protection laws (Bai, Fairhurst, and Serfling, 2020) and employee healthcare costs (Tong, 2020). This paper expands the analysis of the determinants of corporate investments by including climate-induced labor risk as a factor. This paper also expands the scope of empirical work that tries to decompose total capital investments. For example, Ouimet, Simintzi, and Ye (2019) and Kini et al. (2022) explore firm IT investments in response to labor distortions such as labor shortages and unionization. This paper adds to this string of literature by contributing an empirical method to distinguish investment components like automation from total capital investments using textual analysis.

Finally, this paper intersects a wide range of papers that study the effect of labor on firm performance and policies (e.g., Chen et al., 2010; Matsa, 2010/2018; Agrawal and Matsa, 2013; Serfling, 2016; Tate and Yang, 2016; Ghaly, Anh Dang and Stathopoulos, 2017; Mueller, Ouimet, and Simintzi, 2017; Ellul and Pagano, 2019; Ouimet and Zarutskie, 2020; Ma, Ouimet and Simintzi, 2021). My paper exploits the firm-level variations in labor risks related to climate and documents its implications on firms' investment policies and performance.

1. Data

In this section, I describe my main sample at the firm-year level from 2000-2018. Table A1 in Appendix explains the construction of all variables in detail. If not specified, variables in all samples are winsorized at the 1% and 99% levels and all dollar-denominated variables are expressed in 2018 dollars.

1.1. KD Data

KeyDevelopments (*KD*) provides structured summaries of material news and events that may affect the market value of securities dated back to 1998.[8] The dataset collects information on over 250,000 companies worldwide from 20,000 news sources including press releases, regulatory filings, company websites, web mining and call transcripts. Each *KD* item includes the announced date, entered date, modified date, headline, situation summary, type, source, company role, and other identifiers. Over 2,000 new items are added each day. *KD* dataset monitors over 100 types of events such as executive changes, M&As, changes in corporate guidance, delayed filings, and SEC inquiries. Following Park (2022), I only include types potentially related to firm investments, such as business expansions/strategic alliances/business reorganizations, in my sample. After dropping duplicate items collected from different resources, my *KD* sample includes 2.7 million items from 2000 – 2018. Although the information resource of *KD* spans from mandatory disclosure like regulatory filings to voluntary disclosure like news articles and company websites, for simplicity I also refer to any *KD* item as a "disclosure item" in this paper.

1.1. NETS Establishment Data

Walls & Associates teamed up with *Dun and Bradstreet (D&B)* to build *NETS* database of establishment information. *NETS* covers twenty-nine annual snapshots taken every January of the full *Duns Marketing Information (DMI)* file that followed over 71 million establishments between January 1990 and January 2019. It reports plant and headquarters information including locations, industry, employment, and sales. According to Neumark, Zhang, and Wall (2007), *NETS* data shows significant discrepancies in small establishments compared to other data sources, such as *Quarterly Census of Employment and Wages (QCEW)* and *the Current Employment Statistics (payroll) survey (CES)*. Thus, I drop establishments with employees less than 15 from the sample. To match with *KD* data, my *NETS* sample covers 2000 - 2018.

[8] https://www.marketplace.spglobal.com/en/datasets/key-developments-(15)#:~:text=The%20Key%20Development%20dataset%20provides,classes%2C%20trading%20styles%20and%20frequencies.

1.2. OSHA Establishment Specific Injury & Illness Data

The *Occupational Safety and Health Administration (OSHA)* regulates workplace safety for most private-sector employers in the U.S. *OSHA* promulgates workplace safety standards such as equipment safety and employee training and it enforces these regulations by making inspections and investigating worker complaints. Under the *OSHA Data Initiative Program (ODI)* from 1996-2011, *OSHA* collected work-related injuries and illnesses from private-sector establishments with no less than 11 employees unless the industry of the establishment is exempted due to a historically low accident rate.[9] The data provide the establishment name, address, industry, days away, restricted, and transfer (*DART*) case, and the days away from work (*DAFWII*) case. To identify climate-related workplace injuries, I only include injuries related to natural disasters or adverse weather conditions and complete the *OSHA* sample of the establishment universe in 2002-2011 using data from *NETS*.[10]

1.3. Firm-Level Employee Benefit Data

The *Employee Retirement Income Security Act of 1974 (ERISA)* requires firms with more than 100 participants on their welfare and pension benefits plan to file a Form 5500 annually. The main file of Form 5500 contains basic plan information regarding the filing entity, number of participants and coverage period. Several schedules may be attached to the main form and I focus on Schedule A, "Insurance Information" available from 1999 onward. A firm must attach a Schedule A form for each standalone insurance company it hires with information on the plan including insurance carrier information, insurance type (e.g., health, dental, vision, prescription drugs and life), number of persons covered, coverage period, and the plan premium. As climate exposure is associated with workplace safety risk (Park et al, 2021; Xiao, 2023) I retain the plans for health and life benefits and drop plans containing only dental and vision insurance.

---

[9] Internet Appendix A of Xiao (2023) lists the industries exempted by *OSHA* due to the low-hazard rate from 2001-2014. (Source: *OSHA*, https://www.*OSHA*.gov/laws-regs/federalregister/2001-01-19, accessed on 03/10/2022.)
[10] Before 2002, *OSHA* did not report the whether the injuries are related to natural disaster or adverse weather conditions. By matching *NETS* and *OSHA* establishments using names, addresses and industries, I assume establishments only included in *NETS* but not in *OSHA* have no workplace injury or illness cases.

I aggregate Form 5500 plan-level filings to the firm level using the employer identification number (*EIN*). A firm might have separate EINs for its subsidiaries, but Compustat keeps only one *EIN* at the consolidated firm level. Thus, I manually match Compustat and Form 5500 by company name, industry, and address. I also retrieve the subsidiary list for US public firms from *NETS* and conduct the same matching using subsidiary names, addresses and industries. The health insurance expense of a firm aggregates all the insurance expenses on each Schedule A in a given year, which is set to be zero if there is no Schedule A attached.

1.4. Firm Financial Data

I use Compustat to obtain firm financial data from 2000 to 2018. Following previous literature, I discard financial firms (SIC codes between 6000 and 6999) and those with book assets and sales less than zero.

1.5. Daily Weather Data

The historical weather data are provided by the *National Centers for Environmental Information (NCEI)* operated by *National Oceanic & Atmospheric Administration (NOAA)*. The input data used in building these daily summaries are the *Integrated Surface Data (ISD)*.[11] This file contains daily weather observations from roughly 8,000 weather stations throughout the United States. The weather conditions include temperature, wind speed, cloudiness, precipitation, snow depth, etc. I collect the daily records in the US from 1980 to 2018 to generate both contemporaneous and long-term climate trend proxies.

2. Methodology

2.1. Measuring Corporate Investment in Automation

To test my predictions of investment adaptation, I create a novel proxy for firm-level automation investments. In terms of substance, I use over 2.7 million *KD* disclosure of firms to assess their investment strategies following Sabherwal et al. (2019) and Park (2022). In terms of methodology, I build on recent

[11] Source: NOAA, https://www.ncei.noaa.gov/access/metadata/landing-age/bin/iso?id=gov.noaa.ncdc%3AC00532, accessed on 03/10/2022.

work that defines the proportion of corporate filings centered on a particular topic as a measure of that issue at the firm level using the machine learning keyword discovery algorithm (eg., Hassan et al., 2019, 2020a/b; Li et al., 2020b; Sautner et al., 2020). The common practice is to count word occurrences from a word list (dictionary) that share common meanings. For example, dictionaries like Loughran and McDonald (2011) and *Linguistic Inquiry and Word Count (LIWC)* (Pennebaker et al. 2015), have been extensively used to measure the tone or sentiment of corporate filings.

In my practice, I form a dictionary for firms' automation investments including two sub-dictionaries. Following Sabherwal et al. (2019), I define a sub-dictionary containing words such as "spend," "invest," "investment," "expenditure" and synonyms, aiming to filter disclosure potentially related to investments. Similar to the method adopted by Park (2020) for IT investments, I define the second sub-dictionary covering automation-related nouns that focus on the content of investments. However, developing such a sub-dictionary for automation can be hard. The conventional solution, as in Loughran and McDonald (2011) and *LIWC*, is to have experts manually inspect and categorize words that commonly appear in a specific context. While it is theoretically possible for experts with deep knowledge of various aspects of business operations to understand the rich, nuanced meanings of individual words and phrases based on context, their doing so is often impractical and cost-ineffective.

Thus, I resort to a machine learning alternative. Specifically, I start with seed words including "automation", "robot", "machine" and "equipment", which define automation clearly and generally. Next, I automatically create a high-quality dictionary using the word embedding model, which learns the meaning of a word (phrase) based on its context. The goal of word embedding is to represent the meaning of a word using a numeric vector. The word embedding model is based on a simple, time-tested concept in linguistics: Words that co-occur with the same neighboring words have similar meanings (Harris, 1954). Thus, the model identifies synonyms from common neighboring words. A naïve way to embed a word is to construct a count vector that tallies the number of times other words appear near the focal word in the corpus. Once such a vector is constructed for each word by counting its neighbors, the association between any pair of words can be computed using the cosine similarity of their underlying vectors, which allows me to determine the relationship between words.

I rely on a specific word embedding model, global vectors for word representation (*GloVe*), developed by Stanford University (Pennington, Socher, and Manning, 2014). The model is an unsupervised learning algorithm for obtaining vector representations for words. This is achieved by mapping words into a meaningful space where the distance between words is related to semantic similarity. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase linear substructures of the word vector space. I leverage the pre-trained model ("*glove-wiki-gigaword-300*") provided by Python to develop an expanded dictionary for automation.[12] I select the top 200 most similar words of each seed word based on their cosine similarity and manually inspect them in the auto-generated dictionary and exclude words that do not fit.[13]

After generating a dictionary for firm automation investments, I search investment keywords and automation keywords in each *KD* item of a given firm.[14] I defined a *KD* item as automation investment-related only if it satisfies two requirements: 1) it contains at least one investment keyword, which defines investment-related disclosure; 2) it contains at least one automation keyword, ensuring the disclosure is automation related.[15] In the spirit of Sautner et al. (2023) that the "relative frequency" of keywords represents the importance of the topic these keywords describe, I first calculate the *AUTO_INV_K,* the percentage of automation keywords of an investment-related *KD* item (those with at least one investment

[12] "Glove-wiki-gigaword-300" model produces 300-dimension word vectors using *Wikipedia 2014* and *English Gigaword Fifth* as the training dataset. Source: https://github.com/RaRe-Technologies/gensim-data, accessed on 3/21/2022. *English Gigaword Fifth Edition* is a comprehensive archive of newswire text data that has been acquired over several years by the *Linguistic Data Consortiume* (*LDC*). The fifth edition includes all of the contents in *English Gigaword Fourth Edition* (*LDC2009T13*) plus new data covering the 24-month period January 2009 through December 2010. Source: https://catalog.ldc.upenn.edu/LDC2011T07, accessed on 3/21/2022.

[13] Table A2 in Appendix presents examples of the finalized automation keywords.

[14] Firm public announcements are cleaned (removing stop words, numbers, punctuations, entitys and then tokenized) before searching.

[15] Table A3 in Appendix displays examples of four types of firm public announcement: 1) include at least one automation keyword and at least one investment keyword; 2) include at least one automation keyword and zero investment keyword; 3) include at least one investment keyword and zero automation keyword; 4) do not include any automation keywords or investment words. Only the first type is possibly defined as the automation announcement.

keyword) to access how relevant to automation this investment item is. Specially, I take the set of automation keywords *A* to the investment-related *KD* items and count the frequency of these keywords. To account for the disclosure length, I scale the count by the number of words in the item.

$$AUTO\_INV\_K_{kit} = \frac{\sum_{w}^{W_{kit}}(1[w \in A])}{W_{kit}} \tag{1}$$

where $w = 0, 1, \ldots, W_{kit}$ are the words in the investment-related KD item *k* of firm *i* in year *t* and 1[.] is the indicator function. $AUTO\_INV\_K_{kit}$ equals zero for *KD* items that do not have any investment or automation keywords.

I then create an annual measure of automation investment intensity (*AUTO_INV*) for each firm by averaging $AUTO\_INV\_K_{kit}$ over all *KD* items of the firm *i* in year *t*.[16] As robustness checks, I also define a *KD* item as automation investment-related if $AUTO\_INV\_K_{kit}$ is over 3% and then compute the percentage of the automation investment items out of all *KD* items in a firm-year (*AUTO_NEWS*). In addition, I also create an indicator for a firms' automation investments (D_{AUTO}) which equals one if *AUTO_INV* is larger than 3%, and zero otherwise. To distinguish automation investments aimed at solving climate-related issues, I additionally generate a dictionary for climate keywords from Li et al. (2020b) and Sautner et al. (2020) and then define an automation investment item as climate-related if it includes at least one climate keyword.[17] Similar to *AUTO_INV*, I construct a proxy *AUTO_INV_CLIMATE* based on the automation keywords in a subsample of automation investment items related to climate. The results are robust with alternative proxies of firm automation investments.

[Insert Table 1]

Table 1 lists the top 10 public firms with the highest and the bottom 10 with the lowest automation investment intensity (*AUTO_INV*) in 2018. The firms that invest heavily in automation concentrate in the

[16] I scale $AUTO\_INV\_K$ by the annual total of the firm's *KD* items to account for the effect of firm size on the *KD* coverage because the annual number of *KD* items has a correlation of 0.45 with the firm size (assets).
[17] Table A4 in Appendix presents examples of the finalized climate keywords.

manufacturing industries while at the opposite end of the spectrum are firms in the service industries like retail, eduction and accommodation and food services.

2.2. Validate Firms' Automation Investment using the Industry-level Robot Density

I validate the measure of firms' automation investment (*AUTO_INV*) by intersecting the industry-level robot density in 2017 from *IFR* and the industry-level automation investments (*AUTO_INV*) aggregated from firms. *IFR* collects data on industrial robots from the national federations of robot manufacturers. The *IFR* refers to an "industrial robot" as defined by *ISO 8373*: an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications" (*IFR*, 2018).[18] Each element of the definition is crucial for a machine to be considered an industrial robot. For instance, some machines, including textile looms, elevators, or transportation bands, are not industrial robots because they cannot be reprogrammed to perform other tasks, and/or they require human intervention. This definition hereby excludes other kinds of equipment and indicates that robots are different from earlier automation, which provides a precise but narrow estimation of "automation".

As *IFR* only provides robot usage across 19 industries (roughly at the two-digit *NAICS* code level outside manufacturing and at the three-digit level within manufacturing) in 2017, I quantify automation investment at the industry level as the average of firm-level automation investments. The industry-level capital expenditure is defined in the same way.

[Insert Table 2]

Table 2 presents the comparison between actual robot density defined as the number of industrial robots per million hours worked, 100 times *CAPEX*, *AUTO_INV* and *AUTO_INV_CLIMATE* at the industry level in 2017. The actual robot density shows a strong correlation with *AUTO_INV* (0.54) and *AUTO_INV_CLIMATE* (0.53), but not with *CAPEX* (-0.07). When exploring the relative ranking order

[18] See *ISO* definitions at https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en.

rather than raw numbers, the correlation between *CAPEX* and robot density increases to 0.45, which is still lower than that of *AUTO_INV* (0.60) and *AUTO_INV_CLIMATE* (0.47). These results provide evidence that *AUTO_INV* reflects real investments in automation, while *CAPEX* covers overall capital and, thus, is too general to provide information on the specific components of firm investments.

2.3. Validate Firms' Automation Investment using Capital Expenditure

As *CAPEX* is the most common measure of firm investments, it may be necessary to compare the difference between *CAPEX* and *AUTO_INV*. I estimate the panel regressions of the following form:

$$CAPEX_{it} = \alpha_i + \lambda_{jt} + \beta X_{it-1} + \theta AUTO\_INV_{it-1} + \varepsilon_{ijt} \quad (2)$$

Wherein i indexes firm i and j indexes the three-digit *NAICS* industry of firm i. $CAPEX_{it}$ indexes 100 times capital expenditure scaled by lagged assets of firm i in year t; X_{it-1} is a set of lagged firm-level controls; $AUTO\_INV_{it-1}$ proxies for the lagged measures of automation investment intensity of firm i defined in section 2.1. I control for the natural logarithm of sales in 2018 dollars, Tobin's Q, cash holdings scaled by assets, tangible assets scaled by assets, market leverage, RD dummy, dividend dummy, repurchase dummy and the natural logarithm of employment. The definition of all the variables is described in Table A1 in Appendix. Firm fixed effects α_i and industry × year fixed effects λ_{jt} are included. Standard errors are clustered by firm.

[Insert Table 4]

Table 3 reports the regression results in which the dependent variable is 100 times capital expenditure scaled by lagged assets. The main explanatory variable in columns (1) - (4) is a set of textual-based proxies for firm automation investments as described in Section 2.1. Specifically, it is the major proxy for automation investment intensity (*AUTO_INV*) defined as the $AUTO\_INV\_K_{kit}$ averaged across the annual total items in column (1), and three alternative proxies including the percentage of *KD* items of automation investments (*AUTO_NEWS)* in column (2), an automation investment indicator (D_{AUTO}) that equals one if *AUTO_INV* is greater than 3% in column (3), and the investment intensity of climate-related automation ($AUTO\_INV\_CLIMATE$) in column (4). I find a positive coefficient on proxies for automation investment intensity in all regressions, significant at 1% level except for column (3) which is significant at 5% level. The results are robust when I substitute $AUTO\_INV_{it-1}$ with $AUTO\_INV_{it}$. The adjusted R-square in all models is about 0.70. These findings show that automation investment intensity has a significantly positive relation but does not fully overlap with *CAPEX*.

As robustness checks, I also use textual-based proxies for general investments constructed in a similar practice for automation-specific investment in columns (5) – (7). The main explanatory variable includes firm investment intensity (*INV)* defined as the averaged percentage of investment keywords in each *KD* item in a firm-year in column (5), the percentage of a firm's investment items defined as those with more than 3% investment keywords in the context out of the annual total items *(INV_NEWS*) in column (7), and an indicator for investments (D_{INV}) which equals one if *INV* is larger than 3% and zero otherwise in column (8). Table A1 in Appendix describes the definition of these variables. Consistent with findings based on automation investment in column (1) – (4), proxies for investment intensity have a positive relation with *CAPEX* in all regressions in a slightly larger magnitude than column (1)-(4). These findings provide additional evidence of the effectiveness of my approach in capturing investment-related information from *KD* items. [19]

3. Climate-Induced Labor Risk and Corporate Investment in Automation

In this section, I empirically examine the relation between climate exposure of the firms' workforce and their investments in automation. The workforce climate exposure may have two-side effects on corporation investment. The potential labor costs associated with it may increase investments by encouraging firms to satisfy the production demand using a relatively cheaper factor (capital) (e.g., Blanchard, 1997; Caballero and Hammour, 1998). Alternatively, it can also reduce investments by constraining firms' access to external

[19] Table A5 provides correlation between all text-based proxies for firms' general investments and automation investments.

capital due to increased operating leverage (Chen et al., 2010; Simintzi et al., 2015; Serfling, 2016) and encouraging firms to switch to less-costly workers domestically or overseas (Xiao, 2023).

3.1. Sample Overview

To differentiate between these two predictions, I construct a firm-level panel sample over the period 2000 to 2018. I take three steps to measure firms' workforce climate exposure, *FWCE,* using the approach in Xiao (2023). First, I rank working contexts provided by the *Occupational Information Network (O*NET*) according to their sensitivity to climate events. As *O*NET* categorizes each context variable into five frequency groups to reflect the importance of performing the job in this context every year, I define *OCE* as the frequency-weighted average of climate exposure of work contexts. More details and validation of *OCE* can be found in Xiao (2023). Second, I quantify *establishment-level workforce climate exposure* (*EWCE*) by aggregating *OCE* to the establishment level based on the workforce component of the county-industry cohort of each establishment-year observation. The employment information of individuals is from the *American Community Survey (ACS)* provided by *Integrated Public Use Microdata Series (IPUMS)* and the information on establishments is *NETS.* Lastly, I define the weighted average of *EWCE* (with weights based on establishment employment) across all the firm's establishments as the measure of *FWCE*.

In the spirit of Choi, Jiang and Gao. (2020) and Xiao (2023), I decompose the annual temperature of each county into a long-term trend (LT_TEMP) proxied by the 20-year moving averages of annual temperatures, and the abnormal component (AB_TEMP) constructed as the difference between the annual temperatures and LT_TEMP. Then I aggregate these two proxies to the firm level based on the establishment employment provided by *NETS*. Specifically, $FIRM\_LT\_TEMP$ is the long-term temperature at the firm-year level defined as LT_TEMP averaged across the firm and weighted by the firm's employment in a given county in a given year; $FIRM\_AB\_TEMP$ is the abnormal temperature at the firm-year level constructed similarly using AB_TEMP.

I match the *OSHA* workplace safety sample to Compustat firm data. The number of workplace injuries and illnesses related to weather or natural disasters reported to *OSHA* by the firm annually from 2002-2011.

[Insert Table 3]

All variables are described in Table A1 in the Appendix. Table 3 presents summary statistics for the variables. The insurance expense per participant is $1,024 in 2018 dollars and firms suffer 0.26 climate-related workplace safety incidents on average. *FWCE* has a mean of 2.06 and a standard deviation of 0.39. On average, *FIRM_LT_TEMP* is 59.2°F, comparable to the 59.9°F annual temperature of North Carolina in 2021.[20] *FIRM_AB_TEMP* has a mean of 0.32°F and a median of 0.26°F, suggesting that firms, on average, experience increasing annual temperatures over my sample period.

3.2. Baseline Specification

I then estimate panel regressions in the form of:

$$Y_{it} = \alpha_i + \lambda_{jt} + \beta X_{it-1} + \theta FWCE_{it-1} + \varepsilon_{ijt} \tag{3}$$

wherein i denotes firm i and j denotes the three-digit *NAICS* industry that firm i belongs to. Y_{it} denotes a set of proxies for automation investment intensity of firm i in year t; X_{it-1} is a set of lagged firm-level controls; $FWCE_{it-1}$ is the lagged workforce climate exposure firm i. I control for the natural logarithm of sales in 2018 dollars, Tobin's Q, cash holdings scaled by assets, tangible assets scaled by assets, market leverage, RD dummy, dividend dummy, repurchase dummy and the natural logarithm of employment. The definition of all variables is described in Table A1 in Appendix. Firm fixed effects α_i and industry × year fixed effects λ_{jt} are included in the regressions. Standard errors are clustered by firm.

[Insert Table 5]

[20] https://www.ncei.noaa.gov/cag/statewide/mapping/31/tavg/202201/12/value. Accessed in July, 2022.

Table 5 reports the regression results. The dependent variable in columns (1) - (4) is a set of textual-based proxies for firms' automation investment including the main proxy for automation investment intensity (*AUTO_INV*) in column (1) and three alternative proxies including the percentage of the disclosure of automation investments (*AUTO_NEWS)* in column (2), an automation investment indicator (D_{AUTO}) in column (3), and the investment intensity of climate-related automation (*AUTO_INV_CLIMATE*) in column (4). As a robustness check, I also include capital expenditure over the lagged assets (*CAPEX*) as the dependent variable in column (5). To isolate capital expenditures unrelated to automation as a comparison to *AUTO_INV*, I also regress *CAPEX* on *AUTO_INV* and use the residual, *CAPEX Automation-Unrelated*, as the dependent variable in column (6). I find insignificant coefficients on *FWCE* in all regressions, suggesting that firms with more climate-exposed workers do not, on average, invest more in general physical capital or automation. As explained earlier, there are two possible reasons. One is that the costs of investing may outweigh the benefits gained from labor cost savings (*cost-benefit hypothesis*) while the other is that firms facing financial constraints may lack the resources to make investments (*financial constraint hypothesis*).[21]

3.3. Adaptation to Long-term Climate Trends

3.3.1. Firms' Automation Investments

Climate mitigation decisions are driven by expected risk (Dillender, 2019; Kahn, 2016; Barreca et al.; 2016; Heutel et al., 2021), so the projection of climate-induced labor risk will have an impact on firms' demand for adaptation. Therefore, I explore a setting that introduces variations in the expected labor costs faced by firms with different *FWCE* to examine the *cost-benefit hypothesis*. The expected labor costs related to climate have two components. One is climate exposure (sensitivity to climate) of the workforce and the other is adverse climate conditions that will magnify the impact on exposed workers. Thus, holding *FWCE* constant, firms expecting rising temperatures in the long run will bear greater increases in labor costs on an ongoing basis. Hence, I hypothesize that climate-exposed firms will adapt to adverse climate trends through

[21] See, e.g., Fazzari et al. (1988), Rauh (2006), and Lemmon and Roberts (2010).

more automation investments because the expected long-lasting benefits from labor cost savings will offset short-term investment expenditures. To test this hypothesis, I extend Equation (3) by adding an interaction of the *FWCE* and *FIRM_LT_TEMP* and estimate the panel regressions of the following form:

$$AUTO\_INV_{it} = \alpha_i + \lambda_{jt} + \beta X_{it-1} + \theta FWCE_{it-1} + \eta FWCE_{it-1} \times FIRM\_LT\_TEMP_{it}$$

$$+\mu FIRM\_LT\_TEMP_{it} + \varepsilon_{ijt} \tag{4}$$

Wherein i is firm i and j is the three-digit *NAICS* industry of firm i. $AUTO\_INV_{it}$ denotes various proxies for automation investment intensity of firm i in year t; X_{it-1} is a set of lagged firm-level controls; $FWCE_{it-1}$ is the lagged workforce climate exposure firm i and $FIRM\_LT\_TEMP_{it}$ is the long-term temperature over the previous 20 years firm i in year t. The definition of all variables is described in Table A1 in Appendix. All models include firm attributes controlled in Equation (3), firm fixed effects α_i and industry × year fixed effects λ_{jt}. Standard errors are clustered by firm.

[Insert Table 6]

Table 6 presents the regression results. The dependent variable in columns (1) - (4) is a set of textual-based proxies for firms' automation investment including the main proxy for automation investment intensity (*AUTO_INV*) in column (1) and three alternative proxies including the percentage of the disclosure of automation investments (*AUTO_NEWS)* in column (2), an automation investment indicator (D_{AUTO}) in column (3), and the investment intensity of climate-related automation ($AUTO\_INV\_CLIMATE$) in column (4). As additional robustness checks, I replace automation proxies with *CAPEX* as the dependent variable in column (5) and with *CAPEX Automation-Unrelated* in column (6), respectively. The variable of interest is the interaction of $FWCE_{it-1}$ and $FIRM\_LT\_TEMP_{it}$, which captures the adaptation strategies of climate-exposed firms when facing adverse climate trends.

I find a positive coefficient on $FWCE_{it-1} \times FIRM\_LT\_TEMP_{it}$ in column (1) – (3), all significant at 5% level. This indicates increases in either $FWCE$ or $FIRM\_LT\_TEMP_{it}$ will lead to increases in firms' investment in automation. Take column (1) as an example: the coefficient of 0.004 suggests that holding

$FWCE$ constant, one standard deviation increase in *FIRM_LT_TEMP* (6.21°F) is associated with a 0.025 (0.004×6.21) increase in *AUTO_INV*, equivalent to 4.8% of the averaged *AUTO_INV* (0.52). These findings support the *cost-benefit hypothesis* that firms with more climate-exposed workers respond to predictably adverse climate-conditions that increase their expected labor costs through more automation investments. I find an insignificantly positive coefficient on the interaction item in column (5), suggesting that firms do not invest more in capital as adaptation, likely because capital expenditure is too general to quantify specific automation investments. This hypothesis is supported by the insignificant coefficient in column (6), which indicates that firms do not resort to capital investments other than automation (land, plants, etc.) as part of their capital adaptation strategies. Interestingly, the coefficient on the interaction item in column (4) in which the dependent variable of climate-related automation investment, is positive but marginally insignificant (1.51). The potential reason can be that firms do not disclose the detailed usage of automation or the climate-related automation investments have a nonlinear relation with temperatures.

Both extremely hot and cold weather may be hazardous: The deviation from the optimal temperature range can adversely impact workers and firms. To allow for a nonlinear relation between temperatures and the firm's adaptation investments, I extend Equation (4) by replacing $FIRM\_LT\_TEMP$ with a set of quintile dummies. The coefficients of the interaction of *FWCE* and each temperature quintile dummy are displayed in Figure 1. I omit the interaction of *FWCE* and the first quintile dummy of temperatures, so the estimates are the change in firm investments in a certain temperature range relative to the lowest temperature, holding *FWCE* constant.

[Insert Figure 1]

Plot A-D in Figure 1 plots the coefficient of the interaction of *FWCE* and long-term temperature quintile dummies in the regression of the textual-based measures of firms' automation investment. Overall, the relation between long-term temperature and firms' automation investments is almost linear: the automation investments increase along with the increase in temperatures, especially at extremely high temperatures, consistent with the notion in previous literature that heat stress is more averse to human health compared to the cold weather (Deryugina and Hsiang, 2014; Graff Zivin and Neidell, 2014; Park et al., 2021). This relation is robust to all proxies for automation investments. However, holding *FWCE* constant, 100 times *CAPEX* in Plot F and *CAPEX Automation-Unrelated* in Plot G do not respond to changes in long-term temperatures, consistent with findings in Table 3 and Table 4 that capital expenditure is too general to capture specific information on automation investments that directly substitute climate-exposed workers.

3.3.2. The Market Response to the Disclosure of Automation Investments

To assess the valuation implications of firms' automation adaptation, I study the cumulative abnormal stock returns during short trading periods around the disclosure of firms' automation investment decisions. As automation investments can potentially shield firms from climate-induced labor risk in the long run, I predict that the stock market will respond more positively to the automation news of firms facing greater climate-induced labor risk.

To empirically examine this prediction, I defined a *KD* item as automation investment-related if it includes both automation and investment keywords ($AUTO\_INV\_K$ >0) as described in Section 2.1. Alternatively, I also define a disclosure item as automation investment-related if the percentage of automation keywords in the item is greater than 3% ($AUTO\_INV\_K$ >3). I estimate daily abnormal returns around the announcements of automation investments using the *CAPM*, the Fama-French (*FF*) three-factor model, and the Carhart four-factor model. The estimation period starts 280 days before each event and ends 30 days before the event day. I require firms to have return observations during the event window and at least 50 return observations in the estimation period.[22] I then conduct an event study on each *KD* item of firms' automation investment at the *KD* item level of the following form.

$$CAR_{kit} = \alpha_i + \lambda_{jmt} + \theta FWCE_{it-1} + \eta FWCE_{it-1} \times FIRM\_LT\_TEMP_{it}$$

$$+\mu FIRM\_LT\_TEMP_{it} + \varepsilon_{kijmt} \quad (5)$$

[22] The CAR variables have a mean between 0.29% - 0.31% and a *T-Statistics* ranged from 5.5 to 6.6. Details are in Table 3 Summary Statistics.

Where k indexes the *KD* item, i is firm and j is the industry. Y_{kit} is 100 times the three-day cumulative abnormal returns, *CAR [-1,1]* of item k of firm i in month m in year t; $FWCE_{it-1}$ is the lagged one-year climate exposure of firm *i*; $FIRM\_LT\_TEMP_{it}$ is the long-term temperature at the firm-year level as defined in Section 3.4. I control for firm fixed effects (α_i), three-digit *NAICS* industry × year × month fixed effects (λ_{jt}) and year-month fixed effects γ_{mt}. Standard errors are clustered by firm and year-month. Table A1 in the Appendix presents the definition of all variables.

[Insert Table 7]

I report regression results in Table 7. In Panel A, a disclosure item defined as automation investment-related is required to include both automation keywords and investment keywords at the same time (*AUTO_INV_K >0)*. In Table 7 Panel B, I classify disclosure items based on a cutoff of 3% (*AUTO_INV_K >3)*. The dependent variable in each panel is the three-day *CAR* using the *CAPM* model in columns (1) and (2), *FF* three-factor model in column (3) and (4), and Carhart four-factor model in columns (5) and (6), respectively. Odd columns only include *FWCE* as the independent variables, whereas even columns additionally include the interaction term *FWCE* × *FIRM_LT_TEMP*. As shown by the positive but insignificant coefficients on *FWCE* in columns (1), (3), and (5), disclosure of automation investments has no impact on the valuation of climate-exposed firms, potentially because investors anticipate the labor cost savings resulting from the investment do not justify the investment expenditures.

However, this may not be the case for firms facing negative climate conditions in the long run, when the long-term benefits of their investment can potentially dominate short-term spending. In columns (2), (4), and (6). The coefficients on *FWCE* × *FIRM_LT_TEMP* are 12.6, 13.7 and 12.4, respectively, all significant at 1% level. Take column (4) as an example: holding *FWCE* constant, a one-standard-deviation increase in *FIRM_LT_TEMP* (6.21°F) is associated with 0.85% (0.137×6.21) increases in *CAR* using the FF three-factor model, 2.74 times the sample mean (0.31). These results imply that investors anticipate that automation investments will create more value for climate-exposed firms that experience higher temperatures in the long run.

Similar to the practice in Section 3.3.1, I replace *FIRM_LT_TEMP* with a set of quintile dummies to allow for nonlinear effects of temperatures. The coefficients on the interaction between *FWCE* and each temperature quintile dummy are displayed in Figure 5. I omit the interaction of *FWCE* and the first quintile dummy of temperatures. As such, the coefficients report changes in firm investments in a certain temperature range relative to the lowest temperatures, holding *FWCE* constant.

[Insert Figure 2]

Figure 2 plots the coefficient of the interaction of *FWCE* and long-term temperature quintile dummies in the regression of 100 times *CAR [-1,1]* around the disclosure of automation investments of firms. A *KD* item is classified as disclosure of automation investment if the *AUTO_INV_K* is greater than zero in Panel A and greater than 3% in Panel B, respectively. Figure 3 shows that the relation between temperatures and stock market responses documented in Table 7 is almost linear. Consistent with the relation between long-term temperatures and automation investments in Figure 1, abnormal returns of the disclosure of automation investments increase along with the increases in temperatures in all plots, holding *FWCE* constant.

3.4. Heterogeneity by Financial Constraints

Next, I investigate the *financial constraint hypothesis*. Building on a line of studies that explore how financial constraints and variations in the capital supply adversely affect firms' ability to finance investments (e.g., Fazzari et al., 1988; Blanchard et al., 1997; Kaplan and Zingales, 1997; Rauh, 2006), I predict that the relation between climate-induced labor risk and automation investments is sensitive to firms' financial conditions. In other words, I expect that only financially unconstrained firms can afford costly automation investments as adaptation. To examine this hypothesis, I divide the firm sample into two subsets based on firm financial constraints defined by *KZ-Index* (Kaplan and Zingales, 1997; Lamont et al., 2001), payouts (e.g., Kumar and Vergara-Alert, 2018), and 10-K text-based financial constraints (Hoberg and Maksimovic, 2015).

KZ-Index measures reliance on external financing and a higher score indicates tighter financial conditions (Kaplan and Zingales, 1997; Lamont et al., 2001).[23] I define firms as financially unconstrained if their lagged *KZ-Index* is in the bottom quarter within the same industry-year, while the remaining firms fall into the constrained group. I also group firms into the financially unconstrained subsample if their lagged payouts are greater than zero based on the literature that financial constraints negatively impact the payout policy of firms (e.g., DeAngelo and DeAngelo, 1990; Kumar and Vergara-Alert, 2018). The last financial constraint proxy is developed by Hoberg and Maksimovic (2015) by extracting the *Capitalization and Liquidity Subsection ("CAPLIQ")* of the *MD&A* section from each 10-K. A firm must have a machine-readable *CAPLIQ* to be included in this database. Hoberg and Maksimovic (2015) find that firms without such a machine-readable *CAPLIQ* are generally healthy firms that have few if any liquidity issues to disclose. Based on their findings, I classify firms as financially unconstrained if their lagged text-based financial constraint index is missing. Then I repeat Table 5 and Table 6 in the subsamples accordingly and report results in Table 8.

[Insert Table 8]

The results are displayed in Table 8. Subsamples are defined based on lagged *KZ-Index* in Panel A, lagged payouts in Panel B, and lagged text-based financial constraint index in Panel C, respectively. Column (1)-(2) of each pair shows results estimated based on financially unconstrained firms and column (3)-(4) is based on the financially constrained group. The dependent variable is the firms' automation investment intensity, *AUTO_INV*. The variable of interest is *FWCE* in all odd columns like Table 5 and is *FWCE*× *FIRM_LT_TEMP* in all even columns like Table 6. I include all controls and fixed effects in Equation (3).

I find an insignificant coefficient on *FWCE* in all odd columns in all three panels. That is, the findings in Table 5 indicating a lack of significant correlation between firms' *FWCE* and their automation

[23] Companies with a higher *KZ-Index* scores are more likely to experience difficulties when financial conditions tighten since they may have difficulty financing their ongoing operations.

investments are not conditional on firms' financial constraints. This result is robust to different proxies for financial constraints. The possible explanation suggested by Table 6 is that though firms with greater *FWCE* afford to invest, they may not have the incentives to invest because the benefits gained from labor cost savings do not justify the costs of investing. Consistent with the *cost-benefit hypothesis*, column (2) in each panel presents a positive coefficient on *FWCE× FIRM_LT_TEMP* in the financially unconstrained subsample, suggesting that climate-exposed firms will react to increases in long-term temperatures through more automation if they have the financing ability. In contrast, I fail to find a significant relation between *FWCE× FIRM_LT_TEMP* and *AUTO_INV* in column (4) of Panel A and Panel B. Though the coefficient on *FWCE× FIRM_LT_TEMP* (0.005) is significantly positive in Panel C column (4), the magnitude is 44% smaller than that estimated from financially unconstrained firms as reported in Panel C column (2) (0.009). Taken together, these findings indicate that the relation between the projection of long-term climate-induced labor risk (*FWCE× FIRM_LT_TEMP*) and automation investments is more pronounced in financially unconstrained firms that afford to invest.

Then I explore the nonlinearity by repeating Figure 1 in the subsamples accordingly and plotting the coefficients on the interaction between *FWCE* and each long-term temperature quintile dummy in the regression of *AUTO_INV* in Figure 2. The characteristics used to slice the subsamples are lagged *KZ-Index* in Panel A, lagged payouts in Panel B, and lagged text-based financial constraint index in Panel C, respectively. The first plot in each panel of Figure 2 presents results based on the financially unconstrained group while the second plot is drawn from constrained firms. I omit the interaction of *FWCE* and the first quintile dummy of temperatures, and the interpretation of the results is the change in firm investments in a certain temperature range relative to the lowest temperatures, holding *FWCE* constant.

[Insert Figure 3]

Consistent with the *financial constraint hypothesis* and Table 8, findings documented in the full sample in Figure 1 Plot A only hold in the financially unconstrained subset as described in the first plot of each panel of Figure 3. Holding *FWCE* constant, financially unconstrained firms increase investments in automation along with the increase in long-term temperatures, especially at the higher end. Plots A.2, B.2 and C.2. indicate that there is an insignificant relation between the projection of climate-induced labor risk and automation investments in financially constrained firms. These results suggest that only financially unconstrained firms can afford to invest in automation and are also consistent with findings in Xiao (2023) that the availability of cost-effective labor encourages firms to prioritize labor over capital when making adaptation decisions.

3.5. Event Study of the California Heat Illness Prevention Standard in 2005

3.5.1. Background

In previous sections, I aimed to make causal inferences using climate events as exogenous shocks to labor and firms. Meanwhile, climate policies may increase the compliance costs that motivate firms to adapt, and thus, provide additional evidence for causality. In the U.S., there are no Federal regulations concerning labor protection against climate-related hazards. However, in 2005, California imposed the first mandatory heat illness prevention standard. The California Heat Illness Prevention Standard (*CA Standard*) requires employers to make investments to reduce heat-related safety risks for outdoor workplaces, for example, by providing shade structures and paid rest breaks every hour.[24] *CA Standard* was filed on August 8th, 2005 as an emergency measure implemented within 17 days and was initially effective for 180 days, and subsequently passed by the State Assembly on July 7th, 2006.[25]

Since firms with more climate-exposed workers also face greater heat stress, they have to bear incremental costs to comply with this standard. For example, Xiao (2023) finds that *CA Standard* provides better protection to climate-exposed workers by hiring more to supplement their labor force. Alternatively, climate-exposed firms can also resort to automation to substitute riskier (more climate-exposed) workers. Moreover, this regulatory climate shock provides a clean natural experiment because the *CA Standard* was

[24] Additional details regarding the policy can be found in Appendix B of the Xiao (2023) paper.
[25] Emergency measure in California can be filed in "a situation that calls for immediate action to avoid serious harm to the public peace, health, safety, or general welfare." As soon as it is filed, it is effective for 180 days and can be readopted for two 90-day periods.

put into effect as an emergency measure and, therefore, pre-emptive investments by firms are unlikely to happen.

3.5.2. Real Impacts on Firms' Automation Investments

I employ a transformed "difference-in-differences" methodology using a subsample of firm-year observations over the period 2003-2007 to examine the impact of *CA Standard* on firms' investments in automation. The treated group includes firms with greater *FWCE*. The post period is not a dummy but a continuous variable, *AFF_EMP (%)*, which quantifies the extent to which the firms' employees are potentially affected by the shock. Specifically, it is defined as zero before 2005 and equals the percentage of the firm's employment in California after 2005. I then expand Equation (3) by adding an interaction of the *FWCE* and *AFF_EMP* and estimate the panel regressions of the following form:

$$AUTO_{INV}{}_{it} = \alpha_i + \lambda_{jt} + \beta X_{it-1} + \theta FWCE_{it-1} + \eta FWCE_{it-1} \times AFF\_EMP_{it}$$

$$+\mu AFF\_EMP_{it} + \varepsilon_{ijt} \qquad (6)$$

Wherein i is firm i and j is the three-digit *NAICS* industry that firm i belongs to. $AUTO\_INV_{it}$ denotes the intensity of automation investments of firm i in year t; X_{it-1} is a set of lagged firm-level controls; $FWCE_{it-1}$ is the lagged workforce climate exposure firm i and AFF_EMP_{it} is the percentage of California employees of firm i who are affected by the policy in year t . All models include firm attributes controlled in Equation (3), firm fixed effects α_i and industry × year fixed effects λ_{jt}. Standard errors are clustered by firm.

[Insert Table 9]

I present regression results in Table 9 where the dependent variables in column (1)–(4) are various textual-based proxies for automation investments defined in Section 2.1. Specifically, The dependent variable in columns (1) - (4) is a set of textual-based proxies for firms' automation investment including the main proxy for automation investment intensity (*AUTO_INV*) in column (1) and three alternative proxies including the percentage of the disclosure of automation investments (*AUTO_NEWS)* in column

(2), an automation investment indicator (D_{AUTO}) in column (3), and the investment intensity of climate-related automation ($AUTO\_INV\_CLIMATE$) in column (4). As a comparison, I also include 100 times *CAPEX* as the dependent variable in column (5) and 100 times *CAPEX Automation-Unrelated* in column (6), separately. The variable of interest is the interaction item, $FWCE_{it-1} \times AFF\_EMP_{it}$, which captures changes in automation investment of climate-exposed firms when facing increasing regulatory compliance costs. The definition of all variables is described in Table A1 in the Appendix.

I find a positive coefficient on $FWCE_{it-1} \times AFF\_EMP_{it}$ in column (1)-(4), all significant at the 5% level except for column (2) which is significant at the 10% level. This indicates increases in either *FWCE* or AFF_EMP_{it} will lead to increases in firms' investment in automation. Take the coefficient of 0.003 in column (1) as an example: holding $FWCE$ constant, a one standard deviation increase in AFF_EMP (25%) causes 0.075 increases in *AUTO_INV*, equivalent to 14.4% of the average value of *AUTO_INV* (0.52). These findings support the hypothesis that climate-exposed firms invest more in automation in response to increased labor costs resulting from regulatory climate shocks. Meanwhile, they provide causal inferences of the impact of climate-induced labor risk on automation investments. I continue not to find a significant coefficient in the *CAPEX* regression, all expenditures and those unrelated to automation (the residual calculated by regressing *CAPEX* on *AUTO_INV*) in column (5) and (6), respectively, implying that there is an essential difference between capital and automation investments.

4. Climate-Induced Labor Risk, Automation Investments and Firm Operations

4.1. Investment Adaptation vs. Labor Adaptation

In Section 3, I provide evidence that climate-exposed firms treat automation investments as a selective and costly adaptation strategy. Xiao (2023) finds that, in general, firms react to climate-induced labor risk through labor adaptation such as additional hiring, greater employee insurance expenditures and more offshore input. Thus, it is natural to explore the relationship between labor adaptation and investment adaptation. I divide firms into two groups based on firms' automation investments (*AUTO_INV*) in the previous year and compare the differences in their labor adaptation policies including employment, employee insurance and offshore input. Firms belong to the *INV_HIGH* group if the lagged *AUTO_INV* is above zero, while the remaining firms fall into the *INV_LOW* group. I estimate the panel regressions of the following form:

$$Y_{it} = \alpha_i + \lambda_{jt} + \beta X_{it-1} + \theta FWCE_{it-1} + \eta FWCE_{it-1} \times FIRM\_LT\_TEMP_{it}$$
$$+\mu FIRM\_LT\_TEMP_{it} + \varepsilon_{ijt} \quad (7)$$

Wherein i is firm i and j is the three-digit *NAICS* industry of firm i. Y_{it} denotes labor adaptation outcomes including 100 times the natural logarithm of employment and the employee health and life insurance of firm i in year t, and offshore external input at the firm-country-year level provided by Hoberg and Moon (2017); X_{it-1} is a set of lagged firm-level controls; $FWCE_{it-1}$ is the lagged workforce climate exposure firm i. Following Chen, Harford and Kamara (2019), I control for the natural logarithm of sales in 2018 dollars, Tobin's Q, cash holdings assets, R&D expenses scaled by assets, capital expenditure scaled by lagged assets, market leverage and cash flow volatility, net working capital scaled by assets in all regressions. Additional controls include the natural logarithm of assets per employee and the natural logarithm of sales per employee in the employment regressions in the spirit of Chen et al. (2011) and the natural logarithm of employment in the regression of offshore input. All models include firm fixed effects α_i and industry × year fixed effects λ_{jt}. I additionally control for foreign country × year fixed effects in the regression of offshore input and standard errors clustered by firm and foreign country. Standard errors in all other regressions clustered by firm. Table A1 in Appendix presents the definition of all variables.

[Insert Table 10]

The regression results are presented in Table 10. The dependent variable is 100 times the following variables including the natural logarithm of firm employment in column (1)-(3), the natural logarithm of employee insurance per person in column (4)-(6), and offshore external output in column (7)-(9), respectively. The variable of interest is *FWCE*× *FIRM_LT_TEMP* which measures firms' projection of climate-induced labor risk. The first column in each pair presents regression results based on the full sample while the second and third columns report coefficients based on the *INV_LOW* group and the *INV_HIGH* group, respectively.

I find significantly positive coefficients on *FWCE*× *FIRM_LT_TEMP* in column (1), (3) and (7), consistent with Xiao (2023) that firms resort to labor adaptation in response to their projected labor risk related to climate. Column (2), (5) and (8) report results estimated from the *INV_LOW* group without adopting automation. Similar to the full-sample regression results, I find that increases in *FWCE*× *FIRM_LT_TEMP* are associated with significantly more employee insurance expenditures and offshore input purchases. However, the insignificant coefficients on *FWCE*× *FIRM_LT_TEMP* in column (3), (6) and (9) show different patterns in the subsample of firms that have ex-ante invested in automation. These firms do not take labor adaptation actions, partially because their automation adoption has satisfied the adaptation demand. Notably, though the magnitude of the coefficient column (2) (*INV_LOW* subsample) is 38% larger than that in column (3), both coefficients are positive but insignificant in the employment regressions. The muted employment adaptation may be a result of the nonlinear impact of climate-induced labor risk on employment. Thus, similar to Section 3.3, I replace *FIRM_LT_TEMP* with a set of quantile dummies and display the coefficients of the interaction between *FWCE* and each long-term temperature quintile dummy in Figure 4. The dependent variable is 100 times the natural logarithm of employment in Panel A, 100 times the natural logarithm of employee insurance per participant in Panel B and 100 times offshore external input in Panel C, respectively. The first plot in each panel presents regression results based on the full sample while the second and third plots report coefficients based on the *INV_LOW* group and the *INV_HIGH* group, respectively.

[Insert Figure 4]

The first plot of each panel replicates the full-sample results reported in Table 9: holding *FWCE* constant, firms increase employment and employee insurance premiums per participant along with the increase in temperatures, especially at the higher end. Interestingly, Plot A.1 shows an asymmetric U-shape: firms also increase employment in responses to extremely cold weather, although the magnitude is much smaller than that of extremely hot weather. In contrast, the relation is inversed U-shaped regarding offshore input as shown by. Specifically, firms increase the purchases of offshore input significantly at the temperature quintile 3 and 4, holding *FWCE* constant. These two figures suggest that firms' choice of different adaptation strategies also depends on their projection of long-term temperatures. Plot B.1 displays a positive relation between temperatures and employee insurance expenditures, especially at temperatures quantile 4 and 5. A possible reason why employee health insurance is irresponsive to cold weather is that compared to heat stress, cold weather has smaller effects on health (Park et al., 2021) and mortalities (Deschênes and Greenstone, 2011). Accordingly, *OSHA* monitors employers and establishes guidance or regulations only regarding heat stress in the workplace.[26] Therefore, the incremental labor costs such as health insurance, injury compensation, and regulatory compliance costs should be higher in hot weather than in old weather, increasing the need for investment adaptation among firms operating in hot areas.

The second plot in each panel of Figure 4 is based on the *INV_LOW* group and they show a similar pattern to the full sample results. Plot A.2 and C.3 show that firms have to hire additional employees to supplement the labor force when experiencing extremely high (quintile 5) and low temperatures (quintile 1), while they purchase more input overseas in mild to hot weather (quintile 3 and 4). Plot B.2 reports a positive relation between employee insurance and temperatures. Moving from temperature quintile 1 to quintile 5 will increase the employee insurance per person by 57.8%, holding the *FWCE* constant. However, this is not the case in *INV_HIGH* firms. In the third plot of each panel, I find little response of employment, employee insurance and offshore input to temperatures in firms that have invested in automation, suggesting their automation investments have satisfied their adaptation demand and reduced incentives to take labor adaptation actions. Taken together, these results imply that labor adaptation and investment adaptation can act as substitutes for adapting to climate-induced labor risk.

[26] https://www.*OSHA*.gov/heat-exposure/standards. Accessed in July, 2022.

4.2. Reacting to Short-term Climate Surprises

Another question is whether climate-exposed firms are better off through investment adaptation. Studying the effectiveness of automation adaptation has implications for firms' incentives for adaptation. The *cost-benefit* hypothesis indicates that firms' incentive to invest in automation is influenced by the benefits of automation adaptation. Therefore, if automation can effectively mitigate the negative impact of climate surprises to some extent, firms will have greater incentives to take adaptation actions because they can gain competitive advantages relative to peers that do not or cannot adapt. Earlier studies document that climate surprises are hard to predict and can disrupt firms' operating performance (Kahn, 2016; Xiao, 2023). To examine the effectiveness of automation in dealing with these most challenging climate conditions, I explore heterogeneity in firms' performance under climate surprises by their intensity in automation adaptation. Specifically, I re-estimate Equation (7) in which the dependent variable is either firm operating outcomes including *ROA,* or the number of workplace injuries related to weather or natural disasters reported by this firm in a given year. I replace *FIRM_LT_TEMP* in Equation (7) with *FIRM_AB_TEMP*, a measure of the firm-level abnormal temperatures as described in Section 3.1. Following Caskey and Ozel (2017), I estimate a Poisson regression with year fixed effects to count the number of environment-related workplace injuries reported to *OSHA* from 2002-2011 and use the OLS fixed effects model in the regression of *ROA* from 2000-2018. I control for firm attributes in all regressions, including the natural logarithm of sales in 2018 dollars, Tobin's Q, cash holdings assets, R&D expenses scaled by assets, capital expenditure scaled by lagged assets, market leverage and cash flow volatility, net working capital scaled by assets in all regressions. Three-digit *NAICS* industry by year and firm fixed effects are included in the *OLS* regressions of *ROA*. I additionally control for the natural logarithm of the employee over assets and employment in the regression of workplace injuries. Standard errors are clustered by firm.

[Insert Table 11]

I report the regression results in Table 11. The dependent variable is the number of environment-related workplace injuries in column (1)-(3) and is 100 times *ROA* in column (4)-(6), respectively. The variable of interest is *FWCE*× *FIRM_AB_TEMP* which measures the level of short-term labor disruptions induced by abnormal temperatures. The first column in each pair presents regression results based on the full sample while the second and third columns report coefficients based on the *INV_LOW* group and the *INV_HIGH* group, respectively.

The first column of each pair replicates findings in Xiao (2023) that *FIRM_AB_TEMP* magnifies losses of climate-exposed firms. Holding *FWCE* constant, a one-standard-deviation increase in *FIRM_AB_TEMP* (1.56°F) lead to a 0.69 (0.442×1.56) increase in the number of environment-related injuries, 2.7 times the sample mean (0.26). Meanwhile, it decreases *ROA* by 0.4% (0.259%×1.47), 37% of the sample mean (1.08). I find similar patterns in column (2) and (5) based on the *INV_HIGH* subsample, suggesting that temperature surprises disrupt the operation of climate-exposed firms that do not invest in automation adaptation. Column (3) and (6) present regression results estimated from the firms with ex-ante automation investments. The insignificant coefficient on *FWCE*× *FIRM_AB_TEMP* in column (6) indicates that climate surprises have no impact on the operating performance of these firms. Column (3) shows a positive coefficient on *FWCE*× *FIRM_AB_TEMP* (0.779) based on the *INV_HIGH* subset and the magnitude is larger than that in column (2) (0.348). That is, holding *FWCE* constant, any identical increase in *FIRM_AB_TEMP* leads to more workplace injuries in the *INV_HIGH* group than in the *INV_LOW* group. This result seems to contradict the prediction that automation should protect firms from climate surprises. There are two potential explanations. First, the coefficient on *FWCE* is 0.448 (insignificant) in column (3) and 1.847 (significant at 1% level) in column (2). Given the average *FIRM_AB_TEMP* (0.304), an average firm with automation sees 0.68 (0.779*0.304+0.448) injuries, while that number is 1.96 in the *INV_LOW* sample. That is, compared to automation adopters, climate-exposed firms without automation see more injuries unconditionally. Second, temperature shocks may have a nonlinear impact on injuries among firms with and without automation adaptation. To explore the nonlinearity, I replace *FIRM_AB_TEMP* in Table 11 with a set of quintile dummies based on *FIRM_AB_TEMP* as described in Section 3.1.

[Insert Figure 5]

Coefficients on the interaction between *FWCE* and each abnormal temperature quintile dummy are displayed in Figure 5. Panel A repeats the regressions in Table 11 column (1)-(3) while Panel B replicates Table 11 column (4)-(6). The first plot in each panel presents regression results based on the full sample while the second and third plots display coefficients based on a subset of firms with low automation investments (*INV_LOW*) and with high automation investments (*INV_HIGH*), respectively. The definition of the *INV_LOW* and the *INV_HIGH* firms are described in Section 4.1.

Plot A.1 and B.1 of Figure 5 also replicate findings in Xiao (2023) and show that holding *FWCE* constant, the number of workplace injuries increases while the *ROA* decreases linearly with the increases in abnormal temperatures, especially at the high-temperature spectrum. Plot A.2 and B.2 in Figure 5 present similar patterns found in the *INV_LOW* firms: Holding the *FWCE* constant, moving from temperature quintile 1 to quintile 5 will decrease *ROA* by 3% and increase the number of workplace safety incidents by 0.3, comparable to the mean of the workplace safety incidents (0.26). I fail to find the impact of temperature surprises on operating outcomes in firms adopting automation ex-ante (Plot A.3 and B.3), suggesting investment adaptation works effectively in hedging against climate-induced labor risk in firm operation. Additionally, Plot A.3 indicates that the significantly positive coefficient on *FWCE*× *FIRM_AB_TEMP* reported in Table 11 column (3) is a result of non-linearity, as the number of injuries increases the most when moving from temperature quintile 1 to quintile 2 in the *INV_HIGH* group.

Taking Section 3 and 4 together, I provide evidence of the effectiveness and limitations of automation adaptation. Compared to labor adaptation, automation adaptation is more selective and only works for a subsample of firms because of the scale of investment expenditures and firms' financial constraints. However, it effectively helps firms hedge again climate surprises and protects firm performance. These findings have implications for the optimization of firms' climate adaptation plans.

Conclusion

This paper aims to further the understanding of firms' adaptation strategies to climate by exploring how firms respond to climate-induced labor risk through automation investments. Using textual analysis, I quantify the intensity of automation investments at the firm level based on firms' material news and events for the first time. I validate this textual-based measure of automation investment intensity using industry-level robot shipments provided by the *IFR* and firm-level capital expenditures. Built on this text-based proxy for automation investments, I document that firms with greater *FWCE* invest more in automation in two scenarios. First, I find climate-exposed firms have incentives to react to adverse long-term climate trends through automation, as the long-term benefits (labor costs saving) dominate short-term investment expenditures (NPV is positive). A stock market analysis supports this *cost-benefit hypothesis* underneath firms' adaptation strategies. I document that the three-day *CAR* upon the automation news of climate-exposed firms increases along with the long-term temperatures. That is, investors anticipate automation investments will generate greater value for a subset of climate-exposed firms that face high temperatures and consequently higher labor costs in the future. Second, I find the interactive effect of *FWCE* and *FIRM_LT_TEMP* on automation investments only in the subsample of financially unconstrained firms, consistent with the *financial constraints hypothesis* that financially constrained firms lack the capacity for automation adaptation. Further, I conduct an event study on the implementation of the 2005 California Heat Illness Prevention Standard. I show that when labor costs increase as a result of exogenous regulatory climate shocks, climate-exposed firms resort to more automation investments, providing causal inferences about the impact of climate-induced labor risk on firms' automation adaptation decisions.

Next, I investigate how the automation adaptation interacts with labor adaptation like employment, insurance and offshoring buffers documented in Xiao (2023). I divide firms into two subsamples based on their lagged intensity of automation investments and compare their labor adaptation actions. I find some evidence of the substitution relation between labor adaptation and automation adaptation. Employment, employee insurance expenditures and offshore input in firms without ex-ante automation adoption respond to changes in labor risks caused by climate while there are no such patterns in firms that already adopt automation.

Lastly, I explore the effectiveness of automation investments regarding climate adaptation. By comparing different aspects of firm performance, proxied by workplace injuries and *ROA*, of firms with different automation investment intensities, I find evidence that automation investments effectively help mitigate climate-induced labor risk, Holding *FWCE* constant, firms with more automation investments suffer fewer workplace safety incidents and enjoy better *ROA* when experiencing abnormal temperatures. The findings suggest that automation investments help firms cope with adaptation challenges created by climate surprises and effectively reduce climate-induced labor risk. Furthermore, these results provide insight into the motivations behind firms' decisions to implement automation adaptation.

To conclude, this paper shows that automation investments are a selective and costly adaptation strategy that can substitute for labor adaptation to some extent and effectively help firms mitigate climate-induced labor risk. This paper adds to the literature on climate and labor finance by exploring the limitation and effectiveness of automation adaptation and highlighting the importance of access to capital in helping firms adapt. It also contributes to the literature on corporate investments by first quantifying automation investments at the firm level and demonstrating that climate-induced labor risk impacts firms' automation investments. Finally, the study provides policy implications by shedding light on the adaptation strategies that can significantly alleviate economic damages associated with climate change in the corporate sector.

References

Acemoglu, D., and P. Restrepo. 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108: 1488-542.

———. 2020. Robots and jobs: Evidence from us labor markets. *Journal of Political* Economy 128: 2188-244.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea. 2020. Temperature shocks and establishment sales. *Review of Financial Studies* 33: 1331-66.

Agrawal, A. K., and D. A. Matsa. 2013. Labor unemployment risk and corporate financing decisions. *Journal of Financial Economics* 108: 449-70.

Almeida, H., R. Huang, P. Liu, and Y. Xuan. 2019. The impact of Obamacare on firm employment and performance. SSRN Working Paper No. 3073378.

Autor, David H. 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics* 21: 1-42.

Autor, D. H., F. Levy, and R. J. Murnane. 2003. The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118: 1279-333.

Bai, J., D. Fairhurst, and M. Serfling. 2020. Employment protection, investment, and firm growth. *Review of Financial Studies* 33: 644-88.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro. 2016. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy* 124: 105-59.

Bartram, S. M., K. Hou, and S. Kim. 2022. Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics* 143: 668-96.

Bena, J., and E. Simintzi. 2015. Labor-induced technical change: Evidence from doing business in China. SSRN Working Paper 2613248.

Benmelech, E., and M. Zator. 2022. Robots and firm investment. NBER Working Papers 29676.

Berk, J. B., R. Stanton, and J. Zechner. 2010. Human capital, bankruptcy, and capital structure. *Journal of Finance* 65: 891-926.

Blanchard, O. J., W. D. Nordhaus, and E. S. Phelps. 1997. The medium run. *Brookings Papers on Economic Activity* 1997.

Caballero, R. J., and M. L. Hammour. 1998. Jobless growth: Appropriability, factor substitution, and unemployment. *Carnegie-Rochester Conference Series on Public Policy* 48: 51-94.

The Intergovernmental Panel on Climate Change [PICC]. 2014. Climate change 2014: Synthesis report. Contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change.

Chen, H. J., M. Kacperczyk, and H. Ortiz-Molina. 2010. Labor unions, operating flexibility, and the cost of equity. *Journal of Financial and Quantitative Analysis* 46: 25-58.

Chen, Z., J. Harford, and A. Kamara. 2018. Operating leverage, profitability, and capital structure. *Journal of Financial and Quantitative Analysis* 54: 369-92.

Choi, D., W. Jiang and Z. Gao. 2020. Attention to global warming. *Review of Financial Studies* 33: 1112-45.

DeAngelo, H., and L. DeAngelo. 1990. Dividend policy and financial distress: An empirical investigation of troubled NYSE firms. *Journal of Finance* 45: 1415-31.

Deryugina, T., and S. Hsiang. 2014. Does the environment still matter? Daily temperature and income in the United States. NBER Working Paper No. 20750.

Deschênes, O., and M. Greenstone. 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics* 3: 152-85.

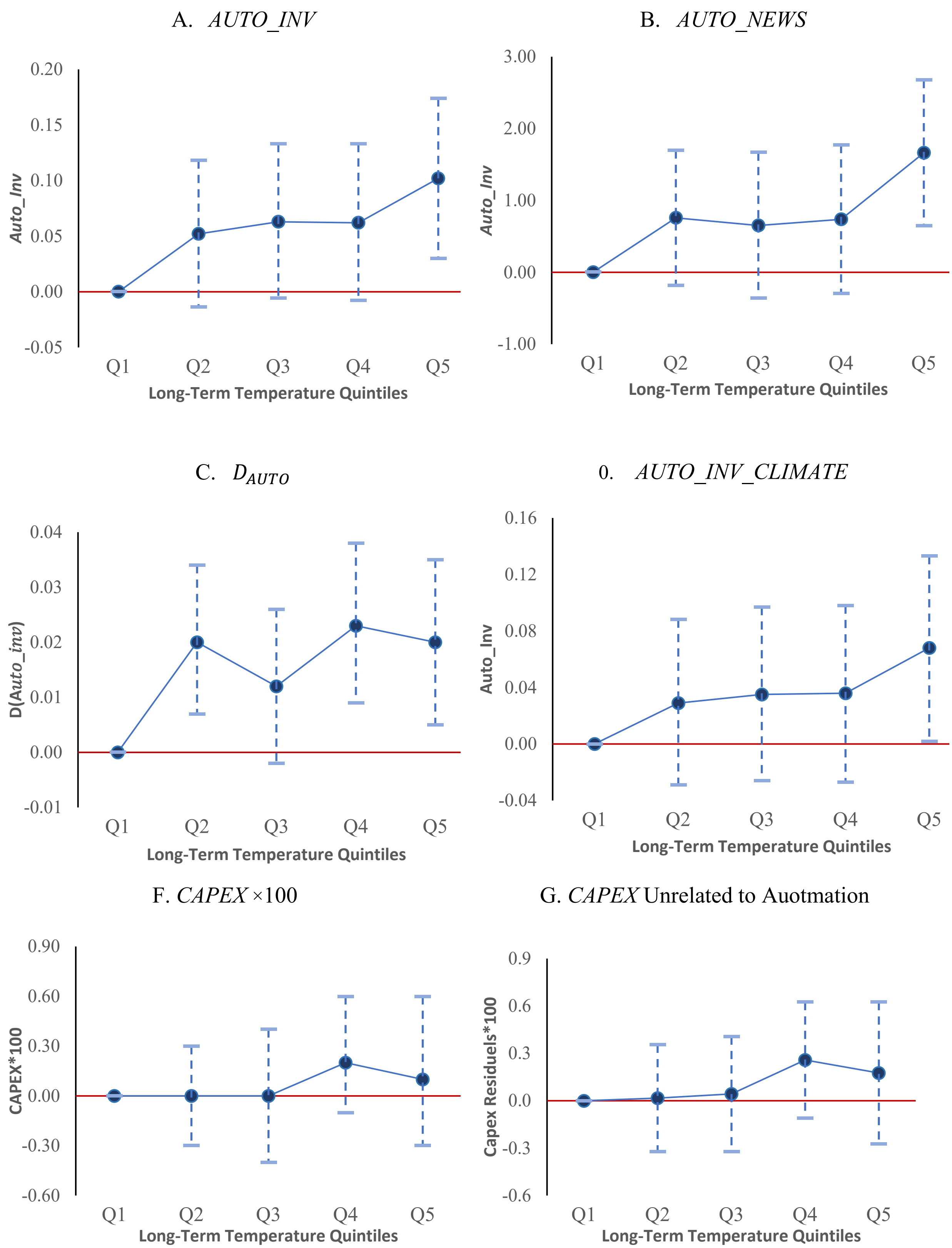
Dillender, M. 2019. Climate change and occupational health: Are there limits to our ability to adapt? *Journal of Human Resources* 56: 184-224.

Donangelo, A. 2014. Labor mobility: Implications for asset pricing. *Journal of Finance* 69: 1321-46.

Donangelo, A., F. Gourio, M. Kehrig, and M. Palacios. 2019. The cross-section of labor leverage and equity returns. *Journal of Financial Economics* 132: 497-518.
Ellul, A., and M. Pagano. 2019. Corporate leverage and employees' rights in bankruptcy. *Journal of Financial Economics* 133: 685-707.
Fazzari, S. M., R. G. Hubbard, and B. C. Petersen. 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity* 1988.
Ghaly, M., V. Anh Dang, and K. Stathopoulos. 2017. Cash holdings and labor heterogeneity: The role of skilled labor. *Review of Financial Studies* 30: 3636-68.
Graetz, G., and G. Michaels. 2018. Robots at work. *Review of Economics and Statistics* 100: 753-68.
Graff Zivin, J., and M. Neidell. 2014. Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics* 32: 1-26.
Gustafson, M., and J. D. Kotter. 2017. Higher minimum wages reduce capital expenditures. SSRN Working Paper 2914598.
Harris, Z. S. 1954. Distributional structure. *Word* 10: 146-62.
Hassan, T. A., S. Hollander, L. van Lent, M. Schwedeler, and A. Tahoun. 2020. Firm-level exposure to epidemic diseases: Covid-19, SASR, and H1N1. NBER Working Paper 26971.
Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun. 2020. The global impact of Brexit uncertainty. NBER Working Paper 26609.
Heutel, G., N. H. Miller, and D. Molitor. 2021. Adaptation and the mortality effects of temperature across U.S. climate regions. *Review of Economics and Statistics* 103: 740-53.
Hoberg, G., and V. Maksimovic. 2015. Redefining financial constraints: A text-based analysis. *Review of Financial Studies* 28: 1312-52.
Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. J. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larsen, and T. Houser. 2017. Estimating economic damage from climate change in the United States. *Science* 356: 1362-69.
Jones, C. I. 2005. The shape of production functions and the direction of technical change. *Quarterly Journal of Economics* 120: 517-49.
Kahn, M. E. 2016. The climate change adaptation literature. *Review of Environmental Economics and Policy* 10: 166-78.
Kaplan, S. N., and L. Zingales. 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112: 169-215.
Karabarbounis, L., and B. Neiman. 2014. The global decline of the labor share. *Quarterly Journal of Economics* 129: 61-103.
Kim, H. 2020. How does labor market size affect firm capital structure? Evidence from large plant openings. *Journal of Financial Economics* 138: 277-94.
Kini, O., M. Shen, J. Shenoy, and V. Subramaniam. 2022. Labor unions and product quality failures. *Management Science* 68: 5403-40.
Koeniger, W., and M. Leonardi. 2007. Capital deepening and wage differentials: Germany versus us. *Economic Policy* 22: 72-116.
Kumar, A., and C. Vergara-Alert. 2018. The effect of financial flexibility on payout policy. *Journal of Financial and Quantitative Analysis* 55: 263-89.
Lamont, O., C. Polk, and J. Saaá-Requejo. 2001. Financial constraints and stock returns. *Review of Financial Studies* 14: 529-54.
Lemmon, M., and M. R. Roberts. 2010. The response of corporate financing and investment to changes in the supply of credit. *Journal of Financial and Quantitative Analysis* 45: 555-87.
Li, F. W., Y. Lin, Z. Jin, and Z. Zhang. 2020. Do firms adapt to climate change? Evidence from establishment-level data. SSRN Working Paper 3573260.
Li, Q., H. Shan, Y. Tang, and V. Yao. 2020. Corporate climate risk: Measurements and responses. SSRN Working Paper 3508497.
Lin, C., T. Schmid, and M. Weisbach. 2019. Climate change, operating flexibility and corporate investment decisions. NBER Working Paper 26441.

Loughran, T. I. M., and B. McDonald. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-ks. *Journal of Finance* 66: 35-65.
Ma, W., P. P. Ouimet, and E. Simintzi. 2016. Mergers and acquisitions, technological change and inequality. European Corporate Governance Institute (ECGI) - Finance Working Paper 485.
Matsa, D. A. 2010. Capital structure as a strategic variable: Evidence from collective bargaining. *Journal of Finance* 65: 1197-232.
Mueller, H. M., P. P. Ouimet, and E. Simintzi. 2017. Wage inequality and firm growth. *American Economic Review* 107: 379-83.
Ouimet, P., E. Simintzi, and K. Ye. 2019. The impact of the opioid crisis on firm value and investment. SSRN Working Paper 3338083.
Ouimet, P., and R. Zarutskie. 2020. Acquiring labor. *Quarterly Journal of Finance* 10: 1-38.
Pankratz, N. M. C., R. Bauer, and J. Derwall. 2019. Climate change, firm performance, and investor surprises. SSRN Working Paper No. 3443146.
Pankratz, N. M. C., and C. Schiller. 2019. Climate change and adaptation in global supply-chain networks. SSRN Working Paper No.3475416.
Park, J. 2022. Essays on it and platform governance from external stakeholder perspectives. Georgia State University Working Paper.
Park, R. J., N. Pankratz, and A. Behrer. 2021. Temperature, workplace safety, and labor market inequality. IZA Discussion Paper 14560.
Pennington, J., R. Socher, and C. D. Manning. 2014. Glove: Global vectors for word representation. *In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)* 1532–43.
Rauh, J. D. 2006. Investment and financing constraints: Evidence from the funding of corporate pension plans. *Journal of Finance* 61: 33-71.
Sabherwal, R., S. Sabherwal, T. Havaknor, and Z. Steelman. 2019. How does strategic alignment affect firm performance? The roles of information technology investment and environmental uncertainty. *MIS Quarterly* 43: 453-74.
Sautner, Z., L. V. Lent, G. Vilkov, and R. Zhang. 2023. Firm-level climate change exposure. *Journal of Finance* 686.
Serfling, M. 2016. Firing costs and capital structure decisions. *Journal of Finance* 71: 2239-86.
Shen, M. 2021. Skilled labor mobility and firm value: Evidence from green card allocations. *Review of Financial Studies* 34: 4663-700.
Simintzi, E., V. Vig, and P. Volpin. 2015. Labor protection and leverage. *Review of Financial Studies* 28: 561-91.
Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari. 2021. The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy* 129: 1797-827.
Tate, G. A., and L. Yang. 2015. The human factor in acquisitions: Cross-industry labor mobility and corporate diversification. US Census Bureau Center for Economic Studies Paper No. CES-WP-11-32.
Tong, T. 2020. Health care costs and corporate investment. SSRN Working Paper 3709588.
Webb, M. 2019. The impact of artificial intelligence on the labor market. SSRN Working Paper 3482150.
Xiao, R. J. 2023. Climate-induced labor risk: Labor market consequences, firm labor adaptation strategies, and firm performance. SSRN Working Paper 4158038.
Xiao, Z. 2022. Labor exposure to climate change and capital deepening. University of British Columbia Working Paper.

Figure 1: Workforce Climate Exposure, Long-term Temperatures and Automation Investments

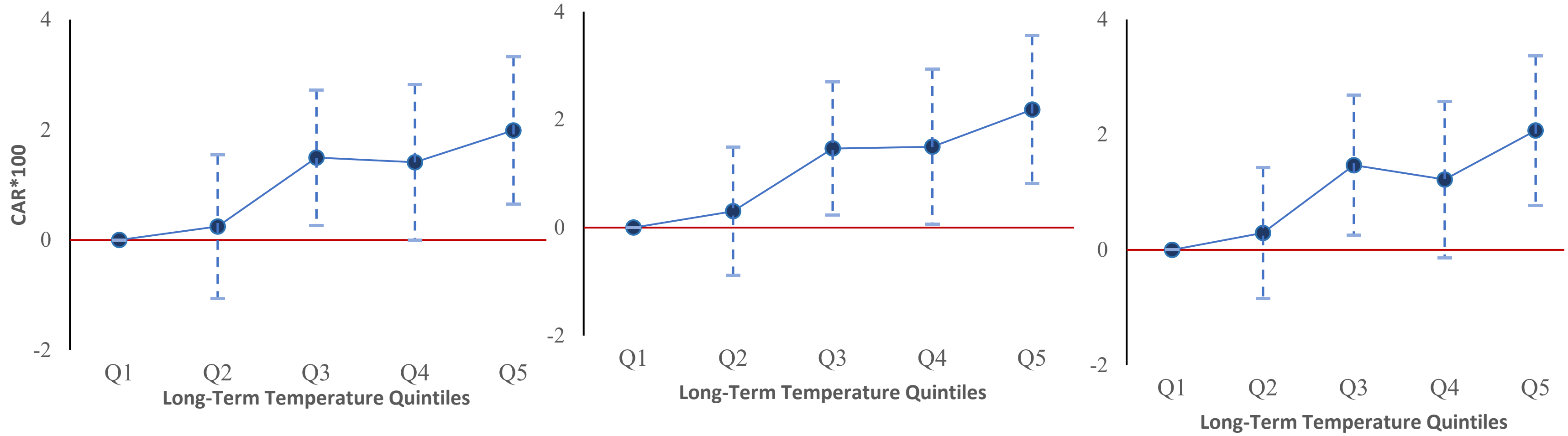


Note: This figure displays coefficients on firms' workforce climate exposure and a set of quantile indicators of long-term temperatures estimated from Equation (4). The tests are based on firm-year observations in 2000-2018 and the dependent variable used in each plot is specified in the title. In Plot A-D, the dependent variable is various textual-based proxies for automation investments constructed by the author including the percentage of automation keywords in an investment-related *KD* item averaged across all *KD* items in a firm-year ($AUTO\_INV$), the percentage of a firm's disclosure of automation investments item out of the annual total while the cutoff used to classify the automation investments item is 3% ($AUTO\_NEWS$), a firms' automation investment indicator (D_{AUTO}) which equals one if $AUTO\_INV$ is greater than 3% and zero otherwise, and the percentage of automation keywords in a climate-related *KD* item averaged across all *KD* items in a firm-year ($AUTO\_INV\_CLIMATE$), respectively. The dependent variable is 100 times *CAPEX (*capital expenditure scaled by assets) in Plot E and 100 times the residual generated by regressing *CAPEX* on *AUTO_INV* in Plot G. The firm-level workforce climate exposure (*FWCE*) is defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. The omitted indicator is the interaction of *FWCE* and the temperature indicator which equals one if *FIRM_LT_TEMP* is in the bottom quintile and zero otherwise. The models include all control variables used in Table 4, firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Bars denote 95% confidence intervals.

Figure 2: Stock Market Responses to the Firm Disclosure of Automation Investments

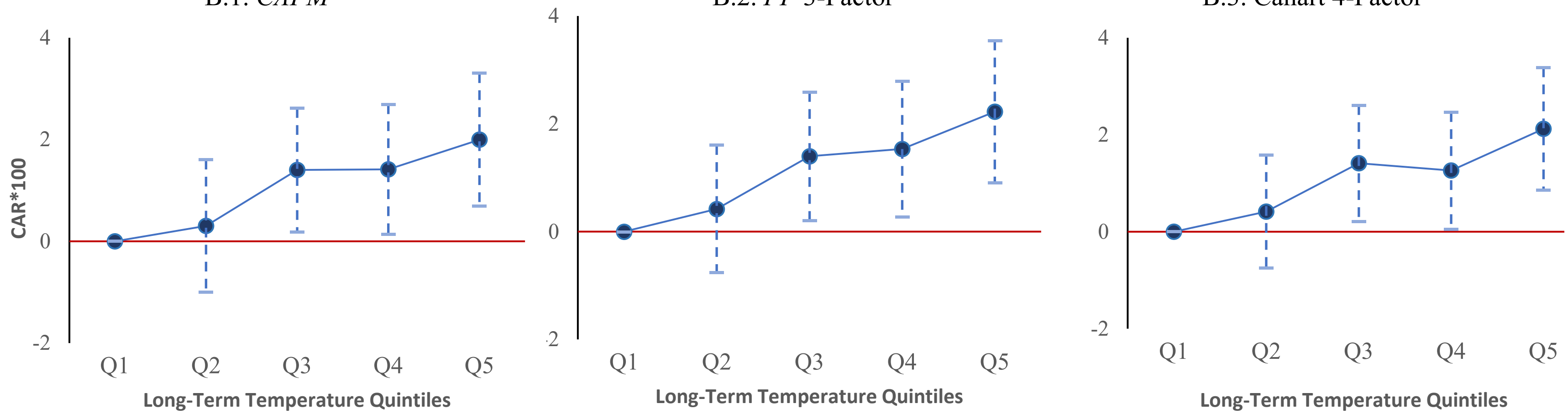
Panel A: *CAR* [-1,1] to Automation Investments Disclosure (*AUTO_INV_K >0*)

A.1. *CAPM* A.2. *FF* 3-Factor A.3. Carhart 4-Factor



Panel B: *CAR* [-1,1] to Automation Investments Disclosure (*AUTO_INV_K >3*)

B.1. *CAPM* B.2. *FF* 3-Factor B.3. Cahart 4-Factor

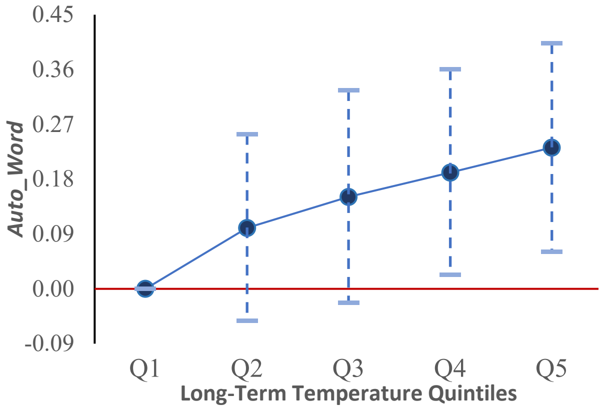


Note: This figure displays coefficients from the regression of stock market responses on the interaction of long-term temperature quintile dummies and firm climate exposure based on Equation (5). The dependent variables are the three-day accumulative returns around the date of firms' disclosure of automation investments adjusted by *CAPM*, or by Fama-French 3-factor model, or by Cahart 4-factor model, as specified by the title of each plot. A disclosure item is defined as automation investment-related if its automation investment intensity (*AUTO_INV_K*) is greater than zero in Panel A and greater than 3% in Panel B, respectively. Automation investment intensity (*AUTO_INV*) of a disclosure item is described in Section 2.1. The firm-level workforce climate exposure (*FWCE*) is defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. The omitted indicator is the interaction of *FWCE* and the temperature indicator which equals one if *FIRM_LT_TEMP* is in the bottom quintile and zero otherwise. The models include firm fixed effects and three-digit *NAICS* industry by year fixed effects. All the variables are described in Table A1 in Appendix. Bars denote 95% confidence intervals.

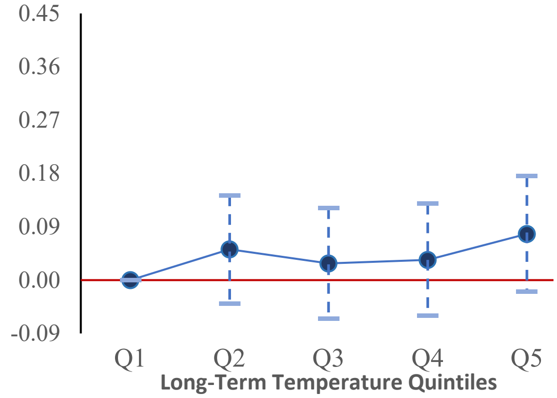
Figure 3: Heterogeneity by Financial Constraints

Panel A: BY KZ Index

A.1. Unconstrained

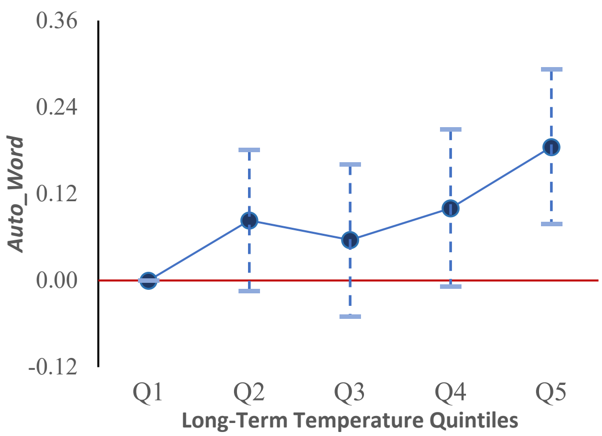


A.2. Constrained

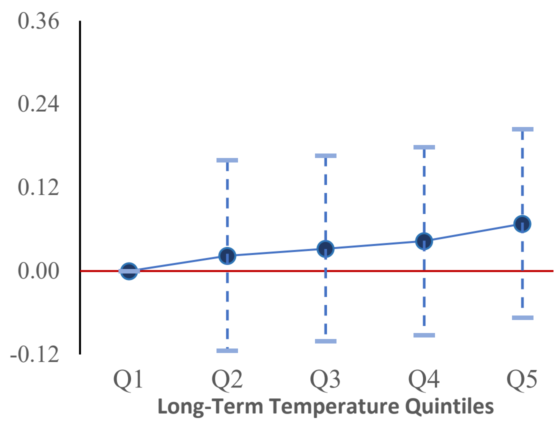


Panel B: By Payouts

B.1. Unconstrained

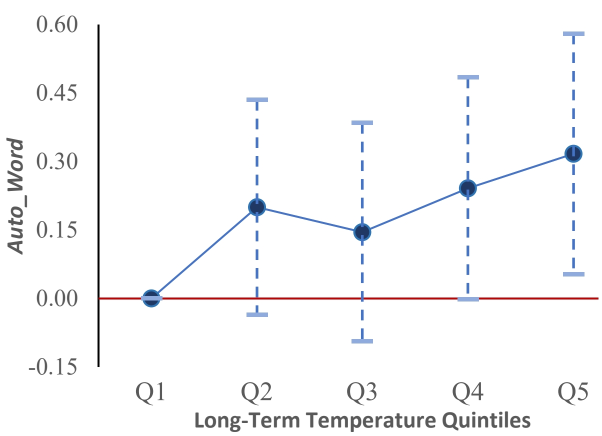


B.2. Constrained

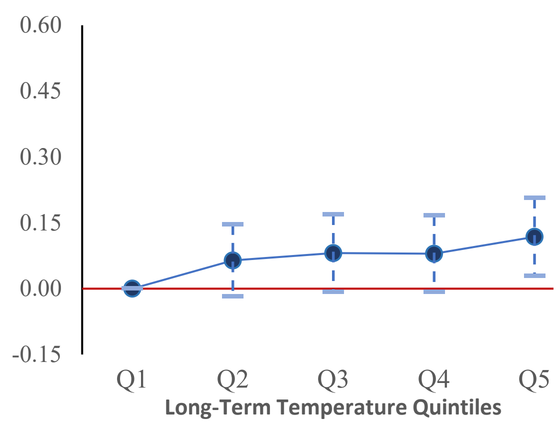


Panel C: By Text-Based Financial Constraint

C.1. Unconstrained



C.2. Constrained

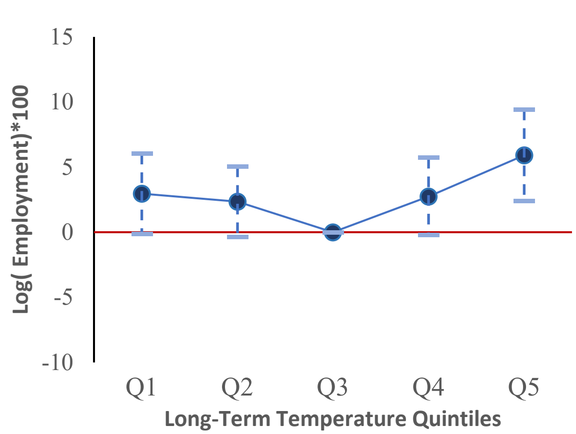


Note: This figure displays coefficients from the regression of firm automation investments on the firm climate exposure at firm × year level based on Equation (4) by firm financial constraints. The tests are based on firm-year observations from 2000-2018 and the dependent variable used in each plot is firms' automation investment intensity (*AUTO_INV*) as described in Section 2.1. In Panel A, firms are defined as financially unconstrained if the lagged Kaplan-Zingales index (*KZ* Index) is in the first quarter of the same industry-year and the remaining firms belong to the financially constrained group. In Panel B, firms are labeled as financially unconstrained if they have payouts in the previous year and constrained otherwise. In Panel C, firms are classified as financially unconstrained if they do not have 10-K text-based financial constraint constructed by Hoberg and Maksimovic (2015) and constrained otherwise. The firm-level workforce climate exposure (*FWCE*) is defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. The omitted indicator is the interaction of *FWCE* and the temperature indicator which equals one if *FIRM_LT_TEMP* is in the bottom quintile and zero otherwise. The models include all control variables used in Table 4, firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Bars denote 95% confidence intervals.

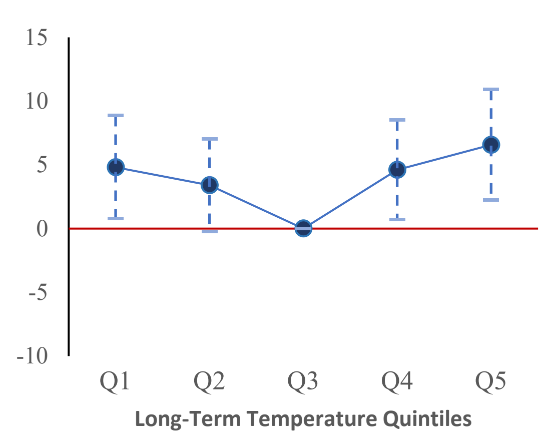
Figure 4: Investment Adaptation vs. Labor adaptation

Panel A: Employment

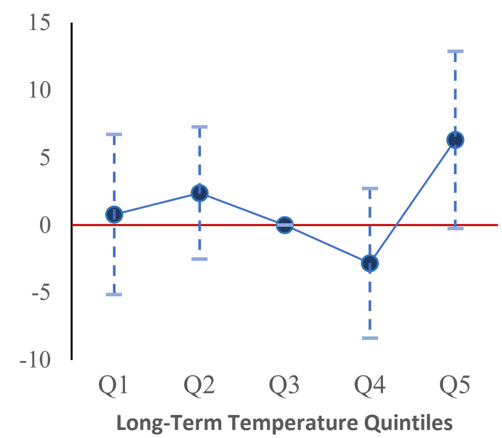
A.1. Full Sample



A.2. *INV_LOW Firms*

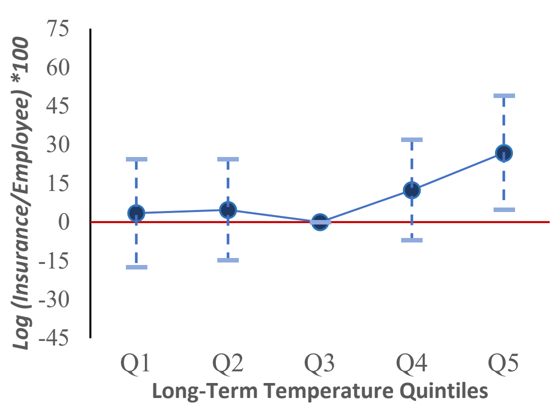


A.3. *INV_HIGH Firms*

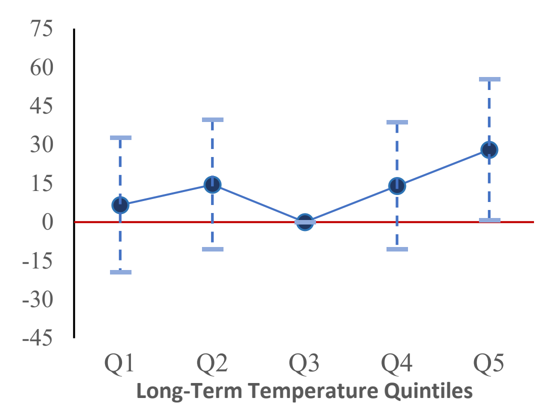


Panel B: Employee Insurance Expenses

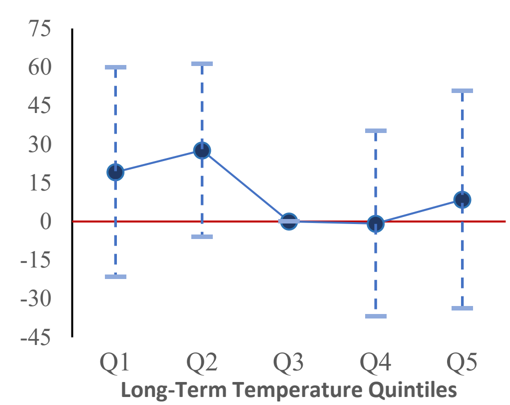
B.1. Full Sample



B.2. *INV_LOW Firms*

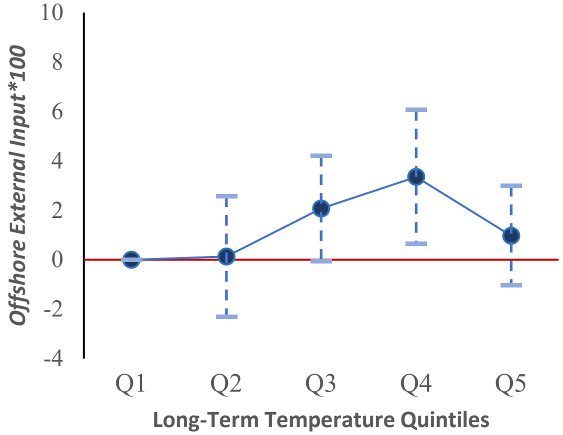


B.3. *INV_HIGH Firms*

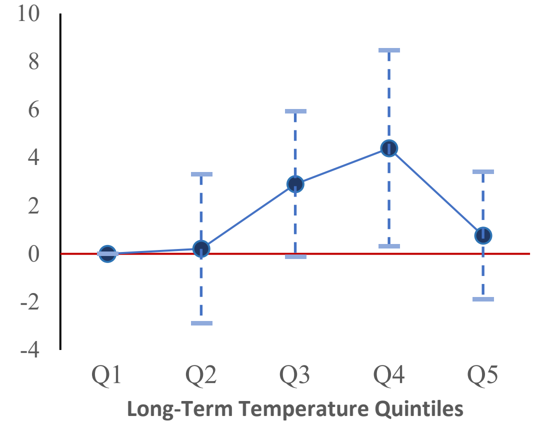


Panel C: Offshore External Input

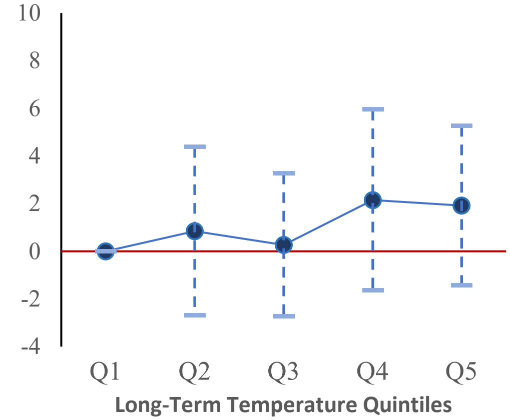
C.1. Full Sample



C.2. *INV_LOW Firms*



C.3. *INV_HIGH Firms*

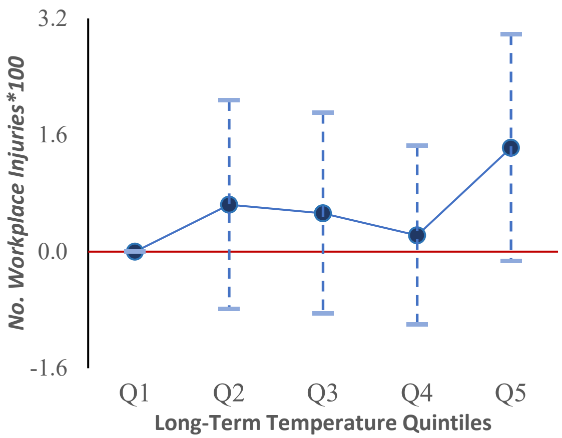


Note: This figure displays coefficients estimated from the regression of firm operation policies on the interaction of long-term temperature quintile dummies and firm climate exposure at the firm level based on Equation (7). Samples used in each plot are specified in the title. Firms belong to the *INV_HIGH* group if the lagged automation investment intensity (*AUTO_INV*) is above zero while the remaining firms fall in the *INV_LOW* group. Panel A and B are based on firm-year observations from 2000-2018. The dependent variable is 100 times the natural logarithm of employment in Panel A, and 100 times the natural logarithm of employee insurance expenses in Panel B, respectively. Panel C is at the firm-country-year observations and the dependent variable 100 times the firm's offshore external input defined as the firm's purchase of oversea inputs without the ownership of producing assets in a given county provided by Hoberg and Moon (2017). Automation investment intensity is the percentage of automation keywords in an investment disclosure item (*AUTO_INV_K*) averaged across all disclosure items in a firm-year (as described in Section 2.1). The firm-level workforce climate exposure (*FWCE*) is defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, cash holdings assets, R&D expenses scaled by assets, capital expenditure scaled by lagged assets, market leverage and cash flow volatility, net working capital scaled by assets in all regressions. Additional controls include the natural logarithm of assets per employee and the natural logarithm of sales per employee in Panel A and the natural logarithm of employment in Panel C. Panel A and B includes firm fixed effects and three-digit NAICS industry × year fixed effects and standard errors in columns clustered by firm. Panel C includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects and standard errors clustered by firm and foreign country. All the variables are described in Table A1 in Appendix. Bars denote 95% confidence intervals.

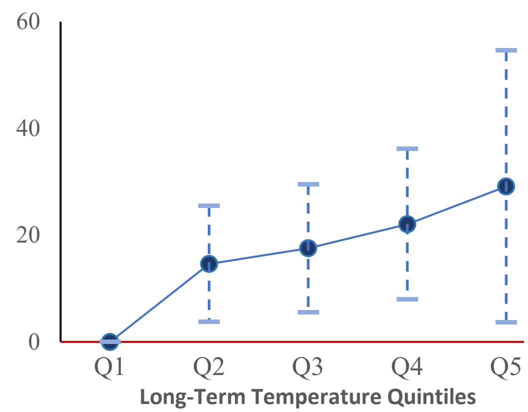
Figure 5: Firm Automation Investments and Operating Outcomes Under Temperature Surprises

Panel A: No. Workplace Injuries

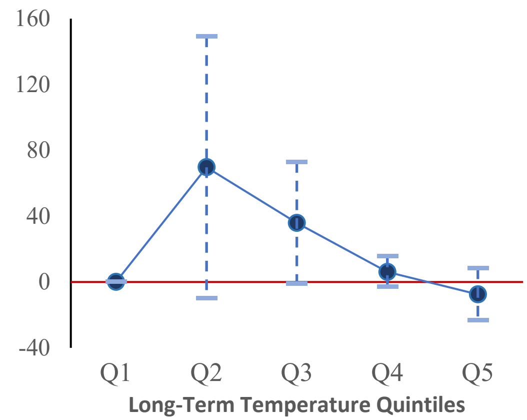
A.1. Full Sample



A.2. *INV_LOW Firms*

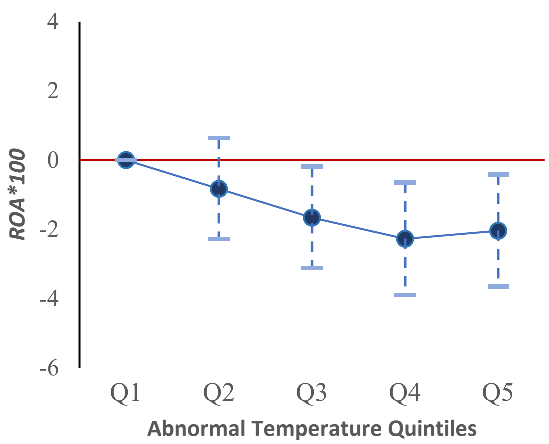


A.3. *INV_HIGH Firms*

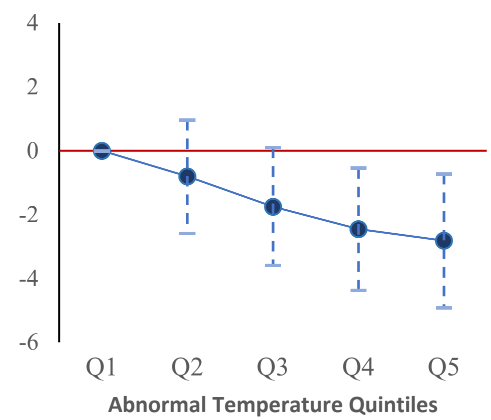


Panel B: *ROA*

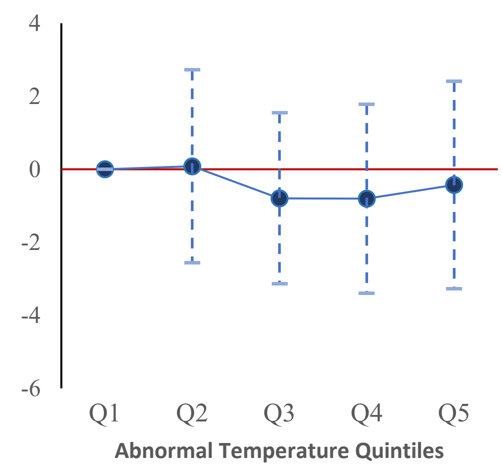
B.1. Full Sample



B.2. *INV_LOW Firms*



B.3. *INV_HIGH Firms*



Note: This figure displays coefficients from the regression of firm operating outcomes on the interaction of abnormal temperature quintile dummies and firm climate exposure at firm × year level based on Equation (7). The tests are based on firm-year observations in 2000-2018 and samples used in each plot are specified in the title. Firms belong to the *INV_HIGH* group if the lagged automation investment intensity (*AUTO_INV*) is above zero while the remaining firms fall in the *INV_LOW* group. Automation investment intensity is constructed by the author as described in Section 2.1. In Panel A, the model is Poisson and the dependent variable is 100 times the number of workplace injuries related to weather or natural disasters reported to *OSHA* in a given firm-year. In Panel B, the model is OLS and the dependent variable is 100 times *ROA*. The firm-level workforce climate exposure (*FWCE*) is defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. The omitted indicator is the interaction of *FWCE* and the temperature indicator which equals one if *FIRM_AB_TEMP* is in the bottom quintile and zero otherwise. Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, and net working capital over assets in all regressions. Additional controls include the natural logarithm of employment and the employment over assets in Panel A. All variables are described in Appendix A Table A1. Panel A only includes year fixed effects while Panel B includes firm fixed effects and three-digit NAICS industry × year fixed effects. All the variables are described in Table A1. Standard errors clustered by firm. Bars denote 95% confidence intervals.

Table 1: Firms with the Highest and Lowest Automation Investment Intensity

Company	State	*NAICS*	Industry	*AUTO_INV*	Assets (2018 million dollar)	Employment
Hyster-Yale Materials Handling	OH	33	Manufacturing	4.38	1,742	7,800
Hawaiian Holdings Inc	HI	48	Transportation and Warehousing	4.38	3,197	7,244
Lubys Inc	TX	72	Accommodation and Food Services	4.38	200	6,589
Astronics Corp	NY	33	Manufacturing	4.38	775	2,690
3D Systems Corp	SC	33	Manufacturing	4.38	826	2,620
Vishay Precision Group Inc	PA	33	Manufacturing	4.38	327	2,600
Proto Labs Inc	MN	33	Manufacturing	4.38	619	2,487
Omnicell Inc	CA	54	Professional, Scientific, and Technical Services	4.38	1081	2,480
Computer Programs & Systems	AL	54	Professional, Scientific, and Technical Services	4.38	328	2,000
Formfactor Inc	CA	33	Manufacturing	4.38	728	1,676
Aramark	PA	72	Accommodation and Food Services	0.00	13,720	274,400
Costco Wholesale Corp	WA	45	Retail Trade	0.00	40,830	245,000
Robert Half Intl Inc	CA	56	Administrative and Support and Waste Management……	0.00	1,903	231,600
Lear Corp	MI	33	Manufacturing	0.00	11,601	169,000
Barrett Business Svcs Inc	WA	56	Administrative and Support and Waste Management……	0.00	756	122,958
Nbcuniversal Media LLC	NY	51	Information	0.00	75,014	64,000
Genesis Healthcare Inc	PA	62	Health Care and Social Assistance	0.00	4,264	61,300
Laureate Education Inc	MD	61	Educational Services	0.00	6,770	60,000
Southwest Airlines	TX	48	Transportation and Warehousing	0.00	26,243	58,803

Note: This table lists the firms with the top 10 and bottom 10 automation investment intensity (*AUTO_INV*) in 2018. *AUTO_INV* is defined as the percentage of automation keywords in an investment disclosure item (*AUTO_INV_K*) averaged across all disclosure items in a firm-year as described in Section 2.1. The information on firm employment and assets is from Compustat.

Table 2: Actual Robot Density and Automation Investment Intensity

Industry	Raw Score				Relative Ranking Order			
	Industrial Robot Density	*CAPEX* ×100	*AUTO_INV*	*AUTO_INV _CLIMATE*	Industrial Robot Density	*CAPEX* ×100	*AUTO_INV*	*AUTO_INV _CLIMATE*
Agriculture, forestry, and fishing	0.20	2.57	0.25	0.25	9	11	9	9
Auto and other transportation manufacturing	29.30	4.27	0.68	0.63	1	5	2	2
Chemical manufacturing	6.00	19.31	0.42	0.33	2	2	3	4
Construction	0.10	3.16	0.34	0.33	11	10	5	3
Education	0.10	4.03	0.00	0.00	10	7	11	11
Food and beverage manufacturing	3.10	5.79	0.23	0.16	4	4	10	10
Metal and electrical/electronic manufacturing	4.70	3.68	0.89	0.82	3	9	1	1
Textile manufacturing	0.30	23.43	0.32	0.31	8	1	6	7
Mining and quarrying	0.50	4.03	0.29	0.27	6	6	8	8
Utilities	0.40	3.96	0.32	0.32	7	8	7	6
Wood and paper manufacturing	1.00	7.59	0.39	0.32	5	3	4	5
Correlation with Industrial Robot Density		-0.07	0.54	0.53		0.45	0.60	0.47

Note: This table presents the industry distribution of industrial robot density, capital expenditure and automation investments in 2017. The industry-level industrial robot density is defined as the number of robots per 1 million hours worked by *IFR*. *CAPEX* is the industry average of capital expenditure over assets from Compustat. *AUTO_INV* is the industry average of firms' automation investments (*AUTO_INV)* and *AUTO_INV_CLIMATE* is the industry average of firm climate-related automation investment intensity. The automation investment intensity proxies are constructed by the author as described in Section 2.1.

Table 3: Summary Statistics

VARIABLES	(1) N	(2) Mean	(3) Std	(4) P25	(5) P50	(6) P75	(7) Min	(8) Max
			Firm-Year Level Variables					
AUTO_INV (%)	45,946	0.52	0.87	0.00	0.00	0.73	0.00	5.01
AUTO_NEWS (%)	45,946	6.60	11.78	0.00	0.00	10.00	0.00	100.00
D_{AUTO}	45,946	0.46	0.81	0.00	0.00	0.62	0.00	4.74
AUTO_INV_CLIMATE (%)	45,946	0.03	0.17	0.00	0.00	0.00	0.00	1.00
INV (%)	45,946	0.57	0.77	0.00	0.32	0.80	0.00	5.56
INV_NEWS (%)	45,946	6.78	13.18	0.00	0.00	9.09	0.00	100.00
D_{INV}	45,946	0.02	0.15	0.00	0.00	0.00	0.00	1.00
CAPEX	45,185	0.05	0.06	0.02	0.03	0.06	0.00	0.50
FWCE	45,946	2.06	0.39	1.86	2.07	2.29	0.86	3.29
FIRM_LT_TEMP	45,946	59.20	6.21	54.60	59.26	63.02	39.72	75.77
FIRM_AB_TEMP	45,946	0.32	1.56	-0.60	0.26	1.10	-4.23	16.32
Sales (Million)	45,926	3,763	9,947	137	666	2,567	0.00	94,390
Employment	45,412	10,955	26,479	418	2,131	8,200	0.00	230,800
Insurance Costs per Participant	45,946	1,024	1,569	0	339	1,322	0.00	9,699
No. Workplace Injuries	17,133	0.26	4.14	0.00	0.00	0.00	0.00	294
No. *KD* Items	45,946	11.48	16.17	3	7	13	0	156
ROA×100	43,602	1.08	27.71	0.68	6.41	11.28	-486.43	37.74
Tobin's Q	42,565	2.16	5.47	1.11	1.47	2.21	0.44	215.80
Net Working Capital/Assets	44,223	0.02	0.71	-0.05	0.04	0.15	-23.88	0.53
RD/Assets	45,946	0.06	0.14	0.00	0.00	0.05	0.00	2.17

RD Dummy	45,946	0.48	0.50	0.00	0.00	1.00	0.00	1.00
Cash/Assets	45,943	0.19	0.22	0.03	0.10	0.27	0.00	0.98
Cash Flow Volatility	49,293	0.14	0.71	0.02	0.04	0.11	0.00	22.98
Market Leverage	45,369	0.17	0.17	0.01	0.12	0.26	0.00	0.77
KZ Index	45,946	-8.17	36.96	-6.18	-0.98	1.01	-659.50	281.50
Dividend Dummy	45,946	0.37	0.48	0.00	0.00	1.00	0.00	1.00
Repurchase Dummy	45,946	0.45	0.50	0.00	0.00	1.00	0.00	1.00
Payout Dummy	45,946	0.60	0.49	0.00	1.00	1.00	0.00	1.00
Payouts/Assets	45,874	0.03	0.06	0.00	0.00	0.03	0.00	0.51
Log(Employment/Assets)	45,412	5.27	7.72	1.34	2.84	5.76	0.00	78.56
Log(Sales/Employment)	45,132	12.47	1.54	12.11	12.58	13.08	0.00	15.56
AFF_EMP (%)	14,712	10.37	25.01	0.00	0.00	4.86	0.00	100.00
Firm-Country-Year Level Variables								
Offshore External Input ×100	346,432	22.70	68.57	0	0	0	0	400
KD Item-Level Variables								
Automation Investments Disclosure (*AUTO_INV >0*)								
CAPM Alpha (%)	26,856	0.31 (5.80)	5.50	-1.96	0.06	2.19	-40.81	34.04
Fama-French 3-Factor Alpha (%)	26,856	0.31(6.26)	5.48	-1.95	0.05	2.20	-40.37	35.49
Carhart 3-Factor Alpha (%)	26,856	0.31(6.62)	5.50	-1.97	0.06	2.20	-41.35	35.01
Automation Investments Disclosure (*AUTO_INV >3*)								
CAPM Alpha (%)	26,560	0.30 (5.56)	5.52	-1.98	0.05	2.18	-40.81	33.89
Fama-French 3-Factor Alpha (%)	26,560	0.29 (5.94)	5.49	-1.97	0.04	2.19	-40.42	34.13
Carhart 3-Factor Alpha (%)	26,560	0.29 (6.25)	5.50	-1.98	0.05	2.19	-41.36	31.66

Note: This table presents summary statistics for the firm sample at the firm × year level in 2000-2018. All dollar-denominated variables are expressed in 2018 dollars. The textual-based proxies for automation investments include: the percentage of automation investment keywords ($AUTO\_INV$) defined as the percentage of automation keywords in an investment disclosure item ($AUTO\_INV\_K$) averaged across all disclosure items in a firm-year, the percentage of the disclosure of automation investments ($AUTO\_NEWS$), an indicator for automation investments (D_{AUTO}) that equals one if $AUTO\_INV$ is greater than 3% and zero otherwise, and the percentage of automation investment keywords generated from climate-related investment disclosure ($AUTO\_INV\_CLIMATE$) constructed by the author as described in Section 2.1. The textual-based proxies for general investment including *INV*, INV_NEWS, and D_{INV} are constructed by the author in a similar practice of automation investment intensity as described in Section 2.3. The firm-level workforce climate exposure (*FWCE*) is defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm. *FIRM_LT_TEMP* is the firm-level 20-year moving average of daily temperatures while *FIRM_AB_TEMP* is firm-level abnormal temperatures. Offshore external input is the firm-nation-year level purchase of input without owning production assets provided by Hoberg and Moon (2017). Insurance premium per person is the health and life insurance expenses per participant of a given firm estimated from Form 5500. No. Workplace Injuries is the number of workplace injury and illness cases related to weather or natural disasters reported by a given firm based on *OSHA* data in 2002-2011. No. *KD* Item is the number of *KD* disclosure items of a given firm in a given year. *AFF_EMP* (%) is the firm-level percentage of employees affected by the California Heat Standard which equals zero from 2003-2004 and equals the lagged percentage of a firm's employment in California from 2005-2007. Alphas are three-day cumulative abnormal returns centered on the date of an automation investment-related disclosure item and the *T-statistics* are provided in parentheses next to the mean. A disclosure item is defined as automation investment-related if its automation investment intensity ($AUTO\_INV$) is greater than the cutoff (0% or 3%). Other financial variables are constructed using Compustat data. A detailed explanation for all variables is in Table A1 in Appendix.

Table 4: Firm Capital Expenditure and Automation Investment Intensity

DV	$CAPEX\times100$						
	Automation Investment Intensity				Investment Intensity		
	AUTO_INV	*AUTO_NEWS*	D_{AUTO}	*AUTO_INV_CLIMATE*	*INV*	*INV_NEWS*	D_{INV}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AUTO_INV	0.112***	0.007***	0.021**	0.101***			
	(3.86)	(3.82)	(2.24)	(3.36)			
Log(Sales)	-0.554***	-0.555***	-0.556***	-0.554***	-0.554***	-0.555***	-0.549***
	(-5.41)	(-5.42)	(-5.42)	(-5.41)	(-5.40)	(-5.41)	(-5.27)
Tobin's Q	0.202***	0.202***	0.203***	0.203***	0.203***	0.203***	0.207***
	(6.46)	(6.45)	(6.46)	(6.46)	(6.47)	(6.47)	(6.15)
Cash/Assets	0.236	0.239	0.231	0.232	0.236	0.231	0.168
	(0.66)	(0.67)	(0.65)	(0.65)	(0.67)	(0.65)	(0.47)
Tangible	2.650***	2.651***	2.645***	2.641***	2.669***	2.659***	2.683***
	(3.59)	(3.59)	(3.58)	(3.58)	(3.61)	(3.60)	(3.59)
Market Leverage	-7.741***	-7.736***	-7.744***	-7.741***	-7.732***	-7.736***	-7.781***
	(-19.89)	(-19.88)	(-19.88)	(-19.89)	(-19.87)	(-19.87)	(-19.74)
Log(Employment)	0.178*	0.178*	0.175*	0.178*	0.178*	0.179*	0.172*
	(1.89)	(1.89)	(1.86)	(1.88)	(1.89)	(1.90)	(1.80)
RD Dummy	0.160	0.162	0.163	0.162	0.163	0.165	0.142
	(0.83)	(0.84)	(0.84)	(0.84)	(0.85)	(0.86)	(0.73)
Dividend Dummy	0.098	0.098	0.099	0.098	0.097	0.098	0.104
	(0.93)	(0.94)	(0.95)	(0.94)	(0.93)	(0.94)	(0.98)
Repurchase Dummy	-0.062	-0.063	-0.062	-0.061	-0.063	-0.062	-0.067
	(-1.05)	(-1.07)	(-1.06)	(-1.04)	(-1.07)	(-1.05)	(-1.13)
Firm FE	√	√	√	√	√	√	√

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry × Year FE	√	√	√	√	√	√	√
Observations	41,534	41,534	41,534	41,534	41,534	41,534	40,810
Adjusted R^2	0.669	0.669	0.668	0.669	0.669	0.669	0.670

Note: This table examines the relation between firm capital expenditure and automation investment intensity. The tests are based on firm-year observations from 2000-2018. The models are OLS fixed effect regressions and the dependent variable is 100 times capital expenditure scaled by lagged assets. The main independent variable is various textual-based proxies for firms' automation investment intensity in column (1) – (4) and a set of proxies for investment intensity in column (5) – (7) as specified in the third row (the construction of these variables is described in Section 2.1). The dependent variable is the percentage of automation keywords in an investment disclosure item averaged across all disclosure items in a firm-year ($AUTO\_INV$) in column (1), the percentage of a firm's automation investments items out of the annual total while the cutoff used to classify the disclosure of automation investments item s is 3% ($AUTO\_NEWS$) in column (2), a firms' automation investment indicator (D_{AUTO}) which equals one if $AUTO\_INV$ is greater than 3% and zero otherwise in column (3), and the percentage of automation keywords in a climate-related investment disclosure item averaged across all disclosure items in a firm-year ($AUTO\_INV\_CLIMATE$) in column (4). *INV (%)* in column (5) is the percentage of investment keywords in a disclosure item averaged across all disclosure items in a firm-year. *INV_NEWS* (%) in column (6) is the percentage of a firm's investment disclosure items (the percentage of investment keywords in a disclosure item is over 3%) out of the annual total disclosure items. D_{INV} in column (7) is a firm investment indicator which equals one if *INV* (%) is greater than 3% and zero otherwise. The models include firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 5: Workforce Climate Exposure and Automation Investments

DV	Automation Investment Intensity				*CAPEX* ×100	
	Main	Robustness				
	AUTO_INV	*AUTO_NEWS*	D_{AUTO}	*AUTO_INV_CLIMATE*	*All*	*Automation-Unrelated*
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	-0.011	-0.188	-0.005	-0.008	0.091	0.085
	(-0.43)	(-0.52)	(-0.94)	(-0.34)	(0.61)	(0.57)
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Industry × Year FE	√	√	√	√	√	√
Observations	41,642	41,642	41,642	41,642	41,534	41,534
Adjusted R^2	0.329	0.295	0.136	0.352	0.668	0.663

Note: This table studies the relation between workforce climate exposure and firm investments in automation at the firm level. The tests are based on firm-year observations in 2000-2018. The models are OLS fixed effect regressions and the dependent variable in column (1) – (4) is various textual-based proxies for automation investment intensity as specified in the third row includes: the percentage of automation keywords in an investment disclosure item averaged across all disclosure items in a firm-year (*AUTO_INV*) in column (1), the percentage of a firm's the disclosure of automation investments items out of the annual total while the cutoff used to classify the disclosure of automation investments items is 3% (*AUTO_NEWS*) in column (2), a firms' automation investment indicator (D_{AUTO}) which equals one if *AUTO_INV* is greater than 3% and zero otherwise in column (3), and the percentage of automation keywords in a climate-related investment item averaged across all disclosure items in a firm-year (*AUTO_INV_CLIMATE*) in column (4). As robustness checks, I also include 100 times *CAPEX (*capital expenditure scaled by assets) as the dependent variable in column (5) and 100 times the capital expenditures unrelated to automation (*CAPEX Automation-Unrelated*) calculated by regressing *CAPEX* on *INV*, as the dependent variable in column (6), respectively. The main independent variable is lagged firm-level workforce climate exposure (*FWCE*) defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm as described in Section 3.1. The models include all control variables used in Table 4, firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 6: Workforce Climate Exposure, Long-term Climate Trends and Firm Automation Investments

DV	Automation Investment Intensity				*CAPEX ×100*	
	Main				*Robustness*	
	AUTO_INV	*AUTO_ NEWS*	D_{AUTO}	*AUTO_INV_ CLIMATE*	*All*	*Automation -Unrelated*
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	-0.247**	-3.729**	-0.056**	-0.156	-0.731	-0.853
	(-2.26)	(-2.47)	(-2.40)	(-1.58)	(-1.14)	(-1.33)
× *FIRM_LT_TEMP*	0.004**	0.060**	0.001**	0.003	0.014	0.016
	(2.20)	(2.39)	(2.25)	(1.51)	(1.27)	(1.44)
FIRM_LT_TEMP	-0.008*	-0.115**	-0.001	-0.004	-0.023	-0.027
	(-1.91)	(-2.10)	(-1.55)	(-1.23)	(-0.99)	(-1.15)
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Industry × Year FE	√	√	√	√	√	√
Observations	41,642	41,642	41,642	41,642	41,534	41,534
Adjusted R^2	0.329	0.295	0.136	0.352	0.668	0.663

Note: This table studies the relation between workforce climate exposure, long-term climate conditions and firm investments in automation at the firm level. The models are OLS fixed effect regressions and the dependent variable in column (1) – (4) is various textual-based proxies for automation investment intensity as specified in the third row including: the percentage of automation keywords in an investment disclosure item averaged across all disclosure items in a firm-year (*AUTO_INV*) in column (1), the percentage of a firm's the disclosure of automation investments items out of the annual total while the cutoff used to classify the disclosure of automation investments items is 3% (*AUTO_NEWS*) in column (2), a firms' automation investment indicator (D_{AUTO}) which equals one if *AUTO_INV* is greater than 3% and zero otherwise in column (3), and the percentage of automation keywords in a climate-related investment disclosure item averaged across all disclosure items in a firm-year (*AUTO_INV_CLIMATE*) in column (4). As robustness checks, I also include 100 times *CAPEX (*capital expenditure scaled by assets) as the dependent variable in column (5) and 100 times the capital expenditures unrelated to automation (*CAPEX Automation-Unrelated*) calculated by regressing *CAPEX* on *INV*, as the dependent variable in column (6), respectively. The main independent variable is lagged firm-level workforce climate exposure (*FWCE*) defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. The models include all control variables used in Table 4, firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 7: The Market Response to the Disclosure of Automation Investments

Panel A: CAR[-1,1] to Automation Investments Disclosure (*AUTO_INV_K >0*)

	CAR[-1,1]					
VARIABLES	CAPM		FF 3-Factor		Carhart 4-Factor	
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	0.378	-7.480***	0.423	-8.257***	0.367	-7.677***
	(1.01)	(-3.10)	(1.26)	(-3.30)	(1.09)	(-3.31)
× *FIRM_LT_TEMP*		0.131***		0.145***		0.134***
		(3.27)		(3.48)		(3.47)
FIRM_LT_TEMP		-0.273***		-0.299***		-0.272***
		(-3.53)		(-3.72)		(-3.69)
Firm FE	√	√	√	√	√	√
Industry ×Year-Month FE	√	√	√	√	√	√
Observations	24,631	23,858	24,631	23,858	24,631	23,858
Adjusted R^2	0.058	0.061	0.058	0.061	0.055	0.058

Panel B: CAR[-1,1] to Automation Investments Disclosure (*AUTO_INV_K >3*)

	CAR [-1,1]					
VARIABLES	CAPM		FF 3-Factor		Carhart 4-Factor	
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	0.245	-7.095***	0.280	-7.846***	0.200	-7.309***
	(0.67)	(-3.13)	(0.82)	(-3.40)	(0.58)	(-3.41)
× *FIRM_LT_TEMP*		0.122***		0.135***		0.124***
		(3.21)		(3.49)		(3.46)
FIRM_LT_TEMP		-0.250***		-0.274***		-0.248***
		(-3.43)		(-3.70)		(-3.64)
Firm FE	√	√	√	√	√	√
Industry × Year-Month FE	√	√	√	√	√	√
Observations	24,318	23,555	24,318	23,555	24,318	23,555
Adjusted R^2	0.054	0.056	0.054	0.056	0.052	0.053

Note: This table studies the stock market responses around the disclosure item of automation investments. The dependent variables are the three-day accumulative returns around the date of the firm's disclosure of automation investments, adjusted by *CAPM*, or by Fama-French (*FF*) three factors, or by Cahart four factors as specified by the title of each plot. A disclosure item is defined as automation investment-related if its automation investment intensity (*AUTO_INV_K*) is greater than zero in Panel A and greater than 3% in Panel B, respectively. Automation investment intensity (*AUTO_INV_K*) of a given disclosure item is the percentage of automation keywords in an investment-related disclosure item as specified in Section 2.1. The main independent variable is lagged firm-level workforce climate exposure (*FWCE*) defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. The models include firm fixed effects and three-digit *NAICS* industry by year-month fixed effects. Standard errors clustered by firm and year-month. All the variables are described in Table A1 in Appendix. Asterisks denote significance levels (***=1%, **=5%, *=10).

Table 8: Workforce Climate Exposure and Firms' Automation Investments by Financial Constraints

Panel A: By *KZ* Index

Dependent Variable	*AUTO_INV*			
Subsample	Unconstrained		Constrained	
	(1)	(2)	(3)	(4)
FWCE	-0.069	-0.670***	0.001	-0.113
	(-1.25)	(-2.83)	(0.03)	(-0.81)
× *FIRM_LT_TEMP*		0.010**		0.002
		(2.53)		(0.83)
FIRM_LT_TEMP		-0.019**		-0.002
		(-2.06)		(-0.40)
Firm Controls	√	√	√	√
Firm FE	√	√	√	√
Year × Industry FE	√	√	√	√
Observations	10,185	10,049	30,161	29,562
Adjusted R^2	0.362	0.354	0.316	0.316

Panel B: By Payouts

Dependent Variable	*AUTO_INV*			
Subsample	Unconstrained		Constrained	
	(1)	(2)	(3)	(4)
FWCE	-0.033	-0.371**	0.005	-0.149
	(-0.92)	(-2.56)	(0.11)	(-0.82)
× *FIRM_LT_TEMP*		0.006**		0.002
		(2.40)		(0.82)
FIRM_LT_TEMP		-0.009		-0.006
		(-1.63)		(-0.99)
Firm Controls	√	√	√	√
Firm FE	√	√	√	√
Year × Industry FE	√	√	√	√
Observations	10,403	10,552	29,593	30,155
Adjusted R^2	0.357	0.355	0.327	0.328

Panel C: By Text-Based Financial Constraints

Dependent Variable	*AUTO_INV*			
Subsample	Unconstrained		Constrained	
	(1)	(2)	(3)	(4)
FWCE	0.013	-0.527*	-0.007	-0.296**
	(0.24)	(-1.84)	(-0.20)	(-2.27)
× *FIRM_LT_TEMP*		0.009*		0.005**
		(1.92)		(2.24)
FIRM_LT_TEMP		-0.022**		-0.010**
		(-2.08)		(-2.05)
Firm Controls	√	√	√	√

Firm FE	√	√	√	√
Year × Industry FE	√	√	√	√
Observations	23,524	23,827	16,045	16,455
Adjusted R^2	0.342	0.342	0.315	0.315

Note: This table studies the relation between workforce climate exposure and automation investment intensity by financial constraints at firm × year level based on Equation (4). The tests are based on firm-year observations in 2000-2018 and the dependent variable is firms' automation investment intensity ($AUTO\_INV$) as described in Section 2.1. Firms belong to the financial unconstrained group if the lagged Kaplan-Zingales index (*KZ* Index) is below the median cutoff of in the same industry-year in column (1) and the remaining firms belong to the constrained group in column (2). Firms are also defined as financially unconstrained if they have payouts in the previous year (column (3)) and constrained otherwise (column (4)). Firms are defined as financially unconstrained if they do not have 10-K text-based financial constraint constructed by Hoberg and Maksimovic (2015) in column (5) and constrained otherwise in column (6). The main independent variable is lagged firm-level workforce climate exposure (*FWCE*) defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm as described in Section 3.1. The models include all control variables used in Table 4, firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 9: Event Study of California Heat Illness Prevention Standard

DV	Automation Investment Intensity				*CAPEX×100*	
	Main	Robustness				
	AUTO_INV	*AUTO_NEWS*	D_{AUTO}	*AUTO_INV_CLIMATE*	*All*	*Automation-Unrelated*
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	0.022	0.093	0.001	0.056	-0.033	-0.034
	(0.38)	(0.13)	(0.11)	(1.10)	(-0.09)	(-0.10)
x AFF_EMP (%)	0.003**	0.026*	0.001**	0.002**	-0.002	-0.001
	(2.20)	(1.66)	(2.22)	(1.99)	(-0.33)	(-0.11)
AFF_EMP (%)	-0.006**	-0.063*	-0.001**	-0.005**	0.005	0.002
	(-2.22)	(-1.85)	(-2.13)	(-2.03)	(0.38)	(0.17)
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Industry × Year FE	√	√	√	√	√	√
Observations	13,090	13,090	13,090	13,090	13,067	13,067
Adjusted R^2	0.335	0.304	0.123	0.356	0.746	0.813

Note: This table reports changes in firms' automation investment around 2005 the California Heat Illness Prevention Standard using DID regressions. The models are OLS fixed effect regressions from 2003-2007 and the dependent variable in column (1) – (4) is various textual-based proxies for automation investment intensity as specified in the third row (details can be found in Section 2.1). The dependent variable includes: the percentage of automation keywords in an investment disclosure item averaged across all disclosure items in a firm-year (*AUTO_INV*) in column (1), the percentage of a firm's disclosure of automation investments items out of the annual total while the cutoff used to classify the disclosure of automation investments items is 3% (*AUTO_NEWS*) in column (2), a firms' automation investment indicator (D_{AUTO}) which equals one if *AUTO_INV* is greater than 3% and zero otherwise in column (3), and the percentage of automation keywords in a climate-related investment disclosure item averaged across all disclosure items in a firm-year (*AUTO_INV_CLIMATE*) in column (4). As robustness checks, I also include 100 times *CAPEX (*capital expenditure scaled by assets) as the dependent variable in column (5) and 100 times the capital expenditures unrelated to automation (*CAPEX Automation-Unrelated*) calculated by regressing *CAPEX* on *INV*, as the dependent variable in column (6), respectively. The main independent variable is lagged firm-level workforce climate exposure (*FWCE*) defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm as described in Section 3.1 *AFF_EMP* (%) is the percentage of employees affected by the California Heat Standard which equals zero from 2003-2004 and equals the lagged percentage of a firm's employment in California from 2005-2007. The models include all control variables used in Table 4, firm fixed effects and three-digit *NAICS* industry by year fixed effects. Standard errors clustered by firm. All the variables are described in Table A1 in Appendix. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 10: Workforce Climate Exposure, Automation Investments and Labor Adaptation Policies

DV	Log (1+ Outcome) ×100								
	Employment			Insurance Costs/Participants			Offshore External Input ×100		
	FULL	*INV_LOW*	*INV_HIGH*	*FULL*	*INV_LOW*	*INV_HIGH*	*FULL*	*INV_LOW*	*INV_HIGH*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FWCE	-6.360	-7.052	-3.565	-69.824**	-47.002	69.027	-6.091*	-8.521*	-7.726
	(-1.21)	(-1.12)	(-0.37)	(-2.13)	(-1.14)	(0.983)	(-1.66)	(-1.76)	(-1.35)
× *FIRM_LT_TEMP*	0.152*	0.130	0.094	1.378**	1.155*	-1.151	0.118*	0.177**	0.144
	(1.68)	(1.25)	(0.55)	(2.48)	(1.69)	(-0.951)	(1.94)	(2.22)	(1.46)
FIRM_LT_TEMP	-0.237	-0.141	-0.192	-2.144*	-1.394	3.328	-0.121	-0.230	-0.181
	(-1.11)	(-0.54)	(-0.51)	(-1.68)	(-0.890	(1.266)	(-0.96)	(-1.29)	(-0.85)
Firm Controls	√	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√	√
Country × Year FE	√	×	×	×	×	×	√	√	√
Industry × Year FE	√	√	√	√	√	√	√	√	√
Observations	37,242	19,821	16,716	38,713	20,207	16,987	315,188	140,985	173,531
Adjusted R^2	0.979	0.977	0.983	0.673	0.668	0.696	0.253	0.271	0.234

Note: This table studies the relation between workforce climate exposure and firm operation performance from 2000-2018. Samples used are specified in the third row. Firms belong to the *INV_HIGH* group if the lagged automation investment intensity (*AUTO_INV*) is above zero while the remaining firms fall in the *INV_LOW* group. The dependent variable is specified in the second row. Column (1) - (6) report OLS regression results using firm-year observations and the dependent variable is firm employment in Compustat in column (1)-(3) and employee insurance per participant defined as the firm-year health and life insurance expenses aggregated from Form 5500 scaled by the number of participants in column (4)-(6). Column (7) – (9) report OLS regression results based on firm-country-year observations and the dependent variable is the firm's purchase of oversea inputs without the ownership of producing assets in a given county constructed by Hoberg and Moon (2017). The main independent variable is lagged firm-level workforce climate exposure (*FWCE*) defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE*) within the firm, and *FIRM_LT_TEMP* is the averaged county-level long-term temperatures (20-year moving average) weighted by the firm's employment in the county, both described in Section 3.1. Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, cash holdings assets, R&D expenses scaled by assets, capital expenditure scaled by lagged assets, market leverage and cash flow volatility, and net working capital scaled by assets in all regressions. Additional control includes the natural logarithm of assets per employee and the natural logarithm of sales per employee Column (1) – (3) and the natural logarithm of employment in Column (7) – (9). Column (1) – (6) include firm fixed effects and three-digit NAICS industry × year fixed effects and standard errors in columns clustered by firm. Column (7) – (9) includes firm fixed effects and three-digit NAICS industry × foreign country × year fixed effects and standard errors clustered by firm and foreign country. All variables are described in Appendix A Table A1. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 11: Workforce Climate Exposure, Automation Investments and Firm Operating Performance

DV	Outcome×100					
	No. Workplace Injuries			*ROA*		
	FULL	*INV_LOW*	*INV_HIGH*	*FULL*	*INV_LOW*	*INV_HIGH*
	(1)	(2)	(3)	(4)	(5)	(6)
FWCE	1.235***	1.847***	0.448	-1.544**	-3.409***	-0.127
	(2.99)	(3.92)	(0.58)	(-2.13)	(-3.02)	(-0.17)
× *FIRM_AB_TEMP*	0.442**	0.348*	0.779**	-0.259*	-0.397**	-0.289
	(2.43)	(1.66)	(2.07)	(-1.76)	(-2.14)	(-1.00)
FIRM_AB_TEMP	-1.052***	-0.818*	-1.865**	0.516*	0.682**	0.698
	(-2.89)	(-1.89)	(-2.52)	(1.82)	(2.10)	(1.20)
Firm Controls	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Industry × Year FE	√	√	√	√	√	√
Observations	17,469	9,914	7,555	37,874	19,674	16,690
Adjusted	0.249	0.266	0.280	0.754	0.739	0.734

Note: This table displays OLS regression results that examine operating outcomes of climate-exposed firms after making automation adaptation. The tests are based on firm-year observations in 2000-2018 and subsamples used in each column are specified in the third row. Firms belong to the *INV_HIGH* group if the lagged automation investment intensity (*AUTO_INV*) is above zero while the remaining firms fall in the *INV_LOW* group. Column (1) – (3) presents Poisson regression results using *OSHA* work-related injury and illness data in 2002-2011 and the dependent variable is the number of workplace injury and illness cases related to weather or natural disasters reported by the firm in a given year. Column (4) - (6) report OLS regression results and the dependent variable is 100 times *ROA*. The main independent variable is lagged firm-level workforce climate exposure (*FWCE)* defined as the employment-weighted average of establishment-level workforce climate exposure (*EWCE)* within the firm (as described in Section 3.3). *FIRM_TEMP* is the firm-level annual average daily temperature. *FIRM_AB_TEMP* is firm-level abnormal temperatures (as defined in 3.1). Firm controls include the natural logarithm of sales in 2018 dollars, Tobin's Q, R&D dummy that equals one if the firm has non-missing R&D expenses and zero otherwise, R&D expenses scaled by assets, capital expenditure scaled by assets, cash holdings scaled by assets, book leverage, cash flow volatility, payout over assets, and net working capital over assets in all regressions. Additional controls include the natural logarithm of employment and the employment over assets in column (1) – (3). All variables are described in Appendix A Table A1. Column (1) – (3) only includes year fixed effects. Column (4) – (6) include firm fixed effects and three-digit NAICS industry × year fixed effects. Standard errors clustered by firm. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix

Table A1: Definition of Firm-Year Variables

Variable	Definition
AUTO_INV (%)	The major proxy for firms' automation investment density. It is defined as the percentage of automation keywords in an investment disclosure item (includes at least investment keywords) averaged across all disclosure items in a firm-year from 2000-2018.
AUTO_NEWS (%)	The percentage of a firm's disclosure of automation investment items (the percentage of automation keywords in an investment disclosure item is over 3%) out of the annual total disclosure items.
D_{AUTO}	Firms' automation investment indicator which equals one if *AUTO_INV* is greater than 3% and zero otherwise.
AUTO_INV_CLIMATE (%)	The percentage of automation keywords in a climate-related investment disclosure item (which includes both investment and climate keywords) averaged across all disclosure items in a firm-year.
INV (%)	The percentage of investment keywords in a disclosure item averaged across all disclosure items in a firm-year
INV_NEWS (%)	The percentage of a firm's investment disclosure items (the percentage of investment keywords in a disclosure item is over 3%) out of the annual total disclosure items.
D_{INV}	A firm investment indicator that equals one if *INV (%)* is greater than 3%.
FWCE	Firm-level workforce climate exposure is defined as the establishment employment-weighted average of *Establishment-level workforce climate exposure (EWCE)* from 2000-2018. *EWCE* is defined as the employment-weighted average of occupational climate exposure (*OCE*) of the same county-industry cohort of a given establishment. *OCE* is constructed based on the working context of each occupation by Xiao (2023). The employment information on individuals is from *ACS* and the establishment employment is from *NETS* establishment data.
FIRM_LT_TEMP	The county-level long-term temperature (20-year moving average of the county-year temperature) averaged across the firm and weighted by firm employment in that county.
FIRM_AB_TEMP	The average county-year abnormal temperature averaged across the firm and weighted by the firm employment in that county. The county-year level abnormal temperature is defined as the difference between the annual temperature and the 20-year moving average of temperatures.
CAPEX	Capital expenditure /Beginning-of-year assets.
CAR [-1,1]	Three-day cumulative abnormal returns. The estimation period starts 280 days before each event and ends 30 days before the event day with at least 50 return observations in the estimation period.
Employment	Firm-level employment from Compustat.
Insurance Costs per Participant	Insurance costs per participants are the firm-year health and life insurance expenses aggregated from Form 5500 and scaled by the number of participants.
No. Workplace Injuries	The number of workplace injury and illness cases related to weather or natural disasters are reported to *OSHA* by any establishment (with more than 10 employees) owned by the firm in a given year from 2002-2011.
NO. *KD* Items	The number of disclosure items about a given firm in a given year in the *KD* database.
Offshore External Input	The number of mentions of the firm purchasing inputs from the given nation when the firm does not also mention owning assets there in 10K (Hoberg and Moon, 2017).
Return on Asset (*ROA*)	Operating profit/total assets.

AFF_EMP(%)	The firm-level percentage of employees affected by the California Heat Standard which equals zero from 2003-2004 and equals the lagged percentage of a firm's employment in California from 2005-2007.
Log(Sales)	Log (1+ Sales in 2018 dollars)
Tobin's Q	(Market capitalization + total assets – common equity)/ total assets
Net working capital/Assets	Net working capital/assets
Cash/Assets	Cash & short-term/total assets
Cash Flow Volatility	Standard deviation of cash flow to net assets for the previous five years
KZ Index	Kaplan-Zingales index = -1.001909*Cash Flows/Net PPE + 0.2826389*Q + 3.139193*Debt/Total Capital -39.3678*Dividends/Net PPE -1.314759*Cash /Net PPE
Market Leverage	(Long-term debt + Short-term debt)/(book assets – common equity + stock price × the number of shares outstanding)
Dividend Dummy	Equals one if a firm pays any dividends and zero otherwise.
Repurchase Dummy	Equals one if a firm has any repurchases and zero otherwise.
Payout Dummy	Equals one if a firm has any payouts and zero otherwise.
Payouts/Assets	(Dividends + repurchases) /total assets
RD Dummy	Equals one if a firm has any R&D expenses and zero otherwise.
RD/Assets	R&D expenses/total assets
Text-Based Financial Constraint	Based on the textual information in the Capitalization and Liquidity Subsection ("CAPLIQ") of the MD&A section from each 10-K. See details in Gerard Hoberg and Maksimovic (2015).
Assets/Employment	Assets in 2018 dollars/Compustat employment
Sales/Employment	Sales in 2018 dollars/ Compustat employment

Note: Data sources include Compustat, Form 5500, *KD*, *NETS*, *OSHA* and *NECI*.

Table A2: Examples of Automation Keywords

Seed word	Keyword	Cosine similarity
robot	robotic	0.81
automation	computerization	0.70
robot	microbots	0.68
robots	automations	0.68
automation	fully-automated	0.66
automation	computerization	0.64
equipments	hardwares	0.64
machine	computer	0.62
equipments	instruments	0.62
robot	microrobots	0.60
equipments	vehicles	0.60
automation	automating	0.60
equipments	technologies	0.59
robots	cybermen	0.59
robots	super-humans	0.59
machine	workstation	0.59
robot	human-machine	0.58
automation	centralization	0.58
machine	machine-processable	0.57
equipments	innovations	0.57
robot	computer-human	0.57
equipments	non-personnel	0.57
automation	automated	0.56
machine	engine	0.56
equipments	material-handling	0.56
robot	machine-controlled	0.56
automation	automaticity	0.56
automation	automates	0.55
automation	mass-production	0.55
robot	self-programming	0.55
automation	assembly-line	0.54

Note: Seed word is the initial word used to generate related keywords, while keywords are most similar words to the seed word generated by *GloVe* by calculating the cosine between the representative vector of the seed word and that of the keyword (cosine similarity).

Table A3: Examples of Firm Disclosure in *KD*

Date	Headline	Text Content	No. Words Total	Automation	Investment
20190521	Weiqiao Textile Company Limited to Construct A New Fully Automated and Smart Spinning and Weaving Production Line	Weiqiao Textile Company Limited announced that, based on the principle of industrial upgrading, increasing the proportion of mid-to-high-end products and achieving high-quality development, the company is building a new fully-automated, smart spinning and weaving production line. This move is in parallel with the Company's continuous effort to identify under-performing infrastructure, transform traditional manufacturing practices and improve productivity. This new textile plant will integrate the spinning and weaving process on an intelligent production line. The plant will require an estimated investment of RMB 820 million to complete. The general equipment installation is scheduled for the end of July and will be in full operation by October 2019. Once in operation, the green plant will have an annual production capacity of 15,000 tons of high-quality compact yarns and 35 million yards of high-grade fabric. The plant will be equipped with full access and control of the smart production line from automatic product inspection, robot application, automatic transportation tool application to energy-saving equipment. An intelligent track conveyor system covers 35 kilometers within the plant, so the yarn is automatically transported from roving, unloading to packaging stages. This full automation process is achieved without any manual labor. Remote management through terminal devices, such as mobile phones, tablets and computers, will be implemented throughout the plant.	430	71	3
20070327	Department of Defense Selects Northrop Grumman for Records Management Software Maintenance	The U.S. Department of Defense (DoD) has awarded Northrop Grumman Corporation a contract to provide technical and training support for software maintenance that will simplify records management and provide added security for more than 8,000 users at 63 sites worldwide. As part of the contract, Northrop Grumman's Information Technology (IT) sector will provide its e.POWER software and Electronic Document Workflow (EDW) application to help the Defense Contract Management Agency effectively manage Defense Department contracts. Combined, e.POWER and EDW provide simple, efficient and secure methods to handle data and simplify business process management by automating processes, eliminating paperwork and enhancing document storage capacity.	51	7	0

20070508	Alitalia Bid Finalists May Be Disclosed By Mid-May	Alitalia SpAâs sale may be narrowed down to the finalist bidders by the middle of this month, a senior official at the Economy Ministry said. The deadline for final binding offers for at least 39.9% of the company is still being determined. It will be sent through letters to the selected finalists, the official said. Bidders will then have access to the data room. The three bidding consortia which have submitted non-binding offers are UniCredit SpA with OAO Aeroflot; TPG and Matlin Patterson, together with Mediobanca; and AP Holding SpA, backed by Intesa Sanpaolo SpA. Italy's prime minister Romana Prodi said the government is open to foreign investors buying Alitalia. However, the government wants to have a nominal Italian identity.	57	0	1
20170110	Sarepta Therapeutics, Inc. Enters into Research Agreement, Option Agreement with Nationwide Children's Hospital for Microdystrophin Gene Therapy Program	Sarepta Therapeutics, Inc. announced it has entered a research and option agreement with Nationwide Children's Hospital on their microdystrophin gene therapy program. Dr. Jerry Mendell, M.D. and Dr. Louise Rodino-Klapac, Ph.D., are the lead principal investigators of the program. The initial trial, expected to go into Phase 1/2a trial in late 2017, will be conducted at Nationwide Children's. Parent Project Muscular Dystrophy (PPMD) has committed 2.2 million dollars to the trial, with support from additional Duchenne foundations and families. Sarepta has committed to the trial through a separate research agreement with Nationwide Children's, and has an exclusive option to license the program. PPMD's grant provided incentive for Sarepta to help expand and accelerate this opportunity.	57	0	0

Note: Automation keywords and investment keywords are defined by the author in Section 2.1.

Table A4: Climate Keywords

Kyoto	air	air conditioner	air conditioning	alternative	arctic	area	atmosphere
available	battery	biomass	capture	carbon	castle	cell	change
climate	climate risk	charge	clean	clouds	coastal	cold	coldest
control	conversion	combine	commitment	comply	construction	cool	cost
costal	customer	damage	decarbonization	degree	department	dioxide	discharge
drought	early	earthquake	east	efficient	electric	electricity	electronic
emission	emissions	employee	energy	environment	environmental	especially	events
exposure	extreme	extreme	farm	focus	forest	fossil	friendly
fuel	gas	geothermal	ghg	gigawatt	global	goal	greenhouse
grid	hail	hailstorm	harsh	hazard	heat	heavy	hot
hurricane	hybrid	ice	infrastructure	install	job	labor	land
landscape	layer	level	lightning	marina	meet	megawatt	methane
natural	neutral	monitor	monsoon	new	nox	flooding	floods
opportunity	florida	oxide	ozone	peak	plug	polar	pollutants
pollution	power	precipitation	price	product	program	protocol	pure
quality	rainfall	rains	receive	recovery	reduce	reduction	region
relate	fl	renewable	reserve	resource	resources	risk	rooftop
safe	save	sea	security	sequestration	service	severe	sewer
sink	snow	snowfall	solar	solution	sox	stability	storage
storm	storm clouds	storms	strike	subsidy	summer	sustainability	sustainable
tax	technology	temperature	temperatures	thermal	ton	tropical	tsunami
type	union	unseasonably	fluorine	value	vehicle	volcano	vortex
warm	warmest	warming	waste	water	wave	way	weather
weight	wildfire	wind	wind hail	windstorm	winter		

Note: Climate keywords are from Li et al. (2020b) and Sautner et al. (2020).

Table A5: Correlation between Text-Based Investment Proxies

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) *AUTO_INV*	1						
(2) *AUTO_NEWS*	0.903***	1					
(3) *AUTO_INV_CLIMATE*	0.941***	0.840***	1				
(4) D_{AUTO}	0.669***	0.579***	0.612***	1			
(5) *INV*	0.308***	0.280***	0.251***	0.212***	1		
(6) *INV_NEWS*	0.229***	0.239***	0.168***	0.160***	0.797***	1	
(7) D_{INV}	0.109***	0.112***	0.063***	0.136***	0.638***	0.647***	1

Note: this table presents correlations between textual-based measures of automation investments and general investments constructed by the author.