Labor Exposure to Climate Change and Capital Deepening

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Internet Appendix available here.

Abstract

Rising temperatures induced by climate change generate two types of climate risks that raise labor costs of firms relying on outdoor workers: (1) physical risk - lower labor productivity in high temperatures; (2) regulatory risk - governments introducing regulations to protect workers against heat hazards. I find that firms exposed to climate change through the labor channel have higher capital-labor ratios, especially when managers believe in climate change or when jobs are easy to automate. After experiencing shocks to physical (abnormally high temperatures) and regulatory (the adoption of the Heat Illness Prevention Standard (HIPS) in California) risks, high-exposure firms switch to more capital-intensive production functions. These firms also respond by innovating more, especially in technologies facilitating automation and reducing labor costs. Furthermore, labor exposure to climate change impedes job creation and hurts workers' earnings. Overall, the findings highlight that climate change accelerates automation in occupations exposed to rising temperatures.

Keywords: Climate change; Capital-labor ratio; Automation; Employment; Innovation.

JEL Codes: D22, G30, J30, J63, O30, Q54.

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

"*Today, I am mobilizing an all-of-government effort to to protect workers, children, seniors, and at-risk communities from extreme heat.*"

- Joe Biden, 09/20/2021

1 Introduction

Rising temperatures induced by climate change have posed severe threats to human health, especially to workers working in outdoor environments (e.g., Naughton et al., 2002; Patz et al., 2005; Luber and McGeehin, 2008; Gubernot et al., 2015). For example, Park et al. (2021) estimate that hot temperatures have caused approximately 360,000 additional injuries in California from 2001 to 2018.[1] More worryingly, the threats are expected to continue and will become even more pronounced, considering that unusually hot temperatures have become more common, and extreme heat events have become more frequent and intense across the U.S.[2] However, little work has been done to understand how firms are affected by their workers' exposure to climate change and how they cope with the challenges.

This paper aims to bridge this gap by exclusively identifying a labor channel of firms' exposure to climate change and studying what mitigation measures firms have taken. More specifically, I examine how the labor-channel exposure to climate change affects firms' decisions on input mix. My key finding is that high-exposure firms adopt more capital-intensive production functions because rising temperatures raise high-exposure firms' labor costs. In response, these firms use capital to replace the expensive labor, resulting in higher capital-labor ratios.

The rising labor costs are driven by two types of climate risks induced by climate change - physical and regulatory risks. The physical risk refers to the detrimental effects of high temperatures on labor productivity. For example, Graff Zivin and Neidell (2014) document that

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

[2] The average surface temperature across the U.S. has risen at an average rate of 0.31 to 0.54°F per decade since the late 1970s. In addition, the number, duration, and intensity of heat waves are all increasing rapidly. See "Climate Change Indicators: U.S. and Global Temperature" and "Climate Change Indicators: Heat Waves".

high temperatures reduce workers' working time across heat-sensitive industries. Somanathan et al. (2021) show that high temperatures in India reduce workers' productivity and increase their absenteeism, leading to a 2% fall in annual plant output. The regulatory risk arises from the possibility of governments introducing regulations to protect workers against heat hazards. These regulations, such as the Heat Illness Prevention Standard (HIPS) passed in California in 2005, often require employers to provide employees with more training and protection, leading to higher operating costs for firms.

Crucial to my empirical investigations is the measurement of a firm's exposure to climate change through the labor channel. To this end, I obtain data on occupations needed in each industry from the Occupational Employment and Wage Statistics (OEWS) and each occupation's outdoor activity score from the O*NET program. The score is based on how often a given job requires working outdoors. Then, I construct an index measuring a firm's labor exposure to climate change at the four-digit NAICS level. This index is a weighted average of all occupations' outdoor activity scores within a four-digit NAICS industry. The weight is the percentage of people working in a given occupation in a four-digit NAICS industry. Based on this index, I create a rank variable of labor exposure to climate change - *LECC*, ranging from 1 to 10, with 10 indicating the highest exposure.

My first set of analyses examines the association between firms' labor exposure to climate change and capital-labor ratios over the period 2002 - 2019. The capital-labor ratio is measured as the natural logarithm of a firm's property, plant, and equipment divided by its number of employees. I find that firms with higher exposure to climate change through the labor channel exhibit higher capital-labor ratios. The finding is also economically significant. A one-unit increase in LECC is associated with an 18.3% increase in the capital-labor ratio. The evidence suggests that firms that are more exposed to climate change through the labor channel adopt more capital-intensive production functions. Further decomposition suggests that both higher capital investment and lower employment contribute to the capital-labor ratio gap.

I then conduct several cross-sectional tests to explore the underlying mechanisms driving the capital-labor ratio gap. I first find that the results are weaker in Republican-led firms, consistent with the notion that Republicans care less about climate change. Second, the results are stronger in industries where jobs are easy to automate. This is consistent with the idea that a prerequisite for upgrading production functions is that automated capital is a substitute for outdoor workers. Otherwise, firms will have to continue relying on outdoor workers. The evidence supports that firms adapt to climate change by increasing automation. Third, the results are weaker when labor unions protect employees from being fired, suggesting that labor unions slow down firms' adaptation actions. Overall, cross-sectional analyses imply that managers' beliefs about climate change and the possibilities of substituting capital for labor are critical in firms' adjustment toward capital-intensive production processes.

Next, I design two empirical strategies to address endogeneity issues in the baseline results and to pin down the underlying mechanisms. In the first strategy, I utilize variations in hot temperatures across counties and examine how firms respond to local temperature shocks. Specifically, I focus on relative temperature shocks that are exogenous to firms' operations, which occur when a county's daily temperatures in the summertime (May - September) exceed the 90^{th} percentile of local summer temperature records. These shocks not only directly hurt workers' productivity (*realized physical risks*) but also cause individuals to revise their beliefs about climate change upward and pay more attention to climate risks (*expected higher physical and regulatory risks*) (e.g., Joireman et al., 2010; Li et al., 2011; Sisco et al., 2017; Choi et al., 2020). The threats caused by realized physical risks and expected higher physical and regulatory risks before long together incentivize managers to adjust to higher capital-labor ratios to optimize their production.

Using temperature shocks matched to firms' operating locations, I first investigate the physical risk mechanism by examining labor productivity. I find that hot temperature shocks significantly hurt labor productivity, leading to lower sales and sales per employee. The economic effects are also significant. After severe temperature shocks, the sales and sales per employee of a firm with a climate exposure ranking of six are 3.6% and 2.2% lower than those of a firm with a climate exposure ranking of four, respectively.

Then, I test the effects of temperature shocks on production functions. The results show that high-exposure firms adjust production functions towards higher capital-labor ratios after the shocks. In particular, in two years after the shocks, a firm with a climate exposure ranking of six increases its capital-labor ratio by 3% relative to a firm with a climate exposure ranking of four. More importantly, the adjustment only happens when short-term temperature shocks agree with long-term temperature projections. Put differently, firms only respond to a one-time temperature shock when model-based climate projections suggest that long-term temperature changes are acute. Otherwise, managers do not take short-term temperature shocks as indicators of climate change and thus do not make adjustments to existing production functions. Combined together, the evidence suggests that the physical risk mechanism alongside rising temperatures is a critical driver of high-exposure firms' adjustment towards capital-intensive product functions.

In the second identification strategy, I design a difference-in-differences test based on the HIPS adopted in California in 2005 to study the regulatory risk mechanism. The HIPS includes new specific requirements that employers should provide their workers with enough drinking water, shade for rest, medical support, training, and other sufficient means and safety plans to abate heat hazards. Violations of these requirements can damage a firm's reputation and expose it to serious litigation risks. Hence, the bill significantly raises firms' operating costs (*realized regulatory risks*). In addition, this bill catches people's attention to climate-related regulations in the labor market, making them anticipate that more and tighter rules will likely be implemented, and stricter enforcement will be conducted as temperatures rise (*expected higher regulatory risks*). Importantly, the bill's adoption is a result of cumulative historical temperature threats rather than a one-time spike in temperatures or significant changes in regulatory environments. Therefore, the adoption is likely exogenous from a given firm's perspective.

To conduct the difference-in-differences analyses, I split firms into two groups - firms with high labor exposure to climate change in California as the treated group and firms with low labor exposure in California as the control group. This is because high-exposure firms have many outdoor workers and thus are more affected by the bill. Estimations on dynamic treatment effects show no significant differences in capital-labor ratios between the treated and the control groups in the pre-treatment period, supporting the parallel trends assumption. Following the adoption of the HIPS, treated firms increase their capital-labor ratios by 15.1%, relative to control firms. The evidence implies that the regulatory risk mechanism alongside rising temperatures is another critical factor driving firms' adjustment towards capital-intensive production functions.

I further investigate firms' innovation strategies in the adaptation process, as existing literature has documented the importance of technological advancement in shaping a capital-intensive economy (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2020). I find that high-exposure firms significantly increase both R&D spending and patent filings after temperature and regulatory shocks. These patents are also more valuable, i.e., receiving more citations and having higher market value. In addition, I examine whether the patents are used to facilitate the automation process by using two patent classifications: automation patents from Mann and Püttmann (2021) and process innovations from Bena and Simintzi (2019). Specifically, automation patents are those used to develop a device that carries out a process independently of human intervention. Process innovations describe new ways to produce an existing good with lower labor costs. Empirical results show that high-exposure firms are more likely to develop automation patents and process innovations after temperature and regulatory shocks. For example, the probability of having an automation patent among high-exposure firms increases by 3.7%, and the probability of having one process claim increases by 5.2%, relative to low-exposure firms.

Firm-level analyses thus far have provided consistent evidence that rising temperatures increase firms' labor costs, and, in response, they use more capital in production. The firm-level effects may add up to an economically important magnitude that leads to an industry-wise employment contraction. I test this conjecture using the job creation data from the Quarterly Workforce Indicators (QWI). I find that the labor-channel exposure to climate change impedes industry expansion and hurts workers' earnings after temperature and regulatory shocks. In particular, high-exposure industries create fewer new jobs, and workers in these industries see lower earnings growth. The findings indicate that climate change leads to job and income losses for outdoor workers, lending further support to prior results.

The advance in the climate finance literature has broadened our understanding of the impact of climate change on the financial market and firms (e.g., Bernstein et al., 2019; Addoum et al., 2020; Krueger et al., 2020; Painter, 2020; Addoum et al., 2021; Ilhan et al., 2021; Pankratz and Schiller, 2021). However, little attention has been paid to how rising temperatures may affect firms' human capital. This paper fills the void by identifying a labor channel of firms' exposure to climate change, and in particular, showing that firms address the challenges by substituting capital for labor, i.e., more capital investment and less hiring.[3] More generally, this paper highlights that climate change accelerates automation in occupations exposed to rising temperature threats. In this regard, this paper echoes the call for more research on adaptation to climate change (Fankhauser, 2017).

To the best of my knowledge, my paper is the first to construct a measure of firms' exposure to climate change through the labor channel. In this regard, this paper contributes to the literature trying to measure firms' climate risk exposure in various ways, e.g., asset exposure to floods or sea level rise, carbon emissions, ESG scores, textual analyses of earnings conference calls or 10-K filings (e.g., Bernstein et al., 2019; Engle et al., 2020; Li et al., 2020; Sautner et al., 2022; Bolton and Kacperczyk, 2021; Nagar and Schoenfeld, 2022). However, few works quantify the temperature threats to firms' human capital. Therefore, this paper suggests a new angle to assess firms' climate risk exposure, echoing the call for improvements in measuring climate risk exposure in different asset classes in Giglio et al. (2021).

With this measure, I propose and identify two risk sources in the labor channel - physical and regulatory risks. My tests on the physical risk mechanism contribute to the discussion about the negative impact of high temperatures on firm performance, regarding which existing evidence is mixed. For example, Addoum et al. (2020) find no evidence that exposure to extreme temperatures affects establishment-level or firm-level sales or productivity in the U.S. Their follow-up work documents bi-directional effects of temperature exposure on firms - some benefit but some get hurt (Addoum et al., 2021). In contrast, other works show that increased exposure to high temperatures reduces firms' operating performance (Custodio et al., 2021; Pankratz et al., 2021). The negative effects also transmit along supply chains to firms' customers (Pankratz and Schiller, 2021). My analyses show that high temperatures negatively affect firm performance through the physical risk mechanism in the labor channel. Regarding

[3] Li et al. (2020) find that firms that mention more climate-related words in earnings conference calls increase their capital expenditure but cut R&D spending. They also document mixed effects on employment. Their work focuses more on developing a measure of firms' climate exposure and does not explain why firms invest differently. Meanwhile, Jin et al. (2021) find that firms exposed to high temperatures over the past five years cut employment, which they argue is because of reduced local consumption demand. My paper diverges from theirs by identifying two risks embedded in the labor-channel exposure to climate change - reduced labor productivity and increased labor protection. Hence, my paper explains why firms cut employment and increase capital and R&D investments. In addition, my results hold in non-consumer-oriented industries, indicating that demand-side forces do not likely drive my findings.

regulatory risks, prior works mainly focus on environmental policies (e.g., Ivanov et al., 2021; Bartram et al., 2022; Seltzer et al., 2022). This paper departs from those studies and focuses on climate-induced regulations in the labor market, i.e., regulations protecting workers against heat hazards. These regulations significantly raise firms' labor costs and thus incentivize them to adopt more capital-intensive production functions.

This paper also adds to the literature on labor and finance, specifically on how frictions in labor markets affect corporate investments and outcomes. Previous works have explored how the adoption of labor-savings technologies depends on rigidities in the labor markets (e.g., Ouimet et al., 2020; Bena et al., 2021; Qiu and Dai, 2022). In line with these studies, I provide empirical evidence which highlights that climate-induced rising labor costs facilitate the adoption of labor-saving production methods. Meanwhile, both lost labor productivity and increased labor protection boost firms' innovation efforts, especially in technologies that facilitate automation and reduce reliance on labor.

Last, a striking trend in the economy over the past several decades is the decline of the labor share and the rise of automation, driven by both the availability of cheaper and more efficient capital goods and the fast-growing labor costs (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2020). This paper proposes a new force driving the increase of labor costs and the shift to a capital-intensive economy: rising temperatures induced by climate change. In response, firms resort to automation to maintain profit margins.

The paper proceeds as follows. Section 2 describes the conceptual framework. Section 3 describes data and measures used in empirical analyses. Section 4 presents the baseline and cross-sectional results. Section 5 presents evidence identifying the underlying mechanisms (physical and regulatory risks) and addressing endogeneity issues. Section 6 investigates firms' innovation activities and section 7 studies industry dynamics. Section 8 concludes the paper.

2 Conceptual Framework

2.1 Climate Change and Labor Costs

Climate risks can be classified into two types - *physical risk* and *transition risk* (Giglio et al., 2021; Stroebel and Wurgler, 2021).[4] In this paper, I argue that both physical and regulatory (one type of transition risks) risks contribute to the rising labor costs of firms relying on outdoor workers as temperatures increase.

Physical risk in this paper refers to the negative effects of high temperatures on outdoor workers' labor supply and productivity. This is because being exposed to heat can cause a series of heat-related illnesses (e.g., Naughton et al., 2002; Luber and McGeehin, 2008), resulting in severe threats to outdoor workers' health and therefore limiting their abilities to work. Existing studies have shown that workers' working hours are significantly shortened during hot days, implying substantial contractions in labor supply (e.g., Graff Zivin and Neidell, 2014; Dillender, 2021). In addition, hot temperatures hurt workers' both physical and cognitive performance (Epstein et al., 1980; Galloway and Maughan, 1997), leading to lower working productivity and efficiency (Somanathan et al., 2021; Zhang et al., 2018). Importantly, even the world's wealthiest economy is subject to non-trivial heat-related output losses (Deryugina and Hsiang, 2014; Burke et al., 2015; Behrer and Park, 2017).[5] Considering the high rigidity in workers' wages (Taylor, 1999), the lost labor productivity significantly raises firms' operating costs and thus hurts firms' profit margins.

Regulatory risk in this paper refers to governments introducing regulations to protect workers against heat hazards. As climate change intensifies, rising temperature threats to workers' health have caught the attention of various U.S regulators. In response, regulators have urged

[4]Physical risk refers to the risk that the increasing frequency and severity of climate-related weather events or long-term changes in climate patterns may directly cause significant economic costs and financial losses. For example, rising sea levels may inundate communities in coastal areas, and wildfires may destroy residential properties and corporate warehouses. Transition risk refers to the risk associated with uncertain financial impacts due to the transition to a low-carbon economy. Examples include changes in policies (e.g., a carbon tax), technological advances, and shifts in consumer preferences and social norms away from high-carbon activities, etc.

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

all parties to take action to address the challenges. For instance, the Environmental Protection Agency (EPA) stated that "*employers, safety professionals, and workers should stay informed about emerging issues and hazards associated with climate change to better develop plans that address worker safety and health.*" Appendix A provides additional evidence of regulators' rising attention to climate threats. Generally speaking, these regulations require employers to provide employees more protection, e.g., rest, training, compensation, and medical support. Enforcing these rules significantly increases firms' labor costs and, therefore, presents big challenges to firms' operations. In section 5.2.1, I provide institutional background on these regulations. I also discuss the HIPS passed in California and its enforcement and impact on firms.

2.2 Climate Change and Production Functions

Assume that firms produce goods and services with two factors: capital (K) and labor (L). Firms choose the optimal capital and labor mix given the costs of capital (r) and labor (w). That is, firms try to minimize production costs per unit of output.

As discussed in section 2.1, over time, intensifying climate change raises firms' labor costs, resulting in higher relative costs of labor to capital - w/r. The underlying mechanisms are physical and regulatory risks. These risks are not evenly distributed across years. Rather, they reflect large downside scenarios, often manifesting as rare but big destructive climate events or regulatory changes in the labor market. The most relevant climate events to this paper are abnormal heat waves, which are unexpected long-lasting high temperatures that negatively affect workers' health and productivity, leading to significant disruptions to firms' operations. An example of regulatory changes is the HIPS adopted in California in 2005. The heat events and regulatory changes are *realized climate risks* that push up labor costs higher than expected, warning firm managers of vulnerabilities of current production facilities. Consequently, these climate and regulatory shocks are indicators that managers should upgrade their production functions to better adapt to rising climate threats.

These salient heat events also make managers and regulators revise their beliefs about climate change upward and pay more attention to climate risks - *expected higher physical and regulatory risks* (e.g., Joireman et al., 2010; Li et al., 2011; Sisco et al., 2017; Choi et al., 2020). Meanwhile, the HIPS catches people's attention to climate-related regulations in the labor market, making them anticipate that more and tighter rules will likely be implemented, and stricter enforcement will be conducted as temperatures rise - *expected higher regulatory risks*. These revised expectations regarding climate risks also incentivize firm managers to upgrade their production facilities to better prepare for future climate and regulatory shocks.

The above discussions suggest that both abnormal heat events and regulatory changes are key moments for firms to make major adjustments to their production functions. Specifically, firms respond to these climate and regulatory shocks by adjusting toward more capital-intensive production processes, which allows them to reduce reliance on labor and thus avoid increasing labor costs driven by rising climate risks.

Assume that all firms face the same capital menu and costs but heterogeneities in labor cost w affected by climate change. Then, firms that are more exposed to climate change through the labor channel face higher w/r and thus should have higher capital-labor ratios.

Hypothesis: Firms whose labor is more exposed to climate change will adopt more capital-intensive production functions to minimize the impact of rising temperatures on their labor costs.

3 Data and Measures

3.1 Labor Exposure to Climate Change

To construct the measure of labor exposure to climate change, I first obtain the industry-level occupational data from the Occupational Employment and Wage Statistics (OEWS) provided by the U.S. Bureau of Labor Statistics (BLS). This data includes occupations needed in each industry (at the three-digit SIC level from 1997 to 2001 and the four-digit NAICS level from 2002 onwards), wage estimates for each occupation, and the number of employees working in each occupation. This data is collected through annual surveys that track employment across about 800 occupations and almost all industries from about 200,000 non-farm establishments in the U.S. every six months, not including self-employed workers.

I also collect data on occupational outdoor activity from the U.S. Department of Labor's O*NET program. The O*NET program on work context gives each occupation a score between

0 and 100 based on the following question - "*How often does this job require working outdoors, exposed to all weather conditions?*". The higher the score is, the more outdoor time an occupation requires to perform the job. Hence, this score helps quantify temperature threats workers face.

Table 1 Panel A presents some examples of occupations with high, medium, or low exposure to weather from the O*NET program. Examples of high-exposure occupations include parking enforcement workers, driver/sales workers, gas plant operators, ship engineers, etc. Most jobs of these occupations are performed in an outdoor environment with direct exposure to all weather conditions. Examples of medium-exposure occupations include real estate sales agents, automotive service technicians and mechanics, civil engineers, retail salespersons, etc. These occupations usually have balanced indoor and outdoor working time. Examples of low-exposure occupations include industrial engineers, human resource specialists, computer hardware engineers, lawyers, pharmacists, etc. Jobs of these occupations are mainly performed indoors with little chance of being affected by the weather.

With the OEWS and the O*NET data, I construct an index of labor exposure to climate change following prior works (Belo et al., 2017; Ghaly et al., 2017). Specifically,

$$\textit{Labor Exposure to Climate Change Index}_{jt} = \sum_{k=1}^{K_{jt}} \left(\frac{E_{jkt}}{E_{jt}} * Z_k \right) \tag{1}$$

where j denotes industry, k denotes occupation, K_{jt} is the total number of occupations in industry j, t denotes year, E_{jkt} is the number of employees working in occupation k in industry j, E_{jt} is the total number of employees in industry j, and Z_k is the occupational score of outdoor activity from the O*NET program. Thus, the index is a weighted average of all occupations' exposure to weather in a four-digit NAICS industry. The weight is the percentage of employees working in a given occupation in an industry. Based on this index, I create a rank variable *LECC*, ranging from 1 to 10, with 10 indicating the highest exposure.

Table 1 Panel B presents examples of industries with high, medium or low exposure to climate change based on the *LECC* in 2015. At the high end, as expected, high-exposure industries are those that need most outdoor workers, such as logging, postal service, oil and gas extraction, basic chemical manufacturing, etc. Examples of medium-exposure industries include dairy product manufacturing, tobacco manufacturing, employment services, radio and television broadcasting, etc. At the low end, hardware manufacturing, motor vehicle manufacturing, office administrative services, and legal services are examples of low-exposure industries. Interestingly, four-digit NAICS industries in the same three-digit NAICS category can have very different exposure ranks - 8 for the facilities support services industry (5612), 5 for the employment services industry (5613) and 1 for the office administrative services industry (5611).

In Appendix B, I validate the measure *LECC* by showing that managers of high-exposure firms discuss more climate-related issues in earnings conference calls and 10-K filings. This suggests that a firm's reliance on outdoor workers does expose the firm to significant climate risks, which builds the foundation for studying firms' adaptation to the labor-channel exposure to climate change.

In Appendix C.2, I construct a firm-level measure by adding information on firms' business operations across industries. The correlation between the industry-level and the firm-level indexes is 0.93. Results are robust to the firm-level measure. I use the industry-level measure in my analyses for simplicity.

3.2 Sample Construction

The main sample used in empirical analyses starts from the Compustat and spans the period 2002 - 2019.[6] I exclude firms from the financial or utility industries. Firms headquartered outside of the U.S. are also dropped. Information on firms' historical headquarter state and county and industry is from the "company header history" file in the legacy CRSP/Compustat Merged database.

Data on establishment-level employment and sales is from Your Economy (YE) Time Series, provided by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin. YE Time Series tracks all establishments at their unique locations from 1998, including

[6] I choose 2002 as the beginning year to avoid the inconsistency of industry classification in the OEWS data - three-digit SIC code before 2002 and four-digit NAICS code from 2002 onwards. Also, there were few discussions on the influence of climate change on the financial market in the 1990s. Nevertheless, results remain robust if I extend the sample back to 1997 by renewing the measure based on three-digit SIC codes for the 1997-2001 period. I choose 2019 as the ending year to avoid disruptions to production caused by the Covid-19 pandemic.

for-profit (both privately-owned and publicly-traded), non-profit, agriculture, and government establishments. All establishments covered by YE Time Series are in-business. Businesses that are created for the purpose of housing financial, real estate, and tax reporting entities, or are suspected of never actually conducting commercial activities, are not included in YE Time Series. The data also provides detailed industry classifications for each establishment.

I obtain data on abnormal temperature patterns from May to September in each county and year in the U.S. from the Historical Temperature & Heat Index managed by the Centers for Disease Control and Prevention (CDC). The data includes the number of extreme heat days, the number of extreme heat events, daily estimates of maximum temperatures, etc. I complement the CDC data with daily data on historical temperature and precipitation records from the Global Historical Climatology Network (GHCN) database, provided by the National Centers for Environmental Information (NCEI). The data is collected from more than 100,000 stations across the globe. I match the stations to each county in the U.S through geographic coordinates.

The CDC also provides data on long-term temperature projections. The raw data is from the Localized Constructed Analogs (LOCA), which is derived from 32 Coupled Model Intercomparison Project (CMIP5) models that are widely used in the climate science literature (Hurrell et al., 2011). The projections are estimated for a high emissions scenario (the Representative Concentration Pathway (RCP) 8.5) and a low emissions scenario (RCP 4.5), respectively. The CDC processes the raw data and aggregates it at the county level. The data gives projected differences in extreme heat days between the time period selected and the referent period (1976 – 2005) for both emission scenarios. There are three time periods available: 2016 - 2045, 2036 – 2065, and 2070 – 2099, of which I use the 2016 - 2045 period as it is more relevant to the study.

In addition, I obtain the following datasets from various sources for empirical analyses.

[1] **ExecuComp**

Data on names, titles, tenure, and annual compensations of top managers of the S&P 1500 firms is from the ExecuComp.

[2] **Individual Political Contributions**

Data on individuals' political contributions is from the Federal Election Commission (FEC). This data provides complete records of individuals' political contributions to Republican or Democratic Senate, House, and presidential candidates, and to party committees established by candidates and political parties to collect and manage campaign funds. The raw data covers political campaigns in federal elections in the U.S. starting in 1975. Initially, any contribution of at least $500 was required to be disclosed to FEC. In 1989, the threshold was reduced to $200. The data reports detailed information on each individual's name, address, occupation, employer, the contribution date, amount, and the political party of the recipient entity. I follow the literature to clean the data and merge it with ExecuComp and Compustat using both individuals' and employers' names. To ensure accuracy, I only keep matched pairs with a matching score above 0.6 and manually check each pair.

[3] **Workplace Automation**

Data on occupational automation score is from the O*NET program. It reports the degree of automation for each occupation based on the question - *"How automated is the job?"*.

[4] **Labor union**

Data on industry-level union coverage is from the Union Membership and Coverage Database at www.unionstats.com, maintained by Barry Hirsch and David Macpherson.

[5] **Innovation**

Data on firms' patenting activities is from Kogan et al. (2017). It includes the applicant's PERMNO number, patent number, filing year, grant year, forward citations and the estimated patent value, etc.

Data on the classification of automation patents is from Mann and Püttmann (2021). The classification is based on textual information in patents. Specifically, the authors apply a machine learning algorithm to all US patents granted from 1976 to 2014 to identify patents related to automation - a device that carries out a process independently of human intervention. The device can be a physical machine, a combination of machines, an algorithm or a computer program. The definition of independence means that the automation device works without human intervention, except at the start and for supervision. This excludes patents that are minor parts of an automation innovation and highly abstract patents with no obvious application. Therefore, their classification is fairly strict, as devices that require a certain amount of labor involvement but are efficiency-enhancing are also desirable for reducing labor costs.

Data on the classification of process and non-process innovation is from Bena and Simintzi (2019). A process innovation describes a new way to produce an existing good, with the aim to lower production costs, e.g., labor costs. A non-process innovation typically describes a new good that did not exist before. The data includes the patent number, the filing and granting date, number of claims per patent, and number of process claims per patent.

[6] **Job creation**.

The job creation data is from the Quarterly Workforce Indicators (QWI), derived from the Longitudinal Employment-Household Dynamics (LEHD) program at the Census Bureau. The QWI is reported based on detailed firm characteristics and worker demographics and is available at the national, state, MSA, county, or workforce investment areas (WIA) level.

3.3 Summary Statistics

Table **2** presents the summary statistics. The mean and median of a firm's capital-labor ratio are 3.687 and 3.549, with a standard deviation of 1.634, indicating significant variations in choices of production functions across firms. The average rank of a firm's labor exposure to climate change is 4.557.

Figure 1 (A) presents the time-series average of all firms' capital-labor ratios from 1980 to 2019. Consistent with the literature, the figure shows that the whole economy is becoming more capital-intensive over time. Figure 1 (B) presents the time-series average capital-labor ratios for high-exposure (*LECC* larger than five) and low-exposure (*LECC* equal to or smaller than five) firms separately. It shows that high-exposure firms, on average, have higher capital-labor ratios than low-exposure firms. The capital-labor ratio gap did not change much over time before 2000. However, after 2000, the gap becomes wider as time goes by, coinciding with the trends of rising temperatures and people's concerns about climate risks over time.

Figure 2 presents the relation between a firm's labor exposure to climate change and its capital-labor ratio at the cross-sectional level. It shows a monotonic increasing relation between the *LECC* and the capital-labor ratio. From group 1 (lowest exposure) to group 10 (highest exposure), the capital-labor ratio increases by 67.9% from 2.8 to 4.7.

4 Labor Exposure to Climate Change and Production Function

4.1 Firm Capital-labor Ratio

I first examine the association between a firm's exposure to climate change through the labor channel and its choice of product functions. My conjecture is that high-exposure firms use more capital-intensive production functions - higher capital-labor ratios. The empirical model is as follows:

$$Y_{it} = \mu_{st} + \pi_{jt} + \beta * LECC_{jt} + \delta \mathbf{X}_{it} + \varepsilon_{it} \tag{2}$$

where i denotes firm, j denotes industry, s denotes a firm's headquarter state, t denotes year. Y_{it} is the dependent variable - the logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP). The key independent variable is the rank variable of a firm's labor exposure to climate change *LECC*, ranging from 1 to 10, with 10 indicating the highest exposure. Controls include a firm's labor skill, the logarithm of total assets, leverage, and a dummy indicating whether a firm pays dividends. μ_{st} is the firm headquarter state-by-year fixed effects, which control for time-varying state-specific trends. π_{jt} is the two-digit NAICS industry-by-year fixed effects, which absorb industry shocks. In more complete models, I use three-digit NAICS industry-by-year fixed effects to replace two-digit NAICS industry-by-year fixed effects.

Table 3 reports the results. The coefficient estimate of *LECC* is positive and statistically significant in column (1), suggesting that firms that are more exposed to climate change have higher capital-labor ratios. The coefficient estimate remains significant after adding firm headquarter state-by-year fixed effects to ensure that state-specific time-varying omitted variables cannot explain the finding. Results also hold after adding two-digit NAICS industry-by-year or three-digit NAICS industry-by-year fixed effects to control for time-varying industry trends. The effect is also economically important. In column (6), a one-unit increase in LECC is associated with an 18.3% increase in the capital-labor ratio.

It is worth emphasizing that even though the climate exposure index is time-variant, it is highly sticky over time. The time-series variations purely come from changes in each industry's needs for different occupations. For example, the four-digit NAICS industry fixed effects absorb 98% variations in the index. Nevertheless, I further add firm fixed effects in column (8). The results remain significant, though the economic magnitude is much smaller. This partly alleviates the concern that unobserved time-invariant firm-level or industry-level factors may explain the findings in columns (1) - (7). Overall, the results are consistent with my conjecture that high-exposure firms adopt more capital-intensive production functions.

In Internet Appendix C, I conduct a battery of robustness checks of the baseline results. First, I add more controls, including market-to-book ratio, cash flow, cash flow volatility, R&D, and annual change in the logarithm of sales. I also try controlling for firms' overall climate exposure using the measures developed by Sautner et al. (2022) (Table C.1). Second, I construct two alternative measures of the labor exposure to climate change index by: (1) adjusting for each occupation's wage; (2) adjusting for firms' business segments across industries (Table C.2). Third, I construct four alternative measures of firms' capital-labor ratios by: (1) using a firm's gross property, plant, and equipment (PPEGT); (2) using a firm's adjusted gross property, plant, and equipment (PPEGT) following Hall (1990); (3) using a firm's labor expense (XLR); (4) using a firm's imputed labor expense (XLR) following Donangelo et al. (2019) (Table C.3). All results are consistent.

4.2 Decomposition of Firm Capital-labor Ratio

In Panel B of Table 3, I decompose the capital-labor ratio into the capital and labor components. In columns (1) and (2), the dependent variable is the logarithm of a firm's property, plant, and equipment - *Log(PPENT)*. The coefficient estimate of *LECC* is positive and statistically significant. The coefficient estimate remains positive and significant when using a firm's capital expenditure scaled by its lagged assets as the dependent variable in columns (3) - (4). The results suggest that high-exposure firms have more capital stock and higher capital investment rates. The capital stock and investment rate of a firm with a climate exposure ranking of six are 23% and 7.6% larger than those of a firm with a climate exposure ranking of four, respectively. Next, I use the logarithm of a firm's number of employees as the dependent variable in columns (5) - (6) and the annual change in the logarithm of a firm's number of employees as the dependent variable in columns (7) - (8). The coefficient estimates of *LECC* are negative and statistically significant in all four columns, suggesting that high-exposure firms have both lower employment levels and lower employment growth rates. The employment level and growth rate of a firm with a climate exposure ranking of six are 12% and 0.6% smaller than those of a firm with a climate exposure ranking of four, respectively.

Furthermore, In Internet Appendix Table C.4, I show that high-exposure firms have higher tangibility, lower symmetric employment growth, and low growth rate in labor expenses. To sum up, the evidence indicates that the capital-labor ratio gap between high- and low-exposure firms is driven by both increased capital investment and reduced employment.

4.3 Cross-sectional Analyses

To better understand what drives the capital-labor ratio gap between high- and low-exposure firms, I conduct several cross-sectional tests in this section.

4.3.1 Top-management Political Beliefs

Existing literature has shown that individuals' political orientation strongly affects their beliefs about climate issues (e.g., McCright, 2011; Bernstein et al., 2022; Zhang, 2022). For example, Bernstein et al. (2022) show that houses exposed to sea level rise (SLR) are more likely to be owned by Republicans, suggesting that Republicans believe less in climate change and are less worried about climate risks. This is consistent with anecdotal evidence that Republicans are less active in taking action to deal with climate challenges.[7] Therefore, I use managers' political orientations as proxies for their beliefs about climate change.

Following the literature, I create a measure of management teams' political leaning using the data on firms' top executives from *EexcuComp* and the data on individuals' political contributions from the FEC (Hutton et al., 2014). Specifically, I first calculate an executive's net cumulative contributions to the Democratic and the Republican parties separately from 1992 to

[7]For example, a report by the Pew Research Center shows that Democrats are more than three times as likely as Republicans to say dealing with climate change should be a top priority (78% *vs.* 21%). See "More Americans see climate change as a priority, but Democrats are much more concerned than Republicans".

2017.[8] Then, I calculate the fraction of each executive's contributions to the Republican party. Last, I aggregate the measure at the firm level using the following equation:

$$\text{Rep}_{it} = \sum_{e=1}^{N_{it}} \omega_{eit} \times \text{Rep}_e \tag{3}$$

where e denotes executive, i denotes firm, and t denotes year. Rep_e is the fraction of an executive's political contributions to the Republican party, N_{it} is the number of top executives a firm has, ω_{eit} is the time-varying weights based on the share of each executive's total annual compensation in the total annual compensation paid to all of a firm's executives. These weights consider that different executives have different influences on corporate decisions, which are often highly correlated with the compensation they receive. Based on the measure, I further create a dummy, *Republican Management*, which equals one if more than 70% of the management team's contributions flow to the Republican party. Therefore, this dummy captures firms with management teams that strongly lean towards the Republican party.

The results are reported in columns (1) - (2) of Panel B, Table 4. It shows that firms managed by Republican management teams do not adjust their capital-labor ratios in response to climate change as much as other firms do. The findings support the notion that Republicans act slower than Democrats in addressing climate threats.[9]

4.3.2 Workplace Automation

A prerequisite for the adjustment of production functions is that outdoor workers can be substituted by automated capital. Otherwise, firms will have to continue relying on outdoor workers, despite high risks and costs. This predicts that the baseline results should be more pronounced in industries where jobs are easy to automate. To test this substitution effect, I construct a measure of workplace automation in the same way as the *LECC*.

[8]The ExecuComp data starts from 1992 and was available until 2017 when I constructed this measure. Using all available contributions made by a manager to measure her political leaning means that the measure for the manager does not vary during the sample period. This is consistent with the idea that party identification is developed and established in adolescence or early adulthood and remains stable during the entire adult life (Green et al., 2004). Nevertheless, the results are robust if I use prior donations of managers up to the current fiscal year.

[9]In Appendix C.5, I use the county-level survey data on beliefs about climate change from the *Yale Program on Climate Change* to gauge managers' views on climate threats. Results show that the labor-channel exposure to climate change has larger effects on capital-labor ratios for firms located in counties with stronger beliefs in climate change.

$$Automation\ Index_{jt} = \sum_{k=1}^{K_{jt}} \left(\frac{E_{jkt}}{E_{jt}} * A_k \right) \tag{4}$$

where j denotes industry, k denotes occupation, K_{jt} is the total number of occupations in industry j, t denotes year, E_{jkt} is the number of employees working in occupation k in industry j, E_{jt} is the total number of employees in industry j, and A_k is the the degree of automation for each occupation from the O*NET program. Then, I create a dummy that equals one if the rank variable of this index (1 to 10) is above five and zero otherwise.

Results are presented in columns (3) - (4) of Panel B, Table 4. Consistent with my prediction, firms in industries with high automation prospects adjust more aggressively toward capital-intensive production processes. The results further support the key argument in this paper - firms adapt to climate change by increasing automation and reducing reliance on labor.

4.3.3 Labor Union

Last, I examine how employee protection provided by labor unions affects firms' adaptation. Prior work has documented that labor unions increase employees' bargaining power and firms' firing costs, leading to lower unemployment risk (Lewis, 1986; Matsa, 2010). Therefore, labor unions add barriers to firms' adjustment toward higher capital-labor ratios, as the adjustment requires firing workers in the first place. I test this prediction in columns (5) - (6) of Panel B, Table 4. The results show that the baseline findings are weaker for firms in more unionized industries, indicating that labor unions slow firms' adaptation to climate change.

Taken together, cross-sectional analyses imply that managers' beliefs about climate change and the possibility of substituting capital for labor are critical in firms' adjustment of production functions. The evidence supports the hypothesis that managers adopt capital-intensive production functions to address concerns over climate-induced rising labor costs.

5 Climate Risks

I hypothesize that physical and regulatory risks induced by high temperatures raise the labor costs of firms relying on outdoor workers. The physical risk refers to the negative impact of high temperatures on outdoor workers' labor supply and productivity. The regulatory risk arises from the possibility that regulators may require employers to pay extra costs to protect their workers from heat hazards. In this section, I design two empirical tests to identify the two risks and examine their impact on production functions. The tests also help address endogeneity issues in the baseline results in Section 4.1.

5.1 Temperature Shocks

My first empirical strategy utilizes variations in hot temperatures across areas and examines how firms respond to local temperature shocks. These shocks affect firms in two ways. First, hot temperatures are real-time physical risks that hurt workers' labor supply and productivity (*realized physical risks*). In consequence, firms' operations get disrupted, and performances deteriorate. Second, hot temperatures cause individuals, including managers and regulators, to revise their beliefs about climate change upward and pay more attention to climate risks (*expected higher physical and regulatory risks*) (e.g., Joireman et al., 2010; Li et al., 2011; Sisco et al., 2017; Choi et al., 2020).

The threats caused by realized physical risks and expected higher physical and regulatory risks before long together incentivize managers to adjust to optimal production functions - higher capital-labor ratios. Importantly, the optimal level of capital-labor ratios is time-dependent - it gradually increases as temperatures become hotter and hotter. That is, each hot temperature shock pushes the optimal level of capital-labor ratio higher.

A big concern regarding this empirical strategy is that firms with certain observed or unobserved characteristics may incorporate local climate into their production decisions (e.g., choices of production functions, product types, operating locations, etc.). To address this concern, I focus on relative temperature shocks that are exogenous to firms' operations. The relative temperature shocks are cases where a county's daily temperatures in the summertime (May - September) are above the 90^{th} percentile[10] of the county's summer temperature records

[10] There are several reasons why I only count relative abnormal temperature shocks in the summertime. First, this is a widely used method to identify the physical climate risk in the literature (e.g., Addoum et al., 2020; Alekseev et al., 2021; Islam and Singh, 2021; Pankratz et al., 2021; Pankratz and Schiller, 2021). Second, using an absolute threshold (e.g., 90°F) can be problematic, as firms' choices of locations and productions are not random. That is, firms located in hot areas may already have many precautionary measures. Third, abnormal temperatures that are relatively mild (e.g., 80°F) in the summertime can be perceived as hot in areas with relatively cool temperatures in history. As long as firms' workers and equipment can not deal with relatively abnormal temperatures, they need to adjust their production process, no matter how high the absolute level is. Fourth, relatively abnormal

from 1979 - 2019[11].

This identification strategy assumes that local relative temperature shocks are not predictable and can not be affected by a specific firm's decisions. This assumption is likely to be true, as the distribution of temperature shocks across years is random (Auffhammer et al., 2013; Dell et al., 2014). As these shocks are unexpected, firms cannot foresee or take any precautious measures against them *ex ante*. Figure 3 presents the distribution of temperature shocks across the contiguous U.S. in 2002, 2007, 2014, and 2019. Consistent with the argument that the relative temperature shocks are exogenous, they are not concentrated in one specific county. Instead, they appear in different counties across the years.

5.1.1 The Physical Risk Mechanism - Effects of Temperature Shocks on Labor Productivity

Before examining production functions, I first test the impact of temperature shocks on firms' labor productivity to pin down the physical risk mechanism. To do the test, I use the establishment-level data on employment and sales from YE Time Series and aggregate the data at the firm-by-county-by-NAICS 4-by-year level. The empirical specification is as follows:

$$Y_{ijct} = \tau_{it} + \mu_c + \pi_{jt} + \beta_1 * LECC_{jt} * Temperature\ Shocks_{ct} + \beta_2 * LECC_{jt} + \beta_3 * Temperature\ Shocks_{ct} + \varepsilon_{ijct} \tag{5}$$

where i denotes firm, j denotes four-digit NAICS industry code of an establishment, c denotes county of an establishment, and t denotes year. Y_{ijct} is the dependent variable - the natural logarithm of a firm's sales or sales per employee in a four-digit NAICS industry j in a county c. The key independent variable is the interaction term between *LECC* and *Temperature Shocks*. *LECC* is a rank variable from 1 to 10, with 10 indicating the highest exposure to climate change.

high temperatures outside the summertime, especially in winter, are good for outdoor workers. For example, McDonald's earnings announcement in 2015 stated that - "fourth quarter comparable sales increased 5.7%, benefiting from... unseasonably mild weather". Untabulated results show that firms' production functions do not respond to absolute temperature shocks (e.g., temperatures above 30° degrees celcius.)

[11] Some may worry about the look-ahead bias in this measure, as it incorporates future temperatures when calculating the threshold for identifying relative temperature shocks. This bias actually raises the bar for identifying relative shocks as temperatures become warmer and warmer. I use this measure in my main analyses to be consistent with the data on climate projections provided by the CDC. In Internet Appendix C, I use a fixed reference period of the past ten years to calculate the 90^{th} threshold for identifying temperature shocks. Results on production functions hold. Untabulated results using a fixed reference of the past twenty years are also consistent.

Temperature Shocks is a dummy indicating that a county has at least 20 days[12] in the summertime with temperatures above the 90^{th} percentile of local summer temperature records. τ_{it} is firm-by-year fixed effects, μ_c is county fixed effects, and π_{jt} is two-digit NAICS industry-by-year fixed effects.

The results are reported in Table 5. Columns (1) and (3) examine the impact of temperature shocks on a firm's labor productivity across industries and counties. The coefficient estimates of the interaction term *LECC*Temperature Shocks* are negative for both sales and sales per employee. However, only the coefficient for sales per employee is statistically significant. In columns (2) and (4), I use firm-by-county-by-year fixed effects to replace firm-by-year and county fixed effects, which allows for comparing a firm's labor productivity across industries within the same county. The coefficient estimates are negative and statistically significant for both sales and sales per employee. Results hold in columns (3) and (6) after using industry-by-year fixed effects to replace industry fixed effects. The effects are also economically significant. In columns (3) and (6), after severe temperature shocks, the sales and sales per employee of a firm with a climate exposure ranking of six are 3.6% and 2.2% lower than those of a firm with a climate exposure ranking of four, respectively.

5.1.2 Effects of Temperature Shocks on Firm Capital-labor Ratio

After presenting evidence supporting the physical risk mechanism, I turn to examine the impact of temperature shocks on firms' production functions. I measure a firm's exposure to relative temperature shocks across counties using data on establishment-level employment as follows:

$$\sum_{c=1}^{C_{it}} \left(\frac{EMP_{ict}}{EMP_{it}} * No.\ days\ with\ relative\ temperature\ shocks_{ct} \right) \tag{6}$$

where i denotes firm, c denotes county of establishments, C_{it} denotes the total number of counties where a firm's establishments locate, and t denotes year. EMP_{ict} is a firm's total employment in county c, EMP_{it} is a firm's total employment, *No. days with temperature shocks* is the number of days with relative temperature shocks in county c in the summertime of year t.

[12]The mean, median, 75^{th} percentile and 95^{th} percentile of the distribution are 21, 19, 29 and 50 days, respectively.

The empirical specification for regression analyses is as follows:

$$
\begin{aligned}
Y_{it} = {} & \tau_i + \mu_{st} + \pi_{jt} + \beta_1 * LECC_{jt} * \mathit{Temperature\ Shocks}_{it} + \beta_2 * LECC_{jt-1} * \mathit{Temperature\ Shocks}_{it-1} \\
& + \beta_3 * \mathrm{LECC}_{jt-2} * \mathit{Temperature\ Shocks}_{it-2} + \beta_4 * \mathrm{LECC}_{jt} + \beta_5 * \mathit{Temperature\ Shocks}_{ct} \\
& + \beta_6 * \mathrm{LECC}_{jt-1} + \beta_7 * \mathit{Temperature\ Shocks}_{ct-1} + \beta_8 * \mathrm{LECC}_{jt-2} + \beta_9 * \mathit{Temperature\ Shocks}_{ct-2} \\
& + \delta \boldsymbol{X}_{it-2} + \varepsilon_{it}
\end{aligned}
\tag{7}
$$

where i denotes firm, j denotes industry, s denotes a firm's headquarter state, and t denotes year. Y_{it} is the dependent variable - a firm's capital-labor ratio. The key independent variable is the interaction term between *LECC* and *Temperature Shocks*. Two lags of the interaction term are allowed to account for delayed responses. *LECC* is a rank variable from 1 to 10, with 10 indicating the highest exposure to climate change. *Temperature Shocks* is a dummy indicating that a firm experiences at least 20 days in the summertime with relative temperature shocks. Controls include a firm's labor skill, the logarithm of total assets, leverage, and a dummy indicating whether a firm pays dividends. Firm-level controls are lagged by two years. τ_i is firm fixed effects, μ_{st} is the firm headquarter state-by-year fixed effects, and π_{jt} is the two-digit NAICS industry-by-year fixed effects.

The results are reported in columns (1) - (3) of Table 6. The coefficient estimates of the three interaction terms are all positive and statistically significant, suggesting that high-exposure firms adjust toward more capital-intensive production functions after temperature shocks. The economic effects are also significant. In column (3), a one-unit increase in *LECC* is associated with a 0.5% increase in capital-labor ratios in the year with severe temperature shocks, a 0.5% increase in the following year, and another 0.5% increase in two years. Put differently, a firm with a climate exposure ranking of six increases its capital-labor ratio by 3% relative to a firm with a climate exposure ranking of four in two years after experiencing the shocks.

Results hold in the following robustness checks in Internet Appendix D. First, to best use the Compustat data, I measure temperature shocks in firms' headquarter counties or states. Second, I redo the tests by controlling for abnormal cold temperatures in winter, abnormal precipitation, and other types of disaster events. Third, I use a fixed reference period of the past ten years to measure temperature shocks. Untabulated results also try using the past twenty years. In addition, results decomposing the capital-labor ratio show that the findings are driven by increased capital and decreased employment.

5.1.3 Projected Long-term Temperature Changes

Results in columns (1) - (3) of Table 6 are consistent with the notion that managers update beliefs about climate change after seeing abnormal temperature patterns. That is, each temperature shock serves as a piece of evidence that long-term dramatic temperature changes are happening. However, this belief update process should mainly manifest in places where short-term temperature shocks agree with long-term temperature projections. Put differently, if model-based climate projections suggest that long-term temperature changes are mild, managers may not take short-term temperature shocks as indicators of climate change and therefore do not make adjustments to existing production functions. More specifically, the effects of a one-time temperature shock on production functions in columns (1) - (3) should primarily exist in areas where projected long-term temperature increases are significant.

To test this conjecture, I split firms into two groups - firms operating in counties with projected temperature increases above the sample median and firms operating in counties with projected temperature increases below the sample median. Then I examine the effects of temperature shocks on production functions for the two groups, respectively. Results in columns (4) - (5) of Table 6 show that short-term temperature shocks only positively affect production functions of firms operating in counties with big projected temperature increases. For firms operating in counties with mild projected temperature increases, short-term temperature shocks do not affect their production functions, suggesting that managers do not take these shocks as indicators of climate change.

Taken together, findings in Section 5.1 confirm that rising temperatures indeed drive high-exposure firms' adjustment towards capital-intensive product functions. The physical risk mechanism, i.e., adverse effects of high temperatures on labor productivity, is a critical underlying force driving the decisions. However, it should be noted that tests on production functions can not separate the physical risk mechanism from the regulatory risk mechanism because high temperatures trigger both physical and regulatory risks.

5.2 The Regulatory Risk Mechanism

In this section, I focus on the regulatory risk exclusively and investigate its effects on firms' production functions. To this end, I examine how firms respond to the HIPS passed in California in 2005, which also serves as the second identification strategy addressing endogeneity issues.

5.2.1 Institutional Background

Federal Regulations on Heat Illness Prevention The Occupational Safety and Health Administration (OSHA), a regulatory agency of the U.S. Department of Labor, was established in 1971 to "assure safe and healthy working conditions for working men and women by setting and enforcing standards and by providing training, outreach, education and assistance". Implicit in this mission is that OSHA must ensure that employees are not working under risks of excessive heat that may cause harm or deaths. However, even though OSHA has been paying attention to workers' heat exposure, it has yet to implement a federal heat standard to safeguard workers against rising temperatures.[13]

OSHA does have the General Duty Clause that requires employers to provide their employees with a workplace free of recognized hazards likely to cause serious physical harm or death, including heat hazards. However, the General Duty Clause is mostly *ex-post* remedies after employees have already become sick or died. The enforcement process can be lengthy, often involving waiting for a death certificate, an autopsy report and other proofs. What is worse, the Occupational Safety and Health Review Commission (OSHRC) sets a very high bar for using the General Duty Clause in cases involving heat exposure.[14] Further, a study by OSHA staff shows that the General Duty Clause fails to incentivize employers to implement common elements of illness prevention programs (Arbury et al., 2016).

[13] The National Institute for Occupational Safety and Health (NIOSH) and public interest groups have tried several attempts encouraging OSHA to issue a heat standard requiring employers to protect their workers. However, all attempts failed. See, for example, the petition from Public Citizen and other organizations https://bit.ly/2KGG1WG and the response from OSHA http://bit.ly/2KFB8wZ.

[14] In the case of A.H. Sturgill Roofing Co. v. Secretary of Labor, an OSHRC judge overturned five heat hazard citations against the U.S. Postal Service, holding that OSHA could not rely on a National Weather Service guide to determine heat severity. This ruling significantly hurts OSHA's ability to cite employers for failing to protect workers from heat exposure.

In March 2021, the congressional Democrats introduced a bill, the Asunción Valdivia Heat Illness and Fatality Prevention Act, mandating OSHA to establish an enforceable standard to protect indoor and outdoor workers against occupational heat exposure. This bill is named after Asunción Valdivia, a California farmworker who died from heatstroke in 2004 after picking grapes for 10 hours straight in 105°F temperatures.[15] In addition, as June 2021 became the hottest June on record in the U.S., the Biden Administration sounded the alarm on heat-induced workplace problems and announced a whole-of-government approach to address extreme heat, including developing workplace heat standards and increasing enforcement.[16]

State Regulations on Heat Illness Prevention Before the Congress's and the Biden Administration's move to fill the void, several states have already implemented permanent workplace safety standards for heat, among them California, Washington, and Minnesota. Of the three, California was the first to adopt a Heat Illness Prevention Standard to protect outdoor workers in 2005. The standard was first used as an emergency tool in August 2005 and then turned into a permanent bill in July 2006. Washington followed suit issuing an emergency heat illness prevention standard in 2006 and 2007 and making it a permanent rule in 2008. Both California's and Washington's standards apply to outdoor workers only.[17]

Under the California Code of Regulations[18], employers are required to provide their outdoor employees with the following protections against heat exposure:

[1] **Provision of water**. Workers shall have access to potable drinking water that is fresh, pure, suitably cool and free of charge.

[2] **Access to shade**. When the temperature exceeds 80°F, the employer shall maintain enough areas with shade at all times that are either open to the air or provided with ventilation or cooling. Timely access to shade should be available upon an employee's request when the temperature is below 80°F.

[15] See "S.1068 - Asuncion Valdivia Heat Illness and Fatality Prevention Act of 2021".
[16] See "FACT SHEET: Biden Administration Mobilizes to Protect Workers and Communities from Extreme Heat".
[17] Even passed as early as 1997, Minnesota's heat standard only applies to indoor places of employment, which is not the focus of this study. Some other states are also in action, such as Florida, Nevada, Oregon, and Virgina.
[18] See "§3395. Heat Illness Prevention in Outdoor Places of Employment" for more details of the standard.

[3] **Rest**. 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. If workers show signs of heat illness, they shall not be ordered back to work until any signs of heat illness have abated.

[4] **High-heat procedures**. The employer shall implement high-heat procedures when the temperature equals or exceeds 95°F, including regular communication with employees, a mandatory buddy system, and intensive monitoring of employee health conditions.

[5] **Acclimatization**. All employees shall be closely observed by a supervisor or designee during a heat wave. 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 employment.

[6] **Emergency Response Procedures**. Employers shall implement effective emergency response procedures. For example, workers with symptoms of heat illness shall be monitored and shall not be left alone or sent home without being offered onsite first aid.

[7] **Prevention and Training**. Employers shall establish, implement, and maintain an effective heat illness prevention plans. Employers must train their employees to recognize the symptoms of heat illness and their rights.

Since the establishment of the HIPS, California OSHA has been strictly enforcing the rules. A recent assessment report suggests that there were in total 45,889 heat-related inspections and 20,904 violations of the HIPS cited from 2005 to 2019.[19] However, the federal OSHA only conducted 142 inspections resulting in at least one heat citation under the general duty clause between 2013 and 2017.[20] Furthermore, using the universe of injury claims in California, Park et al. (2021) show that the effect of hot temperatures on injury risk is much lower after the HIPS. In particular, they find that hot temperatures caused approximately 6,100 injuries per year in 2001 - 2005 versus approximately 4,250 injuries per year in 2006 - 2018.

Violating the HIPS may trigger civil penalties. Depending on the severity of a violation, the fine ranges from hundreds to millions.[21] Moreover, violations can result in criminal penalties

[19] See Internet Appendix Figure E.1.

[20] See page 29 in the report "Extreme Heat and Unprotected Workers" by Public Citizen.

[21] For example, after the death of a pregnant teenage vineyard worker, the Cal/OSHA issued six citations and a fine of $262,700 against Merced Farm Labor Contractor in 2008. See Internet Appendix E.1 for more details.

against managers and safety supervisors, including fines and imprisonment.[22]

The HIPS significantly raises firms' operating costs. On the one hand, workers' working time decreases while their wages are sticky. On the other hand, firms pay large costs to cover facilities providing water, shade, medical support, and training. For example, one respondent in the "*Final Performance and Evaluation Report*" of the California Heat Illness Prevention Campaign in 2012 complained that - *"Having to follow the buddy rule when the job really only needs one employee, but because they are outdoors and working in field, they have to have a buddy. That costs the company."* Another labor contractor also mentioned that supplying enough water was a challenge and the operating costs had increased - *"I have 500 workers and having to keep water within reach and filled to at least half way has made it so that I hire three extra people to just focus on monitoring and moving water up so that it is within reach of workers."*[23]

5.2.2 Effects of the HIPS on Firm Capital-labor Ratio

As discussed above, California was the first state to pass the HIPS to protect outdoor workers from heat hazards. This prevention standard first appeared as an emergency rule in August 2005 and became a permanent one in July 2006. Importantly, the bill's adoption is a result of cumulative historical temperature threats rather than a one-time spike in temperatures. Figure 4 shows no abnormal changes in average temperatures or the number of absolute or relative hot days around 2005. If anything, temperatures were relatively mild in the summer of 2005. This helps exclude the concern that spikes in temperatures before or in 2005 drove both the adoption of the HIPS and firms' responses. The adoption is also not likely driven by significant changes in regulatory environments, as the Democrats have run California since 1992. Therefore, the adoption is likely exogenous from a given firm's perspective.

Building on the adoption of the HIPS in California, I design a difference-in-differences strat-

[22] For example, Bumble Bee Foods agreed to pay $6 million to settle a case regarding the death of a worker in 2012. In addition, Bumble Bee was also required to implement extra safety measures, provide safety training to managers and workers and conduct safety audits of equipment. Furthermore, the company's safety manager Saul Florez and plant director Angel Rodriguez were charged with willfully violating worker safety rules. Eventually, Saul Florez pleaded guilty and was sentenced to three years of formal probation and 30 days of community labor. He also received a fine of $19,000 and was required to take work-safety classes. Angel Rodriguez agreed to do 320 hours of community service, pay $11,400 in fines and take work-safety classes. See, for example, "Bumble Bee to pay $6M in oven death; 2 managers will pay $30K".

[23] See "California Heat Illness Prevention Campaign - Final Performance and Evaluation Report".

egy to test firms' response to climate-induced regulatory changes in the labor market.[24] The pre-treatment period includes the years 2002, 2003, and 2004 and the post-treatment period includes the years 2005, 2006, and 2007. I choose 2007 as the ending year to avoid any disruptions caused by the 2008 financial crisis. To construct the sample, I first drop firms headquartered outside of California or firms whose four-digit NAICS industry classification changed during the 2002 - 2007 period. Then, I require a firm's financial data to be available in the base year 2004 and in at least one year in the post-treatment period. After constructing the sample, I split firms into two groups - high-exposure firms as the treated group (*LECC* larger than five) and low-exposure firms as the control group (*LECC* equal to or smaller than five). The assumption is that high-exposure firms are more affected by the heat standard. Summary statistics of the sample are reported in Internet Appendix Table E.1. The empirical specification is as follows:

$$\begin{aligned} Y_{it} = \tau_i + \mu_{ct} + \pi_{jt} + \beta_1 * \text{High LECC}_{j2002} * \text{Prevention}_t + \beta_2 * \text{LECC}_{j2002} \\ + \beta_3 * \text{Prevention}_t + \delta \boldsymbol{X}_{it-1} + \varepsilon_{it} \end{aligned} \tag{8}$$

where i denotes firm, j denotes industry, c denotes a firm's headquarter county, t denotes year. Y_{it} is the dependent variable - the capital-labor ratio. The variable of interest is the interaction term between a dummy indicating a firm's high exposure to climate change in 2002 ($High\ LECC_{j2002}$) and a dummy indicating the adoption of the HIPS - $Prevention_t$, which equals one for the period 2005 - 2007 and zero for the period 2002 - 2004. Controls include a firm's labor skill, the logarithm of total assets, leverage, and a dummy indicating whether a firm pays dividends. All controls are lagged by one year. τ_i is the firm fixed effects, μ_{ct} is the firm headquarter county-by-year fixed effects, and π_{jt} is the industry-by-year (two-digit or three-digit NAICS) fixed effects.

The empirical results are presented in Table 7. Column (1) reports the coefficient estimate for the interaction term with firm and year fixed effects. The coefficient estimate is positive and statistically significant, suggesting that high-exposure firms adjust to higher capital-labor

[24] I do not include Washington in the analyses because there are only 50 firms in Washington but 446 firms in California based on my sample selection criteria. Only using firms in California avoids heterogeneities in economic conditions and regulations across states. Nevertheless, in Internet Appendix E.2, I show that the results are robust to including firms in California, Washington, and several neighboring states.

ratios after California passes the HIPS. The significance remains in column (3) after adding lagged controls and county-by-year fixed effects. I further add two-digit NAICS industry-by-year fixed effects in column (4) and three-digit NAICS industry-by-year fixed effects in column (5). Results hold. The increase in capital-labor ratios is economically important as well: in column (4), after the HIPS, high-exposure firms increase capital-labor ratios by 15.1%, relative to low-exposure firms.

5.2.3 Dynamic Treatment Effects

In this section, I examine the dynamics of differences in capital-labor ratios between treated and control firms around the adoption of the HIPS. To this end, I replace the *Prevention* dummy with time indicator variables - *Year 2002*, *Year 2003*, *Year 2005*, *Year 2006*, and *Year 2007*. The year 2004 is taken as the base year and thus omitted. The coefficient estimates of the interaction terms between $High\ LECC_{j2002}$ and these time indicator variables measure the differences in capital-labor ratios between treated and control firms in the respective individual years.

The results are reported in Table 8. It shows that there is no statistically and economically significant difference in capital-labor ratios between treated and control firms prior to the adoption of the HIPS. This is also presented in Figure 5, which plots the coefficient estimates of these interaction terms. The figure shows that the treatment effect (the solid green line) hovers around zero in the pre-treatment period 2002 - 2004, supporting the parallel trends assumption. Importantly, once the HIPS is implemented, treated firms adjust toward higher capital-labor ratios relative to control firms. The solid green line in Figure 5 immediately goes up at a significant level in 2005. The results hold after adding firm headquarter county-by-year and industry-by-year fixed effects.[25]

In Figure 6 (A) and (B), I plot the dynamic treatment effects for capital investment and employment growth separately. In both figures, the treatment effect was close to zero in the

[25] A severe heat wave hit California in 2006, with the central valley mostly struck, leading to a concern that this heat wave could fully or partially drive the results. Two pieces of evidence are against this concern. First, Figure 5 shows that the treatment effects of the HIPS appear immediately in 2005, the adoption year, rather than in 2006 when the heat wave happened. Second, in Internet Appendix E.3, I show that the impacts of the HIPS are homogeneous across counties with different relative temperature shocks in the period 2002 - 2007. In untabulated results, I also do not find heterogeneous effects of HIPS when examining counties with different temperature levels or numbers of absolute temperature shocks. The evidence suggests that the HIPS is the dominant factor contributing to rising capital-labor ratios in the period 2005 - 2007.

pre-treatment period but significantly deviate from zero starting from 2005. Empirical tests for the capital and the employment component are reported in Internet Appendix E.4.

In Internet Appendix E.5, I further show that the baseline effects of the labor-channel exposure to climate risk on capital-labor ratios are more pronounced for firms headquartered in Democratic states, especially those in warm regions. This is consistent with the notion that Democrats believe more in climate change, care more about workers' welfare and thus are more likely to take action to pass a heat illness prevention bill. In addition, climate threats are bigger in warm regions. Therefore, firms in Democratic states and warm regions face bigger regulatory risks.

To summarize, results in Section 5.2 provide causal evidence that the regulatory risk is another force driving firms' adjustment towards higher capital-labor ratios to adapt to climate change.

6 Innovation and Automation

I further investigate firms' innovation strategies in the adaptation process, considering the importance of technological advancement in entering into a capital-intensive economy (e.g., Karabarbounis and Neiman, 2014; Acemoglu and Restrepo, 2019, 2020; Bena et al., 2021). For example, Karabarbounis and Neiman (2014) show that the declining labor share since the early 1980s is mostly driven by the decrease in the relative price of investment goods, often attributed to advances in information technology and the computer age. Acemoglu and Restrepo (2020) document that one more robot per thousand workers reduces the employment-to-population ratio by 0.2 percentage points and wages by 0.42%. To deal with rising labor costs induced by climate threats, firms may spend more effort in R&D to innovate machines and equipment or new production methods that can reduce reliance on labor. Results testing this conjecture are reported in Table 9.

Columns (1) - (6) present firms' innovation activities after temperature shocks. Column (1) shows that firms significantly increase R&D spending after experiencing the shocks. In particular, the R&D expenses of a firm with a climate exposure ranking of six increase by 0.8% in the long term relative to a firm with a climate exposure ranking of four. Columns (2) -

(6) report firms' patenting activities. It suggests that high-exposure firms file more patents. Importantly, results in columns (5) show that firms are more likely to develop an automation patent after temperature shocks. The automation patent is mainly used for developing devices that carry out a process independently. Consequently, the automation patent is labor-saving, enabling jobs to be done with less human input. In column (5), the probability of filing an automation patent by a firm with a climate exposure ranking of six increases by 0.78% in the second year of seeing the shocks, relative to a firm with a climate exposure ranking of four. Columns (6) examine firms' development of process innovation that aims at lowering firms' production costs including labor costs. The effects are not statistically significant.

Results in column (7) show that firms impacted by the HIPS in California significantly increase R&D expenses. Relative to low-exposure firms, high-exposure firms increase R&D spending by 15.7%. Meanwhile, high-exposure firms file more patents. These patents are also more influential and valuable, i.e., more citations and higher market value. Furthermore, high-exposure firms are more likely to develop automation patents and process innovation. Relative to low-exposure firms, the probability of having an automation patent among high-exposure firms increases by 3.7%, and the probability of having one process claim increases by 5.2%.

Taken together, results in Table 9 show that high-exposure firms spend more effort on innovation after temperature and regulatory shocks. More importantly, these firms develop more patents that can facilitate automation and reduce reliance on labor, lending further support to the hypothesis that high-exposure firms respond to climate challenges by using capital to replace labor and by increasing automation.

7 Industry Dynamics

In this section, I further investigate the implications of the labor-channel exposure to climate change for industry dynamics. Firm-level analyses so far support the hypothesis that rising temperatures increase firms' labor costs, and in response, firms cut reliance on human capital. This firm-level effect may add up to an economically important magnitude that leads to industry-wise employment contraction. Specifically, the labor-channel exposure may negatively affect industry-wise job creation and workers' earnings, resulting in job and income losses. I test this prediction using the QWI data at the county-by-four-digit NAICS industry level and report the results in Table 10.

Columns (1) - (4) test the impact of temperature shocks. Columns (1) - (2) show that high-exposure industries create fewer new jobs in the year with severe temperature shocks. Specifically, after the shocks, the job create rate of an industry with a climate exposure ranking of six is 0.12% lower than that of an industry with a climate exposure ranking of four, though the negative effect disappears in following years. Columns (3) - (4) show that workers in high-exposure industries have slower earnings growth in the year with shocks. However, their earnings grow much faster in the second year. The two coefficient estimates are the same, indicating almost a full recovery. Columns (5) - (8) show that the HIPS in California hurts both job creation and workers' earnings. Relative to low-exposure industries, job creation and earnings growth rates are 2.2% and 1.6% lower in high-exposure industries, respectively. Overall, the industry-wide patterns suggest that the labor-channel exposure significantly impedes industry expansion and hurts outdoor workers' income.

8 Conclusion

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

Specifically, in this paper, I show that the risks mainly come from two sources: (1) physical risk - lower labor productivity in high temperatures; (2) regulatory risk - the possibility of governments introducing regulations to protect workers against heat hazards. Both risks contribute to rising labor costs for firms with many outdoor workers.

How do firms cope with these risks and adapt to climate change? To answer this question, I utilize information on each occupation's exposure to weather and construct a measure reflecting firms' exposure to climate change through the labor channel. I find that high-exposure firms have higher capital-labor ratios, especially when their managers believe in climate change or when jobs are easy to automate. After experiencing shocks to physical (abnormally high temperatures) or regulatory (the adoption of the HIPS in California) risks, high-exposure firms switch to more capital-intensive production functions. The evidence suggests that, in response to rising labor costs induced by climate change, firms use capital to replace labor. I also find that high-exposure firms respond to the shocks by innovating more, especially in technologies facilitating automation and reducing labor costs. The findings indicate that climate change promotes automation and speeds up our entering into a capital-intensive economy.

An important implication of these findings is that climate change leads to significant job and income losses for those working in outdoor environments. This is further confirmed in the industry-wide evidence that labor exposure to climate change negatively affects job creation and workers' earnings, echoing various reports predicting increased economic losses as global warming intensifies. The evidence reveals unexpected negative effects of firms' adaptation to climate change on workers and local communities. In addition, even though regulators are trying to protect workers from heat hazards, the fact that increasing protection leads to less hiring implies that regulators need to balance between protecting workers and incentivizing firms to create jobs.

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Variable Definitions

Variables	Description
Dependent Variables	
Log(PPENT/EMP)	The logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP).
Log(PPENT)	The logarithm of a firm's property, plant, and equipment (PPENT).
CAPEX/Lag(AT)	A firm's capital expenditure (CAPEX) divided by its lagged assets (AT).
Log(EMP)	The logarithm of a firm's number of employees (EMP).
Change in Log(EMP)	Annual change in the logarithm of a firm's number of employees (EMP).
Log(Sales)	The logarithm of a firms' sales (in thousands), from YE Time Series.
Log(Sales/EMP)	The logarithm of a firms' sales (in thousands) per employee, from YE Time Series.
R&D/Lag(AT)	A firm's R&D expenses (XRD) divided by its lagged assets (AT).
Log(1+No. Patents)	The logarithm of one plus the number of patents a firm files in a year.
Log(1+Citations)	The logarithm of one plus the number of forward citations of a firm's filed patents.
Log(1+Value)	The logarithm of one plus the estimated value of a firm's filed patents.
Automation Patent	A dummy indicating that a firm has at least one automation patent filed.
Process Innovation	A dummy indicating that a firm has at least one process claim in filed patents.
Change in Log(No. Jobs)	Annual change in the logarithm of the number of jobs in each four-digit NAICS industry in a county.
Change in Log(Earnings)	Annual change in the logarithm of average earnings in each four-digit NAICS industry in a county.
Key Independent Variables	
LECC	The rank of the labor exposure to climate change index from 1 to 10, with 10 indicating the highest exposure. The raw index is the weighted average of all occupations' exposure to weather within a four-digit NAICS industry. The weight is the percentage of people working in a given occupation in a four-digit NAICS industry. See Equation (1).
High LECC	A dummy indicating that *LECC* is larger than five.
Temperature Shocks	A dummy indicating that a firm has at least 20 days with relative temperature shocks. The firm-level relative temperature shocks are the weighted average of each county's relative temperature shocks. The weight is the fraction of employees a firm has in a county.
Prevention	A dummy indicating the adoption of the Heat Illness Prevention Standard in California, which equals one for the period 2005 - 2007 and zero for the period 2002 -2004.
Republican Management	A dummy indicating that more than 70% of the management team's contributions flow to the Republican party. See Equation (3).
Workplace Automation	A dummy indicating the rank of a four-digit NAICS industry's workplace automation is above five. See Equation (4).
Labor Union	A dummy indicating that an industry's union membership is above the 75^{th} percentile of the distribution.

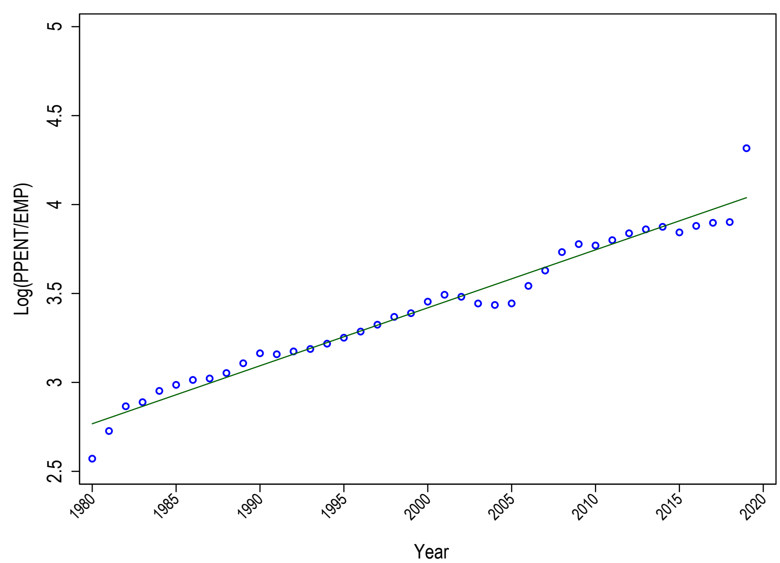
Variables	Description
Control Variables	
Labor Skill	The rank of labor skill from 1 to 5. The raw measure of labor skill is constructed following Ghaly et al. (2017).
Size	The logarithm of a firm's total assets (AT).
Leverage	The book value of long-term debt (DLTT) plus debt in current liabilities (DLC) divided by total assets (AT).
Dividend Payer	A dummy indicating that a firm pays dividends (DVC & DVP).

Figures

Figure 1. Labor Exposure to Climate Change and Firm Capital-labor Ratio: Time-series Patterns

Figure (A) presents the time-series average capital-labor ratio for all firms for the period 1980 - 2019. Figure (B) presents the time-series average capital-labor ratios for high- and low-exposure firms for the period 1980 - 2019, respectively. The high-exposure firms are those with *LECC* above five, and the low-exposure firms are those with *LECC* equal to or smaller than five. I assume that a firm's exposure to climate change from 1980 to 2001 is the same as in 2002.

(A) Average Capital-labor Ratio for All Firms



(B) Average Capital-labor Ratios for High- and Low-exposure Firms

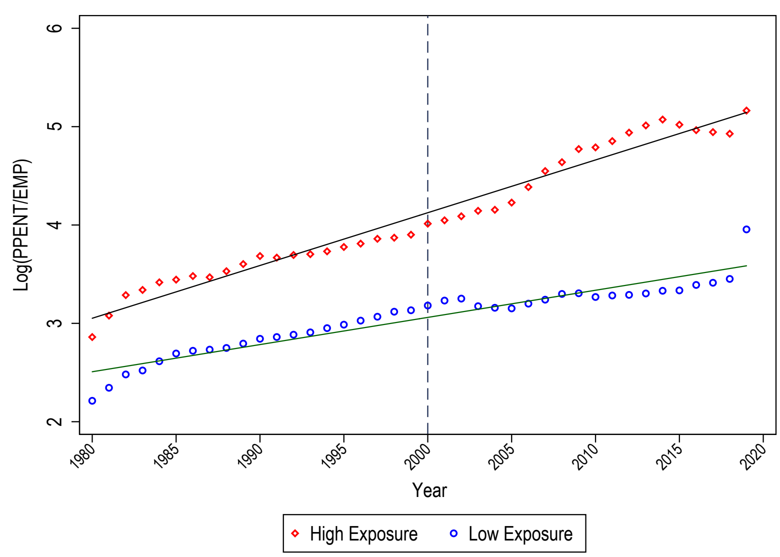


Figure 2. Labor Exposure to Climate Change and Firm Capital-labor Ratio: Cross-sectional Patterns

This figure presents the relation between a firm's labor exposure to climate change and its capital-labor ratio at the cross-sectional level. Group 10 contains firms with the highest exposure, and group 1 contains firms with the lowest exposure. The sample period is from 2002 to 2019.

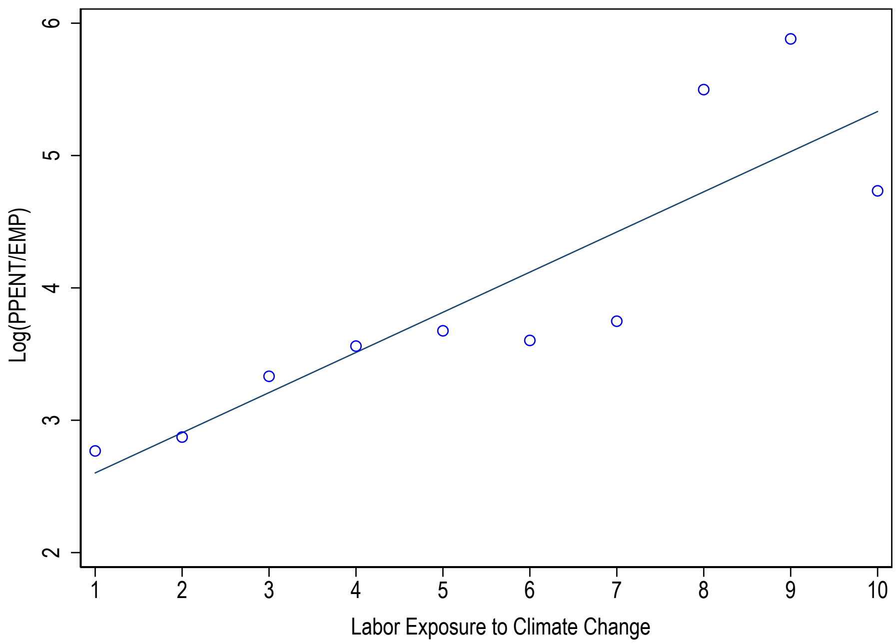
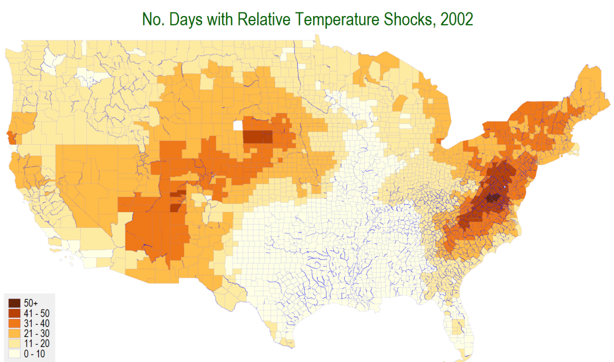


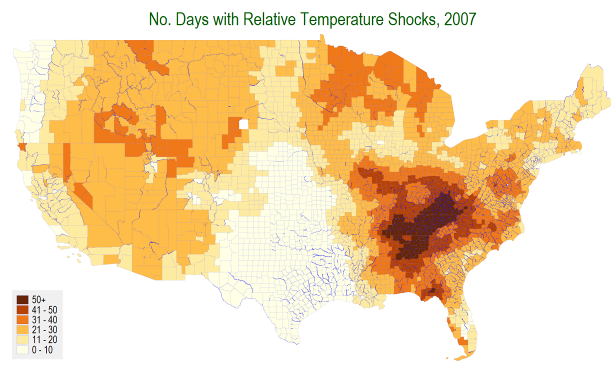
Figure 3. Distribution of Temperature Shocks across Counties

This figure presents the distribution of relative temperature shocks across counties in the contiguous U.S. in 2002, 2007, 2014, and 2019. The relative temperature shocks are cases where a county's daily temperatures in the summertime (May - September) are above the 90^{th} percentile of the county's summer temperature records.

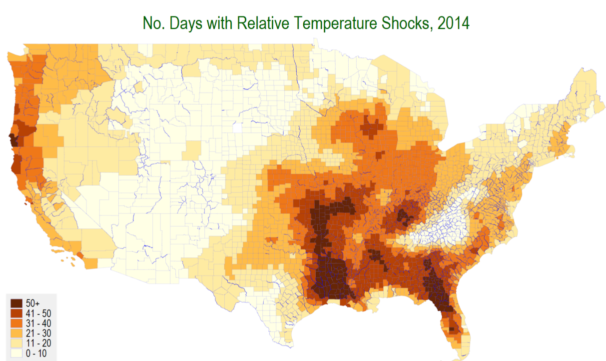
(A)



(B)



(C)



(D)

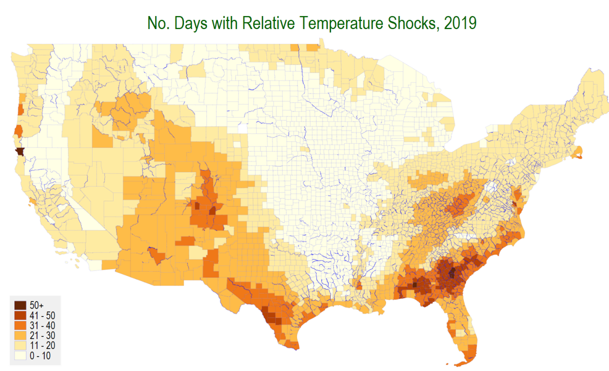
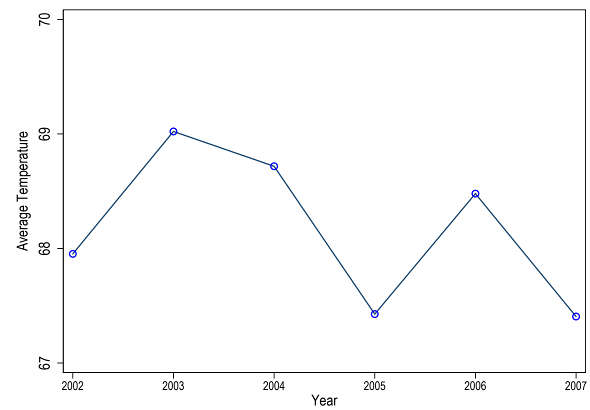


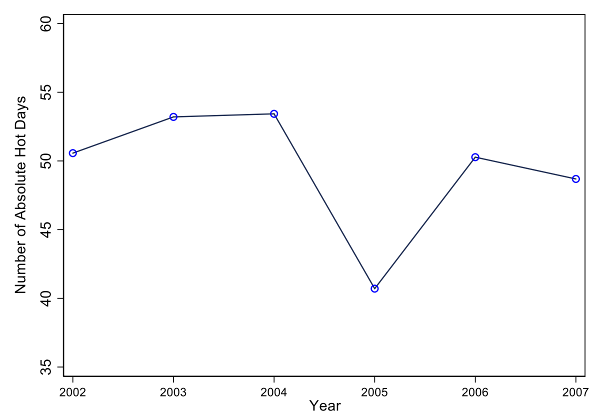
Figure 4. Temperature Patterns Around the Adoption of the HIPS in California

This figure presents temperature patterns in the summertime in California around the adoption of the HIPS. Figure (A) presents the average temperatures in Fahrenheit. Figure (B) presents the number of absolute hot days, i.e., days with temperatures above 90°F. Figure (C) presents the number of relative hot days, i.e., days with temperatures above the 90^{th} percentile of the county's temperature records.

(A) Average Temperature



(B) Absolute Hot Days



(C) Relative Hot Days

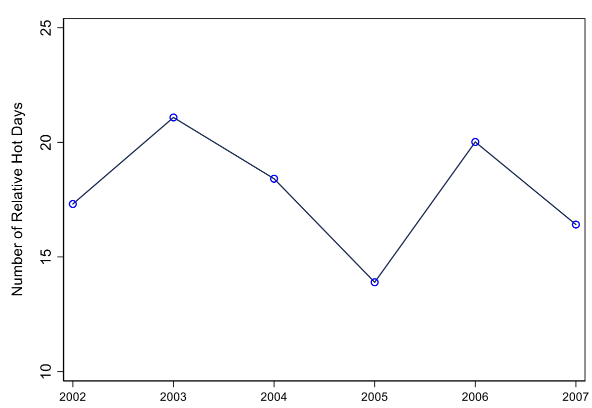


Figure 5. Dynamic Treatment Effects of the HIPS on Firm Capital-labor Ratio

This figure plots the coefficient estimates in Table 8. It shows the dynamic treatment effects of the HIPS on firms' capital-labor ratios. The base year is 2004, and the prevention took effect in 2005. The green solid line represents the coefficient estimates. The red and the blue dashed line represents the upper and lower bound of the 95% confidence intervals of the coefficient estimates, respectively.

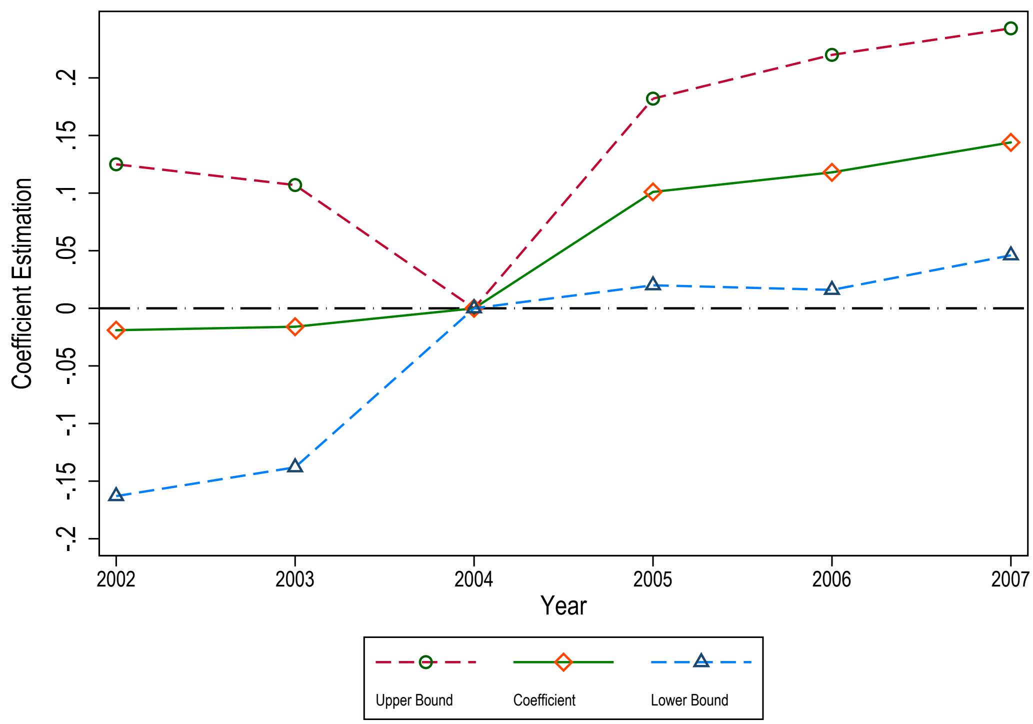
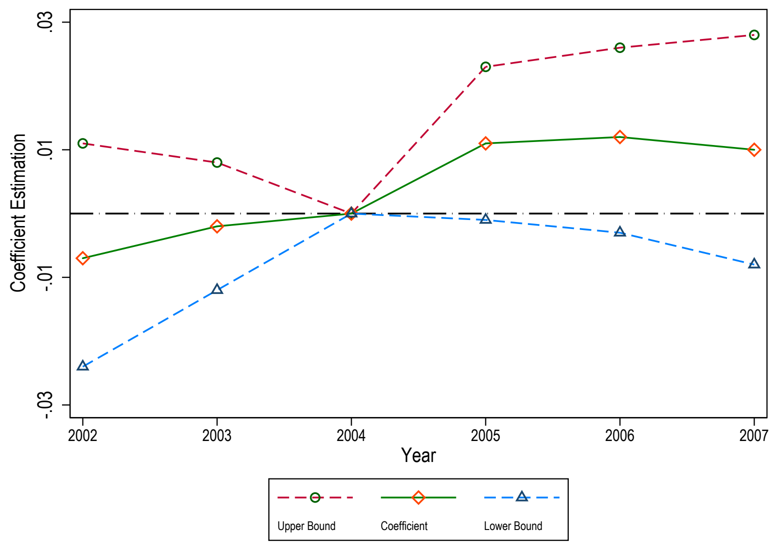


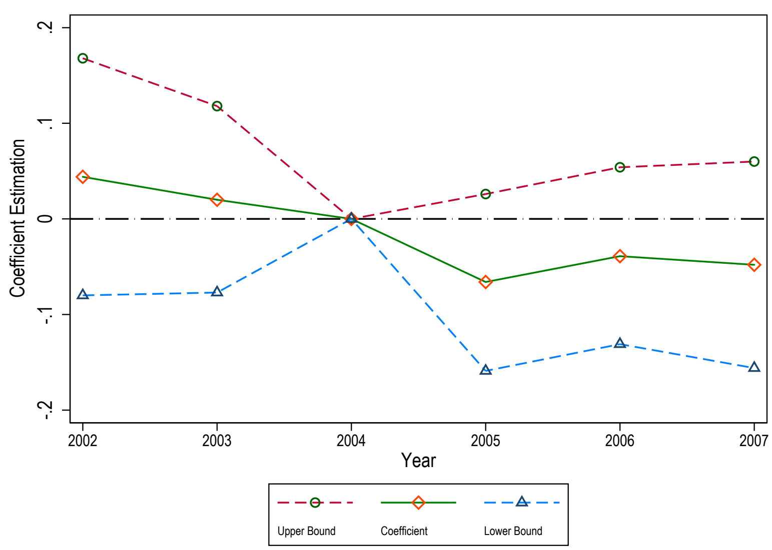
Figure 6. Dynamic Treatment Effects of the HIPS on Firm Capital Investment and Employment

This figure plots the dynamic treatment effects of the HIPS on firms' capital investment and employment, respectively. The estimation method is the same as in Table 8. In both figures (A) and (B), the base year is 2004, and the prevention took effect in 2005. The green solid line represents the coefficient estimates. The red and the blue dashed line represents the upper and lower bound of the 95% confidence intervals of the coefficient estimates, respectively.

(A) CAPEX/Lag(AT)



(B) Change in Log(EMP)



Tables

Table 1. Examples of Occupations and Industries with Heterogeneous Exposures to Weather and Climate Change

Panel A presents examples of occupations with high, medium or low exposure to weather. *Exposed to Weather* is the outdoor activity score for each occupation from the O*NET program. Panel B presents examples of industries with high, medium or low exposure to climate change through the labor channel based on *LECC* in 2015. *LECC* is the rank of the raw climate exposure index from 1 to 10, with 10 indicating the highest exposure.

Panel A. Examples of Occupations with Heterogeneous Exposure to Weather

Occupation Code	Occupation Title	Exposed to Weather
High Exposure		
33-3041	Parking Enforcement Workers	100
53-3031	Driver/Sales Workers	100
47-4051	Highway Maintenance Workers	99
43-5052	Postal Service Mail Carriers	98
49-9052	Telecommunications Line Installers and Repairers	96
11-9013	Farmers, Ranchers, and Other Agricultural Managers	96
53-7121	Tank Car, Truck, and Ship Loaders	95
51-8092	Gas Plant Operators	92
53-5031	Ship Engineers	87
49-2022	Telecommunications Equipment Installers and Repair	84
Medium Exposure		
49-3052	Motorcycle Mechanics	63
17-3031	Surveying and Mapping Technicians	59
41-9022	Real Estate Sales Agents	58
47-2211	Sheet Metal Workers	54
49-9043	Maintenance Workers, Machinery	53
49-3023	Automotive Service Technicians and Mechanics	49
17-2051	Civil Engineers	45
27-3023	News Analysts, Reporters, and Journalists	42
35-9021	Dishwashers	40
41-2031	Retail Salespersons	40
Low Exposure		
17-2112	Industrial Engineers	19
27-3041	Editors	16
13-1071	Human Resource Specialists	12
17-2061	Computer Hardware Engineers	9
23-1011	Lawyers	9
15-1251	Computer Programmers	5
13-2041	Credit Analysts	4
51-3011	Bakers	4
29-1051	Pharmacists	1
41-9041	Telemarketers	0

Panel B. Examples of Industries with Heterogeneous Exposure to Climate Change

Four-digit NAICS Code	Four-digit NAICS Title	Index	LECC
High Exposure			
1133	Logging	75.45	10
2361	Residential Building Construction	65.37	10
4911	Postal Service	61.87	10
3241	Petroleum and Coal Products Manufacturing	51.94	9
2111	Oil and Gas Extraction	48.03	9
3251	Basic Chemical Manufacturing	47.88	8
4413	Automotive Parts, Accessories, and Tire Stores	45	8
5612	Facilities Support Services	41.45	8
3111	Animal Food Manufacturing	37.78	7
3366	Ship and Boat Building	35.92	7
Medium Exposure			
4511	Sporting Goods, Hobby, and Musical Instrument Stores	32.53	6
3115	Dairy Product Manufacturing	31.91	6
3122	Tobacco Manufacturing	30.38	6
5613	Employment Services	29.45	5
5151	Radio and Television Broadcasting	28.97	5
3323	Architectural and Structural Metals Manufacturing	28.91	5
3365	Railroad Rolling Stock Manufacturing	27.52	5
3254	Pharmaceutical and Medicine Manufacturing	27.03	5
6243	Vocational Rehabilitation Services	26.33	5
3113	Sugar and Confectionery Product Manufacturing	26.15	5
Low Exposure			
3325	Hardware Manufacturing	19.63	3
3335	Metalworking Machinery Manufacturing	18.40	2
3361	Motor Vehicle Manufacturing	16.36	2
5182	Data Processing, Hosting, and Related Services	13.61	1
3162	Footwear Manufacturing	13.38	1
5611	Office Administrative Services	13.14	1
3152	Cut and Sew Apparel Manufacturing	10.90	1
5412	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	8.93	1
6215	Medical and Diagnostic Laboratories	8.47	1
5411	Legal Services	6.70	1

Table 2. Summary Statistics

This table presents summary statistics of key variables from the main sample. The sample period is from 2002 to 2019.

	N	Mean	SD	P5	Median	P95
Dependent Variables						
Log(PPENT/EMP)	63,270	3.687	1.634	1.346	3.549	6.641
Log(PPENT)	63,270	3.744	2.823	-0.934	3.851	8.228
CAPEX/Lag(AT)	58,710	0.053	0.071	0.003	0.03	0.185
Log(Emp)	63,423	0.052	2.18	-3.352	0.02	3.706
Change in Log(EMP)	59,220	0.034	0.234	-0.318	0.023	0.421
R&D/Lag(AT)	59,220	0.075	0.149	0	0.005	0.378
Log(1+No. Patents)	47,106	0.676	1.340	0	0	3.761
Log(1+Citations)	47,106	0.321	0.553	0	0	1.561
Log(1+Value)	47,106	1.067	2.130	0	0	6.166
Automation	35,783	0.200	0.400	0	0	1
Process Innovation	47,106	0.256	0.436	0	0	1
Independent Variables						
LECC	63,423	4.557	2.492	1	4	10
Temperature Shocks	47,106	0.453	0.498	0	0	1
Labor Skill	63,423	3.654	1.367	1	4	5
Size	63,423	5.762	2.232	2.06	5.782	9.51
Leverage	63,166	0.263	0.307	0	0.189	0.804
Dividend Payer	63,423	0.346	0.476	0	0	1

Table 3. Labor Exposure to Climate Change and Production Function

This table presents the relation between a firm's labor exposure to climate change and its choices of production functions. Panel A presents results on firms' capital-labor ratios. The dependent variable is the logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP). Panel B presents results on firms' capital and employment, respectively. The dependent variable is the logarithm of a firm's property, plant, and equipment (PPENT) in columns (1) - (2), capital expenditure (CAPEX) over lagged assets in columns (3) - (4), the logarithm of the number of employees (EMP) in columns (5) - (6), and annual change in the logarithm of the number of employees (EMP) in columns (7) - (8). The key independent variable is a firm's labor exposure to climate change (*LECC*). Controls include labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. The sample period is from 2002 to 2019. The industry in industry-by-year fixed effects in Panel B is at the two-digit NAICS level. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Panel A. Firm Capital-labor Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(PPENT/EMP)							
LECC	0.304***	0.302***	0.270***	0.206***	0.173***	0.168***	0.098**	0.016**
	(0.066)	(0.066)	(0.046)	(0.037)	(0.029)	(0.029)	(0.040)	(0.008)
Labor Skill					0.068	0.070	-0.023	0.016
					(0.072)	(0.071)	(0.068)	(0.013)
Size					0.259***	0.260***	0.241***	0.309***
					(0.011)	(0.011)	(0.010)	(0.015)
Leverage						0.259***	0.141***	0.051*
						(0.059)	(0.048)	(0.030)
Dividend Payer						-0.015	-0.058**	-0.014
						(0.032)	(0.025)	(0.017)
Observations	63,270	63,270	63,233	63,217	63,217	62,963	62,879	61,935
Year FE	No	Yes	No	No	No	No	No	No
State*Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Naics 2 Industry*Year FE	No	No	No	Yes	Yes	Yes	No	Yes
Naics 3 Industry*Year FE	No	No	No	No	No	No	Yes	No
Firm FE	No	No	No	No	No	No	No	Yes
Adjusted R-squared	0.214	0.226	0.262	0.435	0.543	0.546	0.610	0.917

Panel B. Decomposition of Firm Capital-labor Ratio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(PPENT)		CAPEX/Lag(AT)		Log(Emp)		Change in Log(EMP)	
LECC	0.117***	0.109***	0.002**	0.002**	-0.056***	-0.060***	-0.004***	-0.003**
	(0.020)	(0.019)	(0.001)	(0.001)	(0.018)	(0.018)	(0.001)	(0.001)
Labor Skill	-0.263***	-0.254***	-0.003	-0.003	-0.331***	-0.325***	0.009***	0.007***
	(0.043)	(0.040)	(0.003)	(0.003)	(0.047)	(0.047)	(0.003)	(0.003)
Size	1.081***	1.074***	-0.000	0.000	0.821***	0.813***	0.009***	0.010***
	(0.008)	(0.008)	(0.000)	(0.000)	(0.009)	(0.009)	(0.001)	(0.001)
Leverage		0.354***		-0.000		0.098		-0.060***
		(0.061)		(0.002)		(0.070)		(0.008)
Dividend Payer		0.116***		-0.005***		0.131***		-0.025***
		(0.039)		(0.001)		(0.039)		(0.004)
Observations	63,217	62,963	58,653	58,418	63,370	63,116	59,161	58,926
State*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.881	0.883	0.294	0.295	0.846	0.847	0.050	0.057

Table 4. Cross-sectional Analyses

This table presents cross-sectional heterogeneities in firms' adaptation to climate change. Columns (1) - (2) examine top-management teams' political beliefs. *Republican Management* is a dummy indicating that a firm's management team strongly leans toward the Republican party. Columns (3) - (4) examine workplace automation. *Workplace Automation* is a dummy indicating that firms' employees can be easily replaced by automated capital. Columns (5) - (6) examine labor union. *Labor Union* is a dummy indicating high industry union membership. The dependent variable is the logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP). The key independent variables are the interaction terms between a firm's labor exposure to climate change (*LECC*) and the partition variables capturing cross-sectional heterogeneities. Controls include *LECC*, the partition variable, labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. The sample period is from 2002 to 2019. The industry in industry-by-year fixed effects is at the two-digit NAICS level. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS industry level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(PPENT/EMP)					
LECC*Republican Management	-0.011**	-0.012**				
	(0.006)	(0.006)				
LECC*Workplace Automation			0.022***	0.022***		
			(0.008)	(0.008)		
LECC*Labor Union					-0.014*	-0.013*
					(0.008)	(0.007)
Observations	22,791	22,720	61,967	61,932	51,935	51,875
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	No	Yes	No	Yes	No	Yes
Adjusted R-squared	0.951	0.952	0.917	0.917	0.922	0.923

Table 5. Temperature Shocks and Labor Productivity

This table presents the effects of temperature shocks on firms' labor productivity. The dependent variables are the logarithm of a firms' sales in columns (1) - (3), and the logarithm of a firms' sales per employee in columns (4) - (6). The key independent variable is the interaction term between a firm's labor exposure to climate change *LECC* and *Temperature Shocks*, a dummy indicating severe relative temperature shocks in a year. Controls include *LECC*, *Temperature Shocks* and labor skill. The sample period is from 2002 to 2019. The industry in industry and industry-by-year fixed effects is at the two-digit NAICS level. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS and the county level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Sales)			Log(Sales/EMP)		
LECC * Temperature Shocks	-0.002	-0.017***	-0.018***	-0.002***	-0.011***	-0.011***
	(0.001)	(0.005)	(0.004)	(0.001)	(0.003)	(0.003)
Observations	2,045,616	453,864	453,864	2,045,616	453,864	453,864
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year FE	Yes	No	No	Yes	No	No
County FE	Yes	No	No	Yes	No	No
Firm*County*Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	Yes	Yes	No	Yes	Yes	No
Industry*Year FE	No	No	Yes	No	No	Yes
Adjusted R-squared	0.565	0.370	0.387	0.827	0.593	0.609

Table 6. Temperature Shocks and Firm Capital-labor Ratio

This table presents the effects of temperature shocks on firms' capital-labor ratios. Results in columns (1) - (3) use the full-sample data. Results in columns (4), "*High Projection*", are based on firms operating in counties with large projected temperature increases. Results in columns (5), "*Low Projection*", are based on firms operating in counties with mild projected temperature increases. The dependent variable is the logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP). The key independent variables are the interaction term between a firm's labor exposure to climate change (*LECC*) and *Temperature Shocks*, a dummy indicating severe relative temperature shocks in a year, and its lagged terms. Controls include *LECC* and its lagged terms, *Temperature Shocks* and its lagged terms, labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. The firm-level controls are lagged by two years. The sample period is from 2002 to 2019. The industry in industry-by-year fixed effects is at the two-digit NAICS level. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(PPENT/EMP)				
	Full Sample			High Projection	Low Projection
LECC * Temperature Shocks	0.010***	0.009***	0.005*	0.006**	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
LECC (T-1) * Temperature Shocks (T-1)	0.009***	0.009***	0.005**	0.005*	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)
LECC (T-2) * Temperature Shocks (T-2)	0.011***	0.009***	0.005*	0.006*	0.008
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)
Observations	34,637	34,577	34,559	17,594	16,576
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes
State*Year FE	No	Yes	Yes	Yes	Yes
Industry*Year FE	No	No	Yes	Yes	Yes
Adjusted R-squared	0.928	0.929	0.930	0.955	0.896

Table 7. The HIPS and Firm Capital-labor Ratio

This table presents the effects of the HIPS on firms' capital-labor ratios. The dependent variable is the logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP). The key independent variable is the interaction between a dummy indicating a firm's high labor exposure to climate change in 2002, *High LECC*, and a dummy indicating the adoption of the HIPS, *Prevention*, which equals one for the period 2005 - 2007 and zero for the period 2002 - 2004. Both *High LECC* and *Prevention* are absorbed by fixed effects. Controls include labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. All controls are lagged by one year. The sample period is from 2002 to 2007. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(PPENT/EMP)				
High LECC * Prevention	0.147**	0.132**	0.132***	0.141***	0.171**
	(0.056)	(0.057)	(0.044)	(0.053)	(0.082)
Size		0.313***	0.307***	0.307***	0.311***
		(0.027)	(0.028)	(0.029)	(0.030)
Leverage		-0.089	-0.096	-0.100	-0.117
		(0.091)	(0.091)	(0.097)	(0.106)
Dividend Payer		0.050*	0.073**	0.078**	0.082**
		(0.029)	(0.032)	(0.034)	(0.035)
Observations	2,522	2,470	2,450	2,431	2,360
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No
County*Year FE	No	No	Yes	Yes	Yes
NAICS 2*Year FE	No	No	No	Yes	No
NAICS 3*Year FE	No	No	No	No	Yes
Adjusted R-squared	0.883	0.898	0.897	0.895	0.891

Table 8. Dynamic Treatment Effects of the HIPS

This table presents the dynamic treatment effects of the HIPS on firms' capital-labor ratios. The dependent variable is the logarithm of a firm's property, plant, and equipment (PPENT) divided by its number of employees (EMP). The key independent variables are the interaction terms between a dummy indicating a firm's high labor exposure to climate change in 2002, *High LECC*, and the year indicators. The year indicator for 2004 is omitted as 2004 is the base year. Controls include labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. All controls are lagged by one year. The sample period is from 2002 to 2007. The industry in industry-by-year fixed effects is at the two-digit NAICS level. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Log(PPENT/EMP)				
High LECC * Year 2002	-0.056	-0.019	-0.003	-0.028	-0.030
	(0.077)	(0.072)	(0.060)	(0.064)	(0.070)
High LECC * Year 2003	-0.008	-0.016	-0.024	-0.033	-0.074
	(0.062)	(0.062)	(0.050)	(0.051)	(0.057)
High LECC * Year 2005	0.096**	0.101**	0.114**	0.113**	0.097**
	(0.040)	(0.041)	(0.048)	(0.043)	(0.047)
High LECC * Year 2006	0.128***	0.118**	0.127**	0.123**	0.111*
	(0.046)	(0.051)	(0.059)	(0.054)	(0.060)
High LECC * Year 2007	0.159***	0.144***	0.130**	0.147**	0.118
	(0.051)	(0.050)	(0.059)	(0.070)	(0.074)
Observations	2,522	2,470	2,450	2,451	2,431
Controls	No	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No
County*Year FE	No	No	Yes	No	Yes
Industry*Year FE	No	No	No	Yes	Yes
Adjusted R-squared	0.883	0.898	0.897	0.896	0.895

Table 9. Innovation and Automation

This table presents the effects of temperature shocks and the HIPS on firms' innovation activities, respectively. Columns (1) - (6) present results on temperature shocks and columns (7) - (12) present results on the HIPS. The dependent variable in columns (1) and (7) is a firm's R&D expenses divided by its lagged total assets. The dependent variable in columns (2) and (8) is the logarithm of one plus the number of patents a firm files in a year. The dependent variable in columns (3) and (9) is the logarithm of one plus the number of forward citations of a firm's filed patents. The dependent variable in columns (4) and (10) is the logarithm of one plus the estimated value of a firm's filed patents. The dependent variable in columns (5) and (11) is a dummy indicating that a firm has at least one automation patent filed. The dependent variable in columns (6) and (12) is a dummy indicating that a firm has at least one process claim in patents filed. The key independent variable in columns (1) - (6) are the interaction terms between a firm's labor exposure to climate change (*LECC*) and *Temperature Shocks*, a dummy indicating severe relative temperature shocks in a year. The key independent variable in columns (7) - (12) is the interaction between a dummy indicating a firm's high labor exposure to climate change in 2002, *High LECC*, and a dummy representing the adoption of the HIPS, *Prevention*, which equals one for the period 2005 - 2007 and zero for the period 2002 - 2004. Controls in columns (1) - (6) include *LECC* and its lagged terms, *Temperature Shocks* and its lagged terms, labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. The firm-level controls are lagged by two years. Controls in columns (7) - (12) include labor skill, the logarithm of total assets, leverage, and a dummy indicating that a firm pays dividends. The firm-level controls are lagged by one year. The sample period is from 2002 to 2014 for the test on automation patents in column (5) and is from 2002 to 2019 for other tests in columns (1) - (6). The sample period in columns (7) - (12) is from 2002 to 2007. The industry in industry-by-year fixed effects is at the two-digit NAICS level. Numbers in parentheses are standard errors. Standard errors are clustered at the four-digit NAICS level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Temperature Shocks	(1)	(2)	(3)	(4)	(5)	(6)
	R&D/Lag(AT)	Log(1+No. Patents)	Log(1+No. Citations)	Log(1+Value)	Automation	Process Innovation
LECC * Temperature Shocks	0.0002	-0.0023	-0.0008	-0.0053	0.0020	-0.0012
	(0.0001)	(0.0020)	(0.0010)	(0.0033)	(0.0015)	(0.0013)
LECC (T-1) * Temperature Shocks (T-1)	0.0001	0.0050**	0.0025**	0.0033	0.0039***	0.0016
	(0.0002)	(0.0021)	(0.0011)	(0.0040)	(0.0014)	(0.0012)
LECC (T-2) * Temperature Shocks (T-2)	0.0003**	0.0036	0.0016	0.0008	0.0022	0.0010
	(0.0001)	(0.0025)	(0.0011)	(0.0041)	(0.0015)	(0.0013)
Observations	34,664	34,664	34,664	34,664	25,799	34,095
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.875	0.891	0.855	0.893	0.670	0.693

The HIPS in California	(7)	(8)	(9)	(10)	(11)	(12)
	R&D/Lag(AT)	Log(1+No. Patents)	Log(1+No. Citations)	Log(1+Value)	Automation	Process Innovation
High LECC * Prevention	0.021**	0.160***	0.082***	0.258***	0.037*	0.052**
	(0.010)	(0.031)	(0.016)	(0.056)	(0.019)	(0.023)
Observations	2,481	2,481	2,481	2,481	2,457	2,481
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.831	0.909	0.859	0.930	0.700	0.665

Table 10. Industry Dynamics

This table presents the effects of temperature shocks and the HIPS on industry dynamics, respectively. Columns (1) - (4) present results on temperature shocks and columns (5) - (8) presents results on the HIPS. The dependent variable in columns (1) - (2) & columns (5) - (6) is the annual change in the logarithm of the number of jobs in each four-digit NAICS industry in a county. The dependent variable in columns (3) - (4) & columns (7) - (8) is the annual change in the logarithm of average earnings in each four-digit NAICS industry in a county. The key independent variable in columns (1) - (4) is the interaction terms between a firm's labor exposure to climate change (*LECC*) and *Temperature Shocks*, a dummy indicating severe relative temperature shocks in a year. The key independent variable in columns (5) - (8) is the interaction between a dummy indicating a firm's high labor exposure to climate change in 2002, *High LECC*, and a dummy representing the adoption of the HIPS, *Prevention*, which equals one for the period 2005 - 2007 and zero for the period 2002 - 2004. Controls in columns (1) - (4) include *LECC* and its lagged terms, and *Temperature Shocks* and its lagged terms. Controls in columns (5) - (8) include *High LECC* and *Prevention*. The sample period in columns (1) - (4) is from 2002 to 2019 and the sample period in columns (5) - (8) is from 2002 to 2007. Numbers in parentheses are standard errors. Standard errors in columns (1) - (4) are clustered at the four-digit NAICS and the county level. Standard errors in columns (5) - (8) are clustered at the four-digit NAICS level. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Temperature Shocks	(1)	(2)	(3)	(4)
	Change in Log(No. Jobs)		Change in Log(Earnings)	
LECC * Temperature Shocks	-0.0006***	-0.0006***	-0.0003**	-0.0003**
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
LECC (T-1) * Temperature Shocks (T-1)	-0.0001	-0.0001	0.0003***	0.0003***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
LECC (T-2) * Temperature Shocks (T-2)	0.0002	0.0002	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	3,003,332	3,003,332	5,725,824	5,725,824
Controls	Yes	Yes	Yes	Yes
NAICS2 Industry*Year FE	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	Yes	Yes
NAICS4 FE	No	Yes	No	Yes
Adjusted R-squared	0.022	0.028	0.007	0.007

The HIPS in California	(5)	(6)	(7)	(8)
	Change in Log(No. Jobs)		Change in Log(Earnings)	
High LECC * Prevention	-0.023***	-0.022***	-0.016***	-0.016***
	(0.008)	(0.008)	(0.006)	(0.006)
Observations	44,854	44,854	60,631	60,631
Controls	Yes	Yes	Yes	Yes
NAICS2 Industry*Year FE	Yes	Yes	Yes	Yes
County*Year FE	Yes	Yes	Yes	Yes
NAICS4 FE	No	Yes	No	Yes
Adjusted R-squared	0.020	0.036	0.007	0.006