Climate Regulatory Risks, Green-Skilled Labor, and Corporate Employment Decisions

Abstract

Using the staggered implementation of state climate adaptation plans (SCAPs) as a quasi-natural experiment, we investigate how firms incorporate climate regulatory risks into their employment decisions. We find that firms headquartered in the states that finalized SCAP are more likely to invest inefficiently in labor resources. We offer two explanations for this finding. First, affected firms direct greater resources toward green innovations to meet climate regulations, limiting their ability to invest efficiently in labor resources. Second, affected firms face inefficiencies during the green transition, either overestimating the demand for green-skilled labor, leading to overinvestment, or struggling with a shortage of such labor, causing underinvestment. We show that local government financial support and clear climate adaptation guidelines are crucial in facilitating firms' green transitions required by climate regulations while mitigating the unintended negative impacts on labor allocation.

Keywords: Climate regulations, SCAP finalisation, Corporate employment, Labor investment efficiency

JEL Codes: G38, D81, J01

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1. Introduction

Global climate is changing rapidly, with recent decades experiencing temperature levels unseen for centuries to millennia (Masson-Delmotte et al., 2021). These shifts profoundly affect human habitats and carry significant economic consequences (Xiao, 2023). For example, weather-related insurance losses have risen dramatically, from an annual average of $10 billion in the 1980s to over $65 billion by 2010 (Benfield, 2018), with future losses projected to grow. Deloitte warns that without effective climate action, economic damages could reach $14.5 trillion by 2070.[1]

In response, a growing number of regulations are being implemented to encourage environmentally responsible corporate practices, driven by investor and policymaker expectations. However, these regulations introduce significant costs for companies as they must quickly adapt their operations. The accompanying regulatory uncertainty further increases capital market expenses, collectively amplifying climate regulatory risks. A survey of 861 finance professionals, academics, and regulators reveals that climate regulatory risk is now the top climate-related concern for businesses and investors (Stroebel & Wurgler, 2021).

Despite its significance, there is a lack of comprehensive studies examining how firms adjust their policies in response to the increasing climate regulatory risk. This is primarily attributed to the challenge of measuring climate regulatory risk (hereafter, CRR) (Krueger et al., 2020). The existing few studies in this area tend to focus on single transnational events, such as the Paris Climate Accord or the Kyoto Protocol (Ginglinger & Moreau, 2023; Nguyen & Phan, 2017), which

[1] Deloitte. (2022). The turning point: A new economic climate in the United States. See https://www2.deloitte.com/us/en/pages/about-deloitte/articles/economic-cost-climate-change-turning-point.html?icid=learn_more_content_click

offer limited variation in implementation timing, making it difficult to assess the causal effects of CRR on firm outcomes.

This paper seeks to fill this gap by leveraging the staggered implementation of state-level Climate Adaptation Plans (SCAPs) as a quasi-natural experiment. SCAPs, which represent state-level responses to climate change, provide a valuable setting for examining the impact of climate regulatory risk on corporate decisions. Unlike federal regulations enforced by agencies like the Environmental Protection Agency (EPA), SCAPs are tailored to state-specific environmental challenges, creating differential regulatory risks for firms based on their location (He et al., 2023; Kovacs et al., 2025). Till now, 20 US states have finalized their SCAPs, with Florida, Maryland, and Virginia being the first SCAP adopters in 2008 and New Jersey being the latest adopters in 2021. The timing of SCAP finalization across U.S. states introduces natural variation in regulatory exposure, allowing us to isolate the causal effects of CRR on labor investment efficiency (LIE) in firms. This setting, therefore, allows us to examine the differential impact of climate regulatory risks on firms' employment decisions.

We are particularly interested in CRR's impact on the allocation of corporate labor resources, or in other words, labor investment efficiency, for several reasons. First, labor is a significant element of corporate investment decisions (Khedmati et al., 2020). Being responsible for two-thirds of economy-wide value added (Bernanke, 1983)[2], corporate labor investment can offer insights into a firm's investment behaviour, reflecting its response to the tightened conditions resulting from CRR (Ha & Feng, 2018).

Meanwhile, policymakers and the public are increasingly focused on how rising climate regulations will impact the labor market. As governments worldwide intensify their efforts to

[2] According to the Annual Report on US Manufacturing Industry Statistics: 2022, payroll and benefits for employees in the manufacturing sector in the United States amounted to $913 billion in 2019, while capital expenditures came to $218 billion.

combat the climate crisis and push corporations toward greener practices, additional regulations are expected. However, the potential impact of such changes on the overall job market remains unclear. While some argue that the promotion of greener corporate practices through climate regulatory policies could stimulate innovation and consequently create more job opportunities,[3] others worry that the new regulations could lead to increased costs, potentially resulting in budget cuts in other areas, including labor investment. A report by EY highlights the scale of this transformation, predicting a global loss of 73 million "gray" jobs in carbon-intensive industries, offset by the creation of 46 million new "green" jobs and potentially millions more in emerging sectors.[4] This transition to a greener economy, spurred by such regulations, could significantly impact corporate employment strategies. Firms will face the challenge of reallocating labor across sectors, potentially amplifying inefficiencies—especially if they struggle to meet the demand for green-skilled workers. Therefore, gaining insights into the effects of climate regulatory changes on corporate employment decisions can aid regulators and firms in better preparing for the consequences of climate regulatory shocks.

We conjecture that the adoption of SCAP would reduce the efficiency of labor resource allocation of the local firms. First, from the cost perspective, firms face significant financial and operational challenges following SCAP adoption, which disrupt efficient resource allocation and hinder labor investment. Compliance costs, including investments in R&D and green technologies, divert resources from labor, while regulatory uncertainty amplifies these costs through increased liabilities, stranded assets, and financing constraints (Barnett et al., 2020; Litterman, 2021; Ilhan et al., 2021). Together, these "green compliance costs" strain firms' ability to allocate labor resources effectively.

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[3] https://blogs.worldbank.org/en/jobs/what-were-reading-about-climate-and-jobs

[4] https://www.ey.com/en_gl/insights/government-public-sector/how-can-workers-find-their-place-in-the-green-economy

Additionally, transitioning to greener practices demands substantial operational adjustments, particularly in restructuring labor (Porter & Linde, 1995). Anticipating sustainability shifts, firms seek green-skilled workers—those with expertise in sustainable practices (Aldy & Stavins, 2012). However, inefficiencies could arise from the following two factors during the transition: overestimation of green labor demand and labor shortages. Uncertainty about the requirements and timeline of the green transition can lead firms to overestimate their needs, resulting in labor overinvestment. Simultaneously, a shortage of green-skilled workers in the labor market[5] could constrain hiring, leading to underinvestment and inefficient labor allocation.

To examine the impact of SCAP on LIE, we employ a sample of US public firms from 1994 to 2021. The SCAPs adoption data are obtained from Georgetown Climate Centre, and the labor investment (in)efficiency is estimated as the deviation of a firm's actual labor investment from its optimal level following Pinnuck and Lillis (2007). Using a stacked cohort difference-in-differences (DiD) framework, we find that firms headquartered in SCAP-adopting states experience a 1.2% increase in labor investment inefficiency compared to firms in states without SCAPs. The dynamic DiD regression further confirms the parallel trends assumption and shows that the impact on labor investment inefficiency becomes evident only after SCAP implementation, suggesting a causal impact of climate regulatory risk on corporate employment decisions. We show that SCAP adoption leads to both overinvestment and underinvestment in labor resources, indicating that firms affected by SCAP are not merely adjusting labor investment in one direction but are struggling to align labor allocation with optimal economic fundamentals.

Our analysis further reveals that the negative impact of SCAP adoption on labor investment efficiency is more pronounced for firms with greater exposure to climate change risks

[5] https://www.weforum.org/agenda/2024/02/green-jobs-green-skills-growth/

and oppotunities. However, we find that local government financial support and clearer climate adaptation guidelines can mitigate this effect. These findings suggest that state-level policies play a crucial role in supporting firms through the transition, reducing the adverse impacts of SCAP adoption on labor investment.

Finally, we conduct channel analyses to explore why firms struggle with labor investment efficiency after SCAP adoption. First, we find that affected firms increase their investment in research and development (R&D) and green innovation. This shift suggests that the compliance costs associated with SCAP adoption lead firms to reallocate resources toward climate-related initiatives, often at the expense of labor investment. This is further supported by the findings that firms facing financial constraint are more likely to involved in labor underinvestment following SCAP adoption. Second, we find that firms in regions with greater green labor shortages are more likely to underinvest in labor after SCAP adoption, while firms in areas with a sufficient labor supply tend to overinvest. These results support the argument that SCAP adoption creates operational challenges during the green transition, disrupting labor investment efficiency.

Our research contributes to several streams of literature. First, we contribute to the growing body of literature that examines the effects of climate regulation on corporate outcomes. We add to the existing literature on climate regulation and corporate decision-making dynamics by Barnett et al. (2020), Kölbel et al. (2020), Mueller and Sfrappini (2022), and Seltzer et al. (2022) and extend climate regulation risk literature (e.g., He et al., 2023; Kovacs et al., 2025) by explaining the relevance of climate regulation on corporate employment decision-making process.

Second, our paper contributes to the large stream of literature related to labor investment efficiency (Ben-Nasr & Alshwer, 2016; Boubaker et al., 2023; Cao & Rees, 2020; Habib & Hasan, 2021; Jung et al., 2014, 2022; Khedmati et al., 2020, 2021; Kong et al., 2018; Sualihu et al., 2021; Xiao, 2023). The findings provide an insight of corporate behaviour in response to tightened traditional prospects during climate regulation implementation. With the emergence of heightened environmental commitments due to climate regulation, firms anticipate potential regulation uncertainty and increased compliance costs. In this context, firms may adjust their policies by allocating more resources to innovation, potentially at the expense of labor investment.

Our findings also have policy implications. By understanding the implications of climate regulatory changes on corporate behaviour, managers can make better decisions to optimize investment strategies. Furthermore, from a policy perspective, this research underscores the potential side effects associated with the implementation of climate regulations, emphasizing the need for policymakers to account for both financial and environmental sustainability when carrying out regulations.

The rest of the paper is structured as follows. We develop the hypotheses in Section 2 following the introduction. We arrange section 3 to describe the data and methodology. All our empirical findings are presented in section 4. Our last section, 5, concludes the study.

2. Literature Review and Hypothesis Development

2.1 Determinants of Corporate Employment Decisions

A substantial body of recent economic literature (e.g., Ha & Feng, 2018; Habib & Hasan, 2021) stresses the importance of preserving an optimal employment level, which significantly impacts a firm's productivity, efficiency, and competitive edge in the market. However, research on how policy and regulatory uncertainty impact corporate employment decisions remains scarce. Given that labor costs are variable and can be entirely covered by current revenues (Dixit, 1997), classical economic thought considers any financial friction, for example backed by possible regulatory uncertainty, as irrelevant to employment decisions (Jung et al., 2014). Therefore, there exists a considerable gap in the literature on labor investment. However, a seminal paper by Pinnuck and Lillis (2007) raise the awareness regarding corporate employment research in financial economics. They explain how the loss heuristic causes a more significant drop in corporate labor investment. The literature has been further contributed by Jung et al. (2014), who demonstrate that accounting quality improves labor investment efficiency, extending the literature of earlier studies of Biddle and Hilary (2006), who document the ability of accounting quality to reduce financial frictions caused by information asymmetry.

One of the major explanations in existing corporate employment literature regarding the causes of inefficient labor investment is related to the agency problem between executives and shareholders. Executives can access recruitment-related determinants such as job skills, contracts, and routine hiring (Jung et al., 2014). Therefore, they may engage in managerial empire-building (Jensen, 1986), and make inappropriate employment decisions. Such prediction shows the relevance of the managerial entrenchment hypothesis, where managers tend to over-hire (or under-fire), thus decreasing labor investment efficiency (Luo et al., 2020).

In response to the agency problem, Sualihu et al. (2021) argue that restricted stock options as executive compensation can mitigate managerial empire-building and improve LIE. The argument shows the usefulness of executive compensation design as a disciplinary force to control agency problems. Besides disciplining through the incentive channel (i.e., compensations), another strand of literature on LIE determinants reveals that internal governance can also mitigate agency conflict and resulting in more efficient labor investment. For example, prior studies documented that CEO-Director ties (Khedmati et al., 2020), conditional conservation (Ha & Feng, 2018), stock market informativeness (Ben-Nasr et al., 2016), institutional shareholders' investment horizon (Ghaly et al., 2020), financial reporting quality (Jung et al., 2014) could all work as internal disciplinary mechanisms and help improve corporate employment decisions. In addition, utilizing the disciplinary model of competition on managerial behaviour, Boubaker et al. (2023) argue that product market competition can act as an external governance mechanism to improve LIE. Other external governance mechanisms include analysts' coverage (Sualihu et al., 2021) and accounting comparability (Zhang et al., 2020), which are shown to reduce inefficient labor investment through monitoring and information intermediary roles.

Apart from the focus on agency theory, a few studies also explain how employee-friendly treatment (Cao & Rees, 2020) and county-level religiosity (Khedmati et al., 2021) improve labor investment efficiency. For example, Khedmati et al. (2021) utilize the social norm theory and argue that religion may be a checking mechanism to prevent unethical behaviour.

2.2 Climate Regulatory Risk and Economic Outcomes

Corporations are increasingly vulnerable to regulatory risks, especially climate regulations, which create significant decisional constraints for those impacted (Sakhel, 2017). While existing literature broadly addresses the effects of policy uncertainty on corporate decisions[6,] this review focuses on the specific impact of climate regulatory risk.

Prior studies (e.g., Krueger et al., 2020; Stroebel & Wurgler, 2021) document that investors view climate regulatory risk as a significant concern. Governments worldwide are enacting climate regulations, including emission limits, carbon taxes, and cap-and-trade systems, which have varying impacts on firms (Ilhan et al., 2021). These regulations raise firms' operating costs and cash flow risks (Karpoff et al., 2005), and future regulatory uncertainty heightens the exposure of businesses to CRR (Pindyck, 1993).

The theoretical and empirical literature on CRR and corporate decision-making has been expanding. Empirically, He et al. (2023) show that firms in areas with implemented climate adaptation plans (SCAPs) face shareholder pressure to reduce executive compensation due to

[6] The literature on policy uncertainty can be categorized into three main dimensions. First, macro-focus studies show that policy uncertainty negatively affects production, employment, and foreign direct investment (Baker et al., 2016; Davis, 2016; Hassan et al., 2019; Julio & Yook, 2012). Second, research on asset pricing highlights the relationship between policy uncertainty and stock prices, with firms' valuations adjusting based on regulatory uncertainty (e.g., Brogaard & Detzel, 2015a; Kelly et al., 2016). Third, micro-level studies (e.g., Bonaime et al., 2018; Çolak et al., 2017) demonstrate that elevated uncertainty leads firms to delay capital expenditures, reduce M&A activities, and accumulate precautionary cash holdings.

anticipated compliance costs. This aligns with the broader view that climate regulatory risk reduces shareholder wealth and impacts executive compensation (Karpoff et al., 2005). Ren et al. (2022) find that climate regulations, by increasing compliance costs, discourage investments in environmentally sensitive industries. Hsu et al. (2023) show that investors demand higher risk premia from firms with higher carbon emissions due to perceived climate-related risks. Other studies (e.g., Dang et al., 2022; Ginglinger & Moreau, 2023) document similar reactions in firms' capital structure decisions under heightened CRR. In contrast, Krueger et al. (2020) argue that addressing CRR is a more effective strategy than divestment.

When incorporating CRR into asset pricing models, studies (e.g., Seltzer et al., 2022) show that it influences equity risk premiums, bond pricing, and the overall cost of capital. Additionally, CRR significantly shapes firm-level behaviors, particularly in employment and operational strategies. In the U.S., climate regulations are accelerating the transition from "gray" (high-carbon) to "green" (low-carbon) industries, influencing labor market dynamics and prompting firms to adjust labor allocation (Dellink et al., 2019). These adjustments underscore the need for a nuanced understanding of CRR, particularly through frameworks like SCAPs, which can enhance the evaluation of CRR's impact on employment and firm decisions.

2.3 Hypothesis Development

We employ the adoption of SCAPs as a proxy for climate regulatory risk, arguing that these plans impose stringent requirements to reduce carbon emissions and promote the transition to green technologies. This heightened regulatory risk introduces both financial and operational challenges for firms in affected states, including increased compliance costs and the challenges of transitioning to greener practices.

The financial challenges stemming from SCAPs are multifaceted. Firms face increased compliance costs, such as investments in R&D and green technologies, which can divert resources away from labor and disrupt efficient resource allocation. These challenges are further compounded by regulatory uncertainty, which amplifies costs by increasing legal and environmental liabilities (Barnett et al., 2020) while creating economic risks, such as stranded assets (Litterman, 2021) and financing constraints (Ilhan et al., 2021). Together, these factors—referred to as green compliance costs—can hinder firms' ability to invest efficiently in their labor resources.

SCAP adoption also introduces additional challenges related to the transition to greener practices. Significant operational adjustments are often required, including restructuring labor to meet sustainability goals (Porter & Linde, 1995). In anticipation of these shifts, firms increasingly seek workers with green skills—specialized expertise in sustainable practices (Aldy & Stavins, 2012). However, inefficiencies can arise throughout the transition process. First, firms may overestimate the demand for green-skilled labor, resulting in labor overinvestment. Prior research highlights that corporate employment decisions are often influenced by managers' perceptions of the firm's future direction (Jung et al., 2014; Khedmati et al., 2020). The adoption of SCAP introduces uncertainty regarding the exact requirements and timeline of the green transition, which can lead managers to overestimate the need for green-skilled labor. This misjudgement may drive excessive hiring, ultimately resulting in inefficient allocation of labor resources. Second, the current labor market faces a shortage of green-skilled workers (Gardas et al., 2019), which makes it difficult for firms to fill green job positions. This scarcity can constrain hiring efforts, resulting in underinvestment and suboptimal allocation of labor resources.

Given the green compliance costs and the challenges of transitioning to greener practices, firms' ability to manage labor investment efficiently is likely to be compromised by SCAP adoption, resulting in labor investment inefficiency. Therefore, we hypothesize that:

Hypothesis: Climate regulatory risk associated with SCAP adoption reduces labor investment efficiency.

3. Data and Methods

3.1 Sample

We start our sample with all US firms recorded in the Compustat database spanning the years 1994 to 2021. The data on SCAP adoption at the state-level[7] is sourced from the Georgetown Climate Center (GCC), one of the leading providers of practical strategies for preparing and addressing the consequences of climate change on a national scale.[8] Additionally, we obtain stock return variable from CRSP database. The dataset is then merged with institutional investor information obtained from Thomson Reuters' 13F database and union coverage information obtained from the Union Membership and Coverage database. We further exclude firms operating in the financial industry (SIC codes 6000-6999) and regulated utilities industry (SIC codes 4900-4999), as they are subject to different regulations. Our pre-stacked sample consists of 27,936 firm-year observations for 3,138 firms over the period from 1994 to 2021. This sample size aligns with other studies in the field of labor investment efficiency. For example, Cao and Rees (2020) employ a sample comprising 20,973 firm-year observations spanning from 1996 to 2016. Chowdhury et al. (2023) examine a sample of 14,495 observations over the period from 1992 to 2016. Similarly, Ha and Feng (2018) conduct their study with a sample size of 31,865 firm-year observations covering a 28-year period.

3.2 Measure of SCAP

Our main variable of interest, SCAP, is a dummy variable set to 1 for firm-year observations in states that have finalized a SCAP, and 0 otherwise. SCAP finalization (SCAP = 1)

[7] The headquarter state information is obtained from from SEC EDGAR. We start our sample from 1994 as this is the earliest year when EDGAR start to report reliable state data.
[8] https://www.georgetownclimate.org/adaptation/plans.html

signals increased climate regulatory risk, as state-level climate adaptation plans impose additional compliance costs on local firms, requiring them to adopt environmentally sustainable practices. The detailed list of states where SCAPs have been finalized is provided in Appendix A.2.

3.3 Measure of Labor Investment Efficiency

We construct the labor investment inefficiency measure ($ABHIRE_{i,t}$) following the methodology employed in prior studies (Jung et al., 2014; Pinnuck & Lillis, 2007). Specifically, we estimate $ABHIRE_{i,t}$ as the absolute value of the residual from the following ordinary least squares (OLS) model:

$$\begin{aligned} Net\_HIRE_{i,t} = {} & \beta_0 + \beta_1 SALE\_GROWTH_{i,t-1} + \beta_2 SALE\_GROWTH_{i,t} + \beta_3 \Delta ROA_{i,t} \\ & + \beta_4 \Delta ROA_{i,t-1} + \beta_5 ROA_{i,t} + \beta_6 RETURN_{i,t} + \beta_7 SIZE\_R_{i,t-1} \\ & + \beta_8 QUICK_{i,t-1} + \beta_9 \Delta QUICK_{i,t-1} + \beta_{10} \Delta QUICK_{i,t} + \beta_{11} LEV_{i,t-1} \\ & + \beta_{12} LossBin1_{i,t-1} + \beta_{13} LossBin2_{i,t-1} + \beta_{14} LossBin3_{i,t-1} \\ & + \beta_{15} LossBin4_{i,t-1} + \beta_{16} LossBin5_{i,t-1} + \beta_{17} AUR_{i,t-1} + IndustryFE \\ & + \varepsilon_{i,t} \end{aligned} \tag{1}$$

The dependent variable, $NET\_HIRE_{i,t}$, is calculated as the percentage change in the number of employees of firm i in year t. This measure is employed as a proxy of the firm's actual investment in labor. The right-hand-side variables are used to predict the firm's optimal investment in the labor resources (Pinnuck & Lillis, 2007). For example, $SALES\_GROWTH_{i,t-1}$ and $SALES\_GROWTH_{i,t}$ are included to capture the demand for the products and services of firm i. As the demand level influences the firm's decision in employment to maximize profitability, these variables are used in predicting optimal labor investment. In line with this concept, $\Delta ROA_{i,t}$, $\Delta ROA_{i,t-1}$ and $RETURN_{i,t}$ are also included in the regression to capture the impact profitability on labor investment decision. Firm-specific characteristics such as firm size ($SIZE\_R_{i,t}$), firm liquidity level ($QUICK_{i,t-1}$, $\Delta QUICK_{i,t-1}$, $\Delta QUICK_{i,t}$, $LEV_{i,t-1}$) and management's ability of utilizing assets ($AUR_{i,t-1}$) are also included to accommodate any variation in labor investment decisions arising from these characteristics. To capture the negative effect of profit loss on labor employment decision, five loss bins ($LossBin1_{i,t}$, $LossBin2_{i,t}$, $LossBin3_{i,t}$, $LossBin4_{i,t}$, $LossBin5_{i,t}$) are further incorporated into the regression. The regression also controls for industry fixed effects based on Fama 12 industry classification, as labor demand may vary across industries.

The absolute value of the residual ($ABHIRE_{i,t}$) from the above model captures the deviation of actual labor investment from its optimal level and is thus used as a proxy for labor investment inefficiency. Specifically, a higher $ABHIRE_{i,t}$ implies a less efficient investment in labor resources whereas a lower $ABHIRE_{i,t}$ denotes a greater labor investment efficiency. We provide the estimation in Appendix A.3.

3.4 Empirical Model

We use a stacked cohort Difference-in-Difference (DiD) regression framework to estimate the impact of climate regulatory risk on labor investment efficiency. As Baker et al. (2022) explain, stacked cohort DiD offers advantages in assessing policies with staggered treatment timing. Specifically, this approach reduces bias in estimating SCAP finalization effects due to heterogeneous treatment impacts and varying treatment timings.

To construct the stacked sample, we first identify treated firms as those headquartered in SCAP-implementing states and control firms as those in states that never finalize SCAPs. Treated firms are then grouped into cohorts based on their SCAP implementation year, with each cohort consisting of firms that share the same implementation year and all control units. We then combine all these cohorts to form our stacked sample and employ the following stacked DiD specification,

$$
\begin{aligned}
ABHIRE_{i,t} = \alpha &+ \beta SCAP_{i,t-1} + \gamma_1 MTB_{i,t-1} + \gamma_2 SIZE_{i,t-1} + \gamma_3 QUICK_{i,t-1} + \gamma_4 LEV_{i,t-1} \\
&+ \gamma_5 DIVDUM_{i,t-1} + \gamma_6 STD\_CFO_{i,t-1} + \gamma_7 STD\_SALES_{i,t-1} \\
&+ \gamma_8 TANGIBLE_{i,t-1} + \gamma_9 LOSS_{i,t-1} + \gamma_{10} INSTI_{i,t-1} + \gamma_{11} AQ_{i,t-1} \\
&+ \gamma_{12} STD\_NET\_HIRE_{i,t-1} + \gamma_{13} LABOR\_INTENSITY_{i,t-1} + \gamma_{14} UNION_{i,t-1} \\
&+ \gamma_{15} AB\_INVEST\_OTHER_{i,t} + State\ Cohort\ FE + Year\ Cohort\ FE + \varepsilon_{i,t}
\end{aligned}
\tag{2}
$$

The coefficient of $SCAP_{i,t-1}$ compare the $ABHIRE_{i,t}$ of the treatment group against that of the control group after accounting for firm-specific characteristic that may affect firms' allocation in their labor resources. The firm-specific characteristics controlled in the regression includes the market-to-book ratio (*MTB*); firm size (*SIZE*); corporate financial reporting quality (*AQ*); liquidity level (*LEV, QUICK*); standard deviation of operating cash flow; sales and labor investment (*STD_CFO, STD_SALES, SD_NET_HIRE*); labor intensity level (*LABOR_INTENSITY*); non-labor investment inefficiency (*AB_INVEST_OTHER*); industry-level rate of labor unionization (*UNION*); and whether the firm is a dividend payer (*DIVDUM*) or reported loss in prior year (*LOSS*). Standard errors are clustered at the state level to address potential statistical issues related to autocorrelated residuals (Petersen, 2008), with state-cohort and year-cohort fixed effects being controlled. Detail definitions of variables can be found in Appendix A. To minimize the impact of outliers, we winsorize all continuous variables at the 1% and 99% levels.

4. Results and Discussions

4.1 Descriptive Statistics

Table 1 reports the descriptive statistics of labor investment efficiency, SCAP as corporate regulatory risk, and all firm-level control variables utilized in our stacked cohort DiD regression. *ABHIRE* has a mean of 0.128 and 0.171 for standard deviations. These values are consistent with recent studies on labor investment efficiency (Ben-Nasr & Alshwer, 2016; Jung et al., 2014;

Khedmati et al., 2020; Sualihu et al., 2021). The *SCAP* variable, our main measure of climate regulatory risk, has a mean value of 0.029, indicating that 2.9% of observations in the stacked sample experienced SCAP adoption. This relatively low percentage is attributed to the stacked sample design, where control firms (SCAP=0) are duplicated. In the pre-stacked sample, *SCAP* has a mean of 23% (untabulated), aligning with He et al. (2023) (i.e., mean=21%), who examine the impact of SCAPs on executive compensation between 1994 and 2018. The mean and standard deviations of the control variables are also consistent with those reported in prior studies (Cao & Rees, 2020; Ghaly et al., 2020; Ha & Feng, 2018; Habib & Hasan, 2021; Jung et al., 2014).

[Insert Table 1 here]

4.2 Baseline Regression Results

Table 2 presents the results of the stacked cohort DiD regression. We find that treated firms exhibit significantly higher labor investment inefficiency (*ABHIRE*) compared to control firms after the implementation of SCAP, both statistically and economically. Specifically, the SCAP coefficient in Column 1 indicates a 1.2% reduction in labor investment efficiency. This decline implies the challenges firms face in managing labor investment efficiently, as higher compliance costs and resource constraints force them to prioritize regulatory adaptation over optimal hiring strategies. These results support the hypothesis that SCAP adoption intensifies climate regulatory risk, limiting firms' ability to invest efficiently in their labor resources.

[Insert Table 2 here]

To pinpoint the timing of treatment effects and address concerns related to potential non-parallel labor investment trends before the treatment year, we conduct a dynamic DiD analysis and report the result in Column 2. We define six timing indicators: *Pre2, Pre1, Current, Post1, Post2, and Post3More*, representing firm-year observations occurring two years before, one year before, during, one year after, two years after, and more than three years after SCAP adoption, respectively. The statistically insignificant coefficients on the pre-SCAP indicators (*Pre2, Pre1*) suggest that our findings are unlikely driven by pre-existing trends. In contrast, the significant post-SCAP coefficients suggest that the increase in labor investment efficiency among treated firms likely results from SCAP adoption, supporting its causal impact on corporate employment decisions.

4.3 Alternative measures and specifications

To further assess the robustness of our findings, we re-estimate our baseline regression model using alternative measures and model specifications. Table A.4 presents the results based on these alternative measures of *ABHIRE*. In column (1), following Biddle et al. (2009), we estimate labor investment inefficiency by regressing net hiring on sales growth in the first-stage regression. The residual from this regression (*ABHIRE_SALES*) serves as our first alternative measure. In column (2), we calculate labor investment inefficiency (*ABHIRE_IND*) as the absolute difference between the firm's net hiring and the industry median net hiring, as suggested by Harvey et al. (2004). This measure assumes that the industry median labor investment level represents an optimal benchmark, with larger deviations indicating greater inefficiency. In column (3), we modify the first-stage regression by adding year fixed effects, alongside industry fixed effects. Our results remain robust across all these alternative *ABHIRE* measures.

Next, we estimate the impact of SCAP on LIE using a single-step regression. As noted by prior studies (Chen et al., 2022; Jackson, 2022; Ranasinghe & Habib, 2024), the two-step design may introduce bias due to incorrect inference, concerning our previous findings. To address this, we re-estimate our baseline regression using the single-step regression model suggested by Chen et al. (2022). Table A.5 shows that our findings are consistent under this alternative model specification.

Additionally, to address concerns that our findings may be driven by non-parallel trends prior to SCAP adoption or by unobservable characteristics associated with the adopting firms, we conduct a placebo test. In this test, we randomize the SCAP adoption year for treatment firms and repeat our baseline regression using the 'pseudo-treatment year'. We then repeat this exercise 1000 times and report the distribution of placebo coefficients of “SCAP” in Figure 1. Specifically, the histogram presents the frequency distribution whereas the dashed line shows the Kernel density of the coefficients. As shown, the true estimation line is significantly distant from the distribution of placebo coefficients, which have mean values close to 0. This provides supportive evidence that our results are not driven by pre-existing trends or unaccounted-for factors.

Finally, we re-estimate the impact of SCAP on LIE under alternative model specifications. In Table A.6, we present the results estimated using standard staggered DiD models. In addition, we use the JWDID program, proposed by Wooldridge (2021, 2023), in Stata to further verify the robustness of our findings from the stacked DiD setup, accounting for potential biases associated with the two-way fixed effects approach. We present the average treatment effect of SCAP on labor investment inefficiency over a 9-year window (i.e., -6 years to +2 years) around the SCAP adoption period in Figure 2. The graph demonstrates that, prior to SCAP adoption, the control group does not significantly differ from the treatment group in terms of labor investment efficiency, confirming the parallel trends assumption. However, following SCAP adoption, treatment firms show a significant increase in labor investment inefficiency, supporting the argument that increased climate regulatory risk imposes constraints on management's ability to invest efficiently in labor resources.

4.4 Additional Analysis

4.4.1 SCAP and the Types of Labor Investment Inefficiency

To identify the specific forms of labor investment inefficiency resulting from SCAP adoption, we decompose inefficiency into over-investment and under-investment, following prior studies (Ghaly et al., 2020; Khedmati et al., 2020; Jung et al., 2014). Over-investment is defined as positive abnormal net hiring when actual net hiring exceeds expected levels, while under-investment is negative abnormal net hiring when is lower than expected net hiring. We further analyse the sources of each inefficiency type by separately estimating effects on firing and hiring decisions. Specifically, over-investment is decomposed into over-hiring (overinvestment when expected net hiring is positive) and under-firing (overinvestment when expected net hiring is negative). Under-investment is broken down into under-hiring (underinvestment when expected net hiring is positive) and over-firing (underinvestment when expected net hiring is negative).

[Insert table 3 here]

Table 3 presents the impact of SCAP on different types of labor investment inefficiency. The positive and significant coefficients in Columns (1) and (4) indicate that SCAP adoption contributes to inefficiency from both under- and over-investment. The remaining columns suggest these inefficiencies likely stem from both suboptimal hiring and firing decisions. Thus, the results imply that firms affected by SCAP adoption are not simply adjusting labor investment up or down but are struggling to align labor resource allocation with optimal economic fundamentals.

4.4.2 Effects of Climate Risk and Opportunities

Next, we examine the heterogeneous effects of SCAP adoption on affected firms. Since SCAP aims to align corporate practices with sustainable climate action, its impact varies depending on firms' exposure to climate risks and opportunities. Previous studies (e.g., Sautner et al., 2023) show that the effects of climate change differ significantly among firms, even within the same industry. For instance, firms facing greater climate risks, particularly those that are more polluting, may incur higher costs in aligning their practices with environmental goals, limiting their ability to invest efficiently in labor. On the other hand, firms with greater climate-related opportunities may have the incentive to direct more resources toward these investments, also at the expense of labor investment. Thus, we predict that the negative impact of SCAP on labor investment efficiency is more pronounced for firms with higher exposure to climate risks and opportunities.

To assess firms' exposure to climate-related opportunities, we use the climate opportunity exposure index (i.e., OPEXP) developed by Sautner et al. (2023). This index captures opportunities related to climate change discussions found in firms' earnings conference call transcripts. We classify firms in the top tercile of OPEXP in a given year as high exposure firms (i.e., *HIGHOPEXP*=1) and those in the bottom tercile as low exposure firms (i.e., *HIGHOPEXP*=0). To identify firms facing greater climate risk, we classify them into high-polluting and low-polluting categories based on their industry classification, following the criteria established by the US Environmental Protection Agency (EPA). Specifically, firms in the following seven sectors—metal mining (NAICS 212), electric utilities (NAICS 2211), chemicals (NAICS 325), primary metals (NAICS 331), paper (NAICS 322), food, beverages, and tobacco (NAICS 311 and 312), and hazardous waste management (NAICS 5622 and 5629)—are categorized as high-polluting firms (i.e., *HIGHPOLLUTE*=1). These sectors account for 92 percent of all disposal and other releases of toxic release inventory (TRI) chemicals (Flammer & Luo, 2017).

[Insert Table 4 Here]

Table 4 demonstrates the effect of SCAP on labor investment inefficiency conditioned on climate risk and opportunity exposure. Consistent with our prediction, Column (1) shows that firms with higher climate opportunity exposure experience greater labor investment inefficiency after adopting SCAP. Similarly, the results in Column (2) indicate that firms in polluted industries face more challenges in allocating their labor resources efficiently following SCAP adoption.

Overall, these findings reveal that the impact of climate regulatory risk on labor investment efficiency varies significantly among firms, primarily due to their differing exposures to climate risk and opportunities.

4.4.3 Effects of Government Support and Climate Regulation Guidance

We then examine whether government support for green transition can mitigate the negative impact of climate regulation risk on labor investment efficiency. Government's financial support for corporate climate-related initiatives enables companies to transition to greener operations with less strain on resources, including labor. In addition, clear local climate adaptation guidelines could also reduce regulatory uncertainty, lowering the risk of reduced labor investment due to concerns about irreversible investments (Gulen & Ion, 2016). Thus, we hypothesize that government financial support and guidance can reduce the unintended negative impact of SCAP adoption on labor resource allocation efficiency.

To estimate local government financial support, we collect environment-related grants data from USASPENDING.gov.[9] Grants funded by the Environmental Protection Agency (EPA) and the US Department of Energy (DOE) treasury accounts are classified as environmental-related grants. We identify firms in states with grants in the top tercile for a given year as receiving higher government support for green transition (*GRANT* = 1), and those in states with grants in the bottom tercile as receiving lower support (*GRANT* = 0).

To assess the clarity of climate adaptation guidelines provided by local governments to support firms in transitioning to greener operations, we count the number of discrete goals in each

[9] https://www.usaspending.gov/search

SCAP.[10] Firms in states with a goal count in the top tercile for a given year are identified as receiving clearer climate adaptation guidelines (*GOAL* = 1), while the rest are classified as receiving less clear guidance (*GOAL* = 0).

[Insert Table 5 here]

Consistent with our arguments, Table 5 shows that the negative impact of SCAP on LIE is less pronounced among firms receiving greater financial support and clearer climate adaptation guidelines from local governments. These findings highlight the vital role of local governments in aiding firms' green transitions and reducing unintended negative effects climate regulations have on labor resource allocation.

4.5 Channel Analysis – Green Compliance Cost

Next, we examine why firms struggle to maintain efficient labor investment following SCAP adoption. As discussed earlier, one potential reason for this inefficiency is that SCAP may impose additional compliance costs, forcing firms to shift resources toward climate-related investments, such as green patents, to align with new climate actions. This reallocation may limit their ability to efficiently invest in labor.

4.5.1 SCAP and Other Investment

To investigate, we first examine whether firms adjust their investment strategies after SCAP adoption. Specifically, we explore whether the compliance costs associated with SCAP adoption arise from firms reallocating resources to climate-related investments in order to align

[10] The number of discrete goals in each SCAP can be obtained from the website of Georgetown Climate Center.

with regulations and maintain competitiveness under resource constraints. To test this, we first examine the impact of SCAP implementation on corporate research and development (R&D) investments. Existing studies (e.g., Ren et al., 2022; Sautner et al., 2023) suggest that firms increase R&D investments during periods of regulatory uncertainty to boost competitiveness. Additionally, to comply with climate regulations, firms are likely to focus on R&D projects related to green innovation (i.e., green investment) to reduce their carbon footprint. Therefore, we argue that firms in states with SCAP implementation will increase R&D and green investments.

[Insert table 6 here]

To test, we examine the impact of SCAP adoption on corporate R&D and green investments separately. Using data from the Global Corporate Patent Dataset (Bena et al., 2017),[11] we estimate corporate green investment based on corporate patents. We categorize patents as either "Green Patents" or "Non-Green Patents" using the classification framework proposed by Haščič and Migotto (2015), based on OECD guidelines for measuring innovation in environmentally relevant technologies. Green Patents include those related to environmental management, water adaptation, biodiversity protection, and climate change mitigation.[12] We then map these patents to their respective firms based on patent numbers and calculate the green investment measure by dividing the number of green patents granted to each firm by the logarithm of their market value of equity for the corresponding year (Cohen et al., 2020).

Consistent with our hypothesis, Columns (1) and (2) of Table 6 show that firms increase R&D and green investments after SCAP adoption. This reflects their efforts to enhance competitiveness and ensure compliance by reallocating resources to climate-related investments. As a result, their ability to efficiently allocate labor resources is constrained.

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[11] https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-assignment-dataset

[12] For a detailed list of environment-related patents, see Haščič and Migotto (2015).

4.5.2 Effects of Financial Flexibility

Firms may seek external financial support to offset rising climate regulatory compliance costs and maintain investment efficiency. However, firms facing significant financial constraints may struggle to raise funds from the capital market for increased green investment expenses. As a result, these firms are more likely to secure funds by reducing labor investments. We therefore predict that firms needing greater financial flexibility will experience more pronounced effects of SCAP finalization on labor investment inefficiency, especially labor underinvestment.

[Insert table 7 here]

To test our hypothesis, we construct two proxies for financial constraints, WW and SA, following prior literature (e.g., Hadlock & Pierce, 2010; Whited & Wu, 2006). Specifically, we classify firms as highly constrained if they are in the top tercile for the WW index (*HIGH_WW* = 1) and SA index (*HIGH_SA* = 1) in a given year, and as less constrained if they are in the bottom tercile (*HIGH_WW* = 0 and *HIGH_SA* = 0). We then assess whether SCAP's impact on LIE differs across firms with varying levels of financial constraint. Consistent with our predictions, the positive and significant coefficient of the interaction terms ($SCAP_{t-1} \times HIGH\_WW$ and $SCAP_{t-1} \times HIGH\_SA$) reported in Column (1) and (3) of Table 6 implies the impact of SCAP finalisation on labor underinvestment is more pronounced for financially constrained firms. However, this effect is not observed for labor overinvestment (Column (2) and Column (4)). These findings further support the green compliance cost channel, suggesting that financially constrained firms cut labor investment after SCAP adoption to redirect resources toward green initiatives to meet regulatory requirements.

4.6 Channel Analysis – Barriers to Green Labor Transfer

Another factor contributing to labor investment inefficiency following SCAP adoption arises from challenges in transitioning to greener practices. SCAP adoption often requires significant operational changes, necessitating adjustments to labor structures (Porter & Linde, 1995). As firms anticipate a shift toward sustainability, they increasingly seek green-skilled workers—individuals with expertise in sustainable practices (Aldy & Stavins, 2012). However, this transition can lead to inefficiencies in two distinct ways.

First, firms may overestimate the demand for green-skilled labor, prompting excessive hiring and resulting in labor overinvestment. This miscalculation often stems from the uncertainty surrounding the exact requirements of green transitions and the anticipated pace of these changes. Second, the broader job market faces a shortage of green-skilled labor, making it difficult for firms to fill green job positions (Gardas et al., 2019). This labor scarcity can constrain hiring efforts, leading to underinvestment and suboptimal labor allocation. The interplay between these dynamics varies by region. In areas with a sufficient supply of green labor, firms may overinvest due to overestimating their needs. Conversely, in regions where green labor is scarce, firms may underinvest, struggling to meet their labor demands.

To test the above conjecture, we examine how the relationship between SCAP finalization and labor investment efficiency varies with local green labor supply. We use two measures to capture green labor supply. The first measure is based on the salary gap between green and brown jobs within each industry. We employ occupation data from O*NET and the classification in Vona et al. (2018) to identify green and brown occupations within each NAIC3 industry. We then obtain salary information for each occupation from the Occupational Employment and Wage Statistics

(US Bureau of Labor Statistics)[13] and calculate the average annual salary for green and brown jobs in each industry. A larger salary gap between the green jobs and brown jobs indicates greater demand or insufficient supply of green labor in that industry. We classify firms in industries with a top tercile salary gap (*GREENGAP* = *1*) as facing greater green labor shortages, and firms in industries with a bottom tercile gap (*GREENGAP* = 0) as facing more sufficient green labor supply.

Our second proxy is the number of science and engineering degrees issued in each state, as these degrees help build green skills and prepare the workforce for in-demand green jobs.[14] We hypothesize that firms in states with a higher supply of such labor—measured by the cumulative number of science and engineering degrees awarded over the past five years—experience fewer green labor shortages. Using state-level data from the US National Science Foundation,[15] we classify firms in states within the top tercile of degree issuance (*SEDEGREE* = 1) as having more sufficient green labor supply, and those in the bottom tercile (*SEDEGREE* = 0) as facing greater green labor shortages.

[Insert Table 8 here]

Consistent with our argument, Columns (1) and (3) of Table 8 indicate that SCAP adoption is more likely to result in overinvestment among firms with a sufficient supply of green labor. Specifically, the negative coefficient of the interaction term in Column (1) suggests that this overinvestment is more pronounced in firms with smaller salary gaps between green and brown jobs. Similarly, the positive coefficient of the interaction term in Column (3) indicates that

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13 https://www.bls.gov/oes/

14 https://www.brookings.edu/articles/why-green-jobs-plans-matter-and-where-u-s-cities-stand-in-implementing-them/

15 https://ncses.nsf.gov/indicators/states/indicator/se-degrees-to-all-higher-education-degrees/

overinvestment is more evident among firms located in states with a higher supply of labor with science and engineering backgrounds.

In contrast, Columns (2) and (4) show that SCAP adoption is more likely to lead to underinvestment in firms facing green labor shortages. These findings align with our argument that labor supply dynamics play a critical role in shaping labor investment efficiency following SCAP adoption.

4.7 SCAP and Green Labor Adjustment Cost

Prior research highlights the significant impact of labor adjustment costs on labor investment efficiency (Cao & Rees, 2020; Khedmati et al., 2020). Higher costs hinder firms' ability to adjust their labor structures efficiently to meet operational needs. For instance, strong local labor protections make it difficult for firms to lay off workers (Banker et al., 2013), which, in turn, may reduce workers' incentives to acquire new skills, further increase the cost of labor adjustment. Given that the green transition under SCAP adoption often requires substantial changes in labor structures, including both hiring and firing decisions, we argue that higher labor adjustment costs can exacerbate inefficiencies in labor investment following SCAP adoption.

To assess whether local labor adjustment cost worsen corporate labor investment following SCAP adoption, we examine whether the association between SCAP finalisation and LIE varies among firms with different labor adjustment costs. We employ two proxies to capture labor adjustment costs. The first proxy is the implementation level of Wrongful Discharge Laws (WDL) in the local area. WDL is the collection of three common-law exceptions to the employment-at-will concept enacted in several US states since the 1970s, with the implied contract exception, the public policy exception, and the good-faith exception. These laws can create barriers to wrongful termination, increase the costs of firing employees, and enhance job security (Cao & Rees, 2020). As a result, firms in areas with stricter WDLs face higher labor adjustment costs.

Therefore, we predict that the negative impact of SCAP implementation on LIE will be more pronounced for firms located in area with stricter WDL laws. We identify firms located in states that have implemented all three exceptions as those facing stricter WDL regulations (*WDL* = 1), resulting in higher labor adjustment costs. Conversely, firms in states that have not implemented any exceptions are classified as facing lower labor adjustment costs (*WDL* = 0).

The second proxy we use is the employment carbon footprint (ECF) developed by Graham & Knittel (2024). The ECF measures local employment vulnerability to the green transition by assessing state-level reliance on fossil fuels for both production and consumption across nearly the entire economy. Firms located in carbon-intensive regions may encounter greater challenges in transitioning to greener practices due to the local community's strong dependence on fossil-fuel-related jobs, which can lead to reluctance and limited knowledge regarding the green transition. This situation can increase the costs for firms seeking qualified labor to meet their sustainability goals, ultimately hindering labor investment efficiency. Therefore, we predict that the negative impact of SCAP implementation on LIE will be more pronounced for firms in carbon-intensive regions. We classify firms located in states with ECF values in the top tercile as carbon-intensive (*ECF* = 1) and those in states with ECF values in the bottom tercile as non-intensive (*ECF* = 0).

[Insert Table 9 here]

Consistent with our prediction, Table 8 shows that the negative impact of SCAP on LIE is more pronounced for firms in regions with stricter WDL compliance and in carbon-intensive areas. These findings are consistent with our argument that local labor stickiness limits firms' ability to adjust labor structures efficiently after SCAP adoption, reducing labor investment efficiency.

5.0 Conclusion

Rising environmental awareness among investors and stakeholders, along with intergovernmental commitments to a low-carbon economy, has made climate regulations a matter of economic or political headwinds. However, the costs of aligning corporate operations with these regulations, combined with challenges in securing skilled labor, can lead firms to allocate their resources efficiently.

In this paper, we show that climate regulatory risk, as captured by SCAP implementation, reduces corporate labor investment efficiency. We attribute this effect to two main factors. First, firms facing these regulations increase their investments in green technologies to meet climate mandates, diverting resources away from labor. Second, climate regulations create operational challenges, such as hiring the right talent, during the transition to greener practices, resulting in less efficient labor investment. We further show that local government financial support and clear climate adaptation guidelines are crucial in helping firms transition to greener practices and mitigate the unintended negative impacts of climate regulations on labor resource allocation.

These findings have important implications for policymakers and market participants. As economies shift to greener models, policymakers should account for temporary labor mismatches and financial constraints driven by green investments. Local governments can ease this transition by supporting targeted education initiatives to prepare a future workforce and by investing in resources that promote knowledge spillover in green industries. Such approaches can help balance the need for environmental sustainability with efficient labor transitions.

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Figure 1: Placebo test result

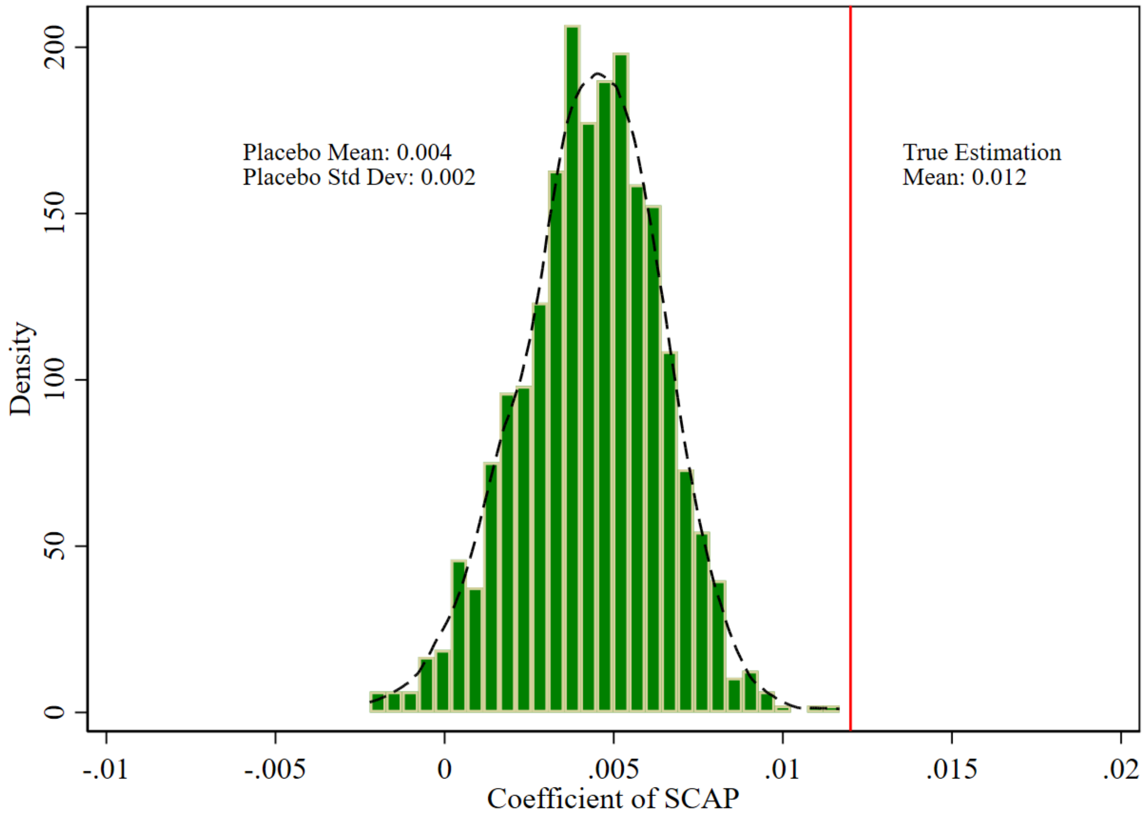

Figure 2: JWDID result

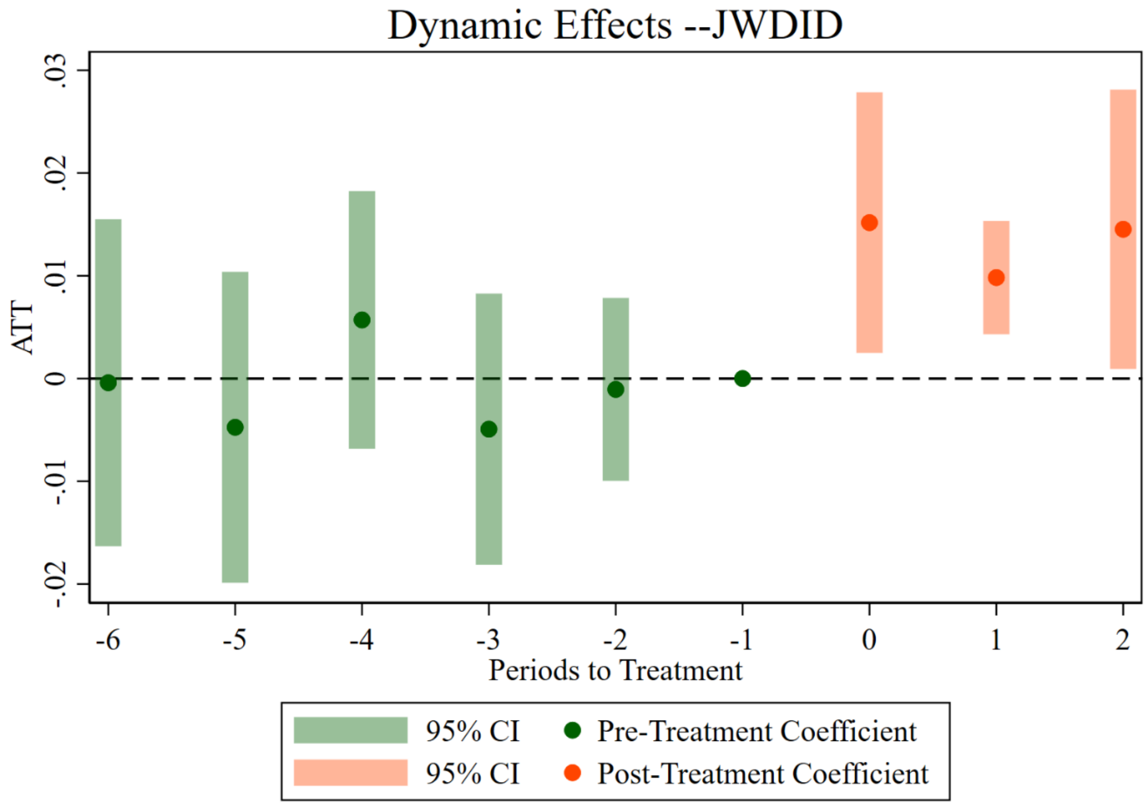

Table 1

Summary Statistics

This table presents summary statistics for the baseline variables used in the stacked cohort DiD sample. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions.

	Obs	Mean	SD	P25	Median	P75
$ABHIRE_t$	225,255	0.128	0.170	0.035	0.077	0.151
$SCAP_{t-1}$	225,255	0.029	0.167	0.000	0.000	0.000
$INSTI_{t-1}$	225,255	0.529	0.315	0.251	0.554	0.796
MTB_{t-1}	225,255	3.007	4.464	1.209	2.051	3.573
$SIZE_{t-1}$	225,255	5.845	2.075	4.299	5.832	7.301
$TANGIBLE_{t-1}$	225,255	0.264	0.219	0.095	0.198	0.370
$LABOUR\_INTEN_{t-1}$	225,255	0.008	0.009	0.002	0.005	0.009
STD_CFO_{t-1}	225,255	0.078	0.092	0.030	0.051	0.088
STD_SALES_{t-1}	225,255	0.192	0.159	0.085	0.145	0.245
$STD\_NET\_HIRE_{t-1}$	225,255	0.210	0.207	0.080	0.142	0.255
AQ_{t-1}	225,255	-0.075	0.074	-0.091	-0.057	-0.036
DIV_{t-1}	225,255	0.382	0.486	0.000	0.000	1.000
$LOSS_{t-1}$	225,255	0.281	0.450	0.000	0.000	1.000
$AB\_INVEST\_OTHER_t$	225,255	0.107	0.139	0.043	0.079	0.112
$UNION_{t-1}$	225,255	0.113	0.057	0.081	0.113	0.146
$QUICK_{t-1}$	225,255	2.031	2.254	0.857	1.327	2.253
LEV_{t-1}	225,255	0.200	0.200	0.011	0.157	0.319

Table 2

Stacked DiD

This table presents the results with the stacked difference-in-differences (DiD) approach. The dependent variable is *ABHIRE*. Independent variable of interest is *SCAP*, which is a dummy variable with the value of one if a firm's headquarter state finalizes state climate adaptation plan (*SCAP*) in a year and onwards, otherwise the variable is set to zero. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1) ABHIRE	(2) ABHIRE
$\boldsymbol{SCAP_{t-1}}$	**0.012*****	
	(4.35)	
Pre2		**-0.004**
		(-0.73)
Pre1		**0.009**
		(1.54)
Current		**0.012****
		(2.13)
Post1		**0.013****
		(2.26)
Post2		**0.018****
		(2.49)
Post3More		**0.011*****
		(3.66)
$INSTI_{t-1}$	0.002	0.002
	(1.34)	(1.33)
MTB_{t-1}	0.000***	0.000***
	(2.75)	(2.76)
$SIZE_{t-1}$	-0.002***	-0.002***
	(-7.74)	(-7.74)
$TANGIBLE_{t-1}$	0.014***	0.014***
	(5.98)	(5.98)
$LABOUR\_INTEN_{\ t-1}$	-0.338***	-0.338***
	(-6.17)	(-6.17)
STD_CFO_{t-1}	-0.041***	-0.041***
	(-4.62)	(-4.62)
STD_SALES_{t-1}	0.019***	0.019***
	(9.18)	(9.19)
$STD\_NET\_HIRE_{t-1}$	0.291***	0.291***

	(116.56)	(116.49)
AQ_{t-1}	-0.045***	-0.045***
	(-5.66)	(-5.66)
DIV_{t-1}	0.002***	0.002***
	(3.26)	(3.27)
$LOSS_{t-1}$	0.005***	0.005***
	(4.35)	(4.35)
$AB\_INVEST\_OTHER_t$	-0.048***	-0.048***
	(-7.37)	(-7.37)
$UNION_{t-1}$	0.346***	0.346***
	(67.69)	(67.68)
$QUICK_{t-1}$	0.008***	0.008***
	(29.36)	(29.37)
LEV_{t-1}	-0.004*	-0.004*
	(-1.70)	(-1.69)
Constant	0.022***	0.022***
	(11.52)	(11.51)
State-Cohort FE	YES	YES
Year-Cohort FE	YES	YES
N	225,255	225,255
R-squared	0.272	0.272

Table 3

Effect of SCAP on over- and under-investing

This table presents the results of the effect of SCAP finalisation on over- and under-investments in labor resources. Independent variable of interest is *SCAP*, which is a dummy variable with the value of one if a firm's headquarter state finalizes state climate adaptation plan (*SCAP*) in a year and onwards, otherwise the variable is set to zero. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1) Over Investment	(2) Over Hiring	(3) Under Firing	(4) Under Investment	(5) Under Hiring	(6) Over Firing
$\boldsymbol{SCAP_{t-1}}$	**0.019*** **	**0.024** **	**0.016*** **	**0.011*** **	**0.008** **	**0.025*** **
	(3.85)	**(2.19)**	**(2.89)**	**(3.40)**	**(2.38)**	**(4.15)**
Controls	YES	YES	YES	YES	YES	YES
State-Cohort FE	YES	YES	YES	YES	YES	YES
Year-Cohort FE	YES	YES	YES	YES	YES	YES
N	83,971	17,036	66,935	141,298	115,713	25,585
R-squared	0.369	0.277	0.421	0.196	0.220	0.136

Table 4

Effects of climate-related opportunities and climate risks

This table presents the results of the effects of climate risks on the association between SCAP finalisation and labor investment inefficiency. Column (1) reports the impact of climate-related opportunities on the association between SCAP finalisation and labor investment inefficiency. We use the climate opportunity exposure index (i.e., *OPEXP*) developed by Sautner et al. (2023) to capture climate-related opportunities. We classify firms in the top tercile of *OPEXP* in a given year as high exposure firms (i.e., *HIGHOPEXP*=1) and those in the bottom tercile as low exposure firms (i.e., *HIGHOPEXP*=0). Column (2) presents the effect of climate risk on the association between SCAP finalisation and labor investment inefficiency. We classify firms into high-polluting and low-polluting categories based on their industry classification, following the criteria established by the US Environmental Protection Agency (EPA). All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1) ABHIRE	(2) ABHIRE
$SCAP_{t-1}$	0.001	0.012***
	(0.23)	(4.35)
$HIGNOPEXP$	-0.003***	
	(-4.17)	
$\boldsymbol{SCAP_{t-1} \times HIGHOPEXP}$	**0.009****	
	(2.30)	
$HIGHPOLLUTE$		-0.021***
		(-7.94)
$\boldsymbol{SCAP_{t-1} \times HIGHPOLLUTE}$		**0.076*****
		(16.97)
Controls	YES	YES
State-Cohort FE	YES	YES
Year-Cohort FE	YES	YES
N	93,549	225,255
R-squared	0.238	0.272

Table 5

Effect of government support and climate regulation guidance

This table presents the results of the effects of government support and climate regulation guidance on the association between SCAP finalisation and labor investment inefficiency. Column (1) reports the impact of government support on the association between SCAP finalisation and labor investment inefficiency. We identify firms in states with grants in the top tercile for a given year as receiving higher government support for green transition (*GRANT* = 1), and those in states with grants in the bottom tercile as receiving lower support (*GRANT* = 0). Column (2) presents the effect of climate regulation guidance on the association between SCAP finalisation and labor investment inefficiency. Firms in states with a goal count in the top tercile for a given year are identified as receiving clearer climate adaptation guidelines (*GOAL* = 1), while the rest are classified as receiving less clear guidance (*GOAL* = 0). All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1) ABHIRE	(2) ABHIRE
$SCAP_{t-1}$	0.004	0.023***
	(0.80)	(4.69)
$GRANT$	0.012***	
	(7.23)	
$\boldsymbol{SCAP_{t-1} \times GRANT}$	**-0.011****	
	(-2.30)	
$GOAL$		0.013***
		(7.42)
$\boldsymbol{SCAP_{t-1} \times GOAL}$		**-0.024*****
		(-4.46)
Controls	YES	YES
State-Cohort FE	YES	YES
Year-Cohort FE	YES	YES
N	68,785	225,255
R-squared	0.248	0.272

Table 6

Effect of SCAP on other investments

This table presents the results of the effect of SCAP finalisation on other investments. Column (1) reports the impact of SCAP on R&D, and Column (2) shows the impact of SCAP on green innovation. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1) R&D	(2) Green Patent/MAV
$\boldsymbol{SCAP_{t-1}}$	**0.174*** **	**0.096** **
	(2.59)	**(2.10)**
Controls	YES	YES
State-Cohort FE	YES	YES
Year-Cohort FE	YES	YES
N	225,255	120,768
R-squared	0.411	0.042

Table 7

Effects of financial flexibility

This table presents the results of the effects of financial flexibility on the association between SCAP finalisation and labor investment inefficiency. Column (1) and (2) employ the WW index developed by Whited & Wu (2006) as a proxy of financial constraint. Column (3) and (4) use the SA index developed by Hadlock & Pierce (2010) as a proxy of financial constraint. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)
	Over Investment	*Under Investment*	*Over Investment*	*Under Investment*
$SCAP_{t-1}$	0.006	-0.001	0.015**	-0.004*
	(0.79)	(-0.34)	(2.50)	(-1.87)
$HIGH\_WW$	-0.011***	0.002		
	(-2.68)	(0.85)		
$\boldsymbol{SCAP_{t-1} \times HIGH\_WW}$	**0.006**	**0.015****		
	(0.72)	**(2.56)**		
$HIGH\_SA$			0.011***	0.001
			(5.61)	(0.53)
$\boldsymbol{SCAP_{t-1} \times HIGH\_SA}$			**-0.006**	**0.017*****
			(-0.86)	**(3.32)**
Controls	YES	YES	YES	YES
State-Cohort FE	YES	YES	YES	YES
Year-Cohort FE	YES	YES	YES	YES
N	41,233	74,377	41,753	75,151
R-squared	0.381	0.213	0.394	0.208

Table 8

Effect of green labor supply

This table presents the results of the effects of green labor supply on the association between SCAP finalisation and labor investment inefficiency. Column (1) and (2) captures green labor supply based on the salary gap between green and brown jobs within each industry. Column (3) and (4) estimates green labor supply based on the number of science and engineering degrees issued in each state. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1) *Over Investment*	(2) *Under Investment*	(3) *Over Investment*	(4) *Under Investment*
$SCAP_{t-1}$	0.023***	0.002	-0.001	0.021***
	(2.99)	(0.62)	(-0.06)	(2.75)
$GREENGAP$	0.020***	-0.005***		
	(9.18)	(-6.29)		
$\boldsymbol{SCAP_{t-1} \times GREENGAP}$	**-0.022****	**0.016*****		
	(-2.09)	**(5.04)**		
$SEDEGREE$			-0.033***	0.026***
			(-11.03)	(10.13)
$\boldsymbol{SCAP_{t-1} \times SEDEGREE}$			**0.030***	**-0.021****
			(1.67)	**(-2.47)**
Controls	YES	YES	YES	YES
State-Cohort FE	YES	YES	YES	YES
Year-Cohort FE	YES	YES	YES	YES
N	39,180	71,270	60,394	96,880
R-squared	0.226	0.172	0.379	0.200

Table 9

Labor adjustment cost

This table presents the results of the effects of labor adjustment cost on the association between SCAP finalisation and labor investment inefficiency. Column (1) captures green labor adjustment costs based on the implementation level of Wrongful Discharge Laws (WDL) in the local area. Column (2) estimates green labor adjustment costs based on local employment carbon footprint. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	(1)	(2)
	ABHIRE	ABHIRE
$SCAP_{t-1}$	-0.020	0.011***
	(-1.43)	(3.03)
$SCAP_{t-1}$× WDL	**0.029****	
	(1.98)	
$SCAP_{t-1}$× ECF		**0.017****
		(2.11)
Controls	YES	YES
State-Cohort FE	YES	YES
Year-Cohort FE	YES	YES
N	115,596	116,904
R-squared	0.271	0.283

APPENDIX

Table A.1

Variable definitions

Variables	Definition
Dependent variables	
ABHIRE	The measure of labor investment inefficiency. Estimated as the residual's absolute value from the following model: $Net\_Hire_{i,t} = \beta_0 + \beta_1 Sales\_Growth_{i,t-1} + \beta_2 Sales\_Growth_{i,t} + \beta_3 \Delta ROA_{i,t} + \beta_4 \Delta ROA_{i,t-1} + \beta_5 ROA_{i,t} + \beta_6 Return_{i,t} + \beta_7 Firm\_Size\_R_{i,t-1} + \beta_8 Quick_{i,t-1} + \beta_9 \Delta Quick_{i,t-1} + \beta_{10} \Delta Quick_{i,t} + \beta_{11} Lev_{i,t-1} + \beta_{12} LossBin1_{i,t-1} + \beta_{13} LossBin2_{i,t-1} + \beta_{14} LossBin3_{i,t-1} + \beta_{15} LossBin4_{i,t-1} + \beta_{16} LossBin5_{i,t-1} + \beta_{17} AUR_{i,t-1} + FMAM12\ Industry\ FE + \varepsilon_{i,t}$
Independent variables	
SCAP	Dummy variable that takes the value of one if the firm is located in a state that has finalized the State Climate Adaptation Plan and zero otherwise.
UNION	The percentage of employees who are members of labor unions.
INST	The portion of shares hold by institutional investors.
MTB	The market-to-book ratio, estimated as the market value of common equity divided by the book value of the equity.
SIZE	The natural logarithm of market capitalization.
TANGIBLE	Tangibility, calculated as the value of property, plant and equipment divided by the total assets.
LABOR_INTEN	Labor intensity, estimated as the portion of employees over total assets in the given year.
STD_CFO	The standard deviation estimated based on previous five years data of operating cash flow to total assets.
STD_SALES	The standard deviation estimated based on the data of operating cash flow to total assets over the preceding five years.
STD_NET_HIRE	The standard deviation estimated based on *NETHIRE* over the preceding five years.
AQ	Accounting quality, estimated following Francis et al. (2005) model.
DIV	Indicator of dividend payer.
LOSS	Dummy variable that takes the value of one if the firm has negative ROA in a given year and zero otherwise.

AB_INVEST_OTHER	Abnormal other investments. Calculated as the absolute value of residuals from the following regression: $$Other\ Investment = \beta_0 + \beta_1 SalesGrowth + \varepsilon$$
QUICK	The quick ratio, estimated as (CHE+RECT)/LCT.
LEV	Leverage ratio, estimated as the portion of total debt over total assets in the given year.
Variables used in additional analyses	
NET_HIRE	The growth of employees in percentage term.
SALES_GROWTH	The change in sales revenue in percentage term.
ΔROA	The change in return of assets.
ROA	Return on assets, calculated as net income divided by the total assets at the beginning of year.
RETURN	Annualized return, estimated based on the daily return reported in CRSP database.
SIZE_R	The percentile rank of firm size.
ΔQUICK	The change in the quick ratio in percentage term.
LOSSBIN1	An indicator variable equals one if ROA ranges from -0.005 to 0.
LOSSBIN2	An indicator variable equals one if ROA ranges from -0.010 to -0.005.
LOSSBIN3	An indicator variable equals one if ROA ranges from -0.015 to -0.010.
LOSSBIN4	An indicator variable equals one if ROA ranges from -0.020 to -0.015.
LOSSBIN5	An indicator variable equals one if ROA ranges from -0.025 to -0.020.
AUR	Annual sales divided by total asset.
Overinvesting	Positive abnormal net hiring measure when actual net hiring higher than expected net hiring (Jung et al., 2014).
Overhiring	Overhiring is captured by overinvestment when expected net hiring > 0 (Jung et al., 2014).
Underfiring	Underfiring is captured by overinvestment when expected net hiring < 0 (Jung et al., 2014).
Underinvesting	Negative abnormal net hiring measure when actual net hiring lower than expected net hiring (Jung et al., 2014).
Underhiring	Underhiring is captured by underinvestment when expected net hiring > 0 (Jung et al., 2014).
Overfiring	Overfiring is captured by underinvestment when expected net hiring < 0 (Jung et al., 2014).
HIGH_WW	Dummy variable that takes the value of one if the firm-year observation has an above sample-year median value of WW index. WW index is estimated as $-0.091 * [(\mathrm{ib} + \mathrm{dp})/\mathrm{at}] - 0.062 * \mathrm{DIVPOS} + 0.021 * \mathrm{dltt}/\mathrm{at} - 0.044 * \ln(\mathrm{at}) + 0.102 * \mathrm{ISG} - 0.035 * \mathrm{SG}$ (Whited and Wu, 2006)
HIGH_SA	Dummy variable that takes the value of one if the firm-year observation has an above sample-year median value *of* SA index. SA index is estimated as

	$0.737 * \text{SIZE} + 0.043 * \text{SIZE}^2 - 0.04 * \text{age}$ (Hadlock and Pierce, 2010)
OPEXP	The climate opportunity exposure index developed by Sautner et al. (2023).
HIGHOPEXP	Dummy variable that takes the value of one if firms belong to the top tercile of *OPEXP* each year.
HIGHPOLLUTE	Dummy variable that takes the value of one if firms belong to the following seven sectors—metal mining (NAICS 212), electric utilities (NAICS 2211), chemicals (NAICS 325), primary metals (NAICS 331), paper (NAICS 322), food, beverages, and tobacco (NAICS 311 and 312), and hazardous waste management (NAICS 5622 and 5629).
GRANT	Dummy variable that takes the value of one for firms in states with grants in the top tercile for a given year.
GOAL	Dummy variable that takes the value of one for firms in states with a goal count in the top tercile for a given year are identified as receiving clearer climate adaptation guidelines.
CAPX	The natural logarithm of corporate capital expenditure.
R&D	The natural logarithm of corporate research and development expenditure, with a value of 0 assigned to companies lacking this expenditure data.
Green Patent/MAV	Corporate green investment, calculated as the number of green patents granted to each firm divided by the logarithm of their market value of equity for the corresponding year.
SEDEGREE	Dummy variable that takes the value of one for firms in states within the top tercile of degree issuance as a symbol of having fewer green labor shortages.
GREENGAP	Dummy variable that takes the value of one for firms in industries with a top tercile salary gap as a symbol of facing greater green labor shortages.
WDL	Dummy variable that takes the value of one for firms located in states that have implemented stricter WDL regulations.
ECF	Dummy variable that takes the value of one for firms located in states with employment carbon footprint (ECF) values in the top tercile as carbon intensive.

Table A.2

List of states where SCAPs are finalized

This table provides a list of U.S states that finalize state climate adaptation plans (SCAP) as reported by the Georgetown Climate Centre (GCC).

State Name	State Abbreviation	Year Finalized
ALASKA	AK	2010
CALIFORNIA	CA	2009
COLORADO	CO	2011
CONNECTICUT	CT	2013
D.C	DC	2016
DELAWARE	DE	2015
FLORIDA	FL	2008
MAINE	ME	2010
MARYLAND	MD	2008
MASSACHUSETTS	MA	2011
MONTANA	MT	2020
NEW HAMPSHIRE	NH	2009
NEW JERSEY	NJ	2021
NEW YORK	NY	2010
NORTH CAROLINA	NC	2020
OREGON	OR	2010
PENNSYLVANIA	PA	2011
RHODE ISLAND	RI	2018
VIRGINIA	VA	2008
WASHINGTON	WA	2012

Table A.3

First-stage model

This table presents the first-stage results to measure labor investment inefficiency. The dependent variable is *NET_HIRE*. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions.

	(1)
	NET_HIRE
$SALES\_GROWTH_{t-1}$	0.031***
	(21.73)
$SALES\_GROWTH_{t}$	0.261***
	(160.86)
ΔROA_{t}	-0.202***
	(-38.74)
ΔROA_{t-1}	0.037***
	(7.56)
ROA_{t}	0.143***
	(33.76)
$\Delta RETURN_{t}$	0.042***
	(31.39)
$SIZE\_R_{t-1}$	0.000***
	(5.22)
$QUICK_{t-1}$	0.002***
	(6.73)
$\Delta QUICK_{t-1}$	0.022***
	(20.82)
ΔQUICK$_{t}$	-0.013***
	(-11.75)
LEV_{t-1}	-0.060***
	(-14.33)
$LossBin1_{i,t-1}$	-0.028***
	(-3.62)
$LossBin2_{i,t-1}$	-0.029***
	(-3.92)
$LossBin3_{i,t-1}$	-0.031***
	(-3.93)
$LossBin4_{i,t-1}$	-0.015*
	(-1.92)

$LossBin5_{i,t-1}$	-0.025***
	(-2.99)
AUR_{t-1}	-0.026***
	(-20.97)
Constant	0.057***
	(18.27)
N	127,856
R-squared	0.220

Table A.4

Alternative measures

This table presents the results employing alternative measures of ABHIRE. Specifically, *ABHIRE_IND* is estimated the absolute value of the difference between the firm's net hiring and the industry median net hiring. *ABHIRE_SALES* estimated the absolute value of the difference between the firm's net hiring and the residual of the following regression: $Net\ Hire = a + \beta\ SALES\ GROWTH + \varepsilon$. All continuous variables are winsorized at the 1st and 99th percentiles. The regressions are clustered by states. Appendix Table A.1 includes variable definitions.

	(1) *ABHIRE_SALES*	(2) *ABHIRE_IND*	(3) *ABHIRE_YF*
$\boldsymbol{SCAP_{t-1}}$	**0.009***** **(3.56)**	**0.010***** **(2.92)**	**0.008***** **(3.22)**
Controls	YES	YES	YES
State-Cohort FE	YES	YES	YES
Year-Cohort FE	YES	YES	YES
N	225,255	225,255	225,255
R-squared	0.183	0.276	0.239

Table A.5

Single-step regression

This table examines the impact of SCAP on LIE in a single step regression following Chen et al., (2022). The definition of the variables is reported in Appendix A. T-statistics are reported in parentheses and measured by clustering the standard errors at the firm-level. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	ABHIRE
$SCAP_{t-1}$	0.006**
	(2.26)
$INSTI_{t-1}$	0.007***
	(4.38)
MTB_{t-1}	0.000
	(0.22)
$SIZE_{t-1}$	-0.000
	(-0.55)
$TANGIBLE_{t-1}$	-0.001
	(-0.73)
$LABOUR\_INTEN_{t-1}$	-0.165***
	(-3.91)
STD_CFO_{t-1}	-0.080***
	(-9.07)
STD_SALES_{t-1}	0.053***
	(29.83)
$STD\_NET\_HIRE_{t-1}$	0.270***
	(94.18)
AQ_{t-1}	-0.018***
	(-3.09)
DIV_{t-1}	0.008***
	(9.12)
$LOSS_{t-1}$	0.007***
	(4.14)
$AB\_INVEST\_OTHER_t$	0.288***
	(51.58)
$UNION_{t-1}$	-0.048***
	(-6.92)
$QUICK_{t-1}$	0.010***

	(4.75)
LEV_{t-1}	-1.123***
	(-10.18)
Constant	0.241***
	(11.43)
1st stage controls	YES
State-Cohort × 1st stage controls	YES
Year -Cohort × 1st stage controls	YES
State-Cohort FE	YES
Year-Cohort FE	YES
N	224,506
R-squared	0.404

Table A.6

Staggered DiD results

This table presents the staggered DiD results. The dependent variable is *ABHIRE*. Independent variable of interest is *SCAP*, which is a dummy variable with the value of one if a firm's headquarter state finalizes state climate adaptation plan (*SCAP*) in a year and onwards, otherwise the variable is set to zero. All continuous variables are winsorized at the 1st and 99th percentiles. Appendix Table A.1 includes variable definitions. Standard errors are clustered at the state level.

	Dependent Variable: *ABHIRE*			
	(1)	(2)	(3)	(4)
$\boldsymbol{SCAP_{t-1}}$	**0.011*** **		**0.009*** **	
	(4.04)		**(2.92)**	
Pre2		**-0.005**		**-0.004**
		(-1.03)		**(-0.52)**
Pre1		**0.006**		**0.007**
		(1.01)		**(1.03)**
Current		**0.011**		**0.010**
		(1.32)		**(1.16)**
Post1		**0.010***		**0.011***
		(1.74)		**(1.71)**
Post2		**0.017*** **		**0.014** **
		(2.96)		**(2.62)**
Post3More		**0.010*** **		**0.007**
		(2.99)		**(1.24)**
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Ind FE	YES	YES	NO	NO
Firm FE	NO	NO	YES	YES
N	27,925	27,925	27,925	27,925
R-squared	0.267	0.268	0.392	0.392