The impact of firm-level climate change risk on investment inefficiency: Does country-level climate resilience matter?

Abstract

This study examines the impact of firm-level climate risk on investment inefficiency, as well as the moderating impact of country-level climate resilience. Using a sample of 7,545 firm-year observations for U.S. firms from 2010 to 2024, we find that increased firm-level climate risk leads to investment inefficiency, primarily by exacerbating underinvestment. Further analysis shows that this negative impact is more pronounced in firms with higher levels of investment irreversibility, greater CO2 emissions, and weaker ESG performance. We also reveal that overall country-level climate resilience, measured by the ND-GAIN index, mitigates this adverse effect, primarily through its readiness component rather than its vulnerability component. Our findings remain robust after accounting for several robustness tests and endogeneity concerns, as well as after controlling for geopolitical risk and external shocks such as the COVID-19 crisis and the first Trump presidency. Our results underscore the importance of strengthening national climate policies to encourage more effective corporate investment in the face of growing climate risk.

Keywords: Firm-level climate risk, Investment inefficiency, Climate resilience, ND-GAIN index, Climate vulnerability, Government readiness.

JEL Classification : Q54, G31, G28, G38

1. Introduction

1. Introduction

Climate change has become a major source of uncertainty for companies, investors, and policymakers, as its economic consequences continue to intensify (Nordhaus, 2006; B. Li et al., 2025). As reported by the NOAA National Centers for Environmental Information (NCEI)[1], the United States (U.S.) experienced 403 extreme weather and climate disasters between 1980 and 2024, each resulting in at least $1 billion in losses and totaling more than $2.915 trillion. Over the last decade, from 2015 to 2024, 190 such incidents resulted in nearly $1.4 trillion in damage costs, highlighting the rapidly increasing financial cost of climate-related shocks.

Investment inefficiency is defined as a firm's deviation from its optimal level of investment, which can manifest as either overinvestment, where a firm invests more than the optimal level, or underinvestment, when it invests below the optimal level (Biddle & Hilary, 2006). We address investment inefficiency because it can reduce corporate cash flows and firm value (Yu, 2024), decrease corporate competitiveness (Barney, 1991), and restrict companies' ability to pursue sustainable development (Kamugisha & Huaping, 2025). To theoretically explain investment inefficiencies, this study draws on two theoretical frameworks. Information asymmetry and agency problems are among the most common and significant drivers of corporate investment efficiency (Ozbas & Scharfstein, 2010; Stein, 2003). The agency theory (Jensen & Meckling, 1976) argues that conflicts of interest arising between managers and shareholders can lead to suboptimal investment decisions that take the form of underinvestment or overinvestment. According to Li et al. (2025), climate change hazards create substantial uncertainty for company operations and performance, leading to increased information asymmetry between managers and shareholders. Managers may use their information advantage to make self-serving decisions and participate in opportunistic behaviors, as they have access to the latest and most accurate information on the firm's fundamentals (Cao et al., 2025). According to Morgado and Pindado (2003), overinvestment arises when managers pursue projects that have a negative net present value to engage in "empire building" (Jensen, 1986). Conversely, firm-level climate risk may drive underinvestment through "quiet life" when managers tend to avoid risk (Bertrand & Mullainathan, 2003).

[1] 2024: An active year of U.S. billion-dollar weather and climate disasters | NOAA Climate.gov

Cheng et al. (2025) show that disaster preparedness measures implemented by local governments can support firm resilience by promoting business continuity and preserving expected returns in the face of climate-related risks. Alves and Menescal, (2025) indicate that climate resilience, particularly the readiness component, significantly mitigates geopolitical risk, demonstrating that countries with greater readiness are more able to manage climate-related shocks, thereby reducing political instability and financial distress. In contrast, countries with greater climatic vulnerability and limited access to liquidity are more exposed to systemic risk. Their findings suggest that climate-related policies may promote green investment, enhance institutional preparedness, and mitigate vulnerability to climate-related shocks. This suggests that country-level climate resilience may moderate the relationship between firm-level climate risk and investment inefficiency.

Using a sample of 7,545 firm-year observations for U.S. firms from 2010 to 2024, we find that greater firm-level climate risk worsens investment inefficiency, mainly through a rise in underinvestment. This effect is especially strong for firms characterized by more irreversible investment, higher CO2 emissions, and weaker ESG performance. The results are robust to several additional tests, including different panel estimation methods, alternative measures of the main variables, and approaches addressing endogeneity, such as propensity score matching (PSM) and the two-step GMM system estimator, which is especially useful for this study because it considers both serial correlation and potential endogeneity in the relationship between firm-level climate risk and investment inefficiency. These results also remain consistent after controlling for geopolitical risk and major external shocks, including the COVID-19 crisis and the first Trump presidency. Our findings show that firms located in a country with greater climate resilience are better positioned to cope with climate-related shocks, thereby reducing their negative impact on corporate investment decisions and investment inefficiencies. In particular, it appears that national climate resilience's moderating effect on the relationship between firm-level climate risk and investment inefficiency is mainly driven by its readiness component rather than its vulnerability component. These results are consistent with Alves and Menescal (2025), who show that climate resilience, specifically the readiness aspect, significantly mitigates geopolitical risk, and they are consistent with institutional theory (DiMaggio & Powell, 1983), which posits that country-level climate change resilience impacts firms' decisions through institutional norms, regulatory frameworks, and pressures that limit managerial discretion and thereby decrease risk-driven inefficiencies.

This paper makes several contributions to existing literature. First, unlike previous studies, which often examine the impact of firm-level climate risk on investment inefficiency across multiple countries (Agoraki et al., 2024; Sahu et al., 2026; Xu et al., 2024), this study considers the U.S. specifically because single-country studies let researchers explore complex topics more deeply within their real-world context (Crowe et al., 2011). Pepinsky (2019) also points out that the increased focus on single-country studies is partially motivated by issues related to internal validity. Second, while prior studies have examined the impact of firm-level climate risk on investment inefficiency (Agoraki et al., 2024; Sahu et al., 2026), none have explored the role of country-level climate change resilience, particularly in terms of climate change readiness, in shaping this relationship. Thus, we contribute to existing literature by investigating how country-level climate resilience influences this relationship, as well as providing practical insights for supporting more resilient and efficient corporate investment under climate change. This contribution is based on institutional theory (DiMaggio & Powell, 1983), which states that firms should adapt their strategy and investment decisions to the institutional framework in which they operate. In this study, country-level climate change resilience is an important institutional condition because it captures countries' vulnerability to climate risks and ability to respond to climate-related difficulties (Chen et al., 2015). As a result, studying its moderating impact helps to explain how national institutional conditions shape companies' investment responses to climate risk. Finally, this study contributes to the literature by using key proxies that reflect essential aspects of the phenomenon and provide particular advantages over the measures commonly used in previous studies.

The rest of the paper proceeds as follows. Section 2 provides a literature review. Section 3 presents the data and methodology. Section 4 reports empirical results and discussion. Conclusion and some policy implications are drawn in Section 5.

2. Literature review and hypotheses development

2.1 Firm-level climate risk and corporate investment inefficiency

Drawing on agency theory (Jensen & Meckling, 1976), various studies propose that firm-level climate risk may affect investment inefficiency by altering the interaction between managers and shareholders in opposing directions.

On the one hand, climate risk can directly damage firms' tangible assets, which could result in additional non-operational expenses, such as property damage, litigation expenses, and other climate-related costs (Cao et al., 2025), thereby disrupting their operations and productivity and reducing their profitability (Rose & Liao, 2005). It can also increase cash flow volatility and illiquidity, thereby decreasing overall financial performance (Hallegatte, 2008; Huang et al., 2022; Nikolaou et al., 2015). These costs may increase financial pressure and shareholder supervision, encouraging managers to make more prudent and added-value investment decisions (Liu & Tian, 2021; Cao et al., 2025). Additionally, Iliev et al. (2021) show that climate risk can help mitigate agency problems and costs by encouraging better shareholder monitoring. Cao et al. (2025) argue that climate risk may serve as a disciplinary mechanism by reducing overinvestment and improving corporate resource allocation, motivating managers to make more prudent investment decisions, thereby reducing inefficient investments.

On the other hand, concerns about climate change create significant uncertainty regarding how companies operate and remain profitable. This, in turn, exacerbates the information gap between management and shareholders (Cao et al., 2025). The agency theory (Jensen & Meckling, 1976) posits that since managers have exclusive access to up-to-date company-specific information about the firm's actual financial situation, they may exploit this advantage for personal gain or engage in opportunistic behavior. For example, the availability of free cash flow may motivate managers to engage in “empire building” behavior, thereby leading to overinvestment (Jensen, 1986). Such behavior can be explained by the fact that more resources under managers’ control might result in greater compensation, as well as more authority and a better reputation (Stulz, 1990; Stein, 1997).

Concerning underinvestment, Bertrand and Mullainathan (2003) argue that in response to firm-level climate risk, managers may become more risk-averse and adopt a “quiet life” behavior, which may make them reluctant to take difficult decisions because of excessive inertia, thereby discouraging the search for profitable investment opportunities and leading to underinvestment (Stein, 2003). In the similar vein, Aggarwal and Samwick (2006) present a model in which underinvestment is caused by managerial laziness. According to this viewpoint, managers may avoid implementing positive net present value initiatives since such investments put private costs on them. Managers often seek to reduce effort, and increased investment requires more time and supervision, which can result in underinvestment.

Using 228,141 firm-year observations spanning 34 countries from 2006 to 2019, Xu et al. (2024) show that climate risk exacerbates overall investment inefficiency, resulting in both overinvestment and underinvestment. In particular, underinvestment may arise when climate risk exacerbates financial constraints, pushing companies to hold more cash and thereby reducing investment activities. Conversely, overinvestment can result from managers perceiving climate-related risk as an opportunity for empire-building, leading them to invest above the optimal level. Agoraki et al. (2024) employ a sample of 8,551 firms from 67 countries, comprising 42,605 firm-year observations between 2002 and 2021, and find that increased firm-level climate risk results in high investment inefficiency, especially under-investment, since firms exposed to climate risk have greater financing constraints, higher capital costs, and fewer growth opportunities, all of which restrict their capacity to make value-added investments. Using a sample of 23,113 firm-year data from Chinese listed A-share companies from 2014 to 2021, Li et al. find that increased climate risk is associated with improved overall investment efficiency. When they separate the two types of inefficiency, this impact mostly reduces overinvestment, while the impact on underinvestment is not statistically significant (Li et al., 2025). Their results are explained by the fact that climate risk increases investment efficiency primarily by reducing management overinvestment incentives. Climate-related shocks can increase a company's non-operating costs and consume internal funds, thereby reducing the resources available for investment. Climate risk also increases operational and policy uncertainty, which reduces the certainty of expected investment returns and promotes more conservative capital allocation. The authors also argue that frequent exposure to climate-related risk can enhance managerial risk aversion, causing managers to avoid making overly aggressive or high-risk investment decisions.

Most previous studies suggest that firm-level climate risk increases investment inefficiency by worsening both underinvestment and overinvestment. Accordingly, we formulate the following hypotheses:

Hypothesis 1a. Firm-level climate risk has a positive impact on overall investment inefficiency.

Hypothesis 1b. Firm-level climate risk has a positive impact on underinvestment.

Hypothesis 1c. Firm-level climate risk has a positive impact on overinvestment.

2.2 The moderating role of country-level climate resilience on the relationship between firm-level climate risk and investment inefficiency

The existing literature identifies several moderators that impact the relationship between climate risk and investment inefficiency, including managerial ownership, which reduces the impact of climate risk (Kim & Kim, 2023), and country-level cultural variables, such as uncertainty avoidance and long-term orientation, that mitigate the adverse impact of climate risk on investment decisions (Xu et al., 2024). Additionally, Xu et al. (2024) argue that industry competition and corporate operational risk amplify the influence of climate risk on investment inefficiency. Further research suggests that insurance coverage, media coverage, and financial constraints significantly influence the relationship between climate risk and investment efficiency (Li et al., 2025). Furthermore, Alves and Menescal (2025) find that climate resilience, as measured by the ND-GAIN index, particularly its readiness dimension, can mitigate the negative effects of geopolitical risks. They also point out that improved institutional preparedness and adaptation can improve a country's ability to absorb external shocks while maintaining financial stability, hence supporting the moderating effect of climate resilience between climate risk and investment inefficiency. Zhou and Ma (2025) argue that governments with high levels of climate change readiness are typically better positioned to address climate-related challenges and are more likely to implement proactive environmental regulations. Therefore, this hypothesis is based on prior studies emphasizing the importance of regulatory frameworks and institutional preparedness in mitigating the impacts of climate-related financial risks (Monasterolo et al., 2024; D'Orazio, 2025).

Drawing on institutional theory (DiMaggio and Powell, 1983), previous research suggests that the local institutional framework shapes corporate behavior, particularly corporate risk management (Cheng et al., 2025; Hodgson, 1998). For example, some studies argue that when local governments employ disaster preparedness measures, they create the framework for company resilience, ensuring operational continuity and maintaining return expectations in the face of climate-related risks (Quarshie and Leuschner, 2020; Cheng et al., 2025).

According to Chen et al. (2015), country-level climate readiness is the capacity of a nation to efficiently use investments for adaptation measures within a secure and productive business environment. Consistent with this perspective, Sarkodie et al. (2022) demonstrate that increased adaptation readiness reduces sectoral climate vulnerability, implying that enhanced adaptation capacities may mitigate the adverse effects of climate exposure.

Investments are considered efficient when they are allocated to projects expected to generate returns above the cost of capital, thereby helping to enhance the firm's value (Modigliani and Miller, 1958; Mendelsohn, 2000; Aakre and Rübbelke, 2010). However, it is often difficult to assess these costs and benefits in advance because the impacts of climate change are uncertain and projects from different organizations and backgrounds are not easily comparable (Persson and Remling, 2014). However, Chen et al. (2018) argue that it is possible to predict investment efficiency by considering the capacities that optimize the use of resources for adaptation, also known as readiness. Therefore, we hypothesize that climate change readiness moderates the relationship between firm-level climate risk and investment inefficiency. Accordingly, we put forward the following hypothesis:

Hypothesis 2. Country-level climate change resilience moderates the relationship between firm-level climate risk and investment inefficiency.

3. Research design

3.1 Data Overview

Panel A of Table *1* depicts the sample construction process employed in this study. The study focuses on companies listed in the S&P 500 index from 2010 to 2024. The initial sample comprises 503 firms, representing 7,545 firm-year observations. To enhance comparability and reduce biases associated with industry-specific accounting and regulatory practices, financial firms were excluded. These exclusions include banks, finance and credit services, investment banking and brokerage services, life and non-life insurance organizations, real estate investment and services, and real estate investment trusts. Firms with missing data were also excluded. After applying these exclusion criteria, the final sample consists of 363 non-financial firms and 5,445 firm-year observations. Panel B shows the industries represented in the final sample. Using the Industry Classification Benchmark (ICB) codes, we observe that the industrials sector is the most represented with 83 firms (22.87%), followed by consumer discretionary with 65 firms (17.91%), technology with 59 firms (16.25%), and health care with 51 firms (14.05%). In contrast, the basic materials and telecommunications sectors represent the smallest proportions of the sample at 4.13% and 1.93%, respectively. Overall, our sample is distributed across a wide range of non-financial companies, which validates the generalizability of the empirical analysis.

INSERT Table *1* ABOUT HERE

3.2 Key variables

3.2.1 Investment inefficiency

According to Gomariz and Ballesta (2014), investment efficiency refers to a company's ability to invest in any project that has a positive net present value (NPV). The existing literature uses several models to assess investment efficiency (Richardson, 2006; McNichols and Stubben, 2008; Biddle et al., 2009). In our paper, we use the model presented by Biddle et al. (2009) because it is the most widely used specification in the literature (Benlemlih and Bitar, 2018; Xu et al., 2024; Arian and Naeem, 2025) and it covers both underinvestment and overinvestment scenarios (Chen et al., 2011). Thus, to determine our dependent variable, we consider the following model:

$$\text{Investment}_{i,t+1} = \beta_0 + \beta_1 \text{ Sales Growth}_{i,t} + \varepsilon_{i,t+1} \tag{1}$$

Where $Investment_{i,t+1}$ is a measure of the firm's overall investment in year t+1, measured by the sum of R&D expenditure, capital expenditure, and acquisition expenditure, minus sales of PPE, scaled by total assets at the end of the previous period and multiplied by 100, and *Sales Growth is t*he annual percentage change in a firm's revenues. The residuals from the regression capture deviations from the expected level of investment, and their absolute value serves as a firm-level proxy for investment inefficiency. Accordingly, larger inefficiency values indicate lower investment efficiency. Positive residuals indicate overinvestment, meaning firms invest more than expected based on their growth opportunities. In contrast, negative residuals indicate underinvestment. In line with Arvidsson et al. (2024), we use the absolute values of the residuals to make the results easier to interpret.

3.2.2 Firm-level climate risk

We use the recent text-based measure of firm-level climate change risk[2] provided by Sautner et al. (2023) as our main explanatory variable for several reasons. First, the authors argue that climate change affects firms differently, which is why their measure distinguishes between opportunity, physical, and regulatory exposures. While climate change poses primarily downside risks in the form of physical damages or regulatory limits, it also presents upside potential for some companies, especially through the shift towards low-carbon markets and green technologies. This decomposition is one of the measure's key strengths, as it considers the various ways in which climate change affects companies, rather than treating climate risk as a single shock. Ultimately, the authors emphasize the importance of a disaggregated measure,

[2] The data are publicly available at https://doi.org/10.17605/OSF.IO/FD6JQ

given that climate change affects companies in different ways and to varying degrees. Another key advantage is that the measure is constructed based on earnings conference call transcripts enabling it to reflect market participants' perceptions of the impact of climate change on individual firms, which is particularly important in the finance, given their role in resource allocation and price discovery, compared to the use of fixed keyword lists or more mechanical proxies (Sautner et al., 2023). This text-based technique captures climate change exposure by measuring the relative frequency of bigrams related to climate change that appear in the same sentence as the words "risk" or "uncertainty" (or their synonyms), scaled by the total number of bigrams in the entire transcript. This approach relies on a machine learning algorithm to identify these important keywords and capture various aspects of climate change, such as climate change-related opportunities, physical shocks, and regulatory pressures. Earnings conference calls are a particularly informative setting for this measurement method, because a variety of stakeholders, such as investors, financial analysts, and media representatives, hear from management and can ask questions regarding the company's current position and future projects. Consistent with this view, Brown et al. (2015) show that analysts consider the question-and-answer sessions during earnings conference calls to be the second most informative channel of communication from management, following private conversations with management. Sautner et al. (2023) therefore claim that this measure is more appropriate than CO2 emissions and natural disasters, which are commonly used as measures of climate change in current studies (Ai and Gao, 2023; Kaur et al., 2026). In this study, we employ the firm-level climate risk measure developed by (Sautner et al., 2023) as our key independent variable (CCRISK), which is expressed as follows:

$$CCRISK_{i,t} = \frac{1}{\beta_{i,t}} \sum_{b}^{\beta_{i,t}} (1\ [b\ \mathcal{E}\ \mathbb{C}])$$

Where $b = 0,1,2,3, \dots, \beta_{i,t}$ denotes the bigrams appearing in the conference call transcripts of firm i at time t and $1[\cdot]$ represents a binary indicator that is equal to one when the condition is satisfied and zero otherwise, whereas $\mathbb{C}$ denotes the set of climate change bigrams capturing risk.

3.2.3 ND-GAIN index

The ND-GAIN index[3] is a combination of a country's vulnerability and readiness scores. These scores measure a country's overall susceptibility to climate-related shocks and its ability to manage and adapt to their repercussions, respectively (Chen et al., 2015). The first component is vulnerability, referring to the "propensity or predisposition of human societies to be negatively impacted by climate hazards" (Chen et al., 2015). The second component is readiness, which is defined as a country's ability to effectively utilize investments for adaptation actions due to a secure and efficient business atmosphere (Chen et al., 2015). We utilize the ND-GAIN climate resilience measure for several reasons. First, rather than focusing on just one aspect of resilience, the ND-GAIN score provides a comprehensive, country-level framework that considers both susceptibility to climate change and readiness to leverage public and private investment for adaptation. It is also more comprehensive than single-indicator measures as it breaks down vulnerability into exposure, sensitivity, and adaptive capacity across six major sectors, as well as readiness into economic, governance, and social components. Second, the ND-GAIN score is designed to be actionable, since many of its indicators reflect areas in which governments, communities, and other stakeholders can enhance resilience over time. Additionally, it is built on a clear and detailed data structure using 45 key indicators obtained from 74 different variables and sources, which makes it easier to compare results over time and between countries. The ND-GAIN score provides a more comprehensive and practical overview of climate resilience than simpler measures such as GDP-based measures, disaster-based indicators, or single institutional factors (Chen et al., 2015). Thus, the ND-GAIN country index is obtained by combining these two scores, as follows:

$$GAIN = (Readiness - Vulnerability + 1) * 50$$

where *GAIN* denotes the ND-GAIN country index, which spans from 0 to 100. Higher values indicate greater climate resilience, reflecting a country's adaptive capacity and readiness to respond to the adverse impacts of climate change. Readiness is an index made up of nine readiness indicators that goes from 0 to 1, with higher values implying greater readiness. In contrast, vulnerability is calculated using 36 vulnerability indicators and runs from 0 to 1, with higher numbers indicating a greater degree of vulnerability. Comprehensive details regarding the methodology adopted to calculate the ND-GAIN score are available on the ND-GAIN website.[4]

[3] Please see Figure 1 for a detailed explanation of the ND-GAIN Index components.
[4] https://gain.nd.edu/our-work/country-index/

3.2.4 Climate change readiness

To measure country readiness, we use the climate change readiness index developed by the University of Notre Dame Global Adaptation Index (ND-GAIN), which provides a multidimensional evaluation of a country's capacity to mobilize public and private investments for climate change adaptation ((Chen et al., 2015). The government readiness index consists of nine measures organized into three interrelated dimensions, namely economic readiness, governance readiness, and social preparation. Economic readiness, which is computed based on 10 key indicators from the World Bank's Doing Business report (DB), evaluates the stability and robustness of a country's investment conditions, including financial and business factors that encourage adaptation-related spending. Governance readiness refers to the stability and quality of a country's institutions and public administration, such as transparency, policy effectiveness, rule of law, and corruption control, all of which help to mitigate investment risk, enhance investor confidence, and facilitate planning and execution of long-term adaptation strategies. Finally, social readiness refers to human and social capital that enables equitable re source use and innovation, with a special emphasis on information and communication technology (ICT) infrastructures, education, as well as social inclusion, which help society to make efficient and equitable use of investments, maximizing their benefits (Chen et al., 2015; Ko et al., 2026). The overall government readiness score (*READINESS*) is obtained by averaging the three equally weighted components, and it varies between 0 and 1, with higher values reflecting a stronger capacity to adapt to climate change.

3.2.5 Climate change vulnerability

According to the ND-GAIN framework, vulnerability is composed of three dimensions: sensitivity, exposure, and adaptive capacity across six key sectors, namely food, water, health, ecosystem services, human habitat, and infrastructure (Chen et al., 2015). Exposure reflects the extent to which these sectors are subject to climate hazards. Sensitivity refers to the extent to which climatic risks harm certain sectors or the portion of the population that is particularly exposed to such hazards ((Pinho-Gomes and Woodward, 2024; Barasa et al., 2025), and adaptive capacity measures the ability to adjust and cope with these impacts. Together, these dimensions provide an overall measurement of a country's climate vulnerability (*VULNERABILITY*).[5]

[5] https://gain-new.crc.nd.edu/about/methodology

3.2.6 Control variables

To better identify the effect of firm-level climate risk on investment inefficiency and reduce potential omitted-variable bias, we construct a group of control variables based on prior studies (Richardson, 2006; Biddle et al., 2009; Benlemlih and Bitar, 2018; Benkraiem et al., 2024; Nasraoui et al., 2025). These variables cover three main dimensions: firm characteristics, financial performance, and macroeconomic factors. The first firm characteristic considered in the model is size (*SIZE*). This choice is supported by literature suggesting that larger firms invest proportionally less than smaller firms, which could lead to investment inefficiency (Lee et al., 2014; Benlemlih and Bitar, 2018). Furthermore, we add return on assets (*ROA*) in the regression equation as a proxy for firm profitability. García-Gómez et al. (2023) argue that enterprises with higher profitability are less financially constrained and thus can more easily take advantage of investment opportunities. Additionally, we utilize Tobin's Q (*TOBINQ*) as a proxy for the firm's future growth opportunities (Hayashi, 1982; Xu et al., 2024; B. Li et al., 2025). Pellicani and Kalatzis (2019) find that firms with greater investment opportunities are more likely to underinvest, while firms with limited opportunities are more likely to overinvest. Market-to-book value (*MTBV*) is also used as a proxy for the firm's investment opportunities, which can impact investment inefficiency (Biddle et al., 2009). Following previous studies, we include tangibility (*TANGIBILITY*) as a control variable since it captures both information asymmetry and the extent to which investments are irreversible. Concerning information asymmetry, firms with less tangible assets are harder to value, exacerbating adverse selection (Harris and Raviv, 1991), whereas tangible assets are more visible and easier to evaluate, making investment inefficiencies easier to detect (S. S. Cao et al., 2024). Regarding investment irreversibility, firms with a greater reliance on fixed assets tend to have less flexibility in adjusting investment decisions, making them more vulnerable to investment inefficiency (Cooper, 2006; Yadav et al., 2025). Debt (*LEVERAGE*) serves as a disciplinary mechanism by limiting managerial opportunism and reducing investment inefficiency (Jensen, 1986). We also incorporate free cash flow (*FCF*) into the model because managers in firms with extra free cash flow may make non-value-enhancing investments for personal gain, leading to overinvestment (García-Gómez et al., 2023; Jensen, 1986). We control for financial slack (*SLACK*) because companies with excess cash may be more inclined to make inefficient investments (Benkraiem et al., 2024). Research and development (*R&D*) is a significant factor influencing investment decisions (Benkraiem et al., 2024). Although R&D is essential for innovation, technological progress, and gaining a competitive advantage, R&D-intensive firms are more likely to face higher levels of information asymmetry because investors find it difficult to understand their investments, and corporations disclose less information to prevent imitation (Baruffaldi et al., 2024). Thus, increased R&D intensity may result in investment inefficiency (Ahmed and King, 2025). Finally, to account for the macroeconomic environment, this study incorporates gross domestic product (*GDP*) growth and the inflation rate (*INFLATION*) into the model. These factors help account for macroeconomic shocks that may influence corporate investment behavior and contribute to fluctuations in investment inefficiency (Yang and Yip, 2026). Taken together, these datasets provide a solid empirical basis for studying the relationship between penalties and climate adaptation.

3.3 Methodology

To test our hypotheses, we use the following model specifications:

$$\mathrm{INEFF}_{i,t+1} = \beta_0 + \beta_1 \mathrm{CCRISK}_{i,t} + \sum_{j=1}^{K} \beta_j \mathrm{Controls}_{i,t} + \varepsilon_{i,t+1} \quad (2)$$

$$\mathrm{UNDER}_{i,t+1} = \beta_0 + \beta_1 \mathrm{CCRISK}_{i,t} + \sum_{j=1}^{K} \beta_j \mathrm{Controls}_{i,t} + \varepsilon_{i,t+1} \quad (3)$$

$$\mathrm{OVER}_{i,t+1} = \beta_0 + \beta_1 \mathrm{CCRISK}_{i,t} + \sum_{j=1}^{K} \beta_j \mathrm{Controls}_{i,t} + \varepsilon_{i,t} \quad (4)$$

$$\mathrm{INEFF}_{i,t+1} = \beta_0 + \beta_1 \mathrm{CCRISK}_{i,t} + \beta_2 \mathrm{MOD}_{i,t} + \beta_3 \mathrm{CCRISK}_{i,t} \times \mathrm{MOD}_{i,t} + \sum_{j=1}^{K} \beta_j \mathrm{Controls}_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

Equation (2) is employed to test the direct impact of firm-level climate risk (*CCRISK*) on investment inefficiency (*INEFF*). Equations (3) and (4) extend the previous analysis by differentiating the two dimensions of investment inefficiency, namely underinvestment (*UINV*) and overinvestment (*OINV*), respectively. Finally, equation (5) examines whether a moderator (*MOD*) (ND-GAIN (*GAIN*), government readiness (*READINESS*), and climate change vulnerability (*VULNERABILITY*) moderates the relationship between firm-level climate risk (*CCRISK*) and investment inefficiency (*INEFF*). We include one-year lagged values for the independent, moderating, and control variables for a variety of reasons. First, we use lagged variables to account for delayed impacts, as the influence of firm-level climate risk on investment inefficiency may persist over time rather than manifesting immediately. This specification is particularly significant when investment is irreversible, since firms may delay investment decisions until uncertainty decreases. Second, we use one-year lagged variables to account for potential simultaneity biases between the dependent and independent variables.

Finally, this approach also helps to address potential reverse causality concerns (Yang and Yip, 2026). We incorporate year and industry fixed effects into our regression models to account for any potential confounding effects arising from time and industry variations. Table A1 in the Appendix contains the definitions for all variables.

4. Empirical analysis

4.1 Descriptive statistics

Table *2* provides a summary of the statistics for the variables used to examine the relationship between firm-level climate risk (CCRISK) and investment inefficiency (INEFF, UNDER, and OVER). The INEFF, UNDER, and OVER variables indicate significant inefficiencies in resource allocation, with respective means of approximately 7.53, 5.50, and 11.87. In contrast, the mean of CCRISK is very low at 0.0000533, indicating that firms generally have minimal exposure to climate risk.

Table A2 shows the pairwise correlation matrix and VIF statistics. In summary, the correlations between the independent variables are moderate, indicating that there are no severe concerns regarding multicollinearity. While GAIN, READINESS and VULNERABILITY have significant positive correlations, this is largely due to their close conceptual relationship between these moderator variables. Crucially, the VIF values are low, ranging from 1.00 to 2.62 with an average of 1.60, suggesting that multicollinearity does not significantly impact the estimations (Hair et al., 2006).

INSERT Table *2* ABOUT HERE

4.2 Main results

4.2.1 Firm-level climate risk and investment inefficiency: Various panel techniques

The pooled OLS regression findings reveal that firm-level climate change risk (CCRISK) significantly affects investment inefficiency and underinvestment, with coefficients of 0.0626 for investment inefficiency (INEFF) and 0.0645 for underinvestment (UINV). These results indicate that higher climate change risk leads to greater investment inefficiency and underinvestment in firms. However, the coefficient for overinvestment (OINV) stands at 0.0815 and is not statistically significant.

Given that there is general agreement that the pooled OLS estimator ignores the data's natural panel structure, resulting in biased estimates when used without any robustness checks (Cameron and Trivedi, 2005). Thus, fixed effects or random effects models are preferred over OLS regression to account for individual-specific characteristics or unobserved variations across different periods. In this study, the Hausman test reveals that the fixed effect estimator should be favored over the random effect estimator. Erreur ! Source du renvoi introuvable. shows the results of a panel fixed-effects analysis examining how firm-level climate risk (CCRISK) affects three proxies of investment inefficiency: investment inefficiency (INEFF), underinvestment (UINV), and overinvestment (OINV). Our findings can be interpreted through the lens of agency theory (Jensen and Meckling, 1976), revealing a positive and statistically significant correlation between CCRISK and investment inefficiency (0.0433), indicating that higher climate risk is associated with greater investment inefficiency. In the context of underinvestment, CCRISK exhibits a significant negative impact, implying that firms confronted with greater climate risk are more likely to underinvest severely. However, the effect of CCRISK on overinvestment is negative but not statistically significant (-0.0316).

Unlike traditional panel estimators, which often struggle to account for both serial correlation and cross-sectional dependence simultaneously, the Driscoll and Kraay method provides accurate estimates even in the presence of such complexities (Reed and Ye, 2011). It is especially appropriate for panels with N>T and offers robust standard errors (Driscoll and Kraay, 1998; Hoechle, 2007). The results remain consistent after applying this technique, indicating that firm-level climate risk increases investment inefficiency, mainly through underinvestment. These findings align with agency theory (Jensen and Meckling, 1976), which posits that increased risk exacerbates information asymmetry and intensifies managerial discretion, and lead to inefficient use of resources.

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4.2.2 The moderating role of country-level resilience

Table *4* examines the impact of ND-GAIN-related indicators on the relationship between firm-level climate risk and investment inefficiency. Column 1 shows a negative and significant interaction effect between CCRISK and GAIN, indicating that increased overall climate resilience mitigates the adverse impact of climate risk on investment efficiency. In column 2, while vulnerability is negatively associated with investment inefficiency, the interaction term between CCRISK and vulnerability is not statistically significant, implying that climate vulnerability does not significantly moderate the relationship between firm-level climate risk and investment inefficiency. Column 3 shows a negative and statistically significant interaction term between CCRISK and READINESS. This implies that higher climate readiness reduces the positive effect of firm-level climate risk on investment inefficiency, possibly because stronger climate readiness enables earlier and more proactive adaptation responses. The findings suggest that, within the ND-GAIN framework, the overall index and the readiness dimension have a significant impact on the effect of firm-level climate risk on investment inefficiency, whereas the vulnerability dimension has no significant moderating effect, meaning that the moderating effect of the overall ND-GAIN index is driven mainly by its readiness component, rather than by climate vulnerability. These results are consistent with institutional theory (DiMaggio and Powell, 1983), which posits that country-level climate change resilience influences firms' decisions through institutional norms, regulatory frameworks, and pressures that limit managerial discretion and thereby decrease risk-driven inefficiencies, and they are in line with Alves and Menescal (2025), who show that climate resilience, specifically the readiness aspect, significantly mitigates geopolitical risk.

INSERT Table *4* ABOUT HERE

5. Robustness checks

Building on Samet and Jarboui (2017) and Xu et al. (2024), we propose an alternative model specification of investment inefficiency:

$$\mathrm{Investment}_{i,t+1} = \beta_0 + \beta_1\,\mathrm{NEG}_{i,t} + \beta_2\,\mathrm{Sales\ Growth}_{i,t} + \beta_3\,\mathrm{NEG}_{i,t} \times \mathrm{Sales\ Growth}_{i,t} + \varepsilon_{i,t+1} \quad (6)$$

Where $Investment_{i,t+1}$ represents the total investment of firm i in year $t+1$, and is computed as the sum of R&D expenditure, capital expenditure, and acquisition expenditure, minus sales of PPE, scaled by total assets at the end of the previous period and multiplied by 100. $Sales\ Growth$ refers to the change in sales over the previous year. NEG is a dummy variable that equals one if the sales growth in the previous period $t-1$ was negative and zero otherwise.

Similar to Equation (1), the absolute values of the model's residuals are used to measure investment inefficiency, while negative values indicate underinvestment and positive values reflect overinvestment.

In line with Choi et al. (2025), we employ a dummy variable to capture firm-level climate risk as an alternative proxy, which equals 1 if the firm's climate change risk exceeds the median and 0 otherwise.

To further test the robustness and reliability of the results, we re-estimate the original model using the firm-level climate change exposure measure (CCEXPO) created by Sautner et al. (2023) as an additional proxy for firm-level climate risk (Agoraki et al., 2024; S. S. Cao et al., 2024).

Table *5* shows the robustness test for the effect of climate change risk on investment inefficiency. Two sets of alternative specifications are used. First, columns 1–6 replace the base climate risk proxy with alternative proxies, namely DummyCcRisk and CCEXPO while maintaining the original dependent variables (INEFF, UINV, and OINV). Second, columns 7-9 employ multiple measures of investment inefficiency (INEFF1, UINV1, and OINV1), while maintaining the original independent variable, CCRISK. The results indicate that DummyCcRisk and CCEXPO have positive and statistically significant correlations with INEFF and UINV, but not with OINV. Similarly, CCRISK has a positive and statistically significant correlation with INEFF1 and UINV1, while the coefficient for OINV1 is positive but not statistically significant. Overall, the findings confirm the fundamental conclusion that firm-level climate risk increases investment inefficiency, primarily through underinvestment rather than overinvestment.

INSERT Table *5* ABOUT HERE

Endogeneity tests

The Propensity Score Matching (PSM) technique

To address potential endogeneity concerns, we use the propensity score matching (PSM) technique. This approach is appropriate because firms facing different levels of climate risk may have different characteristics, which may also affect investment inefficiency, thus biasing the estimated correlation (Sahu et al., 2026).

The implementation of the propensity score matching (PSM) technique follows a series of steps (Rosenbaum and Rubin, 1983; Shipman et al., 2017). First, the propensity score is estimated using a probit model, where the dependent variable is the treatment variable and the control variables included in Model (2) are used as covariates. Second, each firm in the treatment group is paired with a firm in the control group that has the closest propensity score within a specified caliper. Third, balance tests are used to evaluate the quality of the matching and guarantee that the covariates are comparable between the two groups after matching. Finally, Model (2) is re-estimated using the matched sample (Leuven and Sianesi, 2018).

Table *6* shows that the results are consistent even after addressing potential endogeneity concerns. INEFF and UINV have positive, statistically significant HIGH_CCRISK_IY coefficients, while OINV has a positive, but not significant coefficient. This indicates that increased climate change risk continues to impact overall investment inefficiency, primarily through underinvestment.

INSERT Table *6* ABOUT HERE

System GMM estimation for dynamic panel data

To account for potential endogeneity resulting from reverse causality between firm-level climate risk and investment inefficiency, unobserved heterogeneity, and measurement error, we employ the dynamic system GMM estimator (Blundell and Bond, 1998; Wooldridge, 2005; Lahouel et al., 2019). It was selected over difference GMM because it offers more appropriate instruments and minimizes the loss of information associated with first difference (Arellano and Bover, 1995). This approach is particularly relevant to the current research since the model includes a lagged dependent variable and effectively addresses endogeneity issues caused by the correlation between the error term and other explanatory variables (Yadav and Yadav, 2024). The validity of the two-step GMM method is tested using two diagnostic tests: the Hansen test, which checks for over-identifying restrictions, and the Arellano-Bond test, which detects second-order autocorrelation (AR(2)). The Hansen test assesses the validity of the instruments, while the AR(2) test examines the presence of second-order autocorrelation in the error term (Blundell and Bond, 1998; Roodman, 2009).

Table *7* shows the results of the two-step system GMM estimations. It demonstrates that the lagged values of investment inefficiency and underinvestment in Columns 1 and 2 are positive and statistically significant. This indicates that the lagged dependent variables are persistent. However, the lagged overinvestment in Column 3 is not statistically significant. The findings also show that firm-level climate risk positively and significantly affects investment inefficiency in Column 1 and underinvestment in Column 2. However, its effect on overinvestment is smaller and less significant. Therefore, these data demonstrate that firm-level climate risk primarily contributes to investment inefficiency through underinvestment.

Overall, the positive relationship between firm-level climate risk and investment inefficiency remains consistent when using various estimation techniques, including pooled OLS, panel fixed effects, Driscoll-Kraay fixed effects, propensity score matching, and dynamic system GMM. Therefore, these results confirm the validity of the main findings.

INSERT Table *7* ABOUT HERE

6. Additional tests

The effect of firm-level climate risk on investment inefficiency: Controlling for COVID-19, the First Trump Presidency, and geopolitical risk

shows that the positive relationship between firm-level climate risk and investment inefficiency remains strong even when additional macro-political control variables are added. In columns (1) through (3), which account for the influence of COVID-19 and the first Trump presidency, CCRISK is statistically significant and positive for INEFF in column (1) and UINV in column (2). However, it is not significant for OINV in column (3). This means climate risk primarily affects investment efficiency through underinvestment rather than overinvestment, most likely because COVID-19 increased firms' external financing constraints. As banks became more conservative, corporations found it increasingly difficult to finance long-term investment projects, thereby increasing investment inefficiency (Taylor et al., 2023; Hu et al., 2024).

In contrast, the coefficient on the Trump_dummy variable is negative and statistically significant, indicating that investment inefficiency declined during Trump's first presidency. This can be attributed to the pro-business policies that characterized Donald Trump's first presidency. Specifically, the Tax Cuts and Jobs Act of 2017 reduced corporate taxes and encouraged business investment, which potentially improved firms' financial conditions and reduced investment inefficiency (Shahini and Shahini, 2025). When we account for geopolitical risk (Caldara and Iacoviello, 2022) in columns 4 through 6, we find that CCRISK remains positive and significant in columns 4 and 5, but loses significance in column 6, confirming the robustness of the original findings. Meanwhile, the Geopolitical Risk (GPR) coefficient is positive and statistically significant in columns 4-6. This indicates that geopolitical risk leads to greater investment inefficiency, probably because it disrupts the corporate environment and distorts the resource allocation by introducing uncertainty and friction into companies' investment decisions (Li and Cheng, 2024; Wang et al., 2024). This is consistent with the findings of Gupta et al. (2019), who reveal that geopolitical shocks raise the cost of capital and discourage investment.

INSERT

ABOUT HERE

Subsample Analysis of the Effect of Firm-Level Climate Risk on Investment Inefficiency by Investment Irreversibility and CO2 Emissions

The relationship between firm-level climate risk and investment inefficiency can be explained using the real options theory, which states that investment irreversibility exacerbates the negative impacts of uncertainty. According to this viewpoint, when investment is difficult to reverse, climate-related risks enhance firms' motivations to postpone or reduce investment decisions. Such "wait-and-see" behavior may cause companies to delay investment until uncertainty decreases or conditions get better, thereby increasing investment inefficiency (Bernanke, 1983; Dixit, 1994). This argument implies that the positive effect of firm-level climate risk on investment inefficiency is more likely to be apparent in firms with more irreversible investments. Such firms are more vulnerable to inefficiency when climate risk increases because they rely more heavily on fixed assets and have less flexibility to adjust their investment decisions (Yadav et al., 2025). In contrast, other evidence suggests that irreversible investments may encourage more selective and prudent decisions, allowing firms to better respond to uncertainty. High irreversibility costs may also reduce resource misallocation by encouraging managers to use available resources more cautiously and make more disciplined investment decisions (Chu and Fang, 2021). Following Cooper (2006), we employ asset tangibility as a proxy for investment irreversibility

According to (Solomon et al., 2009) and Sautner et al. (2023), enterprises with higher carbon emissions are more vulnerable to climate-related risks. Similarly, Tran et al. (2025) claim that high-emission firms are more likely to be exposed to increased climate risk during earnings calls. Taken together, these findings support the idea of splitting the sample into firms with low and high CO_2 emissions to investigate whether the impact of climate risk on investment inefficiency differs depending on the emissions profile of the firm.

Table *9* shows the results of the subsample analysis for investment irreversibility and CO_2 emissions. Climate-related risks at company level have an even greater impact on investment inefficiencies as the irreversible nature of investments becomes more pronounced. However, this effect is only statistically significant for underinvestment among low-tangibility firms (column 3) and for investment inefficiency among high-tangibility firms (column 2). These results suggest that climate risk exacerbates overall investment inefficiency more when investment is irreversible, although the impact on underinvestment is more evident among firms with lower tangibility. Regarding CO_2 emissions, the coefficient on firm-level climate risk remains positive in all columns; however, it is only significant for high-emission enterprises, as seen in both the investment inefficiency specification (Column 6) and the underinvestment specification (Column 8). This suggests that the negative impact of climate risk is concentrated among enterprises with higher carbon emissions, meaning that highly polluting firms are more vulnerable to climate-related distortions in investment choices. This result can be explained by the fact that firms with higher carbon emissions tend to face greater regulatory risk and increased external financing costs due to strict environmental regulations, which can lead to investment inefficiency (Solomon et al., 2009). Overall, these findings suggest that the negative impact of firm-level climate risk on investment inefficiency is more severe among firms with high investment irreversibility and especially among firms with high CO_2 emissions.

INSERT Table *9* ABOUT HERE

Subsample Analysis of the Effect of Firm-Level Climate Risk on Investment Inefficiency by ESG levels

In this subsection, we split the sample into firms with low and high environmental, social, and governance performance (ESG) to provide further insight on whether the relationship between firm-level climate risk and investment inefficiency varies with firms' ESG performance. The low-ESG group corresponds to the lowest quartile (Q1), whereas the high-ESG group corresponds to the highest quartile (Q4). This analysis is motivated by recent studies suggesting that firm-level climate risk can improve corporate ESG performance (Khan et al., 2024; Yin et al., 2024). Additionally, recent literature shows that improved ESG performance decreases investment inefficiency (Bilyay-Erdogan et al., 2024; Nasraoui et al., 2025).

Table *10* presents an analysis of the impact of firm-level climate risk on investment inefficiency for low- and high-ESG firms. Firm-level climate risk has a positive and statistically significant influence on investment inefficiency in the low-ESG subsample (column 1). In contrast, no significant effect is observed in the high-ESG subsample (column 2). Underinvestment-related climate risk remains positive and significant in both subsamples, but the coefficient is higher and more significant among low-ESG enterprises (Column 3) than among high-ESG firms (Column 4). Therefore, these findings suggest that the negative impact of firm-level climate risk on investment inefficiency is more pronounced among companies with lower ESG performance.

INSERT Table *10* ABOUT HERE

7. Conclusion

This research investigates whether firm-level climate risk influences corporate investment inefficiency. Using a sample of 7,545 firm-year observations covering U.S. nonfinancial firms from 2010 to 2024, we find that higher firm-level climate risk exacerbates investment inefficiency, particularly by increasing underinvestment. This negative effect is most pronounced among companies with more irreversible investment structures, greater CO2 emissions, and lower ESG performance. The findings remain robust across a battery of robustness checks, including the use of various panel estimating techniques, alternative proxies for both independent and dependent variables, and endogeneity-addressing processes such as propensity score matching (PSM) and system GMM, as well as after accounting for geopolitical risk and external shocks such as the COVID-19 crisis and the first Trump presidency. Notably, we discover that country-level climate change resilience mitigates the relationship between firm-level climate risk and investment inefficiency mainly through its climate change readiness component.

Our results offer fresh and significant policy and practical implications for policymakers, managers, and other stakeholders. First, while climate change is unavoidable, improving a country-level climate resilience can mitigate the adverse impact of firm-level climate risk on investment inefficiency by developing more effective regional strategies and policies that reduce vulnerabilities and increase resilience to climate change, thus helping firms to better absorb climate-related shocks and make more efficient investment decisions. For corporate managers, our findings underscore the importance of accurately assessing firm-level climate risk and incorporating this into capital allocation and investment decisions, particularly to prevent inefficient investments. Lastly, our findings are significant to the general public because greater awareness of the impact of climate change on corporate investment decisions may help individuals make more informed decisions as consumers, employees, and citizens. Furthermore, they underline the necessity of working together to address climate change and promote sustainable economic growth.

Future studies could extend this analysis to other countries to discover whether the influence of firm-level climate risk on investment inefficiency, as well as the moderating role of country-level climate resilience, varies across regions. Further research may also investigate whether the impact of firm-level climate risk on investment inefficiency varies depending on cultural and national factors such as long-term orientation, skepticism, the environmental performance index (EPI), and future time reference (FTR).

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Table 1. Sample Construction and Industry Composition

Panel A: Sample Construction

		Firms	Observations
Starting sample: S&P composite index		503	7545
-Banks		(13)	(195)
-Finance and Credit Services		(4)	(60)
-Investment Banking and Brokerage Services		(25)	(375)
-Life Insurance		(4)	(60)
-Non-life Insurance		(18)	(270)
-Real Estate Investment and Services		(2)	(30)
-Real Estate Investment Trusts		(29)	(435)
-Firms lacking data		(45)	(675)
Sample after exclusions		363	5445
Panel B: Industry Composition			
ICB Industry code	Industry	Firms	Firms (Percentage)
50	Industrials	83	22.87
40	Consumer discretionary	65	17.91
10	Technology	59	16.25
20	Health care	51	14.05
65	Utilities	32	8.82
45	Consumer staples	30	8.26
60	Energy	21	5.79
55	Basic materials	15	4.13
15	Telecommunications	7	1.93
	Total	**363**	**100**

Notes: Panel A details the sample selection criteria, while Panel B shows the distribution of firms across various industries within the sample. The Industrials sector has the largest representation, followed closely by Consumer Services and Health Care. In contrast, the Basic Materials and Telecommunications sectors show the least representation.

Table 2.Descriptive statistics

	Mean	Std. Dev.	Min	Max	P25	P50	P75
INEFF	7.534	8.981	0.002	63.718	2.806	5.429	8.527
UNDER	5.495	3.613	0.005	29.342	2.910	5.147	7.554
OVER	11.871	14.033	0.002	63.718	2.414	6.742	15.136
CCRISK	0.0001	0.0002	0	0.0021	0	0	0
GAIN	68.406	2.021	66.245	71.817	66.451	67.778	71.023
READINESS	0.679	0.041	0.635	0.748	0.641	0.664	0.733
VULNERABILITY	0.311	0.001	0.307	0.313	0.310	0.311	0.312
SIZE	16.555	1.374	10.548	20.232	15.629	16.608	17.507
AGE	3.255	0.668	0.693	3.951	2.944	3.466	3.761
ROA	8.805	8.934	-87.28	157.56	4.37	7.86	12.45
TANG	0.279	0.246	0.007	0.961	0.090	0.177	0.448
TOBINQ	2.515	2.348	0.194	34.078	1.119	1.773	2.990
LEVERAGE	30.567	24.733	0	391.59	17.65	28.46	39.945
RD	1493462	4416145	0	8.85e+07	88468	330580	1118310
MTBV	4.123	67.502	-1676.45	1603.61	2.01	3.45	6.515
FCF	0.091	0.085	-0.920	1.192	0.047	0.079	0.120
SLACK	33.546	22.878	0	98.72	14.77	29.18	48.51
INFLATION	2.581	1.834	0.119	8.003	1.465	2.069	3.157
GDP	2.403	1.559	-2.163	6.055	2.118	2.524	2.888

Notes: INEFF, UNDER, and OVER are three measures of investment inefficiency, with INEFF representing overall inefficiency, UNDER indicating underinvestment. and OVER signifying overinvestment. The main independent variable is firm-level climate risk (CCRISK). GAIN and SENSITIVITY serve as moderating variables. Control variables include firm size (SIZE), firm age (AGE), return on assets (ROA), asset tangibility (TANG), growth prospects (TOBINQ), leverage (LEVERAGE), research and development (RD), market-to-book ratio (MTBV), free cash flow (FCF), and financial slack (SLACK).

Table 3.Firm-level climate risk and investment inefficiency: Different techniques

	Pooled OLS			Panel Fixed Effects			Driscoll-Kraay Fixed Effects		
	(1)	(2)	(3)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	INEFF	UINV	OINV	INEFF	UINV	OINV	INEFF	UINV	OINV
CCRISK	0.0626**	0.0645***	0.0815	0.0433*	0.0592**	-0.0316	0.0433**	0.0592**	-0.0316
	(0.0268)	(0.0250)	(0.0693)	(0.0252)	(0.0230)	(0.0640)	(0.0175)	(0.0220)	(0.0332)
SIZE	-0.0724**	-0.0817***	-0.147**	-0.318***	-0.174**	-0.468***	-0.318***	-0.174***	-0.468***
	(0.0292)	(0.0301)	(0.0625)	(0.0623)	(0.0696)	(0.132)	(0.0308)	(0.0499)	(0.0913)
AGE	-0.0350	0.121***	-0.194***	-0.156**	-0.0325	-0.138	-0.156**	-0.0325	-0.138
	(0.0323)	(0.0359)	(0.0610)	(0.0651)	(0.0782)	(0.116)	(0.0559)	(0.0687)	(0.0809)
ROA	-0.0546*	-0.00657	-0.0766	0.0286	-0.0439	0.0879	0.0286	-0.0439	0.0879**
	(0.0280)	(0.0320)	(0.0519)	(0.0299)	(0.0344)	(0.0546)	(0.0331)	(0.0387)	(0.0328)
TANGIBILITY	0.409**	-0.0225	0.788**	0.379	-0.530	0.934	0.379*	-0.530*	0.934**
	(0.173)	(0.178)	(0.368)	(0.384)	(0.426)	(0.728)	(0.178)	(0.269)	(0.404)
TOBINQ	-0.137**	-0.398***	0.0404	-0.00198	-0.203**	0.242*	-0.00198	-0.203***	0.242**
	(0.0611)	(0.0656)	(0.126)	(0.0736)	(0.0818)	(0.143)	(0.0379)	(0.0609)	(0.0914)
LEVERAGE	-0.0333	-0.0280	0.0242	-0.00247	-0.0214	0.00673	-0.00247	-0.0214	0.00673
	(0.0223)	(0.0232)	(0.0466)	(0.0263)	(0.0290)	(0.0499)	(0.0255)	(0.0301)	(0.0234)
RD	0.0688***	-0.0229	0.206***	0.0651	0.0168	0.166	0.0651**	0.0168	0.166
	(0.0224)	(0.0222)	(0.0497)	(0.0462)	(0.0437)	(0.115)	(0.0262)	(0.0513)	(0.135)
MTBV	-0.0188	0.0694**	-0.170**	0.0421	0.0846**	0.0465	0.0421	0.0846*	0.0465
	(0.0281)	(0.0270)	(0.0687)	(0.0351)	(0.0353)	(0.0785)	(0.0426)	(0.0409)	(0.0921)
FCF	0.104	-0.187	0.450	-0.209	-0.440	-0.221	-0.209	-0.440	-0.221
	(0.314)	(0.342)	(0.594)	(0.307)	(0.351)	(0.559)	(0.308)	(0.453)	(0.524)
SLACK	0.106***	0.0671*	0.144*	0.0136	0.0126	0.0977	0.0136	0.0126	0.0977*
	(0.0366)	(0.0355)	(0.0839)	(0.0420)	(0.0400)	(0.110)	(0.0498)	(0.0340)	(0.0545)
INFLATION	-0.0245	-0.0149	-0.0490	-0.0202	-0.0178	-0.0631	0.0311***	0.0245***	0.0156
	(0.0260)	(0.0259)	(0.0537)	(0.0223)	(0.0218)	(0.0464)	(0.00415)	(0.00470)	(0.0101)
GDP	0.0756**	0.0706*	0.112	0.114***	0.0895***	0.146**	0.0295***	0.0200***	0.0168
	(0.0366)	(0.0367)	(0.0760)	(0.0335)	(0.0336)	(0.0708)	(0.00523)	(0.00558)	(0.0173)
Constant	1.761***	2.640***	1.362*	5.817***	4.416***	6.413***	5.618***	4.252***	6.108***
	(0.363)	(0.375)	(0.788)	(0.809)	(0.953)	(1.602)	(0.619)	(0.775)	(1.388)
R-squared	0.042	0.070	0.105	0.039	0.037	0.079			
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the results of regression analyses using three estimation techniques, namely Pooled OLS, panel fixed effects, and Driscoll–Kraay fixed effects, to examine the impact of firm-level climate risk (CCRISK) on investment inefficiency (INEFF), underinvestment (UINV), and overinvestment (OINV). The analysis considers various firm-specific factors, such as size, age, profitability (ROA), tangibility, growth opportunities (TobinQ), leverage, research and development (R&D) intensity, market-to-book ratio, free cash flow, inflation, and gross domestic product (GDP). The models account for year and industry fixed effects. Standard errors in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. The moderating role of climate resilience, climate vulnerability and climate readiness on the relationship between firm-level climate risk and investment inefficiency

	INEFF		
	(1)	(2)	(3)
VARIABLES	ND-GAIN	VULNERABILITY	READINESS
CCRISK	0.942***	2.200	0.480***
	(0.259)	(1.337)	(0.131)
ND_GAIN	-0.0617***		
	(0.0111)		
c.CCRISK#cND_GAIN	-0.0132***		
	(0.00366)		
VULNERABILITY		-25.47**	
		(10.34)	
c.CCRISK#c.VULNERABILITY		-6.892	
		(4.311)	
READINERSS			-3.079***
			(0.551)
c.CCRISK#c.READINESS			-0.647***
			(0.180)
SIZE	-0.270***	-0.181***	-0.272***
	(0.0363)	(0.0413)	(0.0364)

AGE	-0.143**	-0.0827	-0.145**
	(0.0627)	(0.0610)	(0.0625)
ROA	0.0326	0.0344	0.0331
	(0.0333)	(0.0323)	(0.0332)
TANGIBILITY	0.242	0.239	0.248
	(0.181)	(0.179)	(0.180)
TOBINQ	0.00725	0.0813*	0.00551
	(0.0396)	(0.0454)	(0.0400)
LEVERAGE	0.000796	0.0110	0.000262
	(0.0259)	(0.0230)	(0.0260)
RD	0.0794***	0.0547*	0.0792***
	(0.0241)	(0.0256)	(0.0242)
MTBV	0.0628	0.0828*	0.0623
	(0.0417)	(0.0456)	(0.0418)
FCF	-0.223	-0.284	-0.220
	(0.348)	(0.347)	(0.348)
SLACK	0.0243	0.00721	0.0243
	(0.0447)	(0.0447)	(0.0447)
INFLATION	-0.0124	0.00329	-0.0116
	(0.00819)	(0.00832)	(0.00804)
GDP	0.0136	-0.00617	0.0121
	(0.0164)	(0.0152)	(0.0161)
Constant	8.534***	10.81***	6.443***
	(1.153)	(3.421)	(0.809)
Industry FE	YES	YES	YES
Year FE	NO	NO	NO

Notes : This table presents the results of the regression analysis investigating the moderating effects of ND-GAIN (ND-GAIN) and its two components climate vulnerability (VULNERABILITY) and climate readiness (READINESS) on the relationship between firm-level climate risk (CCRISK) and investment inefficiency (INEFF). The control variables are described in the Appendix. All models take into account industry fixed effects. Standard errors are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Table 5. Firm-level climate risk and investment inefficiency: Alternative measures

	Alternative measures of CCRISK						Alternative measure of Investment inefficiency		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	INEFF	UINV	OINV	INEFF	UINV	OINV	INEFF1	UINV1	OINV1
CCRISK							0.0540***	0.0394***	0.0382
							(0.0127)	(0.0123)	(0.0561)
DummyCcRisk	0.105**	0.0982*	0.0740						
	(0.0527)	(0.0514)	(0.110)						
CCEXPO				0.00482***	0.00542***	-0.0000504			
				(0.00159)	(0.00159)	(0.00371)			
SIZE	-0.327***	-0.142**	-0.608***	-0.323***	-0.173**	-0.475***	-0.278***	0.356***	-1.028***
	(0.0666)	(0.0708)	(0.146)	(0.0622)	(0.0694)	(0.131)	(0.0393)	(0.0793)	(0.138)
AGE	-0.134	-0.0220	-0.281	-0.142**	0.00599	-0.141	-0.149*	-0.314***	0.538*
	(0.0984)	(0.108)	(0.189)	(0.0651)	(0.0789)	(0.116)	(0.0814)	(0.0660)	(0.273)
ROA	0.0420	-0.0122	0.0674	0.0280	-0.0447	0.0877	-0.00505	-0.0732	0.0504
	(0.0320)	(0.0363)	(0.0594)	(0.0298)	(0.0343)	(0.0546)	(0.0278)	(0.0433)	(0.0578)
TANGIBILITY	0.404	-0.207	1.395*	0.297	-0.576	0.912	-0.337	-2.570***	2.151***
	(0.408)	(0.433)	(0.802)	(0.385)	(0.426)	(0.732)	(0.341)	(0.626)	(0.542)
TOBINQ	-0.0153	-0.308***	0.356**	0.00338	-0.198**	0.239*	0.0763	-0.430***	0.397***
	(0.0831)	(0.0868)	(0.168)	(0.0736)	(0.0817)	(0.142)	(0.0781)	(0.0769)	(0.0915)
LEVERAGE	0.00500	-0.0233	0.0213	-0.00322	-0.0173	0.0112	0.00474	0.121	-0.00716
	(0.0327)	(0.0325)	(0.0697)	(0.0263)	(0.0290)	(0.0491)	(0.0458)	(0.0818)	(0.0584)
RD	0.0581	0.0143	0.189	0.0673	0.0176	0.177	-0.00497	-0.0966***	0.136
	(0.0477)	(0.0431)	(0.127)	(0.0461)	(0.0436)	(0.114)	(0.0445)	(0.0281)	(0.206)
MTBV	-0.00754	0.0876**	-0.142	0.0442	0.0894**	0.0457	0.0129	0.118***	-0.132
	(0.0402)	(0.0386)	(0.0979)	(0.0350)	(0.0353)	(0.0785)	(0.0387)	(0.0315)	(0.0946)
FCF	0.00743	-0.185	0.494	-0.183	-0.461	-0.211	-0.429*	-0.931*	0.564
	(0.337)	(0.362)	(0.644)	(0.307)	(0.350)	(0.560)	(0.207)	(0.452)	(0.421)
SLACK	0.0260	0.00590	0.235*	0.0171	0.0147	0.0983	0.0702	-0.0781**	0.701***
	(0.0443)	(0.0403)	(0.125)	(0.0419)	(0.0399)	(0.110)	(0.0468)	(0.0328)	(0.116)
INFLATION	-0.0211	-0.0180	-0.0682	-0.0228	-0.0204	-0.0634	0.0286***	-0.00565	0.0781***
	(0.0222)	(0.0212)	(0.0465)	(0.0223)	(0.0218)	(0.0464)	(0.00490)	(0.00590)	(0.0176)
GDP	0.119***	0.0869**	0.207***	0.111***	0.0818**	0.145**	0.0440***	0.0252**	0.0449*
	(0.0348)	(0.0339)	(0.0757)	(0.0335)	(0.0336)	(0.0708)	(0.00623)	(0.00982)	(0.0235)
Constant	6.026***	3.841***	8.463***	5.791***	4.211***	6.371***	6.121***	-1.848	11.03***
	(0.933)	(1.027)	(1.933)	(0.807)	(0.955)	(1.600)	(0.780)	(1.162)	(2.320)
R-squared	0.032	0.030	0.091	0.041	0.040	0.079			
Number of id	195	175	160	195	177	164	195	170	173

Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table summarizes the findings of panel fixed effects regressions with alternative measures of firm-level climate risk and investment inefficiency. While Columns (4)–(6) employ CCEXPO as an additional measure of climate risk, Columns (1)–(3) display estimations based on DummyCcRisk as another proxy for climate risk. Columns 7–9 provide the results using different measures of investment inefficiency, notably INEFF1, UINV1, and OINV1, while maintaining the original climate risk measure (CCRISK). All regressions account for firm-specific factors, including firm size (SIZE), firm age (AGE), profitability (ROA), tangibility (TANGIBILITY), growth opportunities (Tobin's Q), leverage (LEVERAGE), research and development (R&D), market-to-book ratio (MTBV), free cash flow(FCF), financial slack (SLACK), inflation (INFLATION), and gross domestic product (GDP).

Table 6. Addressing Endogeneity: Propensity Score Matching (PSM)

VARIABLES	(1) INEFF	(2) UINV	(3) OINV
HIGH_CCRISK_IY	0.101*	0.103*	0.0652
	(0.0574)	(0.0540)	(0.121)
SIZE	-0.328***	-0.145	-0.609***
	(0.0930)	(0.0916)	(0.192)
AGE	-0.130	-0.0107	-0.277
	(0.120)	(0.111)	(0.182)
ROA	0.0413	-0.0139	0.0675
	(0.0399)	(0.0445)	(0.0504)
TANGIBILITY	0.402	-0.210	1.393*
	(0.541)	(0.506)	(0.776)
TOBINQ	-0.0148	-0.306***	0.355*
	(0.0971)	(0.109)	(0.186)
LEVERAGE	0.00521	-0.0229	0.0210
	(0.0374)	(0.0385)	(0.0678)
RD	0.0576	0.0149	0.187
	(0.0472)	(0.0352)	(0.193)
MTBV	-0.00814	0.0870*	-0.142
	(0.0492)	(0.0444)	(0.120)
FCF	0.0124	-0.170	0.492
	(0.426)	(0.381)	(0.607)
SLACK	0.0254	0.00358	0.236*
	(0.0525)	(0.0469)	(0.142)
INFLATION	-0.0210	-0.0178	-0.0684
	(0.0195)	(0.0157)	(0.0460)
GDP	0.119***	0.0871**	0.208***
	(0.0346)	(0.0339)	(0.0695)
Constant	6.054***	3.857***	8.493***
	(1.313)	(1.453)	(2.204)
R-squared	0.032	0.030	0.091
industry FE	YES	YES	YES
Year FE	YES	YES	YES

Notes: This table shows the impact of firm-level climate risk (CCRISK) on investment inefficiency (INEFF), underinvestment (UINV), and overinvestment (OINV), using the PSM technique to treat the endogeneity issue. Control variables are outlined in Appendix 1, and standard errors are provided in parentheses. The notation *, **, and *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Addressing endogeneity: System GMM

VARIABLES	(1) INEFF	(2) UINV	(3) OINV

L.INEFF	0.184***		
	(0.00724)		
L.UINV		0.217***	
		(0.00558)	
L.OINV			-0.162
			(0.256)
CCRISK	0.0417***	0.0396***	0.334
	(0.00457)	(0.00244)	(0.386)
SIZE	0.120***	-0.220***	1.718
	(0.0393)	(0.0314)	(3.121)
AGE	0.0925*	-0.0569*	7.960
	(0.0546)	(0.0308)	(9.152)
ROA	-0.0276	-0.0179	-0.618
	(0.0274)	(0.0191)	(0.667)
TANGIBILITY	-0.790***	-0.0753	7.239
	(0.211)	(0.126)	(15.03)
TOBINQ	-0.231***	-0.532***	4.833
	(0.0556)	(0.0260)	(3.328)
LEVERAGE	0.0270	0.186***	-0.580
	(0.0245)	(0.0273)	(0.667)
RD	-0.210***	-0.112***	0.577
	(0.0312)	(0.0165)	(3.858)
MTBV	0.0936**	0.0804***	-2.474
	(0.0387)	(0.0180)	(1.727)
FCF	0.610**	-0.0895	9.618
	(0.256)	(0.141)	(9.909)
SLACK	0.0182	0.154***	1.766
	(0.0317)	(0.0187)	(1.995)
INFLATION	-0.0392***	-0.0273***	0.204
	(0.00487)	(0.00252)	(0.217)
GDP	0.00522*	0.0129***	0.00573
	(0.00306)	(0.00166)	(0.267)
year	0.0177***	0.0447***	-1.248
	(0.00546)	(0.00328)	(1.052)
Constant	-34.42***	-84.93***	2,246
	(10.70)	(6.480)	(4,126)
Hansen test (*P*-value)	0.444	0.821	0.403
AR(2) test (*P*-value)	0.237	0.653	0.378
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Notes: This table displays the findings of the GMM system estimator, with standard errors shown in parentheses. All regressions account for fixed factors including year and industry. All variable definitions are found in Appendix A1.GMM estimators are consistent in the absence of second-order serial correlation in the error term, as revealed by the AR(2) test. Furthermore, the instruments are valid, as confirmed by the Hansen over-identifying restriction test. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 8. Impact of external events on firm-level climate risk and investment inefficiency

	COVID-19 and the First Trump Presidency			Geopolitical Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	INEFF	UINV	OINV	INEFF	UINV	OINV
CCRISK	0.0526**	0.0603***	0.000456	0.0526**	0.0603***	0.000456
	(0.0259)	(0.0226)	(0.0719)	(0.0259)	(0.0226)	(0.0719)
SIZE	-0.326***	-0.136*	-0.613***	-0.326***	-0.136*	-0.613***
	(0.0667)	(0.0709)	(0.146)	(0.0667)	(0.0709)	(0.146)
AGE	-0.131	-0.00318	-0.272	-0.131	-0.00318	-0.272
	(0.0996)	(0.111)	(0.190)	(0.0996)	(0.111)	(0.190)
ROA	0.0405	-0.0142	0.0679	0.0405	-0.0142	0.0679
	(0.0320)	(0.0362)	(0.0594)	(0.0320)	(0.0362)	(0.0594)
TANGIBILITY	0.395	-0.242	1.394*	0.395	-0.242	1.394*
	(0.408)	(0.433)	(0.802)	(0.408)	(0.433)	(0.802)
TOBINQ	-0.0141	-0.301***	0.352**	-0.0141	-0.301***	0.352**
	(0.0832)	(0.0868)	(0.168)	(0.0832)	(0.0868)	(0.168)
LEVERAGE	0.00379	-0.0256	0.0185	0.00379	-0.0256	0.0185
	(0.0327)	(0.0325)	(0.0697)	(0.0327)	(0.0325)	(0.0697)
RD	0.0570	0.0114	0.187	0.0570	0.0114	0.187
	(0.0477)	(0.0430)	(0.127)	(0.0477)	(0.0430)	(0.127)
MTBV	-0.00730	0.0881**	-0.141	-0.00730	0.0881**	-0.141
	(0.0402)	(0.0385)	(0.0980)	(0.0402)	(0.0385)	(0.0980)
FCF	0.0121	-0.164	0.485	0.0121	-0.164	0.485
	(0.338)	(0.362)	(0.644)	(0.338)	(0.362)	(0.644)
SLACK	0.0240	0.000163	0.235*	0.0240	0.000163	0.235*
	(0.0443)	(0.0404)	(0.125)	(0.0443)	(0.0404)	(0.125)
INFLATION	-0.0208	-0.0174	-0.0686	-0.00283	-0.00445	-0.0313
	(0.0222)	(0.0212)	(0.0466)	(0.0185)	(0.0178)	(0.0386)
GDP	0.117***	0.0825**	0.208***	0.0377**	0.0251	0.0435
	(0.0349)	(0.0339)	(0.0757)	(0.0168)	(0.0163)	(0.0365)
Trump_dummy	-0.485***	-0.392**	-0.849**			
	(0.187)	(0.182)	(0.408)			
COVID19	0.519***	0.318***	0.795***			

	(0.122)	(0.121)	(0.267)			
GPR				6.838***	4.937**	14.17***
				(2.454)	(2.352)	(5.310)
Constant	6.033***	3.754***	8.564***	5.519***	3.384***	7.501***
	(0.933)	(1.027)	(1.928)	(0.895)	(0.987)	(1.838)
R-squared	0.032	0.032	0.091	0.032	0.032	0.091
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes: This table shows how firm-level climate risk (CCRISK) affects three measures of investment inefficiency: overall inefficiency (INEFF), underinvestment (UINV), and overinvestment (OINV).The analysis accounts for external events, like COVID-19 and the first Trump presidency. Control variables are detailed in Appendix 1. Standard errors are presented in parentheses. Symbols *, **, and *** denote two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Impact of firm-level climate risk on investment inefficiency across investment irreversibility and CO_2 emissions levels

	INEFF		UINV		INEFF		UINV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	LOW_TANG	High_TANG	Low_TANG	High_TANG	Low_CO2emiss	High_CO2emiss	Low_CO2emiss	High_CO2emiss
CCRISK	0.0489	0.0544*	0.134**	0.0447	0.0660	0.150*	-0.0342	0.207***
	(0.0510)	(0.0270)	(0.0613)	(0.0445)	(0.0781)	(0.0875)	(0.0726)	(0.0762)
SIZE	-0.270	-0.320	-0.0198	-0.0140	-0.928***	-1.186***	0.0190	-0.186
	(0.240)	(0.423)	(0.241)	(0.379)	(0.354)	(0.325)	(0.257)	(0.534)
AGE	-0.264	-0.261	-0.179	-0.334	-0.392	0.382	-3.190**	1.126
	(0.195)	(0.439)	(0.195)	(0.953)	(0.922)	(0.875)	(1.336)	(1.692)

ROA	-0.0576	-0.0727	-0.180**	-0.128	0.102	0.149	-0.0677	-0.120
	(0.0698)	(0.110)	(0.0784)	(0.199)	(0.167)	(0.139)	(0.135)	(0.168)
TOBINQ	-0.0774	-0.0965	-0.289	-1.322*	0.00211	-0.976**	0.0963	-1.695**
	(0.129)	(0.414)	(0.195)	(0.656)	(0.629)	(0.471)	(0.351)	(0.662)
LEVERAGE	0.0824	0.144	0.0380	0.103	0.209	0.0431	0.0327	-0.143
	(0.0629)	(0.257)	(0.0580)	(0.383)	(0.210)	(0.245)	(0.179)	(0.382)
RD	0.109	0.0651	0.107	-0.0308	0.0680	0.296	-0.0617	0.144
	(0.147)	(0.0631)	(0.172)	(0.0437)	(0.210)	(0.316)	(0.123)	(0.298)
MTBV	0.249***	-0.0845	0.231**	0.193	-0.0845	-0.0637	0.0131	0.104
	(0.0684)	(0.163)	(0.0946)	(0.200)	(0.299)	(0.130)	(0.134)	(0.0974)
FCF	0.0302	-0.0509	0.0127	-0.390	-0.728	1.198	-0.403	-4.692*
	(0.695)	(1.797)	(0.630)	(2.093)	(1.447)	(1.437)	(0.827)	(2.578)
SLACK	0.0946	-0.0758	-0.0518	-0.000984	0.108	0.0653	-0.00354	-0.0821
	(0.121)	(0.224)	(0.0680)	(0.209)	(0.211)	(0.302)	(0.134)	(0.259)
INFLATION	-0.0343	-0.0472	-0.0509	-0.0440	-0.0570	0.0668	0.0127	-0.00391
	(0.0436)	(0.0494)	(0.0359)	(0.0387)	(0.0616)	(0.0523)	(0.0356)	(0.0654)
GDP	0.0993	0.218	0.0908	0.245	0.745*	0.270	1.024**	-0.702
	(0.0808)	(0.149)	(0.0919)	(0.154)	(0.447)	(0.402)	(0.426)	(0.441)
Constant	4.386	6.999	1.093	3.503	15.09**	15.39***	10.47**	3.022
	(3.385)	(7.058)	(3.055)	(6.766)	(6.187)	(4.867)	(4.894)	(9.436)
R-squared	0.078	0.161	0.124	0.258	0.116	0.180	0.232	0.356
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents subsample regression results on the impact of firm-level climate risk (CCRISK) on investment inefficiency (INEFF) and underinvestment (UINV) for firms with low and high levels of investment irreversibility and CO2 emissions. The low and high groups are determined by the lowest (Q1) and highest (Q4) quartiles of asset tangibility and CO2 emissions, respectively. All specifications contain all control variables, as well as year and industry fixed effects. Robust standard errors are indicated in parentheses. Appendix A1 contains variable definitions. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Firm-Level Climate Risk and Investment Inefficiency across ESG Levels

	INEFF		UINV	
	(1)	(2)	(1)	(2)
VARIABLES	Low ESG	High ESG	Low ESG	High ESG
CCRISK	0.0920**	0.0470	0.115***	0.0496*
	(0.0443)	(0.0343)	(0.0389)	(0.0295)
SIZE	-0.165	-0.454***	-0.0506	-0.176
	(0.102)	(0.124)	(0.113)	(0.125)
AGE	-0.231	-0.131	0.00218	-0.299
	(0.175)	(0.223)	(0.207)	(0.225)
ROA	0.0638	-0.0713	0.00809	-0.0844
	(0.0488)	(0.0543)	(0.0557)	(0.0542)
TANGIBILITY	-0.291	0.853	-1.515*	0.852
	(0.631)	(0.685)	(0.787)	(0.605)
TOBINQ	-0.178	0.164	-0.298**	-0.355**
	(0.128)	(0.140)	(0.134)	(0.153)
LEVERAGE	-0.00363	-0.0717	-0.0339	-0.186**
	(0.0514)	(0.0726)	(0.0498)	(0.0752)
RD	-0.0324	0.107	-0.0617	0.0357
	(0.0591)	(0.107)	(0.0534)	(0.0923)
MTBV	0.0218	0.0157	0.0701	0.104*
	(0.0607)	(0.0673)	(0.0584)	(0.0600)
FCF	-0.661	-0.249	-1.008*	-0.832
	(0.549)	(0.530)	(0.572)	(0.568)
SLACK	0.129*	-0.0129	0.0242	-0.0478
	(0.0742)	(0.0673)	(0.0668)	(0.0615)
INFLATION	0.0199	-0.0266	0.0166	-0.0177
	(0.0438)	(0.0268)	(0.0433)	(0.0253)
GDP	0.111*	0.0921*	0.0665	0.116**
	(0.0599)	(0.0527)	(0.0614)	(0.0504)
Constant	4.188***	8.307***	3.399**	5.755***
	(1.440)	(1.849)	(1.648)	(1.911)
R-squared	0.055	0.058	0.076	0.061
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: This table presents regression results for the impact of firm-level climate risk (CCRISK) on investment inefficiency (INEFF) and underinvestment (UINV) at various levels of ESG performance. The sample is split into low-ESG and high-ESG firms to investigate whether the impact of firm-level climate risk varies with ESG level. The appendix provides definitions for the control variables. All specifications incorporate industry and year fixed effects. Standard errors are shown in parenthesis. The symbols ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

APPENDIX

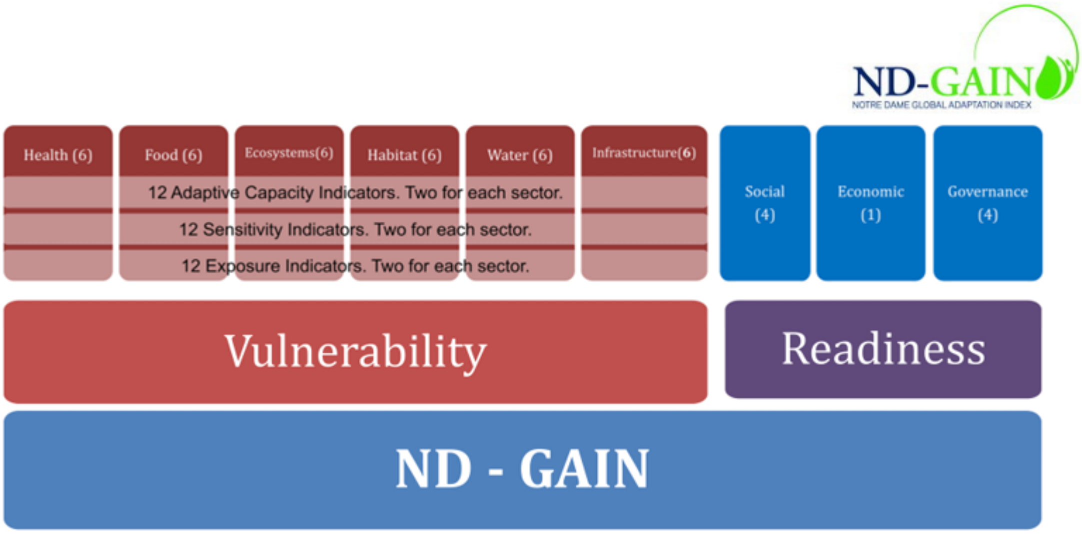

Figure 1. Overview of the ND-GAIN, Readiness, and Vulnerability Indicators

Source: Chen et al. (2015)

Table A1. Definitions of variables

Variable	Acronym	Definition	Source
INEFF	INEFF	The absolute value of the residuals in Biddle et al. (2009) expected investment model.	Authors' calculations
Underinvestment	UNDER	The absolute value of negative residuals in Biddle et al. (2009) expected investment model, capturing investment below the optimal level.	Authors' calculations
Overinvestment	OVER	The positive residuals in Biddle et al. (2009) expected investment model, reflecting investment above the optimal level.	Authors' calculations
Firm-level climate change risk	CCRISK	A firm's exposure to climate change-related risks and uncertainties, including regulatory, physical, and opportunity risks. Higher values indicate greater climate risk.	Developed and supplied by (Sautner et al., 2023) using bigram analysis of quarterly earnings conference calls. OSF | Firm-level Climate Change Exposure
Firm-level climate risk exposure	CCEXPO	A firm's overall exposure to climate change-related issues, including regulatory, physical, and opportunity aspects. Higher values indicate greater exposure.	Developed and supplied by (Sautner et al., 2023) using bigram analysis of quarterly earnings conference calls.

			OSF | Firm-level Climate Change Exposure
Sales Growth	Sales Growth	The annual percentage change in a firm's sales (revenue).	Thomson Reuters Eikon
NEG	NEG	A dummy variable that is equal to 1 when sales growth is negative and 0 otherwise.	Authors' calculations
Climate resilience	GAIN	The ND-GAIN index combines vulnerability and readiness scores to capture a country's susceptibility to and capacity to deal with climate-related shocks.	https://gain.nd.edu/our-work/country-index/download-data/
Climate vulnerability	VULNERABILITY	Climate vulnerability measures a country's exposure, sensitivity, and adaptive capacity to the negative consequences of climate change across six key sectors using 36 indicators.	https://gain.nd.edu/our-work/country-index/download-data/
Climate readiness	READINESS	An index measuring a country's readiness for climate change adaptation. It is based on three factors, namely economic, governance, and social readiness, and ranges from 0 to 1, with higher values indicating greater adaptability.	https://gain.nd.edu/our-work/country-index/download-data/
Firm size	SIZE	The natural logarithm of the firm's total assets.	Thomson Reuters Eikon
Firm age	AGE	The natural logarithm of one plus the number of years since the firm's foundation day.	Thomson Reuters Eikon
Return on assets	ROA	Net income divided by book value of total assets.	Thomson Reuters Eikon
Tangibility	TANGIBILITY	Property, plant, and equipment divided by total assets.	Thomson Reuters Eikon
Tobin's Q	TOBINQ	The sum of the market value of equity and the book value of debt divided by total assets.	Thomson Reuters Eikon
Leverage	LEVERAGE	Total debt divided by the book value of total assets.	Thomson Reuters Eikon
Research and development	RD	Expenses for research and development of new products and services to gain a competitive advantage.	Thomson Reuters Eikon
Market to book value	MTBV	The ratio of market value of assets to total assets (book value).	Thomson Reuters Eikon

Free cash flow	FCF	Calculated using the model developed by (Gul et al., 1997).	Thomson Reuters Eikon
Financial slack	SLACK	Cash and cash equivalents divided by total assets.	Thomson Reuters Eikon
Inflation	INFLATION	Annual percentage change in consumer prices.	World Data Bank
GDP Growth	GDP	Annual percentage growth rate of GDP.	World Data Bank
Year	YEAR	Year fixed effects (year dummies).	Authors' calculations
Industry	INDUSTRY	Industry fixed effects based on the ICB industry codes.	Authors' calculations

Table A2. Pearson correlations and variance inflation factors (VIF)

	INEFF (1)	CCRISK (2)	GAIN (3)	READ (4)	VULN (5)	SIZE (6)	AGE (7)	ROA (8)	TANG (9)	TOBIN Q (10)	LEV (11)	RD (12)	MB (13)	FCF (14)	SLACK (15)	INF (16)	GDP (17)
(1)	1																
(2)	-0.0382*	1															
(3)	0.0242	-0.0531*	1														
(4)	0.0234	-0.0503*	0.9993*	1													
(5)	-0.0093	0.0527*	0.2632*	0.2985*	1												
(6)	-0.0465*	0.1588*	-0.2330*	-0.2317*	-0.0477*	1											
(7)	-0.0825*	0.0895*	-0.1775*	-0.1754*	-0.0053	0.2873*	1										
(8)	-0.0581*	-0.1224*	-0.0648*	-0.0637*	0.0015	-0.1265*	0.0332*	1									
(9)	-0.0506*	0.3305*	-0.0162	-0.0154	0.0137	0.2265*	0.1266*		1								
(10)	0.0376*	-0.1423*	-0.1552*	-0.1545*	-0.0378*	-0.3796*	-0.1173*	0.4477*	-0.2115*	1							
(11)	-0.0244	0.0506*	-0.1179*	-0.1193*	-0.0698*	0.0416*	-0.0322*	0.0891*	0.1442*	0.1167*	1						
(12)	0.0864*	-0.0261	-0.1335*	-0.1320*	-0.0142	0.4322*	0.0375*	0.0749*	0.0461*	0.0590*	-0.0508*	1					
(13)	0.0068	-0.0040	-0.0013	-0.0010	0.0066	0.0057	-0.0023	0.0103	-0.0214	0.0357*	-0.0355*	0.0187	1				
(14)	-0.0060	-0.0980*	-0.0187	-0.0177	0.0132	-0.1605*	-0.0566*	0.7150*	0.0021	0.4153*	-0.0258	0.0826*	0.0092	1			
(15)	0.0459*	-0.1503*	0.0263	0.0266	0.0145	-0.1031*	-0.2436*	0.0906*	-0.2014*	0.3120*	-0.0644*	0.1871*	0.0017	0.1071*	1		
(16)	-0.0277*	0.0599*	-0.3714*	-0.3565*	0.2038*	0.1390*	0.1236*	0.0958*	0.0121	0.0516*	0.0246	0.0894*	0.0223	0.0669*	-0.0542*	1	
(17)	-0.0026	0.0177	-0.0575*	-0.0641*	-0.2006*	0.0316*	0.0269	0.0752*	-0.0037	0.0268*	0.0030	0.0248	0.0025	0.0499*	-0.0512*	0.3278*	1
VIF	2.61	2.58	1.40	1.38	1.18	1.80	1.18	2.58	1.13	1.60	1.09	1.42	1.00	2.62	1.21	1.32	1.13
Mean VIF	**1.60**																

Notes: This table presents the Pearson correlation coefficients and VIF values for the key variables used in the analysis. Table A1 provides variable definitions.The asterisk (*) represents statistical significance at the 5% level.