



Climate Risk Exposure and Firm Default Risk: OECD Insights into the Moderating Role of Innovation

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Abstract

By analyzing 19715 firm–year observations from 2640 companies across 38 OECD member economies between 2002 and 2023, this study examines the effect of climate risk exposure on firm default risk. Our findings suggest that firms with higher climate risk exposure, as measured by physical risk and transition risk indicators, are more likely to default. We then explore how financial constraints influence this relationship and find that innovation mitigates the impact of climate risk on default risk. However, firms should prioritize green innovation instead of increasing overall research and development (R&D) investment. Moreover, the relationship between climate risk exposure and default risk varies depending on financial constraints, industry climate sensitivity, and regulatory stringency. Overall, our study provides practical insights for managers, policymakers, and investors, underscoring the importance of integrating climate risk into firm assessments, investment strategies, and green technology transitions.

Keywords Climate risk exposure; Firm default risk; OECD economies; Green innovation

JEL Classification: G30, G32

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1. Introduction

Climate change and global warming have attracted growing academic and policy attention in recent years. Scholars and policymakers now recognize the direct and indirect effects of climate change on ecosystems, biodiversity, and agriculture, as well as its growing influence on investment decisions and business development (Krueger *et al.* 2020). As extreme weather events escalate, high technology advances, and pressure mounts to transition to a net-zero economy, businesses across industries face growing challenges, including stricter regulations, limited financing options, operational disruptions, and shifts in the global supply chain (Pham *et al.* 2019; Zhou *et al.* 2020).

Climate risk exposure is a key driver affecting firm value and environmental, social, and governance (ESG) performance (Liu *et al.* 2025), corporate green innovation (Tian *et al.* 2024), corporate debt maturity (Goodell *et al.* 2025), market valuation (Berkman *et al.* 2024), cost of equity (Cepni *et al.* 2024), and dividend policy (Ongsakul *et al.* 2024). Krueger *et al.* (2020) categorized research on climate risks into two main approaches: carbon footprint and stranded asset risk. In addition, Capasso *et al.* (2020) demonstrated that firms with poor environmental performance, as measured by carbon emissions and carbon intensity, face higher credit risk. This finding strongly suggests that financial markets actively consider firms' climate strategies when evaluating creditworthiness and lending decisions. Moreover, the positive association between carbon emissions and firm default risk is more pronounced for companies operating in high carbon-emitting industries (Kabir *et al.* 2021).

Other researchers have analyzed how exogenous factors, such as sea-level risk and flood risk, threaten asset value (Baldauf *et al.* 2020). Studies emphasize the importance of evaluating the multifaceted effects of climate risks using diverse external sources, rather than relying solely on internal control assessments (Giglio *et al.* 2021). This perspective defines climate risk in two main streams: physical and transition risk. While physical risk refers to the likelihood of asset damage and supply chain disruptions, transition risk encompasses the regulatory and technological challenges involved in the shift to a low-carbon economy (Bua *et al.* 2024).

In this study, we adopt three indices to measure climate risk exposure: overall climate risk, physical risk, and transition risk. These externally sourced indicators reflect a company's vulnerability to the broader impacts of climate change (Sautner *et al.* 2023). Most prior studies used carbon footprints to assess climate risk exposure (Capasso *et al.* 2020; Kabir *et al.* 2021), but few have examined how externally sourced climate risk indicators relate to business activities. Our study addresses this gap by using physical and transition risk indices to evaluate climate risk exposure.

We define default risk as the probability that a company will fail to meet its financial obligations. To assess this, we use distance-to-default (DTD) measures, where a higher DTD indicates a lower probability of default and greater financial stability. Research on the effect of climate risk on default risk offers valuable

insights for reducing financial uncertainty and developing effective risk mitigation strategies. Markets increasingly factor environmental performance into credit evaluations and lending decisions. As a result, firms with higher ESG ratings tend to experience a reduction in default risk (Li *et al.* 2022).

Wang *et al.* (2024) demonstrate that firms in high-carbon-emitting industries experience significant declines in default risk following the implementation of carbon regulations, primarily due to enhanced legal compliance, strategic green transformation, and reduced financial leverage. In addition, Meles *et al.* (2023) find a negative association between green innovation and default risk, indicating that eco-innovation investment can effectively lower the probability of default. Despite the significance of default risk in financial risk management, research examining its relationship with climate risk exposure remains limited.

Our study fills this gap by exploring how climate risk exposure affects firm-level default risk. We analyze 2640 companies across 38 OECD member countries from 2002 to 2023. These countries span multiple continents and account for approximately 50% of the global gross domestic product (GDP). Although OECD members share common goals, they include mature economies (e.g. in Europe) and emerging economies that are especially vulnerable to climate impacts. This diversity enables us to conduct a comprehensive analysis of climate-related financial risks, contributing to the climate finance literature.

Our findings provide several important insights. First, results from baseline regression confirm that firms with greater climate risk exposure tend to face higher default risk. Second, we consider the moderating effect of innovation and find that it mitigates the positive relationship between climate risk exposure and default risk. However, our findings suggest that firms should prioritize green innovation over general increases in R&D spending to avoid debt burdens and high costs. Third, the risk-magnification effects of climate risk exposure are more significant for firms with high financial constraints, greater sensitivity to climate change, and those operating in countries with stricter environmental policies. Finally, our results remain robust after addressing endogeneity using a two-stage least squares regression. Overall, these results underscore the integral role of climate risk exposure in a firm's risk management. We recommend that firms adopt green technologies to lower default risk in the face of climate change, regulatory tightening, and rising stakeholder expectations.

Our study makes three contributions to the literature. First, we expand research on climate finance and ESG issues by incorporating external-level climate factors. These external factors, such as extreme weather events, technological shifts, and regulatory risks, are beyond the control of individual firms, yet they directly expose firms to significant risks. ESG ratings and carbon emissions are not sufficient to address these climate-related risks. Thus, firms are encouraged to consider climate risk exposure when reassessing their value chain and to enact strategic adaptations in response to these challenges. Second, we address prior limitations by analyzing a large dataset that spans five continents, thereby improving the generalizability of

our findings and capturing institutional and regulatory variation. Previous studies have primarily focused on single-country datasets, such as those from the United States (Safiullah *et al.* 2024), Korea (Park *et al.* 2023), Europe (Abdesslem *et al.* 2025), and China (Li *et al.* 2024). A country's policy, regulatory, and institutional characteristics significantly impact firm performance, and these effects vary between state-oriented economies (e.g. China) and market-driven economies (e.g. Europe and the United States). Our study overcomes these limitations of single-country research by separating the influence of policy stringency from country-specific factors. Our findings remain valid across varying levels of regulatory and institutional environments, making them more robust and relevant for policymakers and investors globally. Third, we advance understanding of the determinants of firm-level default risk by focusing on the role of climate risk exposure. Firms facing climate risk exposure are compelled to innovate in order to mitigate these risks. Our research provides valuable evidence that eco-innovation plays a vital mediating role in reducing firm default risk. Thus, firms are encouraged to pursue more strategic green investment decisions and a more sustainable use of their capital resources.

The remainder of this paper is organized as follows. Section 2 provides an overview of the relevant literature and formulates the research hypotheses. Section 3 describes the methodology employed in this study. Section 4 presents the empirical results. Section 5 concludes with a summary of key findings and a discussion of their implications.

2. Literature Review and Hypothesis Development

Climate risk exposure reflects how external factors influence a firm, indicating the firm's vulnerability to the severe and unpredictable impacts of climate change. Direct physical risks have led to stranded assets, supply chain disruptions, and operational bottlenecks (Bua *et al.* 2024). Huang *et al.* (2018) highlight that firms operating in geographic areas prone to recurrent and severe natural disasters (e.g. floods, earthquakes, droughts) tend to experience significant earnings uncertainty and reduced financial stability. As a result, firms adopt more conservative strategies to manage climate-related risks, such as reducing dividend payouts, relying more on long-term debt, and increasing cash holdings (Huang *et al.* 2018; Dang *et al.* 2023).

A substantial body of literature examines the relationship between climate risk exposure and firm performance. Liu *et al.* (2025) demonstrate that climate risk concerns significantly improve the ESG performance of Chinese companies between 2010 and 2021. Their findings suggest that firms have adjusted their governance and strategies in response to climate risk, underscoring the need to integrate climate considerations into corporate decision-making and investment planning. Berkman *et al.* (2024) report that climate-related risks negatively affect firm market value, as indicated by disclosures in 10-K filings. Investors typically interpret climate-related

news through the lens of a firm's climate risk exposure, resulting in more pronounced negative returns for firms with higher exposure.

The rise in social awareness has encouraged firms to pay greater attention to environmental concerns. Carbon emissions are widely used to measure a company's environmental impact, including both direct and indirect emissions. This indicator is straightforward for stakeholders to use when formulating appropriate strategies. For instance, managers use this measure for internal management to enhance operational efficiency, while policymakers leverage it for regulatory monitoring and enforcement (e.g. carbon pricing mechanisms and emissions trading schemes). As an alternative measure, ESG ratings are calculated using various sources, including financial statements, corporate disclosures, news and media, and stakeholder feedback. Numerous empirical studies have provided evidence of a positive relationship between ESG ratings and firm default risk and a negative relationship between carbon emissions and firm default risk (Kabir *et al.* 2021; Li *et al.* 2022; Li and Hu 2025).

While both carbon emissions and ESG scores are backward-looking metrics based on historical data, climate risk exposure is a forward-looking metric that assesses a firm's vulnerability stemming from physical and transition risks caused by climate change. Our study employs the firm-level climate risk measure proposed by Sautner *et al.* (2023), which is a highly effective indicator for understanding future challenges and opportunities. This measure is an influential determinant of a firm's default risk, especially in the context of unexpected weather events, the rise of advanced technologies, and stricter regulatory requirements. For example, a company with good sustainability and environmental practices may operate in an area highly vulnerable to climate change. In this manner, ESG scores and carbon emissions data fail to capture the threat of stranded assets, whereas a firm-level physical risk metric effectively addresses this issue.

Some studies provide evidence that climate risk reduces a firm's leverage ratios and long-term debt issuance (Ginglinger and Moreau 2023; Goodell *et al.* 2025), suggesting that firms lower their capital demand in response to increased uncertainty, heightened perceived risk, investor pressure, and continuous strategic shifts. Huang *et al.* (2018) show that climate risk alters financing policies, with greater emphasis on liquidity through increased cash holdings and reduced cash dividends. Severe weather events can cause liquidity shocks (e.g. cash flow volatility and illiquidity); therefore, firms located in high climate risk areas are more likely to rely on long-term borrowing to mitigate short-term illiquidity concerns and financial constraints. This indicates that firms proactively adjust their financial decisions to hedge against climate risk and ensure resilience and long-term survival. In addition, climate change exposure has a positive relationship with the cost of equity financing, and the effect of climate risk is amplified for firms with greater financial constraints and a higher likelihood of default, as investors demand a larger premium to compensate for the increased risks (Cepni *et al.* 2024).

Some evidence shows that firms' climate resilience and environmental performance vary significantly across different sectors. For instance, the computer hardware and consumer goods industries lead in environmental performance, whereas the aircraft, natural gas, and petroleum sectors perform poorly in this domain (Borghesi *et al.* 2014). High-emitting sectors are more susceptible to transition risks, which increase operating costs and erode profitability. Environmental regulations further reduce investment efficiency and increase financing costs for firms in carbon-intensive industries (Arian and Sands 2024; Ren *et al.* 2024). Consequently, banks and institutional investors might demand a risk premium when lending to these sectors, thereby increasing credit risk and the likelihood of default. Therefore, to support risk management, it is crucial to examine how climate risk exposure influences default risk, particularly in industries highly sensitive to climate change. Following instrumental stakeholder theory, firms with a strong environmental orientation, evidenced by lower climate risk exposure, are more likely to maintain good relationships with key stakeholders. When companies align their practices with societal and environmental expectations, they build trust and credibility with stakeholders (Choi *et al.* 2022). This alignment can enhance financial performance and reduce the firm's risk of default (Park *et al.* 2023; Safiullah *et al.* 2024). In contrast, firms labeled as "environmentally unsustainable" are more likely to suffer brand damage and face financial constraints, which can subsequently reduce their competitiveness and performance. Accordingly, we propose the following hypothesis:

Hypothesis 1. *Firms facing greater climate risk are more likely to experience higher default risk.*

Grounded in the resource-based view, firms rely on internal resources and capabilities to enhance performance and gain a competitive edge. The emergence of severe climate-related risks poses a significant threat to corporate resource allocation, thereby affecting strategic decision-making and financial outcomes. When firms face high climate risk exposure, they tend to develop greater operational flexibility and strengthen governance, which ultimately leads to better financial decisions and investment outcomes (Phan *et al.* 2022).

The financial markets respond to firms' environmental actions by penalizing or rewarding them accordingly (Faccini *et al.* 2023; Zhang 2022). In response, firms strategically invest in renewable energy technologies to mitigate regulatory compliance burdens and meet the expectations of investors. Tian *et al.* (2024) demonstrate a positive relationship between climate risk exposure and corporate green innovation, particularly in high-tech and state-owned firms. Similarly, Moscona and Sasstry (2023) underscore that agricultural innovations tailored to extreme temperature conditions can significantly reduce local economic damage.

High-tech firms are presumed to face low climate risk exposure due to the nature of their business operations in the context of global warming, severe weather events, and stricter policies. Indeed, environmental policy stringency may impose

additional costs (i.e. carbon taxes) on environmentally unfriendly emitters; however, climate change also presents opportunities for these companies to transition to eco-innovations, such as renewable energy and electric vehicles (Sautner *et al.*, 2023a). Cohen (2020) demonstrates that some of the largest carbon emitters, such as electricity, oil, and gas firms, are concurrently pioneering green technologies. While firms within an industry are exposed to similar regulatory risks, their opportunities differ significantly depending on how they integrate renewable energy and net-zero transitions into their strategic business models (Pickl 2019).

Green innovation refers to capital investments in innovative solutions and environmentally friendly technologies. However, when firms encounter financing constraints, limited access to capital prevents them from pursuing green R&D activities (Zhang *et al.* 2023). While green innovation poses substantial upfront costs, it offers a strategic opportunity for firms to achieve sustainable development and mitigate the impacts of climate-related risks (Xu *et al.* 2024). Indeed, investment in green technologies is subject to considerable uncertainty, as outcomes may result in either gains or losses depending on success or failure. Acemoglu *et al.* (2023) argue that shale gas has lower emissions than other fossil fuels; therefore, these firms have fewer incentives for long-term investment in emission-reducing technologies. However, shale gas fracking negatively impacts the climate due to emission leakage. Moreover, Sautner *et al.* (2023) demonstrate that investors are willing to pay a premium for firms with high regulatory risk that possess upside potential through green innovation activities. We use green innovation scores, which capture firm-level efforts to develop environmentally beneficial products or processes, to examine the moderating effect of green innovation in mitigating firm default risk.

Prior studies show that firms experiencing higher levels of climate risk exposure tend to invest more in R&D and innovation projects (Khanra *et al.* 2022). By adopting new technologies, companies can improve resource efficiency, strengthen competitiveness, and capitalize on emerging market opportunities (Li *et al.* 2023; Zhang *et al.* 2023). These efforts enable firms to reduce their carbon footprint, comply with environmental regulations, and strengthen their market position. Based on this analysis, we propose the following hypothesis:

Hypothesis 2. *Innovation mitigates the impact of climate risk on firms' default risk.*

3. Methodology

3.1. Sample

We construct an international firm-level panel dataset comprising publicly listed companies headquartered in OECD countries from 2002 to 2023. The sample period begins in 2002 to ensure the availability of environmental innovation data. We exclude firms in the financial sector (SIC codes 6000–6999) due to their unique capital structures, regulatory requirements, and accounting practices, which may systematically bias credit risk measurement.

We obtain the primary dependent variable, DTD, from the NUS Credit Research Initiative (<http://d.nuscri.org>), which provides a forward-looking, market-based measure of corporate credit risk based on structural credit risk modeling. We derive the key independent variables, firm-level exposures to climate change risks, from Sautner *et al.* (2023), who use natural language processing to analyze earnings call transcripts and generate firm-specific scores for overall climate risk, physical risk, and transition risk. These measures allow for granular and time-varying assessments of climate-related exposure at the firm level.

We collect financial statement data, including firm-level controls, from LSEG, and retrieve country-level macroeconomic indicators, including GDP growth, consumer price index (CPI) inflation, urbanization rate, and forest area, from the World Bank's World Development Indicators. After merging all datasets and winsorizing at the 1% level to reduce the influence of outliers, we obtain a balanced panel of diverse non-financial industries that is suitable for panel data analysis.

3.2. Variables Measurement

3.2.1. Dependent Variables.

The dependent variable is the distance to default (DTD), obtained directly from the NUS Credit Research Initiative. DTD is a forward-looking, standardized measure of corporate default risk derived from the Merton (1974) structural credit risk model. The model treats equity as a call option on the firm's assets, with default occurring when the asset value falls below a threshold at debt maturity. Formally, if V_t denotes the firm's asset value at time t , L the default point (typically proxied by short-term debt plus half of long-term debt), μ the expected asset return, σ the asset volatility, and T the debt horizon, then asset dynamics follow a geometric Brownian motion:

$$dV_t = \mu V_t dt + \sigma V_t dB_t,$$

where B_t denotes the standard Brownian motion. The probability of default at horizon T is given by:

$$\Pr(V_T \leq L) = N(-DTD);$$

with the distance to default defined as:

$$DTD_t = \frac{\ln\left(\frac{V_t}{L}\right) + \left(\mu - \frac{1}{2}\sigma^2\right)(T-t)}{\sigma\sqrt{T-t}}$$

In practice, CRI estimates DTD using observable market inputs. The asset value (V_t) and volatility (σ) are inferred iteratively from equity market capitalization, equity volatility, and book liabilities, consistent with the option-based framework.

Within-firm variation in DTD is primarily driven by three factors. First, leverage dynamics play a crucial role: an increase in debt obligations raises the default point and thereby reduces the distance to default. Second, equity volatility matters significantly, as higher fluctuations in earnings or market prices increase asset risk and lower DTD. Third, changes in market capitalization directly affect the estimated asset value, which in turn shifts the distance to default. Together, these components explain substantial variation in DTD over time, even after accounting for firm fixed effects, reinforcing its value as a forward-looking proxy for corporate credit risk.

3.2.2. Independent Variables: Climate Risk Exposure.

We obtain firm-level climate risk exposures from Sautner *et al.* (2023). Using a natural language processing approach, they analyze earnings conference call transcripts to identify firm-year references to climate-related topics and generate standardized measures for overall climate risk (*ClimateRisk*), physical risk (*PhysicalRisk*), reflecting exposure to extreme weather, natural disasters, or asset damage, and transition risk (*TransitionRisk*), capturing exposure to regulatory changes, carbon pricing, or technological shifts. Conference call transcripts are segmented into scripted remarks and Q&A interactions, with the latter further separated into investor questions and management responses. The baseline measure aggregates across all sections to capture comprehensive firm-level exposure. As a robustness check, we also analyze measures derived separately from scripted remarks and Q&A sessions, and the results are qualitatively consistent.

3.3. Empirical Models

Our analysis proceeds with two empirical models. The baseline specification examines the direct effect of climate risk on corporate default risk (Kabir *et al.* 2021), expressed as follows:

$$DefaultRisk_{i,t} = \alpha + \beta_1 ClimateRisk_{i,t} + \gamma Controls_{i,t} + \delta_i + \theta_t + \epsilon_{i,t} \quad (1)$$

In this model, *DefaultRisk_{i,t}* represents the DTD of firm *i* in year *t*, while *ClimateRisk_{i,t}* captures the firm's exposure to climate risk over the same period. The vector *Controls_{i,t}* includes firm- and country-level control variables. We include firm fixed effects (δ_i) and year fixed effects (θ_t) to account for unobserved heterogeneity and common temporal shocks, respectively. The error term $\epsilon_{i,t}$ captures idiosyncratic disturbances.

We include control variables to capture firm characteristics and macroeconomic conditions that may influence default risk. We expect firm size, measured as the logarithm of total assets, to correlate positively with DTD, as larger firms generally benefit from economies of scale, diversification, and easier access to capital. We also expect profitability, measured by return on assets (ROA), to correlate positively with DTD, reflecting greater financial resilience. We predict that leverage (total debt over total assets) will exert a negative influence on DTD, as higher indebtedness increases the probability of financial distress. Capital expenditures (CapEx / total

assets) may reflect long-term growth potential but can also introduce financial risk if heavily debt-financed; thus, their expected effect on DTD is theoretically ambiguous. We also anticipate a positive influence of the market-to-book (MB) ratio, which captures growth opportunities and market valuation, on DTD. Similarly, sales growth (measured as a year-over-year percentage change) reflects improving operational performance and should have a favorable impact on DTD.

At the macro level, we predict that GDP growth will enhance corporate solvency and reduce default risk, resulting in a positive association with DTD. In contrast, inflation (as measured by the CPI) may erode purchasing power and distort real asset values and earnings, potentially leading to a negative relationship with DTD.

To test Hypothesis 2, we extend the baseline model to include innovation and its interaction with climate risk:

$$\begin{aligned} \text{DefaultRisk}_{i,t} = & \alpha + \beta_1 \text{ClimateRisk}_{i,t} + \beta_2 \text{Innovation}_{i,t} \\ & + \beta_3 \text{ClimateRisk} * \text{Innovation}_{i,t} + \gamma \text{Controls}_{i,t} + \delta_i + \theta_t + \epsilon_{i,t} \end{aligned} \quad (2)$$

To assess the moderating role of innovation, we employ two complementary indicators. First, we calculate R&D intensity as R&D expenditures divided by total assets (R&D / TA). This input-based indicator reflects a firm's commitment to innovation. Firms with higher R&D intensity are typically more agile in responding to technological and regulatory shifts, including those related to climate change. We hypothesize that R&D-intensive firms are better positioned to mitigate the adverse impact of climate risk, thereby exhibiting higher DTD.

Second, we incorporate an output-based measure of green innovation, the Environmental Innovation Score (ENI), sourced from LSEG's sustainability database. This score captures firm-level efforts to develop environmentally beneficial products or processes. We create a dummy variable (dumENI) that equals "1" if a firm's ENI score exceeds the sample median in a given year. We expect firms with high environmental innovation (dumENI = 1) to exhibit greater resilience to climate transition risks, as reflected in higher DTD.

3.4. Heterogeneity Analysis

To examine the differential effects of climate risk on corporate default risk, we conduct a heterogeneity analysis across three important dimensions: financial constraints, industry-level climate sensitivity, and environmental policy stringency at the country level. First, to assess the role of financial constraints, we classify firms into high- and low-constraint groups based on the widely used Whited–Wu (WW) index. We calculate the WW index at the firm–year level and split the sample at the median. We categorize firms with WW scores above the median as highly financially constrained, while those with scores below the median are less constrained. We expect climate risk to exert a stronger negative effect on DTD for firms facing

greater financial constraints due to their limited capacity to absorb shocks or invest in adaptive strategies.

Second, we investigate cross-industry variation in climate risk exposure. We designate industries more sensitive to physical and transition climate risks, such as agriculture, forestry, and fishing (SIC codes 01–09), mining (10–14), construction (15–17), and manufacturing (20–39), as climate-sensitive sectors. Firms in these industries are more likely to face direct operational disruptions from climate events or regulatory transitions. We expect the negative relationship between climate risk and DTD to be more pronounced among climate-sensitive firms, given their greater vulnerability and exposure to climate-related risks.

Third, we examine heterogeneity based on the stringency of environmental policies in the firm's country of operation. We use the OECD Environmental Policy Stringency Index, a country-level measure of climate policy rigor. We classify countries with index values above the median as having highly stringent policies, while those with scores below the median have less stringent policies. We expect firms operating in more stringent policy environments to be more adaptive or better governed, potentially mitigating the negative impact of climate risk on DTD. Conversely, in less stringent environments, climate risks are more likely to translate into elevated credit risk due to weaker preparedness or enforcement.

3.5. Endogeneity Problem

The relationship between climate risk exposure and firm default risk may be subject to endogeneity, potentially biasing coefficient estimates and weakening causal inference. A key concern is reverse causality, which may arise if financially distressed firms disproportionately locate in areas with specific climate risk profiles or reduce their investments in mitigating climate risk. For example, firms facing financial constraints may emit more carbon or adopt less environmentally sustainable practices due to limited resources to address environmental challenges (Li and Hu 2025). Another concern is omitted variable bias, which could occur if unobserved firm- or country-level characteristics influence climate risk exposure and the likelihood of default. Institutional quality, regulatory stringency, or broader macro-financial conditions may simultaneously affect a firm's vulnerability to climate risk and its creditworthiness.

To address these endogeneity concerns, we employ a two-stage least squares instrumental variable approach. We utilize two country-level instrumental variables: *Urban*, representing the share of population in urban areas, and *Forest*, denoting the percentage of total land area covered by forests (Dong *et al.* 2024). These variables are theoretically relevant and empirically grounded instruments for climate risk exposure. Higher levels of urbanization drive industrial activity, boost energy consumption, expand transport infrastructure, and intensify urban heat island effects, all of which heighten exposure to physical climate risks (Sun *et al.* 2024). Conversely, countries with greater forest coverage have lower climate risk exposure

due to enhanced natural resilience, including stronger carbon sequestration capacity and protection from extreme weather events.

Importantly, while these instruments shape the aggregate climate risk profile of a country, they are unlikely to exert any direct effect on firm-level default probabilities through other economic channels. Their influence on corporate credit risk operates primarily through climate-related physical and transition risks, rather than through alternative macroeconomic or policy factors. In this sense, the instruments satisfy the exclusion restriction by affecting default risk only via their impact on climate exposure.

We use standard diagnostics to assess instrument strength and validity. We evaluate instrument relevance using the Kleibergen–Paap rk Wald *F*-statistic; values above the critical threshold indicate strong instruments. When we use multiple instruments, we test overidentification validity with the Hansen *J*-test. By applying this 2SLS strategy, we enhance the credibility of our causal estimates and reduce bias from reverse causality or omitted variables when examining the effect of climate risk exposure on firm default risk within the OECD context.

4. Results

4.1. Descriptive Statistics

Table 1 presents a summary of descriptive statistics, including the mean, standard deviation, minimum, and maximum values of default risk measures, climate risk

Table 1 Descriptive statistics

This table presents the summary statistics of distance-to-default (DTD), Climate Risk, Physical Risk, Transition Risk, and other control variables used in this study. Appendix A defines all variables.

Variables	Obs	Mean	SD	Min	Max	Skewness	Kurtosis
<i>DTD</i>	19 715	5.043	2.957	−0.329	14.168	0.761	3.481
<i>ClimateRisk</i>	19 715	0.006	0.016	0.000	0.096	3.688	17.628
<i>PhysicalRisk</i>	19 715	0.001	0.005	0.000	0.038	5.385	33.558
<i>TransitionRisk</i>	19 715	0.031	0.070	0.000	0.417	3.629	17.157
<i>Size</i>	19 715	7.982	1.798	3.270	11.724	−0.282	2.767
<i>ROA</i>	19 715	0.037	0.062	−0.255	0.220	−1.238	9.634
<i>Lev</i>	19 715	0.181	0.150	0.000	0.652	0.812	3.281
<i>CapEx</i>	19 715	0.036	0.040	0.000	0.202	1.820	6.769
<i>MB</i>	19 715	2.677	3.110	−1.802	20.329	3.250	16.297
<i>GSales</i>	19 715	0.094	0.297	−0.642	1.685	2.164	12.608
<i>GGDP</i>	19 715	1.769	3.020	−11.167	14.52	−1.285	7.168
<i>CPI</i>	19 715	3.115	5.244	−10.613	96.036	10.088	157.492
<i>RD/TA</i>	19 715	0.013	0.037	0.000	0.227	3.723	17.841
<i>dumENI</i>	19 715	0.432	0.495	0.000	1.000	0.276	1.076

measures, and other control variables. *DTD* exhibits substantial variation, ranging from a minimum value of -0.329 to a maximum value of 14.168 , with a mean of 5.043 and a standard deviation of 2.957 . For climate exposure risk measures (*Climate risk*, *Physical risk*, and *Transition risk*), the minimum value is 0.000 for each, while the maximum values are 0.096 , 0.038 , and 0.417 , respectively. The mean values of *Leverage*, *ROA*, and *Sales Growth* are 18.1% , 3.7% , and 9.4% , respectively. Descriptive statistics show that the average firm size is 7.982 , whereas the average market-to-book ratio is 2.677 . The mean values of *Capital Intensity* and *R&D Intensity* are 0.036 and 0.013 , respectively. On average, countries exhibit GDP growth of 1.769% and a CPI of 3.115% .

Table 2 presents the results of the correlation analysis. The results indicate that among the climate risk variables, *Climate Risk* and *Transition Risk* are significantly negatively correlated with *DTD*. This finding provides preliminary support for the hypothesis that climate risk may increase firms' default risk by reducing their distance to default. These correlations motivate further investigation into the negative relationship between climate risk and *DTD*. We also observe a positive correlation between *Transition Risk* and *Physical Risk*, suggesting that firms struggling to update their technology or adapt to environmental regulations tend to face greater operational and supply chain disruptions.

Among the control variables, *Size*, *ROA*, the market-to-book ratio, and *GDP* growth rate are significantly negatively correlated with default risk, while *Leverage* and the consumer price index are significantly positively correlated. These significant associations between default risk and other control variables underscore the importance of accounting for these variables in our regression models. We also note that the signs of correlations between control variables and climate risk measures—*Physical Risk* and *Transition Risk*—are consistent, indicating similar directional effects for both types of climate risk. For instance, larger firms tend to exhibit higher exposures to physical and transition risks. Finally, the low correlation coefficients among control variables (e.g. the highest is 0.374 between *DTD* and the market-to-book ratio) suggest that multicollinearity does not pose a serious concern when these variables are included simultaneously in the model.

4.2. Empirical Results

Table 3 presents the results of the baseline analysis. Columns (1), (2), and (3) present the individual effects of each climate exposure measure on *DTD*. The estimate in Column (1) indicates that a one-point increase in climate risk is associated with a 3.124 -point increase in default risk, which is statistically significant at the 1% level. Similarly, Column (2) shows that a one-point increase in *Physical Risk* raises default risk by 6.473 points, while Column (3) indicates that a one-point increase in *Transition Risk* is associated with a 2.140 -point increase in default risk. Both variables are statistically significant at the 5% level. Overall, the baseline regression results support our hypothesis that there is a positive relationship between climate exposure risk and default risk. These findings support the view that investors in

Table 2 Correlations matrix
Appendix A defines all variables. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) <i>DTD</i>	1.000										
(2) <i>ClimateRisk</i>	−0.025 (0.000)***	1.000									
(3) <i>PhysicalRisk</i>	−0.008 (0.261)	0.185 (0.000)***	1.000								
(4) <i>TransitionRisk</i>	−0.031 (0.000)***	0.590 (0.000)***	0.197 (0.000)***	1.000							
(5) <i>Size</i>	0.291 (0.000)***	0.099 (0.000)***	0.035 (0.000)***	0.062 (0.000)***	1.000						
(6) <i>ROA</i>	0.374 (0.000)***	−0.001 (0.888)	0.012 (0.083)*	−0.007 (0.331)	0.301 (0.000)***	1.000					
(7) <i>Lev</i>	−0.053 (0.000)***	0.069 (0.000)***	0.019 (0.008)***	0.093 (0.000)***	0.031 (0.000)***	−0.002 (0.806)	1.000				
(8) <i>MB</i>	0.306 (0.000)***	−0.080 (0.000)***	−0.036 (0.000)***	−0.084 (0.000)***	0.097 (0.000)***	0.236 (0.000)***	−0.066 (0.000)***	1.000			
(9) <i>GSales</i>	−0.004 (0.577)	0.000 (0.977)	−0.001 (0.901)	0.021 (0.003)***	−0.020 (0.006)***	0.055 (0.000)***	−0.033 (0.000)***	0.121 (0.000)***	1.000		
(10) <i>GGDP</i>	0.137 (0.000)***	0.010 (0.159)	0.004 (0.581)	0.009 (0.212)	−0.021 (0.003)***	0.040 (0.000)***	−0.040 (0.000)***	0.017 (0.018)**	0.138 (0.000)***	1.000	
(11) <i>CPI</i>	−0.132 (0.000)***	0.036 (0.000)***	0.004 (0.597)	0.060 (0.000)***	−0.091 (0.000)***	−0.005 (0.459)	−0.030 (0.000)***	−0.027 (0.000)***	0.124 (0.000)***	0.131 (0.000)***	1.000

Table 3 Climate change risk increases firm default riskAppendix A defines all variables. Robust *t*-statistics in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Variables	DTD		
	(1)	(2)	(3)
<i>ClimateRisk</i>	−3.124 (−2.917)***		
<i>PhysicalRisk</i>		−6.473 (−2.133)**	
<i>TransitionRisk</i>			−2.140 (−6.153)***
<i>Size</i>	1.195 (35.288)***	1.192 (35.228)***	1.206 (35.564)***
<i>ROA</i>	5.605 (11.095)***	5.615 (11.111)***	5.541 (10.985)***
<i>Lev</i>	−4.013 (−17.809)***	−4.012 (−17.802)***	−4.019 (−17.852)***
<i>CapEx</i>	2.998 (4.437)***	3.056 (4.521)***	2.742 (4.040)***
<i>MB</i>	0.097 (9.819)***	0.098 (9.829)***	0.097 (9.733)***
<i>GSales</i>	−0.595 (−10.662)***	−0.594 (−10.647)***	−0.592 (−10.642)***
<i>GGDP</i>	15.214 (36.991)***	15.195 (36.964)***	15.285 (37.258)***
<i>CPI</i>	−11.324 (−22.092)***	−11.422 (−22.348)***	−10.906 (−21.082)***
Constant	−4.243 (−15.737)***	−4.234 (−15.702)***	−4.281 (−15.871)***
Obs	19 715	19 715	19 715
Adj. <i>R</i> ²	0.433	0.432	0.433
Firm, Year FE	Yes	Yes	Yes

financial markets price firms' vulnerability to climate change when evaluating their creditworthiness.

The estimated coefficients for the control variables are consistent with the existing literature. All variables are statistically significant at the 1% level. The positive coefficients of firm size and ROA support the prevailing view that larger and more profitable firms face lower default risk. As expected, the negative coefficient of *Leverage* in the DTD model confirms that highly leveraged firms face greater default risk than less leveraged firms. Capital expenditure and the market-to-book ratio show a positive association with DTD.

Importantly, the decline in DTD associated with higher climate risk exposure can be understood through three channels embedded in the structural model of default. First, climate shocks can reduce firm asset values, for example, by lowering the market valuation of carbon-intensive or physically vulnerable assets, which brings the firm closer to its default point (Campiglio *et al.* 2023). Second, heightened climate exposure can increase credit spreads and financing costs, effectively raising the default threshold and compressing the distance to default (Trinh *et al.* 2024). Third, consistent with Xu *et al.* (2024), firms facing transition pressures may pursue riskier investment strategies, which raise asset volatility and further reduce DTD. These mechanisms explain why climate risk exposure systematically translates into higher default probabilities, reinforcing the robustness of our baseline findings.

4.3. The Moderate Effect of Innovation

Table 4 highlights the moderating role of R&D intensity in the relationship between climate risk and default risk. The negative coefficient of *R&D Intensity* with respect to DTD indicates that firms with higher R&D intensity are more likely to default. All coefficients of RD/TA in Columns (1), (2), and (3) are statistically significant at the 1% level. While R&D expenditure is crucial for fostering long-term innovation and maintaining market competitiveness, aggressive investment in R&D, especially by firms in emerging economies, can lead to a heavy debt burden and increased financial pressure, making firms more vulnerable in the short term. Column (1) indicates that the interaction term *ClimateRisk* × *RD/TA* is positive and statistically significant, suggesting that R&D expenditure may mitigate the effect of climate risk on firm default risk. In addition, the positive interaction terms for *PhysicalRisk* × *RD/TA* and *TransitionRisk* × *RD/TA* are 2.078 and 0.290, respectively, and both are statistically significant at the 5% level.

Table 5 presents the moderating role of green innovation in the relationship between climate exposure risk and firm default risk. We focus on the role of R&D expenditure specifically targeted at reducing environmental impact and improving environmental protection. The positive coefficient for green innovation in the DTD model indicates that green innovation is effective in reducing firm default risk. Thus, the interaction terms *ClimateRisk* × *dumENI* in Column (1), *PhysicalRisk* ×

Table 4 The role of R&D expenditure

Appendix A defines all variables. Robust *t*-statistics in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Variables	DTD		
	(1)	(2)	(3)
<i>RD/TA</i>	−0.206 (−4.580)***	−0.183 (−4.234)***	−0.169 (−3.609)***
<i>ClimateRisk</i>	−4.700 (−3.291)***		
<i>ClimateRisk</i> × <i>RD/TA</i>	2.968 (1.673)*		
<i>PhysicalRisk</i>		−5.149 (−2.238)**	
<i>PhysicalRisk</i> × <i>RD/TA</i>		2.078 (2.387)**	
<i>TransitionRisk</i>			−1.912 (−4.492)***
<i>TransitionRisk</i> × <i>RD/TA</i>			0.290 (2.637)***
<i>Size</i>	1.213 (35.835)***	1.210 (35.759)***	1.223 (36.059)***
<i>ROA</i>	5.498 (10.902)***	5.503 (10.905)***	5.435 (10.788)***
<i>Lev</i>	−4.009 (−17.810)***	−4.008 (−17.794)***	−4.014 (−17.831)***
<i>CapEx</i>	2.860 (4.228)***	2.898 (4.282)***	2.588 (3.805)***
<i>MB</i>	0.096 (9.685)***	0.096 (9.701)***	0.095 (9.617)***
<i>GSales</i>	−0.612 (−10.917)***	−0.609 (−10.871)***	−0.607 (−10.842)***
<i>GGDP</i>	15.225 (37.111)***	15.218 (37.109)***	15.313 (37.390)***
<i>CPI</i>	−11.356 (−22.062)***	−11.467 (−22.339)***	−10.967 (−21.090)***
Constant	−4.287 (−15.936)***	−4.284 (−15.923)***	−4.332 (−16.082)***
Obs	19 715	19 715	19 715
Adj. <i>R</i> ²	0.633	0.633	0.633
Firm, Year FE	Yes	Yes	Yes

Table 5 The role of green innovationAppendix A defines all variables. Robust *t*-statistics in parentheses, ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Variables	DTD		
	(1)	(2)	(3)
<i>dumENI</i>	5.591 (3.822)***	7.854 (13.932)***	5.183 (3.505)***
<i>ClimateRisk</i>	−3.079 (−2.754)***		
<i>ClimateRisk</i> × <i>dumENI</i>	10.735 (2.225)**		
<i>PhysicalRisk</i>		−6.855 (−2.080)**	
<i>PhysicalRisk</i> × <i>dumENI</i>		10.548 (2.089)**	
<i>TransitionRisk</i>			−2.394 (−6.492)***
<i>TransitionRisk</i> × <i>dumENI</i>			33.717 (2.823)***
<i>Size</i>	1.207 (35.506)***	0.367 (31.946)***	1.216 (35.724)***
<i>ROA</i>	5.820 (11.510)***	13.149 (37.123)***	5.779 (11.444)***
<i>Lev</i>	−3.976 (−17.681)***	−0.776 (−6.179)***	−3.981 (−17.717)***
<i>CapEx</i>	2.891 (4.282)***	1.136 (2.508)**	2.624 (3.870)***
<i>MB</i>	0.095 (9.640)***	0.182 (23.481)***	0.094 (9.553)***
<i>GSales</i>	−0.594 (−10.662)***	−0.600 (−9.149)***	−0.591 (−10.631)***
<i>GGDP</i>	15.199 (36.965)***	14.928 (29.303)***	15.266 (37.236)***
<i>CPI</i>	−11.357 (−22.164)***	−10.082 (−15.764)***	−10.918 (−21.104)***
Constant	−4.416 (−16.147)***	1.232 (12.689)***	−4.434 (−16.200)***
Obs	19 326	19 714	19 326
Adj. <i>R</i> ²	0.633	0.633	0.634
Firm, Year FE	Yes	Yes	Yes

dumENI in Column (2), and *TransitionRisk* × *dumENI* in Column (3) are all positive and statistically significant.

4.4. Heterogeneity Analysis

In this section, we investigate whether specific firm-, industry-, and country-level characteristics, such as financial constraints, climate sensitivity, and regulatory stringency, mediate the relationship between climate exposure risk and firm default risk. While our firm-level climate risk measures capture time-varying perceptions and discussions of climate-related threats derived from earnings calls, the cross-sectional factors represent structural or contextual characteristics that may amplify or mitigate the transmission of these risks into default probabilities. Thus, they complement rather than duplicate the climate risk indicators.

Table 6 reports results by financial constraints, proxied by the WW index. We find that all climate risk measurement variables are negatively and statistically significantly associated with DTD across Columns (1) to (6) at the 5% level. All results are consistent with our baseline regression findings in Table 3. The regression coefficients of climate risk measures for firms with high financial constraints are approximately twice as large as those for firms with low financial constraints. These findings indicate that firms with higher financial constraints tend to struggle with meeting their financial obligations and experience greater volatility in future cash flows, thereby increasing their susceptibility to default risk.

Table 6 High financial constraint and low financial constraint

Appendix A defines all variables. Robust t-statistics in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

DTD					
Variables	High financial constraint			Low financial constraint	
	(1)	(2)	(3)	(4)	(5)
<i>ClimateRisk</i>	-7.444 (-4.972)***	-18.177 (-4.007)***		-3.368 (-2.149)**	-10.466 (-2.443)**
<i>PhysicalRisk</i>					
<i>TransitionRisk</i>					
<i>Size</i>	0.549 (36.497)***	0.545 (36.380)***	-2.282 (-7.071)***	1.541 (25.953)***	1.539 (25.894)***
<i>ROA</i>	8.673 (24.687)***	8.728 (24.876)***	0.548 (36.549)***	5.854 (5.676)***	5.842 (5.658)***
<i>Lev</i>	-2.075 (-13.958)***	-2.095 (-14.093)***	8.637 (24.624)***	-3.781 (-8.929)***	-3.791 (-8.956)***
<i>CapEx</i>	-6.462 (-11.659)***	-6.508 (-11.743)***	-2.071 (-13.926)***	3.608 (3.016)***	3.650 (3.051)***
<i>MB</i>	0.148 (18.425)***	0.150 (18.634)***	-6.331 (-11.430)***	0.102 (4.681)***	0.102 (4.674)***
<i>GSales</i>	-0.559 (-7.239)***	-0.561 (-7.274)***	0.147 (18.302)***	-0.729 (-7.289)***	-0.727 (-7.247)***
<i>GGrowth</i>	0.151 (23.407)***	0.150 (23.310)***	-0.550 (-7.109)***	0.136 (21.212)***	0.136 (21.170)***
<i>CPI</i>	-0.057 (-9.737)***	-0.058 (-9.860)***	0.152 (23.504)***	-0.032 (-6.216)***	-0.033 (-6.336)***
<i>Constant</i>	0.926 (8.208)***	0.937 (8.307)***	-0.055 (-9.425)***	-8.532 (-16.723)***	-8.521 (-16.700)***
<i>Obs</i>	12 143	12 143	0.944 (8.380)***	7572	7572
<i>Adj. R²</i>	0.325	0.325	12 143	0.364	0.364
<i>Firm, Year FE</i>	Yes	Yes	0.326	Yes	Yes
			Yes		Yes

Table 7 High climate-sensitive and low climate-sensitive

Appendix A defines all variables. Robust *t*-statistics in parentheses, ****p* < 0.01, ***p* < 0.05, **p* < 0.1. Firms belonging to agriculture, forestry, and fishing (SIC 01–09), mining (SIC 10–14), construction (SIC 15–17), and manufacturing (SIC 20–39) are climate-sensitive.

DTD					
Variables	High climate-sensitive			Low climate-sensitive	
	(1)	(2)	(3)	(4)	(5)
<i>ClimateRisk</i>	–12.242 (–8.423)***	–12.219 (–3.146)***		–2.793 (–1.731)*	–8.708 (–1.749)*
<i>PhysicalRisk</i>					
<i>TransitionRisk</i>					
<i>Size</i>	0.514 (32.685)***	0.508 (32.337)***	–3.617 (–11.400)***	1.204 (25.194)***	1.202 (25.111)***
<i>ROA</i>	7.087 (19.014)***	7.156 (19.156)***	0.512 (32.749)***	10.221 (11.447)***	10.224 (11.451)***
<i>Lev</i>	–4.444 (–22.186)***	–4.446 (–22.120)***	–4.419 (–22.183)***	–3.264 (–10.153)***	–3.266 (–10.156)***
<i>CapEx</i>	–5.051 (–8.291)***	–5.125 (–8.390)***	–5.033 (–8.262)***	4.773 (4.358)***	4.787 (4.364)***
<i>MB</i>	0.262 (22.964)***	0.265 (23.112)***	0.259 (22.785)***	0.076 (5.777)***	0.076 (5.780)***
<i>GSales</i>	–0.557 (–7.042)***	–0.557 (–7.035)***	–0.535 (–6.770)***	–0.653 (–7.559)***	–0.652 (–7.542)***
<i>GGrowth</i>	0.143 (19.736)***	0.142 (19.368)***	0.144 (19.916)***	0.144 (23.992)***	0.144 (26.070)***
<i>CPI</i>	–0.045 (–8.259)***	–0.048 (–8.546)***	–0.042 (–7.955)***	–0.046 (–8.124)***	–0.046 (–8.219)***
Constant	1.092 (8.787)***	1.085 (8.709)***	1.146 (9.242)***	–4.917 (–12.800)***	–4.902 (–12.752)***
Obs	8543	8543	8543	11 172	11 172
Adj. <i>R</i> ²	0.414	0.411	0.417	0.324	0.324
Firm, Year FE	Yes	Yes	Yes	Yes	Yes
					Yes

Table 7 examines whether industry-level climate sensitivity mediates the relationship between climate risk and firm default risk. The results show that firms in highly climate-sensitive industries face significantly higher default risk than those in less climate-sensitive industries. For example, the interaction term *Climate risk* $\times$ *High climate-sensitive* in Column (1) has a coefficient of -12.242 , which is substantially lower than the coefficient of *Climate risk* $\times$ *Low climate-sensitive* in Column (4) (-2.793). Notably, *Capital Intensity* is negatively associated with DTD in highly climate-sensitive sectors but shows a positive association with less climate-sensitive industries. These findings suggest that firms operating in climate-sensitive sectors (e.g. agriculture, forestry, fishing, mining, construction, and manufacturing) should prioritize green R&D investment, particularly in renewable energy and circular economy initiatives.

Finally, Table 8 compares firms across regulatory environments using the OECD Environmental Policy Stringency Index. This index, compiled annually by the OECD, reflects the rigor of environmental regulations and enforcement mechanisms across member countries. Importantly, because the index is updated each year, it captures both cross-country differences and within-country changes in regulatory stringency over time. To operationalize this measure, we classify countries into high- and low-stringency groups relative to the annual median EPS value, thereby ensuring that our analysis reflects both structural and dynamic variation in policy environments.

Table 8 compares the strength of the negative relationship between climate risk and default risk across varying levels of regulatory stringency. Firms operating in economies with less stringent environmental regulations exhibit a higher likelihood of default. This implies that such firms may experience weaker institutional enforcement and fewer incentives to adopt environmental practices, resulting in greater financial vulnerability and operational disruptions under climate change uncertainty. For instance, the coefficient of the interaction term *Transition risk* $\times$ *Less Stringent Policies* in Column (6) is -3.332 , which is approximately three times larger than the coefficient in Column (3) for *Transition risk* $\times$ *Highly Stringent Policies* (-1.242). This suggests that weak policy enforcement and limited incentives to adopt environmental practices exacerbate the credit consequences of climate exposure, whereas stringent policy environments may induce earlier adaptation and thereby dampen risk transmission. Notably, the policy index reflects country-level regulatory context rather than disclosure intensity, ensuring that it captures an institutional dimension distinct from the firm-specific risk measures.

4.5. Endogeneity Test

We employ a two-stage least squares regression to address potential endogeneity issues. We construct two instrumental variables: *Urban*, which denotes the percentage of the population living in urban areas, and *Forest*, which represents the percentage of total land area under forest cover. Table 9 shows that, in the first-stage regression, the instrumental variable *Urban* is significantly and positively associated

Table 8 Highly stringent policies vs. less stringent policiesAppendix A defines all variables. Robust *t*-statistics in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Variables	DTD					
	Highly stringent policies			Less stringent policies		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>ClimateRisk</i>	-2.385 (-1.628)	-2.824 (-0.644)		-5.211 (-3.361)***	-7.145 (-2.499)**	-3.332 (-6.395)***
<i>PhysicalRisk</i>						
<i>TransitionRisk</i>						
<i>Size</i>	1.321 (27.129)***	0.304 (18.958)***	-1.242 (-3.894)***	1.096 (23.075)***	1.092 (22.961)***	1.109 (23.360)***
<i>ROA</i>	7.666 (9.428)***	12.105 (25.316)***	0.305 (19.059)***	3.815 (5.834)***	3.822 (5.834)***	3.745 (5.748)***
<i>Lev</i>	-3.553 (-11.364)***	-1.115 (-6.065)***	12.095 (25.354)***	-4.434 (-13.653)***	-4.446 (-13.684)***	-4.44 (-13.717)***
<i>CapEx</i>	4.701 (3.909)***	2.352 (2.956)***	-1.109 (-6.036)***	2.392 (2.934)***	2.463 (3.014)***	2.131 (2.606)***
<i>MB</i>	0.079 (6.490)***	0.211*** (21.412)	0.210*** (21.248)	0.121*** (7.297)	0.121 (7.304)***	0.119 (7.220)*
<i>GSales</i>	-0.741 (-8.696)***	-0.505 (-4.897)***	-0.501 (-4.852)***	-0.443 (-5.754)***	-0.441 (-5.723)***	-0.439 (-5.722)***
<i>GGrowth</i>	0.134 (26.337)***	0.133 (20.009)***	0.133*** (20.102)***	0.156 (22.930)***	0.156 (22.851)***	0.157 (23.216)***
<i>CPI</i>	-0.064 (-13.252)***	-0.052 (-8.312)***	-0.050 (-7.941)***	-0.043 (-8.299)***	-0.044 (-8.448)***	-0.041 (-8.103)***
Constant	-5.865 (-14.616)***	1.632 (12.491)***	1.647 (12.640)***	-3.293 (-9.032)***	-3.278 (-8.987)***	-3.313 (-9.081)***
Obs	9709	9709	9709	10 006	10 006	10 006
Adj. <i>R</i> ²	0.328	0.310	0.311	0.328	0.328	0.329
Firm, Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9 Two-stage least squares regression

Appendix A defines all variables. Robust *t*-statistics in parentheses, ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Variables	ClimateRisk			TransitionRisk			DTD		
	First stage						Second stage		
	(1)	(2)	(3)	(4)	(5)	(6)			
<i>Urban</i>	5.679 (6.503)***	0.435 (1.791)*	6.151 (16.559)***						
<i>Forest</i>	−0.493 (−4.908)***	0.049 (3.547)***	−0.346 (−12.125)***						
<i>ClimateRisk</i>									
<i>PhysicalRisk</i>									
<i>TransitionRisk</i>									
<i>Size</i>	0.104 (14.856)***	0.012 (5.383)***	0.033 (5.390)***	0.835 (5.467)***	1.189 (19.150)***	−2.547 (−13.725)***			
<i>ROA</i>	−0.663 (−3.892)***	−0.014 (−0.245)	−0.086 (−0.972)	8.295 (5.348)***	5.936 (6.241)***	1.358 (39.145)***			
<i>Lev</i>	0.550 (7.825)***	0.038 (1.686)*	−0.008 (−0.211)	2.234 (2.351)**	−4.334 (−11.124)***	4.594 (8.813)***			
<i>CapEx</i>	2.987 (10.160)***	0.617 (6.300)***	−1.106 (−6.364)***	17.149 (3.590)***	3.637 (2.835)***	−4.091 (−18.743)***			
<i>MB</i>	−0.039 (−14.560)***	−0.007 (−6.699)***	−0.001 (−1.073)	−0.005 (−0.082)	0.119 (7.366)***	−0.653 (−0.838)			
<i>GSales</i>	0.035 (0.896)	0.005 (0.467)	0.025 (2.378)**	−0.373 (−1.762)*	0.119 (7.366)***	0.086 (9.770)***			
<i>GGrowth</i>	0.007 (1.756)*	0.001 (0.637)	0.005 (5.011)***	0.165 (7.756)***	−0.540 (−5.065)***	−0.555 (−9.395)***			
<i>CPI</i>	0.012 (3.413)***	0.002 (1.868)*	0.005 (5.375)***	0.004 (0.155)	0.135 (13.754)***	0.159 (30.775)***			
Constant	−4.893 (−6.702)***	−0.369 (−1.814)*	−4.875 (−16.563)***	−0.156 (−0.257)	−0.067 (−7.752)***	−0.022 (−5.383)***			
Obs	19 715	19 715	19 715	19 715	19 715	19 715			
Adj. <i>R</i> ²	0.435	0.307	0.722	0.486	0.421	0.463			
1st stage <i>F</i> -stat.	73.986	49.770	23.272						
Sagan overidentification				1.473 (0.225)	2.398 (0.122)	1.380 (0.240)			
Kleibergen–Paap rk LM				146.640 (0.000)	99.094 (0.000)	46.612 (0.000)			

with all three climate risk measures, indicating its relevance. While *Forest* is significantly negatively associated with *Climate risk* and *Transition risk*, it is significantly positively associated with *Physical risk*. Forests play a key role in supporting ecosystems and biodiversity, helping to mitigate climate-related risks. However, they are also interlinked with climate change, which increases companies' exposure to operational risks and infrastructure disruptions. In the second-stage least squares regression, the coefficients for *Climate risk*, *Physical risk*, and *Transition risk* in Columns (1), (2), and (3) are all negative and statistically significant at the 5% level. Thus, the results from the two-stage least squares regression reinforce the baseline findings.

5. Conclusion

This study presents evidence of a relationship between climate exposure risk and firm default risk by analyzing a large international dataset covering 38 OECD economies from 2002 to 2023. The results indicate that firms with higher levels of climate exposure risk are more likely to face greater default risk. We further examine whether innovation moderates this relationship and find that R&D spending and green innovation can help reduce default risk. However, firms should prioritize the efficiency of their innovation investments rather than increasing R&D expenditure. Excessive R&D intensity may lead to short-term financial burdens and increased financing costs, thereby increasing the likelihood of default.

We also account for firm-level characteristics, such as financial constraints and climate sensitivity, as well as country-level characteristics, including the stringency of environmental regulations. Our study reveals that financial markets have increasingly integrated climate risk exposure into credit assessments and investment decisions.

These findings have several practical implications for managers, investors, and policymakers. First, firms should adjust financial strategies to reduce the impact of climate risk exposure on a firm's default risk, for example, by reducing leverage to prevent financial distress. Additionally, companies should implement appropriate environmental strategies before launching new investments.

Second, we show that the negative effects of climate risk exposure vary by industry and country characteristics. Investors should scrutinize their investment decisions in climate-sensitive sectors and countries with weak environmental policy enforcement, as firms in these contexts tend to have higher levels of default risks.

Third, our findings provide policymakers and corporate managers with valuable insights into how climate risk influences default risk. These insights can help identify key factors that drive investment attractiveness and competitiveness, such as promoting regulatory transparency, reducing information asymmetry, and ensuring compliance with Scope 1, Scope 2, and Scope 3 emissions standards.

The lack of Scope 3 emissions data—critical for understanding a firm's upstream and downstream value chains—limits the completeness of transition risk assessment. Existing climate risk metrics often focus on backward-looking indicators (such as historical carbon emissions) or forward-looking estimates (such as uncertainties related to the transition to a low-carbon economy). Future research could develop a new proxy that integrates both perspectives to provide a more comprehensive view of a firm's overall climate risk exposure.

In addition, future studies could expand innovation metrics by including the number of patents, the green patent ratio, and the total economic value of pollution prevention patents to gain a holistic view of “going green” efforts.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix A

Variable measurement

Variables	Measurement
<i>CapEx</i>	Capital expenditures / Total assets
<i>ClimateRisk</i>	Firm-level climate risk exposure overall, Sautner <i>et al.</i> (2023)
<i>CPI</i>	Consumer price index (Inflation rate, annual %)
<i>DTD</i>	Distance to default—NUS Credit Research Initiative http://d.nuscri.org
<i>dumENI</i>	Dummy = 1 if firm environmental innovation scores higher than the median
<i>Forest</i>	Forest area (% of total land area)
<i>GDP</i>	GDP growth rate (Country-level annual % change)
<i>GSales</i>	Growth in sales (Year-over-Year % change)
<i>Lev</i>	Leverage (Total debt / Total assets)
<i>MB</i>	Market-to-book ratio (Market capitalization / Book value of equity)
<i>PhysicalRisk</i>	Firm-level climate risk exposure that captures physical shocks related to climate change, Sautner <i>et al.</i> (2023)
<i>RD/TA</i>	R&D intensity (R&D expenditure / Total assets)
<i>ROA</i>	Return on assets (Net income / Total assets)
<i>Size</i>	Natural logarithms of total assets
<i>TransitionRisk</i>	Firm-level climate risk exposure that captures regulatory shocks related to climate change, Sautner <i>et al.</i> (2023)
<i>Urban</i>	Urbanization rate (% of population living in urban areas)