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Climate Vulnerability and Firms' Default Risk: The Moderating Role of Country-Level Corruption

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Abstract

This paper examines the relationship between a country's climate vulnerability and corporate default risk, utilizing a sample of 2,483 firms across 33 European countries. We find that higher country-level climate vulnerability (as measured by the ND-Gain index) is associated with an increased corporate default risk, as measured by the z-score. In addition, we identify that country-level corruption exacerbates the negative impact of climate vulnerability on corporate financial stability. Even firms with strong financial positions face heightened default risks, highlighting the pervasive threat of climate change. Corruption exacerbates this risk by undermining environmental governance, distorting resource allocation, and weakening climate adaptation strategies. Our results remain robust when considering alternative measures of climate vulnerability and default risk, varying model specifications, and addressing endogeneity using instrumental variables. This study emphasizes the critical interplay between climate vulnerability, governance, and corporate resilience, offering insights for policymakers and practitioners alike.

JEL CLASSIFICATION: G30, G34, D73

Keywords
climate vulnerability, default risk, corruption, Europe

Introduction

Climate vulnerability refers to a nation's susceptibility to the adverse impacts of climate change, encompassing both direct physical effects and indirect economic consequences (Abbass et al., 2022). It is widely observed that climate vulnerability significantly impacts a country's economy through diverse and interconnected channels. Physical damages from extreme weather events, such as floods, wildfires, and storms, disrupt infrastructure and energy systems, resulting in significant repair and replacement costs (Sanstad et al., 2020). In agriculture, rising temperatures, water scarcity, and the spread of pests lead to declining crop yields and food insecurity, particularly in regions like Southern Europe (Wing et al., 2021). Macroeconomic consequences include reduced Gross Domestic Product (GDP)

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growth, disruptions to trade, and increased public expenditure for disaster recovery and adaptation projects, with incremental annual costs in the European Union.[1] Climate risks also strain the financial sector, with heightened insurance payouts, limited coverage, and increased borrowing costs due to reduced creditworthiness (Chalabi-Jabado & Ziane, 2024). Social and health impacts include declining labor productivity due to heat stress and escalating health care expenses linked to extreme weather and pollution (Knittel et al., 2020). Although this is not an exhaustive list of the challenging effects of a country's climate vulnerability on its economy, they reveal the need for comprehensive climate adaptation and mitigation strategies to enhance resilience and reduce long-term economic losses.

In this sense, country-level climate vulnerability and its effect on diverse firm-level decisions is gaining increasing attention among scholars. On the one hand, firms operating in countries with higher climate risks face heightened challenges in maintaining profitability and accessing capital markets. For instance, Huang et al. (2018) find that firms in highly climate-vulnerable countries tend to report lower financial performance due to disruptions caused by extreme weather events, supply chain breakdowns, and increased operational costs. This creates uncertainty in cash flow projections, reducing the attractiveness of these firms to investors. On the other hand, firms exposed to higher climate risks face more stringent loan terms, including higher interest rates, increased collateral requirements, and additional covenant constraints. These adverse financing conditions are attributed to the heightened default probabilities and deteriorating financial performance associated with climate-related disruptions (Huang et al., 2022). Similarly, Kling et al. (2021) reveal that firms in countries with elevated climate vulnerability incur higher costs of debt and encounter restricted access to finance. Their analysis shows that climate vulnerability directly increases the cost of debt by approximately 0.63% and indirectly contributes an additional 0.05% through its impact on financial leverage. This indicates that lenders perceive heightened risks in climate-vulnerable regions, leading to more expensive and limited financing options for firms operating there.

Furthermore, these vulnerabilities influence corporate decision-making concerning risk management strategies (Huang et al., 2022; Kythreotis et al., 2024). Companies often need to divert resources toward mitigating climate-related risks, including investing in resilient infrastructure or diversifying supply chains, which may further constrain their ability to pursue growth opportunities (Addoum et al., 2023; Bolton & Kacperczyk, 2021). Moreover, climate vulnerability increases credit risk, as firms in affected regions are more likely to default on obligations due to revenue losses or increased operating costs (Capasso et al., 2020; Sautner et al., 2023). In this sense, further studying the relationship between climate vulnerability and firms' default risk becomes substantially relevant for understanding financial stability, improving risk management, and integrating climate risks into credit rating models. Addressing this issue is particularly pertinent in Europe due to the region's significant exposure to climate-related financial risks. The European Central Bank (ECB) highlights that approximately 80% of loan exposures are to firms with some level of physical risk, with around 30% of Euro area banking system credit exposures directed toward firms subject to high or increasing physical risk drivers, such as floods, heat stress, or water stress (Alogoskoufis et al., 2021). Moreover, the European Commission's report on monitoring climate-related risks to financial stability in 2024 accentuates that climate change can adversely affect all economic actors, including banks and non-financial companies, thereby posing systemic risks to the financial system.[2]

Yet, a country's institutional dimensions' role in worsening (or moderating) the above-discussed relationship between climate vulnerability and corporate default risk should be also analyzed. In this sense, we focus on country corruption, defined as "the sale by government officials of government property for personal gain" because of its significant expense to economic progress and business expansion (Shleifer & Vishny, 1993). The literature has widely demonstrated that country-level corruption significantly impacts corporate default risk through various mechanisms. First, corruption undermines governance by enabling managerial opportunism and poor oversight, leading to inefficiencies and increasing default risk (Wu, 2005). Besides, firms in corrupt environments face elevated borrowing costs and constrained access to bond markets, exacerbating financial strain (Akron et al., 2024; Alonso et al., 2024). In addition, companies in corrupt countries often reduce cash holdings to avoid expropriation and bribery risks, limiting their ability to weather financial shocks (Elvira-Lorilla et al., 2024). Finally, corruption contributes to heightened stock price volatility, reflecting increased uncertainty and financial instability (Kyriacou et al., 2024). Regarding the relationship between country-level corruption and climate vulnerability, corruption weakens environmental regulations and enforcement mechanisms, exacerbating climate vulnerability (Hwang et al., 2024). Also, corruption in climate finance often results in the diversion of resources meant for mitigation and adaptation projects, diminishing their effectiveness (Aja-Eke et al., 2025). Similarly, corruption undermines the integrity of institutions responsible for climate governance, making it harder to enforce climate policies (Chan et al., 2023). However, to the best of our knowledge, the literature has not yet analyzed the relationship between corporate default risk, climate vulnerability, and country-level corruption. In Europe, where climate change policies and corporate governance are becoming gradually important, studying these factors together is essential for policy development, financial decision-making, and addressing regional challenges.

Accordingly, using a large sample of 2,483 firms in 33 European countries, we document that higher levels of a country's climate vulnerability —captured mainly by the ND-GAIN Index, which reflects a country's exposure and sensitivity to climate risks as well as its adaptive capacity— (Chen et al., 2024) increase corporate default risk, measured through the z-score. The z-score shows how far a firm's performance (profitability and financial strength) is from a level that would put it at risk of collapse. The results are robust when we use alternative definitions of climate vulnerability and default risk, different model specifications, and address endogeneity issues, namely using instrumental variables (IVs; in our case, the length of a country's coastline and population). Furthermore, our findings reveal that country-level corruption intensifies the negative impact of climate vulnerability on corporate financial stability. Notably, even financially stable firms face heightened default risk, underscoring the widespread threat of climate change. Corruption further amplifies this risk by undermining environmental governance, distorting resource allocation, and weakening climate adaptation efforts.

Our paper has several contributions. First, we contribute to the growing body of literature on climate finance by highlighting the direct link between climate vulnerability and financial stability, offering valuable insights for policymakers and financial institutions. Furthermore, we show that climate vulnerability is a distinct and economically significant predictor of firm-level default risk, offering explanatory power beyond traditional macroeconomic and institutional determinants. Second, the study uniquely examines the moderating effect of country-level corruption on the relationship between climate vulnerability and corporate default risk. This issue is particularly relevant for understanding how institutional factors can amplify or mitigate the financial risks associated with climate change, providing a nuanced perspective on the interplay between governance and climate vulnerability. Third, unlike many prior studies focusing on global samples or developed economies, this research explicitly investigates climate vulnerability's impact on corporate default risk within the European context. This regional focus addresses a gap in the literature by exploring how climate risks affect firms in a region characterized by significant exposure to climate-related financial risks. Fourth, the study reveals that the negative impact of climate vulnerability on default risk is more pronounced for firms with low default probabilities, while firms with moderate to high default risks are less affected. This asymmetric effect suggests that stable firms are more sensitive to climate-related risks, which can alter their risk profiles and investor perceptions.

The organization of this paper is as follows: In Section 2, the relevant literature on climate vulnerability, default risk, and corruption is reviewed, setting the stage for the development of the research hypotheses. Section 3 outlines the methodology used for testing the hypotheses and provides details about the dataset. Section 4 presents the results of the empirical analysis along with additional supplementary analyses. The paper concludes in Section 5, highlighting the main conclusions drawn from the study.

Literature Review and Hypotheses Development

Climate Vulnerability and Firms' Default Risk

Firms' default risk, namely the probability that a company cannot meet its debt obligations (Merton, 1974), has been widely studied in financial literature. Internal factors such as financial ratios (Abinzano et al., 2022; Chen et al., 2011; Gallucci et al., 2023; Nguyen et al., 2022) and corporate governance (Ali et al., 2018; Ballester et al., 2020; Gallucci et al., 2023; Switzer et al., 2018) play noteworthy roles. However, external determinants also significantly shape a firm's likelihood of default.

Macroeconomic downturns, characterized by declining GDP, rising unemployment rates, and reduced consumer spending, can harmfully affect a firm's revenue streams, thereby increasing the likelihood of default (Gopalakrishnan & Mohapatra, 2020; Tang & Yan, 2010). Similarly, suppose a firm's costs increase faster than its revenues due to inflation. In that case, profit margins may shrink, enhancing default risk (Bhamra et al., 2023), while rising interest rates increase borrowing costs, which can strain a firm's cash flows and elevate the probability of default (Angbazo, 1997; Johri et al., 2022). Furthermore, a strand of the literature focuses on the adverse effect of economic policy uncertainty on firms' default risk (Lu et al., 2023; Nguyen et al., 2022). Besides, conditions in financial markets, including liquidity and investor sentiment, significantly affect a firm's access to capital and refinancing abilities. During tight liquidity or bearish investor sentiment periods, firms may face challenges in raising funds or rolling over existing debt (Kumari, 2019; Lee et al., 1991), thereby increasing default risk. The credit rationing theory (Jaffee & Modigliani, 1969) posits that in such conditions, even creditworthy firms may be denied financing due to market-wide constraints, leading to potential defaults (Haas & Kempa, 2023; Kallandranis et al., 2023). The regulatory framework within which a firm operates can either mitigate or exacerbate default risk. Stringent regulations may increase operational costs and constrain strategic flexibility (Darnall, 2009), thereby impacting profitability and increasing default risk (Hoque et al., 2015). Conversely, regulations that enforce transparency and corporate governance can reduce information asymmetry between firms and investors, potentially lowering the cost of capital and default risk (Cormier et al., 2010).

Yet, companies are increasingly concerned about the adverse effects of climate-related risks. In a recent study, Kling et al. (2021) analyze the effects of climate vulnerability on firms' cost of capital and access to finance, focusing on a large sample of developing economies from 1999 to 2017. They find that climate vulnerability raises the cost of debt both directly and indirectly through restricted financial access. However, its impact on the cost of equity is limited. Specifically, firms in high climate-risk countries face financial constraints and higher costs of debt, contributing to slower economic development and reduced public investment in adaptation measures. The authors identify a "vicious cycle" where increased climate vulnerability raises costs, hinders growth, and reduces fiscal capacity for climate adaptation. Country-level climate risk affects firm default risk through different channels. According to the trade-off theory of capital structure (Kraus & Litzenberger, 1973), climate-related physical and transition risks[3] increase expected bankruptcy costs, potentially altering firms' optimal debt levels and raising default probabilities. The agency cost framework (Jensen & Meckling, 1976) suggests climate uncertainty may exacerbate conflicts between shareholders and debtholders, particularly regarding risk-shifting behaviors in climate-vulnerable firms. Similarly, the sustainable finance theory (Pedersen et al., 2021) posits that climate risk represents a priced factor in asset returns, increasing firms' cost of capital and financial distress risk as investors demand higher compensation for climate-exposed assets. From a managerial perspective, the institutional theory (DiMaggio & Powell, 1983) explains that climate-related regulations and norms create isomorphic pressures that force firms to make potentially costly adaptations (Chen et al., 2025). A relevant example are the regulatory disclosure frameworks like the Task Force on Climate-related Financial Disclosures (TCFD) and the emerging International Sustainability Standards Board (ISSB) (through IFRS S2), which seek to systematize how firms assess, disclose, and thereby build resilience to these risks. A study focused on Italian and Spanish firms shows that compliance with TCFD leads to more thorough disclosures on governance and risk assessment, aiding investors' understanding of resilience capabilities (Xhindole et al., 2025). Similarly, the resilience theory (Williams et al., 2017) suggests that firms in climate-vulnerable regions face greater default risk due to their limited capacity to absorb, adapt, and transform in response to climate shocks. The relationship between climate vulnerability and firms' default risk is particularly relevant for European firms due to the region's unique combination of climate-related challenges and regulatory pressures. Thus, it is hypothesized that higher levels of national climate vulnerability are positively correlated with increased default risk among firms:

> **H1:** A higher country-level climate vulnerability increases firm-level default risk.

The Role of Country-Level Corruption

As previously discussed, the institutional theory (DiMaggio & Powell, 1983; North, 1990) suggests that organizational behavior is shaped by institutional pressures arising from regulatory, normative, and cultural-cognitive environments (Aguilera et al., 2021; Husted & De Jesus Salazar, 2006). One critical dimension of institutional quality is corruption, which undermines the effectiveness of climate policies, distorts market incentives, and weakens governance structures that are essential for mitigating climate-related risks (Wang & Njangang, 2025). The body of research examining the impacts of corruption at both microeconomic and macroeconomic levels is extensive, with the foundational work of Shleifer and Vishny (1993) serving as a key starting point. At the national level, corruption is commonly described as the "pervasive abuse of public power for private gain, which, ultimately, may be negatively associated with infrastructure development and capital accumulation" (García-Gómez et al., 2024, p. 413). Within the realm of finance, the prevailing view adheres to institutional theory, which posits that corruption impedes firm growth (Amin & Motta, 2023; Fisman & Svensson, 2007; Garrido et al., 2014; Mendoza et al., 2015) and curtails activities that drive economic development, such as innovation (Paunov, 2016; Xu et al., 2017). The underlying argument is that corruption adversely affects firm-level outcomes by exacerbating information asymmetries and transaction costs (Akron et al., 2024), diverting resources to rent-seeking behavior, creating uncertainty about investment returns, increasing the risk of expropriation, and diminishing the quality of public services (Amin & Motta, 2023).

Regarding firms' default risk, corruption at the country level alters the institutional framework within which firms operate (La Porta et al., 1997, 1998), impacting their financial stability in nuanced ways. The "sanding the wheels" hypothesis posits that corruption exacerbates inefficiencies in economic systems. High levels of corruption increase transaction costs, reduce transparency, and encourage rent-seeking behaviors (Mauro, 1995), which may make firms more likely to default on their financial obligations (Fisman & Svensson, 2007). First, operational costs increase since bribes and unofficial payments inflate costs, reducing profitability and liquidity (Shleifer & Vishny, 1993; Zeume, 2017). Second, corruption leads to inefficient allocation of capital, often favoring less productive but well-connected firms, which heightens systemic financial vulnerabilities (Kaufmann & Wei, 1999; Kurer, 1993). Third, corrupt environments generally exhibit weaker enforcement of contracts and property rights, raising credit risk (La Porta et al., 1998). Conversely, the "greasing the wheels" hypothesis suggests that corruption can facilitate economic transactions in rigid regulatory environments (Kong et al., 2017). By enabling firms to bypass cumbersome regulations, corruption can enhance operational efficiency and reduce default risk in the short term (Feng et al., 2023). In some developing economies, bribes serve as informal mechanisms to expedite approvals or secure strategic resources, thus providing firms with a competitive edge (Akron et al., 2024). However, these benefits are often transient and context-dependent. Studies have shown that while firms may benefit from reduced bureaucratic delays in the short-term, long-term reliance on corruption undermines institutional quality and increases systemic risks (Méon & Sekkat, 2005), which is the case for the European setting (Akron et al., 2024; García-Gómez et al., 2024).

According to the institutional theory (DiMaggio & Powell, 1983; North, 1990), robust institutions are essential for effective environmental governance (Dubash, 2021). Corrupt practices undermine the effectiveness of climate policies, distorts market incentives, and weakens governance structures that are essential for mitigating climate-related risks. In high-corruption environments, regulatory enforcement is often arbitrary, and public resources allocated for climate adaptation or infrastructure may be misused or misallocated. Corruption has been shown to intensify the severity and frequency of climate-related disasters, particularly in developing contexts where institutional safeguards are weak. Higher corruption is associated with larger climate shocks, thereby exacerbating the vulnerability of local firms (Zhou et al., 2024). This reduces the capacity of states to provide firms with the institutional support necessary to cope with physical or transition climate risks (Aja-Eke et al., 2025). For instance, in a study examining the impact of corruption on environmental quality in the Commonwealth of Independent States, Hwang et al. (2024) find that corruption directly increases CO_2 emissions by obstructing economic growth and indirectly by weakening environmental regulations. Besides, corruption diverts resources from public investments in infrastructure and services that enhance climate resilience, thereby increasing vulnerability to climate-related disasters. In this sense, countries with higher government quality and lower corruption levels are better equipped to prevent and mitigate the impacts of natural disasters (Tol, 2022).

Recent research finds that strong national governance, including anti-corruption enforcement, helps mitigate the adverse impact of climate risk on financial systems—and by extension, firms' access to credit and cash flows (Liu et al., 2024). Furthermore, firms in more climate-vulnerable countries suffer constrained access to debt finance, higher borrowing costs, and reduced profitability—even after controlling for firm- and sector-level characteristics (Cevik & Miryugin, 2022). When these countries also score poorly on corruption indices, the impact on firm solvency is magnified. In addition, firm-level studies —such as those examining carbon emissions and default risk—demonstrate that poor environmental performance increases default likelihood via cash flow volatility, but the effect is strongest where institutional oversight is weak and enforcement lax (Kabir et al., 2021).

In sum, country-level corruption may exacerbate the impact of climate vulnerability on firms' default risk through several mechanisms. First, corruption leads to lax enforcement of environmental laws, allowing firms to engage in environmentally harmful practices. This not only increases environmental degradation but also exposes firms to future liabilities and operational risks associated with environmental damage (Povitkina, 2018). Second, corruption distorts the allocation of resources, leading to inefficient investments and mismanagement (Aja-Eke et al., 2025). Thus, firms operating in corrupt environments are more likely to face higher compliance costs and regulatory uncertainty, further exacerbating financial distress (Shleifer & Vishny, 1993). Third, corrupt agents may prioritize personal gains over investments in critical infrastructure in the context of climate vulnerability, leaving firms more vulnerable to climate-related shocks (Mauro, 1995). Fourth, in corrupt environments, firms may underestimate the benefits of proactive climate adaptation measures due to anticipated inefficiencies in public policy implementation (Grover & Kahn, 2024). This myopic behavior may increase their exposure to climate-induced default risk.

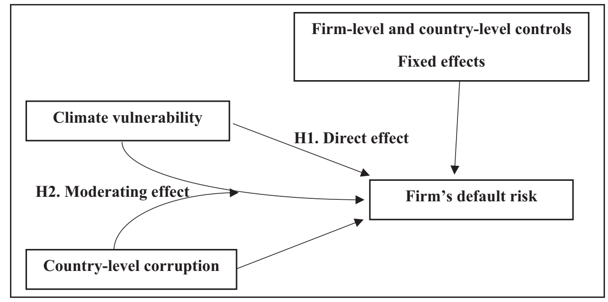

Figure 1. The moderation effect of corruption on climate vulnerability's impact on default risk.

Accordingly, our second hypothesis is defined as follows:

H2: Country-level corruption and climate vulnerability interaction effect increases firm-level default risk.

The proposed hypotheses are reflected in Figure 1.

Research Design

Sample Selection

The data selection process is as follows. First, we selected all European countries (including Russia and Turkey). To build our sample, listed companies from all the TRBC industries (not including financials) were primarily selected for 2010-2022. After removing those companies with missing values for the key variables used in the empirical analysis, our final dataset consists of 2,483 unique firms, which results in an unbalanced panel of 28,585 firm-year observations.

Table 1—Panel A displays the distribution of our sample based on countries, together with the average values

Table 1. Distribution of the Sample across Countries and Industries.

Panel A

Country	No of obs.	No of firms	%	Average GDP per capita (in €)	Average climate vulnerability index	Average corruption perception index	Average control of corruption index
Austria	434	34	1.4	49,087.04	0.30	25.29	−1.48
Belgium	613	50	2.0	46,149.31	0.34	25.43	−1.49
Bulgaria	17	2	0.1	9,054.59	0.35	59.21	0.25
Cyprus	97	10	0.4	29,310.07	0.36	40.29	−0.80
Czech Rep.	39	4	0.2	21,939.92	0.26	47.57	−0.48
Denmark	787	64	2.6	60,379.94	0.34	9.79	−2.29
Finland	872	74	3.0	48,202.78	0.30	11.57	−2.19
France	2,281	180	7.2	40,803.68	0.30	30.00	−1.32
Germany	3,234	267	10.7	46,407.09	0.30	20.21	−1.80
Greece	376	28	1.1	21,393.55	0.34	56.57	0.05
Hungary	76	7	0.3	14,982.05	0.36	52.14	−0.15
Iceland	101	10	0.4	58,271.96	0.35	21.07	−1.83
Ireland	557	49	2.0	69,420.39	0.32	25.57	−1.60
Italy	1,291	122	4.9	34,725.98	0.34	52.86	−0.24
Liechtenstein	28	2	0.1	166,001.85		100.00	−1.87
Lithuania	1	1	0.0	17,040.10	0.37	43.21	−0.54
Luxembourg	332	34	1.4	115,951.27	0.31	18.50	−2.03
Malta	56	16	0.6	28,327.98	0.33	45.07	−0.64
Monaco	26	2	0.1	184,283.19			−1.58
Netherlands	708	65	2.6	52,719.44	0.34	16.21	−1.96
Norway	754	67	2.7	87,488.86	0.27	14.43	−2.13
Poland	474	36	1.4	14,513.47	0,31	42.36	−0.61
Portugal	179	13	0.5	22,321.04	0,33	38.07	−0.88
Romania	71	8	0.3	10,942.78	0,42	56.50	0.21
Russia	468	36	1.4	12,025.30	0,33	72.86	0.97
Slovakia	28	2	0.1	18,533.00	0,35	50.29	−0.19
Slovenia	35	3	0.1	24,469.15	0,32	41.50	−0.82
Spain	849	71	2.8	29,426.30	0,29	39.71	−0.80
Sweden	3,190	305	12.2	54,943.44	0,33	12.50	−2.15
Switzerland	2,270	189	7.6	85,139.45	0,27	14.29	−2.03
Turkey	1,357	116	4.7	10,567.82	0,36	57.79	0.16
Ukraine	14	1	0.0	3,332.93	0,36	72.00	0.94
United Kingdom	6,970	625	25.1	42,849.54	0,28	22.29	−1.71
Total	28,585	2,483	100.0				

Panel B

TRBC sector	No of observations	No of firms	%
Academic and educational services	36	3	0.13
Basic materials	2,732	220	9.56
Consumer cyclicals	4,347	386	15.21
Consumer non-cyclicals	1,956	161	6.84
Energy	4,849	404	16.96
Healthcare	2,457	230	8.60
Industrials	5,627	480	19.69
Real estate	1,680	151	5.88
Technology	3,883	360	13.58
Utilities	1,018	88	3.56
Total	28,585	2,483	100.0

Note. This table presents the country and industry breakdowns of the sample, consisting of 28,585 firm-year observations from 2010 to 2022. The industry breakdown is established based on the Thomson Reuters Business Classification (TRBC), excluding financial firms.

for GDP per capita, climate vulnerability, control of corruption, and the corruption perception index. The biggest portion of our sample belongs to the United Kingdom (25.1%), followed by Sweden (12.2%) and Germany (10.7%). On the other hand, in Panel B, we display the sample breakdown by sector using the Thomson Reuters Business Classification (TRBC), where companies in the Industrials industry represent 19.69% of the sample, which is slightly balanced across industries.

We construct our sample employing several sources. On one hand, all firm-level financial data, including default risk proxies, is extracted from Refinitiv Eikon. On the other hand, the relevant independent variables measuring a country's climate vulnerability are obtained from the ND-Gain Index, the World Bank dataset, and the Yale Center for Environmental Law and Policy. Finally, the corruption and macroeconomic country-level control variables are obtained from the World Bank database, the Heritage Foundation, and Transparency International.

Variables

Dependent Variable: Firms' Default Risk. The primary objective of our study is to investigate whether and how a country's climate vulnerability impacts firm-level corporate default risk. Hence, our first relevant dependent variable is the Z-score. The Z-score is a widely used metric for assessing the stability and risk of firms, especially in the context of financial distress or insolvency (Bao & Cardoza, 2023; Laeven & Levine, 2009; Li et al., 2017). Specifically, it combines how profitable a firm is, how much of a financial cushion it has (equity), and how stable its profits are over time. It is calculated as follows:

$$Zscore = \frac{ROA + CAR}{\sigma ROA} \tag{1}$$

where ROA stands for the return on assets (average profitability of the firm), CAR is the capital-to-asset ratio (equity buffer against losses), and σROA is the standard deviation of ROA over time (volatility of returns). A higher Z-score indicates low insolvency risk; the firm has a strong buffer against losses due to higher profitability or equity. A lower Z-score often correlates with higher default risk as firms operate closer to their solvency threshold (Laeven & Levine, 2009). Our baseline estimations are calculated using a 3-year period for calculating ROA deviation (Zscore3), but in the robustness analysis, we also calculate 5 years for the ROA deviation (Zscore5).

Alternatively, we use the Altman Z-score, a financial metric developed by Edward I. Altman in 1968, which remains a widely used tool in academic research to proxy firms' default risk (Altman, 2018). It combines five financial ratios, each weighted to produce a single score:

$$\begin{aligned} Altman\, Z_i = {} & 1.2 * \frac{working\ capital}{total\ assets} + 1.4 * \frac{retained\ earnings}{total\ assets} + 3.3 * \frac{EBIT}{total\ assets} \\ & + 0.6 * \frac{market\ value\ of\ equity}{total\ liabilities} + 1.0 * \frac{sales}{total\ assets} \end{aligned} \tag{2}$$

The resulting Z-score categorizes companies into three zones, namely low risk of bankruptcy ($Z > 2.99$), moderate risk ($1.81 < Z < 2.99$), and high risk ($Z < 1.81$).

Independent Variables: Climate Vulnerability. Our primary proxy for a country's climate risk exposure is the vulnerability dimension of the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index (Chen et al., 2024), which is widely used by the literature (Alam et al., 2024; Er et al., 2024; Lee et al., 2022; Shear et al., 2023). The ND-Gain index assesses a country's vulnerability to climate change alongside its readiness to enhance resilience. Vulnerability evaluates a country's susceptibility to climate-related disruptions across six critical sectors: food, water, health, ecosystem services, human habitat, and infrastructure. It ranges from 0 (less vulnerable) to 100 (more vulnerable). The second dimension of the ND-Gain index is readiness, which measures a country's capacity to leverage investments for adaptive actions, focusing on economic, governance, and social dimensions. It also ranges from 0 to 100, but in this case higher values mean that the country has greater institutional, economic, and social readiness to adapt.

Otherwise, we use the country-level carbon dioxide emissions per capita (CO2_emissions), which is also used by previous research (Y. Liu et al., 2023; Sarkodie et al., 2022), and the Environmental Performance Index by the Yale Center for Environmental Law and Policy (Wolf et al., 2022), which ranges from 0 (worse performance and, hence, higher climate vulnerability) to 100 (better performance and, therefore, less climate vulnerability).

Control Variables. Following the relevant literature, we incorporate various firm and macro-level factors as controls in our empirical analysis. The firm-level control variables employed in this study are firm size, leverage, market-to-book ratio, cash holdings, and capital expenditures, whereas the macro-level controls are GDP growth, inflation, GDP per capita, and economic freedom.

The first firm-level control variable is firm size (*Size*), whose impact on default risk has been widely found to be negative by previous literature. The rationale is that larger firms typically have more diversified operations, both geographically and across product lines, which can mitigate the impact of adverse events in any single area (Fernández et al., 2019; Simmonds, 1990). This diversification reduces the firm's overall risk profile (Besley et al., 2020). In addition, large firms usually have better access to capital markets and a wider array of financing options, allowing them to secure funds at more favorable terms. This financial flexibility enables them to manage debt obligations more effectively, thereby reducing the likelihood of default (Zhitao & Xiang, 2023).

Second, we expect leverage (*Lev*) to increase corporate default risk. As leverage increases, so do the firm's fixed financial obligations, which can elevate the probability of default (Molina, 2005). A study by Cathcart et al. (2020), using a sample of European firms, documents that financial leverage has a more pronounced impact on the default probability of small and medium size enterprises (SMEs) compared to large corporations, which is attributed to SMEs' greater reliance on short-term debt, which heightens their refinancing risk.

The market-to-book ratio (*MtoB*) reflects investor perceptions of a firm's growth opportunities relative to its current book value. A lower market-to-book ratio suggests that the market perceives the firm as having lower growth prospects or higher risk, while a higher market-to-book ratio indicates the opposite (Balasubramnian et al., 2019; Chava & Purnanandam, 2010).

Cash reserves (*Cash*) can act as a liquidity buffer against financial distress, enabling firms to meet short-term obligations and invest in profitable opportunities, thereby potentially reducing default risk (Harford et al., 2014). Similarly, firms facing uncertain future credit access may issue long-term debt pre-emptively and hold the proceeds as cash to secure their future credit capacity (Sun & Xia, 2022). However, the relationship between a firm's cash holdings and default risk can sometimes be negative due to inefficiencies, agency conflicts, and opportunity costs associated with excessive cash. Large cash reserves may encourage poor managerial decisions, such as wasteful spending or underinvestment (Jensen, 1986). Furthermore, excess cash can also signal a lack of profitable growth opportunities (Opler et al., 1999), potentially raising market perceptions of default risk. In addition, firms with poor governance may mismanage cash resources, reducing their ability to generate future value (Dittmar & Mahrt-Smith, 2007). Excessive reliance on cash to manage high debt levels (Almeida et al., 2004) can strain long-term solvency, increasing default risk.

The relationship between firm capital expenditures (*Capex*) and default risk is mixed. On one hand, higher capital expenditures increase growth and competitiveness, signaling profitability and reducing default risk when managed effectively (Ali & Fan, 2024). However, significant investments can increase earnings variability and business risk, leading to higher default risk (Amir et al., 2007).

Within the macro-level control variables, higher *GDP_ growth* is anticipated to reduce default risk by boosting corporate revenues and credit conditions (Beck et al., 2006). In contrast, higher *inflation* is expected to increase default risk due to greater uncertainty, rising costs, and potential macroeconomic instability (Corhay & Tong, 2025). *GDP_ percapita* should have a negative relationship with default risk, as it reflects higher economic development and stronger institutional quality (Demirgüç-Kunt & Maksimovic, 1998). Similarly, greater economic freedom (*Ec_freedom*) is expected to lower default risk by fostering more efficient markets, better access to finance, and stronger investor protections (Porta et al., 1998).

Country-Level Corruption. We employ two alternative measures. First is the Control of Corruption Index that the World Governance Indicators from the World Bank provide. This index captures perceptions of the extent to which public power is exercised for private gain and ranges from −2.5 (high corruption) to 2.5 (low corruption) (Li et al., 2021; Tran, 2020). Second, the Corruption Perception Index, provided by Transparency International, measures the perceived levels of public sector corruption and ranges from 0 (high corruption) to 100 (low corruption) (Garrido et al., 2014). To analyze country-level corruption as a moderating variable of climate vulnerability and ensure consistency in result interpretation, we transformed both corruption measures so that higher values correspond to higher levels of corruption. In this sense, we calculate the inverse of the Control of Corruption Index (Corruption1) and 100-Corruption Perception Index (Corruption2).

Table 2 displays the details of all variables used in the analysis.

Methodology

We investigate how country-level climate vulnerability affects firm-level default risk using the following baseline model:

$$Default\ riski,t = \alpha_0 + \beta Vulnerabilityc,t + \gamma' X_{i,t} + \theta' Y_{c,t} + \eta_{\mathrm{i}} + \eta_{\mathrm{t}} + \nu_{\mathrm{itc}} \quad (3)$$

In this estimation, X_{it} denotes firm-level and Y_{ct} for macro-level control variables. Moreover, η_{i} and η_{t} stand for industry and time-fixed effects, respectively. Finally, ν_{itc} stands for the error terms.

To begin, the descriptive statistics of the variables are presented to highlight the key features of the sample and assess whether the data aligns with findings from earlier studies. This analysis offers initial insights into

Table 2. Definitions and Data Sources of Variables.

Variables	Notation	Description	Data source
Dependent variables			
Z score (3 years)	Zscore3	(ROA + capital-to-asset) / σROA (3 years for calculating σROA)	Refinitiv Eikon
Z score (5 years)	Zscore5	(ROA + capital-to-asset) / σROA (5 years for calculating σROA)	
Z Altman	Z-Altman	1.2*(working capital / total assets) + 1.4*(retained earnings / total assets) + 3.3*(earnings before interest and tax / total assets) + 0.6*(market value of equity / total liabilities) + 1.0*(sales / total assets)	
Climate risk exposure			
Vulnerability	Vulnerability	ND-Gain's vulnerability: propensity or predisposition of human societies to be negatively impacted by climate hazards. The index values range from 0 to 100.	ND-Gain Index
Readiness	Readiness	ND-Gain's readiness: a country's ability to leverage investments to adaptation actions. The index values range from 0 to 100.	
Emissions score	CO2_emissions	Country-level carbon dioxide (CO2) emissions excluding LULUCF per capita.	World Development Indicators (WDI) from the World Bank
EPI index	EPI	Environmental Performance Index. The index values range from 0 to 100.	Yale Center for Environmental Law & Policy
Firm-level control variables			
Firm size	Size	Natural logarithm of the book value of assets	Refinitiv Eikon
Leverage	Lev	Ratio of total debt to total assets	
Market to book	MtoB	(Market value of common equity + preferred stock + book value of total liabilities) / Book value of total assets	
Cash holdings	Cash	Ratio of cash and cash equivalents to total assets	
Capital expenditures	Capex	Ratio of capital expenditures to total assets	
Macro-level control variables			
GDP growth	GDP_growth	Real GDP growth rate (Annual %)	World Development Indicators (WDI) from the World Bank
Inflation	Inflation	Inflation (Annual %)	
GDP per capita	GDP_percapita	Natural logarithm of the real GDP divided by the mid-year population.	
Economic freedom	Ec_freedom	Index that measures the degree of economic freedom in the world's nations. The index values range from 0 to 100.	Heritage Foundation
Moderating variable			
Control of corruption	Corruption1	Index that captures perceptions of the extent to which public power is exercised for private gain. It ranges from -2.5 to 2.5.	World Governance Indicators (WGI) from the World Bank
Corruption Perception Index	Corruption2	Perceived levels of public sector corruption. It ranges from 0 to 100.	Transparency International

Note. This table displays the variables used in the analysis, their notation, description, and data source. WDI: world development indicators; EPI: Environmental Performance Index; GDP: gross domestic product; WGI: world governance indicators.

the connection between a country's climate vulnerability and corporate default risk. The validity of the hypothesis is tested through a multivariate analysis. First, we employ OLS estimations. In the robustness analysis, we first use the random effects model, as suggested by the Hausman test, and the generalized method of moments (GMM) approach. This methodology allows us to address two key issues: controlling for unobserved fixed effects (captured by the term ν_{itc}) and resolving potential endogeneity problems. Specifically, we employ the "system GMM estimator," which utilizes both the levels of variables and their differences as instruments in the equations (Blundell & Bond, 2000; Blundell et al., 2001; Bond, 2002). While first-order serial correlation in the error term is expected, the validity of the estimates hinges on the absence of second-order serial correlation, as assessed through the AR(2) test. Furthermore, the Hansen test for over-identifying restrictions is used to confirm the appropriateness of the selected instruments.

Table 3. Summary Statistics.

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Zscore3	28,585	5.632	2.039	9.662	−6.579	58.462
Zscore5	26,706	3.212	2.089	4.482	−3.622	22.725
Z-Altman	25,572	7.032	3.045	18.879	−1.825	156.802
Vulnerability	34,706	0.306	0.299	0.027	0.251	0.426
Readiness	34,734	0.664	0.691	0.086	0.319	0.798
CO2_emissions	34,706	6.695	5.869	2.341	2.998	22.119
EPI	31,746	74.487	77.35	10.332	26.300	93.480
Size	31,234	20.896	20.824	2.283	15.372	26.897
Lev	30,892	0.169	0.135	0.160	0.000	0.684
MtoB	28,734	3.314	1.739	5.447	−1.868	40.588
Cash	22,062	0.099	0.058	0.128	0.000	0.733
Capex	28,613	0.177	0.038	0.567	0.000	4.468
GDP_growth	34,736	1.559	1.809	3.720	−28.758	24.615
Inflation	34,706	2.493	1.642	4.965	−4.447	72.308
GDP_percapita	34,760	10.670	10.710	0.506	7.647	12.329
Ec_freedom	34,706	72.326	73.804	6.363	45.800	84.200
Corruption1	34,750	−1.523	−1.749	0.731	−2.435	1.176
Corruption2	34,708	25.539	22	14.636	6.000	100.000

Note. This table displays the summary statistics for all the variables used in the analysis; EPI: Environmental Performance Index.

In addition, we also employ the IV approach to address endogeneity issues in regression analysis. IV estimation resolves this issue by employing instruments—variables that are correlated with the endogenous explanatory variables but uncorrelated with the error term. The IV approach relies on identifying valid instruments to achieve consistent estimation. A valid instrument, Z, must satisfy two key conditions: relevance, i.e., he instrument must be correlated with the endogenous regressor ($Cov(Z,X)\neq 0$), and exogeneity, i.e., the instrument must be uncorrelated with the error term ($Cov(Z,\varepsilon)=0$). The IV estimation involves two stages (commonly referred to as Two-Stage Least Squares, or 2SLS):

- First Stage: Regress the endogenous variable X on the instrument Y and other exogenous covariates to obtain the predicted values:

$$X=\pi_0+\pi_1 Z+\pi_2 W+v \quad (4)$$

where W represents additional control variables

- Second Stage: Use $\hat{X}$ from the first stage as a regressor in the structural equation to estimate β_1:

$$Y=\beta_0+\beta_1 \hat{X}+\varepsilon \quad (5)$$

A weak or invalid instrument (low correlation with X or correlation with ε) leads to weak identification or biased estimates. The F-statistic from the first-stage regression can assess instrument relevance, with values below 10 indicating weak instruments (Stock & Yogo, 2002).

Descriptive Statistics

The summary statistics of all variables employed in the analysis are displayed in Table 3. The average *Zscore3* is 5.632, with a minimum of -6.579 and a maximum value of 58.462. On the contrary, climate vulnerability's mean value is 0.306, ranging from 0.251 to 0.426. Regarding the firm-level and country-level variables, we can observe large variability among the countries in the sample.

Table 4 presents the pairwise correlation coefficients between the main variables employed in the analysis. A strong correlation between our relevant independent variables, namely climate vulnerability and corruption, and firm's default risk can be observed.

Results

Baseline Regressions

The primary purpose of this study is to examine whether and how climate vulnerability affects firm-level default risk in Europe. The findings for *Zscore3* (meaning that higher values of the ratio reflect lower levels of default risk) are displayed in Table 5. We follow a step-by-step procedure, first estimating our baseline model only with vulnerability (column 1), then including the firm-level control variables (column 2), and finally including the country-level control variables (column 3). We find a significant and negative effect, meaning that firms' default risk increases as a country's climate vulnerability increases. Focusing on column 3, a one-unit increase in the vulnerability index has an estimated increase of 12.432 units in default risk. These results confirm our first hypothesis.

Table 4. Correlation Matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
1) Zscore3	1.000																	
(2) Zscore5	0.726***	1.000																
(3) Z-Altman	−0.006	0.002	1.000															
(4) Vulnerability	−0.036***	−0.044***	−0.003	1.000														
(5) Readiness	0.012**	0.010	0.066***	−0.501***	1.000													
(6) CO2_emissions	−0.004	−0.026***	−0.050***	−0.046***	0.055***	1.000												
(7) EPI	0.019***	0.011*	0.057***	−0.339***	0.484***	−0.059***	1.000											
(8) Size	0.139***	0.173***	−0.141***	−0.005	−0.164***	0.107***	−0.096***	1.000										
(9) Lev	−0.052***	−0.056***	−0.231***	0.006	−0.019***	0.065***	−0.019***	0.195***	1.000									
(10) MtoB	0.076***	0.096***	0.273***	0.028***	0.098***	−0.021***	0.040***	−0.174***	0.012**	1.000								
(11) Cash	−0.076***	−0.082***	0.089***	0.003	0.082***	−0.051***	0.051***	−0.355***	−0.218***	0.148***	1.000							
(12) Capex	−0.040***	−0.043***	0.006	0.201***	−0.108***	0.146***	−0.067***	−0.043***	0.032***	0.015**	−0.015**	1.000						
(13) GDP_growth	0.027***	0.055***	0.024***	0.093***	−0.054***	−0.053***	−0.091***	0.008	−0.021***	0.034***	0.010	0.022***	1.000					
(14) Inflation	−0.049***	−0.038***	−0.007	0.252***	−0.324***	−0.031***	−0.474***	0.027***	−0.019***	−0.017***	−0.028***	0.175***	0.210***	1.000				
(15) GDP_percapita	0.018***	0.019***	0.031***	−0.491***	0.769***	0.088***	0.449***	−0.063***	−0.082***	0.030***	0.062***	−0.245***	−0.024***	−0.412***	1.000			
(16) Ec_freedom	0.016***	0.018***	0.084***	−0.527***	0.667***	−0.041***	0.432***	−0.132***	−0.044***	0.078***	0.093***	−0.241***	0.006	−0.026***	0.744***	1.000		
(17) Corruption1	−0.017***	−0.014**	−0.060***	0.466***	−0.917***	−0.023***	−0.503***	0.164***	0.023***	−0.082***	−0.086***	0.278***	0.058***	0.388***	−0.967***	−0.780***	1.000	
(18) Corruption2	−0.019***	−0.018***	−0.056***	0.451***	−0.916***	−0.009	−0.497***	0.167***	0.024***	−0.080***	−0.087***	0.263***	0.046***	0.383***	−0.950***	−0.774***	0.984***	1.000

Note. This table displays the Pearson correlations between the main variables used in the analysis; EPI: Environmental Performance Index.
***, ** and * refer to statistical significance at .01, .05 and .10 levels, respectively.

Table 5. Baseline Findings: Impact of Country Climate's Vulnerability on Firm-Level Default Risk.

	Dep. Var.: Zscore3		
	(1)	(2)	(3)
Vulnerability	−12.657*** (1.964)	−14.466*** (2.343)	−12.432*** (3.074)
Size		0.799*** (0.037)	0.807*** (0.037)
Lev		−7.024*** (0.459)	−7.043*** (0.461)
MtoB		0.199*** (0.017)	0.199*** (0.017)
Cash		−4.530*** (0.554)	−4.592*** (0.554)
Capex		−0.455*** (0.085)	−0.408*** (0.089)
GDP_growth			0.019 (0.026)
Inflation			−0.026*** (0.009)
GDP_percapita			−0.260 (0.190)
Ec_freedom			0.029* (0.016)
Constant	11.489*** (2.305)	−1.782 (2.706)	−1.802 (3.576)
Industry-fixed effects	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Observations	28,531	18,660	18,660
R-squared	0.033	0.075	0.076

Note. This table displays the findings from the regressions of climate vulnerability on firm's default risk. The dependent variable is the Zscore3. The independent variable is the ND vulnerability index. The definitions of all variables are provided in Table 2. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses. Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

Climate-related risks, including vulnerability to climate change and carbon emissions, raise debt costs and financial constraints (Capasso et al., 2020; Kling et al., 2021). Firms with high climate exposure experience greater default risks (Ginglinger & Moreau, 2023), and climate transition risks affect credit risk (Ramos-García et al., 2023). Furthermore, according to the institutional theory (DiMaggio & Powell, 1983), climate-related regulations and norms create isomorphic pressures that force firms to make potentially costly adaptations (Chen et al., 2025).

Within the firm-level control variables, the impact of company size (*Size*) is significantly positive. Larger firms tend to be more resilient due to their diversified operations across regions and product lines, which helps mitigate risks from adverse events (Fernández et al., 2019; Simmonds, 1990). Moreover, large firms benefit from better access to capital markets and a broader range of financing options, enabling them to secure funds on more favorable terms. This financial flexibility enhances their ability to manage debt obligations and reduce the risk of default (Zhitao & Xiang, 2023). In contrast, consistent with previous literature, we find a significant and negative effect of firm's leverage (*Lev*). As leverage increases, a firm's fixed financial obligations rise, which can elevate the risk of default (Molina, 2005). Regarding a company's market-to-book (*MtoB*), we find a significant and positive relationship, i.e., a higher ratio suggests the market perceives the firm as having better growth prospects or lower risk (Balasubramnian et al., 2019; Chava & Purnanandam, 2010). Our results indicate a significant negative relationship between cash holdings (*Cash*) and firm performance. Specifically, high cash levels in European companies serve as a signal of limited profitable growth opportunities (Opler et al., 1999), which may elevate market perceptions of default risk. Furthermore, firms with weak governance structures may mismanage cash reserves, undermining their capacity to generate future value (Dittmar, Mahrt-Smith, 2007). Finally, firms' capital expenditures (*Capex*) are negatively and significantly related to default risk, i.e., significant investments can increase earnings variability and business risk, leading to higher default risk (Amir et al., 2007). Regarding the macro-level control variables, we find that only *inflation* and *economic freedom* are statistically significant. Specifically we confirm that higher inflation rates increase default risk due to greater uncertainty, rising costs, and potential macroeconomic instability (Corhay & Tong, 2025), while greater economic freedom (*Ec_freedom*) reduces default risk by fostering more efficient markets, better access to finance, and stronger investor protections (Porta et al., 1998).

Our results provide interesting insights on the default risk determinants literature. Although traditional macroeconomic and institutional variables are well-established predictors of firm-level default risk (Demirgüç-Kunt & Maksimovic, 1998; Koju et al., 2019; Porta et al., 1998), climate vulnerability adds statistically significant and economically meaningful explanatory power beyond these traditional factors. For instance, increases in climate vulnerability or carbon emissions have been shown to raise firms' borrowing costs by approximately 0.5–1%, reduce profitability and productivity, and lower distance-to-default—effects that persist even after controlling for

Table 6. Baseline Findings: Addressing Endogeneity and Multi-Level Analyses.

	Dep. Var.: Zscore3			
	Random effects	GMM	Mixed-effects regression	Mixed-effects regression
$Zscore_{t-1}$		0.612*** (0.046)		
Vulnerability	**−12.567** (5.624)**	**−19.496** (9.403)**	**−12.360** (5.698)**	**−12.538*** (3.462)**
Size	0.865*** (0.065)	0.440** (0.181)	0.805*** (0.077)	0.806*** (0.061)
Lev	−6.884*** (0.681)	−7.908*** (2.204)	−7.092*** (1.541)	−7.069*** (0.414)
MtoB	0.161*** (0.024)	0.070 (0.091)	0.199*** (0.032)	0.199*** (0.017)
Cash	−1.651** (0.753)	0.459 (1.652)	−4.627* (2.499)	−4.610*** (0.833)
Capex	−0.128 (0.137)	−1.161** (0.581)	−0.404 (0.284)	−0.406*** (0.062)
GDP_growth	0.051** (0.026)	0.329*** (0.093)	0.019 (0.036)	0.025 (0.031)
Inflation	−0.000 (0.009)	0.052 (0.039)	−0.026* (0.015)	−0.030 (0.024)
GDP_percapita	−0.385 (0.326)	−2.124* (1.144)	−0.262 (0.479)	−0.272 (0.238)
Ec_freedom	0.048 (0.027)	0.103* (0.059)	0.029 (0.028)	0.028 (0.019)
Constant	−3.506 (6.315)	−21.125 (40.053)	−7.039 (6.138)	0.018 (2.644)
Industry fixed effects	Yes	Yes	Non	Yes
Time fixed effects	Yes	Yes	Yes	Non
Group variable	Firm	Firm	Industry	Time
Observations	18,660	17,229	18,660	18,660
R-squared	0.138			
Wald test (*df*)	577.92*** (32)	2,805.28*** (32)		
m2		1.45		
Hansen test (*df*)		118.06 (108)		

Note. This table displays the findings from the random effects and system-GMM estimations of climate vulnerability on firm's default risk (columns 1 and 2), and the mixed-effects estimations (columns 3 and 4). The dependent variable is the Zscore3. The independent variable is the ND vulnerability index. The definitions of all variables are provided in Table 2. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses. The Wald test is for the joint significance of the independent variables, and the m2 test is for the lack of second order serial correlation and the validity of the instruments. Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

traditional macroeconomic and institutional variables (Cevik & Miryugin, 2022; Kabir et al., 2021). These findings align with our results, which show that a one-unit increase in climate vulnerability raises default risk (as indicated by a 12.4-unit decrease in Z-score), even after including firm- and country-level controls. This reinforces the growing evidence that climate-related risks represent a distinct and material source of financial distress for firms, complementing the predictive power of more established economic fundamentals.

Addressing Endogeneity and Multi-Level Analysis

We conduct several robustness tests to overcome any endogeneity issues arising from simultaneity, reverse causation, and omitted variable problems. First, we utilize appropriate panel data techniques, namely the random effects model according to the Hausman test, to estimate our baseline model (eq. 3), which results are shown in column 1 of Table 6. The results of the Wald test validate the estimation, which shows a negative relationship between climate vulnerability and default risk. Second, we utilize system GMM estimations, which results are presented in column 2 of Table 6. The estimation does not have a second-order serial correlation, while the Hansen test's nonsignificance assures the validity of the instruments (the levels of variables and their differences). Again, we find a negative effect of climate vulnerability on firms' default risk. Regardless of the econometric technique, our results confirm our main hypothesis. Climate-related risks, such as exposure to climate change and carbon emissions, contribute to increased debt expenses and financial constraints (Capasso et al., 2020; Kling et al., 2021). Firms facing significant climate vulnerabilities tend to exhibit a higher probability of default (Ginglinger & Moreau, 2023), while risks associated with transitioning to a low-carbon economy influence creditworthiness (Ramos-García et al., 2023). Besides, elevated perceived risks drive up capital costs and default likelihood. In contrast, firms actively engaging in environmental management can signal lower financial risk, thereby decreasing default probabilities.

In addition, to account for the multi-level nature of our model —it combines country-level variables, namely climate vulnerability— with firm-level characteristics —namely corporate default risk— we conduct a mixed-effects estimation (Aguinis et al., 2013). These models incorporate both fixed effects (i.e., parameters that are constant

Table 7. Baseline Findings: Addressing Endogeneity with Instrumental Variables.

	Inst. Var.: Length_coastline		Inst. Var.: Population	
	First stage (Dep. var.: vulnerability)	Second stage Zscore3	First stage (Dep. var.: vulnerability)	Second stage Zscore3
Lenght_coastline	0.000* (0.000)			
Population			−0.011*** (0.000)	
Vulnerability		**−78.796*** (33.631)**		**−21.567*** (6.460)**
Size	−0.001*** (0.000)	0.657*** (0.037)	−0.000*** (0.000)	0.799*** (0.038)
Lev	0.000 (0.000)	−6.435*** (0.414)	0.001 (0.001)	−7.020*** (0.495)
MtoB	0.000*** (0.000)	0.288*** (0.022)	0.000 (0.000)	0.202*** (0.013)
Cash	−0.000 (0.001)	−4.383*** (0.633)	0.002 (0.001)	−4.604*** (0.622)
Capex	0.001* (0.000)	−0.395*** (0.114)	−0.003*** (0.000)	−0.403*** (0.121)
GDP_growth	0.002*** (0.000)	0.132*** (0.037)	0.001*** (0.000)	0.035 (0.033)
Inflation	0.000*** (0.000)	0.013 (0.167)	0.000*** (0.000)	−0.023 (0.016)
GDP_percapita	−0.015*** (0.001)	−10.043 (6.925)	−0.032*** (0.000)	−0.402* (0.232)
Ec_freedom	−0.001*** (0.000)	−0.047 (0.039)	−0.001*** (0.000)	0.018 (0.017)
Constant	0.580*** (0.007)	13.702 (15.190)	0.947*** (0.007)	3.652 (4.612)
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	18,660	18,660	18,660	18,660
First stage F-stat	330.28***		657.11***	
R-squared	0.386	0.055	0.530	0.077
Wald Test (*df*)		481.12*** (32)		1,530.08*** (32)

Note. This table displays the findings from the regressions of climate vulnerability on firm's default risk. The dependent variable is the Zscore3. The independent variable is the ND vulnerability index. The definitions of all variables are provided in Table 2. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses. The First stage F-stat test is for the validity of the first stage estimation, and the Wald test is for the joint significance of the independent variables. Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

across all observational units, analogous to coefficients in standard linear regression models), and random effects (components specific to groups), modeled as random variables. Column 3 consider time fixed effects while column 4 considers industry fixed effects. Yet, our results are consistent with those previously obtained.

Finally, we use an IV approach with a two-stage least squares methodology (2SLS), which results are reported in Table 7. We use two complementary instruments, namely the natural logarithm of the country's length of coastline and its population (Boulton et al., 2021). On the one hand, countries with extensive coastlines face heightened exposure to the adverse effects of climate change, including rising sea levels, coastal erosion, and intensified storm surges (Hsiang & Jina, 2014). These factors elevate the risk of flooding, property destruction, and ecosystem degradation. In addition, coastal regions often contain vital ecosystems such as mangroves, coral reefs, and wetlands, which serve as natural barriers against extreme weather events but are highly susceptible to environmental changes like ocean warming and acidification. Furthermore, economic activities such as shipping, tourism, and fisheries are often concentrated along coastlines, increasing economic vulnerability to climate-induced coastal threats. Conversely, densely populated nations experience heightened pressure on essential resources such as water, energy, and food, which may already be strained due to climate change. This challenge is particularly severe in arid or highly populated areas, where resource scarcity is an increasing concern. Given these geographic characteristics, it is reasonable to infer a connection between a country's physical features and its susceptibility to climate risks, thus meeting the relevance criterion for the instruments. Moreover, these instruments are also likely to comply with the exclusion restriction (Kiviet, 2020).

In the first stage of the 2SLS, we regress vulnerability on the exogenous instruments, i.e., *length of coastline* (column 1) and *population* (column 3), including the control variables and the year, and industry fixed effects. In the second stage of the 2SLS, *Zscore3* is the dependent variable, and the predicted values of *vulnerability* are the independent variables. We observe that a climate vulnerability continues to significantly affect firm-level default risk, namely increasing it, even when considering endogeneity issues, demonstrating the robustness of our main findings.

Robustness Analyses

To validate the consistency of our results, we conduct a set of robustness analyses. First, we replace our dependant

Table 8. Baseline Findings: Robustness Analyses (a).

			Dep. Var.: Zscore3		
	Dep. Var.: Zscore5	Dep. Var.: Z-Altman	Excluding UK	Excluding industrials	Board control variables
Vulnerability	−7.645*** (1.475)	38.824*** (4.144)	−12.635*** (3.453)	−12.300*** (3.466)	−10.045** (4.135)
Size	0.474*** (0.018)	−0.246*** (0.038)	0.887*** (0.042)	0.830*** (0.042)	0.570*** (0.070)
Lev	−4.158*** (0.221)	−13.884*** (0.567)	−6.402*** (0.502)	−6.312*** (0.508)	−7.061*** (0.625)
MtoB	0.116*** (0.008)	1.043*** (0.057)	0.166*** (0.017)	0.213*** (0.021)	0.270*** (0.025)
Cash	−2.279*** (0.290)	4.197*** (1.087)	−4.732*** (0.589)	−4.997*** (0.589)	−5.254*** (0.863)
Capex	−0.232*** (0.047)	0.203** (0.094)	−0.404*** (0.090)	−0.414*** (0.093)	−0.516*** (0.124)
GDP_growth	0.032** (0.013)	0.035 (0.036)	0.005 (0.029)	−0.004 (0.029)	0.052 (0.033)
Inflation	−0.016*** (0.005)	−0.032** (0.013)	−0.025*** (0.009)	−0.026*** (0.010)	−0.018* (0.010)
GDP_percapita	−0.202** (0.094)	1.001*** (0.286)	−0.434** (0.216)	−0.476** (0.213)	0.054 (0.272)
Ec_freedom	0.009 (0.008)	0.016 (0.013)	0.049*** (0.018)	0.040** (0.017)	−0.023 (0.022)
Board_size					−0.049 (0.033)
Indep_directors					0.714* (0.366)
Constant	−0.218 (1.628)	−17.697*** (3.771)	2.412 (4.385)	−1.023 (3.826)	0.474 (4.781)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,588	18,205	15,158	14,532	11,350
R-squared	0.099	0.309	0.077	0.082	0.085

Note. This table displays the findings from the regressions of climate vulnerability on firm's default risk. The dependent variable is the Zscore5 (column 1), Z-Altman (column 2), and Zscore3 (columns 3-5). The independent variable is the ND vulnerability index. The definitions of all variables are provided in Table 2. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses. Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

variable with *Zscore5* (which uses a 5 year period to calculate ROA deviation) and *Z-Altman*, and the results are shown in columns 1 and 2 of Table 8. Proceeding this way, we still find that climate vulnerability worsens firms' default risk (the coefficient for Z-Altman is positive since higher values represent higher default probability). In addition, we exclude from the sample companies from the UK (which represent 25.1%) and those belonging to the industrials industry (which represent 19.69%), and the results are reported in columns 3 and 4, respectively. Yet again, we find a negative relationship between climate vulnerability and default risk. Finally, we consider a set of control variables related to the companies' governance, namely board size and the number of independent directors, which are found to be relevant by previous literature. The results are provided in column 5 of Table 8 and show that while larger boards do not affect firms' default risk, independent directors generally enhance monitoring and reduce financial distress (Manzaneque et al., 2015). Nevertheless, the negative impact of climate vulnerability on default risk remains the same.[4]

In addition, we utilize alternative measures of a country's climate vulnerability, and the results are shown in Table 9. Specifically, we test the on-year lagged effect of climate vulnerability on default risk (column 1), and use the CO2 emissions (column 2) and the Environmental Performance Index (column 3) as proxies of country-level climate vulnerability. Once more, the results show that climate vulnerability negatively affects firms' default risk. High CO2 emissions indicate greater contribution to climate change and exposure to related physical and regulatory risks, which increases operational costs and disrupt business activities. Meanwhile, a low EPI reflects poor environmental health (i.e., higher climate vulnerability) and weak resilience to climate shocks, signaling a country's limited capacity to mitigate these risks. Together, these factors heighten the likelihood that firms within such countries face increased financial instability and default risk. Furthermore, we test a country's readiness effect, i.e., whether a country's ability to leverage investments to climate adaptation actions moderates the negative effect of vulnerability on default risk. The results are shown in column 4 of Table 9, and we find that readiness plays a positive moderating role, reducing the negative impact of climate vulnerability. Countries with higher climate readiness might implement measures that protect or reduce the risk related to climate vulnerability (Azócar et al., 2021). Besides, investors may perceive that high levels of climate readiness (such as government policies or sustainable practices) help mitigate future risks, reducing the overall risk associated with investing in vulnerable markets (Gopalan et al., 2023).

Table 9. Baseline Findings: Robustness Analyses (b).

	Dep. Var.: Zscore3			
	1 year lagged vulnerability	CO2_emissions	EPI	Readiness effect
$Vulnerability_{t-1}$	−10.582*** (3.181)			
CO2_emissions		−0.135*** (0.033)		
EPI			0.014* (0.008)	
Vulnerability				−95.518*** (18.582)
Readiness				−46.389*** (9.615)
Vulnerability*Readiness				126.589*** (27.994)
Size	0.822*** (0.039)	0.838*** (0.038)	0.836*** (0.040)	0.755*** (0.037)
Lev	−7.132*** (0.478)	−6.975*** (0.462)	−7.324*** (0.490)	−7.102*** (0.395)
MtoB	0.199*** (0.018)	0.196*** (0.017)	0.199*** (0.018)	0.200*** (0.017)
Cash	−4.727*** (0.573)	−4.565*** (0.555)	−4.705*** (0.579)	−5.024*** (0.555)
Capex	−0.403*** (0.092)	−0.296*** (0.095)	−0.467*** (0.135)	−0.371*** (0.092)
GDP_growth	0.007 (0.027)	−0.007 (0.026)	−0.009 (0.027)	0.012 (0.026)
Inflation	−0.022*** (0.009)	−0.026*** (0.008)	−0.019* (0.010)	−0.002 (0.008)
GDP_percapita	−0.188 (0.198)	0.067 (0.180)	−0.062 (0.197)	0.006 (0.237)
Ec_freedom	0.033** (0.016)	0.042*** (0.015)	0.034** (0.016)	0.049*** (0.018)
Constant	−2.766 (3.685)	−10.157*** (2.971)	−8.876*** (3.128)	25.883*** (7.242)
Industry-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Observations	17,705	18,660	17,390	18,660
R-squared	0.075	0.076	0.075	0.081

Note. This table displays the findings from the regressions of climate vulnerability on firm's default risk. The dependent variable is the Zscore3. The independent variable is the 1 year lagged ND vulnerability index (column 1), CO2 emissions (column 2), EPI (column 3), and the interaction of ND vulnerability and ND readiness (column 4). The definitions of all variables are provided in Table 2. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses.
Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

The Asymmetric Effect of Climate Vulnerability

In this section, we analyze whether the negative effect of climate vulnerability on corporate default risk depends on the greater or lesser probability of default. Consequently, we estimate our baseline model (eq. 3) using adequate quantile regression estimations (Graham et al., 2015), which results are reported in Table 10. This methodology allows the improvement of classical linear regression by estimating the conditional quantiles of a response variable rather than just the conditional mean. Unlike OLS, which minimizes squared residuals, quantile regression minimizes the weighted sum of absolute residuals, making it more robust to outliers and skewed distributions.

Our results reveal that the negative effect of climate vulnerability on corporate default risk is significantly relevant for companies with low default probability (Q75), while companies with moderate or high default risk (Q50 and Q25, respectively) are not significantly affected by climate vulnerability. This result reinforces our first hypothesis. Companies with low default probabilities are usually perceived as stable and financially sound. However, their exposure to climate vulnerability can introduce unforeseen risks, potentially altering their risk profiles. Investors and stakeholders may react more sensitively to climate-related risks in these firms, as such vulnerabilities are inconsistent with their established risk expectations (Ye et al., 2024). This heightened sensitivity can increase scrutiny and demand for robust climate risk management practices. Consequently, the negative effect of climate vulnerability on default risk becomes more pronounced in these companies. In contrast, firms with moderate to high default risks are already operating under heightened risk perceptions. For these companies, climate vulnerability may be viewed as an additional risk factor among many, leading to a relatively muted response from investors and stakeholders. The existing risk premiums associated with these firms may already account for various uncertainties, making the incremental impact of climate vulnerability less significant (Cevik & Jalles, 2020). In the European case, the ECB and the European Systemic Risk Board highlight that climate-related shocks can propagate through the financial system, potentially leading to corporate defaults and credit losses for banks. This emphasizes the systemic nature of climate risks within Europe's financial landscape (ECB, 2022).

The Moderating Role of Country-Level Corruption

To validate our second hypothesis, namely that corruption may grease or sand the wheel on the negative relationship

Table 10. Asymmetric Effect of Vulnerability on Default Risk. Quantile Regressions.

	Quantiles of the Dep. Var.: Zscore3		
	Q75	Q50	Q25
Vulnerability	**−11.498*** (3.749)**	**−2.458 (1.754)**	**−1.148 (1.216)**
Size	0.780***(0.046)	0.458***(0.020)	0.371***(0.018)
Lev	−7.185***(0.391)	−4.664***(0.211)	−3.380***(0.181)
MtoB	0.330***(0.037)	0.142***(0.014)	0.055***(0.005)
Cash	−5.224***(0.608)	−3.963***(0.260)	−3.209***(0.272)
Capex	−0.412***(0.075)	−0.059 (0.60)	0.095* (0.051)
GDP_growth	0.006 (0.024)	0.049***(0.015)	0.045***(0.010)
Inflation	−0.011 (0.006)	0.003 (0.005)	0.010** (0.005)
GDP_percapita	−0.379** (0.180)	−0.169 (0.122)	−0.094 (0.078)
Ec_freedom	0.037***(0.012)	0.025***(0.007)	0.024***(0.005)
Constant	0.879 (3.278)	−2.456 (2.590)	−5.740***(1.527)
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	18,660	18,660	18,660
Pseudo R-squared	0.060	0.042	0.044

Note. This table displays the findings from the quantile regressions of climate vulnerability on firm's default risk. The dependent variable is the Zscore3. The independent variable is the ND vulnerability index. The definitions of all variables are provided in Table 2. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses.
Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

between climate vulnerability and default risk, we estimate the following model:

$$\begin{aligned} \textit{Default risk}_{i,t} = {} & \alpha_0 + \beta_1 \textit{Vulnerability}_{c,t} \\ & + \beta_2 \textit{Corruption}_{c,t} \\ & + \beta_3 \textit{Vulnerability}_{c,t} {*} \textit{Corruption}_{c,t} \\ & + \gamma' X_{i,t} + \theta' Y_{c,t} \\ & + \eta_i + \eta_t + \nu_{itc} \end{aligned} \tag{6}$$

where X_{it} denotes firm-level and Y_{ct} for macro-level control variables, and Corruption stands for the inverse of the Control of corruption index (*Corruption1*) and the Corruption Perception Index (*Corruption2*). The obtained results are reported in Table 11.

It can be observed that the coefficient for the interaction term between *Vulnerability* and *Corruption1* is -13.602 (-0.693 for the case of *Corruption2*), significant. This implies that the adverse effect of climate vulnerability on default risk is amplified in countries with higher corruption. In other words, as corruption increases, the negative impact of climate vulnerability on firm stability becomes stronger, which confirms our second hypothesis. While corruption alone may appear to reduce default risk slightly—possibly due to informal mechanisms that provide short-term support—it ultimately undermines institutional capacity, making firms more exposed to the adverse effects of climate vulnerability. As corruption increases, the negative impact of climate-related risks on firm stability becomes stronger, highlighting a compounding effect between environmental and institutional weaknesses. Figure 2(a) visualizes the interaction effect between climate vulnerability and *Corruption1* on firm default risk (*Zscore3*). The black line (low corruption) shows that as climate vulnerability increases, firm default risk worsens (*Zscore3* decreases), but the decline is more gradual. The gray line (high corruption) displays that the decline in *Zscore3* is much steeper, meaning that in corrupt countries, climate vulnerability has a stronger negative impact on firms' financial stability. Figure 2(b) depicts the marginal impact of climate vulnerability on firm-level default risk, moderated by a country's corruption level as measured by *Corruption2*, with 95% confidence intervals.

Our findings indicate that the adverse impact of climate vulnerability is particularly pronounced in countries with higher levels of corruption. Firms operating in regions with elevated climate risk tend to hold greater long-term debt and cash reserves while distributing lower cash dividends, reflecting a prudent financial management strategy aimed at mitigating climate-related disruptions (Huang et al., 2018). However, in highly corrupt environments, the effectiveness of these financial strategies may be undermined by factors such as resource misallocation, weaker regulatory frameworks, and heightened uncertainty and transaction costs, thereby exacerbating the influence of climate vulnerability on default risk. To validate the robustness of this result, we segmented our sample into four groups based on both corruption measures. The findings consistently support these conclusions. For reasons of parsimony, these additional results are not presented here but are available upon request.

Table 11. Moderating Role of Country-Level Corruption.

	Dep. Var.: Zscore3	
	Control of corruption	Corruption perception index
Vulnerability	−32.011*** (6.612)	−63.330*** (22.587)
Corruption1	4.842*** (1.473)	
Vulnerability*Corruption1	**–13.602*** (4.155)**	
Corruption2		0.246*** (0.076)
Vulnerability*Corruption2		**–0.693*** (0.217)**
Size	0.790*** (0.038)	0.791*** (0.038)
Lev	−7.123*** (0.464)	−7.136*** (0.464)
MtoB	0.198*** (0.017)	0.197*** (0.017)
Cash	−4.626*** (0.555)	−4.625*** (0.555)
Capex	−0.466*** (0.093)	−0.460*** (0.092)
GDP_growth	0.023 (0.026)	0.021 (0.026)
Inflation	−0.010 (0.009)	−0.010 (0.009)
GDP_percapita	−0.056 (0.267)	−0.067 (0.247)
Ec_freedom	0.058*** (0.020)	0.059*** (0.020)
Constant	1.425 (4.443)	12.138** (5.138)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	18,660	18,660
R-squared	0.077	0.077

Note. This table displays the findings from the regressions of climate vulnerability and corruption on firm's default risk. The dependent variable is the Zscore3. The independent variable is the ND vulnerability index. The definitions of all variables are provided in Table 2. Both measures of country-level corruption, namely control of corruption (Corruption1) and corruption perception index (Corruption2) are transformed so that higher values correspond to higher levels of corruption. We include industry and year-fixed effects in all the models. We adjust the error terms for heteroscedasticity at the company level. Robust t-statistics are displayed in parentheses. Statistical significance at 1%, 5%, and 10% are indicated with ***, **, and *, respectively.

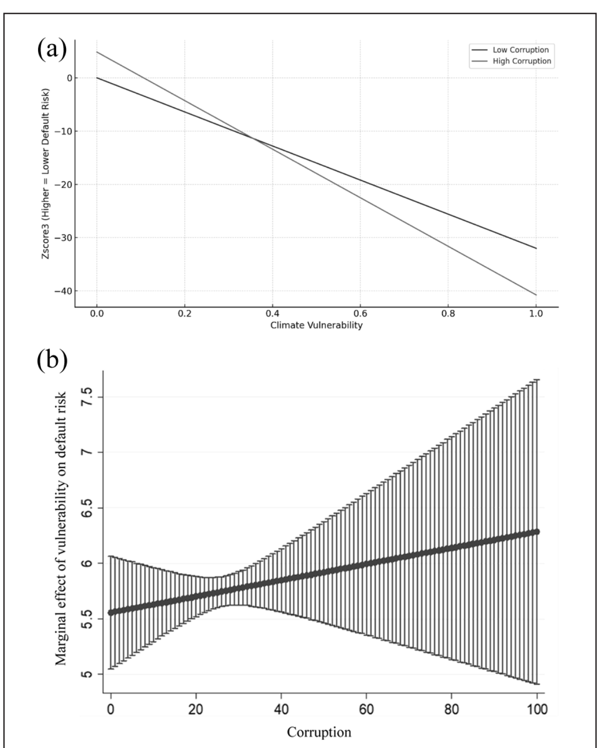

Figure 2. (a) Interaction effect of climate vulnerability and corruption on firm default risk. (b) Marginal effects of the moderation effect of corruption.

Corruption weakens environmental law enforcement, enabling firms to engage in harmful practices that heighten environmental degradation and future liabilities (Povitkina, 2018). It also disrupts resource allocation, leading to inefficient investments and mismanagement, increasing regulatory uncertainty and financial strain for firms (Aja-Eke et al., 2025; Shleifer & Vishny, 1993). In addition, firms in corrupt settings may overlook the advantages of climate adaptation due to inefficiencies in public policy, thereby increasing their default risk (Grover & Kahn, 2024). In Europe, while corruption levels are generally lower than in many other regions (García-Gómez et al., 2024), firms still face challenges related to regulatory enforcement, resource allocation, and climate adaptation. Weak enforcement of environmental laws in certain European countries—particularly in regions with higher corruption perceptions—has allowed some firms to bypass regulations, leading to environmental degradation and future legal risks. Besides, while the European Union has ambitious green policies, inconsistent implementation across member states can discourage firms from investing in long-term climate resilience, increasing their risk of financial distress.

Conclusion

This study provides robust empirical evidence on the impact of country-level climate vulnerability on firm-level default risk across European countries. Our findings confirm that firms operating in countries with higher climate risks face greater financial distress, increased costs of debt, and more stringent financing conditions, ultimately elevating their probability of default. Moreover, our results highlight the significant moderating role of country-level corruption, which exacerbates the adverse effects of climate vulnerability on corporate financial stability. The results obtained are robust across various model specifications, alternative measures of climate vulnerability and default risk, and multiple estimation techniques addressing potential endogeneity concerns. The negative impact of climate vulnerability on default risk is particularly pronounced among firms traditionally perceived as financially stable, indicating that even well-capitalized firms are not immune to the growing challenges posed by climate change. Furthermore, corruption acts as a critical amplifying factor, weakening environmental governance, distorting resource allocation, and reducing the effectiveness of climate adaptation efforts.

The findings of this study offer relevant insights for policymakers. First, strengthening climate adaptation policies at the national level is essential to mitigating the negative effects of climate vulnerability on firms. Governments should prioritize investments in resilient infrastructure, early warning systems, and disaster preparedness programs to reduce firms' exposure to climate risks, considering that climate vulnerability is a distinct and material driver of firm-level default risk, beyond traditional economic and institutional factors. In addition, regulatory frameworks should incentivize companies to integrate climate risk management into their financial strategies, potentially through tax incentives or preferential financing for sustainable investments. Second, financial regulators and central banks should integrate climate vulnerability assessments into macroprudential policies. Given that firms in climate-vulnerable countries face higher borrowing costs and reduced access to finance, regulatory bodies should develop stress-testing mechanisms to assess climate-related financial risks within banking systems. The ECB's emphasis on incorporating climate risks into financial stability monitoring is a step in the right direction and should be further strengthened through enhanced disclosure requirements and risk-adjusted capital requirements for climate-exposed firms. Third, addressing corruption should be a key priority in climate risk governance.

Strengthening anti-corruption policies, improving transparency in public spending, and ensuring effective enforcement of environmental regulations can significantly reduce the negative impact of climate vulnerability on corporate financial stability. Governments must implement stricter oversight mechanisms for climate finance allocation, ensuring that funds designated for climate adaptation projects are used effectively and do not fall prey to mismanagement or misappropriation.

For corporate decision-makers, our findings emphasize the importance of integrating climate risk considerations into financial planning and strategic management. Firms operating in climate-vulnerable regions should enhance their risk management strategies by investing in business continuity planning, supply chain diversification, and insurance mechanisms to mitigate financial shocks from climate-related disruptions. In addition, companies should proactively engage in ESG practices. Strong ESG performance can serve as a mitigating factor against climate risks, enhancing investor confidence and improving firms' access to capital. By adopting sustainable business models and reducing carbon footprints, firms can enhance their resilience to climate risks and gain a competitive advantage in increasingly sustainability-conscious markets. Furthermore, firms operating in highly corrupt environments should strengthen internal governance mechanisms to minimize the risks associated with weak institutional frameworks. Transparent financial reporting, anti-corruption compliance programs, and active engagement with regulatory bodies can help mitigate the negative impact of corruption on corporate financial stability.

While this study provides valuable insights into the relationship between climate vulnerability, corruption, and default risk, some limitations should be addressed in future research. The study focuses exclusively on listed firms across European countries, which may limit the generalizability of the findings. Listed firms tend to be larger, more transparent, and have better access to financial resources compared to small and medium-sized enterprises (SMEs) or privately held firms. Given that SMEs often lack the capacity to absorb climate-related shocks and may face greater financing constraints, the observed effects of climate vulnerability on default risk might be even more pronounced in this segment. Future research should aim to incorporate non-listed firms to provide a more comprehensive picture. Besides, it should be examined the role of firm-level ESG initiatives in moderating climate risk exposure and assess whether companies with strong sustainability strategies exhibit lower default probabilities. In addition, cross-regional studies comparing the European context with other regions, such as North America or Asia, could provide a broader understanding of how institutional quality influences the impact of climate risks on corporate finance. Finally, given the evolving landscape of climate policies and financial regulations, future research should explore the long-term effects of climate-related policy interventions on firm-level financial stability.

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Notes

1. The European Environment Agency (EEA, 2024) reports that extreme weather events, such as storms, heatwaves, and flooding, resulted in economic losses amounting to 738 billion euros during 1980 – 2023 in Europe.
2. The report can be retrieved from: https://finance.ec.europa.eu/publications/report-monitoring-climate-related-risk-financial-stability_en?utm_source=chatgpt.com
3. Carney (2015) and Stern (2008) introduced frameworks categorizing climate risks into physical risks (direct impacts like natural disasters) and transition risks (costs associated with shifting to a low-carbon economy).
4. In addition, we have stratified the sample by: (1) major economies (United Kingdom, Germany, France, Italy, and Spain) vs. all others; (2) Southern vs. Northern Europe; (3) Western vs. Eastern Europe; and (4) EU vs. non-EU countries. Across all subsamples, the results remain consistent with our main findings—specifically, we observe a robust negative relationship between climate vulnerability and firm-level default risk. For the sake of parsimony, these additional results are not included in the manuscript but are available upon request.

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