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Firm-level Climate Vulnerability and Corporate Risk-taking: International Evidence**Md Lutfur RAHMAN¹***Newcastle Business School, the University of Newcastle***Sudipta BOSE²***Newcastle Business School, the University of Newcastle*

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Abstract: *This study examines the association between firm-level climate change risk exposure and corporate risk-taking using a sample of 50,782 firm-year observations from 2003 to 2021 across 58 countries worldwide. Using a time-varying measure of firm-level climate change risk exposure derived from corporate conference call transcripts, we find a negative relationship between firm-level climate change risk exposure and corporate risk-taking. We also find that the negative association is more pronounced for firms with higher environmental innovation and firms domiciled in countries with stakeholder-oriented business cultures and stronger governance. Our key finding is robust under several alternative corporate risk-taking and climate change risk exposure proxies. The findings of this study could be used by policymakers to enact regulations limiting risky investments in climate-vulnerable sectors or to provide economic safety nets for businesses impacted by climate change.*

Keywords: Climate change exposure, corporate risk-taking, Asia Pacific countries

JEL Classification: G32, M14, Q54

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1. Introduction

It is now well-documented that the world's climate is changing with a marked rise in average temperatures and sea levels and extreme weather-related events, such as droughts, cyclones, floods, and wildfires (Intergovernmental Panel on Climate Change, 2021). Climate change influences how firms run their businesses and introduces new challenges for them (Sautner et al., 2023). For instance, Benincasa et al. (2024) report that firms facing weather-related losses are more likely to invest in long-term assets and transition to production processes that integrate climate-friendly measures. Climate finance researchers are committing significant resources to better understand climate change implications for businesses (for example, Huang et al., 2018; Li et al., 2022; Barrot and Sauvagnat, 2016; Pankratz and Schiller, 2024). However, the literature is still in its infancy, and additional research is necessary to fully grasp how climate risks and opportunities affect corporate outcomes. The main objective of this paper is to examine how firm-level climate change risk exposure affects corporate risk-taking.

Climate change creates new uncertainties for firms. For example, physical climate risks (such as sea level rise, cyclones, and wildfires) may adversely affect the value of firms' assets (plants, property, and equipment), operating costs (relocation costs and insurance costs), profitability and repayment capacity (Chava, 2014; Hong et al., 2019). Likewise, transition risks arising from climate change-related policies and regulations (such as carbon taxes), as well as costs associated with disruptive or green innovation resulting from the transition process, can also be significant (Delis et al., 2019; Bolton and Kacperczyk, 2021). On the other hand, climate change may create opportunities for firms in terms of new markets, businesses, and technologies (such as renewable energies, electric vehicles, and energy storage) (Sautner et al., 2023). Therefore, corporate managers must (i) trade-off between climate-related risk and opportunities and (ii) develop climate risk resilience strategies to alleviate the potential negative consequences of climate change. This may affect their risk-taking tendencies. We shed light on this.

The existing literature focusing on the effect of climate change risk exposure on corporate outcomes has several limitations. *First*, several studies use country-level climate risk indicators to explore the impact of climate risk on firms (for example, Huang et al., 2018; Li et al., 2022; Barrot and Sauvagnat, 2016); Pankratz and Schiller, 2024). However, we argue that country-level measures may capture other country characteristics (for instance, institutional and regulatory features and the level of market efficiency) that may directly affect corporate

outcomes. Further, climate change may pose additional costs for some firms whilst bringing opportunities for others. Market participants also may have heterogeneous expectations about how individual firms will be affected by climate change. Therefore, climate risk measures should be disaggregated across firms to capture this variation. This paper uses firm-level climate change risk exposure data from conference call transcripts to address this limitation.³

Second, previous studies also explore the effect of a single climate-related factor, such as drought (Huynh et al., 2020), rainfall conditions (Rao et al., 2022), extreme temperature (Pankratz et al., 2023; Addoum et al., 2023; Addoum et al., 2020; Balvers et al. 2017), sunshine (Sun et al., 2023), and sea level rise (Bernstein et al., 2019; Murfin and Spiegel, 2020), on corporate outcomes. These studies generally argue that climate-related factors are uncertain, systematically affect cash flows and discount rates, and pose significant productivity shocks for firms. As such, this climate risk exposure adversely impacts corporate outcomes, such as the cost of equity capital, revenue and operating income, and the market value of firms, etc.⁴ We, however, contend that a single-factor analysis does not completely capture the consequences of climate risk.

Third, several studies explore the effects of disaggregated firm-level climate risk measures on corporate decisions and performance. For example, high climate change risk exposure is found to be associated with high firm-level green patent generation (Sautner et al., 2023; Li et al., 2024), low Tobin's Q (Li et al., 2024), high cash holdings (Heo, 2021), low leverage (Ginglinger and Moreau, 2019; Li and Zhang, 2023), high cumulative returns (Baz et al., 2023), low market valuation (Berkman et al., 2024), unfavourable loan terms (Huang et al., 2022; Kling et al., 2021) and increased cost of equity capital (Agoraki et al., 2024). None of

³ We are grateful to Sautner et al. (2023) for making the data available.

⁴ Huynh et al. (2020) find a positive relationship between drought risk and the cost of equity capital. Similarly, Sun et al. (2023) reveal that sunshine-induced mood affects investors in the primary market, influencing the cost of equity financing. Rao et al. (2022) report that excess and deficit rainfall conditions significantly decline the market value of rain-sensitive firms. Pankratz et al. (2023) show that firms' exposure to extreme high temperatures leads to a decline in revenue and operating income. They further show that heat exposure negatively affects firm financial performance in relation to analysts' prediction. In similar studies, Addoum et al. (2023) show that 40% of industries' earnings are significantly affected by extreme temperatures, and Balvers et al. (2017) find that uncertainty about temperature changes leads to a significant increase in the cost of equity capital. Contradicting these studies, Addoum et al. (2020), however, do not find evidence of a significant relationship between temperature exposures and establishment-level sales or productivity. At the firm level, they also show that temperature exposure is unrelated to sales, productivity, and profitability. Exploring the relationship between physical climate risk factors and real estate prices, Bernstein et al. (2019) show that houses exposed to sea-level rise are priced lower than unexposed, observably equivalent properties. Murfin and Spiegel (2020), however, show that variation in exposure to relative sea-level rise does not influence real estate prices, potentially due to the availability of mitigation technologies.

these studies, however, examine whether corporate climate vulnerability influences managerial risk-taking. We fill this gap by addressing a topical research question: *Does firm-level climate change risk exposure affect corporate risk-taking?*

Why may climate risk exposure affect corporate risk-taking? This question may be answered using the lens of prospect theory. This theory postulates that individuals' reactions to potential gains and losses can be diverse, and their decision-making about risky alternatives is based on the probable gains/losses in relation to their risk appetite (Kahneman and Tversky, 2013; Barberis et al., 2016; Best and Grauer, 2016). In our context, the level of corporate risk-taking reflects a company's risk appetite regarding its business decisions. As indicated previously, climate risk poses additional uncertainty for companies, which is why managers may consider it an incremental 'business risk' (Huang et al., 2019; Zaman et al., 2021). Therefore, under the prospect theory, firms with high-risk aversion (low-risk appetite) may tend to make conservative management decisions in response to climate change risk exposure. On the other hand, climate risk comprises opportunities, such as new markets, businesses, and technologies. In line with the prospect theory, by generating 'opportunity expectations', firms with a low degree of risk aversion (high-risk appetite) may take more risk in their corporate decisions (Zhang et al., 2021).

The question pertaining to the relationship between climate change risk exposure and corporate risk-taking can also be explained using the stakeholder theory. The classical agency theory (Jensen and Meckling, 1976; 2019) assumes that shareholders are the only party having an incomplete contract with the firm and bearer of residual risk. However, the stakeholder theory argues that other stakeholders (such as employees, lenders, suppliers, and customers) also have incomplete contracts, bear residual risks, and experience significant losses if a firm collapses. In other words, stakeholders care about firms' business or operational risk. Therefore, in response to climate change risk exposure, corporate managers may scale down their risk to create a positive firm reputation and build trust with a firm's economic stakeholders. We empirically explore these arguments.

This paper examines the association between firm-level climate change risk exposure and corporate risk-taking using 50,872 firm-year observations from 3,072 unique firms from 58 countries from 2003 to 2021. We use the firm-level climate change risk exposure data of Sautner et al. (2023) as the primary proxy of firm-level climate risk. We also use firm-level physical risk and regulatory risk exposure, and carbon risk as alternative proxies for climate change risk exposure. This paper uses six alternative corporate risk-taking measures: earnings volatility, operational cash flow volatility, equity issuance, long-term debt issuance, capital

expenditure, and research and development (R&D) expenditure. We find that firm-level climate risk exposure negatively influences volatility measures, long-term debt issuance, and R&D expenditure. This result is consistent with our argument that since climate change poses additional uncertainty and costs from physical climate change and regulatory pressure, this leads to increased risk aversion and conservative management decisions, ultimately resulting in low earnings and cash flow volatility, low long-term debt issuance, and low R&D expenditure. We further find that equity issuance and capital expenditure positively respond to firm-level climate change risk exposure, which may indicate firms' defensive financing and investment strategies in response to their climate change risk exposure. Our key result passes a battery of robustness checks, such as (i) the entropy balancing approach, (ii) Heckman's (1979) two-stage model, (iii) the impact of unobservable confounding variables, (iv) two-stage least squares instrumental variable regressions, and (v) alternative measures of climate risk exposure. In the additional analyses, we explore the moderating effect of firms' climate-related innovations on the relationship between climate change risk exposure and corporate risk-taking. The result indicates that the negative relationship between climate change risk exposure and corporate risk-taking is more pronounced for firms that generate higher environmental innovations.

This research makes several contributions. *First*, prior literature mostly focuses on firm-level determinants of corporate risk-taking capacity, such as corporate governance (John et al., 2008), block holding (Faccio et al., 2011), and managerial incentives (Coles et al., 2006; Low, 2009; Rajgopal and Shevlin, 2002). This paper complements the literature by documenting a contemporary external factor's (climate change risk exposure) influence on corporate risk-taking. *Second*, prior studies concentrating on the effect of climate risk exposure typically use country-level climate risk indicators (Huang et al., 2018; Li et al., 2022) or a single climate-related factor (Huynh et al., 2020; Sun et al., 2023). This study adds to the literature by providing fresh evidence on the relationship between firm-level climate change risk exposure and managerial risk-taking.

The rest of the paper proceeds as follows. Section 2 presents a literature review and hypothesis development; data and methodology are described in section 3; section 4 presents and interprets the empirical results; and section 5 concludes the paper by providing a summary.

2. Literature Review and Hypothesis Development

2.1. Literature Review

This paper intersects two segments of the finance literature: (i) the financial implications of corporate climate change risk exposure and (ii) the external environment affecting corporate risk-taking.

2.1.1. Climate change and corporate outcomes

It has been long recognised that climate changes lead to uncertainties for households, firms, and aggregate economies (Nordhaus, 1977; 2019). Accordingly, researchers examine whether corporate outcomes are affected by the extent to which a country is vulnerable to climate change. For example, Li et al. (2022) report a negative association between a country's climate vulnerability and firm innovation. They attribute this result to a reduced value of innovation, lower incentives to innovate, managerial career concerns, and limited financing. Huang et al. (2018) show that firms located in countries exposed to extreme weather events hold more cash, less short-term debt, and more long-term debt as strategies for organisational resilience to climatic threats. Huang et al. (2022) report that firms in countries neighbouring highly natural disaster-prone countries practice high environmental, social, and governance (ESG) disclosure over the period subsequent to disasters. Javadi and Masum (2021) find that bank loans are more expensive for firms domiciled in geographic locations with higher exposure to climate change. Painter (2020) reveals that countries vulnerable to climate change pay more underwriting fees. Similarly, Kling et al. (2021) show a positive relationship between climate vulnerability and the cost of debt. These pieces of evidence imply that stakeholders (such as banks and underwriters) price climate change risks.

Whilst a growing body of literature examines the economic implications of climate change, little evidence exists on the relationship between corporate policies and firm-level climate change risk exposure. The primary reason for this is the difficulties associated with measuring how individual firms are affected by climate change (Engle et al., 2020; Giglio et al., 2021; Hong et al., 2019). However, this problem has been somewhat addressed recently as researchers have developed measures of firm-level climate vulnerability/risk exposure (Sautner et al., 2023; Li et al., 2024; Kölbel et al., 2020; Ginglinger and Moreau, 2019; Engle et al., 2020).

Several studies rely on these firm-level climate risk measures and explore their implications for corporate performance and policies. For instance, Sautner et al. (2023) and Li et al. (2024) derive firm-level climate risk measures by conducting a textual analysis of

earnings call transcripts. Sautner et al. (2023) report that firms with high climate change risk exposure create more jobs in disruptive technologies and develop more green patents. The authors further show that climate change risk exposure is linked to forward-looking risks and risk premiums. Specifically, climate change risk exposure leads to negatively skewed return distribution, fatter tails, and a positive premium. Li et al. (2024) focus on transition risk and show that transition risk negatively correlates with firms' Tobin's Q, particularly the ones that do not actively manage their transition risk. Supporting Sautner et al. (2023), Li et al. (2024) also show that firms' transition risk exposure increases their green patenting.

Unlike the studies reviewed in the previous paragraph, Baz et al. (2023) and Berkman et al. (2024) estimate firm-level climate risk exposure based on text mining 10-K disclosure statements submitted to the Securities and Exchange Commission (SEC) by individual companies. Baz et al. (2023) report that firms with higher climate regulatory exposures experienced significantly higher cumulative returns after the 2016 Trump election. Berkman et al. (2024) find that market valuations are significantly negatively related to climate risk.

Researchers also apply several other approaches to measure firm-level climate risk exposure. For instance, Ginglinger and Moreau (2019) use two measures of climate change risk exposure. The first one was developed by the French firm Carbone 4, which assesses firm-level climate-related physical risks by breaking down a firm's activity into geographical and industrial segments and assigning a rating, which is a function of location-specific climate hazards. Their second measure of climate risk assigns a score to each firm based on three components of climate risk: operations risk, supply chain risk, and market risk. The authors show that higher climate risk is related to low leverage in the post-Paris Agreement period, potentially due to higher distress and operating costs. The stronger impact of climate exposure after the Paris Agreement may be attributed to rising aggregate investor attention to climate risk and the implementation of climate-related initiatives and regulations around the time. Huang et al. (2022) also use two measures of climate risk. The first is a firm-level management assessment of their physical climate risk exposure as presented in the Carbon Disclosure Project (CDP) survey. The second is a firm's exposure to extreme climate events estimated based on the number of climate-related disasters that occurred in the geographic regions of the firm and its subsidiaries. The authors show that climate change risk exposure results in unfavourable loan terms, such as higher interest rates, collateral requirements, and restrictive covenants. However, firms that adopt climate change mitigation strategies can reduce the negative impact of climate change risk exposure on loan contracting.

Several studies use Sautner et al.'s (2023) measure of firm-level climate change risk exposure and explore its impact on corporate policies. For example, Heo (2021) finds that firm-level climate change risk exposure positively affects corporate cash holdings. This finding is more pronounced after the Paris Agreement and for more vulnerable industries. Mueller and Sfrappini (2022) report that in response to an increase in regulatory risks, banks relocate their credit to United States (US) firms that are more vulnerable to regulatory interventions, whilst in Europe, banks prefer to lend to firms that may benefit from changes in environmental regulation. Agoraki et al. (2024) show that significant climate change risk exposure reduces firms' investment activity and increases the cost of capital.

2.1.2. External environment affecting corporate risk-taking

The impact of firms' external environment on corporate risk-taking has been a research agenda in recent years, particularly after the global financial crisis due to (i) geopolitical tensions, (ii) more stringent public sentiment about climate change, and (iii) good governance. Hege et al. (2021) and Koirala et al. (2020) show that governance reform reduces corporate risk-taking bias. The authors primarily attribute their results to higher compliance costs and expanded liabilities of managers and insiders arising from mandatory or voluntary governance reforms.

The studies of Zhang et al. (2021) and Tran (2019), amongst others, relate economic policy uncertainty (EPU) and corporate risk-taking. Arguing that EPU promotes corporate risk-taking through opportunity expectation (rather than risk aversion), Zhang et al. (2021) show that EPU positively influences corporate risk-taking in China. The authors further show that the positive relationship arises through expanding financial asset holdings and is influenced by product market competition and financial friction. However, contradicting this result, Tran (2019) indicates that EPU is negatively related to corporate risk-taking in an international context. The author attributes this result to uncertainty avoidance and individualistic culture.

Several studies explore the link between religiosity and corporate risk-taking (for example, Berry-Stölzle and Irlbeck, 2021; Gao et al., 2017; Adhikari and Agrawal, 2016; Jiang et al., 2015). These studies generally argue that religious and social norms within a firm or the religiosity of consumers may drive corporate risk-taking. Social, cultural, and religious norms influence personal and professional decision-making. This may translate into corporate outcomes aligned with these norms. Further, if consumers are located locally, their religiosity (rather than the religious norms within a firm) may also affect firms' risk-taking behaviour. In line with these arguments, Berry-Stölzle and Irlbeck (2021) show that firms' risk-taking is

negatively related to both religiosity at firms' headquarters and the religiosity of firms' largest geographic market. Likewise, Gao et al. (2017) show that local religiosity is significantly negatively related to hedge funds' total and idiosyncratic volatilities. A similar result is also found by Adhikari and Agrawal (2016) and Jiang et al. (2015), amongst others.

Prior research also focuses on institutional determinants of corporate risk-taking, such as investor protection (John et al., 2008), creditor rights (Acharya et al., 2011; Houston et al., 2010), and governance (Laeven and Levine, 2009; Boubakri et al., 2013). Specifically, John et al. (2008) find that corporations take riskier but value-enhancing investments in environments with better investor protection. This is because high-quality investor protection reduces the likelihood of private benefits, resulting in excess risk avoidance. Acharya et al. (2011) show that stronger creditor rights lead to corporate risk reduction. Corporations do so by engaging in diversifying acquisitions across industries and national borders. The key argument behind the result is that stronger creditor rights impose private costs on managers by mandating the dismissal of management in bankruptcy. To avoid these costs, managers reduce the likelihood of distress. However, Houston et al. (2010) find that stronger creditor rights promote bank risk-taking and increase the likelihood of a financial crisis. This result may arise as stronger creditor rights provide greater protection in the event of default. This motivates creditors to lend to risky borrowers with weaker creditworthiness. In a similar study, Favara et al. (2017) show that the prospect of imperfect enforcement of debt contracts in default induces firms to take on less risk as they approach financial distress.

Researchers also explore the relationship between regulatory setting and corporate risk-taking. For instance, Langenmayr and Lester (2018) relate corporate risk-taking to the tax system. They find that the length of tax loss periods positively impacts risk-taking as the loss rules allow firms to shift some risk to the government. They also report a positive relationship between tax rates and risk-taking. However, Ljungqvist et al. (2017) show that firms' risk-taking responses are asymmetric to tax rate changes. Specifically, average firms reduce risk with an increase in tax rate; however, their response is insignificant to a tax cut. This result arises as higher taxes lead to a greater decline in expected profits for risky projects than for safe ones. Barger et al. (2010) show that corporate risk-taking declined significantly after the adoption of the Sarbanes-Oxley Act 2002. They attribute this result to the provisions of an expanded role of independent directors, an increase in director and officer liability, and internal control-related rules. In addition to focusing on formal institutions, researchers find that informal institutions (such as culture) also matter in corporate decision-making (risk-taking).

For instance, Li et al. (2013) show that individualism (uncertainty avoidance and harmony) has a positive (negative) and significant relationship with corporate risk-taking.

A related strand of literature examines the effect of macroeconomic outlook and global risk factors (for example, oil prices) on corporate risk-taking. For instance, Gupta and Krishnamurti (2018) find that firms' risk-taking is linked to global oil price changes. However, this relationship is conditional on the macroeconomic outlook. Specifically, they find that firms increase (decrease) their risk-taking in a rising oil price situation if the macroeconomic outlook is favourable (unfavourable). The authors argue that oil prices impact corporate risk-taking as oil is an important direct or indirect factor in the production process, and oil price influences the future cash flows, revenue, and investment of most firms.

Overall, we observe that although prior studies explore the effect of country-level climate risk indicators or a single climate-related factor on corporate outcomes, disaggregated firm-level climate risk measures have received less attention. Further, to our knowledge, no prior studies have examined whether managerial risk-taking is driven by corporate climate vulnerability. We fill this gap in the literature.

2.2. Hypothesis Development

The prospect theory, an alternative to the expected utility theory, suggests that individuals' reactions to potential gains and losses can be diverse, and their decision-making about risky alternatives is based on the probable gains/losses in relation to their risk appetite (Kahneman and Tversky, 2013; Barberis et al., 2016; Best and Grauer, 2016). For example, individuals experiencing risky choices leading to gains (losses) are typically risk-averse (risk-seeking), preferring lower risk-adjusted return (lower return with potential to avoid losses) (Bahadar et al., 2023). In our context, the prospect theory can explain the relationship between the level of corporate risk-taking and firm-level climate change risk exposure. Since climate risk can be considered an incremental 'business risk' (Huang et al., 2019; Zaman et al., 2021), risk-averse firms may overvalue the losses from climate events (physical or regulatory) relative to potential gains and avoid excessive risk-taking. Hence, firm-level climate risk may exhibit an inverse relationship with corporate risk-taking.

On the other hand, as climate risk comprises opportunities, in line with the prospect theory, firms with high-risk appetites (or risk seekers) may overvalue potential gains relative to potential losses, resulting in more risk-taking. In other words, firms with high climate risk exposure may seek ways to adapt and mitigate their risk exposure through climate opportunities (for example, green innovation), which are risky and highly uncertain. Hence, climate risk

exposure may promote risk-taking (Zhang et al., 2021). Managerial loss aversion may also lead managers to take more risks. Extreme climate events may lead to the destruction of firms' assets and disruption of firms' operations and production. Firms with a higher likelihood of such losses due to higher climate risk exposure may take more risks to reduce losses and increase profits.

The potential relationship between climate change risk exposure and corporate risk-taking can also be explained using the stakeholder theory. The classical agency theory (Jensen and Meckling, 1976; 2019) assumes that shareholders are the only party having an incomplete contract with the firm and bearer of residual risk. However, the stakeholder theory argues that other stakeholders (such as employees, lenders, suppliers, customers, and governments) also have incomplete contracts, and they bear residual risks and experience significant losses if a firm collapses. For example, employees with undiversified human capital are perhaps amongst the biggest losers if a firm breaks down. In other words, stakeholders care about firms' business or operational risk. Therefore, in response to climate change risk exposure, corporate managers may scale down their risk to create a positive firm reputation and build trust with a firm's economic stakeholders.

Despite the competing arguments presented above, the theories and prior empirical results dominate the idea that firm-level climate risk exposure leads to conservative decision-making. This is potentially due to operating costs and bankruptcy costs (Ginglinger and Moreau, 2019). Firms exposed to climate risk will incur costs related to operational disruptions, production adjustments, insurance premium increases, and supply chain changes. These will threaten the overall sustainability of the business. Further, they will be impacted by the costs of failure (such as a reduction in the value of a firm's assets). In addition to the physical risk, firms exposed to transition risks will incur costs associated with changes in technology, markets, and regulations. Therefore, we argue that firms with greater climate risk exposure will reassess their vulnerabilities, leading them to reduce their risk-taking. As such, we formulate the following hypothesis.

H1: Firm-level climate risk exposure reduces corporate risk-taking.

3. Data and Methodology

3.1. Sample and Data

Our initial sample consists of all firms covered by the LSEG ESG (formerly Refinitiv ESG) database from 2003 to 2021. We obtain firm-level climate change risk exposure data

from Sautner et al. (2023). Additionally, we obtain firm-level financial data from the Worldscope database, non-financial data from the LSEG ESG database, and country-level macroeconomic data from the World Bank database. After excluding observations due to unavailable climate risk exposure data and insufficient control variables, the final sample includes 50,782 firm-year observations. Panel A of Table 1 presents the sample selection process.

Table 1: Sample Selection and Distribution

Panel A: Sample selection	Firm-year observations	
	Observations	
Climate risk exposure data available after merging with Refinitiv ESG database from 2002–2021	60,101	
Less: Observations dropped due to insufficient control variables	(9,319)	
Final test sample 2003–2021	50,782	
Panel B: Industry-wise distribution of firms in sample	Observations	
Name of industry	Observations	% of sample
Mining/Construction	2,409	5.3
Food	1,634	3.32
Textiles/Print/Publishing	1,505	1.44
Chemicals	1,581	3.14
Pharmaceuticals	2,049	4.02
Extractive	1,729	3.27
Manufacturing: Rubber/glass/etc.	876	1.54
Manufacturing: Metal	1,261	1.67
Manufacturing: Machinery	1,898	2.98
Manufacturing: Electrical	1,320	3.17
Manufacturing: Transport	1,665	3.01
Manufacturing: Instruments	2,022	2.42
Manufacturing: Miscellaneous	274	0.46
Computers	5,130	15.42
Transportation	3,955	12.62
Utilities	2,349	3.26
Retail: Wholesale	1,390	2.49
Retail: Miscellaneous	2,572	3.58
Retail: Restaurant	557	0.16
Financial	6,902	16.33
Insurance/Real Estate	2,748	4.07
Services	4,716	6.33
Others	240	0.47
Total sample	50,782	100
Panel C: Year-wise distribution of firms in sample	Observations	
	Observations	% of sample
2003	861	1.70
2004	1,223	2.41
2005	1,322	2.60
2006	1,555	3.06
2007	1,781	3.51

	Observations	% of sample
2008	1,965	3.87
2009	2,146	4.23
2010	2,168	4.27
2011	2,293	4.52
2012	2,506	4.93
2013	2,865	5.64
2014	2,724	5.36
2015	3,008	5.92
2016	3,075	6.06
2017	3,225	6.35
2018	3,945	7.77
2019	4,383	8.63
2020	4,665	9.19
2021	<u>5,072</u>	<u>9.99</u>
Total sample	<u>50,782</u>	<u>100</u>

Panel D: Country-wise distribution of firms in sample

Country	N	%
Argentina	132	0.26
Australia	1,516	2.99
Austria	242	0.48
Belgium	272	0.54
Bermuda	290	0.57
Brazil	799	1.57
Canada	3,000	5.91
Chile	208	0.41
China	620	1.22
Columbia	90	0.18
Cayman Islands	47	0.09
Cyprus	71	0.14
Czech Republic	27	0.05
Denmark	365	0.72
Egypt	38	0.07
Finland	430	0.85
France	1,148	2.26
Germany	1,309	2.58
Greece	145	0.29
Hong Kong	459	0.9
Hungry	62	0.12
Indonesia	101	0.2
India	956	1.88
Ireland	411	0.81
Isle of Man	18	0.04
Israel	308	0.61
Italy	522	1.03
Japan	1,699	3.35
Luxembourg	175	0.34
Monaco	25	0.05
Mexico	492	0.97

Country	N	%
Malaysia	97	0.19
New Zealand	222	0.44
Netherlands	502	0.99
Norway	360	0.71
Oman	16	0.03
Panama	32	0.06
Peru	65	0.13
Philippines	61	0.12
Poland	158	0.31
Puerto Rico	42	0.08
Portugal	125	0.25
Qatar	19	0.04
Republic of Korea	312	0.61
Russia	306	0.6
Saudi Arabia	12	0.02
Singapore	214	0.42
South Africa	472	0.93
Spain	473	0.93
Sweden	782	1.54
Switzerland	887	1.75
Thailand	111	0.22
Turkey	185	0.36
Taiwan	313	0.62
Uruguay	23	0.05
United Arab States	57	0.11
United Kingdom	2,567	5.05
United States	<u>26,392</u>	<u>51.97</u>
Total	<u>50,782</u>	<u>100</u>

Source: Authors' computation.

In Panels B, C, and D, we respectively present the industry-, year- and country-wise sample distributions. From Panel B, we find that 'financial; (16.33%), 'computers' (15.42%), and 'transportation' (12.62%) are the top three industry contributors to our sample. On the other hand, 'retail: restaurant' (0.16%), 'manufacturing: miscellaneous' (0.46%), and 'textile/print/publishing' (1.44%) industries have the lowest number of observations.

The year-wise distribution of the sample firms (Panel C) reflects that the recent years account for more firms, indicating an extended coverage of firms by the climate change risk exposure database. From Panel D, we find that our sample is dominated by firms from the US (51.97%), the United Kingdom (UK) (5.05%), and Japan (3.35%). On the other hand, Middle Eastern countries, such as Qatar (0.04%), Saudi Arabia (0.02%), and Oman (0.03%), have the lowest number of firms represented in our sample.

3.2. Variables

Following the relevant literature (see, for example, Gopalan et al. (2021); Boubakri et al. (2013); Huang et al. (2018)), we use a set of risk measures: (i) earnings volatility, (ii) cash flow volatility, (iii) equity issuance, (iii) long-term debt issuance, (v) capital expenditure, and (vi) R&D expenditure. As indicated previously, climate change poses additional uncertainty and costs from physical climate change and regulatory pressure, which may lead to increased risk aversion and conservative management decisions. Due to increased risk aversion and conservative corporate policies, climate risk exposure should be associated with low earnings and cash flow volatility. On the other hand, climate risk exposure may promote corporate risk-taking through opportunity expectations and managerial loss aversion. In such circumstances, climate risk exposure may be associated with high risk-taking tendencies that translate to high earnings and cash flow volatility.

Since climate change risk exposure is considered an incremental business risk, in line with the trade-off theory, firms with higher climate change risk exposure may issue more equity and less long-term debt (Frank and Goyal, 2003; Rahman et al. 2024). Further, climate uncertainty may increase the cost of debt and reduce financial flexibility (Huang et al., 2022; Kling et al., 2021). This also may motivate managers to use more equity financing and less debt financing. We, therefore, expect that climate change risk exposure positively (negatively) relates to equity (long-term debt) issuance.

With regard to capital expenditure and R&D expenditure, we argue that capital expenditure is a more defensive investment than R&D as the outcomes of capital expenditure are less uncertain than those of R&D (Bhagat and Welch, 1995; Cassell et al., 2012; Coles et al., 2006; Kothari et al., 2002). Consistent with this argument, higher climate change risk exposure may lead to higher capital expenditure (a positive relationship) and lower R&D expenditure (a negative relationship) as a part of firms' conservative corporate policies.

We utilise firm-level climate change risk exposure data developed by Sautner et al. (2023). This firm-level time-varying measure is derived using a machine learning algorithm. Specifically, the algorithm counts the frequency of certain climate change bigrams in a transcript of corporate conference calls and then scales it by the total number of bigrams in the transcript. This measure captures firm-level exposures to opportunity, physical, and regulatory shocks associated with climate change based on call participants' views on firm-level exposure to different aspects of climate change. Appendix A provides the definitions of all variables.

3.3. Empirical Models

The impact of climate change risk exposure on corporate risk-taking is explored using a pooled multivariate regression framework. We estimate the regressions using ordinary least squares (OLS), and standard errors are clustered by firms and country. Specifically, the following model is estimated:

$$\text{Risk taking measure}_{i,j,t+\tau} = \alpha + \beta \text{CC_EXPO}_{i,j,t} + \delta \mathbf{X}_{i,j,t} + \text{Fixed effects} + \varepsilon_{i,t} \quad (1)$$

where subscript i denotes the individual firm, t equals the time period, j equals the country, $\mathbf{X}_{i,j,t}$ denotes the firm-level control variables and *Fixed effects* include year, industry and country fixed effects. The dependent variable is the alternative risk-taking proxies, and *CC_EXPO* reflects the firm-level climate change risk exposure. The controls include key corporate financial variables (such as firm size, leverage, return on assets, growth opportunities, firm age, market-to-book value ratio, capital expenditure, R&D expenditure, and intangibles) and macroeconomic variables (such as economic development and macroeconomic risks).

4. Empirical Results

4.1. Descriptive Statistics and Correlation Matrix

Table 2 provides the descriptive statistics of the variables used in the empirical estimations. Panels A and B display the full sample descriptive statistics and mean and median tests of the high and low climate change risk exposure subsamples. For this analysis, we split firm-year observations into *HIGH_CC_EXPO* and *LOW_CC_EXPO* subsamples based on the country, industry, and year medians for climate change risk exposure. From Panel B, we observe that the means of earnings volatility (*EVOL*) and operating cash flow volatility (*CFVOL*) are lower (0.049 and 0.039, respectively) for the high climate risk exposure subsample (*HIGH_CC_EXPO*) compared to that (0.055 and 0.043, respectively) of the low climate risk exposure subsample (*LOW_CC_EXPO*). The mean differences are statistically significant at the conventional level. We further observe that the mean capital expenditure (*CAPEX*) is higher, whereas the mean R&D expenditure (*RDINT*) is lower for the high climate risk exposure subsample (*HIGH_CC_EXPO*). These results provide univariate evidence of the negative relationship between climate change risk exposure and firms' risk-taking measures. Additionally, it is found that high climate change risk exposure firms appear to hold higher leverage (*LEV*) and they have higher profitability (*ROA*) (mean values of 0.256 and 0.030, respectively) than their low climate risk exposure counterparts (mean values of 0.253 and 0.026). Further, we observe that high climate risk exposure firms hold less cash; however, they

are relatively large, older, and have fewer intangibles than those with low climate change risk exposure.

The bivariate correlation matrix of the key variables is presented in Table 3. We observe that firm-level climate risk exposure has a statistically significant negative relationship with volatility measures (*EVOL* and *CFVOL*) and R&D expenditure (*RDINT*), whilst a positive relationship with equity issuance (*EQUITY*) and capital expenditure (*CAPEX*). This is consistent with the difference in mean tests discussed in the previous paragraph.

Table 2: Descriptive Statistics

Panel A: Full descriptive statistics						
	N	Mean	Median	Std. Dev.	1st	3rd
<i>EVOL</i>	50,782	0.051	0.028	0.073	0.013	0.058
<i>CFVOL</i>	50,782	0.041	0.027	0.048	0.014	0.048
<i>EQUITY</i>	50,782	0.011	0.000	0.092	-0.007	0.002
<i>DLTT</i>	50,782	0.236	0.194	0.214	0.056	0.345
<i>CAPEX</i>	50,782	0.041	0.028	0.044	0.010	0.056
<i>RDINT</i>	50,782	0.027	0.000	0.056	0.000	0.021
<i>CC_EXPO</i>	50,782	0.001	0.000	0.002	0.000	0.001
<i>SIZE</i>	50,782	7.952	7.952	1.689	6.790	9.123
<i>LEV</i>	50,782	0.255	0.234	0.196	0.092	0.376
<i>ROA</i>	50,782	0.029	0.035	0.109	0.007	0.074
<i>GROWTH</i>	50,782	0.113	0.062	0.350	-0.028	0.174
<i>FAGE</i>	50,782	2.852	2.944	0.597	2.485	3.332
<i>MB</i>	50,782	3.180	2.010	4.936	1.194	3.567
<i>CAPEX</i>	50,782	0.042	0.029	0.045	0.011	0.057
<i>RDINT</i>	50,782	0.057	0.000	0.229	0.000	0.022
<i>INTANG</i>	50,782	0.181	0.098	0.203	0.015	0.297
<i>LNGDP</i>	50,782	10.620	10.791	0.695	10.625	10.966
<i>STD_GDP</i>	50,782	1.583	1.277	1.259	0.490	2.283

Panel B: Mean and median-test						
	HIGH_CC_EXPO (N=4,918)		LOW_CC_EXPO (N=2,726)		Mean-test (p-value)	Median-test (p-value)
	Mean	Median	Mean	Median		
<i>EVOL</i>	0.049	0.027	0.055	0.029	0.000	0.000
<i>CFVOL</i>	0.039	0.026	0.043	0.027	0.000	0.000
<i>EQUIT</i>	0.010	0.000	0.109	0.000	0.253	0.138
<i>DLTT</i>	0.238	0.202	0.235	0.186	0.169	0.000
<i>CAPEX</i>	0.042	0.030	0.039	0.025	0.000	0.000
<i>RDINT</i>	0.026	0.000	0.029	0.000	0.000	0.127
<i>SIZE</i>	8.034	8.037	7.846	7.827	0.000	0.000
<i>LEV</i>	0.256	0.238	0.253	0.228	0.054	0.000
<i>ROA</i>	0.030	0.035	0.026	0.035	0.000	0.101
<i>GROWTH</i>	0.108	0.060	0.118	0.064	0.001	0.001

Panel B: Mean and median-test

	HIGH_CC_EXPO (N=4,918)		LOW_CC_EXPO (N=2,726)		Mean-test (p-value)	Median- test (p-value)
	Mean	Median	Mean	Median		
<i>FAGE</i>	2.863	2.996	2.837	2.944	0.000	0.000
<i>MB</i>	3.026	1.950	3.379	2.097	0.000	0.000
<i>CAPEX</i>	0.044	0.031	0.040	0.026	0.000	0.012
<i>RDINT</i>	0.053	0.000	0.061	0.000	0.000	0.264
<i>INTANG</i>	0.171	0.089	0.194	0.112	0.000	0.000
<i>LNGDP</i>	10.583	10.780	10.667	10.795	0.000	0.000
<i>STD_GDP</i>	1.627	1.350	1.527	1.215	0.000	0.039

Note: Appendix A provides the definitions of all variables.

Source: Authors' computation.

Table 3: Correlation Matrix

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	
<i>EVOL</i>	[1]	1.000																	
<i>CFVOL</i>	[2]	0.703***	1.000																
<i>EQUITY</i>	[3]	0.416***	0.506***	1.000															
<i>DLTT</i>	[4]	0.305***	0.343***	0.047***	1.000														
<i>CAPEX</i>	[5]	0.022***	-0.030***	0.005	0.156***	1.000													
<i>RDINT</i>	[6]	0.347***	0.379***	0.261***	-	-0.120***	1.000												
<i>CC_EXPO</i>	[7]	-0.052***	-0.059***	0.012***	0.058***	0.106***	-0.062***	1.000											
<i>SIZE</i>	[8]	-0.327***	-0.324***	-0.209***	0.023***	0.032***	-0.093***	0.044***	1.000										
<i>LEV</i>	[9]	-0.070***	-0.122***	0.006	0.788***	0.118***	-0.207***	0.076***	0.036***	1.000									
<i>ROA</i>	[10]	-0.382***	-0.308***	-0.422***	-	0.125***	-0.275***	-0.015***	0.306***	-0.115***	1.000								
<i>GROWTH</i>	[11]	0.141***	0.206***	0.149***	0.018***	0.044***	0.106***	-0.028***	-0.027***	-0.042***	0.016***	1.000							
<i>FAGE</i>	[12]	-0.228***	-0.280***	-0.189***	-	-0.057***	-0.124***	0.090***	0.315***	0.004	0.127***	-0.205***	1.000						
<i>MB</i>	[13]	0.099***	0.161***	0.068***	0.013***	0.023***	0.180***	-0.058***	0.129***	-0.052***	0.093***	0.099***	-0.102***	1.000					
<i>CAPEX</i>	[14]	0.029***	-0.025***	0.019***	0.178***	0.812***	-0.116***	0.101***	0.012***	0.132***	0.099***	0.055***	-0.066***	0.017***	1.000				
<i>RDINT</i>	[15]	0.393***	0.475***	0.443***	-	-0.099***	0.607***	-0.045***	-0.151***	-0.103***	-0.501***	0.115***	-0.136***	0.104***	-0.097***	1.000			
<i>INTANG</i>	[16]	-0.040***	-0.089***	-0.070***	0.160***	-0.187***	0.070***	-0.098***	0.038***	0.115***	0.070***	0.007	-0.007	0.057***	-0.189***	-0.046***	1.000		
<i>LNGDP</i>	[17]	0.055***	0.021***	0.020***	0.071***	-0.099***	0.115***	-0.034***	-0.088***	-0.004	-0.098***	-0.044***	0.051***	-0.012***	-0.092***	0.080***	0.118***	1.000	
<i>STD_GDP</i>	[18]	-0.008*	-0.001	-0.020***	-	-0.018***	-0.058***	0.021***	0.032***	0.019***	0.004	-0.050***	0.006	-0.024***	-0.046***	-0.041***	-0.045***	-0.210***	1.000

Note: Appendix A provides the definitions of all variables.

Source: Authors' computation.

4.2. Regression Results

Panel A of Table 4 presents the regression results for the relationship between firm-level climate change risk exposure and the proxies for risk-taking: earnings volatility (*EVOL*), cash flow volatility (*CFVOL*), equity issuance (*EQUITY*), long-term debt issuance (*DLTT*), capital expenditure (*CAPEX*), and R&D expenditure (*RDINT*). All models include year, industry, and country fixed effects. We find that firm-level climate risk exposure negatively influences both volatility measures ($\beta = -1.202$ p -value < 0.01; $\beta = -0.279$ p -value < 0.05, respectively). This result is consistent with our argument that since climate change poses additional uncertainty and costs from physical climate change and regulatory pressure, this may lead to increased risk aversion and conservative management decisions, resulting in low earnings and cash flow volatility. We also observe that climate change risk exposure positively impacts equity issuance ($\beta = 1.048$ p -value < 0.01), whilst negatively influencing long-term debt issuance ($\beta = -0.554$ p -value < 0.10). This result aligns with the trade-off theory and the argument that climate uncertainty may increase the cost of debt and reduce financial flexibility, motivating managers to use more (less) equity (long-term debt) financing as a climate change mitigation strategy. We further find that capital (*R&D*) expenditure positively (negatively) responds to firm-level climate change risk exposure. Both the coefficients are statistically significant at the 1% level. This result supports the notion that investing in capital expenditure is more defensive than investing in R&D. This is because capital expenditure outcomes are associated with more risk than the ones for R&D (Bhagat and Welch, 1995; Cassell et al., 2012; Coles et al., 2006; Kothari et al., 2002).

In terms of economic significance, based on model 1, we find that, on average, a one-unit increase in firm-level climate change risk exposure leads to a 2.4% decline in earnings volatility relative to the sample mean $[(0.001 \times -1.202)/0.051 = -0.024]$. Likewise, based on model 5, we observe that, on average, a one-unit increase in firm-level climate change risk exposure increases capital expenditure by 1.2% $[(0.001 \times 0.482)/0.041 = 0.012]$.

Regarding the control variables, we find that firm size (*SIZE*), leverage (*LEV*), profitability (*ROA*), growth opportunities (*GROWTH*), firm age (*FAGE*), market-to-book value (*MB*), and intangibles (*INTANG*) significantly influence firms' risk-taking behaviour.

Table 4: Regression Results Between Climate Change Exposure and Risk-taking

Panel A: Climate change exposure and risk-taking (without firm fixed effects)						
	DV=EVOL_{i,j,t+1}	DV=CFVOL_{i,j,t+1}	DV=EQUITY_{i,j,t+1}	DV=DLTT_{i,j,t+1}	DV=CAPEX_{i,j,t+1}	DV=RDINT_{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CC_EXPO</i>	-1.202*** (-8.660)	-0.279*** (-2.976)	1.048*** (4.391)	-0.554* (-1.755)	0.482*** (4.578)	-0.359*** (-3.524)
<i>SIZE</i>	-0.008*** (-32.640)	-0.006*** (-42.278)	-0.004*** (-17.108)	0.004*** (8.586)	0.001*** (9.856)	0.002*** (17.524)
<i>LEV</i>	-0.016*** (-7.669)	-0.009*** (-7.345)	-0.002 (-0.936)	0.826*** (173.236)	0.013*** (12.841)	-0.037*** (-33.515)
<i>ROA</i>	-0.156*** (-23.623)	-0.032*** (-8.280)	-0.217*** (-25.459)	0.063*** (6.844)	0.037*** (18.275)	-0.114*** (-39.574)
<i>GROWTH</i>	0.018*** (12.128)	0.017*** (17.170)	0.026*** (12.918)	0.016*** (6.548)	0.005*** (8.275)	0.007*** (9.802)
<i>FAGE</i>	-0.010*** (-16.266)	-0.010*** (-26.333)	-0.011*** (-13.522)	-0.019*** (-15.874)	-0.005*** (-13.268)	-0.006*** (-16.001)
<i>MB</i>	0.001*** (14.077)	0.001*** (18.648)	0.001*** (8.651)	0.001*** (5.676)	0.000*** (2.597)	0.001*** (15.437)
<i>CAPEX</i>	-0.004 (-0.467)	-0.039*** (-7.637)	0.129*** (11.618)	0.326*** (17.963)	—	-0.075*** (-18.022)
<i>RDINT</i>	0.049*** (14.500)	0.061*** (27.250)	0.113*** (18.867)	0.018*** (3.912)	-0.012*** (-14.899)	—
<i>INTANG</i>	-0.025*** (-13.399)	-0.030*** (-25.010)	-0.009*** (-3.888)	0.061*** (15.952)	-0.054*** (-61.078)	-0.021*** (-17.800)
<i>LNGDP</i>	-0.010*** (-3.852)	0.001 (0.572)	0.002 (0.529)	-0.001 (-0.168)	-0.019*** (-10.594)	0.003* (1.781)
<i>STD_GDP</i>	0.001*** (3.665)	0.001*** (3.434)	-0.000 (-1.072)	-0.003*** (-4.917)	-0.001*** (-2.962)	0.000 (0.452)
Intercept	0.247*** (9.329)	0.106*** (5.409)	0.050 (1.610)	0.035 (0.622)	0.257*** (13.188)	0.012 (0.777)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,782	50,782	50782	50782	50,782	50,782
R ²	0.338	0.389	0.301	0.660	0.335	0.545

Panel B: Climate change exposure and risk-taking (with firm fixed effects)

	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CC_EXPO</i>	-0.349** (-2.048)	-0.207* (-1.845)	0.329* (1.938)	-0.490* (-1.751)	0.080 (0.468)	-0.170*** (3.139)
<i>SIZE</i>	-0.011*** (-11.617)	-0.004*** (-9.460)	-0.006*** (-5.291)	0.008*** (5.243)	0.004*** (10.708)	0.000 (0.355)
<i>LEV</i>	0.003 (0.938)	-0.008** (-5.388)	0.037** (6.166)	0.636** (19.670)	-0.013** (-5.825)	-0.004*** (-4.346)
<i>ROA</i>	-0.096*** (-5.637)	-0.005 (-1.097)	-0.092*** (-5.632)	0.059*** (5.228)	0.031*** (9.960)	-0.016*** (-6.608)
<i>GROWTH</i>	0.006*** (4.455)	0.005*** (5.783)	0.007*** (3.438)	0.004 (1.477)	0.003*** (3.320)	-0.001*** (-3.831)
<i>FAGE</i>	-0.032*** (-10.012)	-0.023*** (-19.203)	-0.024*** (-5.029)	-0.017** (-2.109)	-0.011*** (-9.008)	0.002** (1.977)
<i>MB</i>	0.000*** (5.066)	0.000*** (5.749)	0.001*** (10.649)	0.001*** (5.551)	0.000*** (5.010)	-0.000*** (-2.673)
<i>CAPEX</i>	-0.064*** (-5.427)	-0.013* (-1.735)	0.096*** (9.236)	0.326*** (8.898)	—	0.009*** (3.400)
<i>RDINT</i>	-0.010* (-1.779)	0.001 (0.424)	0.044*** (9.720)	0.025*** (4.654)	0.006*** (3.576)	—
<i>INTANG</i>	-0.046*** (-8.743)	-0.019*** (-6.080)	0.000 (0.023)	-0.001 (-0.079)	-0.011*** (-4.692)	0.004*** (3.340)
<i>LNGDP</i>	-0.013*** (-5.328)	-0.002 (-1.050)	0.000 (0.009)	-0.005 (-0.386)	-0.014*** (-5.929)	0.002** (2.560)
<i>STD_GDP</i>	0.001*** (3.547)	0.001*** (4.843)	0.000 (0.383)	-0.002** (-2.123)	-0.000 (-1.214)	-0.000* (-1.720)

Intercept	0.352 ^{***} (14.399)	0.155 ^{***} (10.048)	0.106 ^{**} (2.532)	0.072 (0.520)	0.190 ^{***} (7.829)	0.002 (0.245)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,393	50,393	50,393	50,393	50,393	50,393
R ²	0.682	0.745	0.486	0.758	0.716	0.936

Notes: Superscript ^{***}, ^{**}, and ^{*} represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

We also employ firm fixed effects in our regression models to address the time-invariant omitted variable bias arising from unobservable firm characteristics. Firm fixed-effect regressions eliminate cross-sectional variation and focus solely on variations within a firm over time. They also mitigate the impact of omitted time-invariant firm characteristics, which could otherwise lead to a spurious correlation between firm-level climate change risk exposure and corporate risk-taking proxies. Table 4, Panel B provides the regression results. The results suggest that our findings are qualitatively similar, except for the case of *CAPEX*.

4.3. Entropy Balancing Analysis

Our estimation could be biased due to asymmetric sample characteristics between firms with low and high climate risk exposure. To mitigate this concern, we use the entropy balancing technique (EBT), which reduces the effect of asymmetric firm characteristics between samples and the likelihood that our results are subject to this bias. More specifically, EBT reweights the control group to align with the covariate moments in the treatment group whilst the full sample is still preserved (Hainmueller, 2012).

To implement the entropy balancing approach, we split firm-year observations into a treatment group (*HIGH_CRISK*) and a control group (*LOW_CRISK*) based on the country, industry, and annual medians for climate risk exposure. As indicated previously, this technique assigns weights to adjust for the sample's distribution of control observations, and the adjustment process balances the covariates of mean, variance, and skewness of the distributions (Hainmueller, 2012; Hainmueller and Xu, 2013). Further, this approach assigns a relatively higher weight to under-represented observations and a lower weight to over-represented observations. This weighting scheme results in a 'pseudo' control group, reducing the covariate differences between the treatment and control groups.

The relevant results are presented in Table 5. Panel A shows the descriptive statistics of the entropy-balanced samples, whilst Panel B reports the regression results derived from these samples. From Panel B, we observe that the coefficients of *CC_EXPO* are negative (positive) and statistically significant in the cases of *EVOL*, *CFVOL*, *DLTT*, and *RDINT* (*EQUITY* and *CAPEX*). This finding supports our key result in the previous subsection. It reinforces the hypothesis that a significant association exists between firms' climate change risk exposure and their level of risk-taking.

Table 5: Entropy Balancing Analysis

Panel A: Descriptive statistics of entropy-balanced samples						
	Treatment Group (HIGH_CRISK=1)			Control Group (HIGH_CRISK=0)		
	Mean	Variance	Skewness	Mean	Variance	Skewness
<i>SIZE</i>	8.019	2.867	-0.013	8.019	2.867	-0.013
<i>LEV</i>	0.258	0.036	0.674	0.258	0.036	0.674
<i>ROA</i>	0.029	0.011	-2.417	0.029	0.011	-2.417
<i>GROWTH</i>	0.107	0.116	3.484	0.107	0.116	3.484
<i>FAGE</i>	2.875	0.344	-0.723	2.875	0.344	-0.723
<i>MB</i>	3.008	21.390	3.570	3.008	21.400	3.569
<i>CAPEX</i>	0.044	0.002	1.918	0.043	0.002	1.918
<i>RDINT</i>	0.054	0.050	7.127	0.054	0.050	7.126
<i>INTANG</i>	0.173	0.039	1.235	0.173	0.039	1.235
<i>LNGDP</i>	10.600	0.498	-2.649	10.600	0.498	-2.649
<i>STD GDP</i>	1.585	1.621	1.963	1.585	1.621	1.963

Panel B: Entropy-balancing regression results						
	DV=EVOL_{i,j,t+1}	DV=CFVOL_{i,j,t+1}	DV=EQUITY_{i,j,t+1}	DV=DLTT_{i,j,t+1}	DV=CAPEX_{i,j,t+1}	DV=RDINT_{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CC_EXPO</i>	-1.030*** (-7.777)	-0.186** (-2.062)	1.089*** (4.701)	-0.404 (-1.317)	0.360*** (3.495)	-0.371*** (-3.741)
<i>SIZE</i>	-0.007*** (-31.287)	-0.005*** (-42.606)	-0.004*** (-17.664)	0.003*** (7.960)	0.001*** (9.591)	0.002*** (18.246)
<i>LEV</i>	-0.016*** (-7.995)	-0.009*** (-7.592)	-0.000 (-0.081)	0.823*** (176.464)	0.013*** (12.904)	-0.038*** (-34.728)
<i>ROA</i>	-0.168*** (-25.409)	-0.036*** (-9.524)	-0.214*** (-25.186)	0.067*** (7.269)	0.038*** (18.452)	-0.118*** (-41.480)
<i>GROWTH</i>	0.016*** (11.575)	0.016*** (16.446)	0.025*** (12.681)	0.017*** (6.857)	0.005*** (8.661)	0.007*** (10.701)
<i>FAGE</i>	-0.010*** (-16.459)	-0.010*** (-26.691)	-0.010*** (-13.257)	-0.019*** (-16.143)	-0.004*** (-13.089)	-0.006*** (-17.005)

<i>MB</i>	0.001 ^{***} (13.387)	0.001 ^{***} (18.133)	0.001 ^{***} (8.059)	0.001 ^{***} (5.751)	0.000 ^{***} (2.584)	0.001 ^{***} (16.024)
<i>CAPEX</i>	-0.001 (-0.136)	-0.037 ^{***} (-7.405)	0.132 ^{***} (12.471)	0.322 ^{***} (18.545)	—	-0.075 ^{***} (-18.018)
<i>RDINT</i>	0.049 ^{***} (14.270)	0.062 ^{***} (27.648)	0.116 ^{***} (19.355)	0.019 ^{***} (4.052)	-0.012 ^{***} (-14.046)	—
<i>INTANG</i>	-0.024 ^{***} (-13.856)	-0.029 ^{***} (-25.546)	-0.008 ^{***} (-3.631)	0.060 ^{***} (16.091)	-0.055 ^{***} (-60.993)	-0.021 ^{***} (-18.047)
<i>LNGDP</i>	-0.010 ^{***} (-4.426)	0.000 (0.188)	0.002 (0.716)	-0.001 (-0.287)	-0.018 ^{***} (-10.042)	0.003 [*] (1.900)
<i>STD_GDP</i>	0.001 ^{***} (4.049)	0.001 ^{***} (3.817)	-0.000 (-0.970)	-0.003 ^{***} (-5.095)	-0.001 ^{***} (-2.849)	-0.000 (-0.219)
Intercept	0.248 ^{***} (9.985)	0.109 ^{***} (6.029)	0.041 (1.383)	0.043 (0.790)	0.248 ^{***} (12.693)	0.012 (0.749)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,782	50,782	50,782	Yes	50,782	50,782
R ²	0.345	0.393	0.307	0.658	0.336	0.557

Notes: Superscript ^{***}, ^{**}, and ^{*} represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

4.4. Self-selection Bias Correction

Our sample includes firms with different degrees of climate risk exposure estimated from conference call transcripts. This may result in self-selection bias if there are systematic differences between firms that disclose climate change vulnerability in their conference calls and those that do not. To correct for the potential self-selection bias, we use Heckman's two-stage procedure (1979). In the first stage, we estimate a probit model that explains the likelihood of a firm being self-selected into the sample. The second stage involves estimating the model (Equation 1) incorporating the inverse Mills ratio (IMR) as an additional regressor. The IMR is obtained from the first stage and captures the correlation between the error term in the selection equation and the regression model (Equation 1).

In the first stage, we model firms' decisions to report information on climate-risk exposure. For this purpose, we utilise the full coverage of the LSEG ESG database for our sample period and use the firms that report climate change risk exposure information as the treatment firms, whilst the firms outside our sample serve as the control firms. Specifically, we code the firms with the available climate risk exposure information as 1 and the other firms as 0. The sample size in our first-stage model is 109,051 firm-year observations, of which 46,912 are treatment observations, and the remaining are control observations.

In the probit model, the dependent variable is *CC_EXPO_DUM*, which takes a value of 1 if a firm reports climate change risk exposure information and is 0 otherwise. The independent variables comprise several firm-specific characteristics, the details of which are presented in Appendix A. To ensure identification, the probit model includes several independent variables that were not used in the valuation model. The probit model is estimated using a sample of 109,051 firm-year observations. The results for the probit model are presented in Panel A of Table 6. The likelihood of climate risk vulnerability is significantly and positively influenced by industry peer pressure for climate change exposure (*PROPDISC*), country-level political ideology (*PIDEC*), firm size (*SIZE*), leverage (*LEV*), firm age (*FAGE*), and intangibles (*INTANG*). Profitability (*ROA*), growth opportunities (*GROWTH*), the market-to-book value ratio (*MB*), capital expenditure (*CAPEX*), R&D expenditure (*RDINT*), and economic development (*LNGDP*) inversely affect the likelihood of climate risk vulnerability.

The results of the second stage regression are reported in Panel B in Table 6. In line with our baseline result, we observe that firm-level climate change risk exposure has a negative (positive) relationship with earnings volatility, cash flow volatility, long-term debt issuance, and R&D expenditure (equity issuance and capital expenditure). The IMR is positive (except in the

cases of the *EQUITY* and *DLTT* regressions) and statistically significant, indicating that our results are robust after addressing the self-selection bias.

Table 6: Heckman (1979) Two-stage Analysis

Panel A: Heckman (1979) first-stage regression results			
	Dependent variable = CC_EXPO_DUM		
	Coefficient	z-stat	p-value
<i>PROPDISC</i>	3.276	104.540	0.000
<i>PIDEC</i>	0.011	1.730	0.085
<i>SIZE</i>	0.389	96.460	0.000
<i>LEV</i>	0.206	7.280	0.000
<i>ROA</i>	-0.480	-11.250	0.000
<i>GROWTH</i>	-0.039	-6.960	0.000
<i>FAGE</i>	0.077	8.010	0.000
<i>MB</i>	-0.009	-6.220	0.000
<i>CAPEX</i>	-0.061	-4.010	0.000
<i>RDINT</i>	-0.054	-4.070	0.000
<i>INTANG</i>	0.345	10.620	0.000
<i>LNGDP</i>	-0.098	-2.780	0.005
<i>STD_GDP</i>	0.012	1.700	0.089
Intercept	-3.071	-9.460	0.000
Year Fixed		Yes	
Effects			
Industry Fixed		Yes	
Effects			
Country Fixed		Yes	
Effects			

Observations	109,051
Pseudo- R^2	0.460
Partial- R^2 (PROPDISC)	0.297***
Partial- R^2 (PIDECC)	0.002***
ROC Curve	0.916

Panel B: Heckman (1979) second-stage regression results

	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CC_EXPO</i>	-1.261*** (-8.557)	-0.336*** (-3.417)	1.172*** (4.560)	-0.375 (-1.135)	0.472*** (4.335)	-0.305*** (-2.830)
<i>SIZE</i>	-0.006*** (-21.562)	-0.005*** (-31.315)	-0.005*** (-16.167)	0.002*** (3.012)	0.002*** (11.266)	0.003*** (18.223)
<i>LEV</i>	-0.014*** (-6.592)	-0.009*** (-6.945)	-0.002 (-0.597)	0.829*** (165.509)	0.012*** (11.754)	-0.037*** (-32.512)
<i>ROA</i>	-0.162*** (-23.777)	-0.034*** (-8.685)	-0.217*** (-24.735)	0.066*** (6.900)	0.034*** (16.846)	-0.116*** (-39.590)
<i>GROWTH</i>	0.018*** (11.480)	0.018*** (16.750)	0.028*** (12.795)	0.017*** (6.457)	0.005*** (7.831)	0.007*** (9.067)
<i>FAGE</i>	-0.010*** (-15.692)	-0.011*** (-25.714)	-0.011*** (-13.039)	-0.020*** (-15.666)	-0.004*** (-12.312)	-0.006*** (-15.687)
<i>MB</i>	0.001*** (12.821)	0.001*** (17.386)	0.001*** (8.797)	0.001*** (5.933)	0.000 (0.375)	0.001*** (14.087)
<i>CAPEX</i>	-0.010	-0.042***	0.135***	0.336***	—	-0.080***

	(-1.040)	(-7.762)	(11.445)	(17.574)		(-18.244)
<i>RDINT</i>	0.046 ^{***}	0.059 ^{***}	0.114 ^{***}	0.018 ^{***}	-0.012 ^{***}	—
	(13.222)	(25.684)	(18.623)	(3.809)	(-14.910)	
<i>INTANG</i>	-0.025 ^{***}	-0.031 ^{***}	-0.009 ^{***}	0.060 ^{***}	-0.054 ^{***}	-0.021 ^{***}
	(-13.099)	(-24.667)	(-3.821)	(15.143)	(-59.461)	(-17.092)
<i>LNGDP</i>	-0.011 ^{***}	0.000	0.001	-0.002	-0.017 ^{***}	0.002
	(-3.960)	(0.202)	(0.441)	(-0.392)	(-8.538)	(1.373)
<i>STD_GDP</i>	0.001 ^{***}	0.001 ^{***}	-0.000	-0.004 ^{***}	-0.001 ^{***}	0.000
	(3.866)	(2.828)	(-0.968)	(-4.935)	(-3.549)	(0.771)
<i>IMR</i>	0.011 ^{***}	0.003 ^{***}	-0.005 ^{***}	-0.012 ^{***}	0.004 ^{***}	0.006 ^{***}
	(8.862)	(4.344)	(-3.195)	(-5.171)	(5.305)	(7.689)
Intercept	0.246 ^{***}	0.108 ^{***}	0.060 [*]	0.074	0.230 ^{***}	0.008
	(8.201)	(4.860)	(1.676)	(1.179)	(10.614)	(0.475)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,912	46,912	46,912	46,912	46,912	46,912
R ²	0.339	0.392	0.306	0.658	0.332	0.550

Notes: Superscript ^{***}, ^{**}, and ^{*} represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

4.5. Impact Threshold of a Confounding Variable analysis

Our regression model, which considers various factors influencing corporate risk-taking, faces a potential bias from unaccounted variables that might be related to both corporate risk-taking and the included control variables. To address this, we apply the Impact Threshold of a Confounding Variable (ITCV) method introduced by Larcker and Rusticus (2010). This approach assesses the extent of correlation an omitted variable must have to significantly affect the relationship between the outcome and the variable of interest. Recent studies, such as those by Blaylock et al. (2015) and Chapman et al. (2019), have successfully used this method to tackle omitted variable bias.

In our analysis (Table 7), we report ITCV statistics of -0.048, -0.032, 0.003, 0.087, 0.007, and -0.030, respectively, for the coefficients of the corporate risk-taking variables, indicating that an unobserved variable would require a correlation of at least 0.218, 0.179, 0.054, -0.008, 0.085, and 0.172 with *CC_EXPO* and the corporate risk-taking proxies to challenge our findings. Specifically, for example, for an omitted variable to affect our results in the earnings volatility proxy, its influence must exceed the most significant control variable by at least 10.381 (raw impact) or 24.22 (partial impact) times. This analysis confirms the reliability of our main findings, demonstrating that they are unlikely to be compromised by omitted variable bias.

Table 7: Analysis of the Impact of Unobservable Confounding Variables (ITCV)

	DV=EVOL _{i,j,t+1}		DV=CFVOL _{i,j,t+1}		DV=EQUITY _{i,j,t+1}		DV=DLTT _{i,j,t+1}		DV=CAPEX _{i,j,t+1}		DV=RDINT _{i,j,t+1}	
	Impact (Raw)	Impact (Partial)	Impact (Raw)	Impact (Partial)	Impact (Raw)	Impact (Partial)	Impact (Raw)	Impact (Partial)	Impact (Raw)	Impact (Partial)	Impact (Raw)	Impact (Partial)
<i>CC_EXPO</i>	—	—	—	—	—	—	—	—	—	—	—	—
<i>SIZE</i>	-0.014	-0.006	-0.014	-0.006	-0.009	-0.002	0.001	0.001	0.001	0.000	-0.004	0.001
<i>LEV</i>	-0.005	-0.007	-0.009	-0.009	0.001	0.001	0.060	0.050	0.009	0.014	-0.016	-0.016
<i>ROA</i>	0.006	0.009	0.005	0.007	0.007	0.009	0.001	-0.002	-0.002	-0.002	0.004	0.008
<i>GROWTH</i>	-0.004	-0.001	-0.006	-0.001	-0.004	-0.001	-0.001	-0.001	-0.001	-0.001	-0.003	-0.001
<i>FAGE</i>	-0.021	-0.007	-0.025	-0.011	-0.017	-0.005	-0.005	-0.005	-0.005	-0.005	-0.011	-0.005
<i>MB</i>	-0.006	-0.006	-0.009	-0.009	-0.004	-0.003	-0.001	-0.002	-0.001	-0.001	-0.010	-0.008
<i>CAPEX</i>	0.003	0.006	-0.003	-0.001	0.002	0.005	0.018	0.011	—	—	-0.012	-0.004
<i>RDINT</i>	-0.001	-0.001	-0.001	-0.001	-0.020	-0.008	0.003	-0.001	0.001	0.000	—	—
<i>INTANG</i>	0.004	-0.001	0.009	0.006	0.007	0.003	-0.016	-0.009	0.018	0.022	-0.007	-0.008
<i>LNGDP</i>	-0.014	-0.001	-0.001	-0.001	-0.001	0.001	-0.002	-0.002	0.003	0.002	-0.004	-0.001
<i>STD_GDP</i>	-0.001	0.001	0.000	0.001	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
<i>Impact Threshold for Omitted Variable (ITCV)</i>	-0.048		-0.032		0.003		0.087		0.007		-0.030	
<i>The required correlations between CC_EXPO and DVs with the unobserved</i>	0.218		0.179		0.054		-0.008		0.085		0.172	

Notes: Appendix A provides the definitions of all variables.
Source: Authors' computation.

4.6. Instrumental Variable Regression

Furthermore, our findings may be subject to reverse causality concerns. For example, firms facing higher corporate risk may experience higher levels of climate change risk exposure due to not investing in climate vulnerability solutions. We apply a two-stage least squares (2SLS) regression with instrumental variables to address reverse causality. Following prior studies (Cheng et al., 2014; Maso et al., 2020), we use the peer firms' country-industry average of climate change risk exposure (*CC_EXPO_IND_LOC*) and the country-year average of climate change risk exposure (*CC_EXPO_LOC_YEAR*) as instrumental variables for *CC_EXPO*. Firm-level climate change risk exposure is likely to be correlated with their industry peers due to similarities in industry requirements. However, peer climate change risk exposure is also largely exogenous from the firm's perspective (Lang and Stice-Lawrence, 2015). We, therefore, use the climate change risk exposure of peer firms in the same country-industry and country-year as instrumental variables to identify the outcomes associated with climate change risk exposure.⁵

Table 8 presents the regression results. For each of the risk-taking proxies, the first and second models respectively present the first- and second-stage regression results. The coefficients of *CC_EXPO_IND_LOC* and *CC_EXPO_LOC_YEAR* are positive and statistically significant in all instances, consistent with our expectations. The F-statistic of the Wald-test is significant, rejecting the null hypothesis that the instrument is weak. Further, the values of the Kleibergen-Paap LM statistic and Kleibergen-Paap Wald F-statistic indicate that our instruments are strong.

From the second-stage regressions, we observe that the coefficient of *CC_EXPO* is negative and statistically significant in all cases except models (6) and (8), which aligns with our baseline regression results. Overall, the instrumental variable 2SLS regression result indicates that our main finding is robust to controlling for endogeneity concerns and reaffirming the relationship between firm-level climate change risk exposure and corporate risk-taking.

⁵ For calculating the peer firms' country-industry average *CC_EXPO* (*PEER_CC_EXPO_IND_LOC*) and country-year average *CC_EXPO* (*PEER_CC_EXPO_LOC_YEAR*), we exclude the focal firm's climate risk exposure to eliminate the focal firm's influence on the peer firms. Hence, the instrumental variables reflect the average climate risk exposure of the focal firm's peers within the same country-industry and country-year.

Table 8: Two-stage Least Squares (2SLS) Instrumental Variables Analysis

	DV=CC_EXPO	DV=EVOL _{ij,t+1}	DV=CC_EXPO	DV=CFVOL _{ij,t+1}	DV=CC_EXPO	DV=EQUITY _{ij,t} ⁺¹	DV=CC_EXPO	DV=CAPEX _{ij,t+1}	DV=CC_EXPO	DV=RDINT _{ij,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
<i>CC_EXPO</i>	—	-5.038*** (-10.865)	—	-2.118*** (-7.885)	—	-0.161 (-0.343)	—	-1.297 (-1.100)	—	-4.975*** (-10.685)
<i>SIZE</i>	-0.000 (-1.253)	-0.008*** (-32.601)	-0.000 (-1.253)	-0.006*** (-42.231)	-0.000 (-1.253)	-0.004*** (-17.118)	-0.000 (-1.053)	0.001*** (9.848)	-0.000 (-1.436)	-0.007*** (-30.827)
<i>LEV</i>	0.000 (0.286)	-0.016*** (-7.564)	0.000 (0.286)	-0.009*** (-7.267)	0.000 (0.286)	-0.002 (-0.915)	0.000 (0.720)	0.013*** (12.916)	0.000 (0.670)	-0.023*** (-10.844)
<i>ROA</i>	-0.000*** (-5.031)	-0.158*** (-23.914)	-0.000*** (-5.031)	-0.032*** (-8.500)	-0.000*** (-5.031)	-0.217*** (-25.518)	-0.000*** (-4.747)	0.036*** (17.740)	-0.000*** (-4.489)	-0.205*** (-35.860)
<i>GROWTH</i>	0.000 (1.089)	0.018*** (12.131)	0.000 (1.089)	0.017*** (17.174)	0.000 (1.089)	0.026*** (12.934)	0.000 (1.415)	0.005*** (8.279)	0.000 (0.871)	0.020*** (13.745)
<i>FAGE</i>	0.000*** (3.514)	-0.010*** (-15.901)	0.000*** (3.514)	-0.010*** (-26.049)	0.000*** (3.514)	-0.011*** (-13.462)	0.000*** (3.176)	-0.004*** (-12.984)	0.000*** (3.673)	-0.011*** (-17.244)
<i>MB</i>	-0.000*** (-5.328)	0.001*** (13.520)	-0.000*** (-5.328)	0.001*** (18.254)	-0.000*** (-5.328)	0.001*** (8.557)	-0.000*** (-5.260)	0.000** (2.069)	-0.000*** (-5.545)	0.001*** (15.139)
<i>CAPEX</i>	0.001*** (5.008)	-0.001 (-0.102)	0.001*** (5.008)	-0.038*** (-7.307)	0.001*** (5.008)	0.130*** (11.697)	—	—	0.001*** (5.168)	-0.017* (-1.842)

	DV=CC_EXPO	DV=EVOL_{L_{ij,t+1}}	DV=CC_EXPO	DV=CFVOL_{L_{ij,t+1}}	DV=CC_EXPO	DV=EQUITY_{L_{ij,t}}⁺¹	DV=CC_EXPO	DV=CAPEX_{L_{ij,t+1}}	DV=CC_EXPO	DV=RDINT_{L_{ij,t+1}}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
<i>RDINT</i>	-0.000*** (-2.670)	0.049*** (14.392)	-0.000*** (-2.670)	0.061*** (27.240)	-0.000*** (-2.670)	0.113*** (18.871)	-0.000*** (-3.065)	-0.012*** (-15.094)	—	—
<i>INTANG</i>	-0.001*** (-15.619)	-0.028*** (-14.622)	-0.001*** (-15.619)	-0.032*** (-25.757)	-0.001*** (-15.619)	-0.010*** (-4.209)	-0.001*** (-17.263)	-0.056*** (-58.095)	-0.001*** (-15.680)	-0.035*** (-17.932)
<i>LNGDP</i>	-0.000 (-1.274)	-0.011*** (-4.314)	-0.000 (-1.274)	0.000 (0.249)	-0.000 (-1.274)	0.001 (0.397)	-0.000 (-1.637)	-0.020*** (-10.856)	-0.000 (-1.246)	-0.012*** (-4.597)
<i>STD_GDP</i>	-0.000** (-2.461)	0.001*** (3.379)	-0.000** (-2.461)	0.001*** (3.253)	-0.000** (-2.461)	-0.001 (-1.130)	-0.000*** (-2.605)	-0.001*** (-3.141)	-0.000** (-2.442)	0.001*** (3.113)
<i>CC_EXPO_LOC_IND</i>	0.996*** (30.422)	—	0.996*** (30.422)	—	0.996*** (30.422)	—	0.995*** (30.420)	—	0.996*** (30.412)	—
<i>CC_EXPO_LOC_YEAR</i>	1.182*** (15.221)	—	1.182*** (15.221)	—	1.182*** (15.221)	—	1.181*** (15.196)	—	1.183*** (15.225)	—
Intercept	0.000 (0.494)	0.251*** (9.634)	0.000 (0.494)	0.107*** (5.598)	0.000 (0.494)	0.049 (1.628)	0.001 (0.904)	0.238*** (12.359)	0.000 (0.462)	0.261*** (9.940)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	DV=CC_EXPO	DV=EVOL_{i,j,t+1}	DV=CC_EXPO	DV=CFVOL_{i,j,t+1}	DV=CC_EXPO	DV=EQUITY_{i,j,t}⁺¹	DV=CC_EXPO	DV=CAPEX_{i,j,t+1}	DV=CC_EXPO	DV=RDINT_{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)	Model (9)	Model (10)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,782	50,782	50,782	50,782	50,782	50,782	50,782	50,782	50,782	50,782
R ²		0.330		0.385		0.300		0.330		0.318
Wald test: All coefficients=0			597.83 ^{***}		597.83 ^{***}		597.49 ^{***}		597.60 ^{***}	
Instrument diagnostics tests:										
Durbin–Wu–Hausman stats (Test of endogeneity)		75.154 ^{***}		51.507 ^{***}		69.64 ^{***}		19.499		69.642 ^{***}
Kleibergen–Paap rk LM statistic (Under-identification test)		541.891 ^{**} _*		541.891 ^{***}		541.703 ^{***}		541.355 ^{**} _*		541.703 ^{***}
Kleibergen–Paap rk Wald F statistic (Weak identification test)		2096.22		2096.22		2095.40		2089.29		2095.40

Notes: Superscript ^{***}, ^{**}, and ^{*} represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust z-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

4.7. Additional Analyses

We conduct a set of tests to validate the baseline results. *First*, firm-level exposure and climate change risk responses may differ across firms. For example, firms' climate change risk exposure may lead them to invest more in climate-related innovation (such as solar technology, decarbonisation, energy efficiency, carbon capture, etc.), affecting the relationship between climate change risk exposure and corporate risk-taking. To explore this conjecture, we construct an indicator variable, *HIGH_EINNOV*, taking a value of 1 if a firm's level of environmental innovation is higher than the country-industry-adjusted median value of environmental innovation and 0 otherwise. Then, we interact this variable with the measure of firms' climate change risk exposure (*CC_EXPO*).

The relevant results are presented in Table 9. We observe that the interaction term coefficient (*HIGH_EINNOV* \times *CC_EXPO*) is statistically significant (except in the cases of *EQUITY*, *DLTT*, and *CAPEX*). This result indicates that the negative relationship between climate change risk exposure and corporate risk-taking is more pronounced in firms that generate higher environmental innovation. Overall, the result from this analysis implies that firms with higher exposure to climate change invest in environmental-related innovation to reduce the adverse effects of climate change. This strategy is taken alongside their corporate policy of conservatism and low risk-taking.

Table 9: Regression Results Between Climate Change Exposure and Risk-taking: Role of Environmental Innovation

	DV=EVOL _{ij,t+1}	DV=CFVOL _{ij,t+1}	DV=EQUITY _{ij,t+1}	DV=DLTT _{ij,t+1}	DV=CAPEX _{ij,t+1}	DV=RDINT _{ij,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CC_EXPO</i>	-0.701*** (-2.660)	0.210 (1.085)	0.596* (1.735)	0.521 (0.539)	0.480 (1.454)	0.444** (2.136)
<i>CC_EXPO</i> × <i>HIGH_EINNOV</i>	-0.518* (-1.954)	-0.514*** (-2.626)	0.458 (1.288)	-1.094 (-1.122)	-0.004 (-0.013)	-0.861*** (-4.139)
<i>HIGH_EINNOV</i>	-0.001 (-1.468)	-0.000 (-0.353)	0.003** (2.502)	-0.005** (-2.517)	0.001 (1.382)	0.002*** (2.936)
<i>SIZE</i>	-0.008*** (-32.635)	-0.006*** (-42.271)	-0.004*** (-17.112)	0.004*** (8.588)	0.001*** (9.860)	0.002*** (17.546)
<i>LEV</i>	-0.016*** (-7.686)	-0.009*** (-7.365)	-0.002 (-0.915)	0.826*** (173.194)	0.013*** (12.851)	-0.037*** (-33.513)
<i>ROA</i>	-0.156*** (-23.628)	-0.032*** (-8.299)	-0.216*** (-25.402)	0.062*** (6.753)	0.037*** (18.308)	-0.113*** (-39.479)
<i>GROWTH</i>	0.018*** (12.133)	0.017*** (17.172)	0.026*** (12.912)	0.016*** (6.561)	0.005*** (8.266)	0.007*** (9.780)
<i>FAGE</i>	-0.010*** (-16.225)	-0.010*** (-26.288)	-0.011*** (-13.556)	-0.019*** (-15.805)	-0.005*** (-13.291)	-0.006*** (-16.016)
<i>MB</i>	0.001*** (14.055)	0.001*** (18.630)	0.001*** (8.668)	0.001*** (5.647)	0.000*** (2.614)	0.001*** (15.442)
<i>CAPEX</i>	-0.004 (-0.468)	-0.039*** (-7.639)	0.129*** (11.621)	0.326*** (17.961)	—	-0.075*** (-18.028)
<i>RDINT</i>	0.049*** (14.490)	0.061*** (27.234)	0.113*** (18.866)	0.018*** (3.903)	-0.012*** (-14.908)	—
<i>INTANG</i>	-0.025*** (-13.439)	-0.030*** (-25.025)	-0.009*** (-3.828)	0.061*** (15.877)	-0.054*** (-60.951)	-0.021*** (-17.683)
<i>LNGDP</i>	-0.010*** (-3.805)	0.001 (0.595)	0.001 (0.466)	-0.001 (-0.097)	-0.020*** (-10.619)	0.003* (1.736)
<i>STD_GDP</i>	0.001***	0.001***	-0.000	-0.003***	-0.001***	0.000

	DV=EVOL _{ij,t+1}	DV=CFVOL _{ij,t+1}	DV=EQUITY _{ij,t+1}	DV=DLTT _{ij,t+1}	DV=CAPEX _{ij,t+1}	DV=RDINT _{ij,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	(3.634)	(3.424)	(-1.033)	(-4.970)	(-2.935)	(0.508)
Intercept	0.247***	0.105***	0.050	0.035	0.257***	0.011
	(9.334)	(5.397)	(1.598)	(0.633)	(13.175)	(0.706)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50782	50782	50782	50782	50782	50782
R ²	0.338	0.389	0.301	0.660	0.335	0.545

Notes: Superscript ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

Thus far, our analyses are based on firm-level climate change risk exposure data from conference call transcripts (Sautner et al., 2023). In this robustness check, we consider alternative proxies of climate change risk exposure, namely, (i) physical climate change risk exposure, (ii) regulatory climate change risk exposure, and (iii) carbon risk. The results related to these proxies are respectively presented in Panels A, B, and C of Table 10. We observe that the results are mostly similar to the ones shown in Table 4. Specifically, we find that the alternative risk exposure proxies have a negative impact on the volatility measures (*EVOL* and *CFVOL*) and R&D expenditure (*RDINT*), whilst a positive influence on equity issuance (*EQUITY*) and capital expenditure (*CAPEX*). We, therefore, can conclude that our key finding is robust to different measures of firms' climate risk exposure.

Finally, we explore the effect of firm size on the relationship between climate change risk exposure and corporate risk-taking. We compute *HIGH_SIZE* as a dummy variable that takes a value of 1 if the natural logarithm of the market value of equity is greater than the median value, and 0 otherwise. Table 11 reports the regression results. The results suggest that our findings are mainly driven by smaller firms.

Table 10: Regression Results Between Physical Climate Change Exposure and Risk-taking: Alternative Proxies of Climate Change Exposure

Panel A: Regression results between physical climate change exposure and risk-taking						
	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>PH_EXPO</i>	-23.255** (-5.158)	-11.865*** (-4.224)	13.586** (2.071)	-8.011 (-0.751)	7.130** (2.038)	-12.877*** (-4.757)
Intercept	0.242*** (9.157)	0.105*** (5.373)	0.055* (1.746)	0.033 (0.583)	0.259*** (13.299)	0.011 (0.703)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,782	50,782	50,782	50,782	50,782	50,782
R ²	0.338	0.389	0.300	0.660	0.334	0.545
Panel B: Regression results between regulatory climate change exposure and risk-taking						
	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>RG_EXPO</i>	-6.171* (-1.957)	-0.078 (-0.040)	3.441 (0.861)	-8.035 (-1.231)	3.595 (1.637)	-10.273*** (-5.609)
Intercept	0.243*** (9.168)	0.105*** (5.346)	0.054* (1.736)	0.034 (0.607)	0.259*** (13.266)	0.013 (0.808)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,782	50,782	50,782	50,782	50,782	50,782
R ²	0.337	0.389	0.300	0.660	0.334	0.545

Panel C: Regression results between carbon risk and risk-taking

	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CRISK</i>	-0.002 ^{***} (-5.775)	-0.001 ^{***} (-5.911)	-0.005 ^{***} (-12.455)	-0.007 ^{***} (-10.764)	0.001 ^{***} (3.851)	-0.008 ^{***} (-41.329)
Intercept	0.147 ^{***} (5.178)	0.055 ^{**} (2.494)	0.064 [*] (1.818)	0.119 [*] (1.904)	0.260 ^{***} (11.198)	0.052 ^{***} (2.781)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,241	35,241	35,241	35,241	35,241	35,241
R ²	0.312	0.368	0.304	0.667	0.354	0.555

Notes: Superscript ^{***}, ^{**}, and ^{*} represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

Table 11: Regression Results Between Climate Change Exposure and Risk-taking: Role of Firm Size

	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<i>CC_EXPO</i>	-1.762*** (-9.138)	-0.653*** (-4.829)	0.883*** (2.636)	-0.157 (-0.367)	0.439*** (3.202)	-0.115 (-0.849)
<i>CC_EXPO</i> × <i>HIGH_SIZE</i>	1.180*** (6.321)	0.782*** (6.177)	0.334 (1.074)	-0.841* (-1.927)	0.099 (0.682)	-0.522*** (-4.126)
<i>HIGH_SIZE</i>	-0.017*** (-25.227)	-0.014*** (-33.423)	-0.012*** (-14.221)	0.010*** (7.279)	0.002*** (4.592)	0.004*** (10.129)
<i>LEV</i>	-0.018*** (-8.474)	-0.011*** (-8.173)	-0.003 (-1.229)	0.827*** (173.954)	0.013*** (13.166)	-0.037*** (-32.930)
<i>ROA</i>	-0.175*** (-26.741)	-0.045*** (-11.747)	-0.226*** (-26.876)	0.070*** (7.767)	0.040*** (20.160)	-0.108*** (-38.034)
<i>GROWTH</i>	0.018*** (11.722)	0.017*** (16.761)	0.026*** (12.837)	0.016*** (6.598)	0.005*** (8.381)	0.007*** (10.052)
<i>FAGE</i>	-0.013*** (-21.590)	-0.012*** (-31.874)	-0.012*** (-15.753)	-0.018*** (-15.309)	-0.004*** (-12.053)	-0.004*** (-13.103)
<i>MB</i>	0.001*** (11.774)	0.001*** (16.529)	0.001*** (8.064)	0.001*** (6.059)	0.000*** (3.560)	0.001*** (16.803)
<i>CAPEX</i>	-0.010 (-1.054)	-0.043*** (-8.263)	0.126*** (11.383)	0.328*** (18.056)	—	-0.073*** (-17.613)
<i>RDINT</i>	0.047*** (13.649)	0.060*** (26.326)	0.112*** (18.681)	0.019*** (4.136)	-0.011*** (-14.446)	—
<i>INTANG</i>	-0.028*** (-15.036)	-0.032*** (-26.564)	-0.010*** (-4.513)	0.062*** (16.263)	-0.054*** (-60.576)	-0.020*** (-16.868)
<i>LNGDP</i>	-0.014*** (-5.579)	-0.002 (-1.074)	-0.001 (-0.176)	0.001 (0.139)	-0.019*** (-10.196)	0.004*** (2.880)
<i>STD_GDP</i>	0.001*** (3.976)	0.001*** (3.725)	-0.000 (-0.973)	-0.003*** (-4.973)	-0.001*** (-3.036)	0.000 (0.239)

	DV=EVOL _{i,j,t+1}	DV=CFVOL _{i,j,t+1}	DV=EQUITY _{i,j,t+1}	DV=DLTT _{i,j,t+1}	DV=CAPEX _{i,j,t+1}	DV=RDINT _{i,j,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Intercept	0.253 ^{***} (9.426)	0.106 ^{***} (5.418)	0.047 (1.517)	0.038 (0.672)	0.256 ^{***} (13.068)	0.007 (0.464)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,782	50,782	50,782	50,782	50,782	50,782
R ²	0.327	0.377	0.299	0.660	0.334	0.542

Notes: Superscript ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

Finally, we explore the effect of country-level factors (such as business culture and governance) on the relationship between climate change risk exposure and corporate risk-taking. We first focus on country-level business culture. This analysis is motivated by prior studies reporting a link between a country's business culture and corporate outcomes (Simnett, Vanstraelen, and Chua, 2009). Following the literature (for example, Ball et al. (2000)), firms domiciled in common-law countries are considered to have a shareholder-oriented business culture. In contrast, firms domiciled in code-law countries are deemed to have a stakeholder-oriented business culture. We create a dummy variable (*STAKE*) taking a value of 1 for stakeholder-oriented countries and 0 otherwise. From Panel A of Table 12, we observe that the coefficient of the interaction term ($CC_EXPO \times STAKE$) is positive (negative) and statistically significant for volatility and equity issuance (capital expenditure). This result indicates that although our baseline result reveals a negative relationship between firm-level climate risk vulnerability and corporate risk-taking, this relationship is reversed in stakeholder-oriented business culture.

We also explore the moderating effect of country-level governance on the relationship between climate change risk exposure and corporate risk-taking. The literature reports that corporate governance characteristics have strong climate change mitigation effects (Altunbas et al., 2022). Further, Koirala et al. (2020) contend that corporate governance reform leads to lower corporate risk-taking, primarily attributable to higher compliance costs and the expanded liabilities of insiders or managers. We, therefore, argue that climate change risk exposure's negative effect on corporate risk-taking may be more pronounced for good governance countries. To explore this conjecture, we create a dummy variable *HIGH_GOV*, taking a value of 1 if the country-level worldwide governance indicators are higher than the yearly median of worldwide governance value and 0 otherwise. Then, we interact this variable with our measure of climate change risk exposure (*CC_EXPO*). From Panel B of Table 12, we find that the coefficient of the interaction term ($CC_EXPO \times STAKE$) is negative (positive) and statistically significant for volatility, equity issuance, and R&D expenditure (capital expenditure). In line with our expectation, this result implies that the negative relationship between climate change risk exposure and corporate risk-taking is more pronounced for firms domiciled in a good governance country.

Table 12: Regression Results Between Climate Change Exposure and Risk-taking: Role of Country-level Institutional Contexts

Panel A: Moderating role of country-level business culture					
	DV=EVOL _{ij,t+1}	DV=CFVOL _{ij,t+1}	DV=EQUITY _{ij,t+1}	DV=DLTT _{ij,t+1}	DV=CAPEX _{ij,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
<i>CC_EXPO</i>	-1.564*** (-9.719)	-0.424*** (-3.889)	-3.908*** (-8.892)	0.669*** (5.753)	-0.359*** (-3.063)
<i>CC_EXPO</i> × <i>STAKE</i>	1.298*** (7.157)	0.519*** (4.084)	4.601*** (8.366)	-0.668*** (-4.023)	-0.001 (-0.005)
Intercept	0.245*** (9.269)	0.105*** (5.373)	0.956*** (12.258)	0.258*** (13.239)	0.012 (0.777)
Control variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	50782	50782	50782	50782	50782
R ²	0.338	0.389	0.477	0.335	0.545
Adj. R ²	0.337	0.388	0.476	0.333	0.544
F-statistics	436.209	563.490	788.632	377.613	268.987
Panel B: Moderating role of country-level governance					
	DV=EVOL _{ij,t+1}	DV=CFVOL _{ij,t+1}	DV=EQUITY _{ij,t+1}	DV=DLTT _{ij,t+1}	DV=CAPEX _{ij,t+1}
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
<i>CC_EXPO</i>	-0.669*** (-3.307)	-0.207 (-1.335)	-0.545 (-1.016)	0.188 (1.012)	0.099 (0.695)
<i>CC_EXPO</i> × <i>HIGH_GOV</i>	-0.694*** (-3.354)	-0.094 (-0.602)	-2.673*** (-4.692)	0.380** (2.042)	-0.593*** (-4.106)
<i>HIGH_GOV</i>	0.004*** (4.410)	0.001 (1.194)	-0.011*** (-3.067)	0.000 (0.389)	0.001 (0.692)
Intercept	0.239*** (8.949)	0.104*** (5.294)	0.995*** (12.672)	0.256*** (13.013)	0.013 (0.800)

Control variables	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	50782	50782	50782	50782	50782
R ²	0.338	0.389	0.477	0.335	0.545
Adj. R ²	0.337	0.388	0.476	0.333	0.544
F-statistics	405.362	523.709	726.768	347.328	249.579

Notes: Superscript ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. Coefficient values (robust t-statistics) are shown with standard errors clustered by firm and year. Appendix A provides the definitions of all variables.

Source: Authors' computation.

5. Conclusion and Discussion

5.1. Expected Value Added

This research adds to the existing body of knowledge by shedding light on the relationship between climate vulnerability at the firm level and corporate risk-taking behaviour. Prior research focuses primarily on the effects of climate risk and carbon emissions on diverse outcomes. The majority of these studies concentrate on individual country-level (see, for example, Matsumura et al. (2014); Griffin et al. (2017); Griffin et al. (2021)) or cross-country indicators (see for example, Huang et al. (2018); Li et al. (2022); Barrot and Sauvagnan (2016); Pankratz and Schiller, (2024)). In contrast, this study focuses on cross-country perspectives using data on firm-level exposure to climate risk.

The study's findings can assist businesses in comprehending how climate vulnerability may impact their risk profiles, allowing them to make more informed strategic decisions. Companies may invest more in climate-resilient infrastructure to reduce their climate vulnerability or diversify their operations. Moreover, the study's findings may also be useful for investors. Investors can make more informed decisions about where to invest their funds if they comprehend the risks businesses face due to climate vulnerability. This may result in a reallocation of capital towards firms better prepared for climate change, thereby incentivising all firms to take the necessary precautions. In addition, this study's findings can be incorporated into climate-economic models that project the future economic effects of climate change. Understanding how climate vulnerability affects corporate risk-taking can aid in refining these models and improving their projections. Finally, this study could increase public awareness of the effects of climate change on the economy and individual businesses. This increased awareness may result in greater public support for policies that combat climate change.

5.2. Policy Relevance

The study's findings can help policymakers develop more effective environmental policies by shedding light on how climate change affects businesses. As climate vulnerability is found to decrease corporate risk-taking, this could mean that companies are making conservative corporate policies to trade off against climate risk. Policymakers could use the findings of this study to develop policies that mitigate the effects of climate change on businesses, such as providing incentives for adopting green technologies or implementing adaptive measures.

The findings of this study could be used by policymakers to enact regulations limiting risky investments in climate-vulnerable sectors or to provide economic safety nets for businesses impacted by climate change. In addition, the study's findings could be used to inform corporate governance policies. With climate vulnerability, regulators may need to impose additional monitoring or disclosure requirements. This could include requiring firms to disclose their climate risks to investors or establishing rules to ensure they manage them appropriately.

The study focuses on the international context, so its findings could inform international climate change policies and negotiations, such as the need for cross-country cooperation to mitigate the effects of climate change.

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Appendix A: Variable Definitions

Variable notation	Explanation	
Panel A: Measures of dependent variable		
<i>EVOL</i>	Earnings volatility	One year lead of the standard deviation of quarterly pre-tax income scaled by total assets over the preceding five fiscal years.
<i>CFVOL</i>	Operating cash flow volatility	One year lead of the standard deviation of quarterly cash flows from operations scaled by total assets over the preceding five fiscal years.
<i>EQUITY</i>	Equity issuance	One year lead of the amount of equity issuance which is measured as the difference between the issuance of common stock and preferred shares minus the purchase of common stock and preferred shares scaled by total assets.
<i>DLTT</i>	Long-term debt issuance	One year lead of the amount of debt issuance which is measured as the long-term debt issuance scaled by total assets.
<i>CAPEX</i>	Capital expenditures	One year lead of the ratio of capital expenditure to total assets.
<i>RDINT</i>	Research and development intensity	One year lead of the ratio of research and development expenditures to total revenues.
Panel B: Measures of climate change exposure		
<i>CC_EXPO</i>	Climate-risk exposure	Firm-level climate-risk exposure.
<i>PH_EXPO</i>	Physical risk exposure	Firm-level climate-risk exposure.
<i>RG_EXPO</i>	Regulatory risk exposure	Firm-level climate-risk exposure.
<i>CRISK</i>	Carbon risk	The natural logarithm of total GHG emissions measured in CO ₂ -e metric tonnes.
Panel B: Moderator of variable		
<i>EINNOV</i>	Environmental innovation	The environmental innovation score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products. We create a dummy variable of <i>EINNOV</i> that takes a value of 1 if the firm-level environmental innovation score is higher than country-industry and year-adjusted median value of environmental innovation, and 0 otherwise.
<i>STAKE</i>	Country-level business culture	An indicator variable that takes a value of 1 if the firm domiciled in a cod-law country, and 0 otherwise.
<i>HIGH_GOV</i>	Country-level governance	An indicator variable that takes a value of 1 if the country-level world-wide governance indicators are higher than

yearly median of world-wide governance value, and 0 otherwise.

Panel C: Control variables

<i>SIZE</i>	Firm size	The natural logarithm of market value of equity.
<i>LEV</i>	Leverage	The ratio total debt to total assets.
<i>ROA</i>	Profitability	The ratio of net income to total assets.
<i>GROWTH</i>	Growth opportunities	The ratio of market value of equity to book value of equity.
<i>FAGE</i>	Firm age	The natural logarithm of total number of years since the first-time appear in the World scope database.
<i>MB</i>	Growth opportunities	The ratio of market value of equity to book value of equity.
<i>CAPEX</i>	Capital expenditure	The ratio of capital expenditure to total assets.
<i>RDINT</i>	Research and development intensity	The ratio of research and development expenditures to total revenues.
<i>INTANG</i>	Intangible assets	The ratio of intangible assets to total assets.
<i>LNGDP</i>	Economic development	The natural logarithm of gross domestic product (GDP) per capital.
<i>STD_GDP</i>	Macroeconomic risk	The standard deviation of the growth in GDP capita in a given country and year.

Source: Authors.

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