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The dynamics of corporate climate risk and market volatility: International evidence

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ABSTRACT

This study investigates the impact of firm climate risk exposure on market volatility, with a particular focus on the moderating roles of firm-specific and country-level characteristics. Using a comprehensive global panel of 38,808 firm-year observations across 54 countries from 2002 to 2023, we employ fixed-effects regressions, two-step GMM, and an instrumental variable approach to address endogeneity and unobserved heterogeneity. The analysis reveals that higher climate risk exposure is associated with significantly greater market volatility, reflecting investors' heightened sensitivity to climate-related risks. Importantly, firm-level factors such as strong corporate governance, high R&D intensity, and strategic positioning are found to mitigate these effects. At the country level, weaker environmental policy frameworks and underdeveloped financial systems amplify climate-induced volatility, underscoring the role of institutional quality. We also examine the influence of major climate policy events such as the Paris Agreement and find evidence of a post-policy decline in volatility, suggesting increased investor confidence in global climate governance. Overall, this study contributes to the climate finance literature by offering novel insights into how both corporate strategies and institutional environments shape the financial consequences of climate risk, providing practical implications for firms, investors, and policymakers.

1. Introduction

The rising frequency and severity of climate-related events, along with rising global awareness of climate change, have fundamentally reshaped the business and financial landscapes.[4] Firms across the globe are increasingly exposed to climate risks, which encompass physical risks (e.g., extreme weather events), regulatory risks (e.g., carbon pricing, emissions regulations), and transitional risks (e.g., shifts toward renewable energy). These risks not only impose direct financial costs on firms but also amplify uncertainty in future cash flows (Javadi et al., 2023), operational stability (Kim et al., 2023), and long-term growth prospects (Bagh et al., 2024; Berkman et al., 2024), thereby impacting firm performance (Ozkan et al., 2022; Siddique et al., 2021) and investor confidence (Bolton

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& Kacperczyk, 2023; Sautner et al., 2023a). Consequently, climate risk has emerged as a significant factor influencing market volatility (MVOL), reflecting the uncertainty and stock price fluctuations. Understanding how firm-level exposure to climate risk (FLCR) impacts market volatility and the mechanisms that can moderate this relationship is crucial for firms, investors, and policymakers navigating the evolving climate and financial landscape.

Climate risks are no longer confined to environmental debates; they have become critical financial risks that affect firm valuation, investor sentiment, and capital allocation. Recent high-profile reports, such as the "Task Force on Climate-related Financial Disclosures (TCFD)" and the "Intergovernmental Panel on Climate Change (IPCC)", emphasize the importance of integrating climate risk into financial decision-making. The "International Sustainability Standards Board (ISSB)" recently introduced IFRS S1 and S2[5] standards, promoting climate risk disclosures to enhance trust and inform investment decisions. Empirical evidence highlights that investors increasingly price climate-related risks into stock valuations, leading to heightened volatility for firms with high exposure. For instance, firms in carbon-intensive industries or those lagging in climate adaptation strategies are penalized by the market due to increased uncertainty regarding regulatory compliance, operational resilience, and reputational risks. This trend underscores the need for firms to manage climate risks proactively and for policymakers to create enabling environments that facilitate climate resilience.

Theoretically, the relationship between climate risk exposure and market volatility can be explained by investor risk perception theory, which suggests that heightened uncertainty surrounding a firm's climate risk exposure leads to increased stock return volatility. Firms with high FLCR face challenges such as unpredictable regulatory changes, the transition to low-carbon economies, and increased costs associated with adapting to extreme weather events. These uncertainties are reflected in stock price fluctuations as investors demand higher risk premiums to compensate for the perceived risks. Empirical studies such as Ilhan et al. (2020); Sautner et al. (2023b) confirm that firms with greater climate risk exposure experience higher downside risks and market volatility. However, the extent to which climate risks influence volatility depends on both firm-level characteristics and country-level institutional environments, which can either exacerbate or mitigate the impact of climate risks on firm performance.

While climate risks are widely acknowledged as a significant source of financial uncertainty (Carney, 2015), the mechanisms through which firms' climate risk exposure influences market volatility remain underexplored. Firms differ significantly in their capacity to manage and mitigate climate risks based on their corporate strategies, governance structures, and innovation capacities (Ni et al., 2022; Peters & Romi, 2014; Yin et al., 2025). For instance, strong corporate governance mechanisms, such as independent boards and effective risk management practices, can enhance firms' ability to identify, disclose, and address climate risks (Aggarwal & Dow, 2012), thereby improving investor confidence. Similarly, firms with high R&D intensity may leverage innovation to develop climate-resilient technologies and strategies, mitigating the adverse impacts of climate risks. In contrast, firms pursuing cost leadership strategies may struggle to absorb the costs of climate adaptation, while firms following differentiation strategies face uncertainty related to market acceptance of green innovations. These firm-level channels provide essential pathways through which climate risks may translate into market volatility.

In addition to firm-level factors, the broader country-level environment plays a crucial role in shaping firms' ability to manage climate risks (Hossain et al., 2023; Naseer et al., 2025). Countries with stringent environmental policies provide regulatory clarity and incentives for firms to invest in climate risk mitigation strategies, which can reduce investor uncertainty and stabilize financial markets. Similarly, countries with well-developed financial systems offer firms greater access to financing for climate-related adaptation and innovation, enabling them to manage the costs associated with climate risks better. Strong institutions, such as effective governance frameworks and the rule of law, further enhance transparency, reduce information asymmetry, and improve firms' resilience to external shocks (Bolton & Kacperczyk, 2023). In contrast, firms operating in weaker institutional environments may face amplified volatility due to regulatory ambiguity, financing constraints, and governance deficiencies.

While previous studies have examined the impact of climate risks on firm performance, the existing literature lacks a comprehensive analysis of the mechanisms both at the firm and country levels that shape the relationship between climate risk exposure and market volatility, especially in cross-country contexts (Javadi et al., 2023). Cross-country studies often face significant endogeneity and identification issues stemming from the diverse sources that drive country-level variations (Bolton & Kacperczyk, 2023). Our study addresses these challenges by leveraging detailed variations across countries, industries, and firms concerning FLCR and other characteristics. Moreover, there is limited research on how global events, such as the Stern Review (2006) and the Paris Agreement (2015), influence investor awareness and market responses to climate risks. These global milestones provide natural experiments to assess how significant policy shifts impact firms' exposure to climate risks and the resulting investor behavior.

This study makes several key contributions to the climate finance literature. First, it establishes a systematic link between FLCR and MVOL and highlights the importance of climate risks in driving financial uncertainty. By analyzing a global panel of 5179 firms from 54 countries over the period 2002–2023, this study provides a robust assessment of the relationship across different regions, industries, and economic environments.

Second, this study extends the analysis by conducting a series of robustness tests and additional examinations, including regional and economic development perspectives. It further decomposes climate risk into physical, regulatory, and opportunity exposure, offering a nuanced understanding of the channels through which climate risks influence volatility. Additionally, the study assesses firms' climate adaptation and environmental performance as critical factors in managing market responses to climate risks.

[5] The "International Sustainability Standards Board (ISSB) has released its inaugural standards, IFRS S1 and S2, marking a new era for sustainability-related disclosures in global capital markets. These standards aim to enhance trust in company disclosures and inform investment decisions by providing a clear and unified framework for reporting the impacts of climate-related risks and opportunities on a company's prospects." Details available at https://www.ifrs.org/news-and-events/news/2023/06/issb-issues-ifrs-s1-ifrs-s2/.

Third, the study explores investor awareness and market responses to climate risks by leveraging major climate policy milestones, such as the Stern Review and the Paris Agreement. These events provide natural experiments to evaluate how global commitments to climate action influence investor behavior and firms' exposure to climate-related uncertainties.

Fourth, this study investigates key country-level channels, including environmental policy stringency, financial development, and institutional quality, that shape the relationship between FLCR and MVOL. The study highlights the role of strong governance, policy frameworks, and financial systems in mitigating climate risk-induced volatility by linking the analysis to institutional theory.

Fifth, this study examines critical firm-level channels, such as corporate governance, R&D intensity, and corporate strategies (e.g., cost leadership and differentiation), to assess how internal firm characteristics influence the FLCR-MVOL relationship. By integrating insights from agency theory and the resource-based view (RBV), the study demonstrates the importance of governance structures and innovation capacity in enhancing firms' resilience to climate risks.

The methodological contributions include employing a range of sophisticated econometric techniques designed to ensure robustness and address potential biases in the analysis of the relationship between FLCR and MVOL. Key methodological contributions include the use of fixed-effects regressions to control unobserved heterogeneity, lagged model techniques to tackle endogeneity concerns, and propensity score matching to account for confounding factors. Additionally, the use of the two-step system GMM enhances the robustness of the analysis by addressing potential issues of simultaneity and unobserved panel-specific effects, ensuring dynamic consistency in the data. To strengthen causal inference, we also employ an instrumental variable approach using external climate risk proxies, confirming the robustness of our findings. The study also checks the consistency of results across different economic contexts by excluding periods of major financial disruptions. Furthermore, it enriches the analysis by testing the effects of excluding overrepresented countries' firms and incorporating comprehensive controls and alternative measures, ensuring the findings are both comprehensive and applicable across diverse economic and regulatory environments. These methodological innovations enhance the credibility of the study's conclusions.

In light of these contributions, this study provides a holistic understanding of how climate risk exposure drives market volatility and identifies the mechanisms, both internal and external, that influence this relationship. This research is particularly relevant for firms seeking to strengthen their climate risk management strategies, investors aiming to evaluate climate-related uncertainties better, and policymakers designing regulatory frameworks to enhance market stability in the face of climate challenges.

The remainder of the paper is structured as follows: Section 2 reviews the relevant theoretical frameworks and empirical literature. Section 3 describes the data and methodology used in the study. Section 4 presents empirical results and discusses the findings, linking them to key theories and prior studies. Section 5 concludes the paper, highlighting its contributions, policy implications, and directions for future research.

2. Literature review and conceptual framework

2.1. Related literature

Recent academic research and strategic corporate discussions have increasingly focused on the interplay between FLCR and MVOL, driven by escalating climate change impacts on business operations and evolving stakeholder expectations (Javadi et al., 2023; Mbanyele & Muchenje, 2022; Sautner et al., 2023a). This burgeoning interest is grounded in Stakeholder Theory, which posits that effective management of climate-related risks enhances a firm's relationships with a broad spectrum of stakeholders, customers, employees, regulators, and investors (Giglio, Maggiori, et al., 2021; Lee & Raschke, 2023; Ozkan et al., 2023; Trinh et al., 2024). These relationships are crucial as they influence how external risks like climate change impact market volatility (Naseer et al., 2024).

The literature reveals a complex narrative around the impact of FLCR on market behavior, where traditional factor models provide a comprehensive framework for assessing factors influencing asset returns Schwert (1989). Information Asymmetry Theory Miller (1977) highlights that climate risk uncertainty leads to higher perceived risks and potentially lower stock returns as firms disclose climate-related information.

Chava (2014) provided early insights into how heightened environmental concerns influence investors' expectations of capital costs, consistent with the Capital Asset Pricing Model and established cost of capital theories. Multiple studies have systematically explored how environmental regulatory uncertainty and climate change risks significantly impact portfolio returns. Researchers like Bolton and Kacperczyk (2021, 2023); Bouri et al. (2023); Hong et al. (2019); Hsu et al. (2023); Liesen et al. (2017); Lv and Li (2023); Zhao et al. (2024) have contributed to this growing body of knowledge, revealing the nuanced ways climate-related factors affect investment strategies.

Hong et al. (2019) show that specific climate-related risks, such as increasing drought risk driven by climate change, are not effectively priced by stock markets, highlighting inefficiencies in how investors assess and incorporate climate risk into asset prices. Bolton and Kacperczyk (2021, 2023) demonstrated that firms with higher carbon emissions experience increased stock returns due to elevated risks associated with their environmental impact. This relationship highlights the market's response to the risk-return trade-off inherent in firms' environmental practices, with higher risks from greater emissions potentially leading to higher expected returns. Hsu et al. (2023) develop and test a model demonstrating that firms with higher environmental impact, such as high polluters, face greater exposure to environmental policies' regulatory risks, which results in higher average stock returns as compensation for these risks. Hambel et al. (2024) highlight the complex dynamics between asset diversification strategies and climate action. Their findings suggest a trade-off in the long run between diversification and aggressive climate action, which could influence market volatility as firms adjust their asset bases and investment strategies in response to changing climate policies.

These findings underscore the importance of examining FLCR and its impact on financial outcomes, such as market volatility, in the context of evolving climate challenges and regulatory pressures.

2.2. Conceptual framework

This study constructs a conceptual framework to explore how FLCR influences MVOL, focusing on the moderating roles of firm- and country-level factors. This framework is informed by the RBV, emphasizing a firm's capabilities to manage environmental challenges effectively. Additionally, elements from Information Asymmetry Theory and Agency Theory are integrated to examine how transparency and governance practices impact investor perceptions and firm performance in the context of environmental risks.

Information Asymmetry Theory posits that variability in firms' disclosure and transparency regarding climate risks can lead to incomplete information available to investors, thereby contributing to uncertainty and potential mispricing in stock values. Such dynamics can lead to both overreactions and underreactions in the stock market as investors grapple with assessing the true impact of climate risks on firm performance. Behavioral Finance Theory further enriches this framework by suggesting that as investors become increasingly aware of FLCR, they may perceive firms with higher exposure to climate risks as riskier investments. This perception, influenced by behavioral biases, can increase market uncertainty and volatility (Ginglinger & Moreau, 2023). Additionally, Portfolio Theory offers insights into how investors might adjust their portfolios in response to climate risks. It suggests that investors seek to optimize their portfolios to achieve the maximum return for a given level of risk. In the context of escalating climate change, this may involve reallocating investments to minimize risks associated with climate impacts and to optimize returns, reflecting the changing dynamics as asset prices begin to incorporate the vulnerabilities associated with climate-related risks.

This study delves into how physical, transition, and liability risks associated with FLCR can elevate market volatility. These risks introduce uncertainties that can lead to sudden market shocks as companies vulnerable to climate-related physical risks may experience significant financial impacts. This mechanism is influenced by unexpected climate events that affect investor reactions and contribute to increased market volatility. Moreover, evolving regulations aimed at addressing climate change, potential negative effects on profitability, and the uncertainties surrounding the transition to a low-carbon economy are all factors that contribute to higher MVOL. Thus, the framework positions these elements within a broader discussion of how climate change influences financial markets, emphasizing the need for comprehensive risk management strategies that align with investor expectations and regulatory developments.

2.3. Hypotheses development

Our study examines the relationship between FLCR and MVOL, contributing to the ongoing debate on whether and how effectively financial markets incorporate climate-related risks into stock prices. Prior empirical literature offers mixed findings regarding pricing and the financial impacts of climate risk. Matsumura et al. (2014), for instance, documented a negative association between direct carbon emissions and firm value among S&P 500 firms, suggesting markets penalize high-emission firms. Similarly, Chava (2014) found that firms excluded from environmental assessments due to climate-related concerns face higher equity and debt financing costs, reflecting investors' increased required returns as compensation for environmental risk exposure.

Further studies employing firm-specific measures reinforce the complexity of climate risk valuation. Bagh et al. (2024); Berkman et al. (2019); Naseer et al. (2025) provided evidence that firm-specific climate risk metrics negatively impact firm valuation. Hsu et al. (2023) found that high-polluting firms face increased regulatory exposure, leading to higher expected returns. Görgen et al. (2021) introduced a carbon risk factor, finding differential market responses to carbon-intensive versus low-carbon firms. Bolton and Kacperczyk (2021) further expanded this literature, identifying a premium associated specifically with carbon emissions but not emission intensity, indicating nuanced investor responses to different dimensions of climate risks.

However, the literature also suggests that markets do not uniformly price climate risks efficiently. Liesen et al. (2017) argued that markets are inefficient in incorporating publicly available climate-related disclosures into stock prices. Hong et al. (2019) identified incomplete integration of drought risks, highlighting partial market efficiency regarding climate risk information.

Previous studies have typically measured climate risk directly through physical metrics (e.g., temperature increases or extreme weather events; (Balvers et al., 2017; Coumou & Rahmstorf, 2012; Gregory, 2021) or indirectly via carbon emissions (Bolton & Kacperczyk, 2021, 2023; Bouri et al., 2023; Li et al., 2023; Matsumura et al., 2014). However, Giglio, Kelly, et al. (2021) highlight challenges in accurately capturing firm-specific climate impacts due to their complex and multidimensional nature.

In contrast, our study adopts a novel measure of FLCR developed by Sautner et al. (2023a), they utilize machine-learning techniques to quantify managerial and analyst perceptions of climate risk exposure derived from earnings call transcripts. This approach offers a dynamic, forward-looking indicator of climate risk reflecting managerial insights and market participants' "soft" information, which traditional emission-based metrics may fail to capture adequately.

The theoretical foundation for our study integrates insights from Information Asymmetry Theory, Behavioral Finance, and Portfolio Theory. Information Asymmetry Theory emphasizes that incomplete and inconsistent disclosure about climate risks increases uncertainty among investors, potentially leading to stock mispricing. Behavioral Finance Theory, as discussed by Ginglinger and Moreau (2023), suggests investors perceive firms with higher climate risk exposure as inherently riskier investments, thus intensifying market volatility due to behavioral biases and investor uncertainty. Portfolio Theory, originally introduced by Markowitz, implies that investors actively reallocate portfolios in response to evolving climate risks to optimize returns for given levels of risk, further exacerbating market volatility when climate uncertainty increases. Building upon the theoretical rationale and the empirical evidence discussed, we propose the following hypothesis:

Hypothesis 1 Firm-level climate risk exposure positively influences market volatility.

Through the multi-theoretical approach, the study aims to provide an in-depth understanding of the complex interplay between climate risk exposure and market volatility, highlighting the critical roles of corporate governance, strategic risk management, and investor behavior play in shaping market outcomes. The conceptual framework and hypothesis guide the empirical analysis and align with the broader objective of enhancing our understanding of financial market dynamics in an era of significant environmental challenges.

3. Research design and methods

3.1. Data and sample

For sample construction, we began by identifying unique GVKEYs for global companies from the climate risk dataset. These GVKEYs were matched with Compustat data using the WRDS platform. Next, we merged the fundamental financial data with the climate risk data. Governance data was then incorporated by matching ISIN codes with the LSEG ESG database. Finally, we excluded financial firms categorized under SIC codes 6000–6999, resulting in a sample of 46,111 firm-year observations. In the final step, we removed firms with zero values of FLCR, leading to a concluding sample of 38,808 firm-year observations from 5,179 unique companies spanning 54 countries from 2002 to 2023.

3.2. Variables description

The dependent variable in this study is firm-level market volatility (MVOL), which reflects the fluctuations in a firm's stock returns over a given period. Stock returns are calculated as the natural logarithm of the current month's stock price ratio to the previous month's price. MVOL is then determined as the annualized standard deviation of these monthly stock returns. Specifically, annual MVOL is computed as the square root of the sum of squared monthly returns within a calendar year. A higher value of MVOL indicates greater risk exposure for the firm (He et al., 2023; Paye, 2012). Building upon the frameworks outlined in Bouri et al. (2023); Lv and Li (2023); Noh and Park (2023); Wang and Li (2023); Zhang et al. (2023), we calculate MVOL using the following Eq. (1):

$$MVOL_{i,t} = \sqrt{\sum_{m=1}^{D_{i,t}} r_{i,t,m}^2} \tag{1}$$

Where ($D_{i,t}$) represents the number of trading days in the (t) month for the (i) firm, and ($r_{i,t,j}$) is the (m^{th}) monthly return on the (i) firm in the (t) year.

The key independent variable in this study is firm-level climate change exposure (FLCR), developed by Sautner et al. (2023a). This variable is constructed by analyzing publicly listed firms' quarterly earnings conference call transcripts, providing insights into managers' perceptions of their firms' vulnerability to climate change. Using a machine learning algorithm, Sautner et al. (2023a) identify climate change-related bigrams within these transcripts. The FLCR is calculated as the proportion of climate-related bigrams to the total bigrams in a firm's transcript, scaled by 100 for ease of interpretation Eq. (2):

$$FLCR_{i,q} = \frac{1}{B_{i,q}} \sum_{b=1}^{B_{i,t}} D(b) \times 100 \tag{2}$$

Here, $b = 0,..,B_{i,q}$ represents the total bigrams for firm "i" in quarter "q", and D(b) is a dummy variable equal to 1 if bigram "b" is climate-related, and 0 otherwise.

Following the existing norm of risk-related literature, e.g. (Albuquerque et al., 2018; Bolton & Kacperczyk, 2023; Bouri et al., 2023; Hossain & Masum, 2022; Lins et al., 2017; Sautner et al., 2023a), we employ size, sales growth (SAGR), leverage (LEVE), earning volatility (EVOL), market capitalization (MCAP), return on equity (ROE), capital expenditure (CAPX), assets tangibility (ATA), financial development (FIND), and quality of government (QOG) as control variables. The measurement of all variables is provided in Appendix Table A1.

This approach captures the extent to which managers discuss climate-related risks and opportunities, reflecting the firm's exposure to climate change systematically and quantitatively. This enables a deeper understanding of how firms perceive and communicate their climate risk exposure, making it a robust and reliable variable for assessing its impact on market volatility.

3.3. Model setting

The study employs several empirical models to examine the relationship between FLCR and MVOL and the moderating roles of country-level and firm-level variables. We investigate these relationships using multiple regression models, which help mitigate omitted variable bias (Hossain & Masum, 2022). These models account for other variables such as SIZE, SAGR, LEVE, EVOL, MCAP, ROE, CAPX, ATA, FIND and QOG. Eq. (3) is specified for fixed-effect regression analysis.

$$MVOL_{i,t} = \alpha_1 + \beta_1 FLCR_{i,t} + \gamma_1 \sum Control_{i,t} + \theta_i + \varepsilon_{i,t} \tag{3}$$

FLCR is a firm climate change risk, and control variables include SIZE, SAGR, LEVE, EVOL, MCAP, ROE, CAPX, ATA, FIND and QOG. θ_i

represents firm-specific fixed effects, ε is the error term, i for firm and t for year.

The following empirical model is specified to study the moderating relationship between FLCR and MVOL Eq. (4).

$$MVOL_{i,t} = \alpha_1 + \beta_1 FLCR_{i,t} + \beta_2 M_{i,t} + \beta_3 (FLCR_{i,t} \times M_{i,t}) + \gamma_1 \sum Control_{i,t} + \theta_i + \varepsilon_{i,t} \quad (4)$$

FLCR is a firm climate change risk and control variable that includes SIZE, SAGR, LEVE, EVOL, MCAP, ROE, CAPX, ATA, FIND and QOG. $M_{i,t}$ represents the moderating variable, θ_i represents firm-specific fixed effects, ε is the error term, i for firm and t for year.

3.4. Robustness checks

We conduct several robustness tests to validate the reliability of our findings.

3.4.1. Addressing simultaneity

We employ lagged values of FLCR to mitigate simultaneity bias in the FLCR–MVOL relationship. Using lagged variables helps ensure temporal separation, thus reducing concerns about contemporaneous feedback effects.

3.4.2. Propensity score matching (PSM)

To address selection bias, we match firms with high FLCR (treated group) to similar firms with low FLCR (control group) based on observable characteristics such as firm size, leverage, and industry classification. Following prior literature, we adopt the 75th percentile as the cutoff to enhance the balance and comparability between treated and control groups.

3.4.3. Excluding crisis periods

We exclude data from crisis periods, such as the Global Financial Crisis (2008–2009) and the COVID-19 pandemic (2020), to verify that our findings are robust to extreme market conditions and hold under stable economic environments.

3.4.4. Excluding U.S. Firms

Considering the potential overrepresentation of U.S. firms in our global sample, we re-estimate our main models after excluding U.S.-based companies. This analysis tests the generalizability and external validity of our findings across international contexts.

3.4.5. Alternative measures and estimators

We perform additional robustness checks by replacing the dependent variable MVOL with idiosyncratic volatility (IVOL) and substituting the primary independent variable FLCR with an alternative measure of greenhouse gas (GHG) emission. Furthermore, we employ a two-step system GMM (Arellano & Bover, 1995; Blundell & Bond, 1998) estimator to ensure the robustness of our results to dynamic panel bias and potential endogeneity.

3.5. Endogeneity concerns and mitigation strategies

A central methodological challenge in this study is the potential endogeneity arising from reverse causality between FLCR and MVOL. Firms experiencing elevated volatility might strategically modify their climate disclosures, leading to simultaneity issues. We adopt multiple econometric strategies to alleviate these concerns. Besides using lagged explanatory variables, we employ the two-step GMM estimator, which explicitly accounts for dynamic relationships and unobserved heterogeneity. Additionally, we strengthen causal inference by employing an instrumental variable (IV) approach via two-stage least squares (2SLS). Specifically, we use the Notre Dame Global Adaptation Initiative (ND-GAIN) index, a country-level measure reflecting overall climate vulnerability. This instrument satisfies both theoretical relevance; firms operating in climate-vulnerable countries are more likely to disclose climate risks and

Table 1
Descriptive statistics.

Variables	N	Mean	SD	Min	P25	Median	Max
MVOL	38,808	0.122	0.075	0.001	0.073	0.104	0.553
FLCR	38,808	0.139	0.299	0.002	0.021	0.044	5.560
SIZE	38,808	7.260	2.000	2.350	5.880	7.230	13.00
SAGR	38,808	0.073	0.351	−7.840	−0.015	0.057	7.050
LEVE	38,808	0.283	0.154	0.001	0.186	0.299	0.900
EVOL	38,808	0.025	0.030	0.000	0.002	0.017	0.229
MCAP	38,808	0.905	2.800	0.001	0.035	0.138	70.70
ROE	38,808	0.045	0.053	0.000	0.001	0.036	0.336
CAPX	38,808	0.049	0.053	0.000	0.016	0.032	0.367
ATA	38,808	0.278	0.249	0.000	0.081	0.185	0.931
FIND	38,808	0.858	0.172	0.046	0.906	0.912	0.997
QOG	38,808	0.801	0.160	0.071	0.817	0.833	1.000

The table presents the descriptive statistics for study variables. The sample spans from 2002 to 2023 and includes 5179 unique companies spanning 54 countries. The measurement of all variables is provided in Appendix Table A1.

empirical validity criteria, with first-stage diagnostics confirming its strength and appropriateness. These combined methodological steps ensure rigorous causal identification and substantiate the robustness of our empirical findings.

4. Analysis and results

4.1. Summary statistics

Table 1 presents the descriptive statistics for the study variables, based on 38,808 firm-year observations spanning 5179 unique companies from 54 countries during 2002–2023. The average MVOL is 0.122, with moderate variation (SD = 0.075) and a maximum of 0.553, reflecting significant risk for some firms. FLCR has a mean of 0.139 and considerable variability (SD = 0.299), with values ranging from 0.002 to 5.560 (high climate risk attention). Firms in the sample exhibit an average size (log of total assets) of 7.260, with substantial diversity (SD = 2) and an average annual SAGR of 0.07. However, some firms face declines (minimum = -7.840) while others achieve rapid growth (maximum = 7.050). LEVE averages 0.283, indicating moderate debt reliance, while EVOL remains low on average (mean = 0.025), with variability across firms. MCAP displays a wide range, from 0.001 to 70.70, highlighting the inclusion of both small and large firms in the sample. The sample exhibits mean values of 0.045 for ROE, 0.049 for CAPX, 0.278 for ATA, 0.858 for FIND, and 0.801 for QOG. These statistics provide a detailed dataset overview, showcasing its diversity and relevance for analyzing FLCR and MVOL.

Fig. 1 illustrates the mean values of firm climate risk (FLCR) and its components, opportunity exposure, regulatory exposure, and physical exposure over 2002–2023. Firm climate risk (blue line) shows a gradual increase from 2002, peaking in 2021 before slightly declining in 2022, indicating growing attention to climate risks in firm disclosures. Opportunity exposure (orange line) exhibits steady growth, reflecting an increasing focus on opportunities related to climate change. Regulatory exposure (green line) remains relatively stable over the years, with minor fluctuations, while physical exposure (cyan line) shows minimal variation, staying consistently low throughout the period. This pattern suggests that firms' climate risk discussions are predominantly driven by perceived opportunities and regulatory concerns rather than physical risks.

Fig. 2 illustrates the mean values of market volatility (MVOL) of sample firms from 2002 to 2023. MVOL shows fluctuations, peaking in 2007–09 and 2019–21.

Table 2 pairwise correlations reveal significant but generally weak relationships among the study variables, minimizing concerns about multicollinearity. FLCR is positively correlated with SIZE (0.083), LEVE (0.030), MCAP (0.011), ROE (0.021), CAPX (0.046), and ATA (0.183). FLCR shows a negative correlation with SAGR (−0.010), EVOL (−0.068), FIND (−0.011), and QOG (−0.039). SIZE positively correlates with MCAP, reflecting the intrinsic link between a firm's size and market value. LEVE is positively associated with SIZE, suggesting larger firms tend to use more debt financing while showing a weak negative correlation with MCAP, indicating a slightly lower market value for highly leveraged firms. EVOL has a modest positive correlation with MCAP, implying that firms with higher market value may exhibit some earnings variability. These relationships align with theoretical expectations and underscore the interconnectedness of firm size, financial structure, and climate risk exposure.

4.2. Baseline analysis

Table 3 reports the baseline regression results examining the relationship between FLCR and MVOL. Across all specifications, FLCR is positively and significantly associated with MVOL at the 1 % significance level, indicating that a one-unit increase in FLCR corresponds to a 0.008-point rise in MVOL. These findings are consistent with previous studies (Bouri et al., 2023; Ilhan et al., 2023; Naseer et al., 2024; Noh & Park, 2023; Sautner et al., 2023b) and provide strong empirical support for Hypothesis 1.

Control variables behave as expected. Larger firms (SIZE) and firms with higher SAGR exhibit lower volatility, while higher LEVE is associated with greater risk. EVOL, MCAP, ROE, CAPX, FIND, and QOG are negatively associated with MVOL, which is consistent with theoretical expectations. The results confirm a robust and economically meaningful positive association between climate risk exposure and market volatility, even after accounting for firm, country, and industry-level characteristics. This highlights climate risk as a critical dimension of uncertainty influencing firm-level stock return stability.

4.3. Robustness tests

In order to ensure that the positive association between FLCR and MVOL is not an artifact of omitted variables, model specification choices, or data limitations, a series of robustness tests are conducted. These tests aim to address potential simultaneity, selection bias, measurement issues, and the influence of major macroeconomic events and sample composition. The subsections below detail the rationale for and implications of each robustness check.

4.3.1. Addressing simultaneity in the FLCR-MVOL relationship

A key concern in interpreting the baseline results is the possibility of simultaneity. At the same time, the main analysis suggests that higher FLCR leads to greater MVOL; it could also be that firms experiencing high volatility adjust their climate risk disclosures or that firms' performance and market conditions endogenously determine FLCR. To mitigate concerns about simultaneity or reverse causality, that is, the possibility that elevated market volatility could influence firms' climate risk exposure, the FLCR measure is lagged by one year ($FLCR_{t-1}$). In Table 4 Model 1 under this specification, the coefficient on FLCR remains positive and highly significant (0.006, $p < 0.01$), reinforcing the interpretation that heightened climate risk exposure precedes and contributes to increased market volatility.

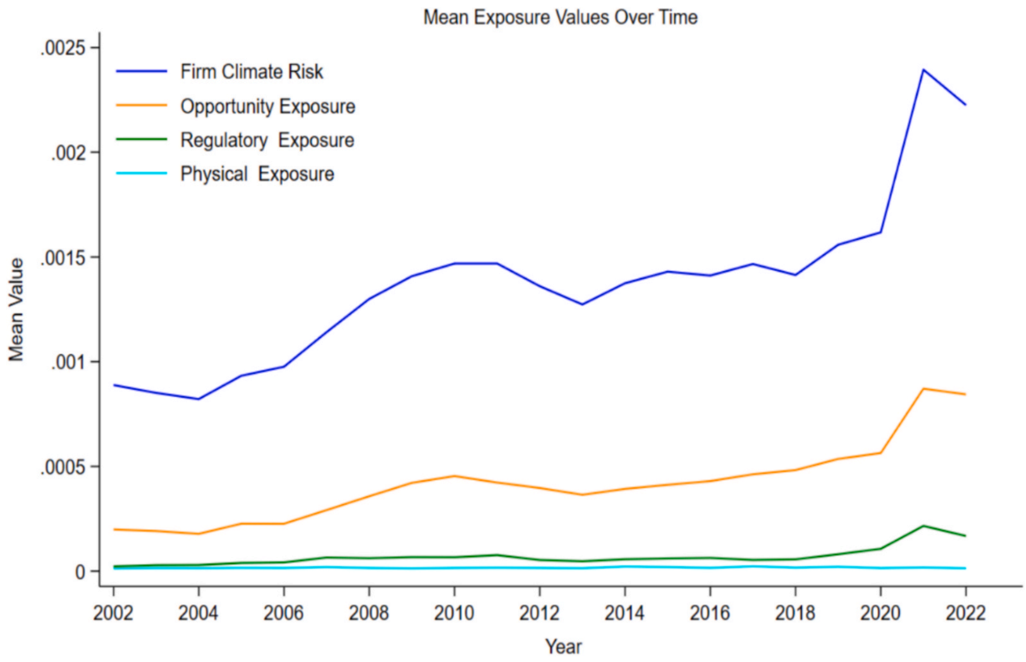

Fig. 1. Average climate risk exposure over the sample period.

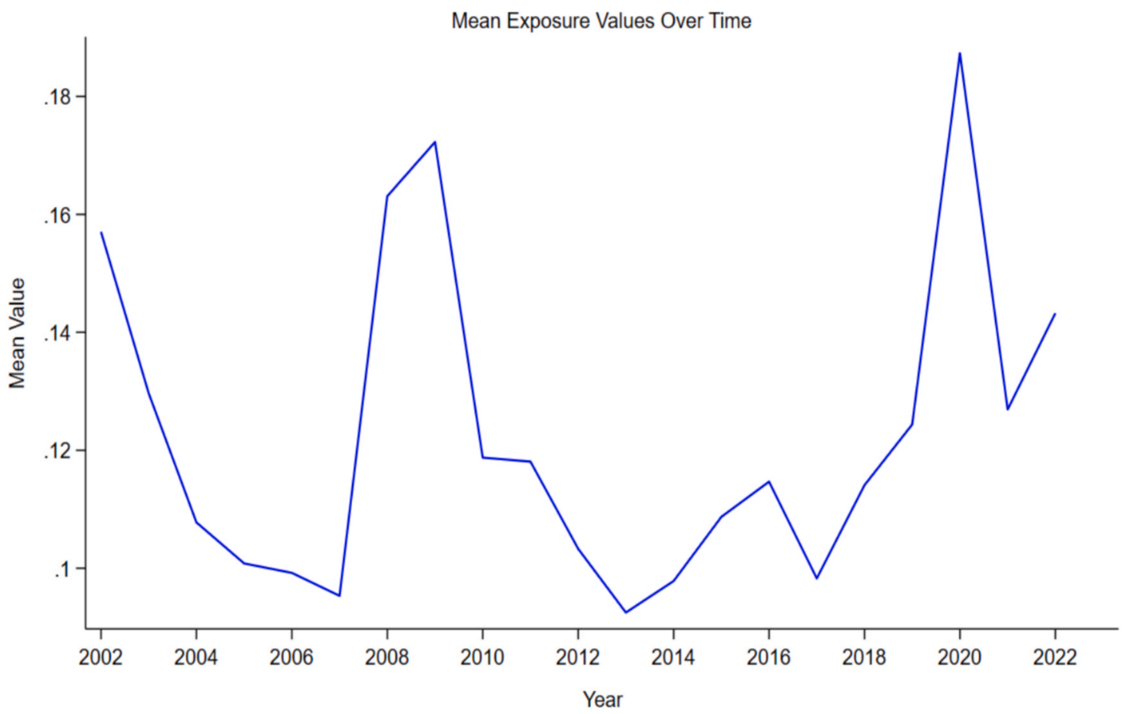

Fig. 2. Mean market volatility over time.

Table 2
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) FLCR	1.000										
(2) SIZE	0.083	1.000									
(3) SAGR	−0.010	0.013	1.000								
(4) LEVE	0.030	0.190	−0.012	1.000							
(5) EVOL	−0.068	0.081	0.016	−0.075	1.000						
(6) MCAP	0.011	0.505	0.013	−0.035	0.091	1.000					
(7) ROE	0.021	0.261	0.055	0.024	0.231	0.094	1.000				
(8) CAPX	0.046	0.156	0.048	0.060	0.103	0.080	0.127	1.000			
(9) ATA	0.183	0.277	−0.024	0.247	0.008	−0.013	0.124	0.618	1.000		
(10) FIND	−0.011	−0.093	−0.010	−0.034	−0.026	−0.025	−0.085	−0.064	−0.096	1.000	
(11) QOG	−0.039	−0.067	−0.013	−0.057	−0.033	−0.017	−0.093	−0.047	−0.082	0.878	1.000

The table presents the descriptive statistics for study variables. The sample spans from 2002 to 2023 and includes 5179 unique companies spanning 54 countries. The measurement of all variables is provided in Appendix Table A1.

Table 3
Baseline analysis using fixed effects regression.

	Dependent variable = Market Volatility		
Variables	(1)	(2)	(3)
FLCR	0.007***	0.008***	0.008***
	(0.003)	(0.002)	(0.002)
SIZE	−0.012***	−0.012***	−0.012***
	(0.001)	(0.001)	(0.001)
SAGR	−0.011***	−0.011***	−0.011***
	(0.002)	(0.001)	(0.001)
LEVE	0.051***	0.051***	0.051***
	(0.004)	(0.003)	(0.003)
EVOL	−0.037**	−0.036***	−0.036***
	(0.017)	(0.014)	(0.014)
MCAP	−0.003	−0.002	−0.002
	(0.002)	(0.003)	(0.003)
ROE	−0.029***	−0.029***	−0.029***
	(0.009)	(0.007)	(0.007)
CAPX	−0.219***	−0.219***	−0.219***
	(0.015)	(0.011)	(0.011)
ATA	0.057***	0.057***	0.057***
	(0.008)	(0.005)	(0.005)
FIND	−0.283***	−0.283***	−0.283***
	(0.027)	(0.018)	(0.018)
QOG	−0.165***	−0.164***	−0.164***
	(0.011)	(0.011)	(0.011)
Constant	0.566***	0.566***	0.566***
	(0.018)	(0.018)	(0.018)
Observations	*38,808*	*38,808*	*38,808*
Adj. R^2	*0.262*	*0.406*	*0.406*
Year/Firm FE	*Yes*	*Yes*	*Yes*
Country/Industry FE		*Yes*	*Yes*
F	*73.37****	*169.92****	*169.90****

The table presents the baseline estimates using fixed-effect regression. Model (1) incorporates year-fixed effects. Model (2) adds country-fixed effects along with year-fixed effects. Model (3) further adds industry-fixed effects alongside year and country-fixed effects. The sample spans from 2002 to 2023 and includes 5179 firms from 54 countries. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

Table 4
Treatment of simultaneity, sample-selection bias, and crisis periods.

	Dependent variable = Market Volatility				
	(1)	(2)	(3)	(4)	(5)
Variables	Lagged model	PSM sample	GFC period exclusion	COVID period exclusion	Non-USA Sample
$FLCR_{t-1}$	0.006***				
	(0.002)				
FLCR		0.007***	0.005***	0.006***	0.020***
		(0.002)	(0.002)	(0.002)	(0.005)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*28,614*	*16,003*	*34,037*	*33,967*	*6289*
Adj. R^2	*0.423*	*0.422*	*0.438*	*0.411*	*0.416*
Year/Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
F	*130.60****	*78.18****	*120.01****	*130.98****	*17.72****

The table reports fixed-effects regression estimates conducted under various robustness conditions. All models include the same set of control variables as used in the main analysis. In Column (1), the firm-level climate risk exposure (FLCR) is lagged by one year. Column (2) uses a propensity score matched (PSM) sample, and Column (3) excludes data from the Global Financial Crisis (GFC) period, while Column (4) omits the COVID-19 period. Finally, Column (5) focuses on a subsample of non-U.S. firms. The sample covers the years 2002–2023. Standard errors are provided in parentheses, with ***, **, and * denoting significance at the 1%, 5%, and 10% levels, respectively. The measurement of all variables is provided in Appendix Table A1.

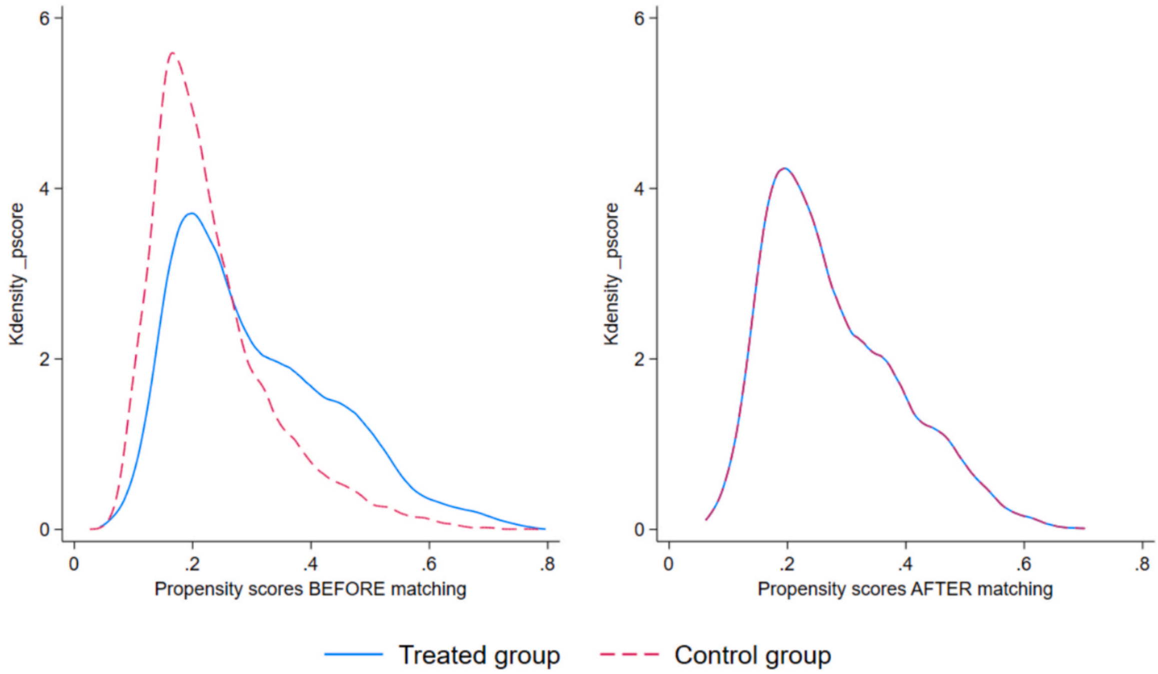

Fig. 3. PSM sample matching plot.

This temporal sequencing strengthens the causal narrative.

4.3.2. Propensity scores matching analysis

Another potential source of bias in the baseline analysis is the non-random distribution of FLCR across firms. To address this selection issue, a propensity score matching technique is employed to construct a subsample of firms based on the 75th percentile[6] of FLCR, designating below-75th percentile firms as the control group and above as the treated group. A logit model calculates the

[6] We thank an anonymous reviewer for suggesting that the propensity score matching (PSM) cutoff based on the median FLCR value may result in unbalanced treatment and control groups due to the right-skewed distribution of FLCR. This imbalance could lead to a disproportionate representation of low-FLCR firms, potentially compromising match quality and causal inference. Following this suggestion, we adopt the 75th percentile as the cutoff to enhance group balance and robustness of results.

propensity scores, and we match treated firms with control firms. Fig. 3 presents both before and after sample distributions. In Table 4 Model 2 within this matched sample, FLCR continues to exert a positive and statistically significant effect on MVOL (0.007, $p < 0.01$). This result suggests that the main finding is not driven solely by inherent differences in firm profiles, bolstering the internal validity of the study.

4.3.3. Global financial and COVID crisis treatment

The 2008–2009 Global Financial Crisis was a period of unprecedented market turbulence that may disproportionately influence volatility measures. Previous studies by Bhagat and Bolton (2014); Cornett et al. (2011), suggest that the GFC can affect results. By excluding the GFC years, the analysis tests whether the FLCR-MVOL association holds under more "normal" market conditions. In Table 4 Model 3, the coefficient on FLCR remains positive and significant (0.005, $p < 0.01$), suggesting that the documented relationship is not merely an artifact of a singular macroeconomic shock. Similarly, the COVID-19 pandemic introduced substantial market uncertainty and could skew the relationship between climate risk exposure and volatility. In Table 4, model 4, excluding the pandemic period, yields a nearly identical coefficient (0.006, $p < 0.01$). This consistency implies that firms with higher climate risk exposure experience higher market volatility even outside extraordinary crisis episodes.

4.3.4. Excluding U.S. firms to address overrepresentation bias

Finally, given that U.S.-listed firms often dominate global samples and may operate under distinct regulatory and market conditions, the analysis is repeated, excluding all U.S. firms. In Table 4, Model 5, the FLCR coefficient in this reduced sample remains both positive and statistically significant (0.020, $p < 0.01$), indicate that the main finding is not driven solely by the unique institutional environment of the United States. The relationship thus holds in diverse international contexts.

4.3.5. Alternative measures and estimators

Table 5 shows that the positive association between FLCR and MVOL is robust across various alternative measures and an alternative estimation technique. Replacing MVOL with idiosyncratic volatility (IVOL) (see Table 5 Model 1) still yields a positive and significant FLCR effect, indicating that climate risk influences firm-specific risk components beyond common market factors. Substituting FLCR with greenhouse gas emissions (GHG) (see Table 5 Model 2) also supports this relationship. Moreover, employing a two-step system GMM approach (see Table 5 Model 3), which includes a lagged dependent variable to address endogeneity, further confirms the robustness of the results. Collectively, these tests strengthen the conclusion that firms exposed to higher climate risks experience greater return volatility, regardless of the model specification, measurement choice, or estimation technique.

4.4. Instrumental variable approach to address endogeneity

To address potential endogeneity, particularly reverse causality, in the relationship between FLCR and MVOL, we implement an IV approach. The key concern is that firms may adjust their climate-related disclosures in response to observed market volatility, which could bias estimates of the impact of FLCR on MVOL. As an instrument, we use country-level climate vulnerability indices, such as the ND-GAIN index, which reflects a country's overall exposure and sensitivity to climate change but is unlikely to be directly influenced

Table 5
Estimations results using additional controls, alternative measures, and estimator.

	(1)	(2)	(4)
Variables	IVOL	MVOL	MVOL
L.MVOL			0.132***
			(0.010)
FLCR	0.005**		
	(0.002)		
GHG		0.003***	0.007**
		(0.001)	(0.003)
Controls	*Yes*	*Yes*	*Yes*
Observations	*38,808*	*38,808*	*34,037*
Adj. R^2	*0.151*	*0.449*	*0.438*
Year/Firm FE	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	
F	*77.61****	*117.82****	
Wald chi^2			*35961****
AR2 [P_value]			*0.179*
Sargan [P_value]			*0.131*

This table is based on alternative measures and estimator. All models include the same set of control variables as used in the main analysis. We used Idiosyncratic Volatility (IVOL) using the Fama-French 3-factor Model as an alternative measure for dependent variable market volatility (MVOL). We employed a natural log of GHG emissions in tons for climate risk (FLCR) as an alternative measure. As an alternative estimation technique, we employed a two-step GMM. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

Table 6
Instrumental variable 2SLS approach.

Variables	(1) FLCR	(2) MVOL
NDGAIN	0.004***	
	(0.001)	
FLCR (Instrumented)		0.180***
		(0.080)
Controls	*Yes*	*Yes*
Observations	*38,808*	*38,808*
Kleibergen-Paap F Statistic		*39.81*
Cragg-Donald F Statistic		*27.65*
Stock-Yogo 10 % Critical Value		*16.38*

This table presents the results of the IV-2SLS regression examining the effect of firm-level climate risk exposure (FLCR) on market volatility (MVOL). The ND-GAIN index is used as an external instrument for FLCR. All models include the same set of control variables as used in the baseline specification. Robust standard errors are clustered at the firm and country levels. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

by individual firm-level stock volatility. The ND-GAIN index, which captures a country's exposure, sensitivity, and adaptive capacity to climate change, is theoretically linked to FLCR. Firms operating in more climate-vulnerable countries face greater physical and transition risks, increasing the salience of climate-related issues in their disclosures (Krueger et al., 2020). Giglio, Maggiori, et al. (2021) highlight how physical climate risks vary by geography and affect firms differently depending on their location, influencing the salience of climate risk at the firm level. Sautner et al. (2023a) show that FLCR, derived from earnings call transcripts, reflects management perceptions of physical, regulatory, and transitional climate risks that are often shaped by country-level vulnerability. Therefore, higher national climate vulnerability is likely to lead to greater firm-level discussion and emphasis on climate risks, as captured by the FLCR metric derived from earnings calls. These indices are strongly correlated with FLCR, as firms in more climate-vulnerable regions are more likely to disclose climate risks, yet they are plausibly exogenous to firm-specific return volatility.

Table 6 presents the IV estimates using the ND-GAIN index as an instrument for FLCR. The results remain positive and statistically significant, indicating that climate risk exposure continues to have a robust effect on market volatility. The first-stage regression (see Table 6 Model 1) confirms a strong relationship between FLCR and the instrument, with an F-statistic above the conventional threshold (>10), alleviating concerns over weak instruments. The findings support our baseline results and strengthen the case for a causal interpretation.

4.5. *Further analysis*

4.5.1. *Regional distribution and economic development*

Table 7 presents regression results examining how the effect of FLCR on MVOL varies by region and level of economic development. Across North America, Europe, and Asia (see Table 7 Columns 1–3), FLCR remains positively and significantly associated with MVOL, though the magnitude and significance levels differ slightly, with Europe showing a notably stronger coefficient (0.019, $p < 0.05$) despite a smaller sample size. When grouped by economic development (G20 vs. non-G20, OECD vs. non-OECD in Table 7 Columns

Table 7
Estimation results for regional distribution and economic development.

	Dependent variable = Market Volatility						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	North America	Europe	Asia	G20	Non-G20	OECD	Non-OECD
FLCR	0.006***	0.019**	0.015**	0.006***	0.026***	0.006***	0.019**
	(0.002)	(0.009)	(0.007)	(0.002)	(0.008)	(0.002)	(0.008)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*32,484*	*3444*	*2557*	*34,909*	*3175*	*35,877*	*2207*
Adj. R^2	*0.406*	*0.497*	*0.289*	*0.412*	*0.370*	*0.413*	*0.328*
Year/Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F	*185.19****	*6.69****	*28.81****	*175.47****	*7.58****	*177.49****	*7.38****

This table is based on regional distribution, including North America, Europe, and Asia, for the sample firms. All models include the same set of control variables as used in the main analysis. Models 1–3 represent the regions where the firm is based. Models 4–7 represent economic development levels, G20, other than G20, OECD, and non-OECD for the sample firms, and the regional economic development level where the firm is based. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

Table 8
Estimation results for the country's climate adaptation environmental performance.

	Dependent variable = Market Volatility			
	(1)	(2)	(3)	(4)
VARIABLES	Low ND Gain	High ND Gain	Low EPI	High EPI
FLCR	0.011***	0.016***	0.013***	0.018***
	(0.002)	(0.002)	(0.001)	(0.004)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*17,804*	*20,997*	*35,703*	*3105*
Adj. R^2	*0.324*	*0.333*	*0.322*	*0.351*
Year/Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*
F	*359.22****	*377.15****	*682.41****	*44.84****

The table is based on the country's environmental performance in terms of climate risk exposure and market volatility. All models include the same set of control variables as used in the main analysis. Categorization of firms into low and high EPI/ND Gain subgroups based on the median values of the Environmental Performance Index (EPI) and ND Gain. Firms with EPI/ND Gain values above the sample median were classified as high EPI/ND Gain, while those below the median were classified as low EPI/ND Gain. Model 1 represents a low ND Gain, and Model 2 represents a high ND Gain. Model 3 represents low EPI; Model 4 represents high EPI. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

4–7), the positive FLCR-MVOL relationship also persists, reflecting its robustness under various institutional contexts and market conditions. With non-G20 shows a notably stronger coefficient (0.026, $p < 0.01$) despite a smaller sample size.

While our dataset includes firms from 54 countries between 2002 and 2023, the sample is heavily concentrated in North America, particularly the United States, which accounts for approximately 84 % of total observations. To address concerns about regional imbalance and ensure the global applicability of our findings, we conduct additional analyses. First, we re-estimate the core regressions after excluding U.S. firms; the results remain consistent in direction, though slightly attenuated in magnitude. Second, we perform regional subsample analyses for North America, Europe, and Asia, as well as for G20 versus non-G20 and OECD versus non-OECD economies. These results reveal meaningful heterogeneity in the FLCR–MVOL relationship across institutional and developmental contexts.

4.5.2. Country's climate adaptation and environmental performance

Table 8 examines how the impact of FLCR on MVOL differs across countries characterized by varying levels of environmental performance, as measured by the ND Gain and Environmental Performance Index (EPI). In Models (1) and (2), firms are categorized based on their host country's ND Gain, with Model (1) representing the low ND Gain group and Model (2) the high ND Gain group. Similarly, Models (3) and (4) classify firms by EPI levels, with Model (3) reflecting low EPI countries and Model (4) high EPI countries. Across all four specifications, FLCR remains positively and statistically significantly associated with MVOL, suggesting that climate risk influences stock return volatility regardless of a country's adaptive capacity or environmental quality. Although the magnitude of the FLCR coefficient is slightly higher in high ND Gain and high EPI contexts, the core finding persists.

4.5.3. Decomposition of climate change risk

Table 9 reports the results from decomposing climate risk exposure into three components, opportunity exposure (OP_CR),

Table 9
Decomposition of firm-level climate risk.

	Dependent variable = Market Volatility			
Variables	(1)	(2)	(3)	(4)
OP_CR	0.015***			0.013***
	(0.004)			(0.004)
RG_CR		0.050***		0.040***
		(0.014)		(0.014)
PH_CR			−0.043	−0.106
			(0.035)	(0.085)
Controls	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*38,808*	*38,808*	*38,808*	*38,808*
Adj. R^2	*0.406*	*0.406*	*0.510*	*0.406*
Year/Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*
F	*170.11****	*169.81****	*84.42****	*145.12****

This table is based on the decomposition of climate risk exposure into opportunity exposure (OP_CR), regulatory exposure (RG_CR), and physical exposure (PH_CR). All models include the same set of control variables as used in the main analysis. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

regulatory exposure (RG_CR), and physical exposure (PH_CR), to explore which specific dimensions of climate risk drive MVOL. Table 9 Model (1) and (4) show that OP_CR is positively and significantly associated with MVOL, implying that climate-related opportunities, perhaps linked to the transition toward a low-carbon economy, contribute to greater return uncertainty. Similarly, in Table 9 Models (2) and (4), the significant positive coefficients on RG_CR indicate that regulatory pressures and anticipated policy changes surrounding climate issues also heighten volatility. In contrast, PH_CR capturing the physical risks from climate change is statistically insignificant in both Models (3) and (4), suggesting that, within this sample and timeframe, the more tangible climate risks (e.g., from severe weather events) do not manifest as higher return volatility, or are less readily priced by investors. Overall, these results highlight that opportunity and regulatory dimensions of climate risk may be more salient factors influencing how investors perceive and price firm-level climate uncertainties.

4.5.4. Changes in investors' awareness

Following the existing literature norm for the Stern Review, we use 4 years of pre- and post-data. The pre-Stern period includes 2002–2005, and the post-Stern period includes 2007–2010. For the Paris Agreement, we use 4 years of pre- and post-data. The pre-Paris period includes 2012–2015, and the post-Paris period includes 2017–2020.

Table 10 evaluates how investors' pricing of FLCR in MVOL influences the following two major climate-related policy events: the Stern Review (2006) and the Paris Agreement (2015). Before the Stern Review (Table 10 Model 1), FLCR is strongly associated with higher MVOL; this relationship remains positive but is slightly reduced in magnitude after its release (Table 10 Model 2), and the interaction term (Table 10 Model 3) does not significantly alter the baseline effect. In contrast, the Paris Agreement period demonstrates a more pronounced change. Before the Paris Agreement (Table 10 Model 4), FLCR is positively related to MVOL, and this effect remains positive after the agreement's enactment (Table 10 Model 5). However, the interaction term with the Paris dummy (Table 10 Model 6) is significantly negative, indicating that, in the post-Paris period, investors may perceive and price climate risk exposure differently, leading to a relative attenuation of the incremental volatility effect. In sum, while FLCR consistently increases MVOL, the enactment of high-profile climate policies, especially the Paris Agreement, appears to influence how markets incorporate climate risk, reflecting evolving investor awareness and sensitivity to climate information over time.

4.6. Channels analysis

4.6.1. Technological, socioeconomic, and regulatory policy channels

We explore country-level channels through which FLCR impacts MVOL, focusing on technological, socioeconomic, regulatory, and reputational risks. Table 11 shows how these country-level factors influence the relationship between FLCR and MVOL. Across all models, FLCR demonstrates a consistently positive and significant association with MVOL, indicating that climate risks heighten stock return uncertainty. Interaction terms reveal that stringent environmental policies (EPSI) (see Table 11 Model 1) and advanced financial development (FDI) (see Table 11 Model 2) significantly mitigate the volatility induced by FLCR, highlighting the capacity of well-regulated markets to absorb and price climate-related risks effectively. GDP per capita (GDP) and renewable energy (REN) exhibit less robust moderating effects (see Table 11 Model 3&4). Governance-related factors, such as the rule of law (ROL) (see Table 11 Model 5) and governance effectiveness (GOVE) (see Table 11 Model 6), also reduce the effect of FLCR on volatility, suggesting that strong institutional frameworks enhance market stability. However, other institutional indicators, such as voice and accountability (VOICE) (see Table 11 Model 7), exhibit less robust moderating effects. These findings emphasize the critical role of economic development and institutional strength in shaping the financial market's response to climate risks.

4.6.2. Environmental sensitive industries

Table 12 model (1) examines how firm-level characteristics of environmentally sensitive industries (ES_Industry) moderate the impact of FLCR on MVOL. The interaction term ES_Industry × FLCR (see Table 12 Model 1) is negative and significant (-0.025, $p < 0.01$), indicating that firms in environmentally sensitive industries experience a weaker positive relationship between FLCR and MVOL. This result aligns with stakeholder theory, which suggests that firms in environmentally sensitive sectors (e.g., energy, utilities, and manufacturing) face greater scrutiny from investors, regulators, and stakeholders. Consequently, these firms are often more proactive in addressing climate risks through sustainability practices, improved disclosures, and resilience strategies, which reduces market volatility linked to climate risk exposure. ES Industry alone has a positive effect on MVOL (0.020, $p < 0.01$), indicating that environmentally sensitive industries are generally associated with higher volatility.

4.6.3. Cost leadership strategy

Table 12 model (2) examines how cost leadership strategy (CL_Strategy) moderates the impact of FLCR on MVOL. The interaction term CL Strategy × FLCR (see Table 12 Model 2) is positive and significant (0.002, $p < 0.01$), implying that firms with a cost leadership strategy experience a slightly higher market volatility effect from climate risk exposure. This could reflect investor concerns about the ability of cost-focused firms to absorb climate-related costs. Cost leadership strategies, as described by Porter's generic strategies, focus on minimizing operational costs to achieve competitive advantage. However, addressing climate risks often requires additional investment in sustainability initiatives, emissions reduction, and climate-related adaptations, which can conflict with the cost-

Table 10
Results for changes in investors' awareness.

	Dependent variable = Market Volatility					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Before Stern	After Stern	Interaction Stern	Before Paris agreement	After Paris agreement	Interaction Paris
FLCR	0.026*** (0.005)	0.019*** (0.003)	0.013** (0.005)	0.014*** (0.002)	0.015*** (0.002)	0.019*** (0.003)
FLCR × Stern			−0.005 (0.005)			
FLCR × Paris						−0.008*** (0.003)
Stern			0.021*** (0.001)			
Paris						0.039*** (0.001)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*5763*	*7440*	*14,277*	*7368*	*7569*	*14,937*
Adj. R^2	*0.264*	*0.286*	*0.237*	*0.271*	*0.385*	*0.299*
Year/Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
F	*33.88****	*49.91****	*216.20****	*167.70****	*168.77****	*368.92****
test			*0.400*			*0.015***

This table is based on estimations of external shocks, using two significant historical events during the sample period: The Stern Review release in 2006 and the Paris Agreement enactment in 2016. We created an indicator variable, Stern, which equals one for observations from 2007 to 2010 and zero for 2002–2005, and an interaction term FLCR × Stern into our primary model. For Paris, which equals one if the observation is from 2017 to 2020 (post-Paris period) and zero for the years 2012–2015 (pre-Paris period). We include the interaction term FLCR × Paris. All models include the same set of control variables as used in the main analysis. Column (1) reflects the impact Before the Stern Review Report, Column (2) after the Stern Review Report, and Column (3) interaction term FLCR × Stern. Column (4) reflects the impact Before the Paris Agreement, Column (5) after the Paris Agreement, and Column (6) interaction term FLCR × Paris. test = test_b[1.FLCR × Stern or Paris] =_b[0.FLCR × Stern or Paris]. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1 %, 5 %, and 10 %, respectively. The measurement of all variables is provided in Appendix Table A1.

minimization approach. CL Strategy alone has a negative effect on MVOL (−0.005, $p < 0.01$), suggesting that cost leadership reduces overall volatility.

Fig. 4 presents predictive margins with 95 % confidence intervals (CIs) for the interaction between FLCR and CL Strategy on MVOL.[7] The linear prediction of market volatility is plotted across low, medium, and high levels of firm climate risk while stratified by low, medium, and high-cost leadership strategies. The graph demonstrates that the positive relationship between FLCR and MVOL is moderated by the firm's cost leadership strategy. Firms with high-cost leadership strategies are significantly better at mitigating the volatility effects of climate risk exposure, as evidenced by the flatter slope. In contrast, firms with low-cost leadership strategies are far more sensitive to climate risks, exhibiting steeper increases in market volatility. This underscores the importance of operational efficiency and cost management in enhancing firms' resilience to climate-related risks.

4.6.4. *Differentiation strategy*

Table 12 model (3) examines how differentiation strategy (Diff_Strategy) moderates the impact of FLCR on MVOL. The interaction term Diff Strategy × FLCR (see Table 12 Model 2) is positive and significant (0.003, $p < 0.01$), showing that firms with a differentiation strategy face heightened volatility when exposed to climate risks. Differentiation strategies, while promoting innovation, may increase uncertainty related to climate investments and market reception. Firms adopting a differentiation strategy focus on innovation, quality, and unique product offerings to gain competitive advantage. While such firms are likely to invest in green innovations and sustainability, these investments come with higher uncertainty regarding returns, investor expectations, and long-term success. Diff Strategy itself positively influences volatility (0.007, $p < 0.01$), likely due to the higher uncertainty associated with innovation-driven strategies.

Fig. 5 presents predictive margins with 95 % confidence intervals (CIs) for the interaction between FLCR and Diff_Strategy on MVOL.[8] Results demonstrate that the positive relationship between FLCR and MVOL is amplified for firms pursuing a high differentiation strategy. While differentiation enables firms to innovate and adapt to climate challenges, it also increases perceived uncertainty and risk, leading to higher volatility. On the other hand, firms with low differentiation strategies exhibit lower volatility, likely due to reduced exposure to innovation-related uncertainties.

4.6.5. *Corporate governance*

Table 12 model (4) examines how corporate governance (C-Governance) moderates the impact of FLCR on MVOL. The interaction

[7] Low = Mean minus one standard deviation, Medium = Mean, and High = Mean plus one standard deviation.
[8] Low = Mean minus one standard deviation, Medium = Mean and High = Mean plus one standard deviation.

Table 11
Technological, socioeconomic, and regulatory policy channels analysis.

	Dependent variable = Market Volatility						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	EPSI	FIND	GDP	REN	ROL	GOVE	VOICE
FLCR	0.013***	0.025***	0.013***	0.015***	0.029***	0.026***	0.020***
	(0.001)	(0.005)	(0.002)	(0.004)	(0.006)	(0.004)	(0.004)
EPSI × FLCR	−0.006**						
	(0.004)						
FIND × FLCR		−0.021***					
		(0.006)					
GDP × FLCR			0.004				
			(0.004)				
REN × FLCR				−0.002			
				(0.002)			
ROL × FLCR					−0.011***		
					(0.002)		
GOVE × FLCR						−0.009***	
						(0.003)	
VOICE × FLCR							−0.007*
							(0.004)
EPSI	−0.002***						
	(0.001)						
FIND		0.007*					
		(0.004)					
GDP			−0.011***				
			(0.001)				
REN				0.002**			
				(0.001)			
ROL					−0.011**		
					(0.006)		
GOVE						−0.006	
						(0.004)	
VOICE							−0.003
							(0.006)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*38,808*	*38,808*	*38,808*	*38,808*	*38,808*	*38,808*	*38,808*
Adj. R^2	*0.242*	*0.172*	*0.324*	*0.326*	*0.324*	*0.324*	*0.324*
Year/Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
F	*5577.8****	*671.65****	*616.95****	*589.11****	*613.92****	*617.12****	*612.71****

The table examines the moderating role of country-level factors in the relationship between firm-level climate risk exposure (FLCR) and market volatility (MVOL). Seven models are presented, each incorporating a distinct country-level moderator: environmental policy stringency index (EPSI), financial development index (FIND), GDP per capita (GDP), renewable energy share (REN), rule of law (ROL), governance effectiveness (GOVE), and voice and accountability (VOICE). Interaction terms between FLCR and the respective moderators test how these country-level characteristics influence the FLCR–MVOL relationship. All models include standard controls for firm-level characteristics. Below the coefficients, the standard errors are presented in parentheses, and asterisks ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The measurement of all variables is provided in Appendix Table A1.

term C-Governance × FLCR (see Table 12 Model 4) is negative and significant (−0.010, $p < 0.05$), indicating that stronger corporate governance mitigates the volatility impact of climate risk exposure. Effective governance structures may enhance firms' ability to manage and disclose climate risks, reducing investor uncertainty. According to agency theory, robust governance practices enhance a firm's ability to identify, manage, and disclose climate risks. Strong governance improves investor confidence and reduces information asymmetry. Corporate governance alone reduces market volatility (−0.013, $p < 0.01$), reinforcing its stabilizing role.

Fig. 6 presents predictive margins with 95 % CIs for the interaction between FLCR and C-Governance on MVOL.[9] The graph demonstrates that corporate governance quality significantly moderates the relationship between FLCR and MVOL. Firms with strong governance (high governance) experience lower volatility, and the impact of rising climate risk exposure is mitigated or even reversed. In contrast, firms with weak governance (low governance) face elevated volatility, with the effect of FLCR being more pronounced. These findings underscore the importance of robust corporate governance as a critical mechanism for enhancing firms' resilience to climate-related risks and reducing investor uncertainty.

4.6.6. R&D intensity

Table 12 model (5) examines how R&D_Intensity moderates the impact of FLCR on MVOL. The interaction term R&D Intensity ×

[9] Low = Mean minus one standard deviation, Medium = Mean and High = Mean plus one standard deviation.

Table 12
Firms level channels analysis.

	Dependent variable = Market Volatility				
	(1)	(2)	(3)	(4)	(5)
Variables	ES_Industry	CL_Strategy	Diff_Strategy	C-Governance	R&D_Intensity
FLCR	0.017***	0.021***	0.011***	0.007	0.004**
	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
ES_Industry × FLCR	−0.025***				
	(0.003)				
CL_Strategy × FLCR		0.002***			
		(0.001)			
Diff_Strategy × FLCR			0.003***		
			(0.001)		
C-Governance × FLCR				−0.010**	
				(0.005)	
R&D_Intensity × FLCR					−0.117***
					(0.021)
ES_Industry	0.020***				
	(0.002)				
CL_Strategy		−0.005***			
		(0.001)			
Diff_Strategy			0.007***		
			(0.001)		
C-Governance				−0.013***	
				(0.001)	
R&D Intensity					−0.026***
					(0.008)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*38,808*	*38,808*	*38,808*	*38,808*	*38,808*
Adj. R^2	*0.353*	*0.295*	*0.294*	*0.366*	*0.511*
Year/Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
F	*601.29****	*179.84****	*177.37****	*92.88****	*75.48****

This table presents the results of fixed-effects regression models examining the interaction effects between firm-level climate risk exposure (FLCR) and various firm-level channels on market volatility (MVOL). All models include standard controls for firm-level characteristics. Model (1) investigates firms in environmentally sensitive industries (ES_Industry), where ES_Industry equals one for firms operating in environmentally sensitive sectors and zero otherwise. Model (2) analyses the interaction of FLCR with cost leadership strategy (CL_Strategy), while Model (3) examines the interaction with differentiation strategy (Diff_Strategy). Model (4) explores the moderating role of corporate governance (C-Governance), and Model (5) tests the role of R&D intensity (R&D_Intensity). Standard errors are reported in parentheses, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The measurement of all variables is provided in Appendix Table A1.

FLCR (see Table 12 Model 5) is negative and significant (−0.117, $p < 0.01$), suggesting that firms with higher R&D investments experience lower volatility when exposed to climate risks. This highlights the role of innovation in mitigating uncertainties related to climate risks. R&D Intensity alone has a strong negative effect on MVOL (−0.026, $p < 0.01$), indicating that higher R&D investment stabilizes firm performance. Firms with higher R&D intensity are better positioned to innovate and adapt to climate-related challenges, consistent with the firm's resource-based view (RBV). Innovation enables firms to develop climate-resilient products, technologies, and processes, enhancing their competitive advantage.

Fig. 7 presents predictive margins with 95 % CIs for the interaction between FLCR and R&D intensity on MVOL.[10] The graph demonstrates that R&D intensity significantly moderates the relationship between FLCR and MVOL. Firms with high R&D intensity experience the least volatility, as their innovation capacity enhances resilience to climate-related risks. In contrast, firms with low R&D intensity face the sharpest increase in volatility, reflecting their limited ability to adapt to or mitigate climate risks. These findings underscore the critical role of R&D investments in stabilizing firm performance in the face of rising climate uncertainties.

4.7. Discussion on key findings

Our analysis reveals several important findings regarding the relationship between FLCR and MVOL. First, we document a robust positive relationship between FLCR and MVOL, which persists across various model specifications, fixed effects, PSM, GMM, and IV 2SLS approaches. The study finds that FLCR significantly increases MVOL, underscoring investor sensitivity to climate risks. At the firm level, environmentally sensitive industries weaken this relationship, supporting stakeholder theory, as firms in these industries are often more proactive in managing risks. In contrast, cost leadership and differentiation strategies amplify volatility, aligning with Porter's framework and the RBV, where cost constraints and innovation uncertainties heighten investor concerns. Strong corporate

[10] Low = Mean minus one standard deviation, Medium = Mean and High = Mean plus one standard deviation.

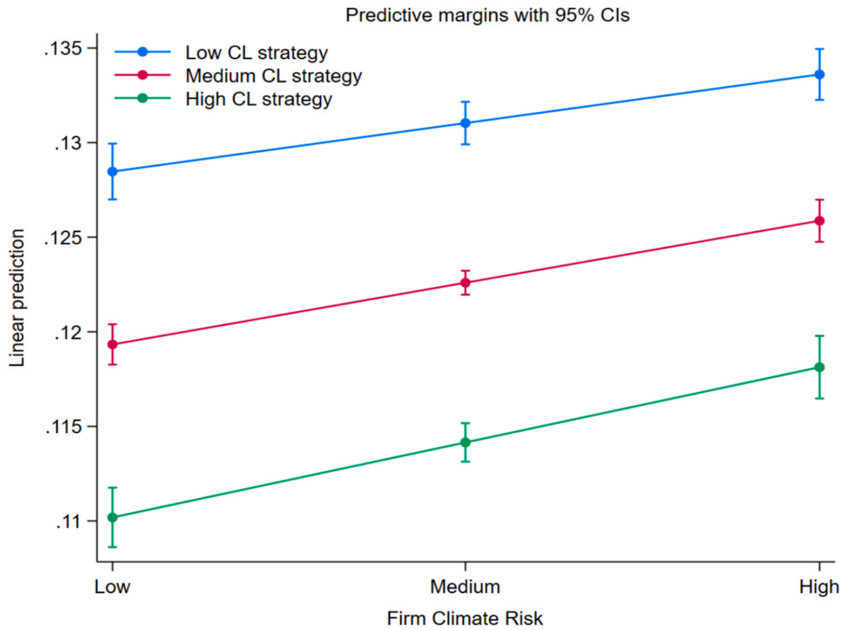

Fig. 4. Cost leadership strategy.

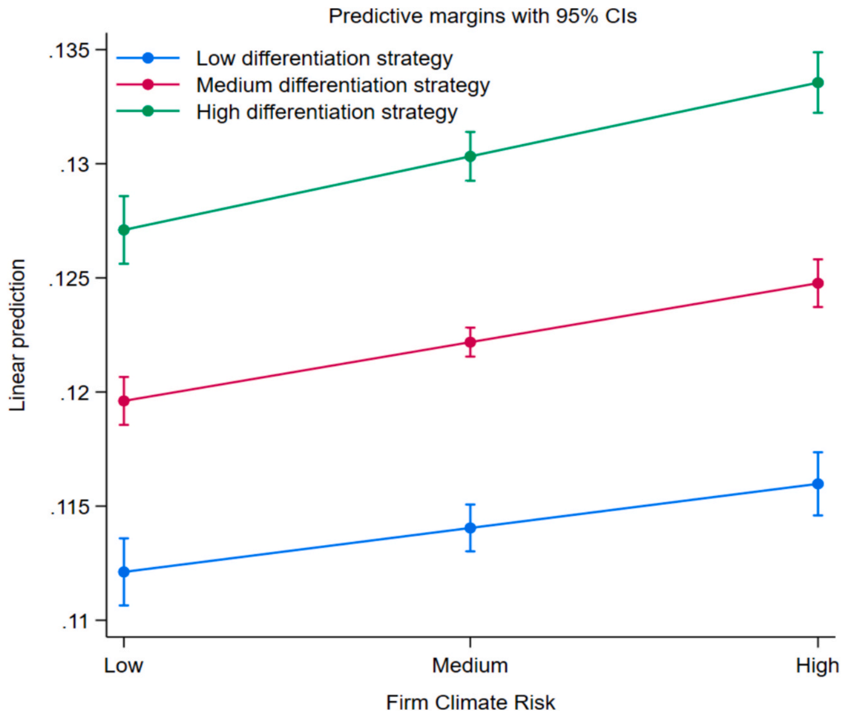

Fig. 5. Differentiation strategy.

governance and high R&D intensity mitigate the FLCR-MVOL relationship, consistent with agency theory and the RBV, as effective governance and innovation capacity enhance firms' resilience to climate risks. At the country level, EPSI FDI dampens volatility by improving risk pricing, aligning with institutional theory, while higher GDP amplifies the effect due to heightened investor awareness in developed economies. Strong institutions, such as GOVE and ROL, further reduce volatility by enhancing transparency and stability.

The findings of this study align with multiple theoretical frameworks and contribute to the growing body of empirical literature on climate finance. The positive association between FLCR and market volatility reflects investor risk perception theory, where

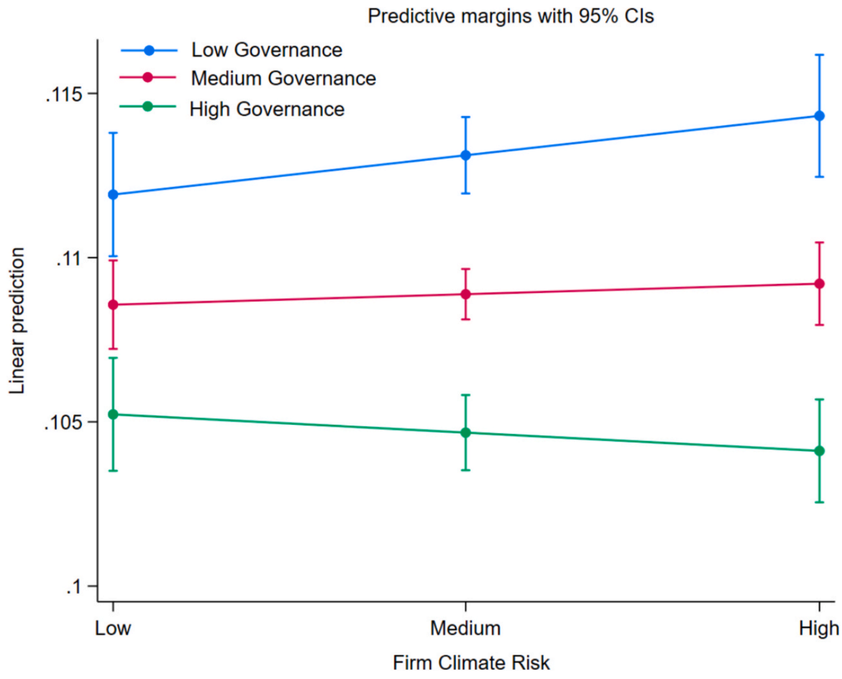

Fig. 6. Corporate governance.

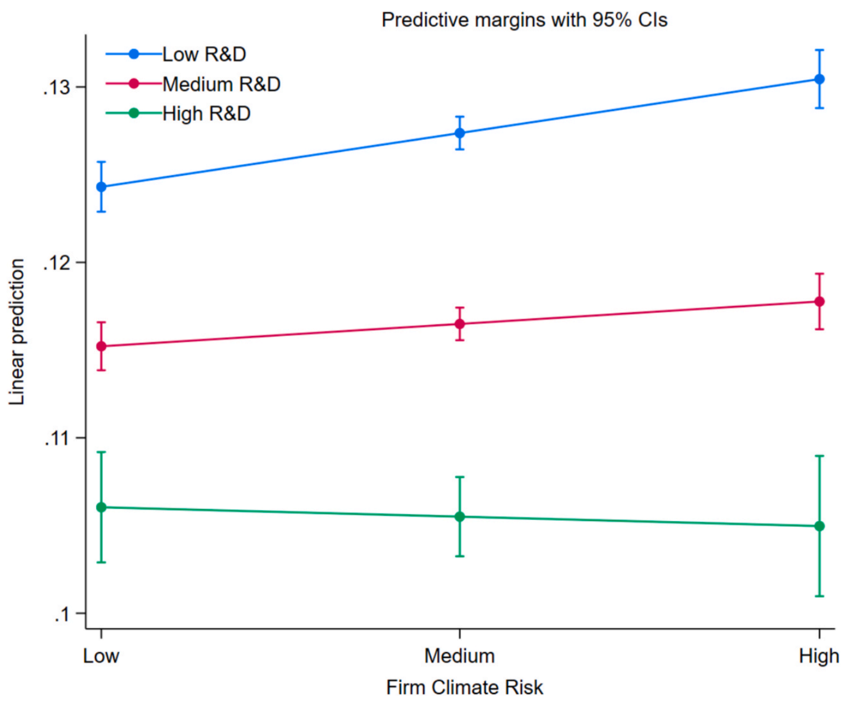

Fig. 7. R&D Intensity.

heightened climate risks introduce uncertainty in cash flows, compliance costs, and operational stability, leading to increased volatility. This result supports prior studies, such as Ilhan et al. (2020); Sautner et al. (2023a, 2023b), which highlights how climate-related risks amplify financial uncertainty. The moderating role of corporate governance aligns with agency theory, as firms with robust governance mechanisms exhibit lower volatility due to better transparency, risk management, and alignment with shareholder interests (Lins et al., 2017). Similarly, the mitigating effect of R&D intensity reflects the RBV, where firms leveraging innovation are better equipped to adapt to climate challenges and enhance resilience (Berrone et al., 2013).

At the country level, the results support the institutional theory, showing that strong environmental policy stringency and financial development reduce volatility by facilitating risk management and improving climate risk pricing (Hambel et al., 2024). Conversely, the amplifying role of GDP per capita aligns with studies suggesting that investor awareness and sensitivity to climate risks are more pronounced in wealthier economies. Strong institutions, such as governance effectiveness and the rule of law, further stabilize markets, consistent with the findings of (La Porta et al., 1999). The study also complements the literature on climate policy effectiveness, as evidenced by the dampened volatility effect following the Paris Agreement, consistent with (Owolabi et al., 2024). These findings extend existing research by integrating firm-level strategies, governance quality, and institutional strength as critical channels through which climate risks impact market volatility.

5. Conclusion

This study examines the impact of FLCR on MVOL while identifying key firm-level and country-level channels that moderate this relationship. The findings reveal that FLCR significantly increases market volatility, underscoring investor concerns regarding firms' exposure to climate-related risks, including regulatory, physical, and transitional challenges. These results align with investor risk perception theory, suggesting that greater climate uncertainty leads to heightened volatility in stock returns.

At the firm level, the moderating role of corporate strategies, governance, and innovation highlights important pathways for managing climate risks. Firms in environmentally sensitive industries and those with strong corporate governance or high R&D intensity experience a weaker FLCR-MVOL relationship, reflecting their ability to effectively manage and adapt to climate risks. Conversely, firms adopting cost leadership or differentiation strategies face amplified volatility, as cost constraints and innovation uncertainties heighten investor concerns. These findings align with stakeholder theory, agency theory, and RBV, highlighting the importance of firm-specific strategies and capabilities in mitigating climate-induced volatility.

At the country level, the results emphasize the role of institutions and policy frameworks in shaping firms' climate risk resilience. Stringent environmental policies and well-developed financial systems significantly dampen the volatility effect of FLCR by providing clear regulatory signals and facilitating risk pricing. In contrast, higher GDP per capita amplifies the effect, reflecting heightened investor awareness in developed markets. Strong institutional quality, measured by governance effectiveness and the rule of law, further reduces volatility, supporting the stabilizing role of effective governance and transparency at the national level. The study also highlights the importance of international climate commitments, as evidenced by the significant reduction in volatility following the Paris Agreement, indicating that coordinated global policies can mitigate climate risk-related uncertainty.

This study contributes to the growing climate finance literature by providing a comprehensive analysis of how firm-level climate risk exposure influences market volatility and identifying critical firm- and country-level factors that shape this relationship. The findings offer practical insights for managers, policymakers, and investors. For firms, strengthening governance structures, fostering innovation, and aligning corporate strategies with climate risk management can mitigate the adverse effects of climate risk exposure. For policymakers, developing stringent environmental policies, enhancing institutional quality, and fostering financial development are essential for reducing climate risk-induced market volatility. For investors, firms with robust governance, innovation capacity, and effective climate risk management present lower volatility, offering more stable investment opportunities.

A notable limitation of this study is the substantial regional imbalance in our sample, with North American firms, particularly those from the United States, accounting for approximately 84 % of the observations. Although we addressed this concern through robustness checks, such as excluding U.S. firms and conducting regional subsample analyses, our findings' external validity and global generalizability might still be constrained. Future research could benefit from employing more geographically balanced datasets or applying weighted regression approaches to better reflect the global distribution of economic activity. Further investigation into specific institutional or regulatory contexts in underrepresented regions could enrich literature by providing deeper insights into how climate risk exposure influences market volatility worldwide. Future research could explore the dynamic effects of climate risks over time, particularly as firms and markets adapt to evolving climate policies. Expanding the analysis to include sector-specific variations and alternative measures of climate risk exposure could provide deeper insights into firms' climate resilience. In conclusion, this study underscores the importance of firm strategies, governance quality, and institutional frameworks in managing climate-related risks and stabilizing market performance, offering valuable insights for firms and policymakers navigating the transition to a low-carbon economy.

CRediT authorship contribution statement

Mirza Muhammad Naseer: Writing – original draft, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Yongsheng Guo:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Xiaoxian Zhu:** Writing – review & editing, Visualization, Software, Methodology, Investigation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT (OpenAI) to enhance readability, refine the language, and improve clarity of the manuscript. After using this tool, the author(s) thoroughly reviewed, edited, and revised the content as necessary, and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1
Variable Measurement.

Variable	Measure	Data Sources
MVOL	Market volatility Equation (1)	CRSP
FLCR	Firm-level climate change exposure Equation (2)	(Sautner et al., 2023a)
SIZE	Firm size = Natural log of total assets	Compustat
SAGR	Sales growth = $SAGR_{i,t} = \ln[sale_{i,t} / sale_{i,\ t-1}]$ (sale item of compustat)	Compustat
LEVE	Leverage = ratio of corporate total debt to firm's total assets	Compustat
EVOL	Earnings volatility = Standard deviation of operating income before depreciation, scaled by total assets, calculated over the period of five years.	Compustat
MCAP	Market capitalization	CRSP
ATA	The ratio of property plant and equipment in the firm's total assets at book value (ppent/at items of Compustat).	Compustat
CAPX	The value of capital expenditure (capex item of Compustat) scaled with the firm's total assets at book value (at item of Compustat).	Compustat
ROE	Return on Equity	Compustat
FIND	"Financial development index is a relative ranking of countries based on the efficiency, accessibility, and depth of their financial markets and institutions."	IMF Financial Development Index Database
QOG	The mean value of the ICRG variables 'Corruption,' 'Law and Order', and 'Bureaucracy Quality,' scaled from 0 to 1. Higher values indicate a higher quality of government.	The International Country Risk Guide (ICRG)
R&D Intensity	Research and development (xrd item of Compustat data) expenses to firm's annual total assets (at)	Compustat
GHG	Total GHG emission in tons reported by a firm across scopes 1, 2, and 3.	LSEG workspace
C-Governance	Corporate governance is a G Score from the LSEG ESG database	LSEG workspace
ES_Industry	Environmental Sensitive Industries is a Dummy variable equal to 1 for the environmental sensitive sector SIC 4-digit code 1000–1399 and 4900–4999 and 0 otherwise.	Compustat
CL_Strategy	"Cost leadership = −(Capital intensity + Cost efficiency + Capital expenditure), where capital intensity is total assets over total sales, cost efficiency is the cost of goods sold over total sales, and capital expenditure is capital expenditures over total sales."	Compustat
Diff_Strategy	"Differentiation = (S&Aexpenses + R&D_Intensity), where S&A expenses are S&A expenses over total sales and R&D intensity is R&D expenditures over total sales."	Compustat
IVOL	Idiosyncratic volatility is based on the Fama-French 3-factor model.	WRDS Beta Suite
GDP	"GDP per capita in current dollars in a given year"	World bank WDI
REN	"Renewable Energy measures a country's share of electricity generated by renewable power plants in total electricity generated by all types of plants in a given year."	World bank WDI
ROL	"Rule of law measures a country's perceptions in a given year of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence."	World Bank WGI
VOICE	"Voice captures perceptions in a given year of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media."	World Bank WGI
GOVE	Government effectiveness	World Bank WGI
EPSI	"Stringent environmental policies is a country-specific and internationally comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior."	OECD iLibrary
ND Gain	"ND-GAIN Country Index summarizes a country's vulnerability to climate change and other global challenges in combination with its readiness to improve resilience. It aims to help governments, businesses, and communities better prioritize investments for a more efficient response to the immediate global challenges ahead."	Notre Dame Global Adaptation Initiative https://gain.nd.edu/our-work/country-index/rankings/
VULN	Measures a country's exposure, sensitivity and capacity to adapt to the negative effects of climate change. ND-GAIN measures overall vulnerability by considering six life-supporting sectors – food, water, health, ecosystem service, human habitat, and infrastructure.	Notre Dame Global Adaptation Initiative https://gain.nd.edu/our-work/country-index/rankings/

(*continued on next page*)

Table A1 (*continued*)

Variable	Measure	Data Sources
EPI	"The Environmental Performance Index (EPI) provides a data-driven summary of the state of sustainability around the world. Using 58 performance indicators across 11 issue categories, the EPI ranks 180 countries on climate change performance, environmental health, and ecosystem vitality."	Yale Centre for Environmental Law and Policy https://epi.yale.edu/

Data availability

Data will be made available on request.

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