THE IMPACT OF FIRMS' CLIMATE RISK ON FIRM VALUE: THE MODERATING ROLE OF ESG AND A MACHINE LEARNING APPROACH

The 13th International Conference on Emerging Challenges: Business Dynamics in Disruptive Economy

Do Hong Nhung[1*], Do Anh Thai[1], Tran Binh Minh[2], Dang Bach Duong[1],

Nguyen Huong Giang[1], Doan Thi Thuy Van[1] and Phan Hoang Hai[3]

[1] National Economics University, Hanoi, Vietnam

[2] Banking Academy of Vietnam

[3] Hanoi University of Science and Technology, Hanoi, Vietnam

[*]Corresponding author: nhungdh@neu.edu.vn

Abstract

Research purpose:
This study investigates the effect of firms' climate risk on firm value and examines whether ESG practices moderate this relationship in emerging and frontier markets.

Research motivation:
Climate risk has become a critical concern for firms in vulnerable economies where exposure to extreme weather events is high, but insurance mechanisms and safeguards remain limited. Although prior studies link climate risk to firm value, evidence remains fragmented and concentrated in developed markets, creating a need for more context-specific research.

Research design, approach, and method:
We analyze 1,683 firm-year observations from 561 firms across Vietnam, India, the Philippines, South Africa, and Malaysia during 2022–2024. To estimate causal effects, we adopt a Double Machine Learning (DML) framework that integrates Random Forest and XGBoost, allowing us to account for nonlinearity and control for confounding bias.

Main findings:
The results show that climate risk significantly reduces firm value, and this negative impact is amplified when interacted with ESG scores. These findings highlight the potential double-edged role of ESG in high-risk environments.

Practical/managerial implications:
Our results emphasize the importance of embedding ESG practices into firms' financial strategies and technological innovation efforts. Moreover, they call for stronger regulatory frameworks and policy support to improve market resilience to climate-related risks.

Keywords: Double Machine Learning, ESG Practices, Firm's Climate Risk, Firm Value, Random Forest, XGBoost

1. INTRODUCTION

In recent decades, concerns over climate change risk have been steadily increasing (Battiston et al., 2021; Bolton & Kacperczyk, 2021; Dowling, 2013; Hong et al., 2020). Investors have increasingly incorporated firms' exposure to climate risk into their portfolio decision-making, with the prevailing view that such risks carry significant financial implications for businesses (Vestrelli et al., 2024), thereby influencing corporate value.

Accordingly, climate risk has long been recognized as a major threat to human society (Xu et al., 2024). According to the Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes (1970–2019) released by the World Meteorological Organization (WMO) on September 1, 2021, climate-related disasters have risen sharply over the past 50

years, accounting for 50% of all recorded disasters, 45% of disaster-related deaths, and 74% of economic losses, with 91% of fatalities occurring in developing countries (Xu et al., 2024). A growing body of research shows that firms with higher climate exposure often face higher costs of capital and lower valuations, as investors demand a greater risk premium (Huang et al., 2022; Jin et al., 2025; Kling et al., 2021). At the same time, the introduction of instruments such as the European Union Emissions Trading System (EU-ETS) has directly increased the operating costs of high-emission firms, thereby affecting their profitability and market value (Dewaelheyns et al., 2023; Lambertides & Tsouknidis, 2024; Makridou et al., 2019). On a broader scale, the investment market has witnessed a profound shift, with global ESG funds surpassing USD 30 trillion in 2022 (GSIA, 2022), indicating that investors are increasingly aligning capital allocation decisions with firms' ability to manage climate risks. Taken together, these developments underscore that examining the impact of climate risk on firm value is not only of academic significance but also of urgent practical relevance for both corporations and the financial markets.

Previous studies have documented various economic consequences of climate risk for firms and financial markets (Dell et al., 2014; Stern, 2007; Xu et al., 2022). However, empirical evidence remains inconsistent (Xu et al., 2024). Some research suggests that climate risk undermines the fundamental drivers of firm value—for instance, by reducing national and regional productivity (Burke et al., 2015), lowering stock and bond returns and thereby weakening investor expectations (Cao & Wei, 2005; Hirshleifer & Shumway, 2003; Huynh & Xia, 2021; Kamstra et al., 2003; Liu & Lin, 2023), increasing the cost of equity and financial risk (Huynh et al., 2020), heightening earnings and cash flow volatility (Huang et al., 2018), as well as decreasing revenue and operating income, which directly determine market value (Pankratz et al., 2023). Conversely, other studies argue that climate risk may generate positive effects on firm value—for example, by stimulating risk-taking behavior and raising market valuations (Xu et al., 2022), improving financial performance in specific industries such as mining (Sun et al., 2020), encouraging carbon reduction in highly polluting sectors and thereby enhancing reputation and competitive advantage (Ren et al., 2022), or fostering employment and breakthrough green innovation that expand long-term growth potential (Sautner et al., 2023). These divergent findings highlight the need for further research to clarify the true impact of climate risk on firm value.

Although climate change is a global phenomenon with far-reaching impacts on economies and societies, existing studies on the effects of climate risk on firm value have thus far concentrated primarily on developed economies or within specific national contexts (Huynh & Xia, 2021; Javadi & Masum, 2021; Lemma et al., 2018). However, evidence indicates that emerging and frontier economies often suffer greater losses from extreme climate events while lacking adequate insurance mechanisms to mitigate these risks (Agoraki et al., 2024; Akhtaruzzaman et al., 2023; Arian & Naeem, 2025; Bals et al., 2007; Lee et al., 2021). This research gap is noteworthy, as the combination of high vulnerability and limited risk-mitigation capacity may amplify the impact of climate risk on firm value in these contexts. Accordingly, extending the scope of analysis to emerging and frontier economies can provide more comprehensive empirical evidence and, at the same time, make an important contribution to policy discussions on enhancing the resilience of firms and financial markets in the face of climate change.

Moreover, while measuring climate risk at the firm level is a critical prerequisite for assessing its impact on firm value, such metrics remain underdeveloped in emerging and frontier economies. Previous studies have primarily relied on data from developed countries, where transparency and climate-related disclosure systems are more advanced (Bolton & Kacperczyk, n.d.; Kölbel et al., 2020; Sautner et al., 2023; Vestrelli et al., 2024). Common indicators, such as carbon emissions, participation in voluntary initiatives, or data from the CDP, typically cover only large firms listed in developed markets (Ding et al., 2024; Grahn, 2025; Siddique et al., 2021). By contrast, in emerging and frontier economies, climate-related disclosure is often limited, participation in international reporting initiatives is low, and carbon data are either missing or inconsistent (Ding et al., 2024; Gerged, 2021; Mansour et al., 2025; Qian et al., 2025). This results in the absence of reliable measures for quantifying climate risk at the firm level. Therefore, empirical research is needed to advance the development of climate risk metrics that are better aligned with the specific contexts of emerging economies.

Accordingly, our study aims to assess the impact of climate change risk on firm value in the context of emerging and frontier economies—regions that often bear severe losses from extreme climate events but lack adequate risk insurance mechanisms and reliable firm-level metrics. By combining data aggregation with machine learning techniques, this research not only provides more comprehensive empirical evidence but also contributes to the ongoing debate on the economic implications of climate risk. Machine learning offers powerful capabilities for economic analysis by moving beyond traditional methods to uncover complex, non-linear patterns in large datasets. This enables economists to make more accurate forecasts and to analyze unstructured data for novel insights.

From an academic perspective, this study addresses an important gap in the literature, as most prior research has concentrated on developed economies or relied on climate disclosure data that predominantly cover large listed firms. By extending the analytical framework to emerging and frontier markets—where climate risks may exert stronger effects on firm value but remain underexplored—this study enriches our understanding of climate-related financial risks.

From a practical perspective, the research offers valuable insights for firms in identifying and managing climate risks, for investors in adjusting capital allocation strategies and firm valuation, and for policymakers in designing regulatory

frameworks, governance tools, and supportive mechanisms to enhance the resilience of financial markets and businesses to climate change.

The study focuses on emerging and frontier economies given their high exposure to climate risks such as storms, droughts, floods, and heatwaves, alongside limited insurance mechanisms and weak climate disclosure systems, which force firms to directly absorb related damages and costs. Investigating this context thus provides a more comprehensive picture of the true effects of climate risk on firm value in vulnerable environments.

Among these economies, we select Vietnam, India, the Philippines, South Africa, and Malaysia. In addition to data availability, these countries represent typical markets with diverse industrial structures, varying degrees of capital market development, and significant carbon-intensive sectors—industries directly affected by climate change.

Furthermore, the financial sector is excluded because business models in this domain—such as banking, insurance, and securities—are primarily exposed to climate risk indirectly through investment portfolios or loan exposures, rather than through direct physical impacts on production and operations. Excluding the financial sector allows for a clearer and more consistent comparison across firms that are directly exposed to climate risks (Huynh et al., 2020; Sautner et al., 2023).

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 describes the data and methodology. Section 4 reports and discusses the empirical results. Section 5 concludes and provides implications.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Firm valuation has become an essential requirement in corporate activities (Stryjakiewicz et al., 2014), particularly as climate risk emerges as a major challenge. Climate risks are commonly categorized into two groups—physical risks and transition risks (TCFD, 2017)—both of which exert profound impacts on corporate operations and sustainable development. The intersection between climate change and firm value represents an intriguing nexus that warrants increasing academic attention worldwide (Pradhan et al., 2025).

The relationship between climate risk and firm value can be explained through various theoretical lenses. From the perspective of stakeholder theory, Freeman (2010) argues that firms must balance the interests of all stakeholders rather than focusing solely on shareholders. When climate risks materialize, shifts in stakeholder support, trust, and cooperation may lead firms to face higher capital costs, unstable cash flows, and weakened market reputation, ultimately resulting in lower valuations. Signaling theory emphasizes the role of reducing information asymmetry and enhancing financial transparency in building trust with stakeholders (Spence, 1973). Firms with greater transparency can signal to investors their commitment to addressing climate change, thereby mitigating the adverse effects of climate exposure on firm value (Jin et al., 2025). Legitimacy theory, meanwhile, suggests that environmental disclosure is not merely a compliance mechanism but also a means to align with societal expectations and values (Barkemeyer, 2007; Deegan, 2006). When such expectations are met, firm value tends to increase. The observed positive correlation between climate risk disclosure and market valuation underscores the importance of effectively communicating climate-related exposures to investors (Vestrelli et al., 2024). This highlights the pressing need for systematic research to further clarify the impact of climate risk on firm value, both theoretically and empirically.

Building on this foundation, we develop the first hypothesis of our study, which posits a significant negative relationship between climate risk and firm value. This hypothesis is grounded in empirical evidence showing that climate risk exerts substantial effects on economic and financial performance (Nordhaus, 2006; Dell et al., 2014; Del Fava et al., 2024; Pradhan et al., 2025). Earlier studies predominantly focused on climate risks at the national or city level, or across specific geographic regions. From this starting point, the growing global concern over climate variability has motivated both policymakers and scholars to broaden the scope of inquiry, aiming to better understand how environmental factors influence corporate valuation.

A growing body of recent empirical studies consistently confirms that climate risk (both physical and transition) exerts a significant negative effect on firm value. At the micro level, climate-related risks directly erode firm value by reducing financial performance, cash flows, debt financing capacity, and market valuation (Naseer et al., 2024; Bagh et al., 2024a). The primary transmission mechanisms arise from direct costs such as physical damages, supply chain disruptions, and emerging legal liabilities (Berkman et al., 2024). In addition, climate risk generates indirect costs through financial volatility, particularly by constraining firms' access to debt financing due to rising financial costs (Liu et al., 2025a), thereby leading to higher capital costs (Lemma et al., 2019; Matsumura et al., 2013) and adverse stock market reactions (Hossain & Masum, 2022; Dzieliński et al., 2022). At the macro level, Naseer et al. (2025a) find that climate risk increases market volatility, reflecting investor sensitivity to policy, physical, and transition risks. These adverse effects are especially pronounced in state-owned enterprises, carbon-intensive industries, and in regions with weak institutional frameworks, where governance lacks resilience (Song et al., 2025; Jin et al., 2025).

Nevertheless, evidence also suggests that this negative relationship is not absolute but can be moderated by managerial capabilities, technological innovation, and institutional policies. Firms with stronger managerial capacity may mitigate

adverse impacts of climate risk through strategic adjustments and enhanced financial adaptability (Almaghrabi, 2023; Song et al., 2025). In addition, the roles of R&D intensity (Naseer et al., 2025a), asset reallocation (Hoang et al., 2025), and capital structure adjustments (Ahmad et al., 2023; Huang et al., 2022) are emphasized in reducing losses, strengthening resilience, and enhancing adaptive capacity. At the institutional and policy level, robust governance frameworks (Jin et al., 2025), transparent markets, and global initiatives such as the Paris Agreement (Naseer et al., 2025b) provide stabilizing effects, enabling markets to more accurately price climate risks. Moreover, the advancement of financial technology has been shown to partially offset the impact of climate risks on firm value and dividends by improving financial management and access to capital (Abbasi et al., 2025). Nonetheless, these moderating factors merely weaken the magnitude of the impact rather than eliminating the overall negative trend.

Although the majority of studies emphasize the adverse effects of climate risk on firm value, there is still evidence suggesting that this relationship may be positive or inconclusive. In certain cases, specific climate factors, such as heavy rainfall or droughts, have been found to enhance financial performance in the power sector, while other climate phenomena exert opposite effects, indicating that the relationship is unstable and highly industry-specific (Sun et al., 2023). From a financial management perspective, climate risk has also been shown to increase the value of cash holdings, as investors perceive them as precautionary signals and assign higher valuations to firms with strong governance and social responsibility (Guizani et al., 2025). Moreover, some studies report heterogeneous results, where transition risks reduce market value but exhibit a positive association with accounting-based financial performance indicators (Mondal & Bauri, 2024). These findings broaden the discussion by suggesting that climate risk not only poses challenges but may also create strategic opportunities for firms, such as proactively pursuing adaptive opportunities (Elijido-Ten & Clarkson, 2019) or leveraging green transitions to enhance ESG reputation and strengthen long-term positioning (Naseer et al., 2024). Nevertheless, other studies also reveal that such opportunities are not consistently reflected in firm valuations, as investors tend to place greater emphasis on legal and market risks, while the benefits from climate-related opportunities are largely sector-dependent (Li et al., 2024). Accordingly, existing research findings remain fragmented and lack consensus, providing insufficient grounds to affirm a sustainable positive relationship.

Based on these foundations, this study develops the first hypothesis:

H1: Climate risk is negatively associated with firm value.

The challenges posed by climate risks to firm value, encompassing both physical and transition risks, are widely recognized as severe. Recent studies highlight that ESG practices may serve as an important moderating mechanism in the relationship between climate risks and firm value. Specifically, ESG is considered a modern risk management tool that not only signals positively to investors but also enhances transparency and meets stakeholder expectations. Implementing ESG practices not only strengthens stakeholder trust but also mitigates adverse impacts of climate change, thereby underscoring the strategic role of ESG in climate risk management (Bagh et al., 2024a, 2024b).

However, most prior research has primarily focused on CSR, which is often viewed as the precursor to ESG. CSR mainly emphasizes social and community responsibilities and has increasingly been demonstrated as a mechanism that enhances corporate resilience against climate risks. Empirical evidence shows that when faced with climate risks, firms tend to intensify CSR activities to mitigate the negative effects on performance (Ozkan et al., 2023). CSR can help maintain stability in the banking sector by enhancing resilience and securing long-term profitability (An et al., 2023; Khemiri et al., 2025), while reducing adverse stakeholder reactions during crises (Christensen, 2016; Flammer, 2013). Even during the COVID-19 pandemic, CSR was found to immediately improve firms' image and market value by strengthening social trust (Qiu et al., 2021). Similarly, Hossain and Masum (2022) emphasize that CSR can act as a "strategic buffer," significantly mitigating the detrimental effects of climate risks.

Although widely studied, CSR has remained largely focused on social and community aspects, whereas ESG is more comprehensive as it integrates environmental and governance dimensions, directly linked to the challenges of climate change. Recent evidence suggests that ESG not only subsumes CSR but also incorporates modern governance mechanisms, green technological innovation, and a sustainability-oriented strategy, thereby generating long-term positive impacts on firm value (Bagh et al., 2024a; Al-Kubaisi & Abu Khalaf, 2025; Liu et al., 2025b; Behl et al., 2022). This implies that ESG may represent a more holistic mechanism than CSR in addressing climate risks. Nevertheless, empirical evidence directly examining the moderating role of ESG in the climate risk–firm value relationship remains scarce. This gap is particularly significant in the context of growing pressures from climate change as well as the increasing demand from investors for sustainability.

Based on the above arguments, we propose the second hypothesis:

H2a: ESG practices positively moderate the relationship between climate risks and firm value.

H2b: ESG practices negatively moderate the relationship between climate risks and firm value.

3. DATA AND METHODOLOGY

3.1. Sample, data, and sources

We constructed a panel dataset comprising 561 publicly listed firms from selected frontier and emerging markets, including Vietnam, India, the Philippines, South Africa, and Malaysia, over the period 2022 – 2024. The study period is determined based on data availability. The dataset is built from annual financial information obtained from the Refinitiv Eikon database, combined with ESG data provided by Refinitiv. Refinitiv's ESG scores are measured transparently and objectively, reflecting firms' relative ESG performance, commitments, and effectiveness across more than 500 comparable indicators covering ESG categories and other controversial issues (Lee & Raschke, 2023). Firm-level climate risk data are estimated using Python-based text mining of information disclosed in annual reports. In addition, macroeconomic variables, including GDP growth and inflation, are collected from the World Bank database.

One note that our dataset covers the period 2022–2024. While we have complete data for both the dependent variable (firm value) and the main independent variable (firm-level climate risk) over a long period, the inclusion of ESG variables as moderators constrains the time horizon. In emerging and frontier markets, ESG data are still limited in coverage and consistency. To maximize the number of firm-level observations with complete information, we therefore restrict our sample to three years.

During data processing, we exclude: (i) firms operating in the financial sector, and (ii) firm-year observations with missing values for key variables. After filtering and cleaning, the final dataset consists of 1,683 firm-year observations, ensuring sufficient reliability for empirical analysis. The research sample is further classified by major industries and years, following the Standard Industrial Classification system.

3.2. Variables definition and measurement

We employ Tobin's Q as the primary measure of firm value. Following the definition of Brainard and Tobin (1968) and Tobin (1969), Tobin's Q is the ratio of the market value of a firm to the replacement cost of its capital, reflecting the firm's incentives to invest in capital. Hayashi (1982) identified the conditions under which the average Tobin's Q equals the marginal Tobin's Q, thereby providing a critical theoretical foundation for the application of this indicator. Subsequent studies, such as Chung and Pruitt (1994), have further refined and extended the concept, reinforcing the role of Tobin's Q as a market-based measure of firm value. In this study, Tobin's Q is defined as the ratio of the total book value of equity and liabilities to the total market value of equity and liabilities, as expressed in Equation (1). This measurement approach has been widely adopted in prior research (Bagh, Bouri et al., 2024; Bagh, Fuwei et al., 2024; Jin et al., 2025).

$$Tobin's\ Q_{i,t} = \frac{Equity\ market\ value_{i,t} + Liabilities\ market\ value_{i,t}}{Equity\ book\ value_{i,t} + Liabilities\ book\ value_{i,t}} \quad (1)$$

The choice of Tobin's Q (TQR) to analyze the impact of climate change risk on firm value is justified by two main reasons. First, Tobin's Q is a comprehensive measure that captures both tangible and intangible assets. Climate change risk can significantly affect both types of assets, for instance, by causing physical damage to plants and equipment while also eroding intangible assets such as brand reputation and customer relationships (Busch & Hoffmann, 2011; Jin & Jorion, 2006). Second, Tobin's Q is a market-based indicator that reflects investors' expectations of a firm's future cash flows (Guenster *et al.*, 2011). Hence, climate change risk can alter these expectations, leading to considerable fluctuations in firm value.

To examine the sensitivity of firm value to climate risk shocks, we construct a climate risk measure based on information extracted from annual reports. This methodology builds on and adapts previous studies, in particular the text analysis approach of Bua et al. (2022) and Nguyen et al. (2023, 2025). Due to our limited access to large amounts of climate news data, and given that our research objective is to measure climate risk at the firm level (rather than relying on news data as in Bua et al. (2022)), we use the natural hazard dictionary developed by Nguyen et al. (2023). Specifically, the measurement procedure is implemented as follows:

1. Text preprocessing: annual reports of enterprises are converted to digital text format and standardized (removal of special characters, standardization of uppercase/lowercase words, word separation).
2. Applying the natural disaster dictionary: we use a list of terms related to hazards and natural disasters from Nguyen et al. (2023). For each report, we identify and count the number of occurrences (term frequency – tf) of these terms.

List of words: adaptive capacity, air burst, airbursts, apocalypse, apocalypses, ash fall, ashfall, avalanche, avalanches, blizzard, blizzards, calamity, calamities, cataclysm, cataclysms, climate change, climate warms, coastal erosion, cold wave, cold waves, coping capacity, cyclone, cyclones, debacle, debacles, derecho, derechos, disaster, disaster risk, disaster risk management, disaster risks, disasters, drought, droughts, earthquake, earthquakes, El Niño, extreme heat, extreme rain, extreme rainfall, extreme rains, extreme temperature, extreme temperatures, extreme weather, firestorm, firestorms, flood, flooded, flooding, floodings, floods, fog, fogs, forest fire, forest fires, freeze, freezes, freezing, gale, gales, geophysical hazard, geophysical hazards, global warming, hail, hailstorm, hailstorms, hazard mitigation, heat wave, heat waves, heavy rainfall, heavy snow, high wind, high winds, hurricane, hurricanes, hydrological hazard, hydrological hazards, La Niña, Landfall, landfalls, landslide, landslides, lava flow, lava flows, microburst, microbursts, mudslide, mudslides, natural hazard, natural hazards, rainfall, rainfalls, rainstorm, rainstorms, rock fall, rock-fall, rockfall, rockfalls, rogue wave, rogue waves, seiche, seiches, severe winter condition, severe winter conditions, snow, snowstorm, snowstorms, storm, storms, thunderstorm, thunderstorms, tornado,tornadoes, tremor, tsunami, tsunamis, twister, typhoon,

volcanic, volcano, volcanos, whirlpool, whirlpools, wildfire, wildfires, wind, winds, windstorm, windstorms, winterstorm, winterstorms

3. Calculating the TF–IDF weight: to assess the importance of each term in each report, we calculate the TF–IDF (term frequency – inverse document frequency). This index allows us to distinguish highly distinctive words (frequently appearing in a company's report but rarely in other reports) from common but less distinctive words.
4. Constructing a climate risk index: we synthesize information from the TF–IDF weights related to the natural disaster vocabulary to form a climate risk measure for each company. This index reflects the level of concern and awareness of the company's management board towards climate risks, as shown through the annual report. High index values indicate that businesses show greater concern for climate risks, while low values indicate limited concern.

For ESG practices, according to previous studies (Aydoğmuş *et al.*, 2022; De La Fuente *et al.*, 2021), we use the firm's overall ESG index based on the ESG scores from Refinitiv. The scoring scale is classified as follows: Scores from 0 to 25 (0–0.25) represent relatively poor ESG performance and a lack of transparency in ESG-related data disclosure. Scores from 26 to 50 (0.26–0.50) indicate acceptable ESG performance with a medium level of transparency in ESG data disclosure. Scores from 51 to 75 (0.51–0.75) reflect good ESG performance and higher-than-average transparency in ESG data disclosure. Finally, scores from 76 to 100 (0.76–1.00) denote excellent ESG performance along with high transparency in ESG data disclosure.

Firm value is used as the outcome variable, firm's climate risk is the treatment variable, and the ESG index is the moderator variable. We employ several confounders at both firm-level and macro-level that may affect firm value. The description and measurement of the control variables are presented in detail in Table 1.

Variables	Measurement	References
Firm size (SIZE)	Firm size (SIZE) = natural logarithm of total assets in year t	(Hossain and Masum, 2022; Naseer et al., 2025a; Song et al., 2025)
Financial leverage (LEV)	Financial leverage (LEV) = debt-to-equity ratio in year t	(Bagh et al., 2024; Hoang et al., 2025; Naseer et al., 2025b, 2024)
lctat	Total current liabilities in year t / Total assets in year t	(Nguyen et al., 2025)
lctlt	Total current liabilities in year t / Total liabilities in year t	(Nguyen et al., 2025)
chlct	Cash in year t / Total current liabilities in year t	(Nguyen et al., 2025)
cheat	(Cash and short-term investments in year t) / (Total assets in year t−1)	(Nguyen et al., 2025)
Inventory ratio (Inventory)	Inventory in year t / Revenue in year t−1	(Kim and Kiymaz, 2024)
Growth	Revenue growth = (Revenue in year t − Revenue in year t−1) / Revenue in year t−1	(Hossain and Masum, 2022; Naseer et al., 2025a; Song et al., 2025)
GDP growth (GDPgrowth)	GDP growth of countries in year t	(Al-Kubaisi and Abu Khalaf, 2025; Liu et al., 2014)
Inflation (INF)	Inflation of countries in year t	(Al-Kubaisi and Abu Khalaf, 2025; Bagh et al., 2024)

Table 1. List of confounders used in the study

3.3. The models

To assess the robustness of the causal effect, we consider two models as presented below. Each model includes several additional firm-specific characteristics as potential confounders. We only present linear regression models. For other

models, for example machine learning–based models, we still use the same set of variables as in the linear regression but allow nonlinear interactions among these variables.

First, we represent the causal relationship in Figure 1 as follows:

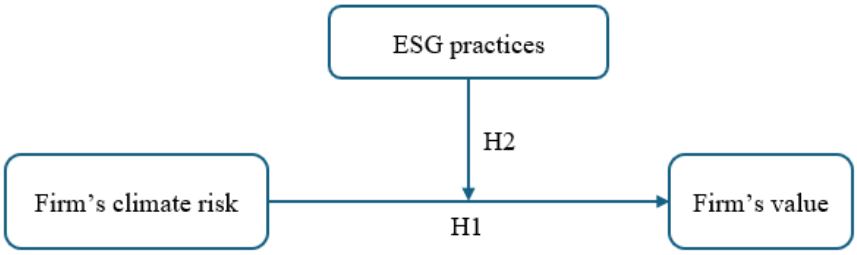


Figure 1. Theorical framework

To specify the causal relationship, we employ the following models: Model 1 (as represented in Equation 2) does not include the moderator variable, whereas Model 2 (as represented in Equation 3) incorporates the moderating effect on this relationship.

Model 1:

$$FV_{i,t} = FCR_{i,t} + SIZE_{i,t} + LEV_{i,t} + lctat_{i,t} + lctlt_{i,t} + chlct_{i,t} + cheat_{i,t} + Inventory_{i,t} + Growth_{i,t} + GDPgrowth_{i,t} + INF_{i,t} \quad (2)$$

Model 2:

$$FV_{i,t} = FCR_{i,t} + FCR_{i,t} \times ESG_{i,t} + SIZE_{i,t} + LEV_{i,t} + lctat_{i,t} + lctlt_{i,t} + chlct_{i,t} + cheat_{i,t} + Inventory_{i,t} + Growth_{i,t} + GDPgrowth_{i,t} + INF_{i,t} \quad (3)$$

3.4. Methodology

In this study, we employ advanced machine learning algorithms within the framework of Double Machine Learning to model the complex relationships among variables. Specifically, Random Forest and XGBoost are selected as the nuisance models to estimate both the outcome and the treatment conditional on the confounders.

The structural Equation (4) specifies the outcome variable as a function of the treatment and the confounders:

$$Y_t^i = f\left(T_t^i, D_t^i\right) + \varepsilon_t \quad (4)$$

In this context, Y_t^i (outcome) denotes the firm value in year t; T_t^i (treatment) represents the firm's climate risk extracted from the company's annual reports in year t; D_t^i (confounders) includes firm-specific characteristics and macroeconomic variables; and ε_t is an error term.

Double or debiased machine learning (DML), as originally introduced by Chernozhukov *et al.* (2018), is an advanced strategy for conducting causal inference with observational data. The key idea of DML relies on the Neyman orthogonality condition of the score function. DML also acknowledges several additional assumptions, such as standard unconfoundedness, nonlinear moment conditions, and other regularity requirements. Despite these assumptions, DML offers several advantages: it leverages the predictive power of machine learning methods, accounts for nonlinear relationships among variables, imposes relatively mild assumptions, corrects bias due to regularization (through Neyman orthogonality) and overfitting (via cross-fitting), and mitigates confounding bias.

Random Forest (Breiman, 2001) is an ensemble learning method that constructs a "forest" of multiple decision trees during training. For regression tasks, the model's final prediction is obtained by averaging the predictions of all individual trees. By averaging predictions across a large number of trees trained on bootstrap samples and by considering random subsets of variables at each node, Random Forest effectively reduces variance and mitigates overfitting. Due to its flexibility and strong performance, Random Forest is well-suited for capturing nonlinear relationships in the estimation models of DML.

XGBoost (Chen & Guestrin, 2016) is a gradient boosting algorithm renowned for its computational efficiency and predictive accuracy. XGBoost builds models sequentially, with each new decision tree added to correct the residual errors of the preceding trees. Its key distinction lies in the optimization of an objective function that incorporates both L1 and L2 regularization terms, thereby controlling model complexity and preventing overfitting. The ability to handle missing data, the flexibility to customize loss functions, and the efficiency when applied to large-scale datasets make XGBoost a powerful tool for modeling prediction functions in causal inference.

4. RESULTS AND DISCUSSION

4.1. Descriptive statistics

Table 2 presents the descriptive statistics of the variables, including the total number of observations, mean, standard deviation, minimum value, maximum value, and variance inflation factor (VIF). The VIF results fall within the acceptable threshold, indicating that none of the variables suffer from multicollinearity issues based on the criterion of VIF > 10.

Variable	Obs	Mean	Std. dev	Min	Max	VIF
FV	1,683	2.727636	3.283673	0.022280	23.668140	
FCR	1,683	1.767157	0.651114	0.000000	3.887897	1.20
ESG	1,683	45.331220	17.131800	5.616526	92.594410	2.39
SIZE	1,683	8.807894	0.660616	6.799331	11.358350	1.99
LEV	1,683	0.191134	0.168927	0.000000	1.317903	2.13
lctat	1,683	0.279163	0.172958	0.000000	2.398591	1.93
lctlt	1,683	0.647132	0.229708	0.000000	1.060532	2.89
chclt	1,683	0.316572	2.703103	0.000000	107.087700	1.06
cheat	1,683	0.162601	0.151462	0.000207	1.341252	1.37
Inventory	1,683	0.144977	0.125917	0.000000	0.791741	1233
Growth	1,683	10.681050	86.200220	-100.000000	3,066.086	1.01
GDPgrowth	1,683	6.661966	2.301560	0.579854	9.190755	1.34
INF	1,683	3.261676	2.472932	-1.872256	6.403485	1.30

Note: VIF values below 10 indicate no multicollinearity problem.

Table 2. Descriptive Statistics and Variance Inflation Factor (VIF)

Table 2 reports the descriptive statistics of the variables employed in this study. Firm value (FV) has a mean of 2.73 with a standard deviation of 3.28, indicating substantial variation across firms in the sample. The firm-level climate risk index (FCR) shows an average value of 1.77, ranging from 0 to 3.89, which suggests heterogeneity in firms' exposure to climate-related shocks. The ESG score has a mean of 45.33, with a relatively large standard deviation of 17.13, reflecting wide dispersion in firms' sustainability practices. Regarding control variables, firm size (SIZE) averages 8.81, while leverage (LEV) averages 0.19. Firm growth (Growth) exhibits strong variability, with a mean of 10.68% but a wide range from –100% to more than 3,000%, highlighting pronounced performance differences among firms. At the macroeconomic level, GDP growth averages 6.66% and inflation (INF) averages 3.26%, broadly consistent with the characteristics of emerging economies. The variance inflation factors (VIFs) reported in Table 2 provide an additional diagnostic for multicollinearity among the explanatory variables. All VIF values are below 2, substantially lower than the conventional cut-off thresholds of 5 or 10 commonly suggested in the literature. This indicates that correlations among independent variables are not sufficiently high to bias the estimation results. In other words, the explanatory power of each variable can be interpreted with confidence, and the regression outcomes are unlikely to suffer from inflated standard errors due to multicollinearity.

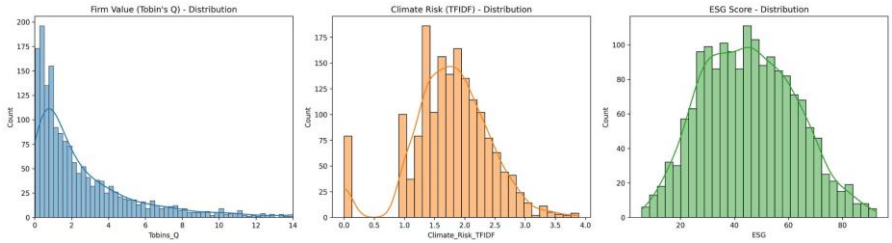


Figure 2. Histogram plots of three main variables

In figure 2, we present three histogram plots, each illustrating the distribution of a key variable in the study. The Firm Value (Tobin's Q) - Distribution plot shows that most firms in the sample have low Tobin's Q values, with a sharp peak on the left and a long tail extending to the right. This represents a right-skewed distribution. This pattern indicates that only a few firms have high Tobin's Q values, while the majority are valued by the market close to their book value. The Firm's Climate Risk (TFIDF) Distribution plot exhibits a near-normal distribution, with a central peak and gradual decline toward both sides. This suggests that the climate risk for firms in the sample is concentrated around a medium level, with very few firms facing extremely low or high climate risk. The ESG Score - Distribution plot also approximates a normal distribution, with a peak in the ESG score range of 60 to 70. This indicates that most firms in the sample have moderately high ESG scores, suggesting that many companies have implemented environmental, social, and corporate governance practices.

4.2. Empirical results and discussion

The study investigates the impact of a firm's climate risk (Treatment) on firm value, measured by Tobin's Q (Outcome). We focus on two main scenarios to clarify the roles of confounders and the moderator variable. Based on the analytical results provided, we interpret in detail the following two cases:

First, we test the direct effect of a firm's climate risk on firm value without incorporating the moderator. In this scenario, the study estimates the Average Treatment Effect (ATE) of a firm's climate risk on firm value, while controlling for the influence of confounders. The LinearDML model is employed, with XGBoost and Random forest serving as the base learner to capture the relationships among variables.

	Direct effect		**Moderating effect**	
	XGBoost	**Random forest**	**XGBoost**	**Random forest**
VARIABLES	(1)	(2)	(3)	(4)
	FV	FV	FV	FV
FCR	-0.132**	-0.103*	-0.132**	-0.103*
	[-0.209, -0.055]	[-0.207, 0.001]	[-0.209, -0.055]	[-0.207, 0.00]
ESG			0.042**	0.038**
			[0.037808, 0.045270]	[0.034752, 0.041154]
FCR*ESG			-0.267**	-0.137*
			[-0.351941, -0.182799]	[-0.245413, -0.028815]
SIZE	-0.151***	-0.089***	-0.197***	-0.052***
	[-0.151, -0.151]	[-0.089, -0.089]	[−0.197,−0.197]	[−0.053,−0.052]
LEV	0.353***	0.801***	0.851***	0.133***
	[0.353, 0.353]	[0.801, 0.801]	[0.851,0.851]	[0.133,0.133]
lctat	-1.353***	-1.567***	-0.997***	-0.995***
	[-1.353, -1.353]	[-1.567, -1.567]	[−0.997,−0.997]	[−0.995,−0.995]
lctlt	-0.524***	-0.309***	-0.492***	-0.659***
	[-0.524, -0.524]	[-0.309, -0.309]	[−0.493,−0.492]	[−0.659,−0.659]
chclt	0.009***	0.017***	0.005***	0.014***
	[0.009, 0.009]	[0.017, 0.017]	[0.005,0.005]	[0.014,0.014]
cheat	-0.662***	-0.346***	-0.641***	-0.439***
	[-0.662, -0.662]	[-0.346, -0.346]	[−0.641,−0.641]	[−0.439,−0.439]

Inventory	-0.172***	-0.024***	-0.281***	0.086***
	[-0.172, -0.172]	[-0.024, -0.024]	[−0.281,−0.281]	[0.086,0.086]
Growth	-0.002**	-0.002	-0.003**	-0.004**
	[-0.003, 0]	[-0.006, 0.001]	[−0.006,0.000]	[−0.009,0.000]
GDPgrowth	-0.008***	-0.022***	-0.017***	-0.031***
	[-0.008, -0.008]	[-0.022, -0.022]	[−0.017,−0.017]	[−0.031,−0.031]
INF	0.011***	0.018***	0.014***	0.024***
	[0.011, 0.011]	[0.018, 0.018]	[0.014,0.014]	[0.024,0.024]

Note, In Table 3, Columns 1-2 display result of the LinearDML Model XGBoost and Randomforest estimation for the direct impact of firm's clumate risk (FCR) on firm's value (FV). Subsequently, we assess the moderating role of ESG practices between FCR and FV, presenting results in columns 5-6. 95% confidence intervals in brackets. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively

Table 3. Results of the LinearDML Model XGBoost and Random Forest

These results imply that, after controlling for confounding factors, corporate climate risk has a significant negative impact on firm value. Specifically, for every unit increase in the climate risk index, Tobin's Q is expected to decrease by an average of 0.132 units in both the XGBoost and Random forest algorithms. In the XGBoost algorithm, the p-value is less than the 5% significance level, indicating that the impact is significant, but this significance level is not maintained in the Random forest algorithm but is still guaranteed to be less than 10%. Furthermore, the 95% confidence interval does not include zero, reinforcing the conclusion that the negative impact of climate risk is real and not random. Climate risk has a significant and negative impact on firm value, suggesting that investors undervalue companies with high levels of climate risk. This finding highlights the importance of controlling for founders to obtain accurate and unbiased causal estimates, thereby providing convincing evidence of the negative impact of climate risk on firm value.

Based on the analysis results, the control variables (confounders) exhibit diverse and statistically significant effects on Firm Value (FV), reinforcing the robustness of the model. Specifically, both micro- and macro-level financial factors show consistent patterns. Financial leverage (LEV) exerts a strong and stable positive impact across all four models, suggesting that prudent use of debt can provide tax shields or enhance managerial discipline, in line with the premises of the Capital Structure Theory (Modigliani & Miller, 1958). In contrast, Firm Size (SIZE) demonstrates a significant negative relationship with FV, which may reflect the complexity, reduced flexibility, or internal governance challenges often observed in large conglomerates, even after controlling for other factors.

Variables related to liquidity and working capital management also play a pivotal role. The cash-to-current liabilities ratio (chlct) is positively associated with FV, highlighting that maintaining sufficient liquidity to meet short-term obligations is valued by the market (Opler et al., 1999). Conversely, the ratio of cash and short-term investments to total assets (cheat) shows a negative sign, particularly in models with high statistical significance. This finding reflects the "Cash Holding Paradox," whereby excessive cash holdings may signal inefficient asset utilization or weak governance, leading investors to assign lower valuations to such assets (Dittmar & Mahrt-Smith, 2007).

At the macroeconomic level, inflation (INF) consistently exerts a positive effect, potentially because firms with strong pricing power can pass on inflationary costs to consumers, thereby preserving or enhancing nominal value (Bagh et al., 2024). Meanwhile, revenue growth (Growth) and GDP growth (GDPgrowth) mostly display negative or insignificant effects, suggesting that during periods of rapid expansion, firms may face higher opportunity costs, greater expansion expenditures, or market expectation pressures, resulting in relatively lower valuations relative to the additional risk (Liu et al., 2014). These findings not only help control for the influence of exogenous factors but also provide critical insights for understanding the operational context in which Firm Climate Risk (FCR) and ESG practices affect FV.

Overall, across both models, firm's climate risk consistently maintains a negative relationship with firm value, which is fully consistent with Hypothesis H1. The findings of the present study are also in line with prior works such as Bagh, Bouri *et al.* (2024); Bagh, Fuwei *et al.* (2024); Jin *et al.* (2025); Naseer *et al.* (2024, 2025) which suggest that climate risk can erode firm value through costs arising from environmental damages (Walker & Wan, 2012). This evidence is also consistent with earlier macro-level research (Dell *et al.*, 2014; Burke *et al.,* 2015), which documented the adverse effects of climate change on economic growth and productivity. Accordingly, the present study not only reinforces the prevailing trend in the literature but also contributes credible causal evidence by applying Double Machine Learning to address confounding, thereby helping to bridge the research gap concerning the direct impact of climate risk on firm value.

Second, we examine the moderating effect of ESG on the relationship between climate risk and firm value. This scenario is more complex, as it not only controls for confounding variables but also incorporates the moderating role of ESG scores. Specifically, we want to examine whether the impact of climate risk on firm value varies depending on the level of ESG practices adopted by the firm. The estimated mean treatment effect in this case is -0.2674, which is significantly

larger in absolute value than in Case 1. This result represents a Conditional Average Treatment Effect (CATE), which is averaged over all values of the ESG moderator. The negative and statistically significant ATE again confirms the adverse impact of climate risk. The increase in magnitude from -0.1316 to -0.2674 shows that when ESG is included in the model, the relationship between climate risk and firm value becomes more pronounced. This suggests that ESG plays an important moderating role in shaping this relationship. Table 3 shows a coefficient of −0.26737 (at the 5% significance level) for the XGBoost algorithm and -0.13711 (at the 10% significance level) for the Random Forest algorithm. The moderating effect of ESG is negative. This means that when climate risk increases, companies with high ESG scores are punished by the market more heavily than companies with low ESG scores. In other words, ESG does not mitigate the negative impact of FCR, but even amplifies it.

When testing the moderating role of ESG through an interaction model to evaluate Hypothesis H2, the results reveal that ESG practices significantly alter the relationship between climate risk and firm value. Incorporating ESG into the model makes the adverse effect of climate risk more evident, thereby supporting Hypothesis H2b, which posits that the interaction between FCR and ESG practices may amplify the negative effect of climate risk on firm value. This implies that overlooking ESG could lead to underestimating the actual magnitude of the impact. Furthermore, the interaction results suggest that ESG is not only a preventive mechanism but may also amplify negative effects when market expectations are not met. This finding contrasts with Bagh et al. (2024) but aligns with signaling theory and stakeholder theory: firms with high ESG scores are expected to manage environmental risks more effectively, so when they still suffer from adverse climate risk impacts, the market reacts more strongly, leading to significant declines in stock prices and firm value (Connelly *et al.*, 2010; Li et al., 2025). These results shed light on the ongoing debate in prior studies (Xu et al., 2022, 2024) and highlight the dual nature of ESG: it can serve both as a mitigating mechanism and as a potential amplifier of negative effects. This constitutes an important academic contribution of the present study in explaining the moderating effect of ESG.

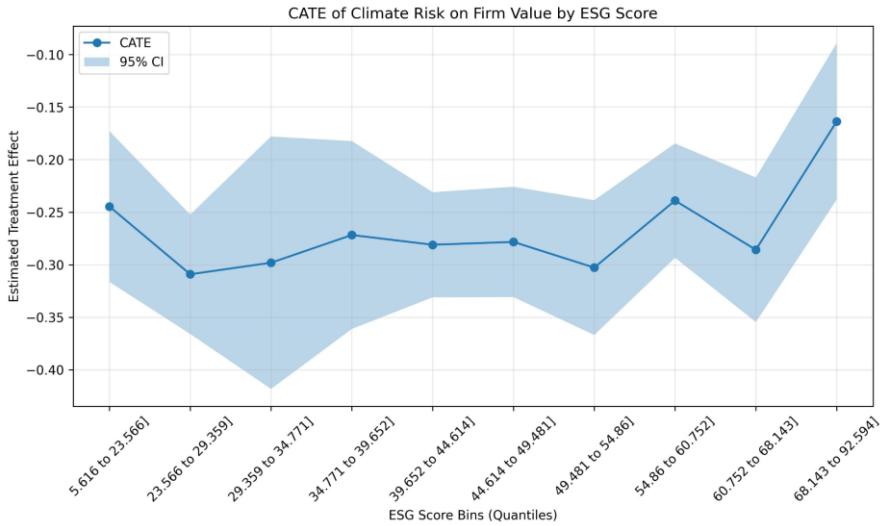


Figure 3. Conditional Causal Effects Plot (CATE Plot)

Next, we provide a conditional average treatment effect (CATE) plot that provides key insights into how climate risk impacts firm value across different ESG performance levels. All estimated impacts are below zero, confirming that climate risk has a uniform negative impact on firm value. This finding is consistent with previous studies showing that environmental and regulatory uncertainty, extreme weather events, and other climate-related risks can reduce firm financial performance (Bagh, Bouri et al., 2024; Bagh, Fuwei et al., 2024; Jin et al., 2025; Naseer et al., 2024, 2025). Notably, the magnitude of this negative impact varies across ESG score quantiles. Companies with the lowest ESG scores (5,616–23,565) suffered the strongest adverse impacts, while those in the lower ESG quartiles suffered the strongest negative effects, with a CATE of approximately -0.31, suggesting that failure to fully engage with ESG may leave companies particularly vulnerable to climate-related shocks. In contrast, companies in the highest ESG quartile (68,143 to 92,594) experienced the smallest value decline, of only -0.16. This difference suggests that adopting ESG standards acts as a financial cushion, helping companies improve their resilience and mitigate the decline in value when faced with climate risks. This reinforces the view that ESG practices, including proactive environmental management and sustainable corporate governance, can act as a buffer against external risks. However, the graph also shows that the negative impact

does not disappear even at the highest ESG levels (68,143–92,594), suggesting that a high ESG score alone does not provide complete protection. This non-linear pattern may reflect several factors. First, although ESG activities improve resilience, extreme or systemic climate risks may still affect all companies regardless of their ESG performance. Second, high ESG scores may be correlated with higher market visibility or reporting requirements, which may increase the exposure to climate risks in the eyes of investors.

The shaded band around the CATE line represents the 95% confidence interval (95% CI), which reflects the uncertainty of the estimate. The fact that the entire shaded band lies below the x=0 axis reinforces the statistical significance of the results, suggesting that the negative impact of climate risks is not random. These confidence intervals tend to be wider at the low and middle ESG quantiles, but remain relatively stable. Notably, at the highest ESG quantile, the confidence intervals appear to narrow, implying that the estimates of ESG-leading companies' resilience are more accurate. Taken together, these results highlight that improving ESG scores is an effective strategy for mitigating financial risks associated with climate change.

5. CONCLUSION

This study provides clear empirical evidence of a negative relationship between climate risk and corporate value, with the magnitude of the impact varying significantly depending on the ESG practice conditions. First, the study adapted previous studies using the tf-idf method, combined with a vocabulary related to natural disasters and climate change to suit the determination of corporate risk levels. Then, using the ability to handle complex non-linear relationships and provide higher prediction accuracy on many real-world datasets, the authors used Random forest and XGBoost algorithms to automatically capture and model the complex and non-linear interactions in this relationship. The analysis results show that although climate risks significantly reduce Tobin's Q, ESG integration does not fully mitigate this impact and may even amplify the negative impact of climate risks on corporate value, especially for companies with weak ESG practices. This result implies that companies with low ESG scores are more vulnerable to climate risks than those with higher ESG practices. This finding emphasizes that ESG for businesses cannot be considered as a superficial risk management tool but must be integrated with sustainable finance strategies and technological innovation. Only by comprehensively integrating these factors can businesses enhance their resilience to climate risks and maintain long-term value. Based on these findings, some recommendations can be proposed. First, businesses should move beyond token ESG adoption and ensure that ESG policies are closely aligned with long-term strategic planning, financial risk management, and low-carbon technology innovation. Second, investors are encouraged to evaluate ESG performance in conjunction with a business's actual exposure to physical and transition climate risks, thereby avoiding over-reliance on ESG scores as a standalone signal. Third, policymakers and regulators in emerging and frontier markets should strengthen disclosure standards, encourage sustainable investing, and promote frameworkssuch as the TCFD recommendations – to enhance transparency in reporting climate-related risks. Finally, global coordination and knowledge-sharing forums should be created to support companies in vulnerable markets in adhering to best practices and building resilience to climate shocks.

This study also acknowledges several limitations, including the limited data coverage, the limited focus on emerging and frontier markets, and the limited three-year data period due to data collection constraints. Future research could expand to analyze each ESG pillar (E, S, G), consider heterogeneous impacts across sectors, and incorporate additional regulatory factors such as corporate governance, green technology innovation, or participation in global climate initiatives. These future directions promise to provide a more comprehensive understanding of the impact mechanisms and corporate resilience to climate risks.

6. REFERENCES

Abbasi, K., Alam, A., Goodell, J. W., Du, A. M., & Brohi, N. A. (2025b). Vulnerability of energy firms to climate risk: Does fintech development help? *Energy Economics*, 108516. https://doi.org/10.1016/j.eneco.2025.108516

Abel, A., & Eberly, J. (1993b). *A unified model of investment under uncertainty*. https://doi.org/10.3386/w4296

Ahmad, M. F., Aktas, N., & Croci, E. (2023). Climate risk and deployment of corporate resources to working capital. *Economics Letters*, *224*, 111002. https://doi.org/10.1016/j.econlet.2023.111002

Al-Kubaisi, M. K., & Khalaf, B. A. (2025). Climate governance, ESG reporting, and the firm performance: Does it matter more for Europe or the GCC? *Sustainability*, *17*(9), 3761. https://doi.org/10.3390/su17093761

Almaghrabi, K. S. (2023). Climate change exposure and firm performance: Does managerial ability matter? *Sustainability*, *15*(17), 12878. https://doi.org/10.3390/su151712878

An, X., Ding, Y., & Wang, Y. (2023). Green credit and bank risk: Does corporate social responsibility matter? *Finance Research Letters*, *58*, 104349. https://doi.org/10.1016/j.frl.2023.104349

Aydoğmuş, M., Gülay, G., & Ergun, K. (2022b). Impact of ESG performance on firm value and profitability. *Borsa Istanbul Review*, *22*, S119–S127. https://doi.org/10.1016/j.bir.2022.11.006

Bagh, T., Bouri, E., & Khan, M. A. (2024). Climate change sentiment, ESG practices and firm value: international insights. *China Finance Review International*. https://doi.org/10.1108/cfri-07-2024-0381

Bagh, T., Fuwei, J., & Khan, M. A. (2024). Corporate ESG investments and Firm's value under the real-option framework: Evidence from two world-leading economies. *Borsa Istanbul Review*, *24*(2), 324–340. https://doi.org/10.1016/j.bir.2024.01.002

Bagh, T., Fuwei, J., & Khan, M. A. (2024b). From risk to resilience: Climate change risk, ESG investments engagement and Firm's value. *Heliyon*, *10*(5), e26757. https://doi.org/10.1016/j.heliyon.2024.e26757

Barkemeyer, R. (2007). Legitimacy as a key driver and determinant of CSR in developing countries. *Paper for the*, 271-350.

Behl, A., Kumari, P. S. R., Makhija, H., & Sharma, D. (2021). Exploring the relationship of ESG score and firm value using cross-lagged panel analyses: case of the Indian energy sector. *Annals of Operations Research*, *313*(1), 231–256. https://doi.org/10.1007/s10479-021-04189-8

Berkman, H., Jona, J., & Soderstrom, N. (2024). Firm-specific climate risk and market valuation. *Accounting Organizations and Society*, *112*, 101547. https://doi.org/10.1016/j.aos.2024.101547

Brainard, W. C., & Tobin, J. (1968). Pitfalls in financial model building. *The American economic review*, *58*(2), 99-122. http://www.jstor.org/stable/1831802

Breiman, L. (2001). Random forests. *Machine learning*, *45*(1), 5-32. https://doi.org/10.1023/A:1010933404324

Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2024). Transition versus physical climate risk pricing in European financial markets: a text-based approach. *European Journal of Finance*, *30*(17), 2076–2110. https://doi.org/10.1080/1351847x.2024.2355103

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239. https://doi.org/10.1038/nature15725

Busch, T., & Hoffmann, V. H. (2011). How hot is your bottom line? linking carbon and financial performance. *Business & Society*, *50*(2), 233–265. https://doi.org/10.1177/0007650311398780

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2010b). Signaling Theory: A Review and assessment. *Journal of Management*, *37*(1), 39–67. https://doi.org/10.1177/0149206310388419

Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785-794). https://doi.org/10.1145/2939672.2939785

Christensen, D. M. (2015). Corporate Accountability Reporting and High-Profile Misconduct. *The Accounting Review*, *91*(2), 377–399. https://doi.org/10.2308/accr-51200

Chung, K. H., & Pruitt, S. W. (1994). A Simple Approximation of Tobin's q. *Financial Management*, *23*(3), 70. https://doi.org/10.2307/3665623

De La Fuente, G., Ortiz, M., & Velasco, P. (2021b). The value of a firm's engagement in ESG practices: Are we looking at the right side? *Long Range Planning*, *55*(4), 102143. https://doi.org/10.1016/j.lrp.2021.102143

Deegan, C. (2006). Legitimacy theory. In *Methodological Issues in Accounting Research: Theories, Methods and Issues* (pp. 161–181). Spiramus Press Ltd.

Del Fava, S., Gupta, R., Pierdzioch, C., & Rognone, L. (2024). Forecasting international financial stress: The role of climate risks. *Journal of International Financial Markets, Institutions and Money*, *92*, 101975. https://doi.org/10.1016/j.intfin.2024.101975

Dell, M., Jones, B.F. & Olken, B.A. (2014). 'What do we learn from the weather? The new climate-economy literature', *Journal of Economic Literature*, 52(3), pp. 740–798. https://doi.org/10.1257/jel.52.3.740

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic literature*, *52*(3), 740-798. 10.1257/jel.52.3.740

Dittmar, A. and Mahrt-Smith, J. (2006) 'Corporate governance and the value of cash holdings,' *Journal of Financial Economics*, 83(3), pp. 599–634. https://doi.org/10.1016/j.jfineco.2005.12.006.

Dzielinski, M., Eugster, F., Sjöström, E., & Wagner, A. F. (2022). *Climate talk in corporate earnings calls*. Mistra Center for Sustainable Markets. 10.2139/ssrn.4021061

Elijido-Ten, E. O., & Clarkson, P. (2019). Going beyond climate change risk management: Insights from the world's largest most sustainable corporations. *Journal of Business Ethics*, *157*(4), 1067-1089. 10.1007/s10551-017-3611-6

Flammer, C. (2013). Corporate social responsibility and shareholder reaction: The environmental awareness of investors. *Academy of Management journal*, *56*(3), 758-781. https://doi.org/10.5465/amj.2011.0744

Freeman, R. E. (2010). *Strategic management: A stakeholder approach*. Cambridge university press

Guenster, N., Bauer, R., Derwall, J., & Koedijk, K. (2011). The economic value of corporate eco-efficiency. *European financial management*, *17*(4), 679-704. https://doi.org/10.1111/j.1468-036X.2009.00532.x

Guizani, A., Nizar, H., Lakhal, F., Hamza, T., & Benkraiem, R. (2025). Does climate risk vulnerability affect the value of excess cash? International evidence. *International Journal of Finance & Economics*, *30*(3), 2662-2681. https://doi.org/10.1002/ijfe.3035

Hayashi, F. (1982). Tobin's marginal q and average q: A neoclassical interpretation. *Econometrica: Journal of the Econometric Society*, 213-224. https://doi.org/10.2307/1912538

Hoang, K., Pham, L., Ha, O. K., & Nghiem, H. X. (2025). Firm-level climate change exposure and firm efficiency. *International Review of Economics & Finance*, *101*(C). 10.1016/j.iref.2025.104220

Hossain, A. T., & Masum, A. A. (2022). Does corporate social responsibility help mitigate firm-level climate change risk?. *Finance Research Letters*, *47*, 102791. https://doi.org/10.1016/j.frl.2022.102791

Huang, H. H., Kerstein, J., Wang, C., & Wu, F. (2022). Firm climate risk, risk management, and bank loan financing. *Strategic Management Journal*, *43*(13), 2849-2880. https://doi.org/10.1002/smj.3437

Jin, S., Gan, C., & Li, Z. (2025). Impact of firm-level climate change exposure on firm value: The moderating role of carbon transparency. *Borsa Istanbul Review*, *25*(2), 360-373. https://doi.org/10.1016/j.bir.2025.01.006

Jin, Y., & Jorion, P. (2006). Firm value and hedging: Evidence from US oil and gas producers. *The journal of Finance*, *61*(2), 893-919. https://doi.org/10.1111/j.1540-6261.2006.00858.x

Kim, W. S., & Kiymaz, H. (2024). Inventory Investment, Firm Value, and Growth: Evidence from Korea. ***한국경영학회 융합학술대회***, 637-671.

Khemiri, M. A., Saidi, H., & Hakimi, A. (2025). Climate Risk and Bank Performance: What Role does Corporate Social Responsibility Play?. *International Journal of Energy Economics and Policy*, *15*(4), 73-82. https://doi.org/10.32479/ijeep.19879

Lee, M. T., & Raschke, R. L. (2023). Stakeholder legitimacy in firm greening and financial performance: What about greenwashing temptations?. *Journal of Business Research*, *155*, 113393. https://doi.org/10.1016/j.jbusres.2022.113393

Lemma, T. T., Feedman, M., Mlilo, M., & Park, J. D. (2019). Corporate carbon risk, voluntary disclosure, and cost of capital: South African evidence. *Business Strategy and the Environment*, *28*(1), 111-126. https://doi.org/10.1002/bse.2242

Li, Q., Liu, C., & Lin, Y. (2025). ESG and Firm Value: The Moderating Effects of Corporate Transparency and Institutional Environment. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.70005

Li, X., Luo, L., & Tang, Q. (2024). Climate risk and opportunity exposure and firm value: An international investigation. *Business Strategy and the Environment*, *33*(6), 5540-5562.https://doi.org/10.1002/bse.3747

Liu, R., Li, J., & Wu, M. (2025a). The Impact of Climate Change Risk on Corporate Debt Financing Capacity: A Moderating Perspective Based on Carbon Emissions. *Sustainability*, *17*(14), 6276. https://doi.org/10.3390/su17146276

Liu, Y., Dong, K., Nepal, R., & Afi, H. (2025b). How do climate risks affect corporate ESG performance? Micro evidence from China. *Research in International Business and Finance*, *76*, 102855. https://doi.org/10.1016/j.ribaf.2025.102855

Matsumura, E. M., Prakash, R., & Vera-Muñoz, S. C. (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review*, *89*(2), 695-724. https://doi.org/10.2308/accr-50629

Modigliani, F. and Miller, M.H. (1958) 'The Cost of Capital, Corporation Finance and the Theory of Investment,' *The American Economic Review*, 48(3), pp. 261–297. https://www.jstor.org/stable/1809766

Mondal, A., & Bauri, S. (2024). The impact of climate transition risk on firms' value–evidence from select Indian-listed companies. *Asian Journal of Accounting Research*, *9*(3), 257-274.https://doi.org/10.1108/AJAR-08-2023-0264

Morck, R., Shleifer, A., & Vishny, R. W. (1988). Management ownership and market valuation: An empirical analysis. *Journal of financial economics*, *20*, 293-315.https://doi.org/10.1016/0304-405X(88)90048-7

Naseer, M. M., Guo, Y., & Zhu, X. (2025a). The dynamics of corporate climate risk and market volatility: International evidence. *The North American Journal of Economics and Finance*, *78*, 102435. https://doi.org/10.1016/j.najef.2025.102435

Naseer, M. M., Guo, Y., & Zhu, X. (2025b). When climate risk hits corporate value: The moderating role of financial constraints, flexibility, and innovation. *Finance Research Letters*, *74*, 106780. https://doi.org/10.1016/j.frl.2025.106780

Naseer, M. M., Khan, M. A., Bagh, T., Guo, Y., & Zhu, X. (2024). Firm climate change risk and financial flexibility: Drivers of ESG performance and firm value. *Borsa Istanbul Review*, *24*(1), 106-117. https://doi.org/10.1016/j.bir.2023.11.003

Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, *103*(10), 3510-3517. https://doi.org/10.1073/pnas.0509842103

Nguyen, M., Ye, T. T., Xiao, Y., & Daniel, S. (2025). Text as Treatment from Financial Reports: Effects of Natural Hazard Risk on Firm Profitability Using Causal Machine Learning. *Available at SSRN*. http://dx.doi.org/10.2139/ssrn.5093225

Nguyen, M., Yeh, T.-T., Xiao, Y., and Daniel, S. (2023). Text as treatment from Form 10-K: Causal effects of perceived natural hazards on firm profitability. *ICIS 2023 Special Interest Group on Big Data Proceedings.*

Opler, T. (1999) 'The determinants and implications of corporate cash holdings,' *Journal of Financial Economics*, 52(1), pp. 3–46. https://doi.org/10.1016/s0304-405x(99)00003-3.

Ozkan, A., Temiz, H., & Yildiz, Y. (2023). Climate risk, corporate social responsibility, and firm performance. *British Journal of Management*, *34*(4), 1791-1810. https://doi.org/10.1111/1467-8551.12665

Pradhan, R. P., Samarakoon, S. M. R. K., Maradana, R. P., & Sahoo, P. (2025, May). Climate change disclosure and firm value in a frontier market: Exploring the determinants. In *Natural Resources Forum* (Vol. 49, No. 2, pp. 1931-1964). Oxford, UK: Blackwell Publishing Ltd. https://doi.org/10.1111/1477-8947.12462

Qiu, S. C., Jiang, J., Liu, X., Chen, M. H., & Yuan, X. (2021). Can corporate social responsibility protect firm value during the COVID-19 pandemic?. *International Journal of Hospitality Management*, *93*, 102759. 10.1016/j.ijhm.2020.102759

Song, Y., Lu, L., Liu, J., Zhou, J., Wang, X., & Li, F. (2025). A Study of the Factors Contributing to the Impact of Climate Risks on Corporate Performance in China's Energy Sector. *Sustainability*, *17*(11), 5139. https://doi.org/10.3390/su17115139

Spence, M. (1973). Job market signalling. *The Quarterly Journal of Economics*, 87(3), 374.

Stryjakiewicz, T., Męczyński, M., & Stachowiak, K. (2014). Role of creative industries in the post-socialist urban transformation. *Quaestiones Geographicae*, *33*(2), 19-35. https://doi.org/10.2478/quageo-2014-0013

Sun, Y., Zou, Y., Jiang, J., & Yang, Y. (2023). Climate change risks and financial performance of the electric power sector: Evidence from listed companies in China. *Climate Risk Management*, *39*, 100474. https://doi.org/10.1016/j.crm.2022.100474

Task Force on Climate-related Financial Disclosures. (2017, June). *Recommendations of the Task Force on Climate-related Financial Disclosures* at https://assets.bbhub.io/company/sites/60/2020/10/FINAL-2017-TCFD-Report-11052018.pdf

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of money, credit and banking*, *1*(1), 15-29. https://doi.org/10.2307/1991374

Vestrelli, R., Colladon, A. F., & Pisello, A. L. (2024). When attention to climate change matters: The impact of climate risk disclosure on firm market value. *Energy Policy*, *185*, 113938. https://doi.org/10.1016/j.enpol.2023.113938

Walker, K., & Wan, F. (2012). The harm of symbolic actions and green-washing: Corporate actions and communications on environmental performance and their financial implications. *Journal of business ethics*, *109*(2), 227-242. https://doi.org/10.1007/s10551-011-1122-4

Field Code Changed